Emissions Trading, Carbon Pricing, and the Impact on Carbon Producing Firms: A Study of Phase III of the European Union Emissions Trading Scheme

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ABSTRACT

This thesis examines the firm level impact of the European Union Emissions Trading Scheme (EU ETS), the ability to hedge carbon price, and the determinants of carbon price. The analysis focuses on phase III of the EU ETS. The work of Koch and Bassen (2013) is extended by investigating whether carbon-adjusted expected returns differ post-2013, as the trading scheme shifted to full auctioning. The findings show a lack of significant exposure to carbon price for the majority of carbon producing European firms. For firms where significant exposure to the price of carbon was found, firms' returns required on equity were substantially higher after carbon exposure was considered. Whether carbon could be hedged effectively using conventional techniques was investigated, and a simple ordinary least squares hedge ratio was found to be the most effective. Further, the hedge ratio for carbon was found to be within the normal 0.5-1 range of typically hedged commodities. Finally, the carbon price determinants were investigated to determine whether energy prices and weather explain the carbon price in phase III, and how this relationship changed since full auctioning came into place in 2013. Energy prices were found to impact carbon price in phase III, however, the best model explained only 12% of carbon price variation. Weather variables were not found to impact carbon price except in one case of unanticipated temperature change. The results indicate that it is not the temperatures themselves that impact carbon price, rather unanticipated changes in temperature.

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1 INTRODUCTION/AIM

Emissions are becoming increasingly important as a commodity and will likely continue to do so. Commitments to climate change are ever increasing, imposing risks for firms which cannot be ignored. The Paris Agreement, which came into force in November 2016, is a global effort. With Nicaragua and Syria both signing in 2017, the United States is the only country in the world to not support the agreement (BBC, 2017; Climate Analytics, 2018; Sampathkumar & Cockburn, 2017). The resulting changes in policy and practice will likely result in increased environmental risk for firms operating worldwide, as restrictions are put in place to limit emissions. The Paris Agreement commits to limiting temperature increases to 2^{o}C above pre-industrial levels; this limit reduces the risks to, and impacts arising from, climate change (United Nations, 2015).

To achieve no more than 2^{o}C of warming means only one-third of proven fossil fuel reserves existing in 2015 can be burned (Kiyar & Wittneben, 2015). The carbon budget for 2000 through 2050 is 886 gigatonnes (Gt) of CO_2, where 325 Gt had already been used by 2010: 282 Gt from burning fossil fuels and 39 Gt from land use changes (Carbon Tracker Initiative, 2011). In the 40 years from 2010 to 2050, the remaining budget is only 565 Gt; comparatively, the world's proven reserves in 2011 totalled 2795 GtCO_2 (Carbon Tracker Initiative, 2011).

McGlade and Etkins' 2015 article in *Nature* found that globally, without carbon capture and storage technology, 35 percent of oil reserves, 52 percent of gas and 88 percent of coal reserves are unburnable if the 2^{o}C goal is to be achieved. In Europe alone, 21 percent of oil, 6 percent of gas and 89 percent of coal reserves cannot be used (McGlade & Ekins, 2015). Thus, fossil fuel companies are faced with stranded assets: reserves recorded as assets that cannot be burned if global goals are to be reached and the environment protected. Citigroup (2015) examined this issue and estimated the value of stranded assets at around US$100 trillion. As stated by Steve Waygood of Aviva Investors, "Valuations of the oil and gas sector still assume that they will be able to take all proven and probable reserves out of the ground and burn them" (as cited in Carbon Tracker Initiative, 2011 p.20). Implicit in the revelation of unburnable carbon and stranded assets is the idea that any further capital expenditure invested in finding new fossil fuels will not yield returns. It is, therefore, puzzling that energy giants continue to pour millions of investors' dollars into these activities each year. In 2017 BP's exploratory activities resulted in approximately a billion barrels of oil being discovered; it was their most successful year for exploration since 2004 (BP, 2018). If current estimates are correct, this oil cannot be burned.

The result for BP is likely significant stranded assets in their balance sheets and exploration expenditure unable to yield profits.

Firms exist for which their entire business model rests on the ability to burn the fossil fuel reserves in their balance sheets; increasingly firms and investors alike are realising that the once brilliant business model of energy giants is becoming outdated (Kiyar & Wittneben, 2015). In a surprise announcement during the 2014 Earth Summit in Lima, Germany's largest electricity producer E.ON declared it would spin off all nuclear and fossil fuel business into an independent entity and focus purely on renewable energy (Kiyar & Wittneben, 2015).

The increasing risks to companies arising from environmental constraints and considerations mean it is important to understand how firms are responding to and managing the risks. Firms in the European Union (EU) have been operating under climate change legislation in the form of the European Union Emissions Trading Scheme (EU ETS) since 2005. Studying the behaviour of these firms may provide insight into the risk faced and responses made by firms in the face of climate regulation.

The EU ETS is a cap-and-trade scheme where firms must surrender one emissions allowance for each metric tonne of carbon dioxide (or equivalent greenhouse gas) emitted. Allowances are traded on the European Energy Exchange as well as the Intercontinental Exchange. Futures and options on the allowances are also traded. The scheme covers the entire European Economic Area with the European Free Trade Association (EFTA) countries also joining: Norway, Iceland and Liechtenstein (European Commission, 2015). The objectives of the EU ETS are to reduce emissions, internalize external costs of CO_2, and to encourage firms to invest in cleaner technology (Urdal, Kopp, & Volker, 2006). The third objective is critical to its success; incentives must be structured so that technological innovation and clean technology choice is promoted (Urdal et al., 2006).

The consensus in the literature is that prior to phase III, the EU ETS has had a modest effect on company performance. However, the auctioning system in place in phase III has the potential to negatively impact profits (Abrell, Ndoye, & Zachmann, 2011). How firms' competitiveness and value will be impacted by the EU ETS in future is uncertain. Current literature has studied phases I and II where allowances were largely allocated to firms for free. Due to this change in regulation, there is no clear answer to whether carbon producing European firms face carbon price risk today.

Research on how this scheme has impacted company decision making and how firms are managing environmental risk is limited. Extensive research has been undertaken to learn from EU ETS performance in reducing emissions as well as to understand the carbon pricing mechanism. Current and prior literature is largely focused on country or industry level effects of the scheme and there remains a gap in the literature for firm-level research. If, as hypothesised, firms in the EU do face carbon price risk, there is no clear answer as to how they should go about managing this risk. As a commodity, the literature addresses carbon as being unique, with its own market characteristics separate from that of traditional commodities. From a firm perspective, does this mean carbon price risk cannot be managed using traditional techniques currently used?

The aim is to learn how the EU ETS and its commitments are currently influencing carbon producing European firms in terms of risk, whether this risk can be managed with traditional hedge ratio techniques and how the carbon price is determined.

Therefore, the following key questions regarding the firm-level impact of the EU ETS will be investigated:

1. Do carbon producing European firms face carbon price risk in phase III?
2. Can carbon price risk be hedged effectively using conventional techniques in phase III?
3. Do energy prices and weather significantly determine carbon price in phase III as they have done in prior phases?

Few other countries, including New Zealand, have implemented an emissions trading scheme since the EU did so. The only country-wide established emissions trading schemes are the European, Australian, and New Zealand schemes; with Mexico planning to implement a cap and trade scheme by 2021 (White & Case, 2017). Other established schemes exist in the Canadian cities of Ontario and Quebec, the American states on the East coast and California, and in the Japanese city of Tokyo (White & Case, 2017).

Since the emissions trading scheme is the principal response by the New Zealand Government to climate change, it is important to understand how this response impacts firms operating under it. Lessons learnt from European firms in managing carbon price risk may be helpful for New Zealand firms operating under the New Zealand scheme.

2 LITERATURE REVIEW

2.1 The European Union Emissions Trading Scheme

2.1.1 Getting here

The prospect of tradable permits used to allocate the burden of controlling pollution between emitters is not new; it was written about in 1966 by Thomas Crocker and in 1968 by John Dales (Morrison, 2008). A cap-and-trade system has been included in academic debate for more than fifty years and can be traced back to work by Ronald Coase (Morrison, 2008). The EU ETS itself has been operating since 2005.

An early leader in supporting quantitative restrictions on greenhouse gases, the European Union argued in favour of binding targets at the Rio Summit in 1992 (Convery, 2009). In the same year, the European Commission attempted to implement a carbon tax as a means to reduce carbon emissions; the tax would be European Union-wide (Convery, 2009). The tax proposal was withdrawn just 5 years later; as explained by Convery (2009) opposition from member states was too strong due to the fierce protection of their right to fiscal autonomy. It was feared that despite the carbon tax being proposed as an exception, further union wide taxes would follow, and fiscal control would slowly transfer to the European Commission.

As early as June 1998 the European Commissioner for the Environment Ritt Bjerregaard said: "We have to get involved in emissions trading …we cannot let others dictate the rules" as quoted in the book by Skjaerseth and Wettestad (as cited in Convery, 2009). The process moved quickly with two other key steps occurring in the same month: Member states agreed to a burden-sharing agreement and the European Commission issued 'Climate Change – Towards an EU Post Kyoto Strategy' which included an important statement that the EU could set up its own trading scheme by 2005 (Convery, 2009). While the EU ETS is entirely independent and unreliant on the 1997 Kyoto Protocol (hereafter: The Protocol), without the events that surrounded its ratification, the EU ETS may never have come into fruition (Ellerman & Buchner, 2007).

The 1997 Protocol was the first international treaty to limit greenhouse gas emissions (Barrett, 1998). Following negotiations, it came into effect in February 2005 (United Nations). Recognition of the greenhouse gas levels in the atmosphere initiated the need for commitment from developed countries to binding targets on their emissions levels. An earlier conference in

Toronto (1988) recognised the need and recommended lowering emissions at a target of 20% reduction by 2005. This was, however, an arbitrary target with no countries bound to this figure. The binding targets committed to by the ratifying countries is arguably the most significant feature of the Protocol (Barrett, 1998). Under the Protocol, countries must monitor and record actual emissions while working to meet their targets. Three market-based mechanisms offer additional means of meeting targets; international emissions trading, clean development and joint implementation (United Nations). A total of 37 industrialised countries ratified the Protocol, committing to its legally-binding targets for the first commitment period of 2008 through 2012 (European Commission, 2015).

The road to ratification was not smooth. In March of 2001, the Bush administration made the announcement that the United States would not ratify the Protocol; this brought its fate into question and led the EU to take the helm (Convery, 2009). The EU's leadership kept Japan and Canada on board and gained the support of Russia (Convery, 2009). With Russia ratifying, the required 55 parties emitting a minimum of 55% of global emissions had ratified and the Protocol came into effect in 2005. The way the EU stepped up when the United States stepped down demonstrated it could be "innovative, courageous and effective in ensuring that its own performance matched its rhetoric" (Convery, 2009 p. 396).

Interestingly, throughout negotiations of the Protocol, the EU fought against an emissions trading mechanism due to the fear that allowances which were 'hot air' – surplus emission allowances from countries that made no effort to reduce emissions and yet still came under the cap – would be traded; the concern was that if allowed to happen, these 'hot air' allowances would undermine the whole emission reduction objective (Convery, 2009).

While the Kyoto Protocol was being negotiated, the European Commission worked on implementing a policy to ensure the EU could meet its share of the commitment; the EU ETS was presented as a credible and effective means of doing so (Convery, 2009). The release of the Green Paper in 1999 marked the move from an idea that the EU could have its own trading scheme to the notion that it would; the Green Paper launched the discussion of key policy choices (Convery, 2009). Remarkably it took only six years to implement and since January 1st, 2005 a price has been paid on carbon dioxide emissions in the EU (Ellerman & Buchner, 2007).

2.1.2 The Scheme

Today the EU ETS covers operators in 31 countries that together are responsible for around half of EU emissions; in total, more than 11,000 power stations and industrial plants are included in the scheme as well as flights between the participating countries (European Commission, 2015). Firms under the scheme must surrender allowances for the carbon they emit. Each allowance in the scheme represents the right to emit one tonne of carbon or equivalent greenhouse gas (European Commission, 2015).

In terms of where liability falls for the emissions produced, a distinct choice was made to go downstream and place liability on the users (power sector and industry) rather than upstream on importers and producers (Convery, 2009). The result is that firms that burn fossil fuels and directly produce emissions are responsible for paying for emission allowances (EUAs). The alternative would be placing liability on providers of fossil fuels that indirectly cause pollution by supplying fossil fuels.

Three key players in the system are the European Commission, the Council of Ministers composed of representatives of member states, and the European Parliament (Convery, 2009). These players form the legislative side of the scheme; making decisions such as the compliance rules, how the scheme evolves through phases, and which sectors and gases are included. The legislative bodies also determine the cap on emissions for each calendar year.

The purpose of the cap is to restrict the level of carbon emissions, placing financial pressure on firms to reduce their emissions. The cap is set in tonnes of carbon and represents the supply of EUAs. Polluting firms provide the demand for EUAs as they are required to surrender allowances for the carbon or equivalent gases they emit.

Setting the cap correctly is of utmost importance; for the scheme to work and emission reductions to transpire, a shortage of allowances must exist (Ellerman & Buchner, 2007). To create a shortage of allowances, the cap must be set below business-as-usual levels. This is the point below which firms need to change their behaviour if they are to surrender sufficient allowances and meet their legal obligations under the scheme. When the cap on emissions is set correctly, the scheme will encourage innovation and investment in new abatement technologies and result in abatement being achieved at least cost (Brohé, Eyre, & Howarth, 2009). Overallocation, has, however, been a problem since the first year of the scheme. In 2005 the cap was overestimated by some 80 million tonnes (Skjærseth & Eikeland, 2016). This issue continued through phases I and II; the consequence was that many firms were able to comply while continuing as usual without any new abatement technologies or innovation.

Due to overestimation of the cap, the carbon price has been too low to encourage changes in firm behaviour ((Commins, Lyons, Schiffbauer, & Tol, 2011; Heindl & Lutz, 2012; Petrick & Ulrich, 2014). The EU ETS relies heavily on firm behaviour being sensitive to prices (Brohé et al., 2009). This means that getting the carbon price right is crucial to the success of the scheme. The price is determined by the cap (supply) and by the level of emissions by polluting firms (demand). The effect on firm behaviour is further discussed in section 3.6.

An issue considered throughout the scheme is carbon leakage. As per the EU ETS handbook (2015), carbon leakage is where the reduction in emissions achieved in one place (such as Europe) are offset by increases in emissions in another location. This occurs in such circumstances as a large power producer moving their production activities out of Europe where they will not be subject to the scheme. To avoid this, rules allow for industry sectors that are exposed to carbon leakage to receive 100% free allocation to prevent the movement of their operations (European Commission, 2015). International competition is the predominant cause of carbon leakage; firms subject to EU ETS may be unable to compete after carbon costs are considered.

Table 1 is reproduced from the EU ETS handbook, it shows the key features of the scheme and differences between phases (European Commission, 2015).

Phase I covered only carbon from power generators and energy-intensive industries, and nearly all allowances were given to firms for free (European Commission). The penalty in phase I for non-compliance was €40 for each allowance not surrendered. Three more countries joined the scheme in phase II and further gases were added (European Commission). Further changes in phase II included the cap declining by 6.5%, free allocation dropping to 90% of allowances, and the penalty increasing to €100 per tonne not paid for with an allowance (European Commission).

Table 1: Key features of the EU ETS

EU ETS Handbook Copyright European Commission (2015)

This table reports the key features of the European Union Emissions Trading Scheme and how they differ in phases I, II, and III.

Key features	Phase 1 (2005-2007)	Phase 2 (2008-2012)	Phase 3 (2013-2020)
Geography	EU27	EU27 + Norway, Iceland, Liechtenstein	EU27 + Norway, Iceland, Liechtenstein Croatia from 1.1.2013 (aviation from 1.1.2014)
Sectors	-Power stations and other combustion plants ≥20MW -Oil refineries -Coke Ovens -Iron and steel plants -Cement Clinker -Glass -Lime -Bricks -Ceramics -Pulp -Paper and board	Same as phase 1 plus Aviation (from 2012)	Same as phase 1 plus -Aluminium -Petrochemicals -Aviation from 1.1.2014 -Ammonia -Nitric, adipic and glyoxylic acid production -CO2 capture, transport in pipelines and geological storage of CO2
GHGs	CO2	CO2, N2O emissions via opt-in	CO2, N2O, PFC from aluminum production
Cap	2058 million tonnes CO2	1859 million tonnes CO2	2084 million tonnes CO2 in 2013, decreasing in a linear way by 38 million tonnes per year
Eligible trading units	EUAs	EUAs, CERs, ERUs	EUAs, CERs, ERUs

Significant changes were made for phase III as outlined by the Commission:

- Single EU-wide cap replaces national caps
- Auctioning becomes the primary method of allocation
- Further sectors and gases are included
- Declining cap introduced, annually the cap will fall by 38 million tonnes

2.1.3 In practice

All installations with a capacity of 20 megawatts or over must comply with the scheme. Small emitters which are below this threshold may opt-out; however, they are required to be subject to equivalent measures.

Since 2013 when the scheme entered phase III, the allowances for the power generation sector are fully auctioned with other sectors receiving some free allocation. This free allocation is decreasing each year to 0% in 2027. The overall cap is reduced by 38 million allowances each year, which is designed to allow firms to slowly adjust to a low-carbon world (European Commission, 2015).

Table 2: Allocation of allowances phase III of EU ETS

EU ETS Handbook Copyright European Commission (2015)

This table reports the percentage of free allocation of EUAs in phase III by sector. It shows the lack of free auctioning to the electricity production industry and the declining free allocation to industry sectors. The table also shows the full allocation of free EUAs to industry sectors that are exposed to carbon leakage and that this will continue throughout phase III.

Share of free allocation calculated based on benchmarks per sector	***2013***	***2014***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Electricity production	0%	0%	0%	0%	0%	0%	0%	0%
Industry sectors	80.0%	72.9%	65.7%	58.6%	51.4%	44.2%	37.1%	30.0%
Industry sectors deemed to be exposed to carbon leakage	100%	100%	100%	100%	100%	100%	100%	100%

In phases I and II when allowances were largely allocated for free, National Allocation Plans (NAPs) written by the member states and approved by the Commission, decided how allowances were distributed to installations. Now called National Implementation Measures

(NIMs), the Commission seeks to apply new harmonized EU-wide rules and does so by controlling the method of allocation in the NIMs. In phase 3, member states prepare allocation plans for the number of allowances allocated to installations in their country (subject to approval by the Commission) and the new rules determine the ratio of free to auctioned allowances for each installation.

Auctioning predominately takes place on the Intercontinental Exchange (ICE). EUA auctions are single-round and take place every other Wednesday in a 2-hour window where bids are sealed. Bids are in lots of 500 allowances and once the 2-hours is up the clearing price is determined; above which all bids are successful. The clearing price is the uniform price at which all allowances are sold (Intercontinental Exchange).

The timeline for firms is depicted in Figure 1 with allowances required to be surrendered by 30 April the year following the emissions:

Figure 1: EU ETS timeline for submissions of allowances

EU ETS Handbook Copyright European Commission (2015)

This figure shows the timeline for compliance with the European Union Emissions Trading Scheme. It outlines the monitoring, reporting and compliance over a calendar year.

If firms fail to surrender sufficient allowances they will be required to pay a significant fine of €100 per missing allowance; they must also purchase and surrender the missing allowances (Ellerman & Buchner, 2007).

2.1.4 Success to date

The trial phase (2005-2007) was used to test the price formation mechanism and to establish the monitoring, reporting and verification systems necessary prior to the first commitment period of the Protocol (2008-2012) (European Commission, 2015). The initial cap was set based on estimates and was heavily overestimated; it became apparent reasonably quickly that firms did not, in fact, need to reduce their emissions to meet the cap and consequently the price of carbon plummeted. The price fell from €29.37 on April 24th 2005, to €9.13 only three weeks later (Borak, Härdle, Trück, & Weron, 2006).

Free allocation initially was necessary to gain the required support for the scheme (Convery, 2009). Overallocation occurred on a firm level as well as in an absolute sense; many firms received more free allowances than they required for business-as-usual emissions. Consequently, many firms sold the excess allowances to those that had not been allocated sufficient EUAs and made windfall profits (Carbon Market Watch, 2016). This outcome has been highly criticized and used as evidence for the schemes failings. However, it must be noted that the first phase of the scheme was always intended to be a trial.

The second phase of EU ETS ran from 2008 through 2012; concurrent to the first Kyoto commitment period. Analysts forecasted long-term prices in this phase to be €25-30 per EUA (Chevallier, 2009). However, the issue of a low carbon price remained throughout phase II. In 2008 EUAs were trading above €20 per tonne, however, the carbon price appears to have now stabilized between €4-€7; a price insufficient to drive innovation or fuel switching behaviour Marcu A et al. (2017).

