Designing Carbon and Energy Markets to Encourage Climate Change Mitigation

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Climate is what we expect, weather is what we get.

Mark Twain

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Preface

Under the Kyoto Protocol, the European Union (EU) committed to reducing greenhouse gas (GHG) emissions by 8 per cent compared to the 1990 level in the period from 2008 to 2012. An obvious way to implement such a reduction target is to cap emissions at the required level and to issue the respective amount of emission allowances which may then be traded on a market. Hence, the European Union Emissions Trading Scheme (EU ETS) was set up to back the Kyoto commitment with a climate policy instrument (Ellerman et al., 2010). In 2005, the world's largest cap-and trade scheme was established and at first covered carbon dioxide (CO_2) emissions from around 10,000 installations such as power plants, cement or metal works.[1] About 40 per cent of European GHG emissions are regulated under the EU ETS. Europe can meet most of its Kyoto mitigation goals with the emission reductions in the EU ETS. Sectors outside of the EU ETS, such as buildings and transport, need to decrease GHG exhaust to a smaller extent. Currently, national energy efficiency standards or investment programs are in place to pave a low-carbon path in non-ETS sectors. These sectors may be included into the EU ETS at a later point, but proposals are not yet on the table. However, the EU ETS was extended to the aviation sector in 2012, and the number of complying entities rose to 12,800. Starting Phase III (2013-2020), the allocation mechanism for emission allowances will change. Until now, the emission rights, so-called European Union Allowances (EUA), were allocated in so-called National Allocation Plans (NAP) by the European Commission (EC) and given out for free. Soon the EC will only decide on the total cap, but not on its allocation, and will auction the respective EUAs centrally.

[1] Covered industries are electricity production, other combustion, refineries, coke ovens, metal ore, iron and steel, cement, glass, ceramics, paper and pulp.

Market-based instruments, such as emissions trading, are the preferred policy option as they assure static efficiency by yielding abatement at least cost. In an emissions trading scheme the installations with the lowest marginal abatement cost reduce their emissions and sell the "freed" emission rights to firms with higher marginal costs. Given an overall reduction target, the carbon price indicates the cost-effective solution (Tiedenberg and Lewis, 2008). In the EU ETS least cost abatement is further promoted by the possibility to comply with credits from abatement activities under the Clean Development Mechanism (CDM). Reduction of GHG may be cheapest in developing countries, and EU ETS installations may tap this potential by complying with a certain share of such CDM credits. A more detailed discussion of the CDM and its link to the EU ETS is provided by Ellerman et al. (2010) or Linacre et al. (2011).

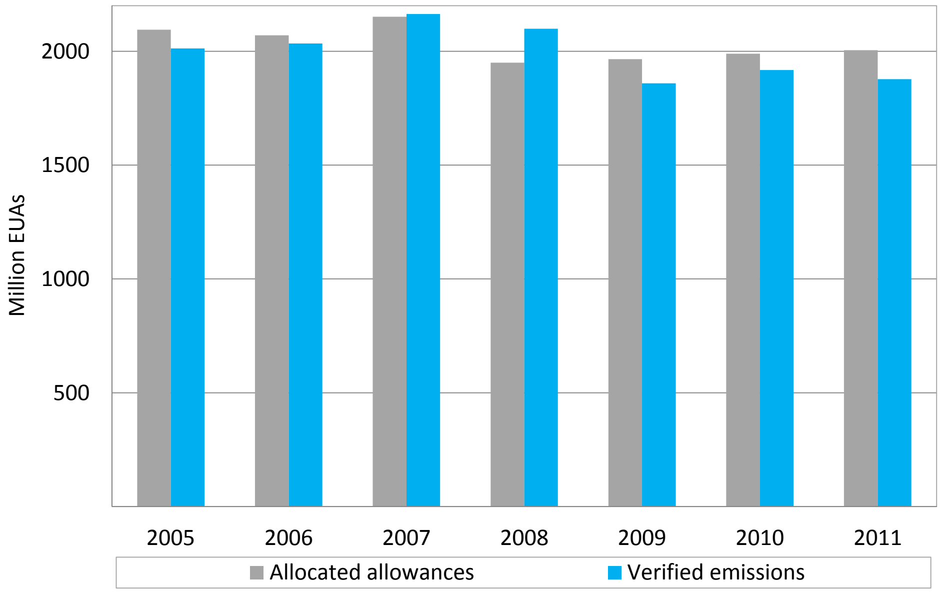
In addition to static efficiency, market-based instruments are said to promote dynamic efficiency in the long-run and thus provide incentives in low-carbon investments (Tiedenberg and Lewis, 2008). These incentives can only be triggered by a carbon price that is high enough to make new abatement technologies profitable. Investments in emission-reducing technologies need to be cheaper in the long-run than maintaining the status quo and buying emission rights. Moreover, investors have to trust in the stringency and credibility of the policy target. Otherwise, firms will hesitate and delay investments in low-carbon technologies that are usually capital-intensive (Hepburn, 2006; Grubb and Newberry, 2008).

After almost eight years of experience with emissions trading in Europe, the success of this policy instrument can be assessed thoroughly. Clearly, regulated installations complied with the national emission caps in the past years. Figure 1 shows that verified emissions remained below the cap in most of Phase I (2005-2007) and Phase II (2008-2012). In 2008, the installations required several allowances more than originally allocated. However, firms could also surrender some of their 2009 EUAs or CDM credits for compliance. EUA allowances did not become scarce in the following years – mainly due to generous EUA allocations and a slump in emissions during the economic crisis. Recent estimates suggest that installations will be oversupplied with 1.1 billion emission rights by 2012.[2] In 2011, only Germany's installations needed more emission allowances than they originally received through

[2]Bloomberg, 12. May 2012, *EUs Hedegaard says CO_2 auctions review is short-term fix*, www.businessweek.com.

their NAP – probably due to strong growth and the nuclear phase-out. In a nutshell, while an institutional infrastructure to cap and trade emissions has been created in recent years, the system currently provides few incentives to deviate from business-as-usual emissions.

Figure 1: Yearly emissions cap and compliance in the EU ETS



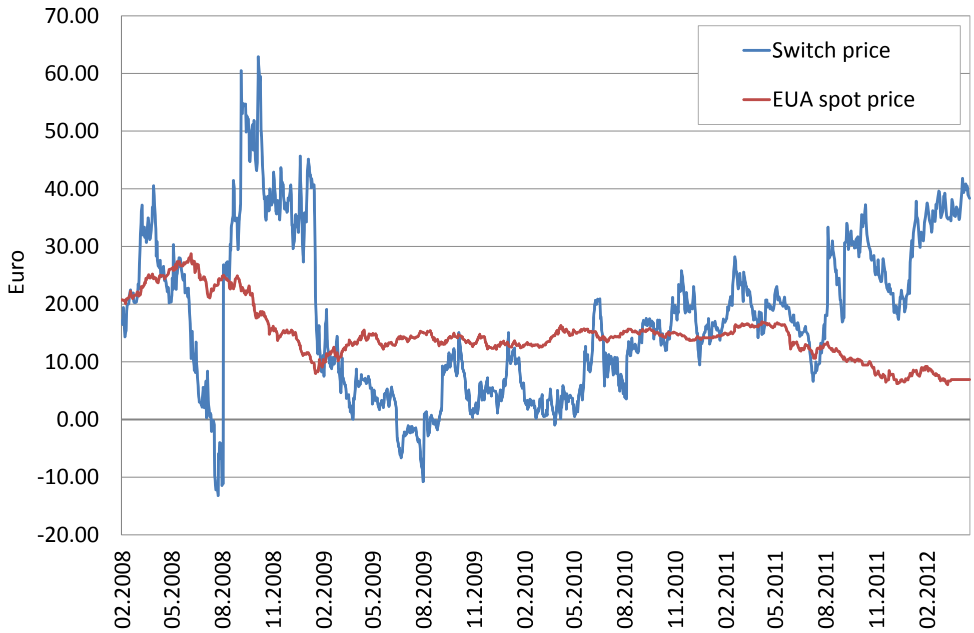
Note: Allocated allowances and verified emissions in Phase I (2005-2007) and Phase II (2008-2012). Data have been aggregated for the EU 27. Source: www.carbonmarketmonitor.com.

But did the EU ETS trigger abatement? This question is rather difficult to assess as it requires assumptions about the counterfactual development without an emission cap. Using patent data, Raphael Calel (2012) find that the EU ETS has so far not significantly encouraged firms to develop new technologies. However, estimates by Ellerman and Buchner (2008) and Grubb and Newberry (2008) indicate that some additional abatement took place Phase I. One of the most likely forms of abatement is fuel-switching in the electricity sector as it does not require investments in new equipment (Ellerman et al., 2010).[3] Fuel-switching is based on the idea that carbon pricing makes electricity generation from coal plants relatively more expensive than generation from gas because coal combustion exhausts more CO_2. Depending on the relative prices of gas, coal, and carbon, it might be profitable to

[3]Notwithstanding that fuel switching is a cheap form of abatement, Ellerman et al. (2010) object that the fuel-switching capacity and therefore abatement potential is rather limited.

switch fuels and burn cleaner gas instead of coal. One has to note that there is not one switch price but rather a band of switch prices depending on the efficiency of given plants. Figure 2 illustrates one possible switch price and the carbon spot price for Phase II. When the CO_2 price is above the switch price, using less carbon-intensive gas instead of coal should in theory be cheaper (Clò and Vendramin, 2012). As depicted in Figure 2, the European carbon price was mostly too low to induce switching in Phase II.[4]

Figure 2: Development of switch and carbon price in Europe



Note: This switch price is calculated on the basis of the month ahead price for coal (CIF ARA) and natural gas, both traded on the Intercontinental Exchange (ICE). This switch price is calculated for a coal plant with a thermal efficiency of 36% and a combined cycle turbine gas plant with an efficiency of 49%. Assumed emission factors are 950 kg CO_2 per megawatt hour (MWh) for coal and 420 kg CO_2 per MWh for gas. Source: Datastream and own calculations.

The carbon price in the EU ETS is a crucial parameter in all abatement decisions.[5] It provides incentives to tap the fuel-switching potential, and more importantly, to invest in low carbon technologies in the long-run. Therefore, understanding what drives the carbon price is absolutely essential. This thesis aims to provide insights into the price development and its determinants. Going from there,

[4]The assumptions that underly this switch price have been altered as a robustness check. The conclusion remains that the carbon price was too low to induce switching.

[5]The European carbon price is in the following also labelled as EUA price.

implications for the design of the carbon market can be derived. The first two chapters shed light into the versatile nature of the carbon price. On the one hand, the EU ETS was created to serve as a policy instrument and is highly dependent on cap decisions of the EC that steer supply (Grubb and Newberry, 2008). On the other hand, carbon has been turned into a commodity that is now embedded into the existing structure of commodity and financial markets. The literature has to some extent identified how these markets interact. One finding is that fuel prices drive the EUA price (Mansanet-Bataller et al., 2007; Alberola et al., 2008; Hintermann, 2010). When coal is cheap, demand for emission rights and their price rises. Hence, coal is usually reported to be negatively correlated with the EUA price, while natural gas is positively correlated with the EUA price. Another finding from the existing literature is that the carbon price influences the electricity price. Various studies show that carbon price shocks are passed through to wholesale power prices (Fell, 2008; Zachmann and von Hirschhausen, 2008; Bunn and Fezzi, 2009).

Chapter 1 further investigates the relationship between carbon, commodity, and financial markets and yields important insights into their dependence.[6] Different copulas are applied to investigate the complex dependence structure between EUA futures returns and those of commodities, equity and energy indices. Copulas are a flexible method to model the relationship between variables as they account for different types of tail dependence. The application of copulas yields possibly better insights than the application of linear correlation models only. This chapter's results illustrate a significant relationship between EUA returns and the other considered return series. The dependence is most appropriately modelled by the Gaussian and the Student-t copula. This contradicts some earlier studies that report no statistically significant or even negative correlations between returns of emission allowances and financial variables. Furthermore, time-varying copulas show that the estimated parameters are not constant over time. The dependence is particularly stronger during the period of the financial crisis. Finally, a Value-at-Risk (VaR)

[6]This chapter is joint work with Stefan Trück and Marc Gronwald. The paper has been published as *Gronwald, M., Ketterer, J., Trück, S., 2011. The relationship between carbon, commodity and financial markets A copula analysis. The Economic Record 87, special issue, 105-124.* For publication in this thesis, I updated Section 1.2.2 and Section 1.3. Where necessary and appropriate, I corrected the wording of the published text. Figures 1.1, 1.2, 1.3 and 1.5 are not included in the final publication, but in the working paper version: *Gronwald, M., Ketterer, J., Trück, S., 2011. The dependence structure between carbon emission allowances and financial markets A copula analysis. CESifo Working Paper, 3418.*

analysis can illustrate the advantages of copula methods in an investment context. The Student-t copula provides an appropriate quantification of VaR at different confidence levels while other models fail to specify the risk correctly. Ignoring the actual nature of dependence could lead to an underestimation of the risk for portfolios combining EUAs with commodities or equity investments. Hence, the findings in Chapter 1 are also relevant for investments which depend on the price development of multiple commodities, such as gas, coal, and carbon. Once the risk structure can be better understood and hedged, investments will be more attractive.

The European carbon price is not a pure commodity market given its strong underlying political influence. The EUA price cannot be sufficiently explained by only investigating the relationship between the EU ETS and the existing structure of financial and commodity markets. This is confirmed by Hintermann (2010) who shows that demand-side fundamentals, such as fuel prices and weather proxies, provide an insufficient explanation of the EUA development in Phase I. To capture the carbon price in an appropriate way, the regulatory framework and related decisions on the supply of emission allowances should be included in a carbon price model.

Chapter 2 is concerned with the influence of the political arena on the carbon price.[7] In a first step, the application of a combined jump-GARCH model illustrates that the behaviour of the EUA price is characterised by large price movements. The results show that between 40 and 60 per cent of the carbon price variance is triggered by jumps. In a second step, a database of regulatory events in the European carbon market is compiled. It shows that these regulatory events help to explain the identified carbon price jumps. Decisions on EUA supply and news from international carbon markets are particularly important drivers of sudden price movements. New regulation places market participants in a changed environment and related price reactions seem quite abrupt. These results can assist regulators the way if the outcome of smoother carbon prices is desired. The EC should avoid imprecise debates on future policy that introduce uncertainty. A clear communication strategy should be adopted that conveys information about the long-term reduction target and the policy strategy. It is certainly difficult to find a balance between flexibility

[7]Chapter 2 is based on joint work with Marc Gronwald. Our paper has been published as working paper *Gronwald, M., Ketterer, J., 2012. What moves the European carbon market? – Insights from conditional jump models. CESifo Working Paper, 3795.* Chapter 2 includes an additional regression analysis in Section 2.5 which is not part of the original paper.

and commitment when designing the carbon market. But credible policy targets and rules are a condition to stabilise the carbon price and carbon price expectations that trigger investments in low-carbon technologies. Discretionary policy steps and a deviation from the announced reduction path might unsettle the carbon market (Helm et al., 2003). Instead of investing in costly and complex low-carbon projects, market participants are likely to mistrust the current climate policy and wait until more information regarding the climate change objective becomes available.

Clearly, policy makers should prevent the carbon price signal from deteriorating. However, whilst a stable price signal is necessary to trigger low-carbon innovation and investment, it may not alone be sufficient (Montgomery and Smith, 2007; Hanemann, 2010). The economic literature has long debated whether one single instrument might be enough to induce mitigation in the long-run. Several studies conclude that additional market failure related to positive externalities from research and development (R&D) or principal-agent problems cannot be tackled by one policy but do justify additional instruments (Jaffe and Stavins, 1994; Newell, 2010; Acemoglu et al., 2012). When facing climate change, investment horizons might be too long, projects too expensive and market failures too diverse to be solved by a single instrument (Hepburn, 2010).

Introducing different national and supra-national climate policies is not without problems. A multitude of climate policy instruments can be beneficial, but the policy mix needs to be well-tuned. If combined instruments are not complementary, the effects can be detrimental (Sinn, 2008; Fankhauser et al., 2010; Monopolkommission, 2011). A straight forward example is the interaction between emissions trading and renewable support schemes. In most European countries, renewable energy support has led to a surge in renewable energy capacity. This is good news with regard to the CO_2-intensity of the energy sector. But because the overall emissions cap remains fixed, emission rights, set free in the energy sector, can be bought cheaply from other sectors. A rough calculation can help illustrating this effect for Germany. Sensfuß (2011) estimates that renewable electricity generation replaced 83.5 terawatt hours (TWh) of conventional power in Germany in 2010. It is assumed that 1 kilowatt hour (kWh) conventional electricity produces on average 679 g CO_2, given the German conventional electricity mix (BMU, 2012).[8] Therefore,

[8]Gruet (2011) assume 696 g per CO_2 for all of Europe. They estimate that additional wind power generation reduced 126 Mt in Europe in 2010.

the additional renewable electricity would have avoided about 57 million tons (Mt) CO_2 in 2010, whereas the total EU ETS cap for Germany was 453 Mt in 2010. Although this example gives only rough estimates, it becomes clear that substantial amounts of CO_2 can be shifted to other ETS-covered sectors or counties, reduce demand for EUA allowances, and lower the CO_2 price but not the overall emissions. To assure the effectiveness of interacting policies, renewable energy growth trends and energy efficiency plans need to be reflected by the EU ETS cap. Otherwise, the market is over-allocated as the demand for EUA allowances reduces, and the carbon price decreases.

Figure 3: Interactions between carbon and energy markets

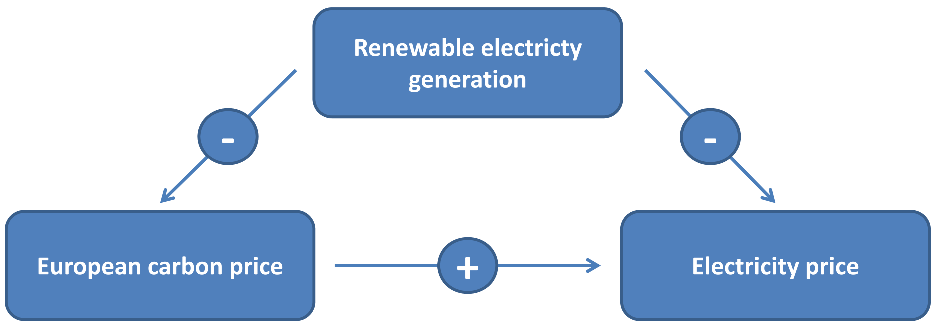


Figure 3 illustrates the interaction between the aforementioned markets. First, the relationship between the carbon and the electricity price has been outlined above and is further illustrated in Chapter 1. Second and as just discussed, additional renewable electricity generation reduces the carbon price, given that the cap is not adjusted.[9] Finally, electricity generation from variable renewable energy sources has a dampening effect on the electricity price.

Chapter 3 of this thesis provides further insight into this relationship and how renewable power generation influences the electricity price. More specifically, Chapter 3 evaluates the effect of wind electricity in-feed on the level and volatility of the electricity price using a GARCH model. Wind electricity is particularly

[9]Certainly, a high carbon price makes renewables more competitive with conventional energy as coal becomes more expensive (Sáenz de Miera et al., 2008). However, under the current feed-in tariff scheme, renewables do not have to compete as they are subsidised. This effect can be neglected in the current market situation.

interesting because its contribution to the German power mix is substantial, but subject to significant variation. The empirical results show that this fluctuation is transmitted to the electricity price. Variable wind power on the one hand reduces the price level, and on the other hand increases its volatility. With a low and volatile wholesale price, the profitability of electricity plants, conventional or renewable, is greatly reduced. Consequently, the construction of new plants is at risk, which has major implications for the energy market and the security of supply. The new challenges with renewables require adjustments to the regulatory and the policy framework of the electricity market. This chapter's results suggest that regulatory change is able to stabilise the wholesale price. The empirical investigation shows that the electricity price volatility has decreased in Germany after the marketing mechanism of renewable electricity was modified. This gives confidence that further adjustments to regulation and policy may foster a better integration of renewables into the power system. Going forward, the stability of the electricity price could be promoted in a dual approach. First, by giving incentives to build flexible power plants that absorb fluctuation of wind and solar PV power in-feed. Second, policy instruments should address the variable in-feed of renewable power itself. As renewable generation gained ground in power markets, support schemes should be increasingly dependent on the wholesale electricity price. So far, German feed-in tariffs do not vary with the wholesale price. But price-dependent subsidies give incentives to feed-in during times of high wholesale prices when electricity supply is needed most. Pursuing both approaches, namely additions of flexible capacity and market-based subsidy payments, smoothes the transition to a low-carbon electricity market with a stable price and secure supply.

Efforts to reduce GHG emissions in Europe resulted in the creation of a common carbon market and various national support schemes for renewable energy. The main focus of this thesis is to explore whether the design of carbon and electricity markets lead to the desired price signals and emissions abatement. The observations in both markets point to challenges that question the success of climate change mitigation. Some of these obstacles could be resolved by better combining policies in both markets. The EU ETS and renewable energy support overlap to a large extent and the desired effects of both policies might cancel out. Making the policy design more coherent is certainly not easy but offers a promising solution.

With respect to emissions trading in Europe, this policy instrument should not rashly be condemned as non-effective. Instead, its long term goal and perspective should be sharpened. The future of the EU ETS will certainly be influenced by the international climate negotiations. But European policy makers should assure that the chosen policy path will be further pursued and emphasise which emissions reductions the EU ETS will deliver after 2020. While the progress towards a global agreement has been sluggish in recent years, national and sectoral initiatives seem on the rise with emissions trading schemes being developed in Australia, China, and the United States. This validates the experience and institutional framework already provided in Europe. In the long-run, the possibility to link all these schemes in a bottom-up approach could give a wider perspective and scope to the emissions trading approach.

Chapter 1

The Relationship between Carbon, Commodity, and Financial Markets - A Copula Analysis

1.1 Introduction

Under the Kyoto Protocol the EU has committed to reducing greenhouse gas (GHG) emissions by 8 per cent compared to the 1990 level in the period from 2008 to 2012. To give a price to carbon emissions and to incentivise the reduction of GHG emissions, an EU-wide CO_2 emissions trading system, the so-called EU ETS, has been set up. The right to emit a particular amount of CO_2 has become a tradable commodity and is now a factor of production that is subject to stochastic price changes. This new market not only requires regulated emitters to run an adequate risk management, it also provides new business development opportunities for market intermediaries and service providers such as brokers or marketeers. It is essential for carbon market players to learn about price dynamics in order to realise trading as well as risk strategies and investment decisions.

Since the beginning of the emissions trading in 2005, a number of studies have analysed the price behaviour of the European Union emission allowances (EUA). Paolella and Taschini (2008), Benz and Trück (2009) as well as Daskalakis et al. (2009) provide an econometric analysis of the behaviour of allowance prices and investigate different models for the dynamics of short-term spot prices. Other studies investigate derivative products in EUA markets, the convenience yield, the term structure of futures prices (Trück et al., 2006) as well as the effects of options trading on market volatility (Chevallier et al., 2009). Studies by Böhringer and Lange (2005) and Schleich et al. (2006) simulate the development of the CO_2 price with respect to changes in different market design parameters.

The aim of this chapter is to provide a thorough analysis of the dependence structure between EUA returns and those of other financial variables and commodities. As EUAs are a factor of production, it is plausible to assume that changes in the emission allowance price are related to the dynamics of other commodity markets. We contribute to the literature in three dimensions. First, we apply different copula models to investigate the nature of dependence between EUA returns and those of other financial assets. Copulas are generally a very flexible method to model the relationship between different variables. Among the advantages are the possibility to account for different types of tail dependence of the return series under consideration. The application of copulas yields possibly better insights than the application of linear correlation models only. To our best knowledge, this chapter is a pioneer study on copulas in the area of carbon market research. Second, we apply time-varying copulas to investigate whether the relationships under consideration are constant over time. This procedure allows us to investigate whether influencing factors on the carbon price changed over time and whether the financial crisis had an impact on the dependence of the considered variables. Finally, we conduct a risk management analysis to further illustrate the usefulness of the application of copulas. It is often argued that the EUA price is more strongly influenced by policy measures and regulatory changes than other commodities (Chevallier, 2009). In consequence, this market provides new challenges to market participants that need to adapt their risk strategy. Therefore, we provide a risk analysis by comparing benchmark models including a standard variance-covariance approach to the estimated copula models. This allows to evaluate the models' ability to quantify market risk. We show that a misspecification of the actual dependence structure might not only lead to an inappropriate specification of the portfolio return distribution but also underestimate the risks from joint extreme returns.

The remainder of the chapter is organised as follows. Section 1.2 provides a brief description of the market mechanism for CO_2 emission allowances as well as price drivers of the market. Section 1.3 provides a review of different copula models with respect to estimation and model testing. Moreover, an overview of the considered data is given. Section 1.4 presents the empirical results of our study and the risk analysis. Section 1.5 concludes and gives suggestions for future work.

1.2 Carbon Pricing in Europe

1.2.1 Regulatory Setting

This section briefly discusses the regulatory setting of the EU ETS. The scheme affects combustion installations exceeding 20 MW including different kinds of industries such as metal, cement, paper, glass as well as power generation and refineries. In total, the EU-ETS included some 10,000 installations in 2005, representing approximately 40 per cent of EU's GHG emissions. After an initial pilot trading period from 2005 to 2007, new National Allocation Plans (NAPs) have been issued for the second trading phase from 2008 to 2012. From 2013 onwards, a third trading period will run until 2020. In this third period, the individual NAPs will be replaced by unified allocation rules applying to all member states. Therefore, the annual quantity of allocated emission allowances has already been specified by the EU-Directive until the year 2020. According to the European Commission, the importance of auctioning will increase in Phase III reducing the number of allowances that is allocated free of charge. Some regulatory settings are particularly important as they shape compliance behaviour and thus are likely to have price effects. Under the current system, banking – the storage of unused allowances – gives more leeway for complying parties and smoothes the CO_2 price. A recent and more detailed discussion of banking and borrowing is provided by Chevallier (2012).

Generally, a lack of allowances requires a company to either buy a sufficient amount of EUAs or to invest in some plant-specific process improvements. A third option is the purchase of additional allowances and emission credits from Clean Development Mechanism (CDM) or Joint Implementation (JI) projects, the so-called Flexible Mechanisms under the Kyoto Protocol. Failure to submit a sufficient amount of allowances at the end of the compliance year results in sanction payments of 100 € per EUA. In addition, companies have to surrender the missing allowances. As a consequence, participating companies face several risks specific to emissions trading. In particular, price risk of fluctuating allowance prices, volume risk, and political risk have to be considered. Because of unexpected fluctuations in energy demand, the emitters do not know ex ante their exact demand for EUAs. As the framework and goals of climate policies may change, market participants face risks from the political arena, see also Chapter 2. Naturally, market generic risks, for example counterparty, operational, and reputational risk, are also present (Bokenkamp et al., 2005).

1.2.2 Literature Overview

To set up a comprehensive analysis, it is of great importance to identify the key price determinants of the CO_2 emission allowances. Following the investigation of the SO_2 permit price by Burtraw (1996), we categorise the principle driving factors of the CO_2 allowance price into (i) policy and regulatory issues, and (ii) market fundamentals that directly concern the production of CO_2 and thus the demand of CO_2 allowances. For our pricing model, we are interested in the determinants of short-term price behaviour. Policy changes might lead to sudden price spikes and phases of extreme volatility if the market was surprised by decisions concerning the allowance allocation or the European commitment to reduce GHG emissions by 30% instead of 20% until 2020 (Sanin and Violante, 2009; Gronwald and Ketterer, 2012). Incorporating part (ii), the allowance price fundamentally depends on the emission level of CO_2 which is influenced by factors such as economic growth and fuel prices. Some comprehensive research on determinants has been conducted by Mansanet-Bataller et al. (2007), Alberola et al. (2008), and Chesney and Taschini (2008). An important force is weather data such as temperature, rainfall, and wind speed. Hintermann (2010) detects a negative effect of availability of hydropower in Nordic countries during the first trading phase. Rickels et al. (2010) confirm this result for the second trading phase and find the same relationship with respect to wind power: higher wind speeds in Germany lead to a lower EUA price. Mansanet-Bataller et al. (2007), Rickels et al. (2007), and Alberola et al. (2008) show that extremely hot or cold days have a positive effect on the EUA price.

Energy variables have a clearly identified impact on the price of emission allowances (Chevallier, 2009). For example, an electricity producer switching from ‘cheap-but-dirty’ coal to ‘expensive-but-cleaner’ gas can significantly reduce emissions per MWh of produced electricity. Therefore, fuel-switching from coal to gas implies less emissions to be covered with permits, and the price of EUAs should be dependent on prices of gas and coal. With respect to the influence of energy prices on the carbon price, the literature reports relatively robust patterns. Mansanet-Bataller et al. (2007) find positive effects of oil and gas prices on the EUA price in Phase I, while there is no significant influence of the coal price. The same results are given by Hintermann (2010). In a study by Rickels et al. (2007), coal shows up with a negative sign. Similarly, Alberola et al. (2008) reports a negative effect of coal on the carbon price and detect positive effects of gas and oil prices.

