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In 2005, the European Emission Trading Scheme (EU-ETS) established a new commodity: the right to emit a ton of CO2 (EUA). Since its launch, the corresponding price has shown rather turbulent dynamics, including nervous reactions to policy announcements and a price collapse after a visible over-allocation in Phase I. As a consequence, the question whether fundamental factors (fossil fuel prices, economic activity, weather) affect the EUA price remained partially unresolved. Today, being halfway through Phase II (2008--2012) and relying on a more mature market, we use more reliable data to investigate the extent to which allowance price dynamics can be explained by market fundamentals. We empirically test for the influence of fuel prices, economic activity, and weather variations. Fuel prices allow to test for fuel switching from coal to gas, the most important short-term abatement option for most installations in the EU-ETS. The empirical results show a significant influence of gas, coal, and oil prices, of economic activity and of some weather variations. When including the relative price of coal to gas on a forward level, we found evidence of a switching effect. Yet, on a spot level the demand effect seems to dominate. However, when including the absolute coal price the coefficient is positive, contradicting theory with respect to both the switching and the demand effect. The significant weather variations suggest that their influence on EUA prices is less driven by their effect on energy demand but more by their effect on the provision of carbon-free renewable energy. Overall, our results show that the price dynamics are much better explained by a model based on fundamentals than by a purely autoregressive model. However, the results also show that fundamentals alone cannot fully explain price dynamics and that forecasting is improved by the inclusion of time series characteristics.

Keywords: Carbon emission trading, EU ETS, Carbon price influence factors, Fuel switching

JEL classification: C22, G14, Q54

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1. Introduction

According to the Kyoto targets negotiated in 1997, European Union member states are required to reduce their CO_2 emissions by 8% by 2012. In order to reach this goal efficiently, the European Commission established the European Emission Trading Scheme (EU-ETS), a cap-and-trade scheme for emission allowances (EUA), in 2005. Each country defines their total amount of emission allowances in their respective National Allocation Plans (NAP), making only a limited amount of emission allowances available to installations operating under the ETS. These installations are required to hold a sufficient number of these allowances, giving them the right to emit the according amount of CO_2. Only a small fraction of allowances has been auctioned since 2008, and firms were allocated most allowances at zero cost. However, active trading can be observed as some firms abate emissions and sell their allowances, while other firms require more allowances than allocated initially. Hence, with its creation, the EU-ETS established carbon emissions as a new tradable commodity. The majority of installations within the EU-ETS are in the energy and heat sector.

The EU-ETS is designed to operate in phases. Phase I (running from 2005 to 2007) can be regarded as a start-up and test period. Currently, the scheme is halfway through Phase II (2008–2012), which coincides with the Kyoto commitment period. Meanwhile, the European Union has decided to prolong the EU ETS beyond the Kyoto Protocol and announced a Phase III, which is designed to run from 2013 to 2020. EUA prices were quite volatile in Phase I, first rising alongside natural gas prices while reacting nervously to news concerning the final NAPs. After the first verification reports in May 2006 revealed an overallocation of EUAs, prices decreased sharply and practically hit zero by mid 2007. The price dynamics of EUAs in Phase I have been studied extensively, coming to the conclusion that (1) the EUA price seems to violate the Markov property and that arbitrage opportunities exist (e.g., Hinterman, 2010), and (2) that the EUA market differs from the price formation in other markets (e.g., Conrad et al., 2010). However, since all the studies analyze EUA prices during Phase I, they had to deal with the problems of a new and immature market. In this paper we will take a closer look at the first half of phase II. Arguably, the market is more mature today and should lend itself better for answering the question to which extent market fundamentals can explain EUA price dynamics. We analyze whether fundamental factors such as fuel prices, economic activity, and weather variations can adequately explain the price dynamics for emission allowances in the world's largest market for carbon emission permits, the EU-ETS.

Understanding price dynamics in the EU-ETS is relevant for an efficient design of such allowances markets and for learning more about carbon abatement cost. Additionally, as it has an annual market volume of 30 billion Euro in Phase I and 47 billion Euro in Phase II (which already amounts to 20% of the estimated annual market value of the European electricity market), it is also highly relevant for carbon funds and traders (Conrad et al., 2010).

Theoretically, the price for EUAs should reflect marginal abatement costs (e.g., Sijm et al., 2005; Kanen, 2006). Carbon abatement can be achieved by investing in cleaner technologies, by reducing production levels, or by fuel switching, which involves switching from more carbon-intensive power generation methods (e.g. coal) to less carbon-