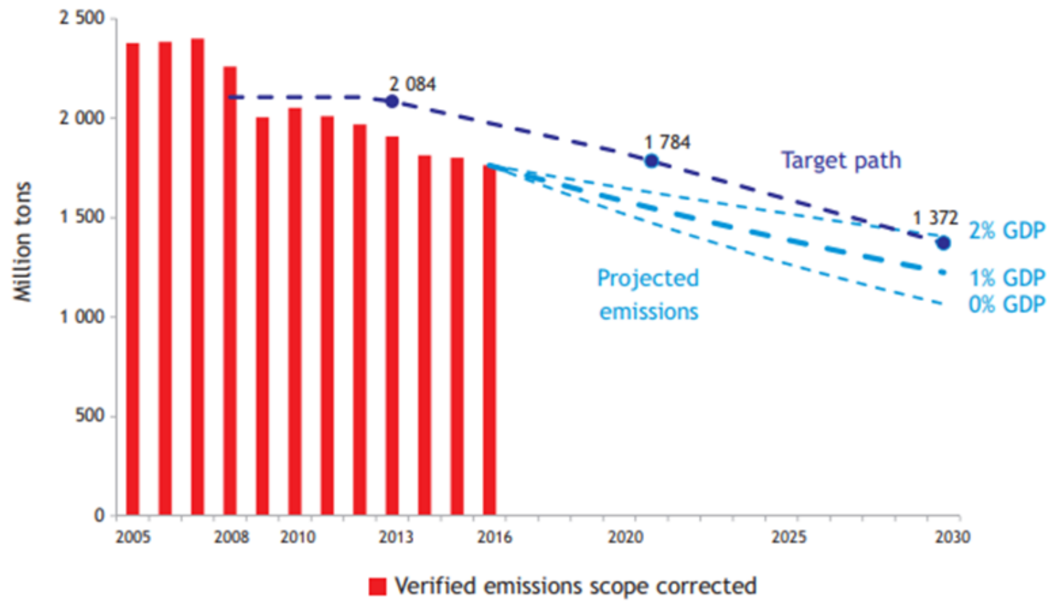
The scheme is delivering on short-term environmental targets; it is not a price signal, however, that has been driving the move towards decarbonization (Marcu A et al., 2017). A significant driver has been regulatory uncertainty and greater public pressure to reduce carbon dependence. Despite the price not reaching levels expected, the market functions well in terms of liquidity, bid-ask spreads and auction participation (Marcu A et al., 2017). It is important to distinguish between the success of the EU ETS market in terms of its functionality, and the delivery of a seemingly correct price for carbon (Marcu A et al., 2017).

In terms of environmental targets, data from the European Environment Agency (EEA) show that the scheme had in 2015 already achieved its 2020 target of 20% lower emissions on 2005 levels (Marcu A et al., 2017). Figure 2 shows the achievement of these targets.

Figure 2: Verified emissions, target path and projected emissions

EU ETS Handbook Copyright European Commission (2015)

This figure shows the decline in verified emissions in the EU while the European Union Emissions Trading Scheme has been operating. It shows verified emissions below the target path from 2008 onwards, and the target path going forward to 2030. The table also shows the projected emissions in three GDP scenarios.



Source: Wegener center elaborations on EEA, 2017 and EU TL, 2017
Note: data for 2016 are based on the EUTL of April 3 missing gaps are estimated by Wegener Center

2.1.5 Future of the scheme

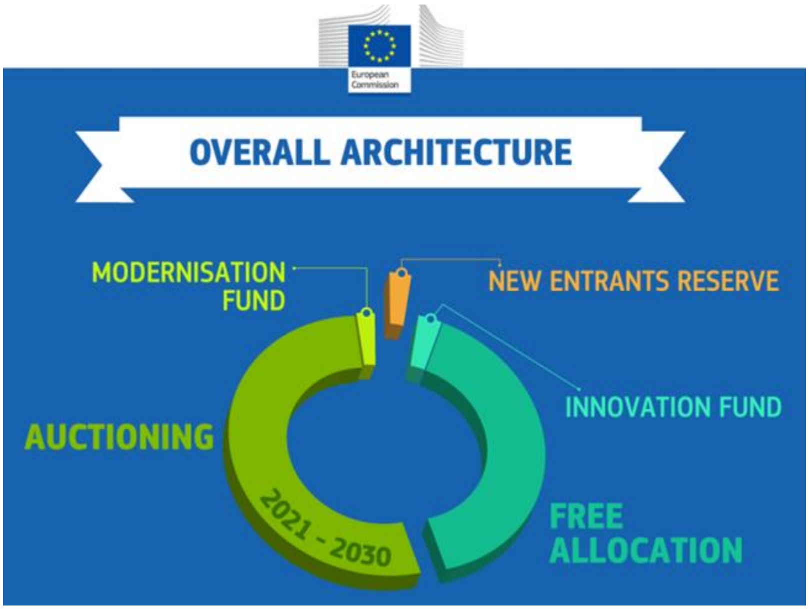
Phase IV of the scheme begins in 2021, only 3 years away at the date of writing. This phase will bring stricter rules with a new target of 40% reduction in emissions by 2030 (European Commission). To achieve this goal, the sectors included in the scheme will have to reduce their emissions by 43% on 2005 levels which amounts to around 556 million tonnes over the ten years to 2030 (European Commission). The cap will change in phase IV; at present (phase III) the cap declines by 1.74% annually, this will increase to a rate of 2.2% after 2020 (European Commission). Further changes involve the introduction of more robust, fair and better-targeted carbon leakage rules and the creation of two new funds to support innovation and modernisation (European Commission). Figure 3 shows the planned allocation of allowances in phase IV.

Free allocation has been decreasing since 2013 and will reach 0% for industry sectors, not at risk from carbon leakage by 2027 (European Commission, 2015).

Figure 3: Architecture of allowance allocation in phase IV

EU ETS Handbook Copyright European Commission (2015)

This figure shows the planned architecture of the European Union Emissions Trading Scheme in phase IV. It shows the ratio of auctioning to free allocation, and highlights the planned modernisation and innovation fund. The figure also shows the new entrants reserve will continue into phase IV, and its approximate size compared to auctioning and free allocation.



2.2 Carbon Pricing

Determinants of carbon price have been investigated since the scheme's initiation. The findings show drivers of the carbon price to be energy prices, weather and electricity prices. The relation between these factors and the price of carbon have not remained stable over time due to regulatory changes and market events. Benz and Trück (2009) confirm that sudden jumps in carbon price can arise from changes in regulation or policy.

Supply of carbon allowances (EUAs) depends entirely on the cap set by the European Commission and on allocations of the cap to firms. In terms of demand for EUAs, influences include weather changes, fuel prices and economic growth, which all impact production levels and therefore energy needs (Benz & Trück, 2009). Weather affects demand for EUAs, as abnormally hot or cold weather increases overall demand for energy, while rainfall and wind affect the share of overall energy produced by renewables and non-carbon power generation (Benz & Trück, 2009). Similarly, a 2007 study found the main carbon price drivers to be extreme weather events and the market prices for oil and gas (Mansanet-Bataller, Pardo, & Valor, 2007). Extreme weather events, such as an unusually cold winter, increase energy demands for heating, which leads to energy producers requiring additional EUAs and forcing the carbon price upwards.

The relative costs of coal and gas may play a significant role in determining the price of carbon. As described by Benz and Trück (2009) the relative cost of coal and gas can increase the volatility of allowance prices. This occurs due to the ability of energy producers to switch between energy sources and the fact that the use of gas results in over 50% fewer allowances being required due to much lower emissions (Benz & Trück, 2009). When the price of coal drops and demand increases, there will be a resulting increase in demand for allowances to cover the increase in emissions. There is thus a logical relationship between the relative price of energy inputs and the supply and demand of allowances, however, the literature on the significance of this relation is not consistent.

Using data from the first year of operation, Mansanet-Bataller, Pardo & Valor (2007) found the prices of gas and oil significant determinants of the carbon price; however, the switching effect between coal and gas was not significant, nor was the coal price itself. Comparatively, Aatola, Ollikainen and Toppinen (2013) examine data from the first 5 years of trading and find a statistically significant dependence of EUA price on the gas-coal difference. Green (2008) places this relation in a slightly different light, explaining that as the carbon price varies it offsets movements in coal and gas prices and actually reduces the risk faced by energy generators. Similarly, Alberola, Chevallier and Cheze (2008) find a relation between carbon prices, movements in energy prices, and unanticipated temperature changes; the importance of fuel-switching behaviour being highlighted. The fuel switching point is important as this is the price below which it becomes profitable to switch from gas with relatively small emissions to the heavy emitter coal even after taking into account the cost of carbon allowances (Alberola et al., 2008).

Chevallier (2009) in investigating the relationship between carbon futures and macroeconomic risk factors, found the EU ETS market to have distinct fundamentals with only a remote connection to macroeconomic variables. Chevallier (2009) further found that the returns of carbon futures can be weakly forecast by equity dividend yields and junk bond premiums and that overall the carbon market is less sensitive to macroeconomic risk factors than equity, bond and other commodity markets.

Current literature is focused on the first two phases of the scheme; it must be noted that price determinants may change in phase III as the end products included in the scheme expands, and events occur such as institutional/political announcements regarding the cap (Alberola et al., 2008). Certain price drivers may also have a greater or less significant impact on carbon price due to the changes in the proportion of free versus auctioned allowances. Little research has been undertaken on the price drivers in phase III.

In terms of modelling carbon prices, Zhu, Wang, Chevallier and Wei (2013) use empirical mode decomposition which accurately explains the formation of the carbon price by decomposing the formation mechanism. Benz and Trück (2009) suggest using Markov switching and AR-GARCH models for modelling carbon pricing, they find these models adequately capture the return characteristics. A regime-switching jump-diffusion model with a hidden Markov chain is proposed by Li, Chen and Lin (2015).

The carbon price determinants which are consistent throughout the literature are the gas price, the coal price, and extreme weather.

2.3 Efficiency and convenience yields in the EU ETS market

As highlighted by Trück and Weron (2006) the relationship between spot and futures prices is significant for risk management and hedging since convenience yields are a key factor in understanding the risks and returns of a commodity. The convenience yield is the yield gained from holding the spot commodity rather than the futures contract. The convenience yield can be positive or negative. Minimal information exists on the convenience yield in the carbon market. However, it has been found that intra-phase futures do not have a convenience yield; no advantage exists in holding long carbon allowance futures instead of a long spot position in carbon allowances (Daskalakis & Markellos, 2008). Trück and Weron (2006) found that during 2008 – 2012 the carbon market changed from backwardation initially to contango with negative convenience yields.

Contango occurs where the futures price is greater than the spot price, backwardation is where the spot price is greater than the futures price. Literature is consistent in finding the carbon market in contango (Benz & Trück, 2009; Borak, Härdle, Trück, & Weron, 2006; Charles, Darne, & Fouilloux, 2013; Pinho & Madaleno, 2010). This was the reverse prior to 2008: spot carbon was expensive compared to futures (Pinho & Madaleno, 2010; Trück & Weron, 2016). Comparatively, many commodity markets exhibit backwardation (Trück & Weron, 2016).

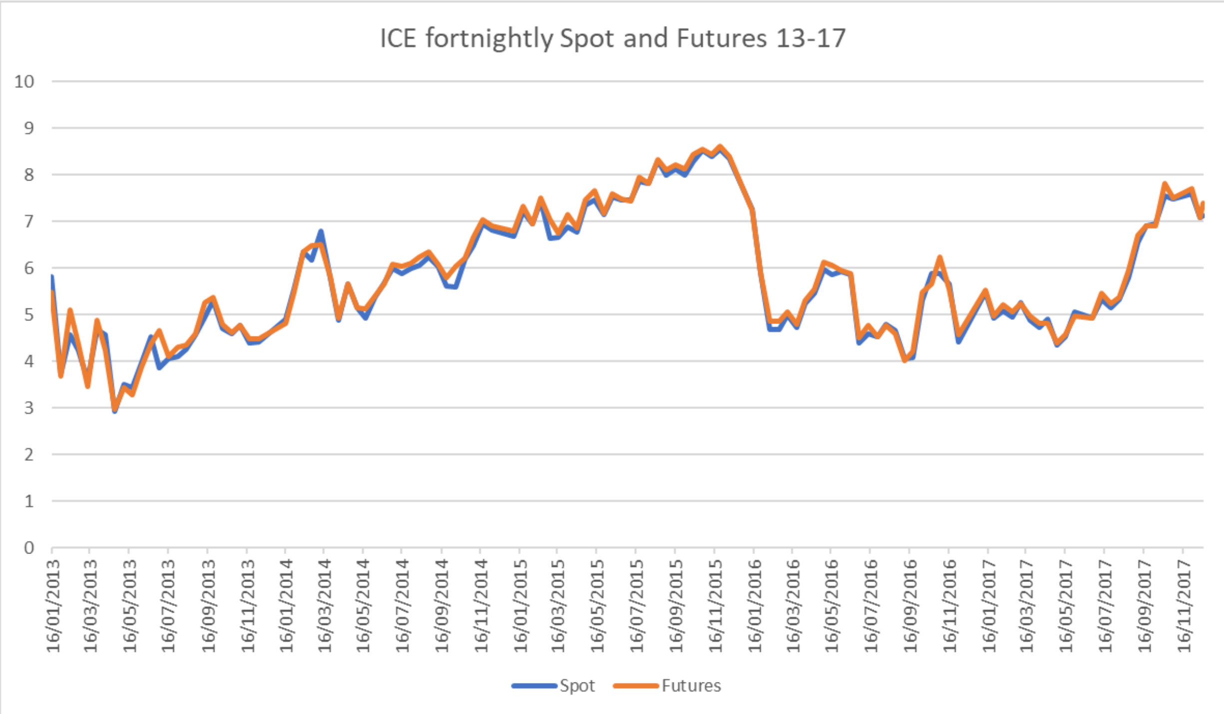
The cost-of-carry model says that in a frictionless, efficient market, futures are priced at a rate equal to the spot price adjusted for the opportunity cost of money, storage costs, and the benefit from holding the spot (including dividends or convenience yield) (Charles, Darne, & Fouilloux, 2013). In the carbon market, the cost-of-carry should simply be the opportunity cost of money since there are no storage costs nor any benefit to physically holding allowances as exist for physical commodities (Bredin & Parsons, 2014). The futures price should, therefore, be determined by the opportunity cost of money, however, the data indicates otherwise and is not consistent with the cost-of-carry model (Bredin & Parsons, 2014; Charles et al., 2013; Trück & Weron, 2016).

Bredin and Parsons (2014) explore the reasons behind spot carbon being cheaper than future carbon; they present two explanations. The first explanation being limits to arbitrage; the carbon market is only open to institutions and a scarcity of financial capital may allow futures prices to fluctuate in a wide band before being corrected by arbitrage. The second explanation presented by Bredin and Parsons (2014) is that the futures prices reveal the market's view on the spot and futures positions; a negative convenience yield implies the holder of the spot allowance expects to be disadvantaged by doing so. This situation may indicate the expectations of carbon price risk (Borak et al., 2006). Trück and Weron (2016) suggest market participants may be willing to incur additional costs to secure a hedge against uncertain increases in EUA prices; they find carbon futures to be prices well above that implied by the cost-of-carry relationship.

During the period studied (2013-2017) there was virtually no variation between the spot and futures prices of carbon. The market was in contango approximately 80% of the time, however, the figure below shows the fractional variation between prices.

Figure 4: Spot and futures prices of carbon

This figure shows the prices of spot carbon and carbon futures contracts in euros. The prices are shown fortnightly over five years from January 2013 to December 2017. The figure shows how close the spot and futures prices track.



Looking further into the reason prices are inconsistent with the cost-of-carry model, raises naturally the question as to whether the carbon market is efficient. The absence of a cost-of-carry relationship between spot and futures is an indicator of inefficiency and potential arbitrage opportunities (Charles et al., 2013). As suggested by Bredin and Parsons (2014), arbitrage may not move quickly to correct prices. Early studies on the efficiency of the carbon market revealed a lack of weak-form efficiency. Daskalakis and Markellos (2008) found that simple technical trading rules and naive forecasts were able to produce substantial risk-adjusted profits; they suggest immaturity of the market or limits on short-selling as reasons for the lack of efficiency. Miclaus, Lupu, Dumitrescu, and Bobirca (2008) use event-study methodology to test the efficiency of the EU ETS carbon market; they also find the market to be inefficient.

Following 2010, possibly due to the market maturing, literature finds efficiency. Daskalakis (2013) studied 2008-2011; finding between 2008-2009 simple trading rules could have generated substantial risk-adjusted returns, however, from 2010 onwards this is not the case. In contrast with other literature, Gregoriou, Healy, and Savvides (2014) using data from 2005-2012 found the market to be informationally efficient.

2.4 Impact of EU ETS on firm competitiveness and value

From the outset, European firms were concerned about a loss of competitiveness owing to the EU ETS contributing to an increase in production costs. The carbon leakage rules of the scheme provide considerable protection. As discussed in section 2.1.2, carbon leakage is where firms move operations out of the EU in order to avoid paying for carbon emissions. The result is no reduction in emissions; undermining the scheme objectives and preventing measurement of emissions. Consequently, the Commission allocates 100% of allowances for free to industries exposed to carbon leakage. This policy is not expected to change in future phases of the scheme and as such, industries where competitiveness may be significantly affected by the scheme are protected.

Demailly and Quirion (2008) studied the European iron and steel industry, using production and productivity measures as a basis for measuring competitiveness. They found losses in competitiveness to be small and losses in production to be weak. Profitability was more difficult to assess due to its’ sensitivity to assumptions, pass-through ability and the number of allowances allocated free. Focusing on power, cement, and the iron and steel industries, Chan, Li and Zhang (2013) found no evidence from the first two phases to substantiate concerns over loss of competitiveness.

Examining German stock returns during the first two phases when allowances were allocated for free, Oestreich and Tsiakas (2015) found a significant carbon premium. Firms that received free allowances experienced higher cash flows due to their ability to pass-through carbon costs to customers and to sell excess allowances for a profit. This carbon premium dissipates after

2013 when phase III began, and auctioning became the primary method of allowance allocation.

Using panel data from 2005 through 2008 on more than 2000 European firms it was found that the emissions trading scheme had no significant impact on firm value, employment or profit margins; the authors describe the effect as modest at best (Abrell, Ndoye, & Zachmann, 2011). No loss was found in regard to competitiveness, however, the authors acknowledge that while full auctioning would likely help reduce emissions, it could negatively impact firm profits (Abrell et al., 2011). Likewise, Anger and Oberndorfer (2008) find no significant impact on performance and employment of German firms.

The effect of carbon price changes on stock returns was found to be positive and significant by Scholtens and van der Goot (2014). A total of 136 firms were studied with the overall result being that the EU ETS has a small positive and statistically significant impact on firm value. The authors conclude their study with the implication that if carbon prices affect stock returns then carbon risk exists and this needs to be realized and managed by firms.

Studying the 2006-2009 period it was found that, logically, the EU ETS is only value relevant to firms to the extent that their emissions exceed the number of allowances they have been allocated for free (Clarkson, Li, Pinnuck, & Richardson, 2014).

2.5 Risk factors arising from EU ETS

In the early stages of the EU ETS, few firms considered climate change to be a financial risk (Busch & Hoffmann, 2007). Koch and Bassen (2013) find that for most European utilities, movements in carbon price were not a relevant risk factor in the first two phases. In phase, I and II allowances were largely given to firms at no charge, whereas in phase III all allowances required by the power sector must be purchased at auction and only a small portion of allowances for other industries will be given freely, carbon price may be a risk factor.

Carbon price risk arises from the EU ETS increasing the cost of using fossil fuels to produce energy (Green, 2008). In comparison with a carbon tax, the EU ETS causes more volatility in electricity prices which determine revenue for electric utilities (Green, 2008). In terms of market risk, the carbon market has less downside risk than the natural gas market and more downside risk than the oil market (Reboredo & Ugando, 2015).

In a paper studying the German electricity industry, Hoffmann (2007), found higher regulatory uncertainty and investment risk post the emissions trading scheme; the result being a focus by firms on flexibility and options available in various scenarios. Hoffmann (2007) found that the EU ETS has an impact on the timing of investment decisions, however, it must be noted that this study was based on a very small sample of qualitative data. Oestreich & Tsiaskas (2015) also investigated carbon risk, finding carbon emitting firms face increased risk since the future price of carbon is unknown and consequently, a higher expected return is demanded on equity.

If firms are to integrate environmental risks into risk management practices Busch and Hoffmann (2007) suggest focusing on the movement of critical materials within their value chain. They find that carbon risk depends on a wide range of factors including the intensity of emissions, fuel mix, abatement costs and trajectory of technology. An active strategy moving towards a non-carbon fuel mix will help firms reduce their exposure to carbon price fluctuations and protect their equity value (Koch & Bassen, 2013). It is important to note, however, that future price drivers may be very different to past ones (Blyth, Bunn, Kettunen, & Wilson, 2009).

The literature is scarce in this area; the consensus of what does exist is that carbon risk does not exist for the majority of carbon producing European firms. However, the rules have changed since the aforementioned literature was published and the regulatory changes may have an impact on the existence of carbon price risk for firms.

2.6 Hedge ratios

In order to transfer the carbon price risk of emitting greenhouse gases, firms can undertake hedging using carbon futures. With the high volatility of the carbon price, management of this risk appears essential (Fan, Roca, & Akimov, 2014). In order to hedge with futures contracts, the optimal hedge ratio needs to be calculated. The hedge ratio is the ratio of derivatives that should be held or sold to hedge the risk of the firm's position in the (spot) underlying asset. The optimal hedge ratio being the ratio of spot to futures at which the portfolio value does not change.