The dependence of carbon and energy prices is studied in bidirectional manner. On the one hand, the driving factors for the carbon price are identified. On the other hand, the reverse effect of carbon on energy and commodity prices is investigated. Kara et al. (2008) report that the EU emissions trading has a price-increasing effect on the electricity price in Finland. Fell (2008) finds a strong response of Nordic electricity prices to EUA price shocks. Thoenes (2011) reaffirms this conclusion for the German market. Fell (2008) and Thoenes (2011) both discover that the relationship between fuel prices and the electricity price is different during peak and off-peak load. Zachmann and von Hirschhausen (2008) show that carbon price changes are passed through to the wholesale power price in Germany during Phase I (2005-2007). This effect seems asymmetric as carbon price increases have a stronger impact on the power price. Prete and Norman (2011) can confirm the pass-through to the electricity price in in several European countries during Phase II (2008-2012), but they cannot confirm the asymmetric price adjustments. Bunn and Fezzi (2009) investigate the impact of the EU ETS on wholesale electricity and gas prices in the UK. Using a structural co-integrated VAR model, they conclude that the prices of carbon and gas jointly influence the equilibrium price of electricity. Nazifi and Milunovich (2010) apply a restricted VAR model to test for existence of causal relationship and long-run links between the price of carbon and prices of energy fuels and electricity. Their results suggest that the dynamics of fuel prices are rather independent from the price of emissions permits during Phase I. Bertrand (2012), however, shows that the carbon price has a significant impact on gas and coal prices during Phase II. The latter study also confirms the effect of the EUA price on the electricity price. Generally, the literature finds a pass-through of the carbon to the electricity price, but the results for fuel prices seem varied.

Less attention is payed to the relationship of the emission allowance price with financial variables. A rising carbon price, as a factor of production, could be related to additional costs and uncertainties for producers and might have an adverse effect on equity markets in general or equities of certain industries in particular. Kosobud et al. (2005) find no statistically significant correlations between monthly returns of the SO_2 emission allowance price in the US market and returns from various financial investments. Hintermann (2010) spots no influence of the British FTSE equity index during the first trading phase of the EU ETS. Oberndorfer (2009) examines the impact of the EUA price development on stock market returns of energy companies and identifies a positive effect that varies across countries. Veith et al. (2009) employ a multifactor model and confirm this finding for the first trading phase: stock market returns of energy companies are positively correlated with the emission allowance price. Daskalakis et al. (2009) detect negative correlations of EUA futures with equity market returns that might offer significant diversification opportunities to European equity investors. They argue that the factors determining stock and bond prices are substantially different from those affecting emission permits. In a study on the relationship between macroeconomic variables and carbon futures, Chevallier (2009) finds that stock and bond markets – as proxies for macroeconomic risk – have little influence on EUA futures. The author suggests that emission allowances are an too easily storable commodity and therefore not prone to react to macroeconomic shocks as much as stock markets.

To our best knowledge, so far there has been no empirical study concentrating mainly on the dependence structure between EUA returns and those of other financial variables or commodity markets. Next to standard approaches investigating linear dependence by correlation analysis, in our analysis we apply different copulas to model the complex dependence structure between the return series of carbon emission, commodity, and equity markets.

1.3 Data and Model

1.3.1 Copula Models

The application of copula models has lately become very popular in empirical finance as copulas are a flexible instrument for modelling the dependence structure of financial time series. Copulas allow to assess various forms of dependence between the variables under consideration. Hence, the application of copulas yields deeper insights into the relationship of financial assets than simple correlation measures. Variables can be related in very specific ways (Hull, 2007). The copula concept is particularly attractive as it allows to reflect various forms of dependance, asymmetric or non-linear, between the variables of interest. This can, for example, be helpful as asset returns tend to be stronger correlated during volatile market phases and market downturns (Longin and Solnik, 2001). Such specific behaviour can be captured by copulas.

In empirical finance, traditional methods of describing the dependence structure between a set of variables have lately been criticised. Assuming that the joint distribution of asset returns is normal and using the covariance matrix as a measure of dependence, might be too simplistic. As shown in studies by Jondeau and Rockinger (2006a), Junker et al. (2006), Luciano and Marena (2003), and McNeil et al. (2005), the relationship between financial assets might not be appropriately described by simple correlations. This might lead to an inadequate assessment of risks in joint extreme price movements. The copula methods offers a more flexible approach to measure the dependence structure of asset returns and a more robust way to assess risks. With respect to analysing the dependence structure between different financial assets, copula models do not necessarily require assumptions of joint normality for the distributions.[1] Instead, a copula allows joining various marginal distributions, sometimes also called unconditional distributions (Hull, 2007), into their one dimensional multivariate distribution. This is possible because the multivariate joint distribution can be decomposed into marginal distributions and an appropriate functional form for the dependence between the asset returns under consideration. As its name suggests, the copula only provides information how the underlying variables are linked or connected, but not about their marginal distributions. Spitting these two components allows to combine a wide range of marginals with different copula functions. A detailed description of the copula method and its application in finance is given by Cherubini et al. (2004).

This section provides a brief review on the estimation as well as goodness-of-fit tests for copulas that will be used in the subsequent empirical analysis. Since this can

[1]Note that the Gaussian copula with the assumption of normal marginals coincides with the multivariate normal distribution and is fully characterised by the correlation coefficient.

be considered as a pioneer study on applying and testing different copula models to emission allowance markets, we also briefly illustrate some basic concepts of copula families and the dependence measure Kendall's τ.

1.3.2 Copula Functions

A copula is a function that combines marginal distributions to form a joint multivariate distribution. Sklar (1959) initially introduced this concept which receives growing attention and is applied to various issues in financial economics and econometrics (Cherubini et al., 2004; McNeil et al., 2005). Patton (2006) used copulas to model exchange rate dependance and Jondeau and Rockinger (2006a) to uncover the relationship of US and European stock market returns. Michelis and Ning (2010) employed the copula method to investigate the dependence structure between stock market returns and exchange rate returns in Canada. Copula functions allow to model relationships without requiring assumptions regarding the joint distributions of the underlying variables. Overall, the use of copulas allows to model the dependence in a more general and flexible setting compared to linear correlation measures: non-linearity, asymmetry, and fat tails can be captured. The following provides an introduction to copulas as in Trück and Rong (2010). The interested reader may find further information in Nelsen (1999), Cherubini et al. (2004), or Hull (2007).

A copula is the distribution function of a random vector in $\mathbb{R}^n$ with standard uniform marginals. The copula approach allows to differentiate between unconditional distributions of respective variables and their dependance structure (McNeil et al., 2005). Given a random vector of random variables $X = (X_1, \ldots, X_n)'$, its dependence structure is completely described by the joint distribution function $F(x_1, \ldots, x_n)$. Each random variable X_i has a marginal distributions F_i that is assumed to be continuous for simplicity. Each continuous random variable X can be transformed, using its own distribution function F. Then, the random variables $F(X)$ are uniformly distributed over $[0, 1]$. Hence, the copula can be extracted from the joint distribution function:

$$\begin{aligned}F(x_1,\ldots,x_n) &= P(X_1 < x_1,\ldots,X_n < x_n)\\ &= P[F_1(X_1) < F_1(x_1),\ldots,F_n(X_n) < F_n(x_n)]\\ &= C(F_1(x_1),\ldots,F_n(x_n)),.\end{aligned} \tag{1.1}$$

The function C is the so-called copula of the random vector X and represents a joint distribution function with standard uniform marginals.[2] The copula combines the marginal distribution of F_i to recover the joint distribution. In particular, any choice of marginal and joint distributions can be connected using the copula method.

1.3.3 Examples of Copulas

There are many different types of copulas from which we chose the most commonly applied functions: the Gaussian, Student-t, Clayton, and Gumbel copula. Given their parametric form, the multivariate Gaussian and Student-t copula belong to the class of elliptical copulas. Probably the most commonly used copula is the Gaussian copula which is constructed from the multivariate normal distribution and is denoted by:

$$C^G_\rho(u_1,\ldots,u_d) = \Phi^d_\Sigma(\Phi^{-1}(u_1),\ldots,\Phi^{-1}(u_d)). \tag{1.2}$$

Hereby, Φ represents the standard normal cumulative distribution function, Φ^{-1} the inverse of the standard normal cumulative distribution function and Φ^d_Σ the standard multivariate normal distribution with correlation matrix Σ. Applying C^G_ρ to two univariate standard normally distributed random variables, results in a standard bivariate normal distribution with correlation coefficient ρ. As the multivariate normal copula correlates random variables rather near the mean, it fails to incorporate dependence in the tail. The Student-t copula, by contrast, is able to capture tail dependence to some extent and is written as:

$$T_{\Sigma,v}(u_1,u_2,\ldots,u_d) = t_{\Sigma,v}(t_v^{-1}(u_1),t_v^{-1}(u_1),\ldots,t_v^{-1}(u_d)), \tag{1.3}$$

[2]If the marginal distributions F_i are continuous, the copula function $C(F_1(x_1),\ldots,F_n(x_n))$ is unique (Sklar, 1959).

where $t_{\Sigma,v}$ is the multivariate Student-t distribution with v degrees of freedom and correlation matrix Σ. Depending on the degrees of freedom parameter, the Student-t copula determines the strength of the tail dependence. Generally, strong tail dependence is illustrated by low values of the parameter v.

Both elliptical copulas can be used to model symmetric tail dependence. In economic and financial applications it might, however, be useful to differentiate the behaviour in the upper and the lower tail. Financial assets often only exhibit tail-dependence in one of the tails, for example when they are stronger correlated during market downturns. Two variables that are characterised by strong tail-dependence in the lower left tail exhibit simultaneous extreme negative returns, whereas high positive returns in one of the variables may be rather independent of the other variable. To model such asymmetric tail dependence, so-called Archimedean copulas can be used (Cherubini et al., 2004). Amongst the Archimedean copulas, the most intensely used functions are the Clayton and the Gumbel copula. On the one hand, the Clayton copula captures greater co-movements in the lower left tail. On the other hand, the Gumbel copula exhibits stronger dependence in the upper right tail. The multivariate Clayton copula is denoted by:

$$C_\theta^{Cl}(u_1, ..., u_d) = \left[\sum_{i=1}^{d} u_i^{-\theta} - d + 1\right]^{1/\theta}, \tag{1.4}$$

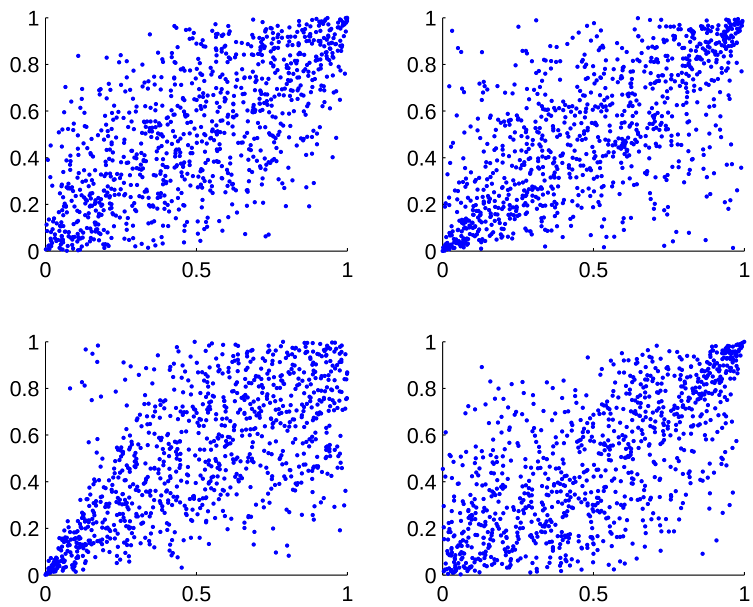
For the Clayton copula, the parameter $\theta > 0$ measures the degree of dependence between the considered variables. A high θ indicates strong dependence, particularly in the negative lower tail. When θ is close to zero, the dependence between the marginals vanishes (Trivedi and Zimmer, 2005). As mentioned above, the Gumbel copula depicts co-movements in the positive upper tail and is denoted by:

$$C_\phi^{Gu}(u_1, ..., u_d) = \exp\left[-\left\{\sum_{i=1}^{d}(-ln(u_i)^{\phi}\right\}^{1/\phi}\right], \tag{1.5}$$

where $\phi > 1$ indicates the dependence between the random variables $X_1, ...X_d$.

Often Kendall's τ is used for characterising the dependence structure. Kendall's τ is a rank-based measure of dependence based on the concept of concordance. When large values of one random variable occur together with large values of another variable, one speaks of concordance (Trivedi and Zimmer, 2005). In the case of discordance, by contrast, large values are linked to low values. Kendall's τ measures the probability of concordance and discordance (McNeil et al., 2005). Values of τ range from -1 to $+1$, while in the case of independence τ will be 0 (Nelsen, 1999). Kendall's τ is a simple concept but allows estimating the true underlying copula as it is shown for example by Deheuvels (1979).[3] In the case of a bivariate one-parameter copula, Kendall's τ is an appropriate dependence measure, as there is a one-to-one relationship between the copula parameter and Kendall's τ.

Figure 1.1: Scatter plot of simulated dependence



Note: Scatter plots of the simulated dependence structure of ranks for different copulas with the same Kendal's $\tau = 0.5$. This figure illustrates the dependence between ranks for the Gaussian (upper left panel), Student-t (upper right panel), Clayton (lower left panel), and Gumbel copula (lower right panel).

For the purpose of illustrating the different copula models, Figure 1.1 shows scatter plots for four different copula functions based on the same Kendall's $\tau = 0.5$.

[3] Another rank-based measure of dependence is Spearman's ρ. Cherubini et al. (2004) explain these measures as well as their differences in greater detail.

The upper panels illustrate the symmetric dependence structure for the Gaussian and the Student-t copula. The Student-t copula exhibits more tail dependence than the Gaussian copula but only captures symmetric tail dependence. However, the asymmetric Clayton copula detect greater dependence in the lower left tail, while stronger co-movements in the upper right tail are captured by the Gumbel copula.

1.3.4 Estimation Procedure

As asserted above, copulas offer an alternative to the correlation coefficient as it comes to modelling the dependence structure. Different approaches to estimate copulas have been suggested in the literature (Cherubini et al., 2004; Schölzel and Friederichs, 2008; Michelis and Ning, 2010). In this article, the copula parameters are estimated using the transforms from the empirical marginal distribution function $\hat{F}_i(x_i)$ by canonical maximum likelihood (CML) estimation (Bouye et al., 2000).[4] The vector of parameters is estimated semi-parametrically by maximising the log likelihood for the copula density using the empirical marginals $\hat{F}_i(x_i)$.

Because of the conditional heteroscedasticity usually present in financial time series, instead of modelling the unconditional return distribution, we concentrate on the conditional returns. We employ the framework of semi-parametric copula-based multivariate dynamic (SCOMDY) models suggested by Chen and Fan (2006). As the name indicates, this class of models arises from a combination of methods. The conditional mean and the conditional variance of a multivariate time series are specified parametrically, while the joint distribution takes a semi-parametric form using a parametric copula and non-parametric marginals. The method creates additional flexibility. The typical non-normal movements of financial time series can be captured more accurately. Still, the copula estimation remains low-dimensional and allows to represent various non-linear and asymmetric dependence structures (Linton and Yan, 2011). Following the notation by Chen and Fan (2006), Y_t is

[4] In the bivariate case, based on the estimated value of τ, the dependence parameter for the chosen copula can be calculated as a function of τ. Genest et al. (2009) explain this procedure for the Gaussian, Student-t, Clayton and Gumbel copula. Under weak regularity conditions on the copula family, this yields a consistent estimator of the dependence parameter. For the Student-t copula, as indicated by Equation 1.3, the econometrician has to also estimate the parameter for the degrees of freedom. In comparison to other estimation techniques, the copula estimation via rank transformation and Kendall's τ is particularly simple and therefore often used in practical applications. Unfortunately, it is limited to a bivariate setting because it makes inference on the dependence structure of the multivariate model from a chosen dependence coefficient.

a d-dimensional process of endogenous and X_t is a vector of exogenous variables, $t = 1, ...n$ denotes a vector stochastic process. A SCOMDY model is then defined as follows:

$$Y_t = \mu_t(\theta_1) + \sqrt{H_t(\theta)}\epsilon_t, \tag{1.6}$$

where the vector $\mu_t(\theta_1)$ denotes the true conditional mean parameter and the vector $H_t(\theta)$ the true conditional variance, both for given values of $Y_{t-1}, Y_{t-2}, ...$ and $X_t, X_{t-1}, ...$ The innovations in vector ϵ_t are i.i.d. with zero mean and unit variance. They have the distribution function $F(\epsilon) = C(F_1(\epsilon_1)), ..., F_d(\epsilon_d))$ with $F_j(\cdot)$ as true but unknown continuous marginal and $C(u_1, ..., u_d)$ as true copula function.

Various non-linear models can be used for modelling the conditional mean and the conditional variance. In combination with the variety of available copula models, this approach allows a great extent of flexibility for the final model specification. The reader may find a more thorough description of the SCOMDY model class in the original paper by Chen and Fan (2006). The estimation procedure can be summarised the following way:

1. Estimate all conditional mean and variance parameters to obtain standardised innovations.
2. The empirical distribution function of these standardised innovations, denoted as $\hat{F}_j(\mu_{j,t}(\theta))$, j=1,...,d, is estimated non-parametrically. Section 1.4 describes this step for our dataset.
3. The copula dependence parameter is derived by using the copula specification as in Equations 1.2 to 1.5 and its density C($\hat{F}_1(\epsilon_{1,t}(\theta))$,..., $\hat{F}_d(\epsilon_{d,t}(\theta))$ for maximisation of the log likelihood.

1.3.5 Goodness-of-Fit Tests

As described in Section 1.3.3, each copula captures a different dependence structure (Trivedi and Zimmer, 2005). The econometrician needs to decide which of the estimated copulas reflects the actual dependence structure of the data most appropriately. According to Berg and Bakken (2007), this decision should not be based on the information criteria such as Akaike's Information Criterion (AIC).

Instead, it is recommended to use goodness-of-fit (GOF) approaches to reject or accept a specific copula (Panchenko, 2005; Genest et al., 2006, 2009). Several GOF test have been suggested by the literature, see e.g. Berg and Bakken (2007) or Genest et al. (2009). In our empirical analysis, we use goodness-of-fit tests that investigate the distance between the estimated and the so-called empirical copula to select the most appropriate among a set of copulas (Genest et al., 2006, 2009). The nonparametric empirical copula is calculated from the empirical margins whereby its functional form is fitted to the data. The distance between the estimated and the empirical copula is then evaluated using the so-called Cramér-Von Mises test statistic. The parametric copula that is closest to the empirical copula represents the most appropriate choice (Trivedi and Zimmer, 2005).

The following section describes the procedure in greater detail. Empirical copulas were introduced by Deheuvels (1979). The empirical copula can be understood as the sample version of the dependance structure (Cherubini et al., 2004). The empirical marginal distribution converges towards the actual distribution function for n approaching infinity. Let $(X_{1i}, ..., X_{ni})$ be n observations of the random variable X_i. Then, the empirical marginal cdf for a random variable X_i is:

$$\hat{F}_i(x_i) = \frac{1}{n+1} \sum_{j=1}^{n} I(X_{ji} \leq x_i) \qquad i = 1, .., d, \tag{1.7}$$

where $I(\cdot)$ returns the value of 1 if $X_{ji} \leq x_i$ and 0 otherwise. The term $n+1$ in the denominator is used to keep the empirical cdf below 1. Given the marginal cdf's, the empirical probability integral can be transformed $u_{ji} = \hat{F}_i(x_{ji})$ for $i = 1, .., d$ and $j = 1, .., n$ for the vector $u = (u_1, .., u_d)$, and the empirical copula can be derived by:

$$C^{emp}(u) = \frac{1}{n+1} \sum_{j=1}^{n} I(\hat{F}_1(x_{j1}) \leq u_1), ..., \hat{F}_d(x_{jd}) \leq u_d)) \tag{1.8}$$

$$= \frac{1}{n+1} \sum_{j=1}^{n} I(U_1 \leq u_1, ..., U_d \leq u_d). \tag{1.9}$$

According to Tsukahara (2005), the empirical copula is a consistent estimator of the true copula and therefore is a well-accepted benchmark for copula goodness-of-fit tests.[5] We concentrate on so-called 'blanket tests' which do not depend on prior categorisation of the underlying data or any arbitrary choice of smoothing parameters, weight functions, or kernels. Genest et al. (2009) specify different versions of such tests and conduct a large Monte Carlo experiment to compare these options. They report particularly good results for the blanket tests using ranks or the Rosenblatt transform. To evaluate the distance between the estimated and the empirical copula, the authors find the best results for the so-called Cramér-Von Mises statistic. Hence, we only describe tests based on ranks that use the Cramér-Von Mises statistic for measuring the difference between the estimated and the empirical copula.

We investigate whether a specific parametric copula represents the dependence structure of a multivariate distribution appropriately. The test procedure can be roughly summarised as follows:

1. Based on the empirical cdfs for the marginal series, estimate the empirical copula $C^{emp}(U_i)$ and the parametric copula $C_\theta(U_i)$.

2. Using the Cramér-Von Mises statistic, calculate the distance between the empirical and the estimated copula:

$$S_n = \sum_{i=1}^{n} [C^{emp}(U_i) - C_\theta(U_i)]^2$$

3. In a bootstrap procedure, for some large integer D, the following steps are repeated:

   (a) Generate a random sample from C_θ and compute the associated rank vectors $(U_1^*, ..., U_n^*)$ as well as the empirical copula $C^{emp*}(u)$.

   (b) Estimate the parametric copula C_{θ^*}.

   (c) Determine $S_n^* = \sum_{i=1}^{n}[C^{emp*}(U_i) - C_{\theta^*}(U_i)]^2$ for the generated sample.

4. From the D bootstrap samples, an approximate p-value, measuring the goodness-of-fit of the copula, can be calculated as the fraction of simulations where $S_n^* > S_n$.

[5]Note that the empirical copula is not a copula according to the definition by Deheuvels (1979), but rather the observed frequency of $P(U_1 \leq u_1, ..., U_d \leq u_d)$.

Under the null hypothesis, a specific copula provides a good fit for the dependence structure of a multivariate distribution. High p-values, which do not reject the null, indicate that the considered copula mirrors the actual dependence structure of the data well. For a copula that does not represent an appropriate choice, given the actual data, the p-value should be low. In this case, depending on the level of confidence, the null hypothesis will be rejected. Note that for the case where several copula families cannot be rejected by the goodness-of-fit tests, an alternative approach as specified in e.g. Chen and Fan (2006) or Diks et al. (2010), needs to be implemented. These tests are particularly designed to compare competing copula models based on their in-sample (Chen and Fan, 2006) or out-of-sample (Diks et al., 2010) log likelihood scores.

1.3.6 Data

In this section, we investigate the dependence structure between daily returns from traded emission allowance contracts and various other financial variables during the time period 2. January 2008 to 31. December 2009. The existing literature discusses the factors which are most important for the carbon price. Based on this research, we examine a number of variables from commodity and financial markets. As illustrated in Section 1.2.2, the literature identifies energy prices to exert a strong influence on the carbon price due to fuel-switching in the power sector. Therefore, from commodity markets, we choose gas and coal futures returns as well as 2010 oil futures returns. The gas and oil futures are obtained from the International Commodity Exchange (ICE). Data on coal futures as well as electricity futures are taken from the European Energy Exchange (EEX) in Leipzig. The underlying for the electricity futures is the Phelix Day Base. Data on the EUA price are obtained from the London-based European Climate Exchange (ECX). As emission levels are related to economic activity, we take stock markets as a proxy for economic development. In addition to the broader European stock market index, the Eurostoxx 50, we consider the more energy-specific DJ Europe Energy Stock Index (E1ENE) and the European Renewable Energy Index (ERIXP). One may assume that the relationship between the carbon price and energy-related stocks is particularly strong. For our analysis, we consider log-returns that are calculated as $r_t = ln(P_t/P_{t-1})$ from the original price series.

1.4 Estimation Results

1.4.1 Dependence Structures

Following the SCOMDY approach described in Section 1.3.4, in a first step we need to find an appropriate model for the marginals. We need to estimate the parameters for the conditional mean $\mu_{j,t}(\theta_1)$ and conditional variance $h_{j,t}(\theta)$ equations.[6] We focus on different ARMA-GARCH specifications for each of the considered series and abstain from using additional exogenous variables. To avoid over-fitting, the best model is chosen based on Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). Table 1.1 summarises the results for the considered series and reports the model choice according to the considered model parsimony criteria. The obtained standardised residuals will then be used in the subsequent empirical analysis. To test for i.i.d property of the standardised residuals, the BDS test for independence was applied to the standardised residuals. The BDS test is a portmanteau test for time-based dependence in a series and can be used to examine whether the residuals are independent and identically distributed. We found that for none of the considered series the null hypothesis of i.i.d could be rejected. In the following, we therefore assume that all standardised residuals exhibit the desired i.i.d. property necessary for the copula estimation. For ease of readability, we will henceforth adhere to the expression returns instead of using standardised residuals.

Table 1.1: Choice of the best ARMA-GARCH model

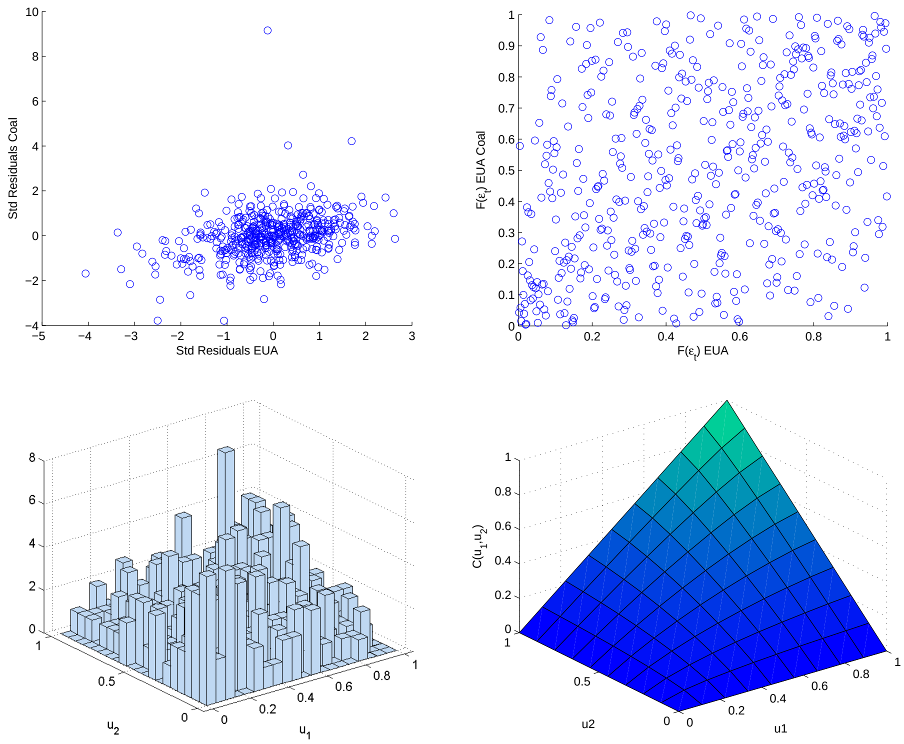
Time series	Suggested model
EUA futures	ARMA(1,0)-GARCH(1,1)
Coal futures	ARMA(1,0)-GARCH(2,3)
Oil 2010 futures	ARMA(0,0)-GARCH(1,1)
Gas futures	ARMA(0,1)-GARCH(1,2)
EEX futures	ARMA(1,0)-GARCH(1,3)
Eurostoxx 50 Spot	ARMA(1,0)-GARCH(1,2)
E1ENE Spot	ARMA(1,0)-GARCH(1,2)
ERIXP Spot	ARMA(1,1)-GARCH(1,1)

Note: The choice of the best ARMA-GARCH model for each of the considered time series is based on AIC and BIC model selection criteria.

In a next step, we investigate the dependence structure between returns of EUAs and the other considered commodities and financial variables based on the

[6] The estimation was conducted in Matlab.