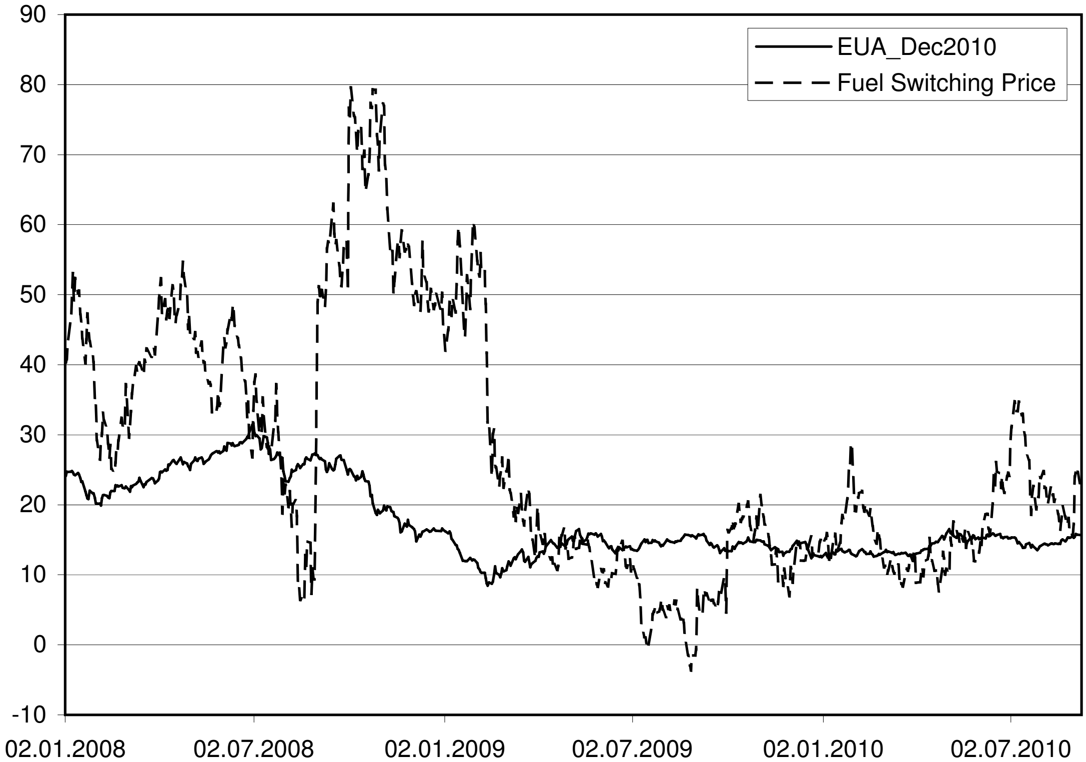

Figure 1: Price dynamics for EUA spot and future market

intensive ones (e.g. gas). While the former is a rather long-term decision, the latter two are short-term decisions. In particular, fuel switching remains to be the single most important abatement mechanism in the short run, as power producers can change the dispatch order of their power plants for the provision of peak load. They decide on the order in which its coal- or gas-fired power plants are put into operation, resulting in higher or lower CO_2 emissions (depending on the direction of the switch). The cost of fuel switching is determined by the (relative) prices of fossil fuels. Consequently, in an efficient market, the EUA price should react to changes in these prices, too. In addition to changes in fossil fuel prices, the EUA price should reflect unexpected changes in energy demand due to extreme weather events and volatility in economic activity. However, as the share of renewable energy capacity (hydro, wind, and solar power) increases in Europe, weather variations also influence the provision of carbon-free renewable energy supply.

Despite these theoretical considerations, the price dynamics of the theoretical price (implied switching price) differ substantially from the realized EUA price, as shown in Figure 1.[1] The EUA Dec2010 price, after a short downturn,

[1]The figure shows the EUA Dec2010 future price because it took over five months until the middle of 2008 for at least some of the spot permits for that year to be issued in the EU ETS so that no spot allowance price was reported until that point in time. Figure A.4 in the Appendix A shows that there is no visible difference between the various future prices and the spot price. The implied fuel switching price is derived based on one month forward prices for gas and coal. The implied fuel switching price simply shows an average price because it depends on the heat rates of coal and gas plants, which varies from power plants to power plant.

reached its maximum value of 31.7 Euro/tCO_2 on July 1st, 2008, followed by an almost monotonous decline during the economic downturn until the start of 2009 (February 2nd, 2009, 8.45 Euro/tCO_2). From then on, it moderately increased to values around 15 Euro/tCO_2 and still fluctuates around this value today. The implied fuel switching price shows much more dynamic than the EUA Dec2010 price, reaching values close to 80 Euro/tCO_2 at the beginning of 2009. The fuel switching price also fell to negative values in mid-2009 until reaching values close to 15 Euro/tCO_2 in 2010. However, the implied fuel switching price fluctuated around this value at a much higher rate of volatility than the EUA Dec2010 price.

The comparison of these two time series shows that other factors in addition to economic activity and weather variations also seem to influence the EUA prices in Phase II. Our econometric analysis reveals that, even though fundamental factors (fuel prices, economic activity, and weather variations) explain EUA price dynamics significantly better than a purely autoregressive model, other unobserved factors beyond economic theory seem to have an influence upon EUA prices.

Our paper makes three contributions to the literature: (1) it is the first paper to analyze EUA prices in Phase II, (2) it tests the performance of a theory-based vs. an autoregressive model, and (3) unlike other studies, it analyzes the effect of carbon-free renewable energy provision by also including wind power feed in its estimations.