Studies of hedge ratios in the European carbon market are very limited; to my knowledge, only three articles explicitly calculate a hedge ratio for firms to hedge their carbon price risk. Fan, Roca and Akimov (2014) made the first attempt to apply widely used hedge ratios to the carbon market and investigate their effectiveness. Despite the supposed novelty of the market, the authors found the hedge ratio to be within the range 0.5-1.0, just as in other commodity markets (Fan et al., 2014). Since emitters are forced to take into account the price of carbon allowances in their production costs, hedging provides much-desired certainty for production planning and decision making. Fan et al, (2014) assumed that since price determinants in the carbon market are unique, so too would be the method for calculating hedge ratios; they found, however, that conventional theory and tools work well in this market for the time period 2005-2009.

The above-mentioned study was concurrently published in another journal in 2013 with one year of additional data (Fan, Akimov, & Roca, 2013). In both articles Fan, Roca and Akimov test the effectiveness of each hedge ratio method by looking at variance reduction and utility improvement. The overall conclusion of both articles is that Ordinary Least Squares method should be used due to its superior effectiveness (Fan et al., 2013; Fan et al., 2014).

The second study finding a hedge ratio for the European carbon market is Philip and Shi (2016) which proposes a Markov regime switching framework for the modelling of carbon allowances. Philip and Shi (2016) find that this strategy significantly outperforms single regime strategies such as those used by Fan, Akimov and Roca (2013). Highlighted by this paper is the minimal attention placed on managing the risk of carbon allowance requirements by literature (Philip & Shi, 2016). Many studies have sought to price the carbon allowances in the EU ETS, whereas the literature on hedging for firms operating under this regulation is virtually non-existent. Philip and Shi (2016) believe the Markov regime switching hedge is superior even after considering transaction costs, despite the authors not actually comparing utility after transaction costs. In the next section, we can see from the literature that the carbon price does not currently appear to be treated as a significant risk factor by managers in practice. If this is the case, transaction costs of such a hedging strategy will likely influence managers' decisions and will need to be considered. While econometrically the Markov regime switching strategy may be superior, in practice this may not be the case.

The third study is that of Feng, Yu, Ouyang, Guo and Li (2016) who find the hedge ratio using a non-expected utility model of disappointment aversion. In contrast to Fan, Roca and Akimov (2014), the hedge ratio is found to be lower in the carbon market than the general market (Feng et al., 2016). The paper also analyses the feasibility of hedging carbon price risk in terms of transaction costs and concludes that the carbon futures market cannot currently provide a good hedging function (Feng et al., 2016). This is in line with practice observed in the market; a large proportion of firms are not currently using carbon allowance futures despite their ability to provide certainty.

2.7 Corporate decision making in response to EU ETS

Prior literature has analysed whether employment, hedging or investment decisions are affected by the EU ETS. According to this literature, the EU ETS has not resulted in decreased employment; higher employment was found in EU ETS firms during the first phase (Commins, Lyons, Schiffbauer, & Tol, 2011). Likewise, Petrick and Wagner (2014) found no evidence of decreased employment in firms complying with the ETS.

In their study on carbon management in German firms, Heindl and Lutz (2012) find that five out of the six firms included in their case study undertook no hedging activities with respect to the carbon price. The predominant reason being that such use of derivatives was considered speculative and against company policy. The authors highlight the tightening of the EU ETS emissions constraint and address the increasing need for firms to thoroughly consider this in their strategies and decisions. The findings, however, show that carbon price risk is considered relatively unimportant at the current price level. Carbon price was not considered explicitly in investment decisions made by the studied firms; efficiency was of great importance with carbon mitigation arising as a side effect (Heindl & Lutz, 2012). One manager from a company in the food industry stated his belief that carbon prices would need to increase to €30-40 to play a prominent role in investment decisions (Heindl & Lutz, 2012). The carbon price has increased from €5.33 in August 2017 to €16.02 in May 2018; however, it appears to have to double before firms consider it a significant risk factor and change their behaviour.

Empirically, Commins, Lyons, Schiffbauer, and Tol (2011) found no statistically significant evidence of change in investment by firms resulting from the EU ETS. Carbon pricing is important in its role of incentivising investment in carbon abatement (Blyth et al., 2009). At current levels, the price of carbon is not providing a real incentive in this respect. Cadez and Czerny (2016) find that carbon-intensive firms engage in efficiency improvements with low investment costs and do not appear to be transitioning to a low-carbon world. The least used strategy for climate change mitigation by European firms is carbon capture and storage, suggesting hesitance by firms to invest significant amounts into the low-carbon transition (Cadez & Czerny, 2016).

In contrast to the findings of other literature, Hoffmann (2007) found that the firms studied did take carbon costs into account when making investment decisions. Hoffmann (2007) studied the effect of the EU ETS on German electricity firms; the overall finding is that the EU ETS was a main driver in small-scale investment decisions, albeit not in large-scale and R&D decisions. The study was based on only 5 firms with an interview process gathering the data. In the case of Germany, Hoffmann (2007) found a different legislative force reducing carbon emissions; existing regulation provided incentives to invest in wind, solar and other renewable energies. A further note from this study was the finding that carbon capture and storage technology will only be profitable if the price of an emissions allowance exceeds €30. Current investment in this technology is therefore considered very risky by firms (Hoffmann, 2007). Where firms are investing in this technology, it is for the beneficial publicity that comes with showing a dedication to climate change.

2.8 Conclusions from prior literature

Carbon pricing literature consistently shows the determinants to be the prices of natural gas, oil, and extreme weather. Significant in some studies and not others are the prices of coal and electricity. How the determinants have changed since the legislative changes in 2013 has not been investigated.

Since 2008 the carbon market has been in a state of contango. Current literature also reveals the market was not efficient prior to 2010, however, it is found to be efficient post-2010. Additionally, literature found an absence of the cost-of-carry relationship in the carbon market.

Despite well publicised concern over the impact of the EU ETS on firm competitiveness and value, current literature finds no evidence to substantiate these concerns. Evidence could not be found to show a loss of competitiveness, nor an impact on firm profit or value. Logically, it was found that the EU ETS only impacts carbon producing European firms to the extent that they must purchase EUAs over and above those allocated freely. In the first phase of the scheme, the impact on firms weighted average costs of capital were found to be marginal by Koch and Bassen (2013). Since the introduction of new rules in phase III, and the significant shift from freely allocated to auctioned EUAs, the impact on firm value may have changed.

Prior to phase III few European firms considered the price of carbon to be a significant risk factor and the majority did not take the scheme into consideration when making decisions. Koch and Bassen (2013) found that while for the vast majority of European utility firms the price of carbon was not a significant risk factor, for the firms where it was, significant carbon risk premiums were borne.

In terms of hedging the risk of carbon price movements the literature is scarce. What does exist shows carbon hedge ratios in the normal range for commodities of 0.5-1. Literature also reveals a similar effectiveness in hedging carbon risk as in hedging the price risk of other commodities. However, literature only exists for phases I and II of the scheme.

With few European firms considering the price of carbon a significant risk factor to their business, the findings on corporate decision making are logical. Literature shows no evidence of decreased employment or change in investment to owing the EU ETS. Due to competitive secrets, very little is known about European firms' responses to the scheme. In an anonymous interview-based study by Heindl and Lutz (2012) firms were asked about their hedging activities in regard to carbon price; 4 out of the 5 firms undertook no such activities.

Prior to 2013 when phase III began, the consensus was that carbon price risk did not exist for European firms; carbon price movements could be hedged using traditional techniques, and the determinants of the carbon price were energy prices and weather events. Post-2013, the rules are different and significantly fewer EUAs are given freely; do the above conclusions still hold? The following research is undertaken to determine whether risk exists, if it can be hedged conventionally, and if the determinants of the price of carbon have changed in phase III of the scheme.

3 HYPOTHESES

Given the consensus in prior literature that firms did not face carbon price risk in phases I or II of the EU ETS, the first null hypothesis is that firms similarly do not face such risk in phase III. This hypothesis seeks to find whether regulation changes in phase III have been significant enough to create risk to European firms.

Hypothesis 1: European firms do not face carbon price risk in phase III

> Alternate hypothesis: European firms face carbon price risk in phase III

Literature speaks of the carbon market as being novel and unlike other commodities. However, empirically, it was found that carbon could be hedged effectively using conventional techniques. The second hypothesis seeks to find whether carbon can be hedged effectively in phase III, and as such, can be treated like other commodities in a firms hedging policies.

Hypothesis 2: Carbon can be hedged like any other commodity and needs no special treatment

> Alternate hypothesis: Carbon risk requires special techniques to be hedged; it cannot be hedged effectively using traditional techniques

The variables consistently used in prior literature to determine carbon price are energy prices and weather events. Energy prices encompass the prices of oil, natural gas, coal, and electricity. The third hypothesis seeks to find whether these determinants hold in phase III after regulatory changes.

Hypothesis 3: Carbon price is determined by energy prices and weather events in phase III

> Alternate hypothesis: Carbon price is not determined by energy prices and weather in phase III

4 DATA

4.1 Hypothesis 1:

In order to find whether carbon price risk exists for carbon producing European firms in phase III of the EU ETS, all data is for the time-period 1 January 2013- 31 December 2017, a 60-month period.

Data from 60-months or 5-years is the common approach for estimating beta coefficients and the cost of capital, as per Alexander and Chervanys' (1980) findings of the optimal estimation interval being 4-6 years.

To assess carbon exposure, a sample of electric utilities is chosen. This makes good sense in theory. Electric utilities have the largest value at risk, in a literal sense, from carbon exposure; the inherent carbon intensity of their operations, longevity of assets and capital intensiveness mean a large exposure to the carbon price (Urdal et al., 2006).

Firms chosen are from the STOXX Europe TMI Utilities index with the addition of Drax, added due to its inclusion in the high-emitting category in Koch and Bassen (2013). Data on the sample utility firms includes hand-collected 2016 and 2017 annual report figures on debt, equity, cost of debt, applicable tax rate, emissions intensity, and fuel mix. Unfortunately, due to their recent IPOs, the firms Innogy and Uniper are excluded from the main sample.

In addition, data is taken from DataStream for calculating the monthly return on the market as well as on carbon, crude oil, natural gas, and coal futures. The market return is calculated using the MSCI Europe index which represents mid- to large-cap firms across 15 European countries. Carbon returns come from the Intercontinental Exchange (ICE) based in London. ICE trades energy futures including carbon allowances, with a significantly greater volume of trading than the European Energy Exchange (EEX) for carbon futures. The crude oil price series used is ICE Brent crude oil futures continuous price series. Natural gas is also an ICE contract, with a continuous price series. While these prices are from ICE, an exchange in the United Kingdom, they are highly correlated with European oil and gas prices. The coal series comes from EEX coal-ARA price series.

As per Koch and Bassen's (2013) methodology, the applicable risk-free rate used is the German Government 10-year bond yield. All returns used are excess returns over the yield on the German Government bonds.

Electricity prices come from firm's respective power exchanges. All power prices are for spot baseload power. Italian firms use data from GME, Spanish from OMEL, Finnish from NordPool, Czech from PXE, British from APX and for German firms from the EEX. French power prices were not available from Datastream at the time of research and thus for the one French firm included, the EEX power prices have been used as a proxy due to the EEX being the largest and most liquid of the power exchanges in Europe.

All data not already in euros is converted to euros at the price prevailing for the month of the data as per WM/Reuters Benchmark Rate from DataStream.

4.2 Hypothesis 2:

The data used to test whether carbon can be hedged effectively in phase III is the spot and futures prices for carbon allowance contracts (EUAs). The period over which the data is taken is 1 January 2013- 31 December 2017 and comes from the Intercontinental Exchange on DataStream. Fan, Akimov and Roca (2013) use daily data to investigate this hypothesis. However, carbon allowances are not traded spot daily, they are sold every second Wednesday. Fortnightly data is therefore used for this hypothesis, 122 observations result with independent variable prices being matched to spot EUA dates.

4.3 Hypothesis 3:

In an effort to explain carbon price movements, the determinants being tested are oil, gas, coal, and electricity prices; as well as the switch price, clean spark spread and clean dark spread.

Daily data is not logical in this setting in that firms do not require EUAs daily. The requirement for submitting allowances is only once per year and allowances are auctioned fortnightly. Therefore, fortnightly data is used for the analysis of price determinants as with hypothesis 2.

Data required includes spot prices for EUAs, obtained from the Intercontinental Exchange data on DataStream, and the Intercontinental Exchange auction results webpage. Oil prices are Intercontinental Brent Crude Oil futures, gas prices are Intercontinental Natural Gas futures, and coal prices are European Energy Exchange ARA Coal futures. Alberola, Chevallier and Cheze (2008) used PowerNext electricity prices in their study; in this study, European Energy Exchange data is used. No one price for electricity will be representative of power prices EU wide, however, the EEX is central and is moderately-to-highly correlated with the electricity prices from the other European electricity exchanges.

The clean dark (spark) spread is the difference between the electricity price at peak hours and the coal (natural gas) price that is input to create the electricity adjusted for the cost of carbon allowances. These variables are obtained from DataStream. The switch price represents the abatement cost and is calculated from data discussed above.

Weather data comes from the temperature in Munich, Germany. Temperature indices were not available at the time of writing. Munich is chosen due to its geographically central location. The fortnightly temperature averages over 2013-2017 are compared with historical averages to determine abnormally cold or hot periods.

All data not already in euros is converted to euros at the price prevailing for the month of the data as per WM/Reuters Benchmark Rate from DataStream.

4.4 Data notes

4.4.1 Intercontinental Exchange data:

The carbon price data is taken from the Intercontinental Exchange rather than the European Energy Exchange due to volume differences. The carbon prices from both exchanges track almost perfectly, however, volume traded on the ICE is on average greater by over 350,000 allowances per month.

4.4.2 Carbon price drop:

As per Figure 5, after a long-run increase in price, allowance prices fell by 45% between November 2015 and February 2016.

Sara Stefanini (2016) presents several explanations for this fall in price including the economy, and other commodity prices. During late 2015 renewable and energy efficient technologies were thriving; coupled with a sluggish European economy, a large surplus of emissions allowances resulted. Related commodities were also struggling, Figure 6 shows the low prices of oil, gas and coal late 2015 - early 2016.

Figure 5: Carbon prices in phase III of EU ETS

This figure presents the spot and futures prices of carbon in euros during phase III of the European Union Emissions Trading Scheme. It shows the drop in carbon price in late 2015.

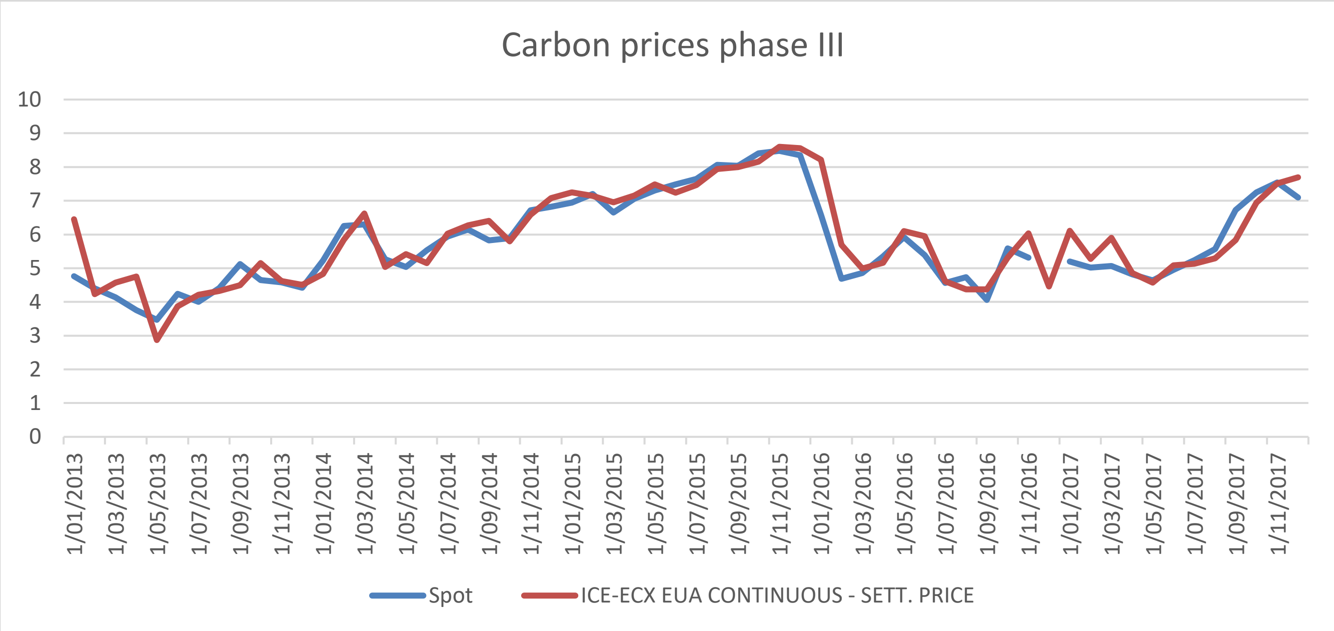
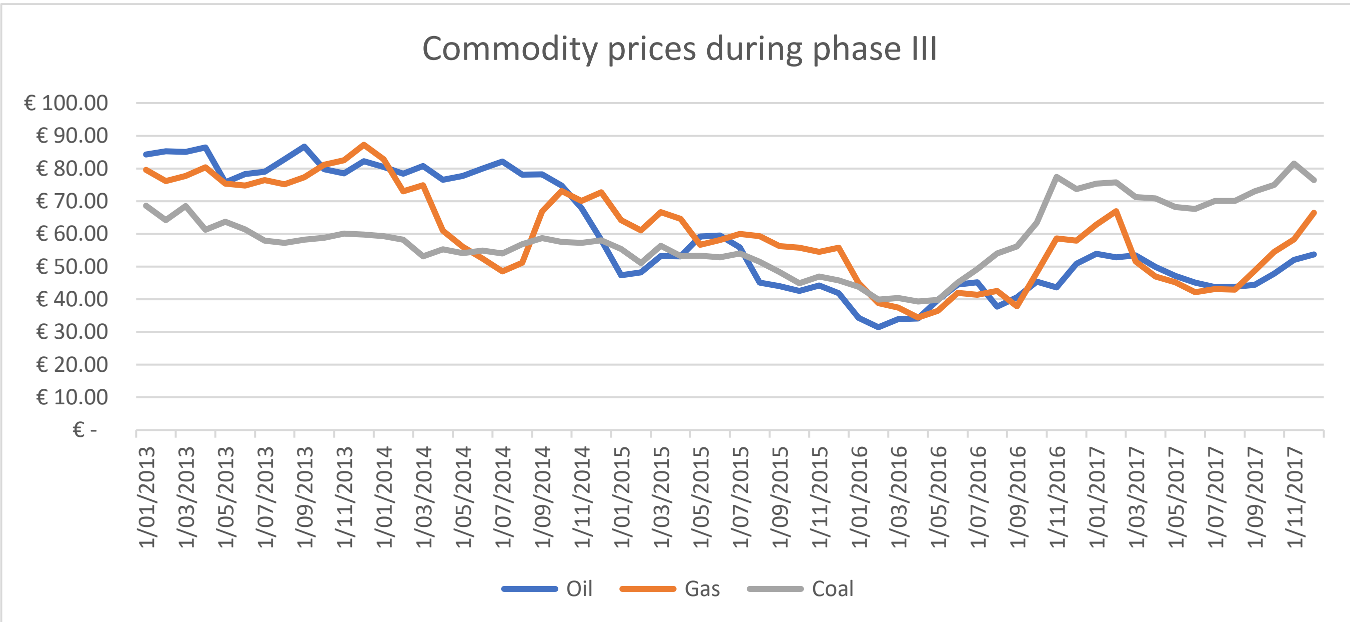


Figure 6: Commodity prices during phase III of EU ETS

This figure shows the prices of crude oil, natural gas, and coal in euros. The time period presented in phase III of the European Union Emissions Trading Scheme. It shows the drop in commodity prices in late 2015.



The previously wide gap between coal and gas prices impacts the price of carbon due to the vast difference in emissions from using these energy inputs. Gas produces significantly less carbon than using coal, and with the low gas price, energy producers could choose gas to create energy and sell excess carbon allowances, thus, creating further surplus carbon allowances and downwards price pressure. This switching behaviour is discussed more in depth in the carbon pricing section of the literature review.

5 METHODOLOGY

5.1 Hypothesis 1:

The methodology chosen is adapted from Koch and Bassen (2013). The first half of the study will be replicated with new data from phase III, while the second half will not be undertaken as discussed below. This methodology allows a comparison with the authors' results for phase I and II which enables a discussion of potential risk faced by firm's due phase III's practice of auctioning. For energy producers, free allocation ceased in 2013 and all EUAs required are fully auctioned; this may impact whether carbon price risk exists today and in future. The analysis of data from 2013 onwards, therefore, provides an up-to-date view of risk faced by European firms.

In part 1, the methodology takes 20 European utility firms and find their carbon price exposure in terms of cost of capital/required return on equity. It calculates their carbon-adjusted weighted average cost of capital. These measures provide insight into the risk faced from complying with the EU ETS to firm value.