Figure 1.2: Illustrating daily EUA 2010 and coal futures

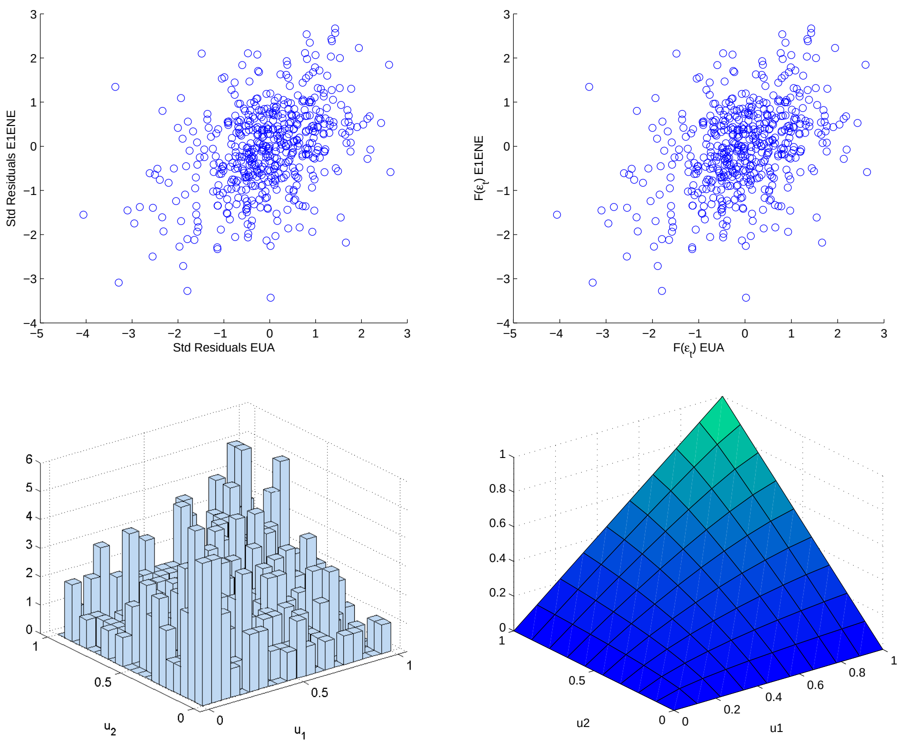


Note: Standardised residuals for daily EUA 2010 futures versus coal futures (upper left panel), ranks for daily EUA 2010 Futures standardised residuals versus ranks for coal futures standardised residuals (upper right panel), 3d histogram of rank transforms for daily EUA 2010 futures versus coal futures (lower left panel), and fit of the Student-t copula to the rank transforms (lower right panel).

fitted models for the marginal return series. As pointed out in Section 1.3.4, after estimating the parameters for the marginal series, the next step is to estimate the empirical distribution functions $\hat{F}_j(\mu_{j,t}(\theta))$. This has the advantage that the possibly unknown distribution for the returns is not required, since the empirical marginal cdf can be used. The CML method is then applied to the transforms from the empirical distribution function to estimate the dependence parameters $\hat{\theta}$ for the Clayton, $\hat{\phi}$ for the Gumbel, the copula correlation parameters $\hat{\rho}_G$ for the Gaussian, and $\hat{\rho}_t$ for the Student-t copula. Note that the degrees of freedom parameter v needs to be estimated for the Student-t copula, so that the results for the copula correlation parameters $\hat{\rho}_G$ and $\hat{\rho}_t$ are not necessarily identical.

Figure 1.2 provides a plot of the standardised residuals for daily EUA 2010 futures versus coal futures, the rank transforms of the standardised residuals for

Figure 1.3: Illustrating daily EUA 2010 futures and E1ENE



Note: Standardised residuals for daily EUA 2010 futures versus E1ENE returns (upper left panel), ranks for daily EUA 2010 futures standardised residuals versus ranks of E1ENE standardised residuals (upper right panel), 3d histogram of ranks transforms for daily EUA 2010 futures versus E1ENE (lower left panel), and fit of the Student-t copula to the rank transforms (lower right panel).

EUA 2010 futures versus coal futures, a 3d histogram of the rank transforms, and the fit of the Student-t copula to the transforms. The analogous graphs are also provided for the series daily EUA 2010 futures versus E1ENE returns in Figure 1.3.

We also estimate Kendall's $\hat{\tau}$ for each of the bivariate series and conduct a significance test for the dependence between returns with $H_0 : \tau = 0$ versus $H_0 : \tau \neq 0$. The test is non-parametric, as it does not rely on any assumptions on the distributions of two variables X and Y. Then under a null hypothesis of X and Y being independent, the sampling distribution of τ will have an expected value of zero. Note that the precise distribution cannot be characterised in terms of common distributions, however, it can be calculated exactly for small samples.[7]

[7]For larger samples, commonly an approximation to the normal distribution, with zero mean and variance $2(2n + 5)/9n(n - 1)$ is used. For further details on the test we refer to Prokhorov (2001).

We find significant dependence at the 1% level between EUA returns and other return series. Only for the oil futures, the estimated coefficient for Kendall's $\hat{\tau}$ is not significant at the 1% or 5% level. The results are displayed in Table 1.2. We find that Kendall's $\hat{\tau}$ ranges from approximately -0.05 to 0.41 for the different series, while the Gaussian and the Student-t copula correlation parameters range from approximately -0.07 to 0.60. The highest dependence can be observed between returns of 2010 EUA and electricity futures contracts, while we observe the lowest rank dependence and correlation between 2010 EUA and oil futures contracts. Interestingly, here the estimated coefficients for Kendall's $\hat{\tau}$, $\hat{\rho}_G$, and $\hat{\rho}_t$ are slightly negative. However, in 2008 and 2009 the oil futures behaved quite particular, dropping from a peak at 140 US Dollars to a price remaining at around 80 US Dollars. This might explain the weak correlation and the negative sign. There is not only a significant dependence between commodity and EUA futures contracts, but also between EUA futures and equity markets. In fact the returns of stock market indices – the Eurostoxx 50, the energy specific index E1ENE, and the renewable energy index ERIXP – seem to exhibit even a higher degree of dependence with EUA futures returns than for example oil and gas futures. Generally, our results contradict some of the earlier studies by Kosobud et al. (2005) and Daskalakis et al. (2009) on the dependence between emission allowances and other financial assets. While the former found no statistically significant correlations between returns of SO_2 emission allowances and returns from other financial variables, the latter observed that EUA futures returns were negatively correlated with equity market returns during the pilot trading period.

To investigate which of the copulas describes the dependence structure best, we use the Cramér-Von Mises statistic to measure the distance between the empirical and the estimated copula. Because the distance between the estimated and the empirical copula alone is not sufficient to determine whether any of the models really provides a good fit to the data, goodness-of-fit tests proposed by Genest et al. (2009) are conducted. Recall that for these tests, the null hypothesis is that the examined copula provides an appropriate fit to the data. Following the test procedure described in the previous section, for each of the copula families, we create $D = 1000$ bootstrap samples and determine the distance between the empirical and

Table 1.2: Kendall's $\hat{\tau}$ and estimated copula dependence parameters

Asset	$\hat{\tau}$	$\hat{\theta}$	$\hat{\phi}$	$\hat{\rho}_G$	$\hat{\rho}_t$	
Coal futures	0.2458**	0.5250	1.2666	0.3680	0.3744	($\hat{v} = 27.90$)
Oil 2010 futures	-0.0544	0.0000	1.0000	-0.0696	-0.0711	($\hat{v} > 1000$)
Gas futures	0.1140**	0.2114	1.1175	0.1804	0.1857	($\hat{v} = 14.96$)
EEX futures	0.4135**	0.9840	1.6010	0.5920	0.6008	($\hat{v} = 14.19$)
Eurostoxx 50 Spot	0.1818**	0.3473	1.2055	0.2954	0.2984	($\hat{v} = 21.47$)
E1ENE Spot	0.2651**	0.5732	1.3067	0.3937	0.4044	($\hat{v} = 8.82$)
ERIXP Spot	0.2005**	0.4761	1.2115	0.3169	0.3203	($\hat{v} = 12.31$)

Note: Kendall's $\hat{\tau}$ and the estimated copula dependence parameters $\hat{\theta}$ for the Clayton, $\hat{\phi}$ for the Gumbel, $\hat{\rho}_G$ for the Gaussian, and $\hat{\rho}_t$, $\hat{v}$ for the Student-t copula for standardised residuals of EUA futures and the considered assets. For Kendall's τ we also report the results of a significance test with $H_0 : \tau = 0$. The asterisk denote significant rejection of the null hypothesis at the 1% ** and 5% * level.

the estimated copula for each sample.[8] The samples are then used to calculate p-values with respect to the null hypothesis. The p-value provides the level of significance at which the null hypothesis would be rejected. The p-value therefore measures how much evidence we have against the null hypothesis of an appropriate fit of the suggested copula. Results for the Cramér-Von Mises statistic as well as p-values for the considered copula families are presented in Table 1.3.

The results indicate that for the majority of the considered bivariate series the Student-t copula yields the smallest distance between the estimated and the empirical copula. The distance is the smallest for five of the considered bivariate series, while it yields the second smallest distance for the other two pairs. Interestingly, the Gaussian copula also provides distances that are only slightly higher than those of the Student-t copula and significantly smaller than those of the Clayton and the Gumbel copula. Only for the relationship between EUA futures and Eurostoxx 50 spot returns, the Gumbel copula yields the smallest distance. For the relationship between EUA futures and ERIXP spot returns, the Clayton copula yields the smallest distance.

Our results are also confirmed by the conducted bootstrap goodness-of-fit tests. We find that the Student-t and the Gaussian copula perform best for most of the considered series. An appropriate fit of the Gaussian and the Student-t copula to the dependence structure cannot be rejected for any of the series at the 5% significance

[8] This is the number of bootstrap samples that is also applied in Genest et al. (2009) providing good results for the considered goodness-of-fit tests.

level. At this significance level, the hypothesis of an appropriate fit of the Clayton and the Gumbel copula is rejected for five out of seven series. An appropriate fit of the Clayton or the Gumbel copula cannot be rejected at the 5% level between EUA and gas futures (Clayton and Gumbel), EUA futures and the ERIXP spot (Clayton) as well as EUA futures and the Eurostoxx 50 (Gumbel). For the Gumbel copula an appropriate fit is even rejected at the 1% level for most of the series.

Table 1.3: Distance between estimated and empirical copula

Asset	Clayton		Gumbel		Gaussian		Student-t	
Coal futures	0.0326	(0.036)	0.0557	(<0.001)	0.0167	(0.536)	**0.0162**	(0.601)
Oil 2010 futures	0.0702	(0.014)	0.0702	(<0.001)	0.0328	(0.064)	**0.0324**	(0.062)
Gas futures	0.0177	(0.471)	0.0211	(0.158)	0.0164	(0.585)	**0.0151**	(0.654)
EEX futures	0.1537	(<0.001)	0.0521	(<0.001)	0.0085	(0.980)	**0.0083**	(0.938)
Eurostoxx 50	0.0519	(0.002)	**0.0162**	(0.478)	0.0235	(0.242)	0.0235	(0.205)
E1ENE	0.0557	(0.003)	0.0471	(<0.001)	0.0155	(0.635)	**0.0130**	(0.797)
ERIXP	**0.0193**	(0.333)	0.0478	(<0.001)	0.0239	(0.209)	0.0220	(0.264)

Note: Either the Student-t or the Clayton copula yield the lowest distance according to the Cramér-Von Mises statistic. The p-values, shown in parentheses, are based on bootstrap goodness-of-fit test (Genest et al., 2009). Bold letters indicate the lowest distance for the considered series.

Overall, we find that the elliptical Gaussian and Student-t copula provide an appropriate fit to all considered bivariate return series. Given the rather symmetric dependence structure for most of the considered variables, the findings of Zachmann and von Hirschhausen (2008) regarding an asymmetric relationship cannot be confirmed by our study. This is in line with Prete and Norman (2011) who report a symmetric structure for emission allowance futures and electricity futures during Phase II. Note that the conducted goodness-of-fit tests are not able to provide information on which copula provides the best fit to the data. The tests do neither reject the Gaussian nor the Student-t at the 1% or 5% level for any of the series. For most of the considered return series, they provide p-values of a magnitude greater then 0.2. To decide which model is closer to the true model among a set of valid models, alternative tests would be required, as described in Chen and Fan (2006) and Diks et al. (2010). We leave this investigation to future work.

1.4.2 Time-Varying Copulas

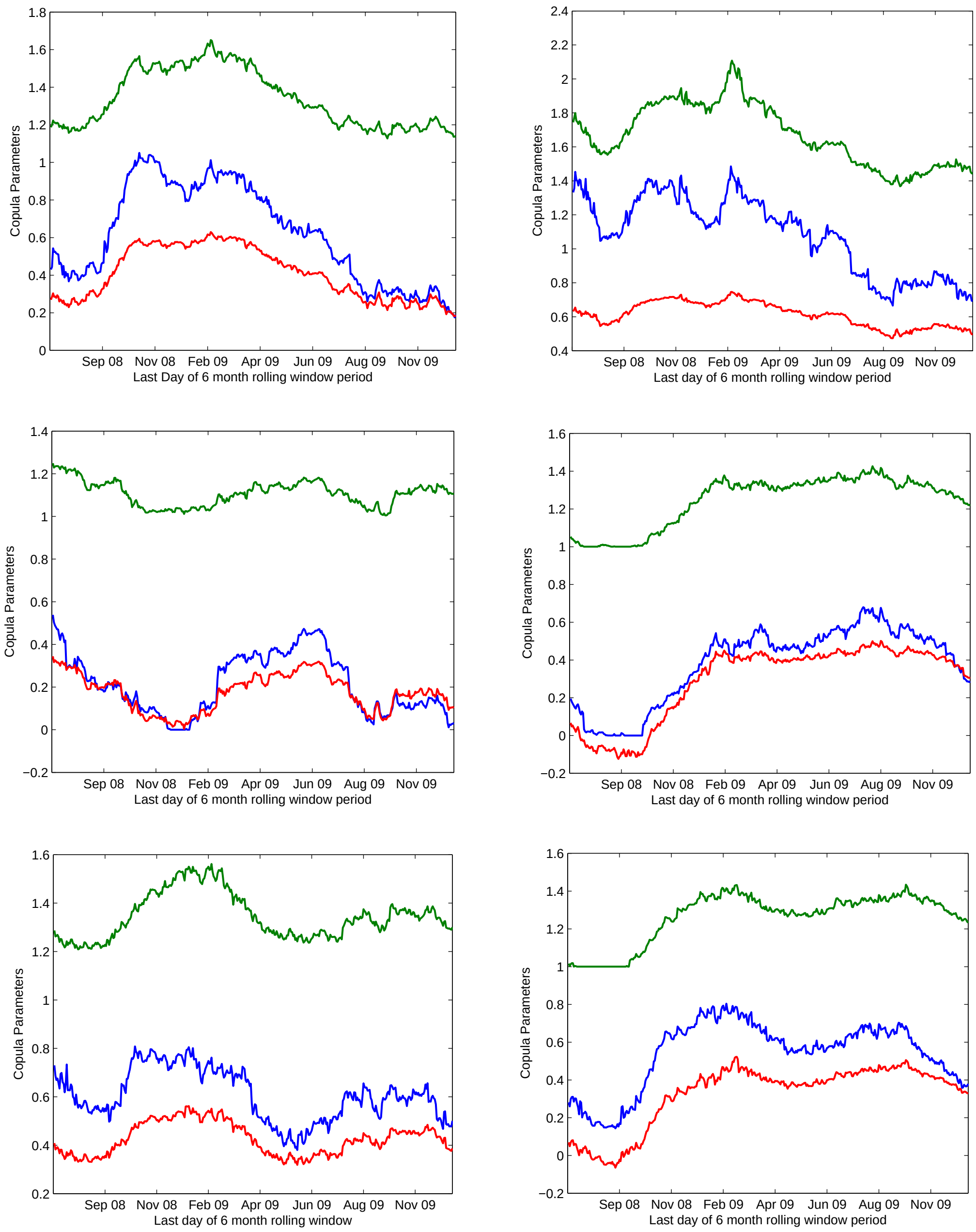
To investigate the nature of the dependence through time, we further apply a time-varying estimation of the copula parameters for the bivariate series. We hereby decide to estimate the different copula parameters using a rolling window approach as it is applied in Giacomini et al. (2009) or Grégoire et al. (2008). Again, we consider a conditional approach such that, in a first step, we estimate ARMA-GARCH models for each return series and calculate the standardised residuals. In a second step, the empirical distribution function is applied to the standardised residuals, and the copula models are estimated based on the derived ranks. We choose a window length of 126 trading days that corresponds to approximately six months. The first period considers returns from 3. January 2008 to 30. June 2008, while the last window uses data from 6. July 2009 to 31. December 2009.[9] Figure 1.4 shows a plot of the estimated copula parameters for the Clayton, Gumbel and Student-t copula. Depicted is the relationship between EUA futures returns and coal, electricity, and gas futures returns as well as the relationship between the Eurostoxx 50, E1ENE, and ERIXP spot returns respectively. Note that for all series the estimated dependence parameter for the Gaussian copula was almost identical to the Student-t copula parameter. Therefore, these parameters are not provided in the graphs.

For most of the considered series, we find that the estimated copula parameters exhibit time-variation. We generally find that the dependence between EUA futures and the considered commodity futures is increasing during the period of the financial crisis in the second half of 2008. The dependence between the return series seems to decrease to a lower level during 2009, in particular in its second half. This confirms general results on time-varying correlation or dependence suggesting that returns from financial markets exhibit higher dependence during periods of economic or market downturn.

The degree of time-variation, however, is considerably different for some of the relationships under investigation. The dependence structure between EUA and coal futures exhibits a particularly strong change: the copula parameters start to increase for samples beginning in the second half of 2008. For example, the parameter of the Clayton copula rises from approximately 0.4 to a value higher than 1. This indicates that joint downward movements of the two series occur considerably more often during this period of time. The parameters of the Student-t and the Gumbel copula exhibit a similar behaviour, but in a more retained manner. The relationship between EUA and electricity futures is generally found to be stronger for the entire

[9] More advanced approaches on the estimation of time-varying copulas, also with respect to the optimal choice of window length, have been suggested by Patton (2006), Rodriguez (2007), and Giacomini et al. (2009). However, our aim in this section is to provide a simple and rather descriptive analysis of the dependence structure through time.

Figure 1.4: Estimated copula parameters over time



Note: Estimated copula parameters for the Clayton (blue), Gumbel (green), and Student-*t* (red) copula for a six month rolling window period. The first window covers observations from January to June 2008, while the last period covers observations from July to December 2009. The graphs show the results for dependence structure between returns for daily EUA 2010 futures and coal futures (upper left panel), electricity futures (upper right panel), gas futures (middle left panel), Eurostoxx 50 spot contracts (middle right panel), E1ENE DJ Europe Energy Stock Index spot contracts (lower left panel) and ERIXP European Renewable Energy Index spot contracts (lower right panel).

time horizon. The relationship of EUA and gas futures seems to change only by the end of 2008.

Analysing the relationship between EUA futures returns and the considered equity indices yields further interesting insights. The dynamics of the dependence structure between EUA futures and E1ENE spot returns are quite similar to those of commodity markets through time. We find, however, different results for the relationship between EUA futures and Eurostoxx 50 spot returns as well as ERIXP spot returns: here the dependence is very low during the first six months of 2008. The estimated parameters for the Clayton and the Student-t copula are close to zero, while the parameter for the Gumbel copula is approximately one, indicating that the dependence is very weak during this period. Three months later the dependence becomes stronger, and the estimated parameters for all of the considered copulas start to increase. For the Eurostoxx 50, this increase continues until August 2009, while the parameters for the ERIXP rise significantly until February 2009. All copula parameters rise in absolute terms, in relative terms the increase is much higher for the Student-t and the Clayton copula. This suggests that joint downward movements are more pronounced during the financial crisis. Towards the end of the investigated period, we find a slightly decreasing dependence structure between EUAs and all of the considered equity indices. Note that conclusions as to whether there is a structural break or a significant change in the dependence structure during the considered period require further statistical tests as suggested by Patton (2006) or Giacomini et al. (2009).

1.4.3 Risk Management Analysis

As mentioned in Section 1.2.2, the EUA price is more likely to be influenced by policy measures and regulatory changes than conventional commodities. This specific feature brings about new challenges how to integrate EUAs in a portfolio. Therefore, we extend the present analysis by a risk management perspective and consider different exemplary portfolios with investments in several of the considered assets. We test the Gaussian and Student-t copula models against two benchmark approaches: a standard (static) multivariate variance-covariance approach and a univariate AR-GARCH type model that is applied directly to the created return series of the constructed portfolios. The forecasting performance of the models is investigated by conducting an out-of-sample analysis comparing one-day-ahead VaR and distributional forecasts for the portfolios. We report the results for portfolios with equal weights for each of the assets. We would like to point out that robustness checks with varied portfolio weights and assets did not change the quality of the results. In the following, results for four different portfolios will be reported:

- Portfolio 1 (PF1) with equal 25% weight for the following futures contracts: EUA, coal, oil and gas.
- Portfolio 2 (PF2) with equal 25% weiht for the following futures contracts: EUA, coal, gas and electricity.
- Portfolio 3 (PF3) with equal 25% weight for the following assets: EUA, electricity, Eurostoxx 50 and ERIXP.
- Portfolio 4 (PF4) with equal 25% weight for the following assets: EUA, Eurostoxx 50, E1ENE and ERIXP.

Value-at-Risk Analysis

For each portfolio (PF1-PF4) we create the return series based on the assumed equal weights $w = 0.25$ for each asset. Then, in an out-of-sample forecasting study, the performance of the copula models is tested against a standard multivariate normal (MVN) approach and a univariate AR(1)-GARCH(1,1) model for the portfolio return series. Note that the multivariate normal approach does not consider the conditional variance of the individual assets, so we expect the forecasts to vary significantly less through time for this model. Therefore, we assume that the multivariate normal approach cannot react to significant volatility changes in any of the assets and might underestimate the risk, in particular during times of high volatility.

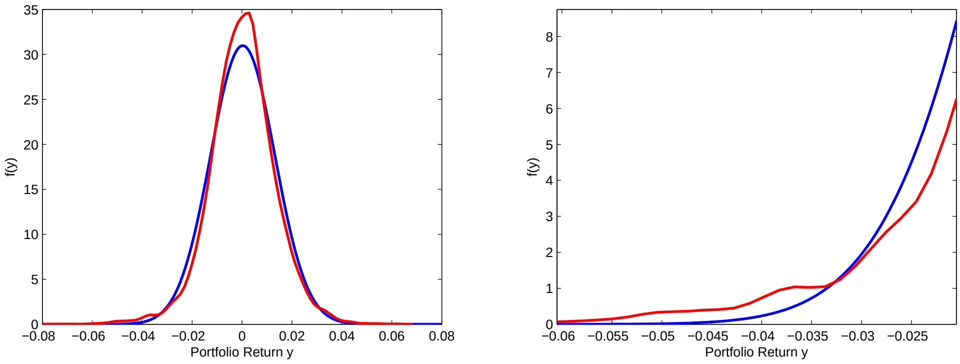
With respect to copula models, we decide to examine the forecasting performance using the Gaussian and the Student-t for the multivariate dependence structure between returns of the individual assets. Note that while these copulas provide an appropriate fit to the dependence structure in the bivariate case, we cannot generally extrapolate these results to a multivariate setting. Before conducting our risk analysis, the fit of both copulas to the dependence structure between individual assets of the four portfolios was tested using the goodness-of-fit tests described in Section 1.3.5 and 1.4. The results indicated that an appropriate fit of both, the Gaussian and the Student-t, to the multivariate data could not be rejected.

Similar to Section 1.4.2, our risk analysis is conducted using a rolling window of $t = 126$ days length, corresponding roughly to six months of observations. For the univariate model, we derive the distributional forecast for the returns based on the fitted AR-GARCH model and the most recent forecast for the conditional volatility. For the benchmark variance-covariance approach, we assume that the return series and the dependence structure can be described by a multivariate normal distribution. Under this assumption, we simply need to estimate the variance-covariance matrix Σ for the return series. Using portfolio theory, the mean of the marginal return series, the given portfolio weights, and the estimated variance-covariance matrix allow us to calculate a distributional forecast of portfolio returns for the next day. For the copula approach, we apply the discussed SCOMDY model with an AR(1)-GARCH(1,1) process for the marginal series.[10] Therefore, for each time step, we initially fit an AR-GARCH model to the individual return series and calculate the standardised residuals. Then, using the transforms from the empirical distribution function for the standardised residuals, the Gaussian and the Student-t copula are fitted to the multivariate series. We estimate the multivariate Gaussian and Student-t copula for each time step, and therefore obtain the correlation matrix $\hat{C}_{Gaussian}$ and $\hat{C}_{Student}$ as well as the degrees of freedom parameter $\hat{v}$ for the Student-t copula. Then, we use the estimated copulas to simulate 10000 vectors of dependent uniformly distributed random variables (u_1, u_2, u_3, u_4) from both copulas. Thereafter, the inverse of the empirical distribution function and the conditional forecast for the volatility for the marginal series are used to calculate the simulated conditional asset returns for the series. Finally, using the portfolio weights we can then determine a simulated return distribution for the portfolio in $t + 1$.

An exemplary plot of the simulated return distribution for two of the methods and Portfolio 4 is provided in Figure 1.5. Here, the distributional forecast for one of the time steps using the Student-t copula model in comparison to a standard

[10] Because the analysis was conducted in a rolling window setting, different AR-GARCH type models will provide the best fit to the data at different points in time. Because choosing the optimal model for each series at any time step based on a parsimonious model selection criteria would be tedious, we decided to stick to a simple AR(1)-GARCH(1,1) that generally provided a good fit to all of the series.

Figure 1.5: Exemplary plot of return distribution forecast

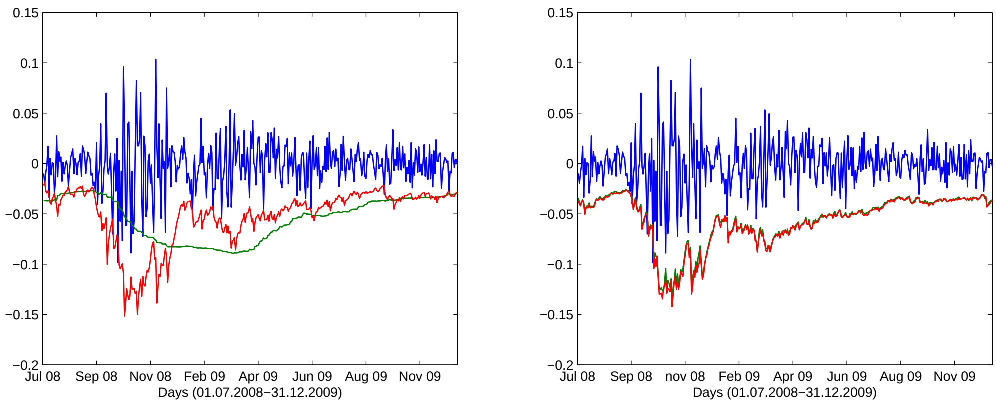


Note: Exemplary plot of the return distribution forecast (left panel) and the tail of the return distribution forecast (right panel) for the multivariate normal and the Student-t copula approach with $v = 8.03$ for Portfolio 4. For both plots the blue line is the probability density for the multivariate normal approach, while the red line provides the simulated density for a model using the Student-t copula to model the dependence structure between rank transforms.

variance-covariance approach is plotted. Our results indicate that the standard variance-covariance approach provides a lower estimate for the risk in particular in the extreme tail of the distribution. Generally, for the model using the Student-t copula, the simulated portfolio return distributions often exhibit some skewness and excess kurtosis.

The first six months were chosen as calibration period such that forecasts for the time period 1. July 2008 to 31. December 2009 are compared. As mentioned above, the forecasts are determined using a rolling window technique with re-estimation of the marginal distributions and dependence parameters after each time step. The length of the in-sample period is fixed with 126 trading days, while the start date and end date successively increase by one observation. Figure 1.6 provides a plot of the actual portfolio returns as well as the estimated 99%-VaR forecasts for Portfolio 4 using the univariate AR-GARCH model, a standard MVN approach as well as the conditional copula models (Student-t and Gaussian). The left panel illustrates that since the MVN approach does not take into account conditional volatility, there is significantly less variation in the VaR forecasts. During periods of extreme returns, for example in October - December 2008, the model continuously underestimates the risk. The second benchmark model, namely the univariate AR-GARCH model for the portfolio returns, seems to provide reasonable forecasts for the 99%-VaR. The right panel shows that also the considered copula models seem to provide an appropriate quantification of the 99%-VaR with only a small number of VaR exceptions. At a first glance, we also observe that there is only a minor difference with respect to VaR quantification between the Gaussian and the Student-t copula model. A more rigourous analysis based on VaR exceptions and distributional forecasts will be conducted in the following.

Figure 1.6: Portfolio returns and 99%-VaR forecasts for Portfolio 4



Note: The VaR forecasts are based on using a univariate GARCH model for the portfolio return series (red) and standard multivariate normal approach (green) *(left panel)* and for the conditional copula model using a Student-t (red) and Gaussian (green) copula *(right panel)*.

Given the estimated model parameters for the marginal distributions and dependence structure, we are able to calculate a model-dependent confidence interval for the next observation of the portfolio return y_{t+1}. Following Kupiec (1995), Christoffersen (1998) and Hull (2007), we evaluate the quality of the VaR forecasts by comparing the nominal number of exceptions of the models to the true number of exceptions. Because comparing the nominal and true coverage might be sensitive to the choice of the confidence level α, we decided to investigate the coverage for three different values of α. For each of the models we calculate the VaR for the 95%, 99%, and 99.9% confidence level. If the implied VaR forecasts are accurate, the percentage of exceedances should be approximately 5%, 1% and 0.1%, respectively. We further conduct a statistical test investigating whether a model provides an acceptable number of VaR exceptions. The test is based on the binomial distribution and simply investigates whether the number of exceedances is significantly higher than the expected number for $p = 0.05$, $p = 0.01$, and $p = 0.001$ (Hull, 2007). The null hypothesis is that the model provides an adequate number of exceptions such that rejection of the null indicates that the model significantly misspecifies VaR estimates.