The paper proceeds as follows. In Section 2 we explain the fundamental factors influencing the EUA price in more detail; in particular, the influence of fuel switching and weather variations. In Section 3 we review previous findings on determinants of the allowance price in Phase I, focussing on the four studies which tried to analyze the fundamental influence on EUA price dynamics. In Section 4 we explain the data used for Phase II and present our regression results. Section 5 discusses the results and Section 6 concludes.

2. Supply and Demand of EUAs: Policy, Economic Activity, Fuel Switching, and Weather

The supply and demand of EUAs, which essentially determines their price, are influenced by policy and fundamental aspects, respectively. Since the market for EUAs, the European Emission Trading Scheme, was artificially created by policy-makers, policy decisions mainly determine the supply of allowances. Policy decisions were made on the total amount of allowances available, the allocation and auctioning of allowances, usage of Certified Emission Reductions (CER) from the Clean Development Mechanism (CDM) and Emission Reduction Unit (ERU) from Joint Implementation (JI), the extent of banking and borrowing, and penalty for non-compliance. Demand is driven by three fundamental factors: economic activity, climatology, and fuel prices (Springer, 2003; Sijm et al., 2005; Christiansen et al., 2005; Kanen, 2006).

The EU-ETS members divide the country-specific emission reduction target between reductions within and outside of the ETS.[2] Aggregating the reduction targets within the ETS determines the total supply of allowances. For Phase

[2]The European Union Kyoto emission target is shared between member states according to the Burden Sharing Agreement. New member states that joined the EU in 2004 have their own Kyoto targets.

I and Phase II, ETS-member states specified this division in the National Allocation Plans (NAPs) which had to be approved by the EU Commission. The NAPs also specify the maximum share of carbon credits from CDM and JI that can be used for compliance. CERs and ERUs can be converted into EUAs so that the total supply of EUAs can increase by this specified maximum share. The possibility to bank or borrow EUAs also influences their supply. While the possibility of banking limits the supply of allowances in one period and thus puts an upward pressure on allowance prices, the possibility of borrowing has the opposite effect. Throughout Phase I, banking and borrowing was allowed over the years, but no bringing forward into Phase II was permitted.[3] From Phase II onwards, unlimited banking is allowed (European Union, 2009).[4]

Once the overall supply of EUA allowances is defined, the demand for EUAs, and therefore the price, is determined by business-as-usual (BAU) carbon emissions (carbon emissions in the absence of EU-ETS) and marginal carbon abatement costs. The BAU carbon emissions determine the extent to which the market is short in allowances. If the market is *not* short, EUAs are not scarce and the price drops to zero as it occurred towards the end of Phase I. Given the market *is* short, short-run energy demand and hence daily demand for EUAs is determined by economic activity, the choice of the dispatch order (alterations of which are known as fuel switching), and weather variations.

Economic activity has a straightforward effect on emissions and EUA demand. Obviously, in times of lower economic activity, production levels are lower and CO_2 emissions decrease. For example, the recent economic downturn due to the financial crisis was accompanied by an estimated decrease in energy-related CO_2 emissions of 3% (IEA, 2009). Fewer emissions imply lower demand for EUAs and prices should decrease. Correspondingly, higher economic activity is associated with increasing emissions and a higher demand for EUAs. *Ceteris paribus*, the EUA price should thus increase.

The choice of the dispatch order plays a crucial role for short-run carbon abatement in the presence of an emission market (such as the EU-ETS).[5] In fact, changing the order of dispatch has been argued to be the single most important abatement measure in the short run for installations in the power and heat sector (e.g., Christiansen et al., 2005; Kanen, 2006; Bunn and Fezzi, 2008). The dispatch order determines the sequence of different power plants brought into operation (Kanen, 2006). It is applied particularly in the provision of medium and peak load energy, which is mainly provided by coal and natural gas (Schiffer, 2005). Changing the dispatch order, e.g. switching from coal to natural gas, allows a power producer to reduce its carbon emissions per MWh by between 40 and 60%.[6] Installations in the power and heat sector dominate the EU-ETS, accounting for around 75 % of verified emissions around 65 % of allocated emissions in 2009 (see Figure 2). This dominance makes fuel switching an important abatement

[3]The only exception was France, where a small portion of allowances could be transferred from Phase I to Phase II.

[4]From Phase III onwards, the decision on emission reductions inside the EU ETS will be moved from the national to the Community level (European Union, 2009, Art. 51). Additionally, the provision of allowances will be changed from mainly allocation to mainly auctioning. In Phase II only 0.25 % of total allowances are supposed to be auctioned, whereas in Phase III full auctioning becomes the rule for the power sector (European Union, 2009, Art. 19). For other sectors free allocation gradually decreases to 30 % until 2020, while there are exceptions for sectors exposed to international competition with industries not subject to comparable carbon constraints (European Union, 2009, Art. 21 and 24).

[5]Normally, firms face two options for carbon abatement: a reduction of production levels or the investment in new, cleaner technologies. A third option available to firms in the power and heat sector is fuel switching, i.e. changing the order of dispatch in their installations.

[6]See (Bunn and Fezzi (2008) and http://www.pointcarbon.com/news/marketdata/methodology/forward/modeldescriptions/).