In part 2, Koch and Bassen (2013) calculate earnings and expenses for the sampled firms to find the equity value at risk. This part of the study is not repeated due to the requirement of significant estimation. Forecasting each firm's efficiency rates, fuel costs, carbon costs, revenues and such is highly unreliable due to heavy fluctuations in these prices. The authors forecast the capital investment costs for the firms as well as their fuel mix. These figures cannot be estimated with any certainty; not 12 years into the future as the authors have done. In fact, since the authors' 2013 paper, one of the firms, E. ON, has significantly altered their fuel mix from 69% fossil fuels to only 1.8% fossil fuels. The announcement of this dramatic change came as a shock to market participants and demonstrates the inability to forecast firm decisions.

The methodology chosen, therefore, follows Koch and Bassen (2013) only as far as the calculation of the carbon-adjusted weighted average cost of capital.

Part A:

Koch and Bassen (2013) estimate the firm-specific carbon risk premium to adjust the cost of capital. The following model is used:

$$Re = \mu_i = rf + \beta_M (\mu_M - rf) + \beta_{Energy} (\mu_{Energy} - rf) + \beta_{co2} (\mu_{co2} - rf) \qquad \textit{Equation 1}$$

Where μ_i is the expected rate of return on the stock, calculated as the risk-free rate plus the market, carbon, and energy risk premiums. Each respective beta represents the stock's sensitivity to the risk factor.

A correlation matrix is prepared for the explanatory variables, with the market returns being taken from the MSCI index as explained in the data section.

Ordinary Least Squares (OLS) regression is used to find the beta coefficients for each firm in the sample with the following model:

$$R_{it} = \alpha_i + \beta_{iM} r_{Mt} + \beta_{ico2} r_{co2t} + \beta_{iO} r_{Ot} + \beta_{iG} r_{Gt} + \beta_{iC} r_{Ct} + \beta_{iE} r_{Ei} + e_{it}$$ *Equation 2*

The dependent variable is the monthly excess return on the stock. Explanatory variables are the monthly excess return on the market and the monthly excess return on carbon futures. The control variables of oil, gas, coal and electricity prices changes are also included.

If stock returns are impacted by carbon price risk, the carbon beta coefficient is expected to be significantly different from zero.

For completeness, the stocks are formed into an equally-weighted portfolio and the regression run again on this portfolio of all stocks. Following which two portfolios are created, one for high-emitting stocks and the other for low-emitting stocks and the regression run on each of these portfolios.

Results are compared, and the following tests are also conducted: F test, BG LM test, ARCH LM test, RESET test.

The betas found in equation 2 are then used in equation 1 to find the carbon-adjusted return required on equity. This is compared to the carbon-unadjusted return required on equity.

<u>Part B:</u>

Using the carbon-adjusted return on equity found with equation 1, along with equity and debt weights, return required on debt and the firm's tax code, equation 3 calculates the weighted average cost of capital for the firms:

$$WACC = D/V\ (1\text{-}T)\ r_{Debt} + E/V\ r_{Equity}$$ *Equation 3*

Where D/V represents the portion of total value funded by debt, 1-T adjusts for tax benefits of using debt, E/V represents the portion of total value funded by equity.

Table 3: Sample firms and their emissions details

This table reports data on sample firms. It reports their generation capacity, fuel mix, and emissions intensity. Generation capacity is in mega-watts, and emissions intensity in metric tonnes of carbon (or equivalent greenhouse gas) per mega-watt hour. In the fuel mix, 'other' includes biomass, cogeneration, and nuclear. Table 3 divides the sample firms into three categories based on their emissions intensity. The data comes from the firms' 2017 annual reports.

	Generation capacity (MW)			Fuel mix			Emission intensity tCO2/MWh
		Coal	Gas	CO2 free	Other *	Total	
High-emitting utilities							
RWE	44,000	55%	25%	5%	15%	100%	0.686
CEZ	15718	52.0%	3.0%	6.0%	39.0%	100%	0.5
Endesa	23691	33.0%	6.0%	15.0%	46.0%	100%	0.42
a2a	8405	17.0%	41.0%	32.0%	9.0%	99%	0.417
ERG	2727	0%	0.0%	64.0%	36.0%	100%	0.41
Average emitting utilities							
Enel	83,000	28.0%	26.0%	33.0%	13.0%	100%	0.395
Gas natural Fenosa	15500	14%	61%	21.9%	3.9%	100%	0.371
Engie	115300	5.0%	53.0%	39.0%	3.0%	100%	0.3544
EVN	2389	31%	43%	26%	0%	100%	0.32183
Scottish and Southern Energy	10643	19%	50%	31%	0.0%	100%	0.304
Drax	3870	31.0%	0.0%	0.0%	69.0%	100%	0.297
EDP	25223	25.0%	7.0%	65.0%	3.0%	100%	0.271
Fortum	13334	3.8%	33.2%	28.3%	34.6%	100%	0.188
Low emitting utilities							
Iberdrola	47751	2.0%	39.0%	41.0%	18.0%	100%	0.176
EDF	137542	5.7%	8.3%	8.8%	77.2%	100%	0.084
Verbund	9,724	0.9%	3.1%	96.0%	0.0%	100%	0.031
Centrica	3149	2.0%	30.0%	33.0%	35.0%	100%	0.00137
E.ON	4176	0.0%	1.8%	24.9%	73.0%	100%	0.00003703

Table 3 presents data on the firms included in the study of carbon price risk. It shows their generation capacity in mega-watts, along with the fuel mix used to generate energy. The fuel mix is shown for coal and gas, which are the main fossil fuels. Percentage of carbon free generation is also given, along with 'other' which includes biomass, cogeneration and nuclear. Biomass is a renewable form of energy but is not carbon free, cogeneration is fossil fuel based, and nuclear produces minimal emissions but is not carbon free.

In the last column, the emissions intensity for each firm is given. Emissions intensity is the amount of carbon (or equivalent greenhouse gas) in metric tonnes produced for each mega-watt hour of electricity produced. The firms are ordered in respect to their emissions intensity.

5.2 Hypothesis 2:

This hypothesis is investigated by finding the optimal hedge ratio (OHR) for carbon. To calculate the OHR appropriate to mitigate carbon price risk Fan, Roca & Akimov (2014) is used as a basis. Conventional hedge ratios are applied to the carbon market and a comparison is made between carbon and other commodities in terms of effectiveness in variance reduction and utility maximisation. Priority is given by the authors to carbon emitters who are forced to participate in the scheme and likely have an objective of minimum-variance. This makes good sense, and due to this study's objective being investigation of the carbon risk faced by firms, this will be followed.

Fan, Roca & Akimov (2014) apply four approaches to calculating the hedge ratio, all of which are widely used in other markets. The methods are the naïve approach, ordinary least squares, Engle and Granger's error correction model, a vector error correction model, and a vector error correction model with GARCH and BEKK error. Concurrent with the abovementioned article, Fan, Roca & Akimov published their findings in the Journal of Cleaner Production (2013); both articles have been used to formulate the methodology.

The authors found OLS performs best overall, in line with their expectations about hedge ratios where no structural break exists (Fan et al., 2013). Since the data for this study is from phase III, no structural breaks are expected and therefore the OLS method is expected to outperform the other strategies.

It is expected that the models tested will provide the same level of variance reduction as can be achieved in hedging in other markets, such as gold, crude oil, currencies, and wheat. This result would mean that carbon can be hedged as effectively as other commodities without the need for special techniques.

Part 1:

The naïve model:

This model is simply a 1-1 hedge ratio; for each carbon allowance required, one carbon futures would be purchased to hedge the price. This method does not minimise the variance of the hedged portfolio, it simply offsets the movements in the spot position (Fan et al., 2013).

Ordinary Least Squares:

This model gives the hedge ratio from the regression coefficient β where the OLS model is given by:

$$\Delta S_t = \alpha + \beta \Delta F_t + \varepsilon_t$$ *Equation 4*

ΔS_t being the continuously compounded return on the spot carbon allowances.

ΔF_t being the continuously compounded return on the carbon futures

β being the slope coefficient or minimum variance hedge ratio

εt being the error term

The minimum variance hedge ratio formula is as follows:

$$\beta = \frac{\mathrm{Cov}(\Delta S_t, \Delta F_t)}{\mathrm{Var}(\Delta F_t)}$$ *Equation 5*

Engle and Granger's Error Correction Model

This model is chosen by Fan, Akimov and Roca (2013) due to the inability of OLS to consider non-stationarity. If the spot and futures prices are cointegrated then included in the model should be an error correction term. Assuming S_t is ICE EUA spot price, F_t is ICE EUA futures contract price, the OHR is estimated as follows:

$$\Delta S_t = \alpha \varepsilon_{t-1} + \beta \Delta F_t + \sum_{i=1}^{m} \delta_i \Delta F_{t-1} + \sum_{j=1}^{n} \theta_i \Delta S_{t-j} + \mu_t$$ *Equation 6*

Where β is OHR, $\Delta S = S_t - S_{t-1}$, $\Delta F = F_t - F_{t-1}$ and ε_{t-1} is the first lagged error from the cointegration equation $S_t = \beta_0 + \beta_1 F_t + \varepsilon_t$. To ensure μ_t is a white noise, enough lags will need to be added to the equation.

Vector Error Correction Model (VECM)

This model incorporates the simultaneous determination of the spot and futures prices; the long run cointegration equation is given as:

$$S_t = \beta_0 + \beta_1 F_t + \varepsilon_t$$ *Equation 7*

β_0 being the constant term

β_1 being the co-integration factor

Next, the lagged regression residual is inserted in the VECM from the cointegration equation.

$$\Delta S_t = \alpha_{10} + \alpha_{11}\hat{\varepsilon}_{t-1} + \sum_{j=1}^{n} \varphi_{s1i}\Delta S_{t-j} + \sum_{i=1}^{m} \varphi_{s2i}\Delta F_{t-i} + v_t^s$$
$$\Delta F_t = \alpha_{20} + \alpha_{21}\hat{\varepsilon}_{t-1} + \sum_{j=1}^{n} \varphi_{f1i}\Delta S_{t-j} + \sum_{i=1}^{m} \varphi_{f2i}\Delta F_{t-i} + v_t^f$$

Equation 8

α_{10} and α_{20} are intercepts

α_{11}, α_{21} and φ are parameters

v_t^s and v_t^f are white noise disturbance terms

$\hat{\varepsilon}_{t-1}$ is the error correction term that measures dependent variable adjustment to previous long-term disequilibrium. $\hat{\varepsilon}_{t-1} = F_{t-1} - \beta_0 - \beta_1 S_{t-1}$

The parameters α_{11} and α_{21} measure the speed of adjustment, the more negative they are the greater the response of ΔS and ΔF to the error correction term.

The minimum variance hedge ratio is calculated as:

$$h = \frac{\sigma_{\mathrm{sf}}}{\sigma_{\mathrm{ff}}}$$

Equation 9

Where we let $\mathrm{Var}(v_t^s) = \sigma_{\mathrm{ss}}$, $\mathrm{Var}(v_t^f) = \sigma_{\mathrm{ff}}$ and $\mathrm{Cov}(v_t^s, v_t^f) = \sigma_{\mathrm{sf}}$,

VECM with GARCH-BEKK error

As explained by Fan, Akimov and Roca (2013) the first three models assume a mean of zero and a time-invariant variance for the error term. In the data we may find spot and futures prices display changes in volatility over time; we, therefore, consider a model with more relaxed assumptions allowing the second moment to be time-varying (Fan et al., 2013).

The GARCH-BEKK error structure is inserted into the VECM equation to do so. We then have:

$$\Delta S_t = \alpha_{10} + \alpha_{11}\widehat{\varepsilon}_{t-1} + \sum_{j=1}^{n} \varphi_{s1i}\Delta S_{t-j} + \sum_{i=1}^{m} \varphi_{s2i}\Delta F_{t-i} + \varepsilon_t^s$$
$$\Delta F_t = \alpha_{20} + \alpha_{21}\widehat{\varepsilon}_{t-1} + \sum_{j=1}^{n} \varphi_{f1i}\Delta S_{t-j} + \sum_{i=1}^{m} \varphi_{f2i}\Delta F_{t-i} + \varepsilon_t^f$$
Equation 10

$$\varepsilon_t = \begin{pmatrix} \varepsilon_t \\ \varepsilon_t \end{pmatrix} | \Omega_{t-1} \sim D(0, H_t)$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B$$

$$h_{ss,t} = c_{ss} + \alpha_{ss}\varepsilon_{s,t-1}^2 + \beta_{ss}h_{ss,t-1}$$
$$h_{sf,t} = c_{sf} + \alpha_{sf}\varepsilon_{st-1}\varepsilon_{ft-1} + \beta_{sf}h_{sf,t-1}$$
$$h_{ff,t} = c_{ff} + \alpha_{ff}\varepsilon_{f,t-1}^2 + \beta_{ff}h_{ff,t-1}$$

Where we have an error term which is conditionally normally distributed with a mean of (0,0), and a time-varying covariance matrix. Matrices A, B and C are parameter matrices, where C is a lower triangular and A and B are diagonal.

The hedge ratio is calculated as follows:

Equation 11

$$h^* = \frac{h_{sf}}{h_{ff}}$$

h_{sf} being the conditional covariance between spot and futures

h_{ff} being the conditional variance of futures return

The minimum variance hedge ratio calculated using this method is time-varying.

Part 2:

To assess the effectiveness of the hedge ratios calculated, the percentage of variance reduction is calculated (Fan et al., 2013).

$$\mathrm{VR} = \frac{\mathrm{VAR}(\Delta S_t) - \mathrm{VAR}(\Delta S_t - h^*\Delta F_t)}{\mathrm{VAR}(\Delta S_t)} = 1 - \frac{\mathrm{VAR}(\Delta S_t - h^*\Delta F_t)}{\mathrm{VAR}(\Delta S_t)}$$
Equation 12

Where Var (ΔS_t) is the variance of the unhedged position, and Var($\Delta S_t - h^*\Delta F_t$) is the variance of the hedged position.

To further assess the hedging effectiveness, utility maximisation is calculated (Fan et al., 2013).

$$\mathrm{MAX}\left[E(R_h|\Omega_{t-1})\ -\frac{1}{2}\varphi\mathrm{Var}(R_h|\Omega_{t-1})\right]$$ *Equation 13*

Where R_h is the hedged portfolio, $E(R_h)$ is the return on the hedged portfolio, $Var(R_h)$ is the variance of the hedged portfolio, φ is the risk aversion level of the investor, and Ω_t-1 is the information set available at time t-1.

5.3 Hypothesis 3:

As discussed in the literature review, prior studies show a relation between energy prices and carbon price in phases I and II. The question is whether these price determinants still apply in phase III with its new rules. Since allowances are now fully auctioned to energy utilities, the relation between energy prices and carbon allowance prices should, in theory, be stronger than in prior phases.

Alberola, Chevallier and Cheze (2008) is used as the basis for the methodology; it was chosen due to it being the most widely cited study of carbon price determinants at the time of writing. Temperature changes, as well as energy prices including natural gas, oil, coal, electricity and the clean spark and clean dark spread, were found to have a relation with the carbon price in the first phase (Alberola et al., 2008). It is expected that this relation will hold for phase III.

Alberola, et al (2008) use the switch price as provided by Tendances Carbone, however, this data is no longer available so must be calculated using the following equation which comes from Tendances Carbone as given in Creti, Jouvet and Mignon (2012).

$$0.36 * \text{switch} + 50\% * \text{Pgas} = 0.86 * \text{switch} + 0.36 * \text{Pcoal}$$ *Equation 14*

Where: Pgas = price of gas for the fortnight, Pcoal = price of coal for the fortnight.

The clean spark and clean dark spreads are obtained from DataStream; the below equations are given to show their calculation as per S&P Platts methodology (Platts, 2018).

Spark spread = Power price – (Gas price / fuel efficiency 45%)

Clean spark spread = Spark spread – (EUA emissions price * emissions intensity factor of 0.053942 * energy conversion factor of 3.412141 / fuel efficiency 45%)

Dark spread = Baseload power price – (Coal price/ energy conversion factor 6.978) / fuel efficiency factor 35%

Clean dark spread = Dark spread – (EUA emissions price * carbon intensity factor 0.973)

The variables, natural gas, coal and oil, are inputs to the carbon-emitting process of energy production. The relation between the price of these inputs and the price of carbon is, therefore, logical, particularly since carbon emissions from the inputs vary and the switch between, for example, gas and coal due to price variation has a large impact on total carbon emissions. Often energy utilities are able to easily switch between gas and coal and around 50% fewer carbon allowances are required when using gas (Benz & Trück, 2009). Likewise, electricity has a logical relation with the price of carbon since electricity is the output of a carbon emitting process. As discussed in prior sections, the weather also has a relation to the price of carbon in that colder or hotter than usual weather increases demand for electricity.

In considering the relation between carbon price and oil price, it is necessary to take into consideration the oil price collapse in 2014. The price of Brent crude oil fell sharply in the fourth quarter of 2014. The price of oil dropped by over 60% between June 2014 and January 2015 (Kemp, 2015). The main causes of the collapse are said to be an oversupply of oil in the global markets, coupled with increased supply of a cheaper substitute product (shale). The data is therefore split into two sub-samples: prior to the fourth quarter of 2014 and beginning the fourth quarter of 2014 through 2017.

Alberola et al (2008) use two models of the carbon price, the first following prior literature of Mansanet-Bataller et al (2007) and the second being a new model of the authors.

Data in this study comes from phase III of the EU ETS with no structural breaks expected.

Model 1:

$$\begin{aligned} p_t = {} & \alpha_i + \beta_i(L)p_t + \chi_i break_1 + \delta_i break_2 \\ & + \phi_i(L)brent_t + \varphi_i(L)ngas_t \\ & + \gamma_i(L)coal_t + \eta_i(L)switch_t \\ & + \iota_i(L)elec_t + \kappa_i(L)clean\ dark_t \\ & + \lambda_i(L)clean\ spark_t + \Theta_i Temp \\ & + \mu_i Tempext5 + \nu_i Tempex95 + \varepsilon_{i,t}, \end{aligned}$$

Equation 15

This model of the spot price of carbon includes variables for: the lagged spot carbon price, two structural breaks, Brent crude oil, natural gas, coal, switch price, electricity, clean dark spread, clean spark spread. The aforementioned variables are daily and are lagged one period (L). Weather variables represent extreme temperatures and determined using the 5^{th} and 95^{th} percentile.

Model 2:

$$\begin{aligned} p_t = {} & \alpha_i + \beta_i(L)p_t + \chi_i break_1 + \delta_i break_2 \\ & + \phi_i(L)brent_t + \varphi_i(L)ngas_t \\ & + \gamma_i(L)coal_t + \eta_i(L)switch_t + \iota_i(L)elec_t \\ & + \kappa_i(L)clean\ dark_t \\ & + \lambda_i(L)clean\ spark_t + o_i Jul05 + \theta_i Win06 + \vartheta_i Jul06 \\ & + \rho_i Sepoct06 + \sigma_i Win07 + \varepsilon_{i,t}, \end{aligned}$$

Equation 16

Model 2 departs from the previous model in terms of the weather variables. Here weather variables are cross products of the dummy variables representing an extreme temperature and absolute deviations from the average temperature. For example, Jul05 is a cross product of the dummy variable characteristic of July 2005 and the absolute value of deviation from the seasonal average temperature (Alberola et al., 2008).

The models are analysed using the following tests:

- R-squared and adjusted R-squared values for explanatory value of the model
- The F-statistic for the overall significance of the full model
- Durbin-Watson test statistic for autocorrelation
- Breusch-Godfrey serial correlation
- Lagrange multiplier for serial correlation
- White's test for heteroscedasticity
- Akaike Information Criterion for quality of the model
- Schwarz criterion for choosing between the models

Method chosen:

This study departs from the method of Alberola et al, (2008) in that fortnightly data is used. This is logical as firms can only purchase spot carbon allowances at auction fortnightly. With the use of fortnightly data, the independent variables have not been lagged. Equation 17 will be used for model 1. Model 2 will use equation 18 with the addition of cross products for extreme weather variable found in the data.

$$P_t = \alpha_i + \beta(L)P_t + \phi_i \text{ Brent}_t + \varphi_i \text{ Ngas}_t + \gamma_i \text{ coal}_t + \eta_i \text{ switch}_t + \iota_i \text{ elec}_t + \kappa_i \text{ clean dark}_t + \lambda_i \text{ clean spark}_t + \mu_i \text{ Tempext5} + \ddot{\upsilon}_i \text{ Tempex95} + \varepsilon_{i,t}$$

Equation 17

$$P_t = \alpha_i + \beta(L)P_t + \phi_i \text{ Brent}_t + \varphi_i \text{ Ngas}_t + \gamma_i \text{ coal}_t + \eta_i \text{ switch}_t + \iota_i \text{ elec}_t + \kappa_i \text{ clean dark}_t + \lambda_i \text{ clean spark}_t + \varepsilon_{i,t}$$

Equation 18

6 RESULTS:

6.1 Hypothesis 1:

6.1.1 Data:

Prior to calculating the regression for each firm, the data was inspected. Testing for stationarity with the augmented Dickey-Fuller test revealed all return variables to be stationary; rejecting the null of a unit root at the 1% significance level.

Homoscedasticity was checked using White's test; heteroscedasticity was present in the returns of Iberdrola and Centrica. The Durbin-Watson and Breusch-Godfrey tests were used to test for autocorrelation and revealed autocorrelation in the returns of RWE, ERG, EDP, and Iberdrola. Accordingly, Newey-West standard errors are applied to the regression results for robustness.