Table 1.4: Testing different VaR specifications

	95% VaR		99% VaR		99.9% VaR	
Portfolio	# Exc.	Fraction	# Exc.	Fraction	# Exc.	Fraction
PF1 Univariate	31	8.05%**	6	1.56%	3	0.78%**
PF2 Univariate	28	7.27%*	8	2.08%*	2	0.52%*
PF3 Univariate	31	8.05%**	8	2.08%*	2	0.52%*
PF4 Univariate	27	7.01%*	9	2.34%**	2	0.52%*
	95% VaR		99% VaR		99.9% VaR	
Portfolio	# Exc.	Fraction	# Exc.	Fraction	# Exc.	Fraction
PF1 MVN	25	6.49%	12	3.12%**	2	0.52%*
PF2 MVN	26	6.75%	9	2.34%**	2	0.52%*
PF3 MVN	28	7.67%*	14	3.64%**	6	1.56%**
PF4 MVN	28	7.67%*	11	2.86%**	6	1.56%**
	95% VaR		99% VaR		99.9% VaR	
Portfolio	# Exc.	Fraction	# Exc.	Fraction	# Exc.	Fraction
PF1 Gaussian	26	6.75%	6	1.56%	0	0.00%
PF2 Gaussian	24	6.23%	4	1.04%	1	0.26%
PF3 Gaussian	21	5.45%	5	1.30%	3	0.78%**
PF4 Gaussian	21	5.45%	3	0.78%	2	0.52%*
	95% VaR		99% VaR		99.9% VaR	
Portfolio	# Exc.	Fraction	# Exc.	Fraction	# Exc.	Fraction
PF1 Student-t	26	6.75%	6	1.56%	0	0.00%
PF2 Student-t	24	6.23%	4	1.04%	0	0.00%
PF3 Student-t	21	5.45%	6	1.56%	1	0.26%
PF4 Student-t	21	5.45%	3	0.78%	1	0.26%

Note: Number and fraction of exceedances for 95%-, 99%-, and 99.9%-VaR for the multivariate normal (MVN), the univariate GARCH model as well as the Gaussian and the Student-t copula approach. The asterisk denote rejection of an appropriate VaR specification for specific confidence level at 1% ** and 5% * significance (Hull, 2007).

With a total number of 385 days, the expected number of VaR exceptions is approximately 19.25 for the 95%, 3.85 for the 99%, and 0.385 for the 99.9% confidence level. Table 1.4 reports the actual number and fraction of exceedances as well as the results for the significance test for the number of VaR exceptions. We find that for a vast majority of considered portfolios and confidence levels the copula models are superior to the benchmark models with respect to the difference between the actual and the expected number of exceedances.

For the 95% confidence level, all models provide a slightly higher number of exceedances than expected. In particular for the portfolios containing investments in commodities and equity (PF3 and PF4), the coverage is worse for the univariate GARCH and the MVN model. For these portfolios, both copula approaches provide a better estimation of the risk quantile and yield a lower number of exceptions than the benchmark models. The conducted tests for VaR exceptions indicate that a correct specification of VaR levels is rejected for Portfolio 3 and 4 at the 5%, often even at the 1%, significance level for the multivariate normal and the univariate GARCH model. However, an appropriate specification of VaR for Portfolio 3 and 4 cannot be rejected for the Student-t copula at any of the considered VaR confidence level. For the 99% and 99.9% confidence levels, the copula models seem to provide better VaR estimates. Here, the univariate GARCH and the multivariate normal approach do not yield appropriate VaR forecasts such that the observed number of exceptions for any of the considered portfolios consistently exceeds the expected number. Table 1.4 clearly illustrates that both copula models offer better results, where the nominal number of exceptions for the considered confidence levels is much closer to the theoretical number.

Overall, with respect to backtesting the VaR models, the copula approach consistently outperforms the multivariate normal model. The univariate GARCH yields better results than the multivariate normal model but still shows a higher number of exceptions than the copula models almost at all confidence levels. In comparison to the Gaussian copula, the Student-t copula provides very similar results for the 95% and 99% confidence levels and slightly better results at the 99.9% confidence level. At this confidence level, an appropriate VaR specification is rejected for almost all portfolios for the two benchmark models, while it is only rejected twice for the Gaussian copula and never for the Student-t copula. Therefore, we conclude that the Student-t copula model provides the best results for the VaR specification.

Distributional Forecasts

We investigate the ability of the models to provide accurate forecasts of the portfolio return distribution. Tests that are based on the confidence intervals might be unstable as they are sensitive to the choice of the confidence level α. Therefore, we also apply tests that investigate the complete distributional forecast, instead of a number of quantiles only. We perform a distributional test that evaluates the accuracy of the density forecasts, following Crnkovic and Drachman (1996) and Diebold et al. (1998). We are interested in the distribution of the return $y_{t+1},\ t > 0$ that is forecasted at time t. Let $f(y_{t+1})$ be the probability density, and the associated distribution function of y_{t+1} is denoted by:

$$F(y_{t+1}) = \int_{-\infty}^{y_{t+1}} f(x)dx. \tag{1.10}$$

To conduct the test, we determine $\hat{F}(y_{t+1})$ using the estimates for the marginal return distributions and copula or correlation parameters from the rolling window in-sample period. Based on this information, we can calculate a rolling forecast of the portfolio return distribution for the next day. Given that $\hat{F}$ is the correct forecast for the distribution, Rosenblatt (1952) shows that the transformation of y_t:

$$u_{t+1} = \int_{-\infty}^{y_{t+1}} \hat{f}(x)dx = \hat{F}(y_{t+1}), \tag{1.11}$$

is i.i.d. uniform on $[0, 1]$. Crnkovic and Drachman (1996) and Diebold et al. (1998) provide tests that can be used to investigate violations of either independence or uniformity in the forecasts.

Testing for uniformity, Crnkovic and Drachman (1996) suggest to use a test based on the distance between the empirical and the theoretical cumulative distribution function of the uniform distribution. This may be done using the Kuiper statistic $D_{Kuiper} = D^+ + D^-$ with $D^+ = sup\{F_n(u) - \hat{F}(u)\}$ and $D^- = sup\{\hat{F}(u) - F_n(u)\}$. Hereby, $F_n(u)$ denotes the empirical distribution function for the probability integral transforms of the one-day ahead return forecasts and $\hat{F}(u)$ the cdf of the uniform distribution. Table 1.5 presents the results for the conducted tests. Again, we find that the Gaussian and the Student-t copula models generally provide better results than the multivariate normal model and the univariate GARCH model. Probability integral transforms of the one-day ahead return forecasts for the multivariate normal model are non-uniformly distributed. For Portfolio 1, 2 and 3, the test rejects the hypothesis of a uniform distribution even at the 1%

level while for Portfolio 4 the uniformity assumption is rejected at the 5% level. In comparison to the univariate model, the Gaussian and the Student-t copula model perform better for Portfolio 1 and 2, while the univariate model provides the smallest distance to the uniform distribution for Portfolio 3 and 4. While the appropriateness of the three models is not rejected for Portfolio 3 and 4, the Student-t copula model is the only one that cannot be rejected at the 1% level for Portfolio 1. For Portfolio 2, appropriate distributional forecasts are rejected for all considered models. Furthermore, all models seem to provide better forecasts for PF3 and PF4 with a higher share in equity indices, while they perform worse for PF1 and PF2 consisting of commodity futures only. The Student-t copula model clearly outperforms the multivariate normal model and seems to deliver slightly better results than the univariate GARCH and the Gaussian copula approach.

Table 1.5: Kuiper test statistics

	PF1	PF2	PF3	PF4
Univariate GARCH	0.1311**	0.1367**	0.0593	0.0577
Multivariate Normal	0.1183**	0.1149**	0.1121**	0.0985*
Gaussian Copula	0.1063**	0.1055**	0.0750	0.0710
Student-t Copula	0.0966*	0.1054**	0.0807	0.707

Note: Results for Kuiper test statistics. The asterisk denotes rejection of the model at the 1% ** and 5% * significance level, for n=386 observations.

Overall, our results suggest that copula models are particularly useful for risk management purposes and short-term forecasting of future return distributions for portfolios containing investments in emission allowances. These results could be important not only for risk management or hedging, but also for the purpose of portfolio optimisation. Deviating from the standard variance-covariance approach could be of interest, in particular when higher moments of the portfolio return distribution are considered or when risk-adjusted measures are used (Jondeau and Rockinger, 2006b; Keating and Shadwick, 2002). Note that our results were also robust when alternative portfolio weights, combination of assets, and different window sizes for the rolling estimation were considered.

1.5 Conclusions

The aim of this chapter is to deepen the understanding of the relationship between European carbon, commodity, and financial markets. We apply different copulas to analyse the dependence structure between EUA futures returns and those of other financial assets and commodities during the Kyoto commitment period. Copulas offer great flexibility for modelling the relationship between different financial variables. The application of copulas also yields insights with respect to non-linear dependence and tail dependence between the considered variables. We first investigate which copulas are most appropriate to model the dependence structure. Second, we focus on the time-varying properties of the dependence structure. The latter step allows us to examine whether the relationship has changed over time and whether the financial crisis had an influence on the dependence between EUA futures and other financial variables. The usefulness of copulas is further illustrated in a Value-at-Risk and density forecasting analysis. We consider different portfolios combining investments in EUAs with several other assets and test the Student-t as well as the Gaussian copula model against two benchmark models: a standard variance-covariance approach and a univariate AR-GARCH model that is applied directly to the portfolio returns.

The following insights emerge from these efforts. First, a significant positive dependence structure is found between EUA futures and coal, gas, and electricity futures returns as well as between EUA futures and equity spot returns. Only between EUA and oil futures we find the dependence to be insignificant. Our results contradict earlier studies by Kosobud et al. (2005) and Daskalakis et al. (2009) suggesting no statistically significant or even negative correlations between emission allowances and other financial variables. We confirm results by Mansanet-Bataller et al. (2007) and Hintermann (2010) who find a positive relationship between several commodities and the emission allowance prices. Regarding the nature of dependence, we find evidence of a symmetric dependence structure between emission allowances and other financial assets. For the majority of the considered bivariate series, the Student-t and the Gaussian copula are most appropriate, significantly outperforming the Clayton and the Gumbel copula with respect to a goodness-of-fit test. Second, we obtain interesting results on time-variation of the estimated copula parameters. In particular, we find a stronger dependence between EUA futures returns and most of the considered variables during the global financial crisis. This confirms general results on asset returns from financial markets exhibiting higher dependence during periods of extreme economic or market downturn. Finally, our risk analysis illustrates that applying a standard variance-covariance approach to the multivariate series is likely to underestimate the kurtosis and in particular the tail risk of the portfolio return distribution. The application of an AR-GARCH model to the portfolio returns also underestimates the risk in the lower extreme tail. A Student-t copula model that generally performs better with respect to interval and density forecasts than all the other considered models, including the implemented Gaussian copula model, gives indication of some tail dependence.

In a nutshell, our results recommend copulas as an appropriate tool for describing the dependence structure between returns from EUA contracts and those of other financial variables. The application of copulas may be particularly useful for risk management purposes and short-term forecasting for investments in a portfolio containing emission allowances. Given the potential tail dependence, our findings are also relevant for investors or portfolio managers, in particular when higher moments of the portfolio return distribution or risk-adjusted measures are considered.

Chapter 2

How Political is the European Carbon Market? – Insights from Conditional Jump Models

2.1 Introduction

As I have long-argued, investment in green energy will never be certain unless we bring some stability to the price of carbon.
George Osborne, Chancellor of the Exchequer, 2011

With the aim of reducing greenhouse gas emissions, different climate policies are implemented around the world. They range from command and control regulation to more market-based approaches. One renowned instrument is emissions trading which establishes a quantitative emissions target and requires offsetting climate-active gases with tradable certificates. The European Union Emissions Trading Scheme (EU ETS), established in 2005, is currently by far the largest existing carbon market. But in the meanwhile other trading schemes have developed: the first compliance period of the Regional Greenhouse Gas Initiative, an emissions trading initiative of ten north-eastern US states, has started in 2009. New Zealand has an emissions trading scheme in place which is stepwise extended to more sectors, Australia will introduce carbon trading in 2015.[1] Moreover, China recently announced the implementation of six regional ETS by 2013.[2]

As more systems are set in place and policy makers aspire to link them, it is necessary to gain confidence that these systems spur emission abatement. Incentives to reduce emissions are provided by the carbon price signal as already outlined in the Introduction of this thesis. However, there are several reasons for concern regarding the reliability of the price signal. First, Hintermann's (2010) paper finds that fundamentals related to the marginal abatement costs, such as gas and coal prices or weather variables, provide an insufficient explanation of the carbon price in Phase I of the EU ETS. Second, Gronwald et al.'s (2011) finding of a stronger relationship between the European Allowance Unit (EUA) price and those of other financial commodities during the financial crisis suggests that undesirable influences are present. Finally, concerns about price volatility in the newly established carbon market have been raised repeatedly, especially since the price for a EUA dropped by almost 50% in April 2006 (Chevallier, 2011b). Variation of the carbon price is the central feature of emissions trading, but excessive volatility reduces the efficiency of this policy instrument (Fankhauser et al., 2010). A capricious price development increases abatement cost uncertainty in the short-run and is possibly detrimental to investments in the long-run. With a carbon price that is weakly connected to market fundamentals and instable, the desired transition to a low-carbon economy might be at risk. Therefore, policy makers and economists worry about the efficiency of emissions trading as a climate policy instrument. With the aim of improving the European policy mechanism, it is necessary to better understand the carbon price fluctuations and their sources.

This chapter's aim is to deepen the understanding of the EUA price behaviour in the EU ETS. The focus lies on the more detailed description of carbon price volatility. Our main contribution is to disentangle the carbon price fluctuation and to provide new insights regarding the sources of these disturbances. The carbon market literature has addressed various statistical features of the EUA price such as volatility clustering or the occurrence of price jumps. This study goes beyond the existing literature and treats these statistical features in an integrated approach by applying Chan and Maheu's (2002) combined jump-GARCH model. This method

[1] More information is available at: www.climatechange.gov.au/government/reduce/carbon-pricing.aspx.

[2] Reuters, 11.4.2011, *China planning emissions trading in 6 regions*, www.reuters.com.

allows to systematically explain the volatility structure and to differentiate between smooth price fluctuation and sudden, extreme price movements. Moreover, the variance decomposition proposed by Nimalendran (1994) is employed to determine which portion of the variance is attributable to jumps. The empirical strategy helps to shed light into the different components of carbon price fluctuation. More importantly, explanations for the observed patterns are provided, particularly for price jumps that disrupt the market most.

On the one hand, a smooth and continuous price fluctuation is likely to arise from market fundamentals providing steady information about the demand for emission allowances. On the other hand, the high prevalence of jumps is probably related to news which introduce unexpected or essential changes to the market structure. Various studies show that markets, subject to political influences, are likely to exhibit extreme price movements, see in particular Jorion (1988). This chapter investigates to what extent political events trigger jumps in the European carbon market. In contrast to other commodity markets, the possibility to trade emission rights is a purely political decision. As the policy framework is such an essential feature to the market, it is a potential explanation for the dominance of jumps in the carbon price. This is further motivated by previous research on the EU ETS which finds a strong influence of the regulatory framework and related political decisions on the carbon price (Mansanet-Bataller et al., 2011; Chevallier, 2011b; Conrad et al., 2012). Therefore, the present analysis assesses which jumps are related to decisions of the EU Commission or news from the international climate change arena. Understanding how and why the carbon price develops, gives a sound basis to possibly counteract the volatile price development.

The results can be summarised as follows. First, the jump-GARCH model provides a good fit to the data and thus explains the capricious carbon price movements well. Second, no fewer than 40% to 60% of the carbon price variance are attributable to jumps. Third, a considerable number of the extreme price movements captured by the model's jump component can be related to information regarding EUA supply and changes in the administrative framework. This source of disturbance has not been researched widely in the empirical literature. Given our results, it seems an important information channel in a strongly regulated market.

The remainder of this chapter is organised as follows: Section 2.2 further explains this study's contribution to the literature, Section 2.3 provides a description of the data and the empirical approach. Section 2.4 presents the estimation results and the variance decomposition. Section 2.5 discusses the occurrence and source of carbon price jumps. Finally, Section 2.6 ends by some concluding remarks.

2.2 Literature Overview

This chapter builds on two streams of empirical literature: studies assessing the carbon price determinants and studies analysing the carbon price behaviour. Generally, the carbon price reflects supply as well as demand information of EUAs (Chevallier, 2011a). While the supply of emission rights is determined by the European Commission who decides on the total cap and the final allocation, the demand for EUAs is related to the amount of emissions that firms need to cover. This, in turn, depends on factors like weather conditions or differences between the coal and the gas price (Mansanet-Bataller et al., 2007). If the use of less carbon-intensive gas becomes cheaper than the use of coal, power producers with switch-capacity can opt for gas and therefore reduce their need for carbon allowances (Christiansen et al., 2005; Chevallier, 2009). The weather, on the one hand, affects the availability of renewable energy which can replace fossil energy sources (Hintermann, 2010; Rickels et al., 2010). On the other hand, particularly hot and cold temperatures increase the demand for air-conditioning or heating which thrives up the electricity demand.

Apart from these fundamentals, the literature is less clear about the driving forces of the carbon price. The dependence with financial markets has been discussed controversially. Hintermann (2010) cannot find a relationship of carbon with the British FTSE equity index during the first trading phase. Chevallier (2009) shows that different variables from stock and bond markets have little influence on EUA futures. However, Daskalakis et al. (2009) identify negative correlations of carbon futures with equity market returns in Phase I. Notwithstanding this debate, the relationship between the EUA market and other financial markets grew stronger during the period of the financial crisis (Gronwald et al., 2011).[3]

Many explanations for carbon price changes have been given, but Hintermann (2010) shows that these demand-side fundamentals provide an insufficient explanation of the EUA development in Phase I. To better explain the carbon price, the

[3]For a more detailed discussion, the reader is referred to Chapter 1.

regulatory framework and related decisions need to be included in a price model. The existing literature has touched upon this issue by assessing the effect of NAP decisions on the carbon price (Chevallier, 2011b; Mansanet-Bataller et al., 2011; Conrad et al., 2012). In addition, Alberola and Chevallier (2009) emphasise the importance of the regulation which bans the transfer of allowances from Phase I to Phase II. Furthermore, Neuhoff et al. (2006) illustrate which distortions can arise depending on the allocation mechanism of EUAs. This study will provide further insights into the importance of such regulatory events.

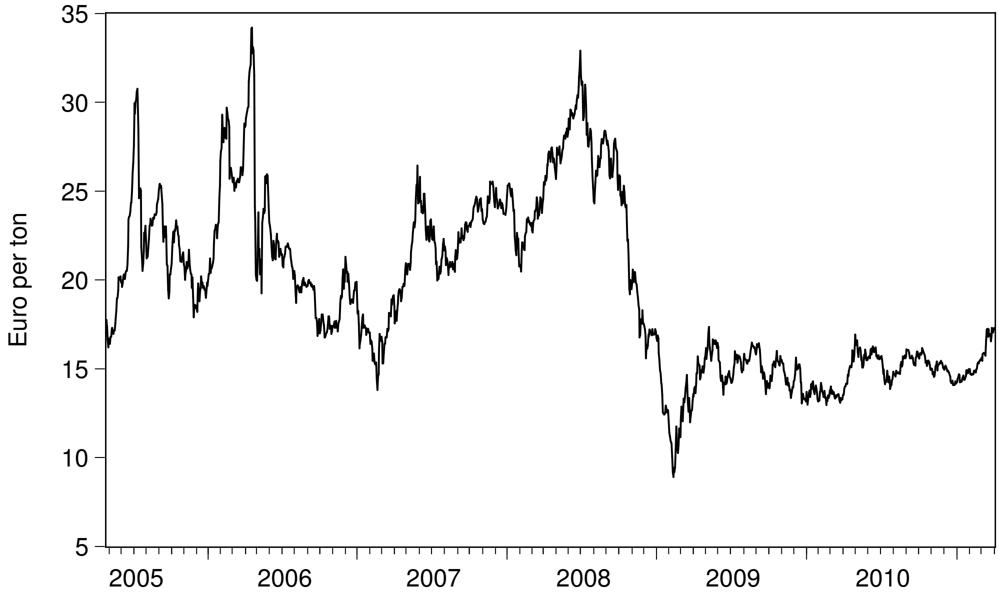
Regarding the behaviour of the carbon price, the most relevant results for this chapter arise from papers by Paolella and Taschini (2008), Benz and Trück (2009), Chevallier (2011b), and Daskalakis et al. (2009). As a common feature, these papers apply univariate time series approaches to investigate the empirical properties of the EUA price. While the former papers provide evidence of a GARCH structure in carbon price returns, Daskalakis et al. (2009) show that EUA futures prices are characterised by jumps. Jumps are also included in the framework of Chevallier and Sévi (2010) when modelling the implied volatility of carbon price returns. In contrast to previous studies, the present analysis treats jumps and conditional heteroscedasticity in a single approach to explain the carbon price behaviour. Chan and Maheu's (2002) autoregressive jump intensity (ARJI-)GARCH model is applied to EUA futures returns covering both Phase I and II.

Since the prevalence of jumps has been emphasised in the literature, the ARJI-GARCH lends itself well to capture the fluctuations present in the series. The model allows to differentiate between smooth price movements and more disruptive ones. The latter is captured by the model's jump component which identifies sudden, extreme market fluctuations exceeding the usually observed price movements. Most importantly, the intensity of jumps can vary over time and allows tracking when jumps happened. The derived jump series is purely data-driven as it does not require any pre-specification which sample period to study or which events cause price spikes. By contrast, Sanin and Violante (2009) take ex-ante decisions regarding the events that potentially cause price jumps and then include these in their model. The ARJI-GARCH therefore provides an unbiased measure of jumps in Phase I and II of the EU ETS. Moreover, the contribution of jumps to the total volatility is assessed by employing Nimalendram's (1994) variance decomposition procedure.

2.3 Data and Model

Figure 2.1 illustrates the development of the EUA futures price from May 2005 to April 2011.[4] The EUA futures initially traded at levels between 20 to 30 €. When the market learned about the oversupply with emission allowances in April 2006, the carbon price crashed. Until mid 2007, it did not recover and traded around 20 €. With the beginning of 2008 (Phase II), however, the EUA futures price rose back to levels between 25 € and 30 €. During the economic crises, the market finally experienced a second large price decline. The price depression was less abrupt, but the EUA futures were steadily pushed below 10 €. Together with the levels of production, demand for allowances declined, and excess allowances were sold to quickly access liquidity. In autumn 2009, the price picked up again and traded between 10 € and 15 €, probably driven by allowance demand for Phase III.

Figure 2.1: European Union Allowance 2011 futures prices



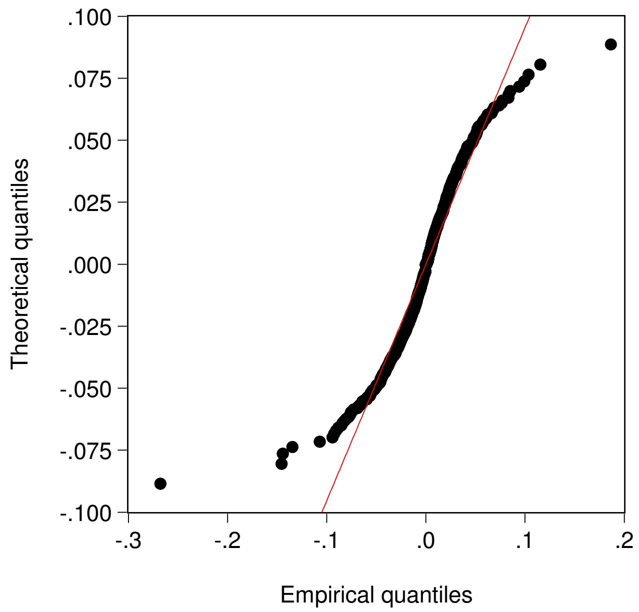
Source: Intercontinental Exchange (ICE) London.

The quantile-quantile plot displayed in Figure 2.2 vividly illustrates that extreme price movements are present, and an empirical model needs to be able to account for this behaviour. Almost every financial market variable is characterised

[4]The data is obtained from the Intercontinental Exchange (ICE) London.

by times of high volatility followed by more tranquil periods. This price behaviour is referred to as volatility clustering.

Figure 2.2: Quantile-quantile plot



A generalised autoregressive conditional heteroscedasticity (GARCH) model, as introduced by Bollerslev (1986), is able to capture this behaviour by allowing the conditional variance to change over time. GARCH models are able to depict the smooth volatility patterns but cannot explain large discrete price movements. To include volatility clustering as well as discrete price spikes, Chan and Maheu's (2002) ARJI-GARCH approach is used to describe the EUA price movements. It extends a traditional GARCH model by a conditional-jump component which also influences the overall volatility. The ARJI-GARCH has been successfully applied to stock market indices (Chan and Maheu, 2002), exchange rates (Chan, 2003, 2004), and the oil price (Lee et al., 2010; Gronwald, 2012). As asserted above, the carbon market is heavily influenced by political decisions which supply the market with new information in a discrete manner. The application of a jump model is a natural choice when assuming that these events represent a potential source of discrete price movements (Jorion, 1988; McCurdy and Maheu, 2004). The following model is considered:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k} \tag{2.1}$$

where y_t is the EUA return and $z_t \sim NID(0,1)$. $\sqrt{h_t} z_t$ contains the GARCH(p,q) term h$_t$ (Bollerslev, 1986) which follows an ARMA process:[5]

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}. \tag{2.2}$$

The last expression in Equation 2.1 represents the so-called jump component. The conditional jump size $X_{t,k}$, given the history of observations $\Phi_{t-1} = \{y_{t-1}, \ldots, y_1\}$, is assumed to be normally distributed with mean θ_t and variance δ_t^2: $X_{t,k} \sim N(\theta_t, \delta_t^2)$. The number of jumps n_t that arrive between $t-1$ and t follow a Poisson distribution with $\lambda_t > 0$:

$$P(n_t = j|\Phi_{t-i}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t}, \tag{2.3}$$

where λ_t measures the jump intensity that captures the average number of jumps in a time interval. Two variants of the model are considered here: a constant jump intensity model with $\lambda_t = \lambda$, $\theta_t = \theta$, and $\delta_t^2 = \delta^2$, and a time-varying jump intensity model. For the case of the latter, λ_t is assumed to follow the autoregressive process:

$$\lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i}. \tag{2.4}$$

The conditional jump intensity is changing over time influenced by the previous jump intensity λ_{t-i}. This persistence parameter illustrates the occurrence of jump clusters. When many jumps are expected today, the number of jumps tomorrow is expected to be high as well. For stationarity, $|\rho| < 1$. Furthermore, the jump intensity is driven by new innovation ξ_{t-i}. This jump intensity residual is an unpredictable component or jump innovation entering Equation 2.4. The empirical strategy of Chan and Maheu (2002) is to infer the probability of j jumps at time $t-i$, $P(n_{t-i} = j|\Phi_{t-i})$,

[5]For details regarding the basic GARCH model, please refer to Chapter 3 or Enders (2004).

ex post from the observed returns by using a filter.[6] The derived jump distribution is compared to the expectation regarding the number of jumps, λ_{t-i}, based on information at time $t-i-1$. The unexpected component is captured by ξ_{t-i} which changes the forecast regarding the number of jumps when the information set is updated from $t-i-1$ to $t-i$. The proposed jump distribution has two main advantages. First, the ARMA structure is a flexible parametrisation to model different autoregressive dynamics. Second, the jump intensity changes endogenously, and fluctuation is derived from the data only (Chan and Maheu, 2002). λ_t measures the expected number of jumps conditional on information Φ_{t-i}, but independent from other market variables.

Finally, let Σ^2 denote the total variance of y_t. According to Nimalendran (1994), Σ^2 can be decomposed in the diffusion-induced and the jump-induced variance and be written as follows:

$$\Sigma^2 = h_t + \lambda_t(\theta^2 + \delta^2). \tag{2.5}$$

This decomposition allows one to study the share of jumps in the total variance. As in the time-varying version of the jump-GARCH model, the decomposition analysis yields a flexible measure of jump development over time.

2.4 Estimation Results

The estimation is based on the EUA 2011 futures series from 2005 to 2011. The model is estimated in first log-differences and a constant is included. Table 2.1 provides the estimation results for the constant and the time-varying jump intensity models.[7] The results for the GARCH component are depicted in the upper part of Table 2.1. The conditional variance exhibits strong persistence with β ranging between 0.82 and 0.86. The GARCH parameters take similar values in both specifications and assure a well-behaved variance: all coefficients are positive and fulfil the restriction of $\alpha+\beta < 1$. The results for the jump component are shown in the lower part of Table 2.1. It is evident that all jump parameters are highly significant.

[6] For a more thorough discussion of the method, the reader is referred to the original paper by Chan and Maheu (2002).

[7] The estimations are calculated in R and Eviews.

This already demonstrates that the jump-augmented GARCH model is appropriate for modelling carbon price returns. For both models θ indicates that jumps in the carbon market are on average negative and therefore have some dampening effect on returns. In the constant jump model λ is 0.2. Allowing for time dependence in the expected arrival rate of jumps, gives further insights about its development. The fluctuation of the time-varying jump intensity is illustrated in Figure 2.3: λ_t ranges from zero to 2.5. At times no jumps are expected, in contrast to periods where several jumps are likely. The λ_t process is highly persistent with ρ reaching 0.88 and therefore indicates the occurrence of jump clusters.

Table 2.1: Constant and time-varying jump intensity models

Parameter	Constant	ARJI
μ	1.4E-03 (0.0086)	1.7E-03 (0.0010)
ω	1.1E-05 (0.0241)	1.3E-05 (0.0034)
α	0.1039 (<0.0001)	0.0571 (0.0013)
β	0.8227 (<0.0001)	0.8602 (<0.0001)
δ	0.0297 (<0.0001)	0.0268 (<0.0001)
θ	-7.0E-03 (0.0438)	-5.6E-03 (0.0349)
λ	0.2003 (0.0180)	0.0427 (0.0431)
ρ	-	0.8806 (<0.0001)
γ	-	0.4819 (0.0035)

Note: μ is the constant, ω, α and β are the usual GARCH parameters. The jump parameters are displayed in the bottom part of the table. The jump mean and variance are denoted by δ and θ. λ denotes the jump intensity which follows an ARMA process with parameters ρ and γ in the time-varying model. p-values are in parentheses.