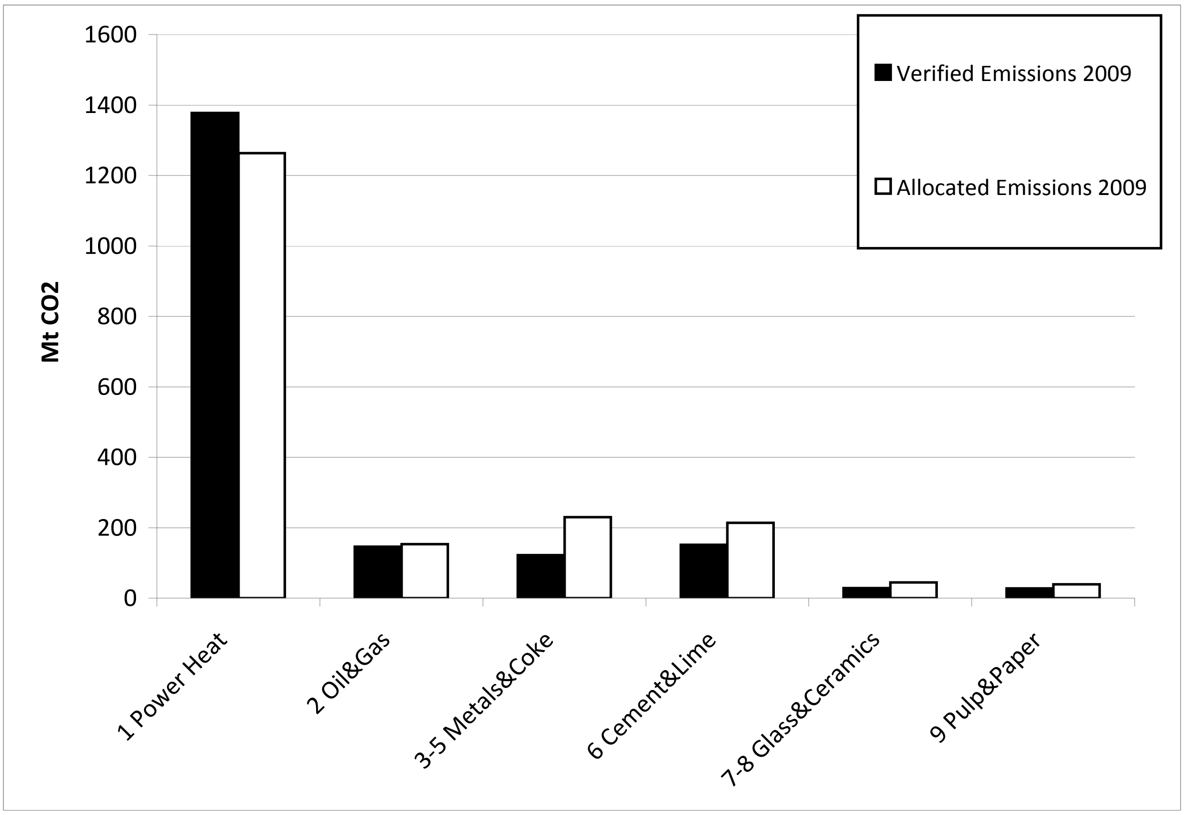

Figure 2: Verified and allocated emissions in the EU ETS in 2009

measure within the EU-ETS zone. However, the potential for reducing carbon emissions by changing the dispatch order varies between countries due to the country-specific composition of the power sectors (see Figure 3 and Table A.1 in Appendix A).

In the absence of carbon prices, the dispatch order between coal and natural gas can be determined by comparing the dark and spark spread. The dark (spark) spread is the gross margin between the revenue from selling one MWh of electricity from a coal(gas)-fired power plant having bought the amount of coal (gas) necessary to produce one MWh of electricity.[7] Thus, the spreads allow for a comparison between the relative profitability of coal- and gas-fired power plants. In the presence of carbon prices, the dark and spark spread have to be corrected to the *clean* dark and *clean* spark spread by including the price of an EUA and the emission factors of coal and gas. Equalizing the clean dark and clean spark spread allows the calculation of the fuel switching price. This is the price that makes a power producer indifferent between producing electricity by using either coal or gas. The fuel switching price is increasing in the gas price and decreasing in the coal price. For example, if the price of gas increases (and hence the fuel switching price), power producers would switch to coal. The resulting additional emissions would lead to a higher demand for EUAs and their price would increase. The induced EUA price reaction to the change of the relative price of coal to gas is

[7] See http://www.pointcarbon.com/news/marketdata/methodology/forward/modeldescriptions/