Non-normality was tested for using the Jarque-Bera test. The null hypothesis of normality could be rejected for firms A2A, ERG and EVN. Upon inspection of returns, the issue of non-normality is ignored as the 'outlier' in the data is not a true outlier, rather, a natural peak in stock price.

A correlation matrix for all explanatory variables was prepared as Table 4 shows. Moderate to low correlation is found between the electricity prices. This is logical, we can expect some level of correlation between the electricity prices on different exchanges around Europe. No evidence of multicollinearity is found.

Table 4: Correlation matrix of coefficients for hypothesis 1 explanatory variables

This table reports the correlation coefficients of the explanatory variables used in hypothesis 1. reM is the excess return on the market as proxied by the MSCI Europe Index. Reco2 is the excess return on carbon futures. reO is the excess return on crude oil futures. reG is the excess return on natural gas futures. reC is the excess return on coal futures. reAPX is the excess return on spot baseload electricity on the APX power exchange. reEEX is the excess return on spot baseload electricity on the EEX power exchange. reGME is the excess return on spot baseload electricity on the GME power exchange, reNP is the excess return on spot baseload electricity on the NP power exchange. reOMEL is the excess return on spot baseload electricity on the OMEL power exchange. rePXE is the excess return on spot baseload electricity on the PXE power exchange.

Pearson Correlation Coefficients, N = 59
Prob > |r| under H0: Rho=0

	reM	**reco2**	**reO**	**reG**	**reC**	**reAPX**	**reEEX**	**reGME**	**reNP**	**reOMEL**	**rePXE**
reM	1.00000										
reco2	0.11823 0.3725	1.00000									
reO	0.22748 0.0831	0.17630 0.1816	1.00000								
reG	0.14707 0.2663	0.27084 0.0380	0.29312 0.0243	1.00000							
reC	0.11492 0.3861	0.08651 0.5147	0.16202 0.2202	0.47434 0.0001	1.00000						
reAPX	0.06183 0.6418	0.06793 0.6092	0.16281 0.2179	0.39560 0.0019	0.23175 0.0774	1.00000					
reEEX	-0.00433 0.9740	0.11215 0.3977	0.18184 0.1681	0.13557 0.3059	0.04002 0.7635	0.44029 0.0005	1.00000				
reGME	-0.04623 0.7281	0.09201 0.4883	0.20623 0.1171	0.29055 0.0256	0.01141 0.9316	0.10389 0.4336	0.42688 0.0007	1.00000			
reNP	-0.08105 0.5417	-0.03925 0.7679	0.18117 0.1697	0.19530 0.1382	-0.02078 0.8758	0.36465 0.0045	0.54956 <.0001	0.39074 0.0022	1.00000		
reOMEL	-0.09454 0.4763	-0.36679 0.0043	-0.08163 0.5388	-0.11574 0.3827	0.28025 0.0316	0.06225 0.6395	0.31411 0.0154	0.19501 0.1388	0.26167 0.0453	1.00000	
rePXE	-0.06143 0.6440	0.10331 0.4362	0.11373 0.3911	0.17801 0.1774	0.13761 0.2986	0.28608 0.0281	0.56610 <.0001	0.09747 0.4627	0.31292 0.0158	0.13385 0.3122	1.00000

6.1.2 Regression results:

Results of regression run for each firm are presented in Table 5. All p-values for the regression coefficients are based on Newey-West standard errors to be consistent with both heteroscedasticity and autocorrelation. Overall, the adjusted R-squared for each firm is not overly high, with a maximum of 42% for Verbund.

The F-test looks at the overall significance of the model, the null hypothesis is that a model with no dependent variables fits the data just as well as the model created. The alternative is that the model with dependent variables fits the data better than an intercept-only model. The null hypothesis is rejected at the 5% level of significance for 15 out of the 18 firms. For 3 of the firms in the sample, the model created with dependent variables of carbon and energy prices fits the data no better than a model with only an intercept. The F-test is not valid for those estimated with GARCH.

Testing for serial correlation with the BG LM test reveals an autocorrelation problem for several of the firms; to remedy this, as above, Newey-West standard error consistent p-values are reported for all coefficients. The ARCH LM test has been performed to check for autoregressive conditional heteroscedasticity (ARCH) effects in the data. ARCH effects were detected for 1 of the 18 firms (A2A). As a result, the presented coefficients and their p-values are estimated using ARCH specification. These results are presented in Table 5.

Looking into the regression output, all firms except Drax and ERG, have a statistically significant exposure to market returns, as per the Capital Asset Pricing Model (CAPM). It is possible that since the MSCI Europe index was used as a proxy for market returns, these firms do not have a significant exposure to the market as the index contains. The market exposure varies considerably between the firms, RWE has the highest with a market beta of 1.57, while Scottish and Southern Energy has the lowest with 0.273. The market beta tells us the premium demanded by the shareholders to compensate for exposure to market risk.

The results for our control variables show a lack of significance. Oil price returns are only significant for 3 firms (Endesa, Engie and Verbund), while gas is only significant for 1 firm at a 5% level (Gas Natural Fenosa). Coal prices are significant for 4 firms (RWE, CEZ, A2A, and Verbund). The majority of the firms have exposure to one or none of the energy price return series. The exception being Verbund which has significant exposure to two of the three energy variables. The energy betas, significant or not, are positive for some firms and negative for others. Overall, there is little evidence to show significance or direction of exposure. The results are the same for electricity prices; for the majority of firms in the sample, there is no significant exposure.

The lack of significant exposure to electricity prices is puzzling. As explained, all firms in the sample are utility companies that produce and sell electricity as their core business. The electricity prices in their local market determine the price the firm receives for their product. Yet only one firm has a statistically significant electricity beta. Fortum's electricity beta is significant at a 10% level. This finding is, however, consistent with Koch and Bassen (2013), who do not discuss this finding.

The crucial results of the regression analysis are the carbon betas; 28% of the firms have a statistically significant exposure to carbon prices. Comparatively, only 15% of the firms in Koch and Bassen's 2013 research had significant exposure to carbon at a 5% or better level. Looking more closely at the firms included in both studies yields Tables 6 and 7.

No consistency exists between a large change in emissions intensity and a large change in carbon exposure from 2013-2017. The biggest change in emissions intensity was by Endesa, with a 367% increase in emissions intensity from their operations. Puzzlingly, Endesa experienced a decrease in carbon exposure of 110%, however, this was not the largest change. Enel's carbon exposure increased by 600% over the period 2010-2017. Consistency is also lacking in the direction of the change. Endesa demonstrates this with a large increase in carbon emissions per megawatt hour of energy produced, while the firm experienced a significant decrease in its exposure to carbon prices.

The regression results show that in-sample, 28% of firms exhibit evidence of carbon price risk. Consistent with the findings of Koch and Bassen (2013); for the majority of European firms' carbon price is not a significant risk factor. For hypothesis 1, we cannot reject the null hypothesis that firms do not face carbon price risk.

Table 5: Regression results hypothesis 1

This table reports the results of the regression analysis for the complete sample of firms. The equation used is the excess return on firm stock = $R_{it} = \alpha_i + \beta_{iM} r_{Mt} + \beta_{ico2} r_{co2t} + \beta_{iO} r_{Ot} + \beta_{iG} r_{Gt} + \beta_{iC} r_{Ct} + \beta_{iE} r_{Ei} + e_{it}$ The excess returns on the market, carbon futures, crude oil futures, natural gas futures, coal futures, and electricity prices are presented as the explanatory variables. P-values are presented below regression coefficients in brackets. Superscripts *, **, *** denote significance at the 10%, 5% and 1% levels.

	Intercept	Market	Carbon	Oil	Gas	Coal	Electricity	Adj R2	F-test	BG LM test	ARCH LM test	RESET test
Panel A: High emitting												
RWE	-0.008	1.572***	0.067	-0.172	-0.219*	0.575**	0.035	22.98%	0.0028	0.862	0.9698	0.7296
	(0.5355)	*(0.0058)*	*(0.4325)*	*(0.1130)*	*(0.0967)*	*(0.0161)*	*(0.1381)*					
CEZ	-0.009	0.705***	0.101**	-0.057	0.042	0.246**	-0.020	25.60%	0.0013	0.3837	0.2394	0.6611
	(0.2448)	*(0.0002)*	*(0.0126)*	*(0.4938)*	*(0.6859)*	*(0.0320)*	*(0.1295)*					
Endesa	0.004	0.922***	-0.003	-0.164***	-0.044	0.092	0.004	27.13%	0.0008	0.8022	0.7952	0.0785
	(0.5737)	*(0.0000)*	*(0.9434)*	*(0.0038)*	*(0.4934)*	*(0.4007)*	*(0.7288)*					
A2A	0.017***	1.207***	0.105**	-0.038	0.065	-0.114***	-0.030	20.57%		0.3946	0.048	0.6905
	(0.0017)	*(0.0000)*	*(0.0173)*	*(0.6455)*	*(0.2386)*	*(0.0000)*	*(0.3085)*					
ERG	0.000	0.464	0.094*	-0.025	-0.171*	0.051	-0.052019	9.21%	0.0854	0.6912	0.4979	0.9506
	(0.9594)	*(0.1152)*	*(0.0673)*	*(0.7638)*	*(0.0905)*	*(0.7367)*	*(0.1404)*					
Panel B: Average emitting												
ENEL	0.003	1.052***	-0.033	-0.058	-0.115	0.183	-0.020	29.81%	0.0003	0.5931	0.6423	0.3882
	(0.6687)	*(0.0000)*	*(0.5393)*	*(0.5065)*	*(0.1384)*	*(0.1006)*	*(0.5857)*					
Gas Natural Fenosa	-0.001	0.997***	-0.029	-0.054	-0.215**	0.155	0.018	32.42%	0.0001	0.9197	0.5647	0.3323
	(0.8329)	*(0.0000)*	*(0.6464)*	*(0.6164)*	*(0.0421)*	*(0.1804)*	*(0.1246)*					
Engie	-0.008	1.218***	0.012	-0.161**	-0.098	0.069	0.015	30.98%	0.0002	0.7297	0.1355	0.4385
	(0.2905)	*(0.0000)*	*(0.8245)*	*(0.0450)*	*(0.2367)*	*(0.5435)*	*(0.4444)*					
EVN	-0.008	0.353**	0.079***	-0.064	0.064	-0.098	0.010	14.50%	0.0261	0.3808	0.7659	0.6015
	(0.1199)	*(0.0163)*	*(0.0061)*	*(0.3949)*	*(0.2605)*	*(0.3145)*	*(0.3673)*					
Scottish and Southern	-0.012**	0.280**	0.045	-0.004	-0.058	0.088	-0.040221	2.24%	0.3104	0.3287	0.9463	0.5736
	(0.0376)	*(0.0480)*	*(0.2944)*	*(0.9512)*	*(0.4073)*	*(0.3488)*	*(0.0919)*					
Drax	-0.015	0.114	0.022	0.318	-0.026	0.335	-0.045	3.32%	0.2599	0.8265	0.8199	0.8852
	(0.1882)	*(0.7555)*	*(0.8482)*	*(0.1157)*	*(0.8197)*	*(0.1873)*	*(0.3601)*					
EDP	-0.008*	0.773***	0.039	-0.127	-0.151*	0.008	0.003	15.03%	0.023	0.0021	0.9798	0.7217
	(0.0992)	*(0.0000)*	*(0.5804)*	*(0.3175)*	*(0.0517)*	*(0.9567)*	*(0.6577)*					
Fortum	0.000	0.701***	0.113**	-0.040	0.018	0.224*	0.049*	25.63%	0.0013	0.5727	0.1164	0.1376
	(0.9698)	*(0.0009)*	*(0.0148)*	*(0.6689)*	*(0.8171)*	*(0.0915)*	*(0.0917)*					
Panel C: Low emitting												
Iberdrola	0.002	0.876***	0.073	-0.020**	-0.086*	0.086	0.013	40.17%	8E-06	0.016	0.8381	0.321
	(0.7081)	*(0.0000)*	*(0.1379)*	*(0.0128)*	*(0.0918)*	*(0.3383)*	*(0.1041)*					
EDF	-0.003	1.449***	0.051	-0.041	0.007	0.040	0.033	20.01%	0.0063	0.955	0.8606	0.7527
	(0.8606)	*(0.0000)*	*(0.4930)*	*(0.6921)*	*(0.9421)*	*(0.7688)*	*(0.5927)*					
Verbund	-0.002	0.825***	0.143***	-0.128	0.034	0.387***	-0.005	39.50%	5E-06	0.5168	0.7551	0.3912
	(0.7939)	*(0.0000)*	*(0.0093)*	*(0.1387)*	*(0.6466)*	*(0.0084)*	*(0.7147)*					
Centrica	-0.026**	0.641***	-0.031	-0.020	-0.047	-0.058	-0.070	9.11%	0.0871	0.8578	0.3466	0.1788
	(0.0141)	*(0.0043)*	*(0.5391)*	*(0.8234)*	*(0.5545)*	*(0.7339)*	*(0.1499)*					
E.ON	-0.009	1.152***	0.024	-0.150	-0.091267	0.312	0.012	18.20%	0.0104	0.7478	0.5377	0.2916
	(0.3796)	*(0.0013)*	*(0.6584)*	*(0.1161)*	*(0.4075)*	*(0.1633)*	*(0.5999)*					

Looking deeper into the results shows the carbon exposure is not consistently larger for the higher emitting firms. Verbund, with a carbon beta of 0.11 is in the lowest emitting category, where CEZ, the second highest emitter, has a carbon beta of 0.107. The distribution of carbon exposure does not appear to be determined by how much a firm emits for each megawatt hour of energy produced.

Table 6: Comparison of 2013 and 2018 emission intensities

This table reports the emission intensity in tonnes of carbon (or equivalent greenhouse gas) per megawatt hour of electricity produced. It compares 2013 and 2018 results for the same firms.

	Emissions intensity tCO2/MWh		
	Koch and Bassen (2013 results)	2018 results	Trend
RWE	0.24	0.686	186%
Drax	0.33	0.297	-10%
CEZ	0.24	0.5	108%
Scottish and Southern	0.21	0.304	45%
A2A	0.17	0.417	145%
Centrica	0.12	0.00137	-99%
Enel	0.15	0.395	163%
E.ON	0.17	0.00004	-100%
Gas Natural Fenosa	0.17	0.371	118%
EDF	0.09	0.084	-7%
EDP	0.1	0.271	171%
Endesa	0.09	0.42	367%
Fortum	0.11	0.188	71%
Iberdrola	0.11	0.176	60%

From the reported results, the level of emissions intensity does not appear determine whether a firm is exposed to carbon price risk. A larger percentage of high-emitting firms are found to have carbon risk, however, those in the average and low emitting categories also experience carbon price risk. Firms in the low emitting category still have a positive carbon coefficient and as such do not experience any sort of discount for having lower exposure to carbon risk.

Table 7: Comparison of 2013 and 2018 carbon betas

This table reports the carbon betas for sampled firms as found in Koch and Bassen (2013) article, and in this thesis.

	Carbon Beta		
	Koch and Bassen (2013 results)	2018 results	Trend
RWE	0.11 ***	0.067	-39%
Drax	0.16**	0.022	-86%
CEZ	0.14**	0.101**	-28%
Scottish and Southern	-0.01	0.045	350%
A2A	-0.07	0.105**	50%
Centrica	-0.1	-0.031	-69%
Enel	0.01	-0.033	-430%
E.ON	0.07	0.024	-66%
Gas Natural Fenosa	0.04	-0.029	-173%
EDF	0.03	0.051	70%
EDP	-0.09*	0.039	57%
Endesa	0.1	-0.003	-103%
Fortum	0.06	0.113**	88%
Iberdrola	0.03	0.073	143%

These findings suggest that Europe's success in lowering emissions is not the result of the EU ETS. The scheme does not appear to place adequate pressure on firms in Europe to reduce their emissions. RWE is the highest emitting utility firm in the sample and yet no evidence is found of exposure to carbon price risk. One possible explanation is that the firms which are actively lowering their emissions are doing well enough that other firms can free-ride. RWE's fuel mix is 80% fossil fuels; if the EU ETS is functioning effectively, we would expect evidence of carbon price risk for RWE, particularly compared to Verbund, with low emissions intensity and 96% carbon free fuel mix and carbon price risk.

With very different emissions intensities between firms, the question arises as to why some firms have carbon price risk when others do not? Table 8 presents the fuel mix for each of these five firms. The data available currently does not provide in-depth information on the carbon allowance requirements of each firm. It is, therefore, a topic for further research as to what determines which European firms are exposed to carbon price risk.

It is the five firms with significant carbon betas that are used for part B of hypothesis 1 to calculate the carbon-adjusted weighted average cost of capital (WACC) for each firm.

Table 8: Emissions data for firms showing evidence of carbon exposure

This table reports the generation capacity, fuel mix and emissions intensity for the sampled firms that show evidence of carbon exposure. Generation capacity is in mega-watts. The fuel mix is shown as percentages, where 'other' includes biomass, cogeneration and nuclear. Emissions intensity is in tonnes of carbon (or equivalent greenhouse gas) per mega-watt hour of electricity produced.

	Generation capacity (MW)	Coal	Gas	CO2 free	Other *	Total	Emission intensity tCO2/MWh
CEZ	15718	52.00%	3.00%	6.00%	39.00%	100%	0.5
A2A	8405	17.0%	41.0%	32.0%	10.0%	100%	0.417
EVN	2389	30.60%	43.30%	26.10%	0.00%	100%	0.32183
Fortum	13334	3.83%	33.24%	28.32%	34.61%	100%	0.188
Verbund	9724	0.90%	3.10%	96.00%	0.00%	100%	0.031

Creating an equally weighted portfolio of all firms, of high emitting firms and of low emitting firms the following results are found:

Table 9: Portfolio regression results

This table reports the regression results of the portfolio including all sample firms, the portfolio including only high-emitting firms, and the portfolio including only low-emitting firms. The equation used is the excess return on firm stock = $R_{it} = \alpha_i + \beta_{iM} r_{Mt} + \beta_{ico2} r_{co2t} + \beta_{iO} r_{Ot} + \beta_{iG} r_{Gt} + \beta_{iC} r_{Ct} + \beta_{iE} r_{Ei} + e_{it}$ The excess returns on the market, carbon futures, crude oil futures, natural gas futures, coal futures, and electricity prices are presented as the explanatory variables. P-values are presented below regression coefficients in brackets. Superscripts *, **, *** denote significance at the 10%, 5% and 1% levels.

	Intercept	Market	Carbon	Oil	Gas	Coal	Electricity	Adj R2	F-test	BG LM test	ARCH LM test	RESET test
All	-0.013***	0.394***	0.047	0.021	-0.056	0.129**	0.002	13.00%	0.037043	0.0564	0.1309	0.8354
	(0.0014)	*(0.0033)*	*(0.3009)*	*(0.7081)*	*(0.2787)*	*(0.0257)*	*(0.8474)*					
High-emitting	-0.009	0.772***	0.09**	-0.085	0.009	0.235**	0.013	24.52%	0.001798	0.127	0.2706	0.8281
	(0.2090)	*(0.0000)*	*(0.0409)*	*(0.2540)*	*(0.9220)*	*(0.0219)*	*(0.3648)*					
Low-emitting	-0.022**	0.711***	-0.013	-0.036	-0.081	-0.025	0.000	9.56%	0.079233	0.7907	0.0821	0.725
	(0.0157)	*(0.0004)*	*(0.7728)*	*(0.6459)*	*(0.2717)*	*(0.8644)*	*(0.9807)*					

From the portfolio results, we can see that placing all firms in one portfolio confirms our previous finding that firms in Europe do not face carbon price risk. However, an interesting finding appears when the portfolio is split into high-emitting firms and low-emitting firms. Significant carbon exposure does exist for a portfolio of high emitting firms.

Like Koch and Bassen (2013), it is found that investors do consider carbon price movements to be an important risk factor for firms with high emissions intensity from their operations.

However, as discussed, when this category is looked at firm-by-firm, only 2 of the high emitters show evidence of carbon price risk.

Another interesting finding that appears above is that for high-emitting firms the carbon coefficient is positive, whereas for low-emitting firms the coefficient is negative. This would indicate a risk premium demanded of high-emitters and a risk discount for low-emitters. However, the coefficient for low-emitting firms is not significant.

6.1.3 Calculating the carbon-adjusted WACC

Return demanded by investors on equity:

$$Re = \mu_i = rf + \beta_M (\mu_M - rf) + \beta_{Energy} (\mu_{Energy} - rf) + \beta_{co2} (\mu_{co2} - rf) \qquad \text{Equation 1}$$

Where rEnergy is only included for energy variables which are significant, the rf is approximated by the 10 year German Government bond rate of 3%, and rM is the historical average of MSCI returns over the time-period 2013-2017. At the time of writing, the 2017 annual report was not available for A2A, therefore, the interest expenses are approximated by doubling the interest expense reported for the first 6 months of 2017.

The results show in Table 10 that for the five firms in the sample that have statistically significant carbon exposure, this exposure has a considerable impact on their WACC. The average increase in WACC from incorporating carbon exposure is 3.44%. Verbund experienced the largest increase, with a 9.63% higher rate demanded.