In comparison to a simple GARCH model, the extended jump-GARCH models clearly improve the model fit. The model selection criteria for a simple GARCH model (estimated as benchmark) and the augmented models show that the latter should be preferred (Table 2.2). All three criteria, the AIC, BIC and HQ indicate a better performance of jump-augmented GARCH models. A likelihood-ratio (LR) test is conducted to emphasise these results. The LR test allows to compare two nested models and to evaluate whether an extended (unrestricted) model outper-

Table 2.2: Model selection criteria

	Information criteria		
Criterion	GARCH	Constant	ARJI
LogL	3,588.263	3,639.028	3,648.04
AIC	-4.716	-4.779	-4.788
BIC	-4.702	-4.754	-4.757
HQ	-4.711	-4.770	-4.776

	Likelihood-ratio test	
Compared models	Test statistic	
Constant vs. GARCH	101.53 (<0.0001)	
ARJI vs. GARCH		119.55 (<0.0001)

Note: AIC is short for Akaike's Information Criterion, BIC for Bayesian Information Criterion and HQ for Hannan-Quinn Information Criterion. p-values are in parentheses.

forms a simple (restricted) model. The distance between the log likelihoods of both models is calculated and then tested whether this difference is statistically significant. The test statistic is χ^2-distributed with degrees of freedom equal to the number of restrictions. If the null hypothesis is rejected, a model without restrictions increases the log likelihood significantly (Verbeek, 2008). Hence, the results in Table 2.2 show that the jump-augmented specifications provide a better model fit than a simple GARCH model. The LR test for the constant versus the time-varying model is non-standard and therefore not explicitly reported (Chan and Maheu, 2002). The LR test statistic of 18.02 should be large enough to indicate an improvement of the model fit for the time-varying model.

Figure 2.3 also displays the share of the EUA variance that is triggered by jumps, based on Nimalendran's (1994) variance decomposition procedure. Careful analysis of the decomposed variance yields interesting insights into the functioning of this market. After the first turbulent months, the portion of variance triggered by jumps is generally found to fluctuate around 50%. Only in two cases this portion falls below 40%: in the aftermath of the 2006 price drop and during the price recovery that followed the financial crisis' price collapse.[8] The variance generally increased during these periods but a larger portion of this increased variance is captured by the GARCH component of the model. This is plausible as the respective movements

[8]The variance share also drops below 40% in early 2005. As this was an extremely early stage of the EU ETS, price movements of that time should not be deemed very meaningful, see e.g. Hintermann (2010).

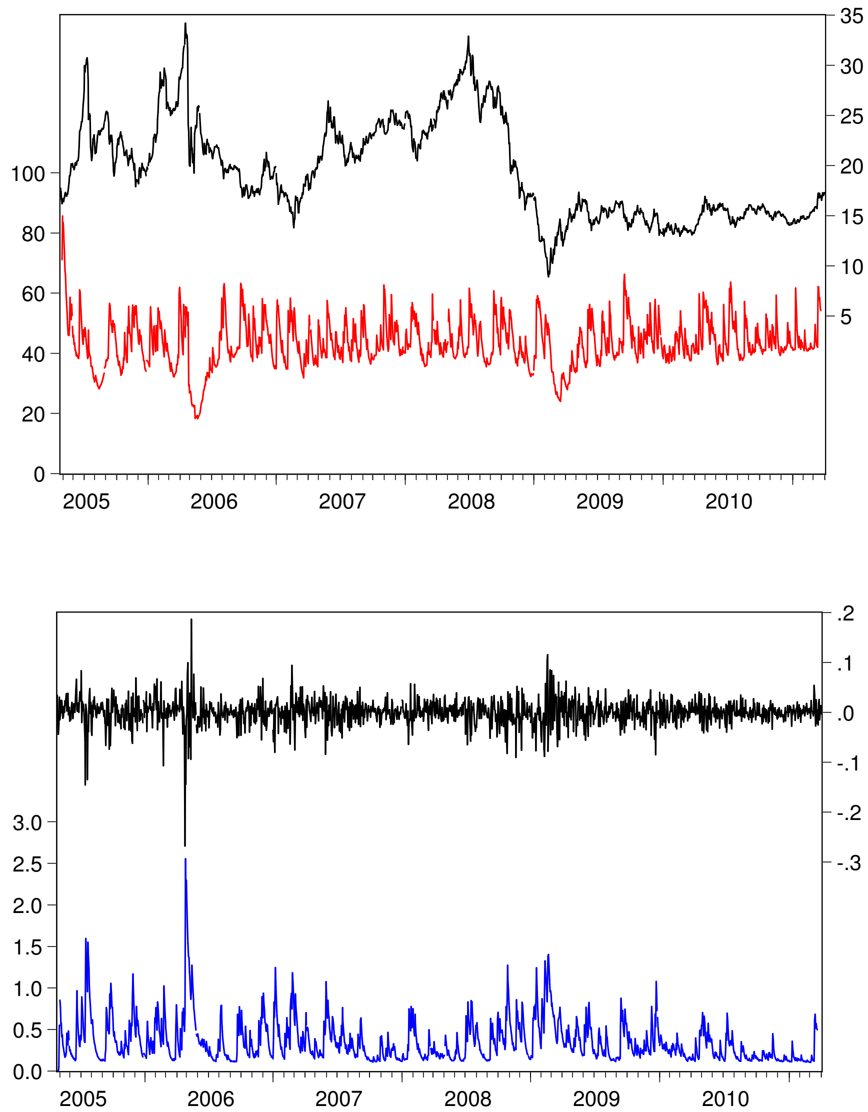
do not reflect reactions to single events, but rather price movements in a “nervous” carbon market. Comparing these values to those obtained in other applications of Chan and Maheu’s (2002) method clearly indicates that price jumps play an important role in the EU ETS. Gronwald’s (2011) study of the oil market shows that in periods after 1998 the portion of variance triggered by jumps is about 30%, while this portion is found to be about 50% during the 1980s. At first, the oil market was characterised by a generally tranquil price movement with only few extreme movements while later periods were generally more volatile with less influence of single events. Hence, carbon price behaviour seems to be similar to the behaviour of the oil price during the 1980s. What is more, Huang et al. (2007) find that less than 30% of the variance in the Taiwanese stock index is triggered by jumps. During the election period, when the political uncertainty is particularly high and jumps are more likely to occur, this share increases to around 40%.

To summarise, the application of Chan and Maheu’s (2002) method yields strong evidence of conditional jumps in the emission allowance price. The EUA price is not only characterised by conditional heteroscedasticity but is also subject to large price movements which occur with time-varying intensity. A considerable portion of the total variance is triggered by jumps. It is therefore worthwhile studying the underlying causes of these price jumps.

2.5 Role of Policy

It is a purely political decision that CO_2 is a tradable asset. In comparison to other commodity markets, the carbon market exhibits much stronger ties with its policy and regulatory frameworks. Various studies show that markets with strong political influence are more likely to exhibit extreme price movements (Jorion, 1988). This chapter investigates to what extent policy events in the carbon market trigger the jumps identified in the previous section. A number of studies show that the EC decisions on National Allocation Plans (NAPs) influence the EUA price (Mansanet-Bataller et al., 2011; Conrad et al., 2012). Furthermore, the importance of banking, when EUAs are kept for future compliance periods, and the importance of the allowance allocation mechanism have been emphasised (Neuhoff et al., 2006; Alberola and Chevallier, 2009; Chevallier, 2012). This line of research is extended

Figure 2.3: EUA prices, jump intensity and variance decomposition



Note: The upper panel shows the EUA price in Euro per ton (black) together with the share of the variance that is triggered by jumps in per cent (red). The lower panel shows the growth rate of the EUA price (black) and the time-varying jump intensity (blue). Source: ICE and own calculations.

by the present study as it assesses to which extent such regulatory decisions lead to extreme price jumps.

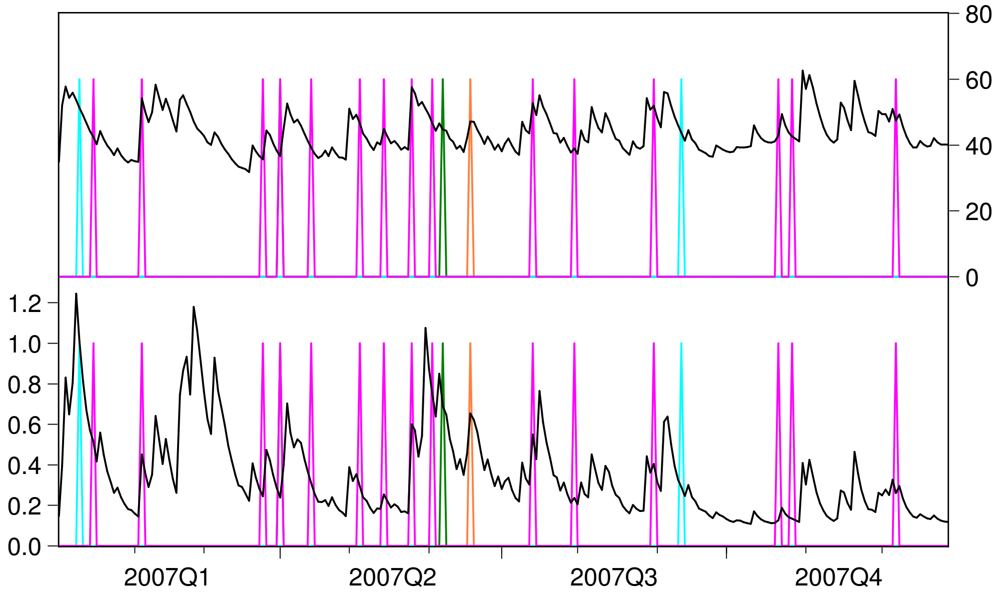
For this purpose, a data base has been developed which captures important decisions by the European Commission as well as changes in the global carbon market framework. These events are assigned to different categories. The group *EU ETS NAPs* summarises decisions by the European Commission on the supply with EUAs in Phase II through so-called National Allocation Plans. *EU ETS Compliance* lists the publication dates of compliance and emissions data which regularly inform the market about EU ETS demand. The category *EU ETS III* consists of the main decisions regarding the EU ETS framework and supply with EUAs in Phase III. Similarly, the category *Global Carbon Market* covers influential events in the international carbon market. Some categories are easier to complete than others. NAP decisions or compliance data publication are well known and have a regular pattern. By contrast, the categories *EU ETS III* and *Global Carbon Market* are harder to record as these events are more divers and not pre-scheduled. To obtain a coherent list, regular carbon market publications by CDC Climat Research, Euractiv, and Unicredit as well as the European Commission's communication have been considered.[9] Tables of the selected events can be found in Annex A.

To study the temporal connection between regulatory events and the depicted jumps, Figures 2.4 to 2.7 present the respective time series from 2007 to 2010. Each upper panel presents the jump-related variance share derived from the decomposition analysis, while the lower panel shows the time-varying jump intensity from the GARCH model. The first observation from these graphs is that the jump intensity as well as the jump-induced variance exhibit different phases over time. The years 2007 and 2010 appear less steady as there are considerably more sharp spikes in the jump measures. In 2008 and 2009, with the beginning of Phase II and the financial crisis, the movements of the jump intensity measures were more sedate.

Figure 2.4 illustrates the results for the year 2007 which was dominated by the EC's decisions regarding so-called National Allocation Plans (NAPs). NAPs determined the final supply with allowances in Phase II and therefore conveyed fundamental information. Figure 2.4 shows that *EU ETS NAPs* events coincided with sudden carbon price changes in 2007. This result is generally in line with the existing

[9] Available at: www.bluenext.eu/publications/tendances.html; www.euractiv.de; www.ec.europa.eu/clima/policies/ets.

Figure 2.4: Jumps and regulatory events 2007

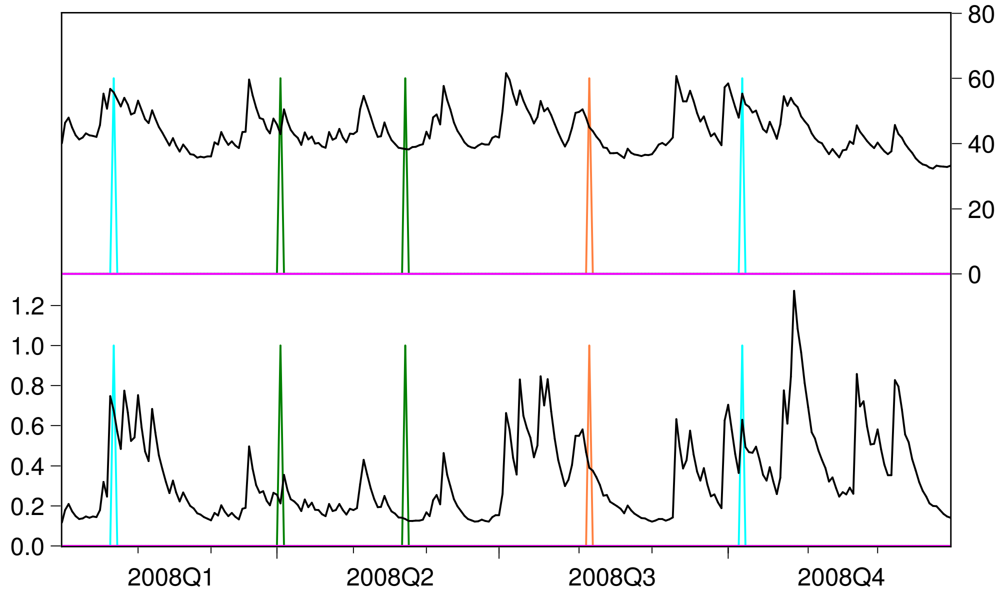


Note: The upper panel shows the jump-related variance share in per cent, the lower panel the GARCH jump intensity measure. Both measures are combined with the same event variables: *EU ETS III* (light blue), *EU ETS NAPs* (pink), *EU ETS compliance* (green) and *Global Carbon Market* (orange). Source: see Tables A.1 to A.4 in Annex A.

literature (Mansanet-Bataller et al., 2011; Sanin and Violante, 2009). Information regarding NAPs, however, was not only influential in 2007. The European Court's decision on 23. September 2009 that Estonia and Poland obtained to few EUAs in their original allocation, led to an EUA price drop.

The importance of the NAP events shows that information about EU ETS supply is crucial for market participants. The influence of the demand side can also be evaluated when concentrating on the EU ETS compliance events. Every spring, the European Commission publishes two sets of information: the emissions data at the beginning of April and the amount of surrendered EUAs in a press release mid of May. These publications clarify whether installations are over- or undersupplied with allowances. In 2006, this information led to the distinct price crash shown in Figure 2.1. After 2007, the publication of emissions data has not surprised the market. This can be depicted when concentrating on the green lines in each graph which do not overlap with the jumps. Accordingly, the demand side has been more predictable after the market adjusted in 2006. This confirms the

Figure 2.5: Jumps and regulatory events 2008



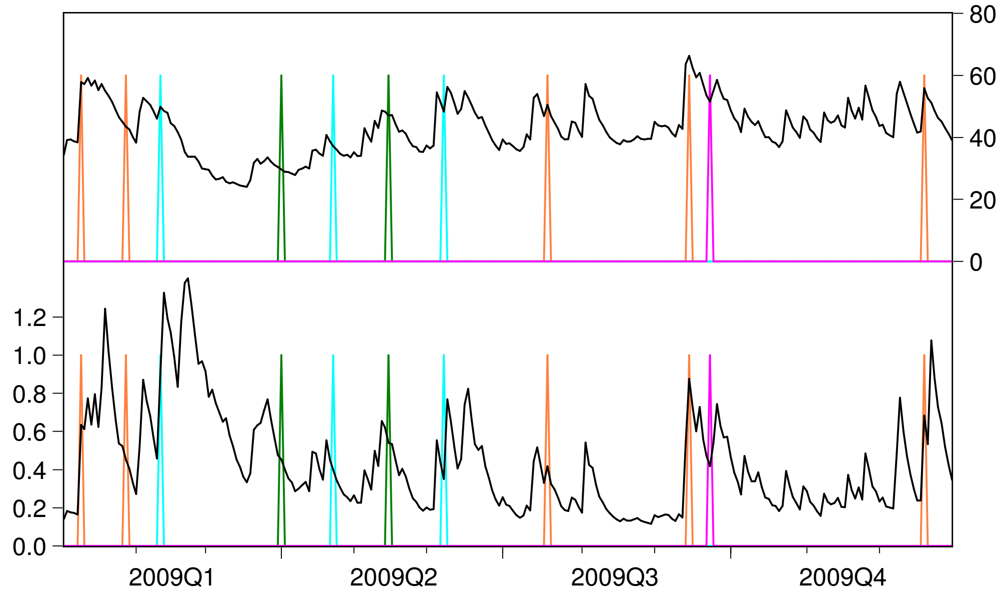
Note: The upper panel shows the jump-related variance share in per cent, the lower panel the GARCH jump intensity measure. Both measures are combined with the same event variables: *EU ETS III* (light blue), *EU ETS NAPs* (pink), *EU ETS compliance* (green) and *Global Carbon Market* (orange). Source: see Tables A.1 to A.4 in Annex A.

expectation of Seifert et al. (2008) who conclude that market participants have had a better estimate of EUA demand after the first EU ETS emissions report in 2006.

In 2008, only a few decisive events changed the price pattern. The adoption of the EU Climate Package on 23. January 2008 and the supportive vote of the EU Parliament's environment committee on the EU's climate policy in early October seemed to move the market. These decisions emphasised the European ambitions to implement a rigourous climate policy. Another small jump can be observed on 16. October 2008, when the link between the registries ITL und CITL was announced. The events in 2008 represented important landmarks for the future of the carbon market and attracted the traders' attention in an otherwise rather silent phase.

In 2009, the market was very interested in the decisions regarding aviation. Several steps needed to be taken before the flight sector can be included in 2012, and the market received many new signals related to this extension of the market scope. Moreover, surprising news came from the international arena: Russia was

Figure 2.6: Jumps and regulatory events 2009



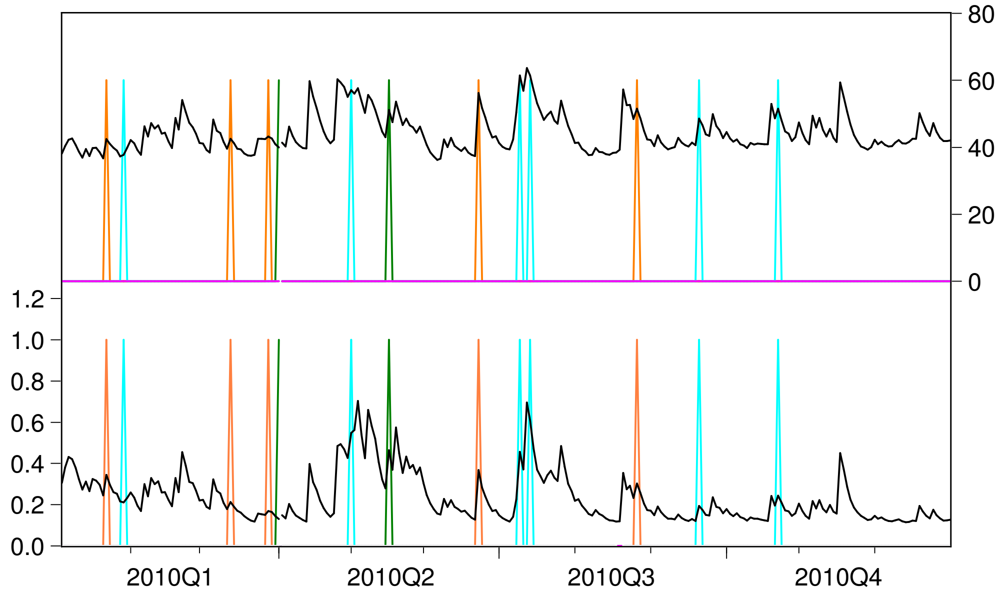
Note: The upper panel shows the jump-related variance share in per cent, the lower panel the GARCH jump intensity measure. Both measures are combined with the same event variables: *EU ETS III* (light blue), *EU ETS NAPs* (pink), *EU ETS compliance* (green) and *Global Carbon Market* (orange). Source: see Tables A.1 to A.4 in Annex A.

expelled from the international carbon trade and the COP15 climate conference in Copenhagen could not live up to global expectations.

The year 2010 was exceptionally eventful. In the beginning of 2010, unusual news moved the carbon market. The debate about the mistakes in IPCC reporting and the phishing attack of European registries agitated the public. Another concern was the so-called CER recycling in March when it became obvious that governments sold CERs which had already been submitted for compliance before.[10] From mid-year onwards, the market reacted sensitively to news regarding the cap in Phase III as well as to auctioning decisions. Both were crucial events because they updated market participants about the future supply with EUA allowances. Finally, a spurt of the carbon price can be observed when HFC projects were banned from the international and the European carbon market in summer 2010.

[10]For more information, please check: CMIA, 12.3.2010, *CER recycling will damage credibility of EU member states and depress CER and EUA prices*, www.cmia.net.

Figure 2.7: Jumps and regulatory events 2010



Note: The upper panel shows the jump-related variance share in per cent, the lower panel the GARCH jump intensity measure. Both measures are combined with the same event variables: *EU ETS III* (light blue), *EU ETS NAPs* (pink), *EU ETS compliance* (green) and *Global Carbon Market* (orange). Source: see Tables A.1 to A.4 in Annex A.

Table 2.3 underlines that the presented event series can explain the jumps we derived using the jump-GARCH model. The different categories from our database are used as explanatory variables in a regression for the λ_t series. Except for the EU ETS compliance variable, all event categories are significant and show a positive sign. Hence, the regulatory events influence the carbon price jumps to a certain extent. The Volatility Index measures the implied volatility of Standard and Poor 500 options and is used to proxy overall market volatility.

The results of this event analysis depict that decisions regarding the availability and the restrictions of EUAs are important information for the carbon market. The existing literature only focused on the NAP decisions in Phase II. These decisions are key regulatory events but not the only source of turbulence. The EUA allocation decisions for Phase III also introduced new information. Moreover, news regarding the global carbon market design have an astonishingly strong feed-back on the EUA price. This study shows that price spikes are not only related to decisions on EUA allocation. Some events are related to the administration of the EU ETS, for example

Table 2.3: Using regulatory events to explain jumps

Category	Coefficient
c	0.157 (<0.0001)
Global Carbon Market	0.139 (0.0176)
EU ETS NAPs	0.095 (0.0442)
EU ETS III	0.144 (0.0306)
EU ETS compliance	0.024 (0.7221)
Volatility Index	0.007 (<0.0001)
Adjusted R^2	0.129
Log likelihood	177.958
AIC	-0.321
BIC	-0.293

Note: OLS regression with the λ_t as dependent variable using heteroscedasticity-robust standard errors. The Volatility Index is calculated by the Chicago Board Options Exchange. p-values are in parentheses.

the phishing attack on the registries or the recycled CERs. Such incidents are bound to happen in a newly established scheme, but they can be prevented if regulators learn from these events. Finally, not all regulatory events lead to price jumps, and some of the large jumps cannot be explained by our database. Still, visual inspection shows that the selected events often coincide with the detected price spikes. The regression analysis for the event categories confirms that the chosen regulatory and policy news can help explain the jump intensity movements.

All this underlines that influences from the political arena drive the carbon price development, in addition to fundamentals like commodity prices or economic development. However, the nature of this institutional price driver is different. Political and regulatory events seem to take effect in a discrete manner rather than to steadily influence the price. Market participants who are used to hedge risk in other commodity markets have to deal with an additional source of uncertainty. This is mainly problematic because political risks are difficult to evaluate and to manage (Grubb and Newberry, 2008). Market risks are potentially easier to diversify than discrete events related to the regulatory framework.

The European Commission should therefore aim to provide a transparent and secure policy environment for market participants. Changes with respect to the EUA supply, allocation rules, or the acceptance of CDM credits should be kept at a minimum. The EC decision to announce the overall EUA allocation in Phase III by a single cap, instead of publishing 29 individual NAPs, is a step in the right direction. The same information is conveyed, but in a less interfering manner. Moreover, the regulator should opt for long commitment periods regarding the emissions cap (Hepburn, 2006). The longer commitment period for Phase III, which runs for 8 and not 5 years, is a positive development. Adjusting the EUA supply during the commitment period would give the impression that discretionary policy changes are an option and unsettle market participants. It is rather recommended to set and to respect clear rules when adjustments to the EUA supply are to be expected. Otherwise, the policy's credibility and efficiency is at risk (Hepburn, 2006).

2.6 Conclusions

Emissions trading seems to be the prevalent policy to reduce carbon emissions. Theoretical arguments state that emissions trading is a cost-efficient approache to reduce carbon emissions and that it provides dynamic incentives to adapt existing abatement technologies and to develop new ones (Hahn and Stavins, 1992). Even more important, establishing a market for emission rights might be politically easier to enforce than the introduction of carbon taxes (Hepburn, 2006; Tiedenberg and Lewis, 2008). However, the main criticism of cap-and-trade schemes relates to the volatility of the carbon price (Parry and Pizer, 2007; Chevallier, 2011b). To validate these statements, it is of particular importance to analyse the performance of existing systems and to have a sufficient understanding of the emission allowances price and its determinants. As the globally largest cap-and-trade system, the EU ETS, has been in operation for almost 8 years now, an increasing number of studies has been using data from this market to investigate its performance.

This study sheds light on the behaviour of the carbon price by applying Chan and Maheu's (2002) jump-augmented GARCH model to the EU ETS. The empirical results clearly indicate that the EUA price is characterised by both GARCH and strong conditional jump behaviour – in Phase I and Phase II. Based on the estimation results, it is shown that a considerable portion of the variance, between 40 and 60 per cent, are triggered by jumps. Studying the underlying reasons of these price jumps yields valuable insights in the functioning of the European carbon market. It is shown that a considerable amount of extreme EUA price movements is related to new information regarding emissions allowance supply. This is epitomised by the price reactions in response to the announcements of the EU ETS NAPs and equally the EU ETS cap for Phase III. However, information regarding the EUA demand seems less influential. The carbon price peaks when relevant news from the global carbon market is released as international carbon credits can be used for compliance in the EU ETS. The policy framework appears to be an essential driver of carbon price developments.

Another market, which is also under strong influence of regulatory authorities, is the money market. The central bank controls the base rate with the aim of achieving low inflation (European Central Bank) and possibly additional goals such as the general economic performance (US Federal Reserve Bank). The vast literature on monetary policy discusses optimal central bank behaviour. It is often argued that, in addition to controlling the level of inflation, a central bank should also ensure that inflation volatility is not overly large as this would have negative consequences for economic growth (Friedman, 1977; Sack and Wieland, 2000; Rudebusch, 2002).

The same can be said for the carbon market. Here, the regulator influences the level and the volatility of the carbon price by setting an emissions cap. At the same time, the carbon price is an important determinant of investments in abatement technology. The price level is a crucial parameter for the profitability of abatement techniques. In addition, an unduly volatile carbon price makes the investment decision more complex. This chapter's results show that the regulator has some scope in this regard and that controlling price volatility does not seem out of reach. The authorities should keep in mind that the EUA price is easily disrupted by their decisions. Regulatory changes should be kept to a minimum. Therefore, the transition in Phase III from 29 individual NAPs to a single cap decision is a welcome move. The same information is conveyed, but in a less interfering manner. The European Commission should further, similar to a central bank, monitor the carbon price level and its fluctuations. Decisions on essential framework parameters should be clearly communicated and implemented in a transparent and credible manner. The experiences from central bank policy should not be neglected. For monetary policy, clearly communicated policy goals play an important role to steer market expectations. A good example is the current record low of the EUA price which induces speculation regarding a set-aside of allowances or a more ambitious European emissions reduction target of 30% until 2020. This is precisely the sort of debate which is undesired as it leads to uncertainty about future policy. A more clear communication by the European Commission would assure market participants that no discretionary policy changes will be taken.

One of the main criticisms concerning existing carbon markets is their price uncertainty. Emissions trading schemes are established in many parts of the world and probably the most realistic policy option to combat climate change. Therefore, it would be advisable to counteract this criticism.