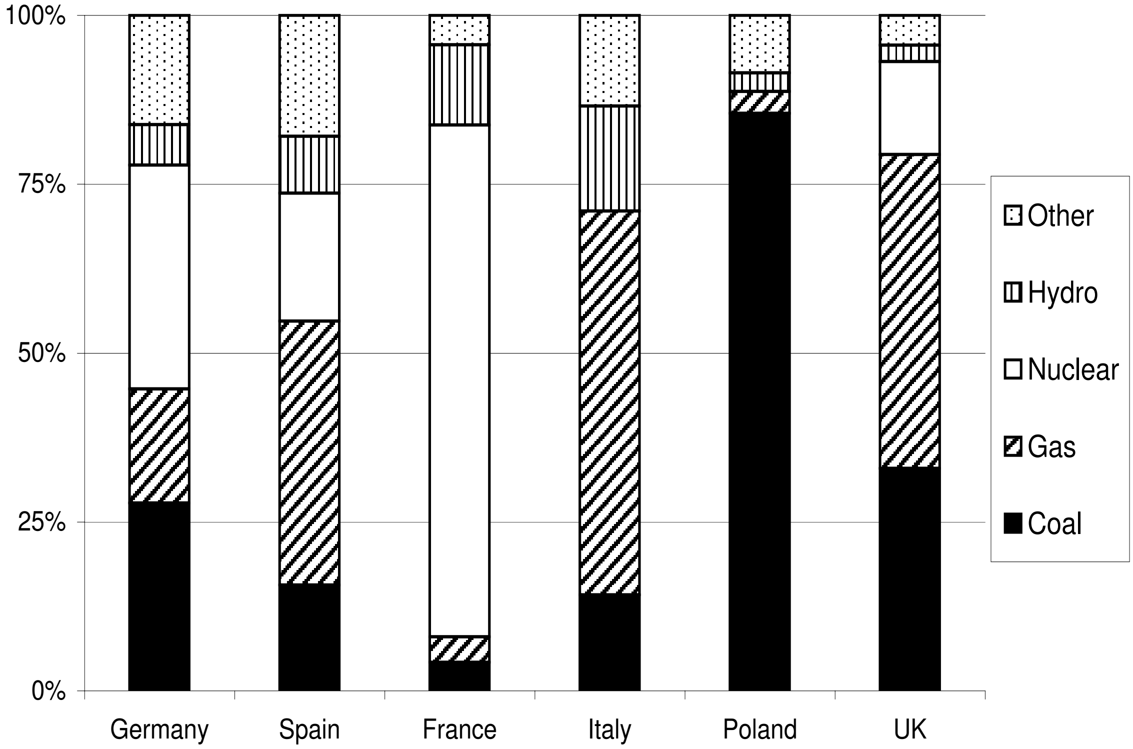

Figure 3: 2008 Electricity production profiles

denoted as the switching effect. In contrast, an absolute change in fuel prices is expected to have a corresponding effect on the demand for fuels and therefore also on EUAs which is denoted as the demand effect.

Weather variations can have an ambiguous impact on demand for EUAs. They influence energy demand but also the provision of carbon-free renewable energy provision. We, in turn, explain the effects of temperature, precipitation, wind, and solar radiation. Extreme temperatures, i.e. more heating or cooling degree days, should have a significant impact on energy demand, emissions and thus on EUA demand (e.g. Considine, 2000). Note that the relation between temperature and energy demand is nonlinear (u-shaped) (Boudoukh et al., 2007; Bunn and Fezzi, 2008). Temperatures below a certain threshold can lead to an increase in electricity and heat demand for heating purposes. Similarly, temperatures above a certain threshold can lead to an increase in electricity demand for cooling purposes. Both events can therefore result in more emissions, higher EUA demand and, hence, a higher EUA price. In temperature-price space, the slope is negative below the lower threshold, positive beyond the upper threshold, and constant in between.

Precipitation, wind speed, and solar radiation influence the provision of carbon-free energy due to their effect on hydro-, wind-, and solarpower generation, respectively (e.g., Hinterman, 2010). Precipitation determines reservoir levels for hydropower generation. Hydropower is a common traditional renewable energy source and constitutes a significant share in power production in several countries, in particular in Nordic countries, ranging from about

50 to almost 100% in Sweden and Norway, respectively. Hydropower has lower marginal costs than conventional generation (Hinterman, 2010) and is mainly used for base load provision instead of peak load provision (Schiffer, 2005). Consequently, lower reservoir levels in particular are expected to have an influence on EUA prices because they imply that base load provision from hydropower has to replaced by conventional generation. In Denmark, for example, carbon emissions from the power and heat sector almost doubled in 1996 compared to 1990 because 1996 was an exceptionally dry year. This implied an increase in coal-fired power generation for exports to Norway and Sweden (Christiansen et al., 2005). Hence, lower precipitation levels are expected to have a positive impact on the EUA price as they lead to a lower amount of carbon-free hydropower and consequently a hihger demand for EUAs.

Similarly, wind speed influences the supply of windpower; solar radiation that of solarpower. The capacity of wind- and solarpower increased rapidly over the past decade, e.g., wind power capacity accounted for 39% and solar photovoltaics for 16% of newly installed European power generating capacity in 2009 (Wilkes and Moccia, 2010; Jäger-Waldau, 2010).[8] In particular, their power provision for peak load and therefore spot electricity provision has rapidly increased. In fact, we already observed the adverse situation of negative spot electricity prices for some hours during the last two years due to very favorable weather conditions (Beneking, 2010). Hence, a higher provision of carbon-free energy due to higher wind speeds or higher solar radiation is expected to decrease the EUA price.