Overall, the findings reveal that most carbon producing European firms do not face carbon price risk. However, those that do, experience an average increase in return demanded by shareholders of 7.3%. The firms facing carbon price risk have a considerably higher weighted average cost of capital when carbon risk is factored in.

Table 10: Carbon adjusted weighted average cost of capital for firms exhibiting carbon risk

This table reports the results of carbon-unadjusted and carbon-adjusted return on equity, and weighted average cost of capital (WACC) for the firms that show evidence of exposure to carbon prices. Carbon-unadjusted Re = $\mu_i = rf + \beta_M (\mu_M - rf)$. Carbon-adjusted Re = $\mu_i = rf + \beta_M (\mu_M - rf) + \beta_{Energy} (\mu_{Energy} - rf) + \beta_{co2} (\mu_{co2} - rf)$. Weighted average cost of capital = WACC = D/V * Rd (1 - t) + D/V * Re, where Re is unadjusted and adjusted to calculate carbon-unadjusted and carbon-adjusted WACC respectively.

	CEZ	**A2A**	**EVN**	**Fortum**	**Verbund**
Risk free rate	3.00%	3%	3.00%	3.00%	3.00%
Market excess returns	3.20%	3.20%	3.20%	3.20%	3.20%
Market beta	0.705	1.207	0.353	0.701	0.825
Oil excess returns					
Oil beta					
Gas excess returns					
Gas beta					
Coal excess returns	0.75%	0.75%			0.75%
Coal beta	0.246	-0.114			0.387
Electricity excess returns					
Electricity beta					
Carbon-unadjusted rEquity	5.44%	6.78%	4.13%	5.24%	5.93%
Carbon excess returns	67.36%	67.36%	67.36%	67.36%	67.36%
Carbon beta	0.101	0.105	0.079	0.113	0.143
Carbon-adjusted rEquity	12.24%	13.85%	9.45%	12.85%	15.56%
Cost of debt	1.01%	1.67%	1.98%	1.94%	2.32%
Tax	19%	24%	25%	20%	25%
Cost of debt after tax	0.82%	1.27%	1.48%	1.55%	1.74%
Equity	40.61%	33.10%	48.80%	61.08%	50.43%
Debt	59.39%	66.90%	51.20%	38.92%	49.57%
Carbon-unadjusted WACC	2.70%	3.09%	2.78%	3.81%	3.85%
Carbon-adjusted WACC	5.46%	5.43%	5.37%	8.45%	8.71%
Change in WACC	2.76%	2.34%	2.60%	4.65%	4.86%
Change in Re	6.80%	7.07%	5.32%	7.61%	9.63%

6.1.4 Hypothesis 1 conclusions

This hypothesis sought to investigate whether carbon producing European firms face carbon price risk in the third phase of the EU ETS. Firm stock returns were run as the dependent variable in regression and no consistent relation was found between firm returns and energy prices. The relation between firm returns and carbon price returns was the result of interest and 28% of firms were found to have a statistically significant carbon betas. The conclusion being that nearly a third of the firms studied exhibited significant exposure to the price of carbon. However, the results were not consistent in regards to firm emissions. High and low emitting firms had significant carbon betas.

The second portion of this hypothesis was to calculate the weighted average cost of capital (WACC) for 5 firms which exhibited carbon exposure. The WACC was compared with the carbon adjusted WACC for the same firms. The result showed an average increase in WACC, of 3.44% after carbon exposure was considered. The conclusion being that for the majority of European firms, the carbon price is not a relevant risk factor. However, for those for which it is, the increase in return demanded by shareholders is substantial. The average increase in return on equity was found to be 7.3%. Oestreich and Tsiaskas (2015) also found a higher expected return to be demanded on equity owing to carbon price risk.

While significantly higher returns are demanded for some firms owing to carbon and energy price exposure, the null hypothesis that European firms do not face carbon price risk cannot be rejected; only a small portion of firms in this study had a statistically significant carbon beta. This is in line with Koch and Bassen's (2013) phase I and II findings.

If European firms on the whole do not face risk from the varying price of carbon, is the EU ETS effective? It appears from previous studies and from the conclusions drawn by this thesis, that it is not the price signal driving the change towards a low-carbon economy. The function of the EU ETS is to reduce emissions by placing price pressure on firms through a cap. If no such price pressure exists, what does this mean for the scheme?

As discussed in the literature review, the EU ETS met its 2020 targets in 2015, however, this does not mean that the scheme was the reason those targets were met. The European Commission touts the success of the EU ETS, however, it is not clear whether these environmental wins can be attributed to the scheme at all. Public and political pressure on 'dirty'energy firms has pushed towards cleaner energy production and away from fossil fuels. Efficiency has been a driving force in reducing emissions; as technology advances, a reduction in emissions is an incidental benefit of more efficient processes. Government schemes promoting the adoption of cleaner energy production, and the building of renewable energy infrastructure, have encouraged firms to alter their fuel mix.

For the firms found to have significant carbon betas in the sample, fuel mix was not consistent. A high proportion of fossil fuels in the fuel mix was not found to correlate with a higher chance of carbon price risk. Two firms of interest are CEZ and Verbund whose fuel mixes are 55% fossil fuels and 96% carbon free respectively. Interestingly, both firms were found to have significant carbon betas and higher returns demanded by shareholders as a result. In fact, Verbund's return demanded on equity nearly tripled when carbon was taken into consideration in hypothesis 1. The explanation for this perhaps lies in investor perception of risk; Verbunds' share price is sensitive to the variability in the price of carbon despite having a fuel mix almost completely carbon free. Alternatively, the answer may lie in the determinants of carbon price; what the price of carbon is sensitive to.

6.2 Hypothesis 2

6.2.1 Data

Price data for spot EUAs are fortnightly as this is the frequency of auctions. The futures data has therefore been matched to the dates of the spot auction prices. The resulting data is fortnightly with a break over each Christmas period.

Stationarity is tested for using both the Augmented Dickey-Fuller and Philips-Perron tests. In both cases, the data was found to be stationary. Cointegration is then tested for using both Engle-Granger and Johansen methodologies. In both cases, spot and futures prices of carbon are found to be cointegrated. Table 11 below presents the results of the Johansen cointegration test.

Table 11: Johansen cointegration results

This table reports the results of the Johansen cointegration test for spot and futures prices. The p-value in all cases is less than 0.05, therefore the null hypothesis of no cointegration is rejected. Cointegration is present.

	No. of cointegration equations	**Trace statistic**	**P-value**
Trace	None	22.21103	0.0042
	At most 1	3.85584	0.0496
Max Eigenvalue	None	18.35519	0.0107
	At most 1	3.85584	0.0496

Following Fan et al (2014) the lag length is tested using Akaike Information Criterion and the Schwartz Information Criterion. The stability of the vector autoregressive (VAR) model is also checked (Fan et al., 2014). The lag order selected by the criterion is l lag, thus one lag has been used. In terms of stability of the VAR, no root lies outside the unit circle and therefore the stability condition is satisfied.

Looking at the spot and future carbon prices 2013 through 2017 there is a noteworthy price drop in late 2014. This was discussed in the data section, and as spot and futures track closely in this fall, it should not overly influence the calculation of hedge ratios in this study.

6.2.2 Hedge ratios

Hedge ratios are calculated as per the methodology section and presented in the table below. The calculation is undertaken for each year in the sample and for the full period. Annual hedge ratios are logical in this setting as firms must surrender carbon allowances once per year in April.

Table 12: Hedge ratios for phase III

This table reports the results of hedge ratio calculations for hedging carbon price risk with carbon futures contracts. It shows the hedge ratios for each year of phase III of the European Union Emissions Trading Scheme, and the full period, as calculated using each method.

Hedging horizon	2013	2014	2015	2016	2017	Full period
Naïve	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
OLS	0.8563	1.0466	0.8699	1.0055	0.9454	0.9284
ECM	0.8226	0.9844	1.0372	0.9620	0.9349	0.9310
VECM	1.0010	0.8900	1.1420	0.9269	0.8998	0.9950
VECM w GARCH BEKK	1.0011	0.8904	1.1420	0.9269	0.8998	0.9950

As shown in Table 12, the hedge ratios calculated with each method are all within a band of 0.8 and 1.15. The VECM and VECM with GARCH BEKK produce nearly identical hedge ratios; this is unsurprising since they share fundamentals in the way they are calculated.

6.2.3 Variance reduction

Following the methodology explained, the reduction in variance for each hedge ratio is calculated and compared.

Table 13: Variance reduction for each method of hedge ratio

This table reports the variance reduction achieved by using carbon futures to hedge carbon price risk. The results are presented for each year in phase III of the European Union Emissions Trading Scheme, and for the full period. Each method is compared, with the method achieving the greatest reduction in variance presented in the last row of the table. The equation used to calculate variance reduction = VR= [Var(ΔSt) – Var (ΔSt - h*ΔFt)] / Var(ΔSt), where Var (ΔS_t) is the variance of the unhedged position, and Var(ΔS_t – h*ΔF_t) is the variance of the hedged position.

Variance reduction						
	2013	2014	2015	2016	2017	All
Variance unhedged	300.765	74.728	19.782	164.021	57.525	121.023
Naive variance	68.088	11.527	3.400	12.955	4.575	19.248
Naive variance reduced	77.4%	84.6%	82.8%	92.1%	92.1%	84.1%
OLS variance	61.909	11.401	3.051	12.957	4.732	18.639
OLS variance reduced	79.4%	84.7%	84.6%	92.1%	92.1%	84.6%
ECM variance	62.385	11.625	3.636	13.190	4.799	18.640
ECM variance reduced	79.3%	84.4%	81.6%	92.0%	92.0%	84.6%
VECM variance	68.180	12.818	4.629	13.793	5.105	19.166
VECM variance reduced	77.3%	82.8%	76.6%	91.6%	91.6%	84.2%
VECM GARCH BEKK variance	68.186	12.811	4.629	13.793	5.105	19.166
VECM GB variance reduced	77.3%	82.9%	76.6%	91.6%	91.6%	84.2%
Best method	OLS	OLS	OLS	Naïve	Naïve	OLS

Table 13 presents the variances of the spot position and of the hedged positions using each different hedge ratio. It also shows the reduction in variance for each hedged position compared to the spot position for that year. Lastly, it presents the best method for hedging for each period and overall. Interestingly, the simplest of the hedging techniques prevail. The ordinary least squares method achieves the highest variance reductions for 2013-2015 and overall, while the naive method reduces variance by the greatest amount in years 2016 and 2017.

The OLS method is the most effective in terms of hedging variance. However, in all years, the naïve method achieves a reduction in variance only slightly differing from that of the OLS. In comparison to Fan et al (2014) slightly better variance reductions are found. The phase I study found variance reduction between 60%-91% could be achieved, while this phase III study found variance reduction between 77%-92%. A significant reduction in risk is achieved through hedging with carbon futures. Like Fan et al (2014) this study cannot support the superiority of the vector error correction model, with or without the GARCH BEKK specification.

6.2.4 Utility improvement

A second method of measuring hedging effectiveness is the utility improvement of the hedged position over the spot position. Tables 14, 15 and 16 show the utility improvement of each hedge ratio, based on different risk aversion levels.

With a risk aversion level of 1, the greatest utility improvement overall is achieved by the ordinary least squares hedge ratio. Utility improvements of the other methods are very close, and all achieve improvement greater than 77% compared to the unhedged spot position.

The risk aversions of 2 and 3 tell a similar story; ordinary least squares method performs best, and utility improvement is above 77%. The largest improvements in utility are also consistent; 92% is the largest utility improvement for all risk aversion levels.

Results from phase III, while within a smaller band, are largely consistent with those from phase I as presented by Fan et al (2014). The authors found a minimum utility improvement of 57.53% and a maximum of 99.67%. Ordinary least squares is found to be the best method for utility improvement in both phases I and III (Fan et al., 2014). Again, the VECM and VECM with GARCH BEKK are not found to be superior methods of calculating hedge ratios.

Table 14: Utility of positions in spot and futures with risk aversion of 1

This table reports the utility of unhedged and hedged positions in carbon futures during phase III of the European Union Emissions Trading Scheme. It presents the utility for each method of hedge ratio and compares them; the method with the highest utility is presented in the last row. The equation used is: MAX[$E(R_h \mid \Omega_{t-1}) - \frac{1}{2} \varphi \, Var(R_h \mid \Omega_{t-1})$] where R_h is the return on the hedged portfolio, $Var(R_h)$ is the variance of the hedged portfolio, φ is the risk aversion level which in this case is 1, and Ω_{t-1} is the information set available at time 1.

Risk aversion = 1						
	2013	**2014**	**2015**	**2016**	**2017**	**All**
Unhedged	-151.084	-35.935	-9.082	-84.670	-26.846	-60.343
Naïve	-34.211	-5.895	-1.677	-6.610	-2.285	-9.703
Utility improvement naïve	77.36%	83.60%	81.53%	92.19%	91.49%	83.92%
OLS	-31.198	-5.905	-1.400	-6.598	-2.259	-9.381
Utility improvement OLS	79.35%	83.57%	84.58%	92.21%	91.58%	84.45%
ECM	-31.454	-5.919	-1.825	-6.824	-2.272	-9.382
Utility improvement ECM	79.18%	83.53%	79.91%	91.94%	91.54%	84.45%
VECM	-34.256	-6.369	-2.403	-7.214	-2.358	-9.661
Utility improvement VECM	77.33%	82.28%	73.53%	91.48%	91.22%	83.99%
VECM with GARCH BEKK	-34.259	-6.366	-2.403	-7.214	-2.358	-9.661
Utility improvement VECM GB	77.32%	82.29%	73.53%	91.48%	91.22%	83.99%
Best method	OLS	Naïve	OLS	OLS	OLS	OLS

Table 15: Utility of positions in spot and futures with risk aversion of 2

This table reports the utility of unhedged and hedged positions in carbon futures during phase III of the European Union Emissions Trading Scheme. It presents the utility for each method of hedge ratio and compares them; the method with the highest utility is presented in the last row. The equation used is: MAX[$E(R_h \mid \Omega_{t-1}) - \frac{1}{2} \varphi \, Var(R_h \mid \Omega_{t-1})$] where R_h is the return on the hedged portfolio, $Var(R_h)$ is the variance of the hedged portfolio, φ is the risk aversion level which in this case is 2, and Ω_{t-1} is the information set available at time 1.

Risk aversion = 2						
	2013	**2014**	**2015**	**2016**	**2017**	**All**
Unhedged	-301.466	-73.299	-18.973	-166.680	-55.609	-120.855
Naïve	-68.255	-11.658	-3.377	-13.088	-4.573	-19.327
Utility improvement naïve	77.36%	84.10%	82.20%	92.15%	91.78%	84.01%
OLS	-62.152	-11.605	-2.925	-13.076	-4.625	-18.701
Utility improvement OLS	79.38%	84.17%	84.58%	92.15%	91.68%	84.53%
ECM	-62.646	-11.732	-3.643	-13.419	-4.672	-18.702
Utility improvement ECM	79.22%	83.99%	80.80%	91.95%	91.60%	84.53%
VECM	-68.346	-12.778	-4.718	-14.110	-4.911	-19.244
Utility improvement VECM	77.33%	82.57%	75.13%	91.53%	91.17%	84.08%
VECM with GARCH BEKK	-68.352	-12.771	-4.718	-14.110	-4.911	-19.244
Utility improvement VECM GB	77.33%	82.58%	75.13%	91.53%	91.17%	84.08%
Best method	OLS	OLS	OLS	OLS	Naïve	OLS

Table 16: Utility of position in spot and futures with risk aversion of 3

This table reports the utility of unhedged and hedged positions in carbon futures during phase III of the European Union Emissions Trading Scheme. It presents the utility for each method of hedge ratio and compares them; the method with the highest utility is presented in the last row. The equation used is: MAX[$E(R_h \mid \Omega_{t-1}) - \frac{1}{2} \varphi \, Var(R_h \mid \Omega_{t-1})$] where R_h is the return on the hedged portfolio, $Var(R_h)$ is the variance of the hedged portfolio, φ is the risk aversion level which in this case is 3, and Ω_{t-1} is the information set available at time 1.

Risk aversion = 3						
	2013	**2014**	**2015**	**2016**	**2017**	**All**
Unhedged	-451.849	-110.663	-28.864	-248.691	-84.372	-181.367
Naïve	-102.299	-17.421	-5.077	-19.566	-6.860	-28.951
Utility improvement naïve	77.36%	84.26%	82.41%	92.13%	91.87%	84.04%
OLS	-93.107	-17.306	-4.451	-19.555	-6.991	-28.021
Utility improvement OLS	79.39%	84.36%	84.58%	92.14%	91.71%	84.55%
ECM	-125.031	-23.357	-7.279	-26.609	-9.471	-28.022
Utility improvement ECM	72.33%	78.89%	74.78%	89.30%	88.77%	84.55%
VECM	-102.437	-19.187	-7.032	-21.007	-7.463	-28.827
Utility improvement VECM	77.33%	82.66%	75.64%	91.55%	91.15%	84.11%
VECM with GARCH BEKK	-102.446	-19.177	-7.032	-21.007	-7.463	-28.827
Utility improvement VECM GB	77.33%	82.67%	75.64%	91.55%	91.15%	84.11%
Best method	OLS	OLS	OLS	OLS	Naïve	OLS

6.2.5 Hypothesis 2 conclusions:

The following table has been reproduced from Fan et al (2014). It shows the hedge ratios for common commodities, plus the carbon hedge ratio found in this study. The table demonstrates the similarity of hedging carbon and other commodities. All hedge ratios are within a band of 0.5-1 except for electricity. Similar to the carbon hedge ratio are the S&P 500, wheat, crude oil and several of the currency hedge ratios.

Table 17: Comparison of hedge ratios as reproduced from Fan et al (2014)

This table reports the hedge ratios for common commodities as reported in Fan et al (2014). The carbon hedge ratio in the table coming from this study, and not from Fan et al (2014).

Category	Commodity	OLS
Currency	British Pound	0.9520
	Canadian Dollar	0.8750
	Japanese Yen	0.9910
	Swiss Franc	0.9740
Stock Index	S&P 500	0.9473
	NIKKEI	0.7993
	FTSE100	0.7495
	All ordinaries	0.6740
Agriculture	Corn	0.6100
	Wheat	0.9600
	Canola	0.5800
Power	Electricity	0.2833
	Crude oil	0.9900
Metal	Gold	0.5000
Emissions	Carbon	0.92841*

The variance reduction and utility improvement that hedging with carbon futures provides questions the practice of European firms to not hedge carbon risk. The findings presented contrast Feng et al (2016) who found the market to not provide a good hedging function. Based on the variance reduction and utility improvement in this study, a good hedging function is provided by the market for 2013-2017.

6.3 Hypothesis 3

6.3.1 Data

Spot prices for carbon from the Intercontinental Exchange are fortnightly, as auctions are held every two weeks. The independent variables required are therefore matched with the dates of the auctions to obtain fortnightly data.

For method 1, Alberola et al (2008) consider temperatures ‘extreme’ and include a dummy variable for them when the temperature is in the 95th or 5th percentile. For 2013-2017 no extreme temperatures are found in the 95th percentile. To capture ‘extreme’ temperatures the percentiles are changed to the 90th and 10th percentile and the results compared with that of the 95th and 5th in terms of the significance of the dummy variables as well as of the model.

For method 2, for each fortnight, the absolute deviation of the actual temperature from the average seasonal temperature is calculated. Temperatures are considered ‘unanticipated’ when the absolute deviation is above the 95th percentile, which is 5.68 degrees Celsius. This yields seven fortnights for which the temperature unanticipatedly differed from the seasonal average.

A unit root is found for all variables upon running the Augmented Dickey-Fuller test. To remove the unit root and induce stationarity, all variables are differenced by one. Upon testing the differenced variables, they are found to be stationary. Differenced price series are therefore used in regression modelling.

Before running regression, the following tests were performed on each model separately: stationarity, heteroscedasticity, and autocorrelation.

Table 18: Tests for hypothesis 3

This table reports the results of White’s test for heteroscedasticity, and Durbin-Watson’s and Breusch-Godfrey’s test for autocorrelation. It shows the test results for two different methods of including temperature variables: percentiles and cross products. The null hypothesis of homoscedasticity is rejected for method 1, but not for method 2. For both methods, the null hypothesis of no autocorrelation is not rejected.

Method 1 using temperature percentiles					Method 2 using temperature cross products			
Test:	**Statistic**	**p-value**			**Test:**	**Statistic**	**p-value**	
White's test	73.77	0.0202			White's test	37.09	0.3283	
Durbin-Watson	2.0703				Durbin-Watson	2.1412		
Breusch-Godfrey		0.7911			Breusch-Godfrey		0.5605	

White’s test for heteroscedasticity provides evidence to reject the null hypothesis of homoscedasticity for method 1, but not method 2. Neither the Durbin-Watson or the Breusch-Godfrey tests for autocorrelation find evidence to reject the null hypothesis of no autocorrelation. Thus, autocorrelation is not found in either model.

Looking at the independent variables prior to the inclusion of temperature data, low correlation exists between several variables; however, multicollinearity is found only in two cases. Switch price difference and gas price difference are highly correlated, and gas price difference and electricity price difference are moderately correlated. Due to this correlation, regression is run with and without the highly correlated variables to assess the impact on the overall results and determine which variables to include.