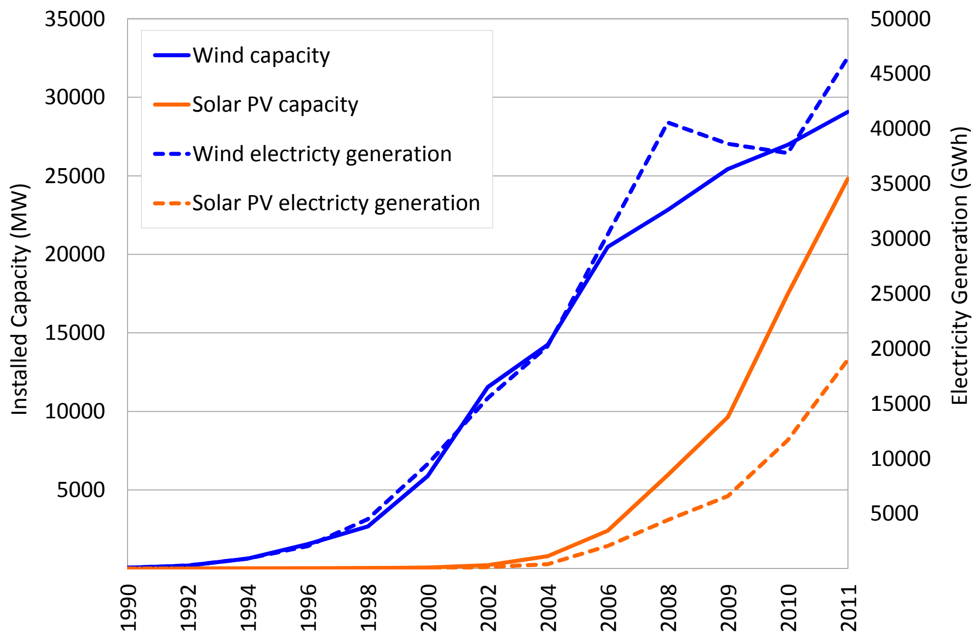
Chapter 3

The Impact of Wind Power Generation on the Electricity Price in Germany

3.1 Introduction

Renewable electricity has come to dominate the debate over and the development of the European electricity market. Among European countries, most wind turbines and solar panels are installed in Germany where renewable electricity has become even more important since the March 2011 decision regarding the nuclear phase-out. Figure 3.1 shows that Germany's wind capacity reached 29 gigawatt (GW) in 2011. Its solar photovoltaic (PV) capacity soared in the last two years: overall installed solar PV capacity reached almost 25 GW in 2011 (BMU, 2012). In 2011, wind electricity accounted for 8 per cent of gross electricity production in Germany, solar PV for 3 per cent. All renewable sources combined made up 20 per cent of gross electricity production in 2011 and are Germany's second most important source of electricity generation after lignite (BDEW, 2011). The German government plans to raise this share to 35 per cent by 2020 and to 50 per cent by 2030 (BMU and BMWi, 2011). Onshore and offshore wind will play an important role in this expansion of renewable electricity capacity.

Figure 3.1: Installed capacity and generated electricity in Germany



Source: BMU (2012).

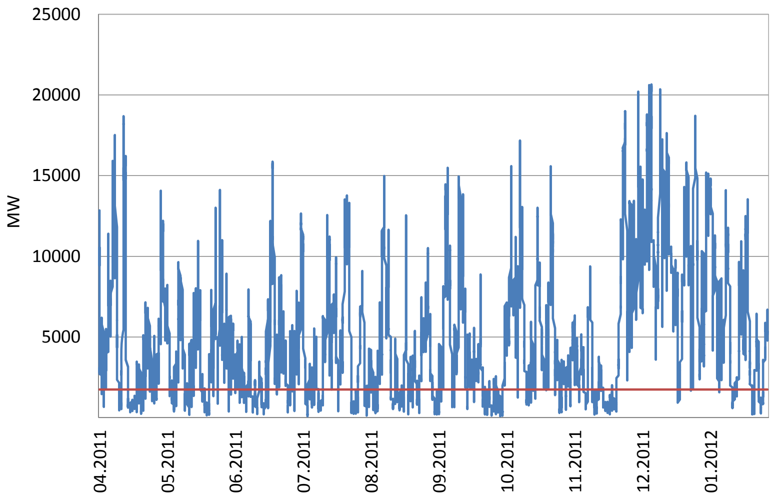
System and market operators face two main challenges as more renewable power generation is added. First, electricity generated by wind turbines and photovoltaic panels is intermittent and hardly adjustable to electricity demand.[1] Therefore, variable electricity generation is not a perfect substitute for conventional energy sources. Figure 3.2 shows the variability of wind electricity generation. The horizontal line, the so-called capacity credit, gives an impression how much conventional capacity can be replaced by the existing wind power capacity, given the current power plant fleet and maintaining the security of supply (IEA, 2011).[2] The graph illustrates that the wind power generation is subject to strong variation and that only a fraction of installed wind capacity, depicted by the capacity credit line, is expected to contribute to the power mix with certainty. Second, Germany's renewable energy policy grants priority dispatch and fixed feed-in tariffs for renewable electricity generation. Renewable electricity can be fed into the grid whenever it is produced,

[1]By contrast, electricity generation from hydro or biomass sources can be managed more easily. The following conclusions hold for sources like wind and solar PV where intermittency is particularly pronounced.

[2]In line with calculations from Hulle (2009), IEA (2011), and Schaber et al. (2012), the capacity credit is assumed to be 6%. A wind installation of 29075 MW in 2011 was used in the calculation for this capacity credit line (BMU, 2012).

regardless of energy demand, and in-feed can be switched off only if grid stability is at risk (Bundesnetzagentur, 2011).[3] As storage is not yet a viable option, high levels of variable renewable electricity production can be balanced only by adjusting output from traditional power plants or by exporting excess electricity. Similarly, when too little wind or sunshine is available during times of peak demand, reserve capacity has to be dispatched at higher costs.

Figure 3.2: Hourly wind in-feed



Note: Hourly wind in-feed in MW. The horizontal line illustrates how much electricity German wind installations (29075 MW in 2011) are expected to reliably generate during peak demand. This measure is referred to as capacity credit. In line with calculations from IEA (2011), Schaber et al. (2012) and Hulle (2009) the capacity credit is assumed to be 6%. Source: www.eeg-kwk.de.

Grid operators are obliged to feed-in renewable electricity independent of the market price. However, the spot electricity price is not independent from renewable electricity. On the one hand, variable renewable power production is negatively correlated with the electricity price. Whenever large volumes of intermittent renewable electricity are fed into the power grid, the electricity price tends to decline. As renewable installations are very capital-intensive but have almost zero operational generation cost, they are certainly dispatched to meet demand. More expensive conventional power plants are crowded out, and the electricity price declines. This dampening of the wholesale electricity price is called merit-order effect. Various assessments uncover this effect for wind electricity generation (Neubarth et al., 2006;

[3]The operator continues to receive feed-in tariff payments even if the installation is disconnected from the grid due to capacity constraints of transmission cables.

Nicolosi, 2010; Ray et al., 2010). Due to increasing production levels, the merit-order effect can also be observed for solar PV electricity (Milstein and Tishler, 2011). On the other hand, intermittent renewable power not only influences price level, but also price volatility (Klinge Jacobsen and Zvingilaite, 2010; Cramton and Ockenfels, 2011). This is confirmed by Jónsson et al. (2010) and Woo et al. (2011) who show that wind generation tends to lower the spot price but increase its variance. The aim of this chapter is to further investigate the effects of intermittent wind power generation on the electricity price development in Germany.

The literature shows that wind power generation has a dampening effect on the electricity price but does not explicitly model the impact of wind power on the volatility of the electricity price nor elaborate on the development of this relationship over time. The present analysis introduces daily levels of German wind power generation as explanatory variable in the mean and the variance equation of a GARCH model of the German day-ahead electricity price.[4] This study makes two contributions to the literature. First, it explores the effect of wind power generation on the level and volatility of the electricity price in an integrated approach. In Germany, where renewables prospered exceptionally from feed-in tariffs, the effect on the electricity market should be particularly pronounced. Second, it investigates a regulatory change in the German marketing mechanism of renewable electricity and its impact on the relationship between wind power and the electricity price.

This study's findings suggest that wind power generation decreased the wholesale electricity price in Germany in the period from 2006 to 2011 but increased the price volatility. These results are particularly important given European and German aspirations to usher an energy system dominated by renewables. A low and volatile electricity price might alter or delay investment decisions in new capacity, renewable and conventional, required for the transformation of the energy system. To advance the energy transformation, it should therefore be in the interest of policy makers to secure a reliable and predictable electricity price. The present analysis shows that adjusting the electricity market design can stabilise the development of the electricity price to some extent. Price volatility reduced in Germany after a modification to the renewable electricity regulation.

[4]The wind in-feed is estimated in megawatt hours (MWh) per day. Data on solar PV in-feed are only available a much shorter period from 2010 onwards. Due to data restrictions, the impact of solar PV electricity is not explicitly estimated in this chapter. It would be interesting to evaluate this issue at a later point in time.

The remainder of this chapter is structured as follows. Section 3.2 summarises the relevant literature on the interaction of wind power generation and the electricity price. Section 3.3 describes the data, Section 3.4 the employed methods. The results are presented and discussed in Section 3.5. Section 3.6 gives some policy recommendations and Section 3.7 concludes.

3.2 Literature Overview

It is widely argued that electricity from variable renewable energy sources – wind and solar PV – is hard to incorporate in the generation mix. Although the interruptive effect of variable wind electricity can already be observed today, little empirical research evaluates its current influence on the wholesale electricity price.

Most studies employ power system models to simulate the effect of increased var-RE production on the level of electricity price. In the short term, the so-called merit-order effect is quantified as the difference between a simulated electricity price with and without the renewable in-feed.[5] For Germany, Bode and Groscurth (2006) and Sensfuß (2011) find that renewable power generation lowers the electricity price. Despite being very capital-intensive, renewable installations have almost zero marginal generation cost and thus are certainly dispatched to meet demand. More expensive conventional power plants are crowded out, and the electricity price declines. This dampening of the wholesale electricity price is also shown for Denmark (Munksgaard and Morthorst, 2008) and Spain (Sáenz de Miera et al., 2008). A recent literature overview of the merit-order effect in the European context is provided by Ray et al. (2010). Taking a more long-term perspective, Green and Vasilakos (2010) and Pöyry (2011) simulate the effects of fluctuating renewable electricity for the next two decades. Green and Vasilakos (2010) find that the British electricity price level will be significantly affected by variable wind power generation in 2020. Pöyry (2011) reports a strong merit-order effect by 2030 that decreases the wholesale electricity price. The consumer price is expected to rise due to soaring costs for subsidies to renewable electricity. Both studies conclude that the volatility of electricity price will increase remarkably in the next 10 to 20 years.

[5]The merit-order effect can be observed for the wholesale price but not for the end-use price which also reflects the increasing costs for renewables support and for investments in the electricity grid. The end-use price does therefore not necessarily decrease.

Very few papers investigate the importance of intermittent renewable power production for the electricity price using current market data. Neubarth et al. (2006) evaluate the relationship between wind and price for Germany using an OLS regression model. Woo et al. (2011) estimate an AR(1) model for high-frequency power data from Texas, controlling for the gas price, nuclear generation and seasonal effects. Jónsson et al. (2010) analyse hourly Danish electricity data in a non-parametric regression model, assessing the effects of wind power forecasts on the average electricity price and its distributional properties in western Denmark. Both studies conclude that wind power in-feed has a significant effect on the level and volatility of the electricity price. The present analysis builds on these findings but takes a different methodological approach. It explicitly models the influence of intermittent renewable electricity generation on the price level and volatility in Germany by using a GARCH model. The aim is to track the development of both components over time and discover whether a regulatory change in the German electricity market had an impact on the relationship between wind power in-feed and the wholesale price.

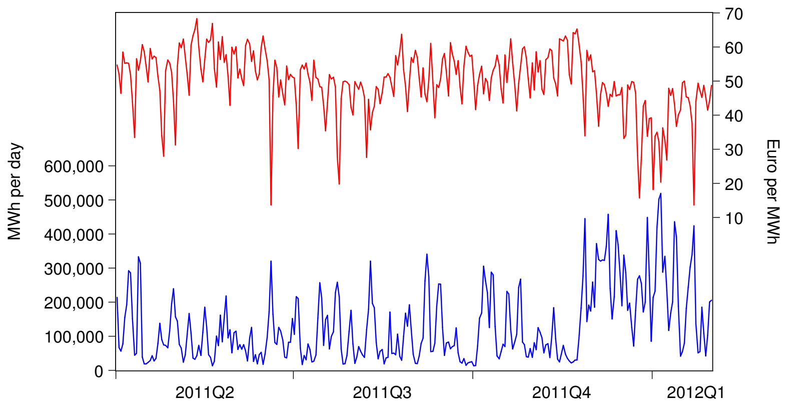
3.3 Data

This chapter introduces daily data for wind electricity generation in the mean and variance equation of a GARCH model to better explain the unsteady behaviour of the electricity price. Figure 3.3 illustrates the negative correlation of daily wind in-feed and the spot electricity price. Whenever high wind speeds allow above-average electricity generation, one can observe a price dip. An in-depth study will reveal more insights into this relationship as well as the development of price volatility.

In the following analysis, I use the day-ahead spot electricity price, Phelix Day Base, from the European Energy Exchange (EEX) as dependent variable.[6] Electricity is traded on the day-ahead spot market for physical delivery on the next day. Separate contracts for every hour of the next day are available. Prices and volumes for all 24 contracts are determined in a single auction at noon. The Phelix Day Base is then calculated as the average, weighted price over these hourly contracts. Generally, the German electricity wholesale market is dominated by over-the-counter

[6] The time series is downloaded from Datastream.

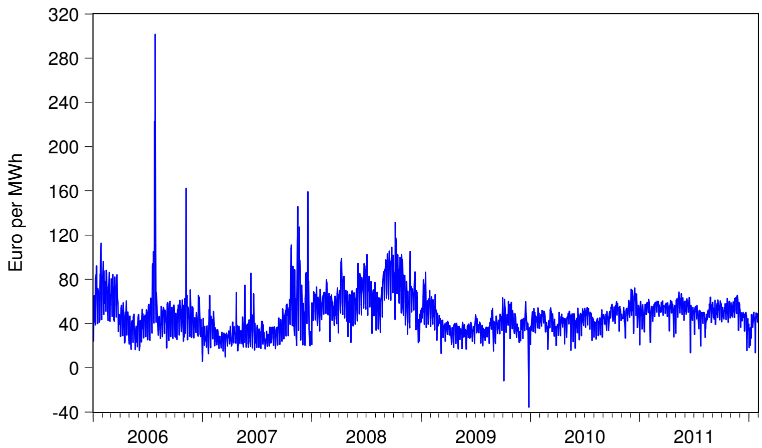
Figure 3.3: Forecasted wind in-feed and day-ahead electricity price



Note: Daily wind electricity generation in MWh per day (blue line) and spot electricity price Phelix Day Base (red line). Source: European Energy Exchange (EEX).

trading, and the contracts are mostly of a long-term nature (Bundesnetzagentur, 2010). However, trading volumes on the spot market are increasing and the Phelix is an important benchmark for all other electricity market transactions (Nicolosi, 2010; Monopolkommission, 2011).[7]

Figure 3.4: Electricity price development



Source: Datastream and EEX.

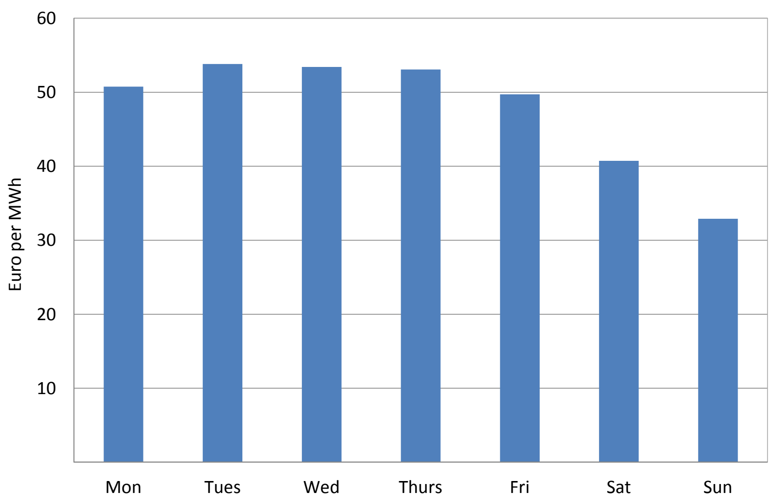
[7]The volume on the EEX spot market increased from 203 TWh in 2009 to 279 TWh in 2010. For comparison, the German gross electricity production was 628 TWh in 2010 (AG Energiebilanzen, 2011). Electricity is also traded on the intraday market, but this market is less liquid and mainly used to address electricity market imbalances in the short-run.

The development of the electricity price, Phelix Day Base, is illustrated in Figure 3.4. This study covers the period from January 2006 to January 2012. As illustrated in Figure 3.1, the wind installation already exceeded 20 GW during this period and played an important role in the German electricity mix. Table 3.1 reports extreme kurtosis and skewness for the electricity price which can either arise from extreme values or autocorrelation (Bierbrauer et al., 2007). Therefore, outliers are detected before conducting the empirical analysis. In line with the literature, I filter values that exceed three times the standard deviation of the original price series (Mugele et al., 2005; Gianfreda, 2010).[8] The outliers are replaced with the value of three times the standard deviation for the respective weekday.[9]

Table 3.1: Descriptive statistics

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
Original Price	48.06	46.07	301.54	-35.57	18.80	2.31	22.94
Deseasonalized	48.06	45.80	114.52	1.96	15.18	0.85	4.11
Log Deseasonalized	3.82	3.82	4.74	0.67	0.32	-0.70	8.09

Figure 3.5: Electricity price variation within the week



Note: Average electricity price on different weekdays over the sample period.

[8]The standard deviation is calculated individually for all seven weekdays to compare like with like. For example, a Monday is compared with the mean and the standard deviation of all Mondays in the sample (Bierbrauer et al., 2007).

[9]The outlier detection is repeated after the first round of outliers have been replaced, but no additional outliers are found. In an alternative run, the median is used to replace outliers. This does not lead to significant differences in the regression results.

After smoothing outliers, the seasonal cycle is removed from the time series. Given that p_t=y_t+s_t, the observed price p_t comprises a stochastic part y_t and a seasonal component s_t. Figure 3.5 shows that the average electricity price varies across the week because of changes in the electricity demand. Similarly, the price follows a yearly pattern as the different seasons influence the energy demand. Weekly and yearly seasonality is addressed by using constant step functions which consist of dummies for each seasonal cycle (Trück and Weron, 2004). Dummies for week days d_i and months m_j are included in the following function to capture seasonality:[10]

$$s_t = c + \sum_{i=1}^{7} \xi_i d_i + \sum_{j=1}^{12} \nu m_j. \tag{3.1}$$

The results for the deseasonalisation are shown in Table 3.2. The coefficients for weekday dummies in Table 3.2 follow the same pattern as shown in Figure 3.5: the price remains high at the beginning of the week, declines from Friday onward, and reaches its minimum on Sundays. The dummies for months are not all significant, but a relevant electricity price reduction is observed in March, April, May, and August. In October and November, the price is significantly higher than in January. Finally, the seasonal component is deducted from the original price series, and the mean of both series is aligned.

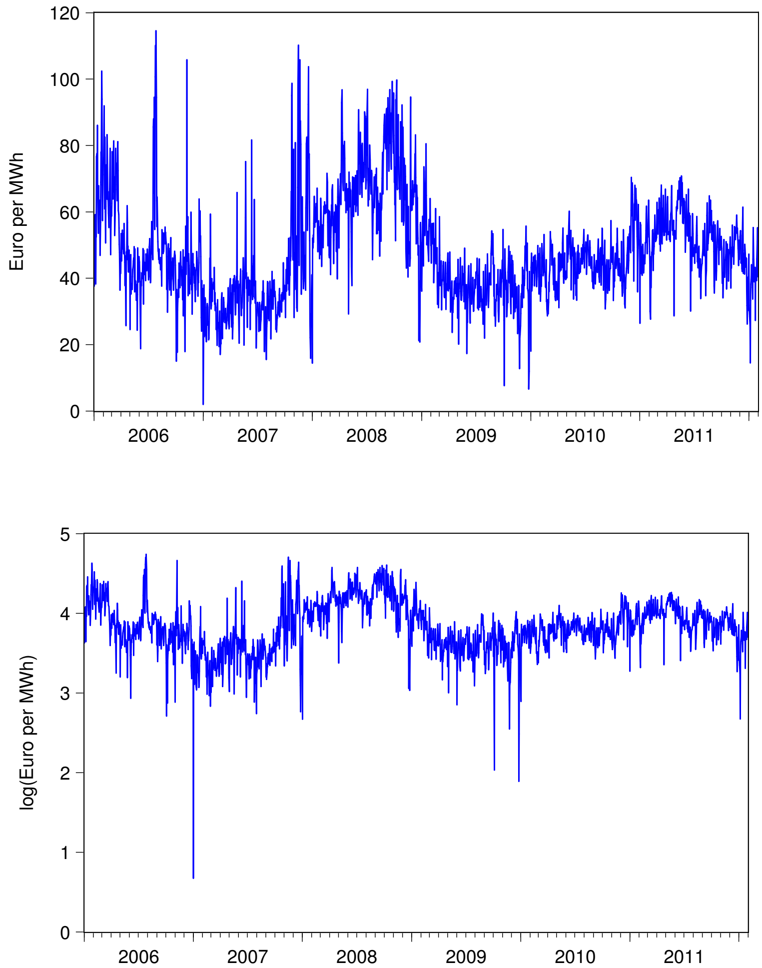
Finally, the logarithmic electricity price is calculated and employed in the following analysis.[11] Figure 3.6 illustrates the original and the deseasonalised electricity price series. The descriptive statistics of both series can be found in Table 3.1.

The main explanatory variable is the wind electricity generation in Germany. An illustration how the in-feed of variable renewable electricity affects the existing power system can be found in Annex B, Figure B.1. To match the day-ahead horizon of the dependent variable, I use the predictions for daily wind power generation. These short-term forecasts are accurate and, more importantly, reflect the infor-

[10]Seasonal effects could also be addressed by trigonometric components (Lucia and Schwartz, 2002; Bierbrauer et al., 2007). However, such sinusoidal trends cannot be detected in the German electricity data from 2006 to 2012.

[11]Estimating the logarithmic price series has the advantage that the coefficients have a straight forward interpretation. The augmented Dickey-Fuller test statistic is -3.57274 whereas the 1% critical value is -3.4331. The null hypothesis of a unit root is therefore rejected. The same holds for the Phillips-Perron test, employed by Knittel and Roberts (2005), with a test statistic of -17.37986 and a 1% critical value of -3.4330. Hence, it is not necessary to estimate the differences or returns.

Figure 3.6: Deseasonalised electricity price



Note: The upper panel shows the wholesale electricity price after outliers have been filtered and seasonal trends removed. The lower panel shows the log level of this series.

Table 3.2: Removing seasonality

	Coefficient	p-value
c	51.89	(<0.0001)
Tue	2.76	(0.0226)
Wed	2.59	(0.0321)
Thu	2.04	(0.0912)
Fri	-0.85	(0.4784)
Sat	-9.47	(<0.0001)
Sun	-17.49	(<0.0001)
Feb	1.07	(0.4934)
Mar	-3.80	(0.0126)
Apr	-4.54	(0.0032)
May	-6.90	(<0.0001)
Jun	-2.82	(0.0670)
Jul	-0.56	(0.7100)
Aug	-5.66	(0.0002)
Sep	2.00	(0.1913)
Oct	6.27	(<0.0001)
Nov	3.73	(0.0152)
Dec	-2.39	(0.1170)

Note: OLS regression with the Phelix Day Base, corrected for outliers, as dependent variable. Monday and January are used as reference variables. p-values in parentheses.

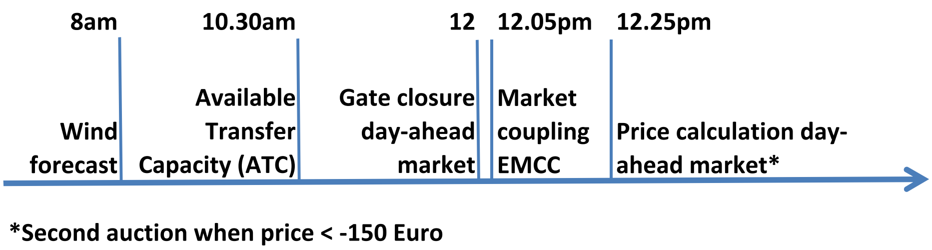
mation available to participants in the day-ahead market. The forecasts are made and published by the four German transmission system operators (TSO). The TSOs then sell the predicted amount of renewable electricity on the day-ahead electricity market.[12] The wind volumes are normally placed as price-independent bids to assure that they are certainly sold in the day-ahead auction. When the price falls below -150 € in the daily auction, the energy exchange calls a second auction, in which the wind volumes can be auctioned with a price limit between -350 € and -150 € (Bundesnetzagentur, 2012). This rule was first introduced by the regulator in 2010 and revised in 2011 to avoid extreme negative prices as experienced during 2009. It was only necessary once, on 5. January 2012, to call a second auction.[13] The daily schedule of forecasting and selling wind is schematically illustrated in Figure 3.7. The TSOs should have no incentive to systematically mispredict the expected renewable electricity generation: if the TSOs sell too much or too little renewable

[12]The data can be downloaded from the homepages of Tennet, Amprion, EnBW and 50Hertz. For a shorter period they are also available from www.eeg-kwk.de and the EEX Transparency Platform, www.transparency.eex.com. The data are available in hourly and 15-minute format. For this study, 15-minute MW data are averaged for each hour and then summarised to MWh per day.

[13]Personal communication with Thomas Drescher, Head of Market Operations EPEX Leipzig, in May 2012.

electricity on the day-ahead market, they have to balance it on the intraday market the following day (von Roon, 2011). The wind electricity generation depends on the weather development and installed capacity but is independent from the electricity price.[14]

Figure 3.7: Stylised scheduling in the day-ahead electricity market



Note: ATC stands for Available Transfer Capacity, EMCC for European Market Coupling Company. Information regarding the daily operations is obtained from www.marketcoupling.de and www.epexspot.com.

Of course, electricity price is not solely determined by wind electricity generation. Several papers indicate that the total electricity load, which reflects the demand profile, plays an important role in price behaviour. In fact, research shows that the combination of both factors is particularly important in this regard. Jónsson et al. (2010) show that the ratio between wind and conventional power production affects the electricity price most. They use the ratio between wind and load which is termed *wind penetration*. Similarly, Nicolosi and Fürsch (2009) find that the residual load, the electricity demand that needs to be met by conventional power, is a crucial parameter. The share of wind shows how much wind power contributes to meeting total electricity demand and illustrates its relative importance. The same amount of wind electricity will have a different impact on the price during a phase of high electricity demand than it will during low demand. Load data which reflect

[14]How much renewable capacity is installed depends greatly on subsidies, namely, the German feed-in tariff (FIT) system. The FIT does not influence the wholesale electricity price traded on the energy exchange, but it influences the end-use price because the FIT costs are socialised among almost all electricity users.

the demand for electricity should be used in the estimations in order to put the wind data into context.[15]

ENTSO-E, the association of European transmission operators, publishes data on the vertical load and the total load in Germany. The vertical load reflects the net flows from the transmission to the distribution grid and therefore only a fraction of total electricity demand.[16] Therefore, a better proxy for the demand profile on a given day is the total load which also includes electricity from small and renewable sources in the distribution grid (ENTSO-E, 2012).[17] ENTSO-E does not yet provide forecasts for the total load. In line with Jónsson et al. (2010), the predicted load is constructed according to the following relationship:

$$L_t = \hat{L}_t + e_t, \tag{3.2}$$

where L_t is the actual load, $\hat{L}_t$ is the predicted load, and $e_t \sim N(0, \sigma^2)$ a residual. By adding noise to the actual load, a load forecast is simulated. The standard deviation of the error is chosen, in line with Jónsson et al. (2010), as 2 per cent of the average load in the sample. According to Jónsson et al. (2010) and Weber (2010), this is consistent with the errors that modern forecasting models produce.[18] The advantage of Jónsson et al.'s (2010) method is that the error of the simulated load forecast and the wind forecast are independent. Otherwise, both errors would be influenced by the weather forecast.[19] When the wind forecast is put in perspective with electricity demand $\hat{L}_t$, its relative importance for the power system becomes clear. Figure 3.8 shows that the share of wind fluctuates between 0 and 40 per cent. The discussed explanatory variables, wind and load, will be included in an extended GARCH model of the electricity price. The methodology is elaborated in the next section.

[15]The demand for electricity should be independent from the variable wind in-feed and should therefore be an appropriate variable choice to avoid endogeneity problems.

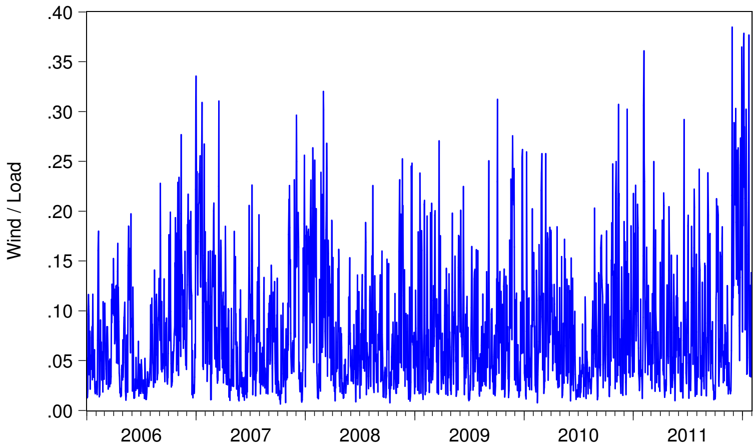
[16]As the wind electricity is fed into the distribution grid, it is not included in the vertical load data. However, the vertical load data are most accurate as this can be measured directly by the TSO.

[17]However, care should be taken with the quality of the total load data. TSOs can only estimate the total load, as they do not directly observe all flows in subordinated distribution grids.

[18]ENTSO-E publishes forecasts and actual values for the vertical load for 2010 and 2011. The error has a standard deviation of 1.1 per cent of the average load in this period. However, the vertical load data are more accurate and easier to predict than the total load. Therefore, 2 per cent seems a reasonable assumption.

[19]The load forecast is simulated several times to test whether the regression results depend on the randomly generated noise process. This is not the case.