With respect to our exercise of analyzing short-run determinants of EUA prices, we conclude that EUA price variations are only driven by demand variations. Taking into account that unlimited banking is allowed between Phase II and Phase III and that European Union (2009, Art. 13) already specifies the total amount of EUAs for Phase III, supply can be treated as fixed until 2020. Note that this implies that supply cannot be adjusted to deviations in economic activity from the underlying BAU scenario (e.g. due to an economic downturn), which essentially determines to which extend the EUA market is in a short or a long position.

3. Previous Findings

Previous articles on the EU-ETS fall broadly into two categories. The first set analyzes the influence of fundamental factors, such as fuel prices or weather variations, on the EUA price dynamics during Phase I of the ETS. The second set focusses on the stochastic properties of EUA prices by applying term structure or pure time series models in order to explain price dynamics.

The first set contains four papers: Mansanet-Bataller et al. (2007); Rickels et al. (2007); Alberola et al. (2008); Hinterman (2010). We summarize these papers in Table 1 and in Table B.2 in Appendix B.[9]

[8]The installed capacity of windpower amounted to 74 GW and of solarpower to 16GW in Europe at the end of 2009, accounting for around 11 % of European installed power generation capacity (Wilkes and Moccia, 2010; Jäger-Waldau, 2010).

[9]It is important to note that all authors do not estimate only one specification but various specifications as well as for different time periods due to a structural break in the EUA price series during phase I.

Table 1: Empirical studies about influence of fundamental factors in Phase I of the EU ETS

	Mansanet-Bataller et al. (2007)	Rickels et al. (2007)	Alberola et al. (2008)	Hinterman (2010)
Dependent variable	EUA OTC forward price	EUA OTC spot price	EUA OTC spot price	EUA OTC spot price
Influence of fuel switching	prices for brent oil, coal, gas and price ratio gas/coal	prices for brent oil, coal, gas, and price ratios gas/coal and oil/coal	prices for brent oil, coal, gas, electricity and the clean dark spread, clean spark spread, implied fuel switching price	gas and coal price
Influence of weather	Inclusion of either German climatology (mean temperature, mean precipitation, dummies related to extreme hot, extreme cold, extreme dry, and extreme wet days) or European climatology (mean temperature and dummies related to extreme hot and extreme cold days)	European climatology (temperature at extreme cold and hot days, wind speed)	European climatology (mean temperature and dummy variables related to extreme hot and cold days, cross products of 5 dummy variables indicating extreme weather periods and the absolute deviation from the seasonal average)	European Climatology (5 day moving average deviation from their expectation for temperature and precipitation, where temperature deviation is multiplied with dummy variables for winter and summer). Additionally, deviation from expected reservoir levels in Nordic countries.
Other explanatory variables				Financial Times Stock Exchange Eurotop 100 (FTSE), dummy variable for first round of emission verification
Main Findings	Positive effect of oil and gas price and of extremely hot and cold days in Germany, no significant influence of coal price, mean temperature and European climatology .	Positive effect of oil and gas price and of extremely hot and cold days in Europe, negative influence of coal price, no significant influence of wind speed.	Positive effect of oil, gas, and electricity price, and of extremely cold days, negative effects of coal price.	Positive effect of gas price, negative effect of availability of hydropower, no effect of coal, temperature only non-linear effect, no effect of FTSE

The overview shows that all studies find that both the gas and oil price (except Hinterman, 2010)) have a positive influence on the EUA price. However, concerning the oil price effect, it remains unclear if the positive influence can be attributed to a fuel switching effect, to the correlation between the oil and gas price, or rather to the correlation between the oil price to economic activity. Interestingly, Mansanet-Bataller et al. (2007) and Hinterman (2010) find no influence of the coal price, while in Rickels et al. (2007) and Alberola et al. (2008) it is negative, as theory would predict.[10]

All studies find some evidence of the influence of extreme weather events, but following different approaches for capturing the nonlinear relationship between temperature and energy demand. Mansanet-Bataller et al. (2007) and Alberola et al. (2008) construct dummy variables for extreme hot and cold days, Rickels et al. (2007) and Hinterman (2010) use the deviation on extremely hot and cold days from the longtime average. Additionally, Alberola et al. (2008) also include interactions of dummy variables for extreme weather events and the deviations from their longtime averages. Hinterman (2010) includes weather variables in a nonlinear manner by using interactions of weather variables and fuel prices.

In contrast to the other studies, Alberola et al. (2008) also include the switch price and the electricity price in their estimations. This allows testing for the switching effect directly, whereas in the other studies it can only be seen through the influence of the gas and coal price. Including the electricity price allows them to consider the influence of the clean spark and dark spread as well (see Section 2), but might also weaken the theoretical foundation of the model because there seems to be a two-way relationship between electricity price and EUA price.[11]

All four studies reveal that the fundamental influence was still limited when explaining the EUA price dynamics in Phase I, yet EUA prices were often influenced by other non-fundamental factors, like policy announcements and seem to violate the Markov property (e.g., Hinterman, 2010). In all articles, models improve if lagged prices are included, suggesting that market fundamentals are only internalized with some lag.