Table 19: Correlation matrix for hypothesis 3 variables.

This table reports the correlation coefficients for variables used in hypothesis 3. DCarbon is the differenced by 1 price series of spot carbon allowances. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread.

	DCarbon	**LDCarbon**	**DOil**	**DGas**	**DCoal**	**DSwitch_price**	**DElec**	**DClean_dark**	**DClean_spark**
DCarbon	1								
DCarbon									
LDCarbon	-0.0693	1							
	0.452								
DOil	0.10443	-0.09908	1						
DOil	0.2543	0.2816							
DGas	0.20625	-0.01213	0.349	1					
DGas	0.0232	0.8954	<.0001						
DCoal	0.03931	0.03352	0.2865	0.3179	1				
DCoal	0.6686	0.7163	0.0014	0.0004					
DSwitch_price	0.18945	-0.03124	0.1973	0.8472	-0.23443	1			
DSwitch_price	0.0374	0.7348	0.0301	<.0001	0.0097				
DElec	0.2891	0.12372	0.0811	0.5169	0.40006	0.30579	1		
DElec	0.0013	0.1782	0.3764	<.0001	<.0001	0.0006			
DClean_dark	0.05137	-0.06303	0.0395	0.2894	-0.12409	0.3663	0.00769	1	
DClean_dark	0.5758	0.494	0.6672	0.0013	0.1751	<.0001	0.9333		
DClean_spark	0.08615	0.00253	-0.2739	-0.1995	0.2014	-0.31738	-0.06766	0.09299	1
DClean_spark	0.3474	0.9781	0.0024	0.0283	0.0268	0.0004	0.4609	0.3103	

When adding the temperature variables, no multicollinearity is not found. Furthermore, as would be expected, the temperature dummies and temperature cross products are not correlated with each other.

Table 20: Correlation matrix temperature dummies

This table reports the correlation coefficients for temperature dummy variables with the explanatory variables in Table 19. DCarbon is the differenced by 1 price series of spot carbon allowances. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread. Temp_10 is the 10th percentile of temperature data, Temp_90 is the 90th percentile of temperature data, Temp_5 is the 5th percentile of temperature data, and Temp_95 is the 95th percentile of temperature data.

	Temp_10	**Temp_90**	**Temp_5**	**Temp_95**
DCarbon	0.09415	0.04125	0.04372	.
DCarbon	0.3043	0.6532	0.634	.
DOil	-0.05298	-0.06671	-0.08037	.
DOil	0.5638	0.4672	0.3809	.
DGas	0.01179	0.05379	-0.04088	.
DGas	0.8979	0.5579	0.6562	.
DCoal	-0.12659	0.10801	-0.11858	.
DCoal	0.1665	0.2383	0.1952	.
DSwitch_price	0.08302	-0.00537	0.02453	.
DSwitch_price	0.3653	0.9533	0.7894	.
DElec	0.04153	-0.04488	0.00287	.
DElec	0.651	0.625	0.9751	.
DClean_dark	-0.0169	-0.15771	0.10815	.
DClean_dark	0.854	0.0841	0.2377	.
DClean_spark	-0.09214	0.11344	-0.04814	.
DClean_spark	0.3148	0.2154	0.6	.
Temp_10	1	-0.09746		
Temp 10		0.2855		
Temp_90		1		
Temp 90				
Temp_5			1	.
Temp 5				.
Temp_95			.	.
Temp 95			.	.

Table 21: Correlation matrix temperature cross products

This table reports the correlation coefficients for temperature dummy variables with the explanatory variables in Table 19. DCarbon is the differenced by 1 price series of spot carbon allowances. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread. Jun_13, Nov_13, Sep_15, Nov_15, Feb_16, May_17, and Nov_17 are the cross products of the dummy variable for these dates and the absolute deviations of temperature from the seasonal mean for these dates.

	Jun_13	**Nov_13**	**Sep_15**	**Nov_15**	**Feb_16**	**May_17**	**Nov_17**
DCarbon	0.08712	0.02671	-0.05216	-0.02363	-0.20485	-0.09578	-0.01524
DCarbon	0.342	0.7712	0.5699	0.797	0.0242	0.296	0.8682
LDCarbon	-0.0152	-0.02023	0.07877	0.0385	-0.22999	0.02675	0.10226
	0.8691	0.8264	0.3924	0.6763	0.0115	0.7718	0.2664
DOil	-0.02073	-0.00519	0.07609	-0.04124	-0.07912	-0.07732	0.08757
DOil	0.8215	0.9549	0.4068	0.6533	0.3883	0.3993	0.3395
DGas	-0.06882	0.06568	0.0369	-0.04685	-0.08695	-0.00822	0.04806
DGas	0.4533	0.4742	0.6878	0.6099	0.343	0.9287	0.6006
DCoal	-0.08937	-0.10182	-0.03607	-0.00687	-0.14036	-0.06184	0.05816
DCoal	0.3296	0.2665	0.6945	0.9404	0.1246	0.5004	0.5263
DSwitch_price	-0.02047	0.1244	0.05805	-0.04419	-0.01049	0.02622	0.01669
DSwitch_price	0.8236	0.174	0.5271	0.6303	0.9091	0.7752	0.8558
DElec	-0.01793	-0.15706	-0.03165	-0.23292	-0.16926	-0.03089	-0.11208
DElec	0.8453	0.0853	0.7304	0.0101	0.0635	0.7366	0.221
DClean_dark	0.05405	0.06143	-0.0124	-0.00059	-0.06998	0.09243	-0.10542
DClean_dark	0.556	0.5033	0.8926	0.9949	0.4456	0.3133	0.2498
DClean_spark	0.00883	-0.03272	-0.02305	0.14603	-0.02982	0.04458	0.0098
DClean_spark	0.9234	0.7217	0.8018	0.11	0.7454	0.6273	0.9151
Jun_13	1	-0.00826	-0.00826	-0.00826	-0.00826	-0.00826	-0.00826
Jun-13		0.928	0.928	0.928	0.928	0.928	0.928
Nov_13		1	-0.00826	-0.00826	-0.00826	-0.00826	-0.00826
Nov-13			0.928	0.928	0.928	0.928	0.928
Sep_15			1	-0.00826	-0.00826	-0.00826	-0.00826
Sep-15				0.928	0.928	0.928	0.928
Nov_15				1	-0.00826	-0.00826	-0.00826
Nov-15					0.928	0.928	0.928
Feb_16					1	-0.00826	-0.00826
Feb-16						0.928	0.928
May_17						1	-0.00826
May-17							0.928
Nov_17							1
Nov-17							

Prior to including the temperature variables in the model, the equation below was performed.

$$P_t = \alpha_i + \beta(L)P_t + \phi_i \text{ Brent}_t + \varphi_i \text{ Ngas}_t + \gamma_i \text{ coal}_t + \eta_i \text{ switch}_t + \iota_i \text{ elec}_t + \kappa_i \text{ clean dark}_t + \lambda_i \text{ clean spark}_t + \varepsilon_{i,t}$$

The independent variables were removed from the equation one at a time to determine which variables add to the model's significance overall by assessing the change in adjusted R^2. As each variable is removed, the significance and sign of the remaining variables are also investigated to determine the effect of removing each variable.

Including the switch price as well as the gas and coal prices, gives a model that is not full rank. This is due to the switch price being determined by the gas and coal prices. Either the switch price (equation 6 Table 22) or one of gas and coal prices will need to be removed. Removing the switch price or the gas price does not affect the model's adjusted R^2. Either of these variables can therefore be removed to solve the problem of the model not being full rank.

The following can also be ascertained from Table 22:

- Removing the lag of carbon price improves the model
- Removing oil price worsens the model
- Removing electricity price dramatically worsens the model
- Removing the clean dark spread improves the model
- Removing the clean spark spread worsens the model

The best equation to determine carbon price, therefore likely includes the prices of oil, coal, and electricity, as well as the clean spark spread.

Those prices which worsened the model are removed and the resulting regression is shown in Table 23. The adjusted R^2 increases by 3.78% on the original model (equation 1).

Table 22: Hypothesis 3 regression results

This table reports the results of the regression on carbon price. The equation used is Carbon price = $P_t = \alpha_i + \beta(L)P_t + \phi_i \text{ Brent}_t + \varphi_i \text{ Ngas}_t + \gamma_i \text{ coal}_t + \eta_i \text{ switch}_t + \iota_i \text{ elec}_t + \kappa_i \text{ clean dark}_t + \lambda_i \text{ clean spark}_t + \varepsilon_{i,t}$

This table reports the effect on overall significance and individual variable significance of removing one variable at a time. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread

	1	2	3	4	5	6	7	8	9	10
Intercept	0.03232	0.01557	0.02638	0.03232	0.03232	0.03232	0.02962	0.033	0.03929	0.02884
	(0.4829)	*(0.7451)*	*(0.5695)*	*(0.4829)*	*(0.4829)*	*(0.4829)*	*(0.5304)*	*(0.4697)*	*(0.3987)*	*(0.5325)*
LDCarbon	-0.07505		-0.08897	-0.07505	-0.07505	-0.07505	-0.04852	-0.07457	-0.07862	-0.07444
	(0.3754)		*(0.2962)*	*(0.3754)*	*(0.3754)*	*(0.3754)*	*(0.5730)*	*(0.3760)*	*(0.3592)*	*(0.3813)*
Doil	0.0309*	0.02972		0.0309*	0.0309*	0.0309*	0.02242	0.03084*	0.02038	0.02021
	(0.0767)	*(0.1015)*		*(0.0767)*	*(0.0767)*	*(0.0767)*	*(0.2006)*	*(0.0759)*	*(0.2244)*	*(0.1983)*
Dgas	0.01113	0.01616	0.01864		-0.04428	0.01113	0.03115*	0.01012	0.00359	
	(0.5265)	*(0.3781)*	*(0.2797)*		*(0.1606)*	*(0.5265)*	*(0.0560)*	*(0.5298)*	*(0.8363)*	
Dcoal	-0.03989*	-0.04481**	-0.02766	-0.03188		-0.03989*	-0.02317	-0.03908*	-0.02295	
	(0.0623)	*(0.0452)*	*(0.1747)*	*(0.1606)*		*(0.0623)*	*(0.2654)*	*(0.0575)*	*(0.2461)*	
Dswitch	0	0	0	0.01113	0.05541*		0	0	0	0.02066
				(0.5265)	*(0.0623)*					*(0.2056)*
Delec	0.06297**	0.07386***	0.05483**	0.06927**	0.06297**	0.06297**		0.06324***	0.05856**	*0.04488***
	(0.0105)	*(0.0035)*	*(0.0241)*	*(0.0105)*	*(0.0105)*	*(0.0105)*		*(0.0096)*	*(0.0180)*	*(0.0314)*
Dclean_dark	-0.01203	-0.03207	-0.00834	-0.01203	-0.01203	-0.01203	-0.02802		0.02786	-0.00875
	(0.8833)	*(0.7074)*	*(0.9197)*	*(0.8833)*	*(0.8833)*	*(0.8833)*	*(0.7381)*		*(0.7298)*	*(0.9154)*
Dclean_spark	0.11043**	0.1284**	0.000802	0.11043**	0.11042**	0.11043**	0.09724*	0.10843**		0.09034*
	(0.0486)	*(0.0281)*	*(0.1348)*	*(0.0486)*	*(0.0486)*	*(0.0486)*	*(0.0883)*	*(0.0450)*		*(0.0957)*
Adj R2	**0.066**	**0.097**	**0.048**	**0.066**	**0.066**	**0.066**	**0.018**	**0.074**	**0.041**	**0.057**

Table 23: Hypothesis 3 regression refined

This table reports the results of two regression equations used to explain carbon price.
Equation 11: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + η_i switch$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + $\varepsilon_{i,t}$
Equation 12: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + $\varepsilon_{i,t}$
This table reports the effect on overall significance and individual variable significance of the two equations. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread

	11	**12**
Intercept	0.01723	0.017360
	(0.7169)	*(0.7145)*
LDCarbon		
Doil	0.02095	0.03349*
	(0.1026)	*(0.0539)*
Dgas		
Dcoal	*-0.03294*	*-0.04111**
	(0.1640)	*(0.0539)*
Dswitch	0.01350	
	(0.4227)	
Delec	*0.07475****	*0.08381****
	(0.0029)	*(0.0002)*
Dclean_dark		
Dclean_spark	*0.12318***	*0.11730***
	(0.0293)	*(0.0359)*
Adj R2	**0.1034**	**0.1061**

Equation 12 is the best model of spot carbon prices prior to the inclusion of temperature variables. It shows the significance of the oil price, coal price, electricity price and clean spark spread. The coal price has a negative sign which is logical in that if the coal price increases, utilities will likely switch from coal to gas, emitting less carbon in the process and therefore demanding fewer carbon allowances and placing downwards pressure on the carbon price.

Looking at Table 22, the sign of the gas coefficient is logical for the reverse reason to the coal coefficient. If the price of gas increases, firms will switch to coal, burn more carbon and place upwards price pressure on the carbon price when they must purchase additional allowances. The oil price may be connected to the EUA price through the gas price according to Kanen (2006). It was not found to be significant in phase I by Alberola et al (2008), however, oil price is significant in phase III.

The electricity price represents the price the utility firm can charge for its goods, and therefore its revenue. When increased demand pushes the electricity price up, utility firms have an incentive to produce more electricity to sell; this will result in an increase in carbon emissions, as more fuels are burnt to produce further electricity. The increase in carbon emissions will place upwards price pressure on the carbon allowances as firms are forced to purchase further allowances.

The clean spark and clean dark spreads look at gas and coal independently. The clean spark spread is the difference between the electricity price and the price of gas used to produce the electricity after accounting for the price of carbon. If this spread increases, there is a higher profit margin and therefore more electricity will be produced for firms using gas, leading to higher emissions and more carbon allowances needing to be purchased. Hence the positive sign of the clean spark spread. Throughout the period studied (2013-2017) the clean dark spread was consistently higher than the clean spark spread, however, the difference narrowed considerably over the 5 years.

While removing the clean dark spread from the model improves its' significance, the negative sign must still be understood. If clean dark spread decreases (negative sign) there is less profit margin and therefore less incentive to produce electricity for coal users. The result is fewer emissions and downwards pressure on the carbon price.

After determining these results, the temperature variables are added to the model and their significance investigated.

6.3.2 Introduction of temperature variables

As previously discussed, no extreme variables were found in the 95th percentile of the temperature data. Equation 13, as shown in Table 24, shows the addition of the 95th and 5th percentile temperatures to equation 1. The temperature variable was not statistically significant and its addition reduced the explanatory power of the model, as per the lower adjusted R^2. Equation 14 uses equation 12, the best model before temperatures are added, and includes the 5th temperature percentile. In comparison with equation 12, the explanatory power has decreased and the temperature variable is not significant.

Table 24: Hypothesis 3 regression with temperature percentiles

This table reports the results of two regression equations used to explain carbon price.
Equation 13: Carbon price = $P_t = \alpha_i + \beta(L)P_t + \phi_i$ Brent$_t$ + φ_i Ngas$_t$ + γ_i coal$_t$ + η_i switch$_t$ + ι_i elec$_t$ + κ_i clean dark$_t$ + λ_i clean spark$_t$ + $\varepsilon_{i,t}$ μ_iTemp 95 + υ_i Temp5 + $\varepsilon_{i,t}$
Equation 14: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + υ_i Temp5 + $\varepsilon_{i,t}$
This table reports the effect on overall significance and individual variable significance of the two equations. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread. Temp 95 is a dummy variable for temperatures above the 95th percentile. Temp 5 is a dummy variable for temperatures below the 5th percentile.

	13	14
Intercept	0.02781	0.01338
	(0.5534)	*(0.7814)*
LDCarbon	-0.07613	
	(0.3702)	
Doil	0.03137*	0.03398*
	(0.0736)	*(0.0516)*
Dgas	0.01178	
	(0.5047)	
Dcoal	-0.03923*	-0.04010*
	(0.0680)	*(0.0627)*
Dswitch	0	
Delec	0.06223**	0.08330***
	(0.0118)	*(0.0002)*
Dclean_dark	-0.01767	
	(0.8312)	
Dclean_spark	0.1125**	0.1183**
	(0.0458)	*(0.0351)*
Temp 95	0	
Temp 5	0.16319	0.15541
	(0.5831)	*(0.6126)*
Adj R2	**0.0597**	**0.1004**

Table 25: Hypothesis 3 regression with 90th and 10th percentiles

This table reports the results of four regression equations used to explain carbon price.
Equation 15: Carbon price = $P_t = \alpha_i + \beta(L)P_t + \phi_i$ Brent$_t$ + φ_i Ngas$_t$ + γ_i coal$_t$ + η_i switch$_t$ + ι_i elec$_t$ + κ_i clean dark$_t$ + λ_i clean spark$_t$ + μ_i Temp 90 + υ_i Temp 10 + $\varepsilon_{i,t}$
Equation 16: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + μ_i Temp 90 + υ_i Temp 10 + $\varepsilon_{i,t}$
Equation 17: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + μ_i Temp 10 + $\varepsilon_{i,t}$
Equation 18: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + υ_i Temp 90 + $\varepsilon_{i,t}$
This table reports the effect on overall significance and individual variable significance of the four equations. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread. Temp 90 is a dummy variable for temperatures above the 90th percentile. Temp 10 is a dummy variable for temperatures below the 10th percentile.

	15	16	17	18
Intercept	0.00759	-0.01147	0.00089277	0.00715
	(0.8809)	*(0.8267)*	*(0.9859)*	*(0.8843)*
LDCarbon	-0.07648			
	(0.3696)			
Doil	0.03278*	0.03541**	0.03408*	0.03467**
	(0.0633)	*(0.0429)*	*(0.0501)*	*(0.0472)*
Dgas	0.00842			
	(0.6392)			
Dcoal	-0.03826*	*-0.04118**	-0.03872*	-0.04350**
	(0.0772)	*(0.0582)*	*(0.0720)*	*(0.0444)*
Dswitch	0			
Delec	*0.06398***	*0.08363****	*0.08197****	*0.08544****
	(0.0104)	*(0.0002)*	*(0.0003)*	*(0.0002)*
Dclean_dark	0.00242			
	(0.9771)			
Dclean_spark	0.10927*	*0.11867***	*0.12061***	*0.11531***
	(0.0532)	*(0.0345)*	*(0.0315)*	*(0.0396)*
Temp 90	0.12203	0.16293		0.14861
	(0.5034)	*(0.3747)*		*(0.4167)*
Temp 10	0.15306	0.15875	0.14825	
	(0.3074)	*(0.3067)*	*(0.3378)*	
Adj R2	0.0597	0.1039	0.1055	0.1035

The process is repeated using the 90th and 10th percentiles. The equations are once again compared to the original model and to the best model thus far (equation 12).

Adddition of temperature variables does not improve the model; neither are statistically significant. Equations 16, 17 and 18 compare the addition of the temperature percentiles with the best model (equation 12); none of which explain the carbon price as well as equation 12 where adjusted R^2 is concerned. The model without temperature percentiles remains the best at explaining carbon price.

As discussed in the methodology section, in order to look at unanticipated temperature changes, Alberola et al (2008) use cross products of dummy variables for 'extreme' temperatures and absolute temperature deviation from the mean. This method was replicated for phase III, and seven extreme variables were found using the 95^{th} percentile. Table 26 shows the results.

First, the temperature cross products are added to the original model and an increase in adjusted R^2 results. One temperature variable, February 2016 is significant, at the 5% level. Next, in equation 20, the temperature variables are added to equation 12 and regression is performed again. The results show an improved adjusted R^2 and the February 2016 variable remains significant, though at a 10% level. Finally, equation 21 replicates the method performed by Alberola et al (2008) where the authors run regression with only the temperature variable which is significant. This method provides the best model thus far with an adjusted R^2 of 0.1227 with all variables except the intercept being significant.

Table 26: Hypothesis 3 regression with temperature cross products

This table reports the results of three regression equations used to explain carbon price.
Equation 19: Carbon price = $P_t = \alpha_i + \beta(L)P_t + \phi_i$ Brent$_t$ + φ_i Ngas$_t$ + γ_i coal$_t$ + η_i switch$_t$ + ι_i elec$_t$ + κ_i clean dark$_t$ + λ_i clean spark$_t$ + μ Jun-13 + θ Nov-13 + υ Sep-15 + ζ Nov-15 + $\varkappa$ Feb-16 + ϖ May-17 + ϑ Nov-17 + $\varepsilon_{i,t}$
Equation 20: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + μ Jun-13 + θ Nov-13 + υ Sep-15 + ζ Nov-15 + $\varkappa$ Feb-16 + ϖ May-17 + ϑ Nov-17 + $\varepsilon_{i,t}$
Equation 21: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + $\varkappa$ Feb-16 + $\varepsilon_{i,t}$
This table reports the effect on overall significance and individual variable significance of the three equations. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread. Jun_13, Nov_13, Sep_15, Nov_15, Feb_16, May_17, and Nov_17 are the cross products of the dummy variable for these dates and the absolute deviations of temperature from the seasonal mean for these dates.