Figure 3.8: Share of wind power generation



Note: The share is calculated as MWh of wind in-feed per MWh electricity load per day. Source: EEX and ENTSO-E.

3.4 Model

The liberalisation of power markets turned electricity into a tradable commodity and engendered a great deal of interest in understanding and modelling its price performance. Deng (2000), Huisman and Mahieu (2003), Lucia and Schwartz (2002), and Knittel and Roberts (2005) pioneered this research area. These studies emphasise that distinct features of the electricity price should be included in an empirical price model. Electricity, for example, is not storable: supply and demand have to be matched instantly to avoid temporary imbalances. This can lead to extreme prices that usually revert quickly once supply and demand reconciled. Hence, mean reversion is common in electricity markets and should be included in a price model (Deng, 2000; Huisman and Mahieu, 2003). Another important characteristic of electricity, reflected in its price, is seasonality. Demand varies throughout the day and during the week, as well as across the year. Therefore, models of electricity price should incorporate seasonality, as exemplified by Knittel and Roberts (2005) or Lucia and Schwartz (2002).

Given the pronounced volatility in the liberalised markets, conditional heteroscedasticity models lend themselves well to correctly explain price performance (Higgs and Worthington, 2010). These so-called GARCH models date back to Bollerslev (1986). As they appropriately capture the fluctuation and clustering of volatility, GARCH models are a widely employed method in financial and commodity markets. Knittel and Roberts (2005) were among the first to apply a GARCH model to the electricity price. They use an asymmetric GARCH model to capture price responses to positive and negative shocks and do indeed detect an inverse leverage effect. Other GARCH applications that have a bearing on this study are Solibakke (2002) and Mugele et al. (2005). Furthermore, Escribano et al. (2011) contribute to the literature by combining jumps and GARCH to explicitly control for price spikes. They show that taking into account mean reversion, seasonality, and jumps improves the GARCH model.

To better understand the performance of the electricity price, market fundamentals should be reflected in the calculations (Janczura and Weron, 2010). Mount et al. (2006) and Karakatsani and Bunn (2010) emphasise that variables for demand and reserve margins should be included to better understand price movements. Huisman (2008) also recognises the need to enrich the price model with fundamentals and uses temperature variables to detect changes in price behaviour. Similarly, Hadsell and Marathe (2006) and Gianfreda (2010) estimate an asymmetric GARCH model and include traded electricity volume in the variance equation. They find that the trading volume has an effect on price volatility, which is in line with findings from stock markets, see for example Bollerslev and Jubinski (1999) or Le and Zurbruegg (2010). Hadsell (2007) and Petrella and Sapio (2010) touch on another decisive factor for the electricity price and use a GARCH model to test whether changes in market design have an effect on price volatility.

Using a GARCH model allows to explicitly test the effect of the wind power generation on the mean and volatility of the electricity price in an integrated approach. Moreover, a GARCH model seems most appropriate to mimic the volatility behaviour of the electricity price. Figure 3.6 illustrates that volatility clustering is present which is typical in financial markets. This feature hints at autocorrelation in the data, which is emphasised by the Q-statistic for the squared and the absolute returns (Zivot, 2009).[20] Furthermore, Engle's (1982) test for autoregressive conditional heteroscedasticity (ARCH) in the residuals confirms that ARCH effects are present.[21]

[20]From an auxiliary OLS regression with the log price, autoregression is detected in the squared returns. This suggests the estimation of a GARCH model.

[21]The null hypothesis of no ARCH effects in the residuals is rejected with a highly significant test statistic of 54.720 (<0.0001) when including two significant lags of ϵ^2.

As electricity is not storable, the price tends to spike and then revert as soon as the divergence of supply and demand is resolved (Bierbrauer et al., 2007; Escribano et al., 2011). This mean reverting characteristic of the electricity price motivates the specification of the GARCH mean equation. To capture mean reversion, the electricity price can be described by an Ornstein-Uhlenbeck process (Vasiček, 1977),

$$dp_t = \kappa(\mu - p_t)dt + \sigma dw_t. \tag{3.3}$$

Here, p_t is the electricity price and w_t a standard Wiener process. After deviating from the mean, $\mu - p_t$, the price is corrected back to its mean. The speed of the reversion is given by κ. According to Bierbrauer et al. (2007), Equation 3.3 can be rewritten for the deseasonalised log price in discrete time as Gaussian AR(1) process: $y_t = c + \phi y_{t-1} + \eta_t$, where $c = \alpha \cdot \mu$, $\phi = 1 - \kappa$ and $\eta \sim iidN(0, \sigma^2)$.[22] Hence, the speed of the mean reversion can be calculated from the coefficient for the autoregressive parameter. Mean reversion models have often been employed in the literature (Clewlow and Strickland, 2000; Lucia and Schwartz, 2002), but a plain mean-reverting process is found to overestimate the variance and the mean reversion driven by volatile periods (Huisman and Mahieu, 2003). Similar to Knittel and Roberts (2005), this motivates the estimation of an AR-GARCH model, including a mean reversion parameter, in the following specification:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \epsilon_t \tag{3.4}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}, \tag{3.5}$$

where y_t is the log electricity price and h_t is its conditional variance. $\epsilon_t = \sqrt{h_t} z_t$ and $z_t \sim NID(0, 1)$. ω is the long-run variance. For the model to be stationary, $\alpha_i + \beta_j < 1$ and $\alpha_i, \beta_j > 0$.

The daily data for wind generation, w_t, are included in the mean and the variance equation of this model. Given this extension, the specification for the

[22] For the deseasonalised log price, Equation 3.3 can be written in discrete time as $\triangle y_t = \kappa(\mu - y_t)\triangle t + sigma \triangle w_t$. Given $\triangle y_t = y_{t+1} - y_t$, the formula becomes $y_t = \kappa\mu + (1-\kappa)y_{t-1} + \eta_t$. Check for example Dixit and Pindyck (1994) for a more detailed description of the transformation from continuous to discrete time.

ARX-GARCHX model becomes:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \sum_{j=1}^{m} \theta_j w_{t-j} + \epsilon_t \tag{3.6}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{k=1}^{s} \gamma_k w_{t-k}. \tag{3.7}$$

In the normal GARCH model, the coefficients in the variance equation, including the additional coefficients for γ, should be positive to ensure that the variance is always positive (Gallo and Pacini, 1998; Zivot, 2009). When a coefficient in the GARCH variance equation is negative, one can inspect the conditional variance and check whether it is always positive. In case of a negative coefficient, the variance stability of the GARCH is linked to the specific sample.[23] The problem with negative coefficients is resolved when estimating an EGARCH where the variance equation is positive by construction (Nelson, 1991; Gallo and Pacini, 1998). The EGARCH is an extension in which the additional term allows differentiating between the effect of negative and positive price shocks to the variance. This asymmetry component is often referred to as the leverage effect.[24] In an EGARCH representation, Equation 3.7 becomes:

$$log(h_t) = \omega + \sum_{i=1}^{q} \alpha_i \left|\frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}}\right| + \sum_{l=1}^{r} \delta_i \frac{\epsilon_{t-l}}{\sqrt{h_{t-l}}} + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{k=1}^{s} \gamma_k w_{t-k}. \tag{3.8}$$

The empirical strategy of this paper is to first estimate the GARCH model with Equation 3.7 for the German day-ahead electricity price, extended by covariates for the wind power forecast. All specifications are first estimated including one AR(1) parameter as derived from the Ornstein-Uhlenbeck process. To capture serial correlation present in the price series, I then include the number of autoregressive lags which minimise the Bayesian information criterion (Escribano et al., 2011). I will report both specifications to show that the coefficients vary only slightly. Finally, the EGARCH is employed to investigate possible asymmetric influences on the variance and to double-check variance stability.

[23]As the aim of this study is not to forecast the price, checking that the actual conditional variance is positive assures stability.

[24]If $\delta \neq 0$, the impact is asymmetric. A positive coefficient of δ indicates that positive price shocks have a larger impact on volatility than negative shocks. The contrary holds for a negative δ. The EGARCH is covariance stationary when $\beta < 1$ (Zivot, 2009).

The aim of this study is not only to investigate the impact of wind power generation on the electricity price, but also the regulatory modification to wind electricity marketing. The German regulator amended the rules applicable to marketing of renewable electricity in the so-called *Ausgleichsmechanismusverordnung* in January 2010. In line with Antoniou and Foster (1992), Holmes and Antoniou (1995), Bomfim (2003), and Hadsell (2007), a dummy variable is introduced to capture this regulatory change. The dummy takes the value of 1 after the change. This gives a first impression as to whether change can be observed in the volatility of the electricity price after the regulation was amended. However, the dummy imposes a restriction regarding the expected change ex ante on the model. Therefore, the influence of the new regulatory design is double-checked by consulting structural break tests. The OLS-Cusum and the Bai-Perron breakpoint test are employed to find structural changes in the conditional variance of the GARCH model. This procedure seems more objective than the dummy variable approach as the results are not driven by a prior assumption.

The OLS-Cusum test is a generalised fluctuation test (Zeileis et al., 2001) designed to discover whether a series changes over time. In an auxiliary regression, a constant is fitted to the GARCH volatility. An OLS-based empirical process is derived from the cumulative sums of standardised residuals of this regression (Ploberger and Krämer, 1992). For the OLS-Cusum, this empirical fluctuation process starts and ends in zero. A breakpoint is detected at the peak of the process (Zeileis et al., 2003).[25] This test is useful to uncover whether a series is characterised by structural changes and to arrive at a rough impression as to when they occurred. The so-called Bai-Perron breakpoint test goes into more detail and allows dating the structural shifts (Bai and Perron, 2003). A least squares regression is partitioned and the minimal residual sum of squares (rss) is calculated for each segment. The rss for all segments are summarised. Breakpoints that minimise this sum over all partitions are calculated. For more detail, see Bai and Perron (2003) or Zeileis et al. (2003).

[25] As a robustness check, the F-test is also calculated (Andrews and Ploberger, 1994). The conclusions for the OLS-Cusum test can be confirmed.

3.5 Estimation Results

3.5.1 Impact of Wind Power

The results for the GARCH(1,1) estimations can be found in Table 3.3.[26] All standard errors are calculated using the Bollerslev and Wooldridge (1992) method which assured that the test statistics are robust to non-normality of the residual. The first column (A) shows the GARCH benchmark specification for the log level of the electricity price. All coefficients are highly significant, the variance parameters are all positive, and their sum is smaller than one. The size of the GARCH term β with 0.56 indicates that the autoregressive persistence β is not particularly strong for the electricity price. The GARCH term α reflects the impact of new shocks the conditional variance h_t, transmitted though the error term ϵ_t from Equation 3.4. The AR term depicts a specificity of the power market. The coefficient of 0.88 in (A) shows that the price reverts back to its long-run mean. But the speed of reversion, given by $1 - \phi_1$, is low.

The Ljung-Box Q-statistic suggests that serial correlation is not well approximated by a single autoregressive term. Therefore, a more dynamic specification is estimated and further autoregressive parameters added. By minimising the Bayesian information criterion, seven lags are included in the specification (A*) in Table 3.4. The significant seventh lag mirrors the weekly seasonal component and is in line with Escribano et al. (2011). The GARCH coefficients remain fairly stable with an increase in β and, vice versa, a reduction of α. Their sum, however, stays below 1. This shows that the conditional variance is mean-reverting, and shocks only have a temporary effect on h_t (Hadsell, 2007).[27]

In column (B) and (B*) the logarithms of wind and load are included in the mean as well as the variance equation of the GARCH(1,1).[28] The negative coefficient for the wind variable shows that the day-ahead price decreases when high wind electricity generation is forecasted. This confirms findings by Jónsson et al. (2010) as well as Woo et al. (2011) and underlines the merit-order effect. In the

[26]The ARCH LM test confirms that the volatility clustering is well captured for all further specifications. Hence, no ARCH effects remain.

[27]The half-live of shocks can be calculated by $\ln(0.5)/\ln(\alpha+\beta)$, and the conditional variance reverts back to its mean after 5.91 days (Zivot, 2009).

[28]Both variables added in logarithms to normalise the size and fluctuation of the series.

present specification (B) and (B*), the coefficients can be interpreted as elasticities. When the wind electricity in-feed (MWh per day) increases by 1 per cent, the price decreases between 0.09 and 0.10 per cent. In the variance equation, the wind variable is significantly different from zero and positive. Hence, the fluctuating wind in-feed increases the volatility of the electricity price. To make sure that these results are not driven by the outliers that remain in the log electricity price, an outlier dummy is included in all mean equations.[29] The coefficient for the load variable is only significant in specification (B*) in Table 3.4, and illustrates that the price increases with higher electricity demand. The variance, however, is reduced in times of high demand, which might arise from higher liquidity of the electricity market.

A similar picture arises in column (C) and (C*) when the share of wind is included in the GARCH model. The wind variable reflects the share of wind relative to total electricity load. The coefficient for this wind penetration measure turns out as expected: a strong wind in-feed lowers the electricity price but increases its variance. When the share of wind rises by one percentage point, the electricity price decreases by 1.32 or 1.46 per cent in specification (C) and (C*). The coefficient is higher than before because the wind variable is now expressed as a share of total load. For the wind share to rise by one percentage point, the wind electricity production needs to gain quite substantially.[30] When the wind variables are added in (B) and (C), respectively (B*) and (C*), the coefficient for the GARCH term α increases slightly, accompanied by a downward adjustment of β. This suggests that a omitted variable bias skewed their coefficients in the previous specification (A*). Generally, the fit of the model, measured by the information criteria, improves when more autoregressive parameters are included in specifications (B) and (C), respectively (B*) and (C*).

To arrive at a first impression of how wind power's influence on the electricity price evolved over time, rolling regressions are calculated for specification (C).[31] Figure 3.9 shows how the coefficients evolve, using a three-year window. The rolling

[29] The dummy captures the 1.1.2007, 1.1.2008, 4.10.2009, and 25.12.2009. When AR terms are included in the regression, the respective number of lagged dummies is included as well.

[30] This can be illustrated as follows. The mean wind forecast is 111 GWh per day, the mean load reaches 1.332 GWh. The average share therefore is 8 per cent. To reach 9 per cent, wind has to rise a substantial 13 MWh or 12 per cent.

[31] Rolling regressions with a 2 year window have been calculated as well and give a broadly similar picture. However, a longer window is preferred for the coefficients to be significant. Moreover, the picture for specification (B), including log levels for wind and load separately, looks very much the same.

Table 3.3: Results AR(1)-GARCH(1,1) models with additional explanatory variables

Dependent variable: log electricity price
Sample: 1/1/2006 1/31/2012

	(A)		(B)log(Wind) log(Load)		(C)Wind/Load		(D)Wind/Load Regulation dummy	
Mean equation								
Constant	3.838	(<0.0001)	5.351	(<0.0001)	3.952	(<0.0001)	3.934	(<0.0001)
ϕ_1	0.881	(<0.0001)	0.899	(<0.0001)	0.901	(<0.0001)	0.874	(<0.0001)
log(Wind)			-0.089	(<0.0001)				
log(Load)			-0.035	(0.1945)				
Wind/Load					-1.315	(<0.0001)	-1.249	(<0.0001)
A dummy for outliers in the log price and its first lag are included in all mean equations.								
Variance equation								
ω	0.007	(<0.0001)	0.324	(<0.0001)	0.003	(0.0076)	0.011	(<0.0001)
α_1	0.243	(<0.0001)	0.273	(<0.0001)	0.267	(<0.0001)	0.250	(<0.0001)
β_1	0.557	(<0.0001)	0.541	(<0.0001)	0.555	(<0.0001)	0.300	(<0.0001)
log(Wind)			0.002	(0.0059)				
log(Load)			-0.024	(<0.0001)				
Wind/Load					0.031	(0.0155)	0.052	(<0.0001)
Regulation dummy							-0.010	(<0.0001)
Adj. R^2	0.686		0.726		0.739		0.742	
Log likelihood	829.291		1083.401		1075.098		1150.745	
AIC	-0.741		-0.966		-0.961		-1.028	
BIC	-0.723		-0.938		-0.937		-1.002	

Note: AIC stands for Akaike information criterion, BIC for Bayesian information criterion. p-values are in parentheses.

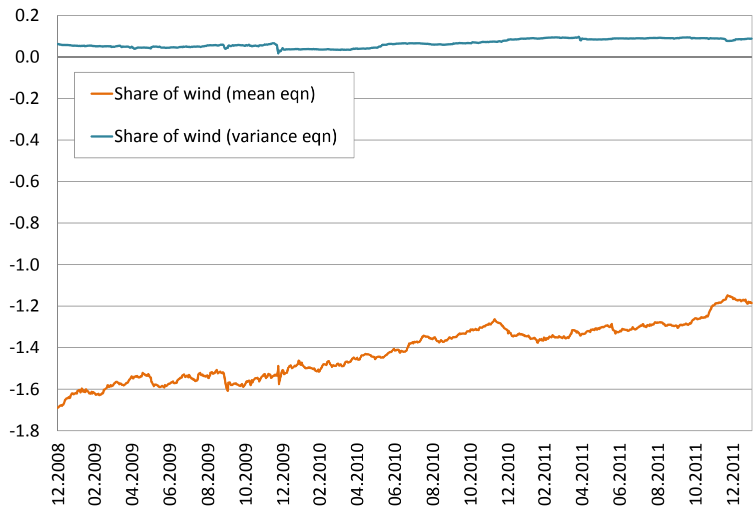
Table 3.4: Results AR(7)-GARCH(1,1) models with additional explanatory variables

Dependent variable: log electricity price
Sample: 1/1/2006 1/31/2012

	(A*)		(B*)log(Wind) log(Load)		(C*)Wind/Load		(*D)Wind/Load Regulation dummy	
Mean equation								
Constant	3.862	(<0.0001)	3.862	(<0.0001)	4.042	(<0.0001)	3.970	(<0.0001)
ϕ_1	0.652	(<0.0001)	0.581	(<0.0001)	0.589	(<0.0001)	0.597	(<0.0001)
ϕ_2	-0.035	(0.2539)	-0.005	(0.8668)	-0.040	(0.1968)	-0.010	(0.7238)
ϕ_3	0.096	(0.0010)	0.083	(0.0036)	0.097	(<0.0001)	0.060	(0.0313)
ϕ_4	0.008	(0.7707)	0.029	(0.3343)	-0.003	(0.9116)	-0.009	(0.7283)
ϕ_5	0.036	(0.2199)	0.024	(0.4522)	0.028	(0.3483)	0.049	(0.1744)
ϕ_6	0.104	(0.0010)	0.113	(<0.0001)	0.130	(<0.0001)	0.121	(<0.0001)
ϕ_7	0.093	(<0.0001)	0.136	(<0.0001)	0.165	(<0.0001)	0.149	(<0.0001)
log(Wind)			-0.098	(<0.0001)				
log(Load)			0.081	(0.0185)				
Wind/Load					-1.489	(<0.0001)	-1.414	(<0.0001)
A dummy for outliers in the log price and seven lags are included in all mean equations.								
Variance equation								
ω	0.003	(<0.0001)	0.281	(0.0004)	0.002	(0.0310)	0.009	(<0.0001)
α_1	0.164	(<0.0001)	0.250	(<0.0001)	0.227	(<0.0001)	0.253	(<0.0001)
β_1	0.725	(<0.0001)	0.563	(<0.0001)	0.638	(<0.0001)	0.313	(<0.0001)
log(Wind)			0.002	(0.0470)				
log(Load)			-0.021	(0.0003)				
Wind/Load					0.020	(0.0631)	0.045	(<0.0001)
Regulation dummy							-0.008	(<0.0001)
Adj. R^2	0.720		0.772		0.784		0.783	
Log likelihood	948.598		1253.431		1264.987		1333.351	
AIC	-0.842		-1.115		-1.127		-1.188	
BIC	-0.792		-1.055		-1.072		-1.131	

Note: An asterisk * labels the specifications that include seven autoregressive lags of the price. AIC stands for Akaike information criterion, BIC for Bayesian information criterion. p-values are in parentheses.

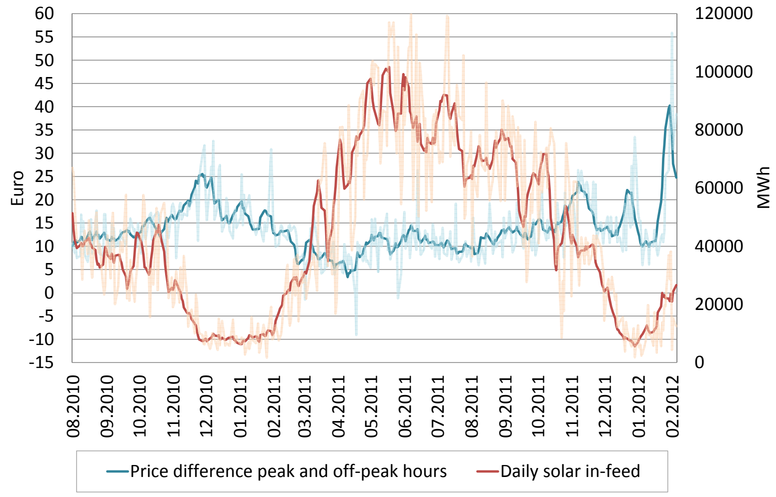
Figure 3.9: Rolling regressions for specification (C) with a three year window



Note: The regressions have been estimated for a moving window of three years. The first window starts on 1.1.2006 and ends on 31.12.2008. The dates in the legend indicate the end of each three-year window. The lines show the development of the coefficients for each consecutive regression.

regressions illustrate, on the one hand, that the wind coefficient from the variance equation remains fairly constant. On the other hand, the coefficient for the wind share in the mean equation, depicted by the orange line, becomes less negative over time. The wind in-feed can no longer decrease the price level as much. Stated differently, the merit-order effect lessens over time. Sensfuß (2011) find the same effect for Germany. A plausible explanation for the weaker merit-order effect is the increasing share of solar PV in-feed. Already, a merit-order effect from wind power can be observed for solar PV in Germany (Bundesnetzagentur, 2012). As Figure 3.10 shows, electricity generation from solar PV depresses mainly peak power prices. Lower peak power prices reduce the daily average wholesale price used in this study. When the average price is lower on days with little wind, the calculated merit-order effect for wind will be smaller. This also explains the dip during winter 2010 when solar PV was not able to lower peak prices. Investigating this interaction in an analysis with hourly prices would be interesting but is left for further research. Another reason for the weakening merit-order effect could be the stronger electivity trade within Europe. The possibility to export excess wind electricity generation smoothes the price development (Hulle, 2009). This effect is further explained at the end of this section.

Figure 3.10: Solar PV in-feed and peak prices



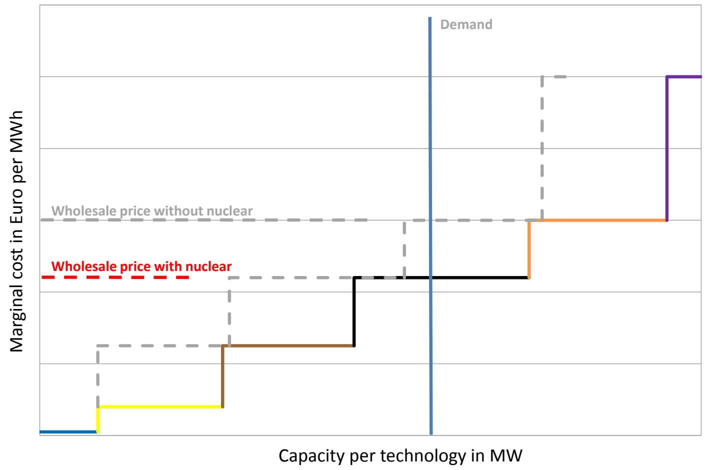
Note: The solid lines denote the 7-day moving average. The transparent lines the daily values. The difference between peak and off-peak prices shows that solar PV mainly depresses peak hour prices. In summer 2011 the off-peak price was even above the peak price on three days. Source: Bundesnetzagentur (2012).

After April 2011, the impact of wind on the electricity price diminishes even further. This is most likely related to the nuclear phase-out in Germany. Shutting down nuclear power plants shifts the merit-order curve as illustrated by Figure 3.11. The price decrease, induced by wind, is less strong when the nuclear capacity is removed. This results are confirmed by findings of Thoenes (2011).

3.5.2 Impact of Regulatory Change

The empirical framework is used to evaluate modifications to the power market design and the renewables regulation. The German regulator amended the marketing of renewable electricity in the so-called *Ausgleichsmechanismusverordnung* in January 2010. All TSOs are now required to forecast the renewable power production one day in advance and to sell the total predicted amount on the day-ahead market. TSOs then receive the revenues from selling the renewable power volumes at the wholesale market price (see Figure 3.12). However, these funds are most likely insufficient to remunerate the producers of renewable electricity according to the feed-in tariff rates. Therefore, TSOs also receive the so-called

Figure 3.11: Stylised merit-order curve before and after the nuclear phase-out



Note: Simplified merit order curve in line with von Roon and Huck (2010) and Gruet (2011). The blue line illustrates marginal costs for electricity from wind, yellow stands for nuclear, brown for lignite, black for hard coal, orange for gas, and purple for oil. The dotted line illustrates the case without nuclear.

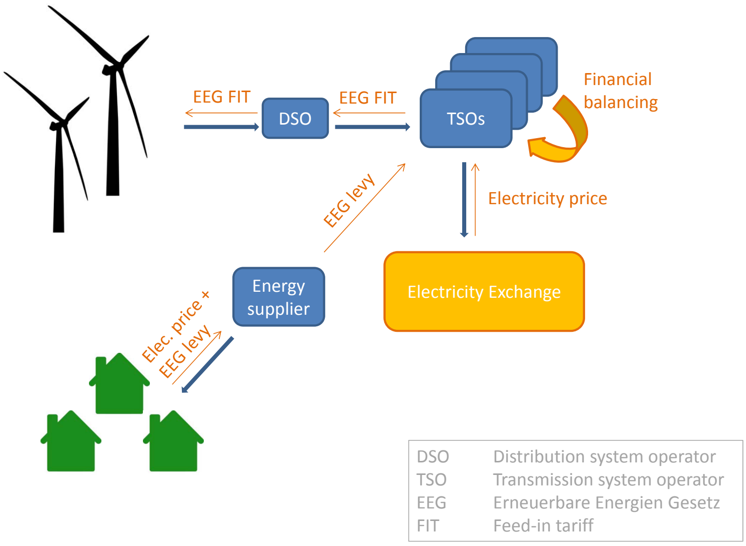
EEG levy which is after all raised from the electricity users.[32] The EEG levy covers payments for feed-in tariffs as well as costs from forecasting, balancing, and marketing of renewable electricity.

The previous marketing mechanism was more complicated. TSOs had to predict the renewable electricity production a month in advance. These forecasts were quite inaccurate as the wind and solar PV power production is highly dependent on meteorological factors.[33] Energy suppliers and TSOs then agreed on a fixed schedule for renewable electricity delivery on each day of the following month (Buchmüller and Schnutenhaus, 2009). These volumes had to be physically delivered from a TSO to the energy supplier (see Annex B, Figure B.2 for an illustration). As the final wind in-feed was uncertain, the physical delivery of renewable electricity via the TSOs to the energy companies was an inefficient mechanism (Monopolkommission, 2009). When wind power generation was lower than expected, the missing electricity volumes had to be bought by the TSOs on the day-ahead or intrady market. A surplus of renewable electricity, on the contrary, had to be sold on the market

[32]EEG stands for *Erneuerbare Energien Gesetz.* The EEG levy is payed by the energy suppliers who then pass the costs to consumers and industry. Some electricity users are exempt from the levy.

[33]Other renewable electricity generation, for example biomass, is less problematic in this respect.

Figure 3.12: Marketing mechanism after the regulatory change in 2010



Note: Illustration adapted from Buchmüller and Schnutenhaus (2009). Blue arrows show the flows of renewable electricity from the installations to the final electricity users. Orange arrows indicate monetary flows that finally remunerate the operators of renewable electricity installations. More detailed information is available at: www.bundesnetzagentur.de

(Erdmann, 2008). More sudden shortfalls had to be fixed on the balancing market. This mechanism led to substantial balancing costs for adjustments in the spot markets. In 2008, they reached 595 million Euro for all TSOs (Bundesnetzagentur, 2012). With the new regulation, the forecasting uncertainty and interventions on the spot markets could be reduced. The related costs shrank substantially to 127 Mio in 2010, and the electricity users were disburdened (Bundesnetzagentur, 2012).[34] Under the old regulation, the expenses for spot and balancing market interventions were hidden in the network charge (Buchmüller and Schnutenhaus, 2009). Since 2010, these costs are added to the EEG levy. This increases the transparency for electricity users who get a clearer picture of the renewable subsidy and system costs.

Transparency also increases with regard to the marketed renewable energy volumes as they have to be sold on the day-ahead market. The additional wind volumes increase liquidity of the day-ahead and the intraday market significantly (Bundesnetzagentur, 2012). This is expected to reduce price volatility as smoother prices can generally be observed in a more liquid market (Figlewski, 1981; Weber,

[34]The overall EEG levy still continues to rise due to high liabilities from feed-in tariff payments, just the burden from the balancing costs is reduced.

2010). Moreover, TSOs had no incentive under the old regulation to optimise activities on the day-ahead and the intraday market because they could socialise these expenses via the network charge (UoSC) to electricity users (Buchmüller and Schnutenhaus, 2009). According to Klessmann et al. (2008), integration of renewable electricity in Germany was opaque and inefficient before 2010. Under the new regulation, the interventions on the day-ahead market become obsolete and related disturbances are expected to reduce.