The second set of articles focusses more on the stochastic properties of EUA prices, rather than on the impact of fundamentals. These studies on carbon finance analyze the differences in EUA price dynamics between periods by considering jumps and spikes as well as phases of high volatility, volatility clustering and heteroscedasticity. They apply term structure models or autoregressive models.

Two papers address the liquidity and efficiency of the EU-ETS. Borak et al. (2006) investigate the pattern of the EU-ETS market focussing on the term structure between future and spot prices of allowances and their stochastic properties. They find that the EUA price behavior differs from those of other commodities, having changed from backwardation towards contango during Phase I.[12] Consequently, for the early period of the EU-ETS, the market was

[10] It is possible that the studies used different coal price series, some of which show rather low daily variations so that their explanatory power for daily EUA prices seems rather limited.

[11] Bunn and Fezzi (2008) and Fell (2010) find evidence for a long-run relationship between the carbon price and the equilibrium price of electricity on a national level (Germany, Uk) as well as in the Nordic region. In contrast, Rickels et al. (2007) find that the long-run relationship between the variables seems not be established on the European level. They conclude that there is no economically relevant long-run relationship in the data as long as the electricity price is not included.

[12] When the future price at point t with delivery in T, is less or equal the spot price at point t, this situation is described as backwardation.

not liquid or efficient due to a positive convenience yield on futures. Daskalakis et al. (2009) focus on the implications of restrictions on banking between the different EU-ETS phases when analyzing the pricing of EUA futures. They show how the fact that EUAs practically became worthless at the end of Phase I leads to problems in efficient pricing of derivatives on EUAs and therefore to additional costs in terms of a positive convenience yield, which again implies adverse effect on market liquidity and efficiency. The two examples show that the pricing of EUAs during Phase I was likely to be error-ridden so that an analysis of price determinants during this phase may not be reliable.

A number of articles focus on the stochastic dynamics in daily EUA prices and returns, confirming the presence of stylized facts like skewness, excess kurtosis, and different phases of volatility behavior (e.g., Paolella and Taschini, 2008; Benz and Trück, 2009; Conrad et al., 2010). They show that the influence of fundamentals can be included in the mean equation, but that the presence of heteroscedasticity requires a carefully specification of the variance equation (e.g. Paolella and Taschini, 2008). Even though the studies differ in how they model the mean equation, all of them suggest the use of GARCH-type models for the variance equation. The articles from the previous set either apply the Newey-West estimator (Mansanet-Bataller et al., 2007), or specify the variance equation as GARCH (Rickels et al., 2007; Alberola et al., 2008; Hinterman, 2010) in order to obtain heteroscedasticity consistent covariances.

4. Method

4.1. Data

We collected our data according to the theoretical considerations in Section 2 in the following categories: EUA prices, fuels prices, economic activity, and climatology. Table 2 provides an overview of the various variables.

We took EUA spot and forward prices from Point Carbon.[13] The EUA spot price series ranges from June 12th, 2008 until September 7th, 2010; the EUA future December 2010 price series ranges from January, 2nd, 2008 until September 7th, 2010. The EUA spot price series is only available from June 2008 onwards due to a delayed introduction of EUAs for the spot market.

We collected the spot prices for gas, coal, and oil from the Dow Jones, IHS McCloskey, and ICIS Pricing, respectively. The coal spot price is calculated as an average of coal prices from South Africa, Columbia, and Australia delivered to Amsterdam-Rotterdam-Antwerp (ARA). We collected the forward prices for gas, coal, and oil from the Intercontinental Exchange (ICE) Futures Europe and another two forward gas prices from the National Balancing Point (NBP) in UK. The NBP is the pricing and delivery point for the ICE natural gas future contracts.[14] We converted the gas price from Pence/therm into EUR/MWh by

$$\mathrm{G}\frac{pence}{therm} * \frac{3.6\frac{GJ}{MWh}}{0.1055\frac{GJ}{therm}} * \frac{1}{0.5} * \frac{1}{100} * \text{exchange rate}\frac{EUR}{GBP} = \mathrm{G}\frac{EUR}{MWh}, \tag{1}$$

Oppositely, the market is said to exhibit contango, when the future price for delivery in T exceeds the spot price in t.

[13]http://www.pointcarbon.com/news/marketdata/euets/forward/eua/

[14]We used two different data providers because the gas price time series shows a remarkable jump from August 29th, 2008 to September 2nd, 2008. The price jump was present in both time series.