	19	20	21
Intercept	0.04195	0.02254	0.02506
	(0.3756)	*(0.6462)*	*(0.5956)*
LDCarbon	-0.11297		
	(0.1998)		
Doil	0.02752	0.03138*	0.03170*
	(0.1168)	*(0.0742)*	*(0.0658)*
Dgas	0.01298		
	(0.4775)		
Dcoal	*-0.04309***	*-0.04324***	-0.04283**
	(0.0454)	*(0.0452)*	*(0.0437)*
Dswitch	0		
Delec	*0.05856***	*0.08318****	*0.07866****
	(0.0294)	*(0.0005)*	*(0.0005)*
Dclean_dark	-0.02758		
	(0.7407)		
Dclean_spark	0.10789*	*0.11316***	*0.11313***
	(0.0553)	*(0.0452)*	*(0.0412)*
Jun-13	0.06087	0.06068	
	(0.3680)	*(0.3906)*	
Nov-13	0.03948	0.06427	
	(0.6247)	*(0.4389)*	
Sep-15	-0.06065	-0.06077	
	(0.4932)	*(0.5098)*	
Nov-15	0.01659	0.03477	
	(0.8376)	*(0.6779)*	
Feb-16	*-0.20424***	-0.15853*	*-0.16202**
	(0.0258)	*(0.0874)*	*(0.0763)*
May-17	-0.08426	-0.08313	
	(0.2608)	*(0.2882)*	
Nov-17	0.01111	0.02085	
	(0.9027)	*(0.8223)*	
R2	**0.0759**	**0.1007**	**0.1227**

6.3.3 Selection of the best model to explain the carbon price:

Thus far the models have been compared based on adjusted R^2 alone. Table 30 reveals the best models based on the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC); both of which assess the quality of models with the highest quality having the lowest statistic.

Before the addition of temperature data, the AIC and adjusted R^2 criteria reach the same conclusion: the best determinants of carbon price are the prices of oil, coal and electricity, along with the clean spark spread. The SC, however, chooses only the electricity price as being the best determinant of carbon price.

When temperature percentiles are used to include weather variation, the same model is chosen by the AIC and the adjusted R^2 as above. The SC again chooses only the electricity price. Based on adjusted R^2 alone, the best model is the AIC's chosen model (oil, coal, electricity, and clean spark spread) with the addition of the 10^{th} pecentile weather variable.

Using temperature cross products to include weather variation gives the lagged price of carbon a place in the model. The AIC chooses the highest quality model as the lagged carbon price, oil, coal, and electricity prices, as well as the clean spark spread and the variable for February 2016. The best model according to the SC is the same as the AIC, without the lagged carbon price, while the adjusted R^2 criterion given the same model as the AIC with the addition of the May 2017 variable.

The best model, consistently, for explaining the price of carbon is:

$$DCarbon = \alpha + \beta1*DOil + \beta2*DCoal + \beta3*DElec+ \beta4* DClean\_Spark + \varepsilon$$

Where D, as explained prior, represents the fact that the variables were differenced once to induce stationarity.

Table 27: Criteria for selection of best model

This table reports the results of the tests undertaken to determine the best quality model. The tests are the Akaike Information Criterion, the Schwarz Criterion and the adjusted R^2. The model chosen by each test is presented along with its score for each test. The table is divided into three categories: before temperatures are considered, with temperature percentiles considered, and with temperature cross products considered.

	Based on:	**Based on:**	**Based on:**
	Akaike Information Criterion	**Schwarz Criterion**	**Adj R^2 alone**
Best model before temperatures added			
DCarbon = DOil DCoal DElec DClean_spark	-165.0998		
DCarbon = Delec		-158.29831	
DCarbon = DOil DCoal DElec DClean_spark			10.61%
Best model with temperature percentiles			
DCarbon = DOil DCoal DElec DClean_spark	-165.0998		
DCarbon = DElec		-158.29831	
DCarbon = DOil DCoal DElec DClean_spark Temp10			10.27%
Best model with temperature cross products			
DCarbon = LDCarbon DOil DCoal DElec DClean_spark Feb_16	-167.5779		
DCarbon = DOil DCoal DElec DClean_spark Feb_16		-150.67449	
DCarbon = DOil DCoal DElec DClean_spark Feb_16			12.27%

6.3.4 Oil price collapse:

In order to take into account the oil price collapse of 2014, the data is divided into two sub-periods. Regression of the original model, best model before temperatures, best temperature percentile model, and best temperature cross product model are repeated for the sub-periods. The results consistently show that the dependent variables, though differing, explain the carbon price better in the period after the oil price collapse than the period before. The adjusted R^2 of the models are larger post-oil price collapse in all cases. Notable differences occur in the significance of individual variables post-oil price collapse. In particular, the electricity price is insignificant in all models prior to the oil price collapse, and very significant in all models post the collapse. While not consistent, it is noteworthy that the clean spark spread is significant in more models in the period prior to the collapse than the period after.

Table 28: Hypothesis 3 regression with subperiods

This table reports the regression results for carbon price before and after the oil price collapse.

Equation 1: Carbon price = $P_t = \alpha_i + \beta(L)P_t + \phi_i$ Brent$_t$ + φ_i Ngas$_t$ + γ_i coal$_t$ + η_i switch$_t$ + ι_i elec$_t$ + κ_i clean dark$_t$ + λ_i clean spark$_t$ + $\varepsilon_{i,t}$

Equation 2: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + $\varepsilon_{i,t}$

This table reports the effect on overall significance and individual variable significance of the two equations. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread.

	Eq1- Before	Eq1- After	Eq12 -Before	Eq12-After
Intercept	0.07541	0.01533	0.03822	0.01884
	(0.3889)	*(0.7795)*	*(0.6977)*	*(0.7224)*
LDCarbon	-0.11781	0.00384		
	(0.4494)	*(0.9723)*		
Doil	0.02805	0.02805	0.02878	0.03223
	(0.5263)	*(0.1691)*	*(0.5190)*	*(0.0851)*
Dgas	0.0165	0.01916		
	(0.5958)	*(0.4031)*		
Dcoal	-0.0825*	-0.04678*	-0.08167	-0.03784
	(0.0755)	*(0.0764)*	*(0.1178)*	*(0.1162)*
Dswitch	0	0		
Delec	-0.00815	*0.08179****	0.06847	*0.08966****
	(0.8751)	*(0.0048)*	*(0.1609)*	*(0.0004)*
Dclean_dark	0.12394	-0.07626		
	(0.4473)	*(0.4265)*		
Dclean_spark	*0.27446***	0.07696	*0.30862***	0.05893
	(0.0362)	*(0.2233)*	*(0.0230)*	*(0.3135)*
R2	**0.746**	**0.1059**	**0.0800**	**0.1305**

Table 29: Hypothesis 3 regression with temperature variables and subperiods

This table reports the regression results for carbon price before and after the oil price collapse.
Equation 17: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + μ_i Temp 10 + $\varepsilon_{i,t}$
Equation 20: Carbon price = $P_t = \alpha_i + \phi_i$ Brent$_t$ + γ_i coal$_t$ + ι_i elec$_t$ + λ_i clean spark$_t$ + μ Jun-13 + θ Nov-13 + υ Sep-15 + ζ Nov-15 + $\varkappa$ Feb-16 + ϖ May-17 + ϑ Nov-17 + $\varepsilon_{i,t}$
This table reports the effect on overall significance and individual variable significance of the equations. LDCarbon is DCarbon lagged once. DOil is the differenced by 1 price series of crude oil futures. DGas is the differenced by 1 price series of natural gas futures. DCoal is the differenced by 1 price series of coal futures. DSwitch_price is the differenced by 1 switch price series. DElec is the differenced by 1 EEX electricity price series. DClean_dark is the differenced by 1 series of the clean dark spread. DClean_spark is the differenced by 1 series of the clean spark spread. Temp 90 is a dummy variable for temperatures above the 90th percentile. Temp 10 is a dummy variable for temperatures below the 10th percentile. Jun_13, Nov_13, Sep_15, Nov_15, Feb_16, May_17, and Nov_17 are the cross products of the dummy variable for these dates and the absolute deviations of temperature from the seasonal mean for these dates.

	Eq 17- Before	Eq- 17 After			Eq 20- Before	Eq 20- After
Intercept	0.01949	0.01201		**Intercept**	0.02513	0.03983
	(0.8626)	*(0.8309)*			*(0.8060)*	*(0.4650)*
LDCarbon				**LDCarbon**		
Doil	0.03186	0.03189*		**Doil**	0.03080	0.03092*
	(0.4888)	*(0.0906)*			*(0.5006)*	*(0.0990)*
Dgas				**Dgas**		
Dcoal	-0.07870	-0.03615		**Dcoal**	-0.07123	-0.04438*
	(0.1408)	*(0.1419)*			*(0.1976)*	*(0.0687)*
Dswitch				**Dswitch**		
Delec	0.0647	0.08891***		**Delec**	0.07421	*0.08792****
	(0.2004)	*(0.0005)*			*(0.1521)*	*(0.0011)*
Dclean_dark				**Dclean_dark**		
Dclean_spark	0.29961**	0.06330		**Dclean_spark**	*0.29822***	0.04911
	(0.0317)	*(0.2909)*			*(0.0326)*	*(0.4257)*
Temp 10	0.09307	0.08654		**Jun-13**	0.04573	
	(0.7224)	*(0.7005)*			*(0.6084)*	
Temp 90				**Nov-13**	0.05266	
					(0.6229)	
R2	**0.0578**	**0.1204**		**Sep-15**		-0.06477
						(0.4257)
				Nov-15		0.05223
						(0.4875)
				Feb-16		-0.16131*
						(0.0514)
				May-17		-0.08034
						(0.2439)
				Nov-17		0.020301
						(0.7794)
				R2	**0.0407**	**0.1488**

6.3.5 Hypothesis 3 discussion and conclusions

Using fortnightly data, the price determinants of carbon were investigated. Prior to the inclusion of temperatures, the best model was found to contain coal, oil, and electricity price series along with the clean spark spread. This model explained 10.61% of the variation in the spot price of carbon allowances. The oil price was significant at the 10% level, as was the coal price. The clean spark spread was significant at the 5% level, and the electricity price at the 1% level.

Two methods of including temperature data were tested. The first used temperature percentiles to decide on dummy variables. No fortnights existed for which the temperature exceeded the 95th percentile, and the 5th percentile was not significant. As such, the 90th and 10th percentiles were trialled. The results revealed such temperature dummies did not impact the carbon price, none of the percentile dummies were statistically significant.

The second method of including temperatures involved cross-products of absolute deviations from the average temperatures, with the dummy variables for fortnights where the absolute deviation from the average temperature exceeded the 95th percentile. This method resulted in seven fortnights being designated as 'unanticipated'. Including these variables lowered the adjusted R^2 of the overall model, however, one fortnight was found to be significant. February 2016 variable was significant at the 10% level. When this significant temperature was included alone, following Alberola et al (2008), the highest adjusted R^2 resulted.

With explanatory power of only 12.27%, the final result still did not explain variation in spot carbon allowance prices as well as Alberola et al's (2008) results of between 13.27% and 36.94% of variation being explained. This suggests the fundamentals included in these models may not explain the carbon price as well in phase III as they did in phase I. There are other factors not included which also determine the carbon price. Such factors could include regulatory or policy events such as announcements of new or future rules for the EU ETS.

The final portion of hypothesis 3 investigated the impact of the fourth quarter 2014 oil price collapse. It was found that all models explain the carbon price better in the period post-oil price collapse. This indicates the changing nature of the carbon price determinants. Several variables' significance differed greatly between pre- and post-oil price collapse.

In terms of the results compared to prior literature, electricity was consistently significant in each model as it was in Alberola et al (2008). Gas prices were significant at the 5% or better in phase 1 in the studies of Alberola et al (2008) and Mansanet-Battaller et al (2007) whereas, in phase III the gas price was found to not be statistically significant. Similarly, the clean dark spread was found to be significant in phase I but not phase III (Alberola et al., 2008). In phase I, both Alberola et al (2008) and Mansanet-Battaller et al (2007) found the price of crude oil to be a statistically significant determinant of the carbon price; the oil price was similarly significant in phase III.

Aatola, Ollikainen & Toppinen (2013) found electricity, coal and gas prices to be significant determinants of the carbon price in phase I. In regard to future phases, the authors discuss the changing price determinants as the market evolves and matures. Indeed the Aatola et al (2013) predicted that price fundamentals would diverge from a tight connection with energy markets. In phase I, nearly 40% of carbon price variation was explained by the variation in prices of electricity, gas and coal, whereas in phase III the fundamental energy prices explain only 11% of variation in carbon price (Aatola et al., 2013; Alberola et al., 2008; Mansanet-Bataller et al., 2007).

In contrast to Alberola et al (2008) the switching price between coal and gas was not found to be important in determining the carbon price. When the switch price was removed from the model no change occurred in the overall explanatory power of the model. Additionally, the switch price was problematic in preventing the model from being full rank due to its calculation involving other variables in the model.

Consistent with Alberola et al (2008), the temperature percentile variables were not found to impact the carbon price. Both the 95^{th} (90^{th}) and the 5^{th} (95^{th}) percentiles have a positive sign; this is logical in that colder than average temperatures lead to increased heating and hotter than average temperatures lead to increased cooling, both of which result in increased energy demand. The increased energy demanded would logically lead to an increase in carbon price as utility firms burn more fuel to meet demand, however, the insignificant coefficients indicate otherwise. In the first year of the EU ETS, Mansanet-Battaller et al (2007) found extremely hot and cold days to be statistically significant determinants of the carbon price; quantiles were used to determine extreme temperatures. The authors also found the inclusion of the temperature dummies to increase the overall adjusted R^2 of the model.

Only one temperature variable was significant when using the second method of including temperatures. This was mid-February 2016 when the temperature was 5.786 degrees Celsius above the average temperature for February. Interestingly, this was only 0.101 degrees Celsius greater than the 95^{th} percentile, whereas, other fortnights such as early-June 2013, experienced a larger absolute deviation from the mean and were not statistically significant.

These results indicate that absolute deviations from the average temperature are more significant to the carbon price than simply looking at the coldest and hottest days by using percentiles. At the same time, the results show that large deviations from the average temperature are not consistently significant, which may indicate that absolute deviations do not capture 'unanticipated' temperature changes well. If the temperatures have been consistently getting colder (hotter) over time, then a particularly cold (hot) fortnight may not result in any further increase in energy use, as the cold (hot) *has been* anticipated and energy use is consistent.

When comparing subperiods prior to and post the 2014 oil price collapse, the model explains more variation in carbon price in the period post. Additionally, more variables are significant in the period post the oil price collapse. This result supports the conclusion that the price determinants are not fixed over time.

In the year this thesis was undertaken (2017-2018), the price of carbon tripled. Energy prices are found to impact carbon price, whereas weather abnormalities were largely insignificant. With a modest amount of variability in carbon price being explained by these factors, further research is required to find further determinants of carbon price. Possible determinants are regulatory factors and political uncertainty.

7 CONCLUSIONS

The null hypothesis of hypothesis 1 was that carbon producing European firms do not face carbon price risk in phase III of the EU ETS. The overall finding was that less than a third of carbon producing European firms in the sample were significantly exposed to carbon price risk, suggesting tht even in phase III, the EU ETS is effectively a non-binding constraint for the firms. However, those that were exposed, experienced a substantial increase in return demanded by shareholders. The null hypothesis cannot be rejected and despite the changes in regulation and policy in phase III, no evidence can be found to suggest that the majority of European utility firms face any such risk.

Hypothesis 2 investigated whether carbon can be hedged like any other commodity. It has been widely accepted that carbon behaves differently to other commodities and is unique. The findings in regard to hedging carbon price risk show quite the opposite. Carbon hedge ratios are within the common band for commodities of 0.5-1 and are effective in variance reduction and utility maximisation. The null hypothesis that carbon can be hedged like any other commodity and needs no special treatment cannot be rejected.

The findings of the first 2 hypotheses tie together in that while the majority of firms do not face carbon price risk, those that do, experience significantly larger costs of capital owing to exposure to the carbon price. The hedging results, however, show that firms are able to hedge this exposure effectively using carbon futures.

The third hypothesis sought to understand the determinants of the carbon price in phase III and investigate how they have changed since phase I. The findings showed consistent significance of the coal and electricity prices, as well as the clean spark spread. Significance of the oil price was dependent on the other variables included in the model. Inclusion of weather variables had mixed results. Temperature percentile dummies were not significant. One of the seven temperature cross products was found to be significant.

Overall, the best model for explaining carbon price, considering the Akaike Information Criterion, Schwarz Criterion and the adjusted R^2, included the prices of oil, coal, electricity, and the clean spark spread. All of these variables were significant, while weather was not found to significantly impact the carbon price. Therefore, the null hypothesis that the price of carbon is determined by weather as well as energy prices is rejected. The price of natural gas, the switch price, and the clean dark spread were not significant. Even with the significance of the oil price, coal price, electricity price and clean spark spread, only 11% of variation in carbon price could be explained. Futher research is required to identify further determinants of carbon price.

8 RELEVANCE TO NEW ZEALAND SCHEME

New Zealand was the first country to introduce an emissions trading scheme after Europe. The New Zealand scheme differs from the European scheme significantly in that it does not have a cap; it is not a cap-and-trade scheme (International Carbon Action Partnership, 2018). New Zealand emissions allowances (NZUs) are obtained by either free allocation by the Government, purchase from the Government for a fixed NZ$25 per allowance, or purchase from another participant in the scheme (Ministry for the Environment, 2016a, 2016c). Unlike the European scheme, the New Zealand scheme not only covers polluters, it also works to reward those who aid climate goals. The forestry industry earns NZUs for its role in creating carbon sinks which absorb carbon; the industry can sell those NZUs for a profit (Ministry for the Environment, 2016b).

While not including as many gases as its European counterpart, the New Zealand scheme includes synthetic greenhouse gases: hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphur hexafluoride (SF6) (Ministry for the Environment, 2016d). Those importing HFC and PFC in bulk amounts, and those that use SF6 above a threshold are required to register and comply with the NZ ETS (Ministry for the Environment, 2016d). The Ministry for the Environment (2016d) also details how importers of motor vehicles are affected; a levy is applied when motor vehicles are first registered in New Zealand which will represent the carbon price of the import.

The Environmental Protection Authority (EPA) oversees the operation of the Emissions Trading Register and is responsible for allocating emissions units, receiving reports from participants, receiving surrendering units, monitoring compliance and other related activities (Environmental Protection Agency).

Firms can purchase international allowances to offset their obligations. The NZ Government is starting to place limits on this as at the beginning of the scheme firms were buying fraudulent credits from Russia and Ukraine for 14 NZ cents and surrendering these credits to meet their obligations (Ministry for the Environment, 2017; Wannan, 2014). These international credits represented illusionary carbon reduction as they were not the result of achieving emissions reductions, rather, they were the result of economic meltdown which saw industry collapse (Wannan, 2014). The result is no real benefit to the climate.

Despite its failings, the EU ETS has achieved its ambitious goals. While New Zealand's targets, which are described as being insufficient by Carbon Tracker (2017), are struggling to be met under the current scheme. Targets for emissions reduction are 5% reduction on 1990 levels by 2020, 11% reduction on 1990 levels by 2030, and a 50% reduction on 1990 levels by 2050 (International Carbon Action Partnership, 2018). Gross emissions decreased over the period 2008-2013 by only 0.8 metric tonnes (Ministry for the Environment, 2015). As presented by the Ministry for the Environment (2015) gross emissions in 2008 were 81.8 metric tonnes while in 2013 gross emissions amounted to 81.0 metric tonnes. By 2016 gross emissions were slightly lower at 78.7 metric tonnes, however, this can hardly be viewed as a success with an 8-year achievement of only 3.8% lower emissions (Ministry for the Environment, 2018).

Greenpeace (2008) foresaw this result when the scheme was first introduced. With no cap there is no guarantee that emissions will be reduced and Greenpeace predicted the impact of the NZ ETS on emissions would be minimal. Carbon Tracker (2017) reports New Zealand's current rating as 'insufficient' which is below ratings which see the achievement of 2-degree reduction. Under current legislation, the NZ ETS doesn't provide the incentives necessary to drive real reductions in emissions levels (Carbon Tracker, 2017).

Looking into enforcement of the NZ ETS, if a firm does not surrender sufficient NZUs annually they are required to pay a penalty of $30 for each unit missing (International Carbon Action Partnership, 2018). With a penalty only 20% higher than the cost of purchasing allowances, there does not exist a strong incentive to comply on time. This, coupled with significant levels of free allocation begin to explain the lack of emissions reductions in the 8 years of operation. Another significant factor in the failings of the scheme is the exclusion of agriculture.

Agriculture is responsible for approximately half of all emissions annually and at present no incentive exists to reduce emissions in this sector. In 2016 emissions from the agriculture sector were greater than the stationary energy and transport sectors combined (Ministry for the Environment, 2018). Greenpeace (2008) calls for agriculture to be included in the scheme or the very least for some other measures to be put in place to encourage emissions reductions from this sector. The New Zealand Government, however, remains hesitant to introduce any such measures. Long-term this could jeopardise the success of the NZ ETS if agriculture emissions rise faster than emissions from other sectors are falling.

Given the conclusions of the European study and the negligible emission reductions in New Zealand, it would appear that no carbon related risk exists for New Zealand firms. Any carbon price risk is likely to confined to a small number of firms as in Europe, with investor perception magnifying sensitivity to carbon price changes. This is a question for further research.

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