To test for the effect of the regulatory change on the price volatility, a dummy variable is included in the variance regression. This procedure follows Antoniou and Foster (1992), Holmes and Antoniou (1995), Bomfim (2003), and Hadsell (2007). The dummy variable captures the effect on the variance after the regulatory change in 1. January 2010. The dummy is not included in the mean equation as the new regulatory design only alters the way renewable electricity volumes are absorbed from the market. The overall electricity supply – whether it be generated from renewable or conventional power plants – remains unaffected by the regulation. Therefore, the price level should not be affected from the regulatory change, and the focus lies on the price variance.[35]

The results from specification (D) and (D*) can be found in Table 3.3 and Table 3.4. In both cases, the negative and significant coefficient for the dummy variable indicates a reduction of the conditional variance after the regulatory change. The effects of wind and load, discussed earlier, remain robust. Despite the negative coefficient for the dummy, the conditional variance does not become negative for the given sample. Therefore, the specification remains valid. The findings are still cross-checked in an EGARCH (1,1) which yields a stable variance even with negative coefficient in the variance equation. The results can be found in Table 3.5. The effect of the wind share as well as the negative coefficient for the regulatory dummy remain unchanged. The leverage parameter in specification (E1) and (E1*) is insignificant, and asymmetry seems not to be present.

Defining a dummy imposes assumptions regarding the structural shift. A more objective approach is to use a pure time series approach that detects irregularities in the variance from investigating the data. Following Chevallier (2011b), changes in the conditional variance are evaluated using various break tests. The OLS-Cusum

[35]This assumption was double-checked by adding the dummy variable to the mean equation. It stays insignificant and the results for the variance equation are not affected.

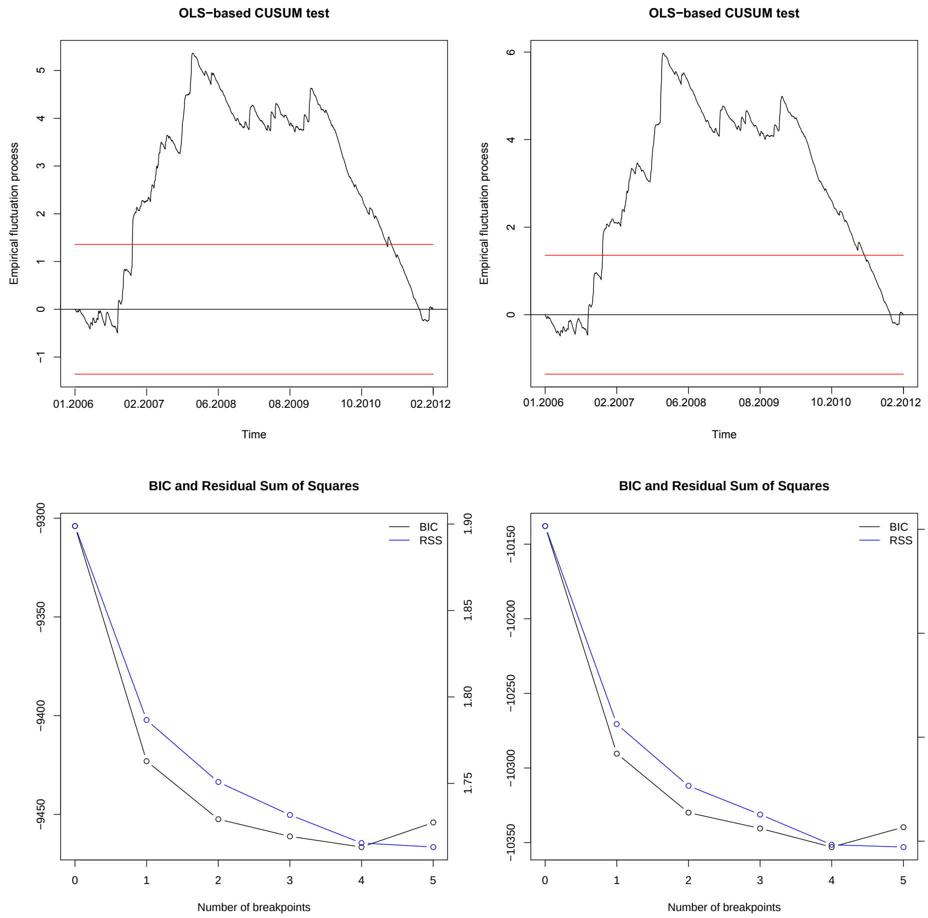
Table 3.5: Results AR-EGARCH models with additional explanatory variables

Dependent variable: log electricity price
Sample: 1/1/2006 1/31/2012

	(E1)Wind/Load Regulation		(E1*)Wind/Load Regulation		(E2) Wind/Load Regulation EMCC capacity		(E2*) Wind/Load Regulation EMCC capacity	
Mean equation								
Constant	3.939	(<0.0001)	3.992	(<0.0001)	3.850	(<0.0001)	3.726	(<0.0001)
ϕ_1	0.882	(<0.0001)	0.592	(<0.0001)	0.882	(<0.0001)	0.587	(<0.0001)
ϕ_2			-2.7E-03	(0.9188)			0.008	(0.7588)
ϕ_3			0.064	(0.0101)			0.056	(0.0233)
ϕ_4			-0.013	(0.5921)			-0.01	(0.6985)
ϕ_5			0.0339	(0.2889)			0.038	(0.2441)
ϕ_6			0.125	(<0.0001)			0.129	(<0.0001)
ϕ_7			0.156	(<0.0001)			0.149	(<0.0001)
Wind/Load	-1.239	(<0.0001)	-1.396	(<0.0001)	-1.24	(<0.0001)	-1.369	(<0.0001)
log(EMCC capacity)					0.009	(0.4996)	0.025	(0.0543)
A dummy for outliers in the log price and its lags are included in all mean equations.								
Variance equation								
ω	-2.379	(<0.0001)	-2.635	(<0.0001)	-0.608	(0.5463)	-0.543	(0.6472)
α_1	0.499	(<0.0001)	0.476	(<0.0001)	0.504	(<0.0001)	0.491	(<0.0001)
β_1	0.489	(<0.0001)	0.442	(<0.0001)	0.482	(<0.0001)	0.408	(<0.0001)
Leverage δ	-0.023	(0.5450)	-0.062	(0.1750)	-0.014	(0.7210)	-0.045	(0.3273)
Wind/Load	2.862	(<0.0001)	3.011	(0.0004)	2.719	(0.0002)	2.976	(<0.0001)
Regulation dummy	-0.588	(<0.0001)	-0.623	(<0.0001)	-0.577	(<0.0001)	-0.634	(0.0008)
log(EMCC capacity)					-0.170	(0.0658)	-0.212	(0.0588)
Adj. R^2	0.741		0.784		0.741		0.784	
Log likelihood	1146.069		1332.274		1150.167		1339.457	
AIC	-1.023		-1.186		-1.025		-1.191	
BIC	-0.994		-1.127		-0.991		-1.126	

Note: An asterisk * labels the specifications that include seven autoregressive lags of the price. EMCC capacity is the day-ahead available transfer capacity from Germany to Sweden and Denmark. AIC stands for Akaike information criterion, BIC for Bayesian information criterion. p-values are in parentheses.

Figure 3.13: Structural break tests for specification (C) and (C*)



Note: The upper panels depict the OLS-Cusum test for specification (C) on the left and (C*) on the right. The lower panels show the respective Bai-Perron break tests.

test is performed for the conditional variance from (C) and the more dynamic specification (C*). The upper panel of Figure 3.13 shows the empirical fluctuation process for the OLS-Cusum test together with the boundaries at the 5 per cent significance level. If the cumulative sum of squares stays within the boundaries, the residual variance is relatively stable. If it crosses the lines, the fluctuation is too large, and the null hypothesis of no structural change is rejected. The instability is depicted by two main peaks that indicate structural shifts in January 2008 and in January 2010. The next step is to date the volatility shifts in more detail. As shown in the lower panels of Figure 3.13, the Bai-Perron break test finds four breakpoints where the BIC is minimised.[36] The breaks in the conditional variance are identified on 25.12.2006, 8.1.2008, 22.12.2008, and 13.1.2010. It is not surprising that multiple irregularities are depicted in the volatility structure, given the rather unsteady electricity market. The breakpoint test confirms the structural shifts shown in the OLS-Cusum test. The conditional variance seems to undergo a change in early January 2008 and 2010. This confirms the previous regression results and connotes that the break in early January 2010 relates to the amendment of the marketing of renewable electricity. As a robustness check, the same test strategy is applied to specification (B) and (B*). These results can be found in Annex B, Figure B.3.

3.5.3 Impact of Market Coupling

The German market is not isolated, and electricity flows to neighbouring countries are important, especially for the integration of intermittent renewable electricity. A good example is the wind power from northern Germany which can often not be transmitted to the southern parts of the country due to capacity constraints in grid. High wind energy generation results in exports to neighbour countries, although the electricity could be used in southern Germany. To make sure that the reduction in the variance from 2010 onwards is not simply a result of the better integrated electricity market, I control for cross-border trade in the European electricity market.

The integration of the European electricity market has gained considerable importance from the creation of the European Market Coupling Company (EMCC). Since November 2009, Germany and Denmark pursuit day-ahead volume coupling

[36] Bai and Perron (2003) argue that the Bayesian information criterion is the best measure to determine the number of breaks.

on the two interconnectors between Germany and Denmark. In May 2010, the Baltic cable between Germany and Sweden joined. On 10. November 2010, the countries of the CWE region (Belgium, France, Germany, Luxembourg and the Netherlands) and the so-called Northern region (Denmark, Sweden and Norway) coupled their electricity markets.[37] The electricity flows of these countries are now jointly optimised, and electricity is exported from low-price to high-price areas, as a matter of efficiency. The necessary congestion management is carried out by the EMCC in a so-called interim tight volume coupling (Monopolkommission, 2009).[38] For this study, I use the interconnector capacities that can be used to export excess wind production.[39] The capacities are reported to the EMCC before the price setting on the day-ahead market and are therefore exogenous from the dependent variable.[40] For reasons of data availability, I use data for the interconnectors between Germany and the Northern region only (Baltic Cable, DK West and DK East).

The "north-bound" interconnector capacity is included in specification (E2) and (E2*) in Table 3.5. The coefficient of the EMCC capacity is positive in the mean equation. With a better connected power market, electricity flows are jointly optimised, and exports flow from low-price areas to countries where demand and price are higher. When the electricity price is low in Germany, more export capacity can stabilise the German price. A higher interconnector capacity also decreases the conditional variance as a better integrated electricity market is more flexible, and shocks are more easily absorbed. Finally, the conclusions regarding the regulatory change and the wind in-feed remain valid. Therefore, previous specifications that omit the interconnector capacity seem not to be misspecified.

[37] CWE stands for Central Western Europe. Countries connected in the CWE and the Nordic region account for approximately 55% of the European electricity generation (Böttcher, 2011).

[38] The TSOs from the participating countries report the interconnector capacities one day in advance to the EMCC (see Figure 3.7). In addition, the EMCC receives the anonymised order books from the participating electricity exchanges after the day-ahead spot market closed at 12am. The buying and selling orders, including the volumes of renewable electricity and the interconnector capacity, are optimised by the EMCC. The algorithm determines the price-independent volumes that have to be sold additionally on those markets that had too high prices. The EMCC only calculates the additional electricity quantities that are needed to equalise the price amongst participating countries. The auctioning and price setting remains in the hands of the local exchanges (Böttcher, 2011).

[39] The so-called Available Transfer Capacity (ATC) is included in the regressions. ATC is the physical interconnector capacity which is not yet allocated and is free to use. This export potential reflects the technical and physical restrictions in the neighbour country.

[40] The electricity trade flows are an outcome variable as they are determined together with the price on the day-ahead markets. The data on the electricity trade are therefore not included in this study.

3.6 Policy Implications

This chapter shows that intermittent renewable generation already transmits volatility to the electricity price. The question is how to integrate electricity from variable sources more smoothly.

First, better geographical integration is important. Building renewable installations throughout Germany would even out the regional fluctuation and assure that wind and sunshine are captured at different sites (Klinge Jacobsen and Zvingilaite, 2010). However, optimal sites for renewable installations are limited within one country. It seems more efficient to connect renewable installations throughout Europe. Schaber et al. (2012) project that improved interconnection within Europe will reduce market effects of variable renewable electricity substantially. Hulle (2009) also emphasise that grid extensions lead to steadier wind generation levels. Better grid connection can be fostered by new cables but also by using existing capacity more efficiently. Experience in Europe has shown that modifying the market coupling regime is helpful in this regard (Hulle, 2009; Monopolkommission, 2011). The presented results, regarding the EMCC market coupling, link in with these conclusions.

Second, flexible conventional power plants as well as electricity storage help balancing fluctuations of renewable energy. In times of high renewables in-feed, storage can collect and save excess electricity. Flexible generation units are power plants with low ramping costs, for example gas turbines. These plants operate at high variable but low fixed costs and can therefore be switched on and off to equalise low renewable power in-feed. The main difficulty of both options, storage and flexible generation capacity, is their investment cost. Providing responsive generation capacity needs to be profitable. With more and more renewables in the power system, conventional plants will mainly balance renewable fluctuation and therefore operate fewer full-load hours. Recovering the investment costs for flexible conventional units during these load hours will become more difficult (Klessmann et al., 2008; Klinge Jacobsen and Zvingilaite, 2010; Steggals et al., 2011). Periods with peak prices, which allow plant operators to generate revenues, become less certain and predictable due to the high variability of renewable electricity generation. The increased refinancing risk questions the viability of investments in flexible conventional capacity, and the market mechanisms might fail to give sufficiently strong investment signals. The literature discusses various policy options, such as capacity markets, capacity payments, or reliability options, to support the construction and availability of flexible capacity. All these policy models are subject of some controversial debate (Cramton and Ockenfels, 2011). It is not clear that introducing such new policy instruments is beneficial and necessary. For the time being, ifo and FfE (2012) rather suggest using the existing structure of the balancing market to auction more long-term capacity.

Finally, this study emphasises that regulatory changes can encourage a better integration of intermittent renewable electricity in the power system. Going forward, the regulatory and the policy framework should be further adjusted to the challenges arising from the decarbonisation of the electricity market. Regarding the regulatory setting, on the one hand, intermittent renewables could be better integrated if gate closure on day-ahead and intraday markets would be later (Hiroux and Saguan, 2010). A later gate closure would reduce uncertainty on the spot markets and balancing costs because a shorter forecasting horizon makes actual wind generation more predictable.[41] Another small step towards a better integration of renewables is to offer different products on the spot markets. Since December 2011, the German intraday market offers not only hourly, but 15 minute electricity blocks (Bundesnetzagentur, 2012). Given the stochastic generation profile of wind and solar PV, this product increases flexibility for market participants. Such smaller products should probably be introduced to the day-ahead market as well. With respect to the policy framework, on the other hand, renewable support schemes should be revisited. Currently, renewable energy is not exposed to any market risk in Germany due to guaranteed feed-in tariffs. A more market-based system would give incentives to realign renewable electricity supply with demand. Support schemes that depend on the wholesale electricity price make generation most attractive during peak load. Germany already offers renewable electricity producers to choose between fixed feed-in tariffs and price-dependent feed-in premiums. Since the beginning of 2012, renewable electricity producers are given a third option: they can sell their renewable electricity directly on the market without using TSO services. They forego the feed-in tariff but currently receive a similar payment to make this option attractive. This so-called *Direktvermarktung* does not yet reduce subsidy

[41]The implementation may not be straight forward as all action needs to be coordinated among European states.

payments but creates another market-based channel to integrate renewable power. Together with a transition to feed-in premiums, this approach should be rigorously pursued. Simultaneously, balancing costs should be partly shifted to the operators of renewable installations. In Germany, these integration costs are currently passed on to energy users, in other countries, for example Spain or the UK, the operator of renewable installations has to bear these costs partly (Klessmann et al., 2008). When exposing renewables to more market risk, the maturity of the technology and the functionality of the market need to be taken into account. Surely, intermittent installations have a limited ability to respond to price signals and should not be exposed to full risk (Klessmann et al., 2008). But renewable electricity generation now plays an important role in the German power system and should therefore assume more responsibility. A completely protected environment can hardly be sustained when planning to increase the renewables share to 35 per cent of gross electricity production in 2020. Market-based support could give positive long-run incentives to exploit portfolio effects, to choose optimal installation sites, and to improve the generation forecasts (Hiroux and Saguan, 2010).

3.7 Conclusions

With the aim of reducing carbon emissions and increasing energy security, renewable electricity generation is strongly supported by politicians and interest groups. This has led, especially during the last decade, to a rapid increase of renewable electricity generation in many parts of the world. In Germany, renewables now make up 20 per cent of the country's gross electricity production. The share of intermittent electricity generation from wind and solar PV has grown particularly quickly. Large amounts of stochastic wind electricity pose new challenges for the power system. Assuring a stable electricity supply and price becomes increasingly difficult. Given that Germany strives for an electricity mix with 35 per cent renewables in 2020 and 50 per cent in 2030, resilient integration of intermittent renewable electricity becomes absolutely crucial.

The presented results show that intermittent wind power generation does not only decrease the wholesale electricity price in Germany but also increases its volatility. This conclusion holds across various specifications underlining the robustness of the results. The disruptive effect of variable renewables on the wholesale price is relevant for the entire energy system. A lower and more volatile electricity price probably provides insufficient incentives to investment in new generation capacity, both in renewable as well as conventional capacity. The higher price volatility introduces uncertainty which, according to Dixit and Pindyck (1994), might lead to a delay of investments. After all, flexible generation plants become more important to back-up an increasing share of intermittent renewable electricity, but more difficult to finance. It is of the utmost importance that the electricity price continues to induce investments – in carbon-free renewables capacity and in back-up capacity needed to maintain security of supply.

This study finds evidence that a more reliable price signal can be achieved. The volatility of the German electricity price decreased after a regulatory change in 2010. Hence, the market design can to some extent smoothen the volatility of the electricity price and stabilise its level. Going from here, renewable electricity regulation should be developed further, towards a more market-orientated structure that remunerates renewable electricity during phases of high electricity prices. In Germany, the transformation of the energy system brings along many challenges. A framework that sets appropriate incentives for new investments and stabilises the wholesale price is prerequisite to meet these requirements. An efficient and more market-based integration of variable renewable electricity would unburden the consumers who currently pay most of the energy transition. This, in turn, could strengthen public support for the necessary transformations.

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Appendix A

Annex for Chapter 2

List of Selected Policy Events

Table A.1: EU ETS NAPs

Date	Event
16.01.2007	NAP Belgium, Netherlands
05.02.2007	NAP Slovenia
26.03.2007	NAP Czech Republic, France, Poland
02.04.2007	NAP Austria
16.04.2007	NAP Hungary
04.05.2007	NAP Estonia
15.05.2007	NAP Italy
25.05.2007	Poland and Czech Republic plan to sue EU over NAPs[1]
04.06.2007	NAP Finland
13.07.2007	NAP Ireland, Latvia, Lithuania, Sweden
31.07.2007	Latvia does not accept EU cap[2]
31.08.2007	NAP Danmark
22.10.2007	NAP Portugal
26.10.2007	NAP Bulgaria, Romania
07.12.2007	NAP Slovakia
23.09.2009	Court decision on Polish NAP[3]

[1] www.euractiv.com (Article 164066).
[2] www.euractiv.com (Article165990).
[3] www.euractiv.com (Article 185715).
Source: www.ec.europa.eu/clima/policies/ets/allocation/2008.

Table A.2: Global Carbon Market

Date	Event	Source
19.06.2007	German *Bundestag* decides on 22% CER use in EU ETS	Unicredit
06.08.2008	Link ITL und CITL announced	Unicredit
09.01.2009	Russia is expelled from international trade	Unicredit
28.01.2009	Commission's proposal for a global pact in Copenhagen	EC[1]
20.07.2009	Czech, Poland, Romania, and Ukraine sell AAUs	Unicredit
15.09.2009	CDM validator SGS is suspended	Unicredit
18.12.2009	COP Copenhagen 07.12.09-18.12.09	Unicredit
21.01.2010	IPCC mistakes	Unicredit
29.03.2010	Validator TÜV and Cemco suspended	Unicredit
12.03.2010	Recycled CERs	Unicredit
23.06.2010	Discussion on HFC projects in the CDM EB	Unicredit
26.08.2010	Discussion on HFC projects reaches EU ETS	Unicredit

[1]EC, Climate change: Commission sets out proposals for global pact on climate change at Copenhagen, Press Release IP/09/141, 28.01.2009.

Table A.3: EU ETS III

Date	Event	Source
10.01.2007	EC invites members to 'unilaterally' reduce GHG by 20% in 2020	Unicredit
12.09.2007	Strong divergences regarding the plan to cap GHG from aviation	Euractiv[1]
23.01.2008	European Climate Change Package	EC[2]
07.10.2008	EP environment committee votes in favour of 3 reports on climate change policies[3]	
11.02.2009	EC publishes preliminary list of aviation operators included in the EU ETS	EA[4]
23.04.2009	Revised EU ETS Directive 2009/29/EC	EC[5]
08.06.2009	Detailed interpretation of the aviation activities	EC[6]
28.01.2010	Registries closed due to phishing	Unicredit
03.05.2010	Brussels discusses a 30% CO_2 reduction target	Euractiv[7]
09.07.2010	Cap first step: number of EUAs to be issued for 2013	EC[8]
14.07.2010	CC Committee agrees on auctioning	Unicredit
21.09.2010	Debate on aviation activities in the EU ETS	EC[9]
22.10.2010	Cap second step and publication of benchmark study	EC[10]

[1] www.euractiv.com (Article 166690).
[2] www.eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2008:0016:FIN:en:PDF.
[3] www.euractiv.com (Article 176099).
[4] www.environment-agency.gov.uk/business/topics/pollution/112384.aspx.
[5] www.ec.europa.eu/clima/policies/ets/documentation_en.htm.
[6] www.eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:149:0069:01:EN:HTML.
[7] www.euractiv.com (Article 493637).
[8] www.europa.eu/rapid/pressReleasesAction.do?reference=MEMO/10/314.
[9] www.ec.europa.eu/clima/news/articles/news_2010092101_en.htm.
[10] www.eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2010:279:0034:0035:En:PDF.

Table A.4: EU ETS Compliance

Date	Event
02.04.2007	Verified emissions
07.06.2007	Compliance data publication
02.04.2007	Verified emissions
23.05.2008	Compliance data publication
01.04.2007	Verified emissions
15.05.2009	Compliance data publication
01.04.2007	Verified emissions
18.05.2010	Compliance data publication

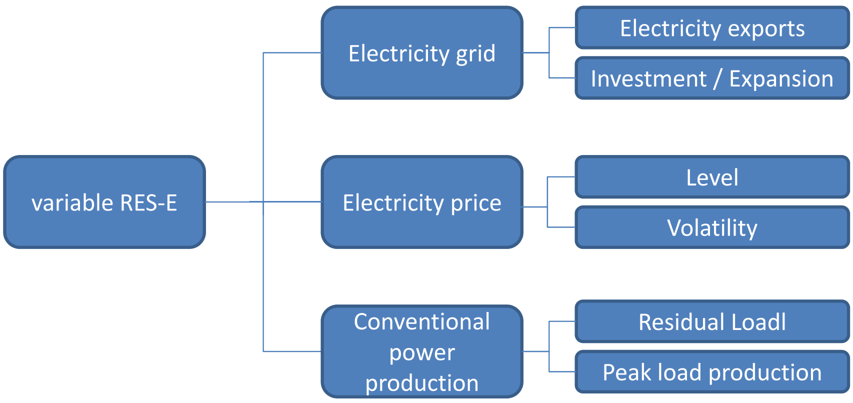
Source: www.ec.europa.eu/clima/policies/ets/monitoring.

Appendix B

Annex for Chapter 3

Renewables and the Power System

Figure B.1: Variable renewable electricity and the power system

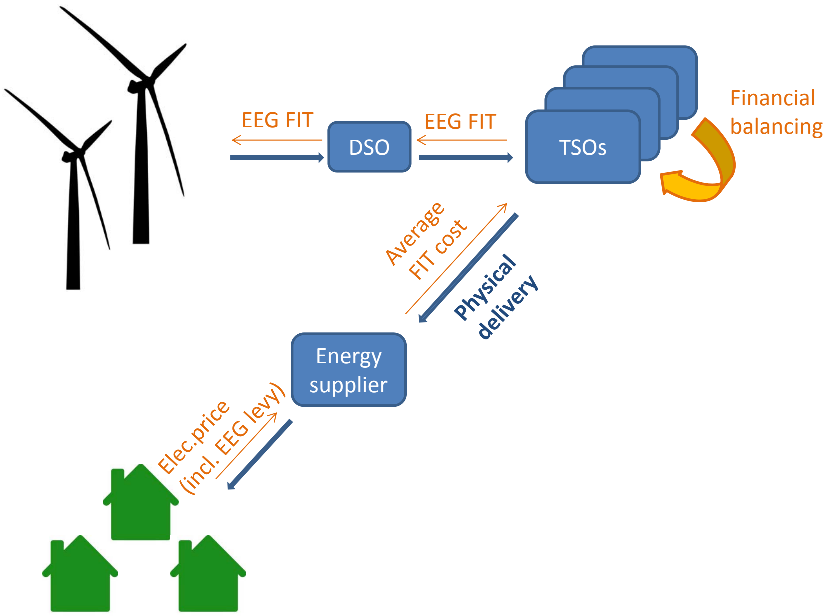


Source: Illustration adapted from Neubarth (2011).

This figure shows how variable renewable electricity influences the power system. First, the variable renewable electricity in-feed poses challenges to the grid which has to absorb the electricity at any point in time. Currently, the German transmission grid does not have enough capacity to transport the renewable electricity in-feed southwards. This problem is particularly apparent for wind power which is mainly generated in northern Germany but is needed in the south. This implies the need for massive investment in additional transmission cables. Until these cables are in place, any electricity that exceeds the demand in northern Germany is exported to neighbouring countries. Second, the impact on the level and volatility of the electricity price is studied in Chapter 3. Finally, renewable installations affect the existing power plants which need to balance the intermittent renewable electricity in-feed. Gas and coal plants in Germany have to satisfy electricity demand not met by renewables generation but have to be switched off when enough renewable electricity is generated.

Marketing Mechanism Before 2010

Figure B.2: Marketing mechanism before 2010

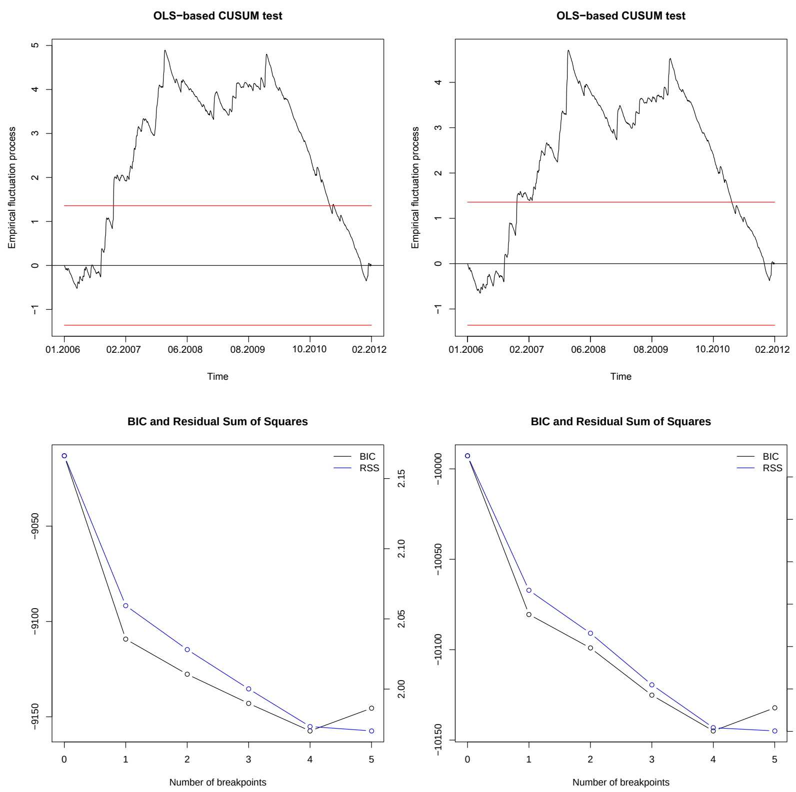


Note: Illustration adapted from Buchmüller and Schnutenhaus (2009). Blue arrows show the flows of renewable electricity from the installations to the final electricity users. Orange arrows indicate monetary flows that finally remunerate the operators of renewable electricity installations. Source: Illustration adapted from Buchmüller and Schnutenhaus (2009).

Structural Break Tests

The OLS-Cusum and the Bai-Perron breakpoint strategy are also applied to specification (B) and (B*) where wind and load are included separately. Results are shown in Figure B.3 and confirm the previous conclusions. Two main peaks can be detected, in January 2008 and 2010. The Bai-Perron breakpoint test also indicates multiple breaks on 22.12.2006, 8.1.2008, 22.12.2008, 6.1.2010. Hence, the structural break in January 2010 – after the redesign of the renewable electricity marketing – is confirmed.

Figure B.3: Structural break tests for specification (B) and (B*)



Note: The upper panels depict the OLS-Cusum test for specification (B) on the left and (B*) on the right. The lower panels show the respective Bai-Perron breakpoint tests.

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