Table 2: Data for EUA estimation

Category	Variable	Specification	Source	Name	Unit
CO_2	EUA	Spot	Point Carbon	co2_spot	Euro/tCO_2
		Dec2010	Point Carbon	co2_dec10	Euro/tCO_2
Fuel	Zeebrugge Natural Gas	Spot	Dow Jones	gas_spot	Euro/MWh
	UK Natural Gas	1M Future	ICE	gas_f1_ice	Euro/MWh
		1M Future	NBP	gas_f1_nbp	Euro/MWh
		6M Future	NBP	gas_f6_nbp	Euro/MWh
	ARA Coal	Spot	IHS Mc Closkey	coal_spot	Euro/MWh
		1M Future	ICE	coal_f1	Euro/MWh
	Crude Oil Brent	Spot	ICIS Pricing	oil_spot	Euro/barrel
		1M Future	ICE	oil_f1	Euro/barrel
		3M Future	ICE	oil_f3	Euro/barrel
	Switching Price	Spot	Own Calculation	switch_spot	Euro/tCO_2
		1M Future	Own Calculation	switch_f1	Euro/tCO_2
Economic activity	Oil & Gas Industry	Price Index	EUROSTOXX Oil & Gas	index_og	Euro
	Electricity Industry	Price Index	EUROSTOXX Utilities	index_elec	Euro
	Top 100 Companies	Price Index	Euronext	index_euronext	Euro
Climatology	Temperature	Deviation at cold days	ECA&D	cold_dev	$^\circ$C
		Deviation at hot days	ECA&D	hot_dev	$^\circ$C
	Wind	Deviation per day in GER	ECA&D	wind_dev	m/s
	Windpower	per day in GER	windmonitor	windpower	MWh
		deviation per day GER	windmonitor	wp_dev	MWh
	Reservoir-levels	deviation per week Scandinavia and Spain	nordpool and Department of Environment Spain	res_dev_high and res_dev_low	dummy

where the value in the denominator in the second fraction assumes a heat rate of 0.5 for a gas fired power plant. We converted the coal price from USD/t into EUR/MWh by

$$\text{C}\frac{USD}{tSKE} * \frac{3.6\frac{GJ}{MWh}}{29.308\frac{GJ}{tSKE}} * \frac{1}{0.38} * \text{exchange rate}\frac{EUR}{USD} = \text{C}\frac{EUR}{MWh}, \tag{2}$$

where SKE is an abbreviation for the German energy unit "Steinkohleeinheit" (coal equivalent) to measure the energy content of hard coal. The value in the denominator in the second fraction assumes a heat rate of 0.38 for a coal fired power plant. Both heat rates are taken from Point Carbon[15] and Tendances Carbone[16], where the heat rate of 0.5 for gas fired power plants is used by both; the heat rate of 0.38 for coal fired power plants is calculated as an average between their two differential rates. We converted the oil price from USD/BBL into EUR/BBL and not in EUR/MWh

[15] http://www.pointcarbon.com/news/marketdata/methodology/forward/modeldescriptions/

[16] http://www.caissedesdepots.fr/fileadmin/PDF/finance_carbone/document_methodologie_tendances_carbone_en_v4.pdf

because we assume the oil price to be an indicator for economic activity or an indicator for gas price development, rather than for an input fuel for power generation. The daily exchange rate is provided by WM/Reuters. All fuel price series range from January 2nd, 2008 until September 7th, 2010.

Additionally, we calculated the implied fuel switching price, which is the artificial carbon price that makes an emitter indifferent between generating electricity by gas or coal if he has to pay for the carbon emissions:

$$\text{switching price}\frac{EUR}{tC_2} = \frac{\text{generation costs gas}\frac{EUR}{MWh} - \text{generation costs coal}\frac{EUR}{MWh}}{\text{carbon emission coal}\frac{tCO_2}{MWh} - \text{carbon emission gas}\frac{tCO_2}{MWh}}, \tag{3}$$

where the carbon emissions for coal and gas are

$$CO_2^{coal} = 0.094\frac{tCO_2}{GJ} * 3.6\frac{GJ}{MWh} * \frac{1}{0.38} \quad \text{and} \quad CO_2^{gas} = 0.056\frac{tCO_2}{GJ} * 3.6\frac{GJ}{MWh} * \frac{1}{0.50}. \tag{4}$$

Again, 0.38 and 0.50 are the heat rates, and 0.094 and 0.056 are the emission factors for coal and gas, respectively. The energy unit conversion values are taken from Schiffer (2005). The emission factors are also taken from Point Carbon and Tendances Carbone.

Moreover, we collected three price indices to measure overall economic activity (Euronext 100), economic activity in the electricity sector (EUROSTOXX Utilities), and economic activity in the oil and gas sector (EUROSTOXX Oil & Gas). For the latter two, the companies are categorized by the Industry Classification Benchmark according to their primary source of revenue.

The climatology category includes weather variables, daily mean European temperatures and daily mean German wind speed, but also variables which *depend* on weather variables, such as daily German wind power feed (wind speed) and weekly reservoir levels for hydropower in Scandinavia and Spain (precipitation).

We took the daily mean temperature values and daily mean wind speed values from the European Climate Assessment and Dataset (Klein Tank et al., 2002)[17], the daily German wind power feed from Windmonitor[18], and the weekly reservoir levels from Nord Pool ASA[19] and from the Spanish Department of the Environment[20].

Daily mean temperature values stem from various stations in Germany, France, Italy, Poland, Spain, and UK. We used them to calculate the temperature deviation on hot and cold days at the European Level. The six countries represent 66 % of allocated carbon emissions in the ETS.[21] The German data range from January 1st, 1948 until July 31st, 2010. All other temperature data range from January 1st, 1946 until July 31st, 2010. We calculated the average mean temperature for each country and for each day by weighting the various stations by population. We used these values to calculate country-specific long-term average temperature values for each day of the year. We picked

[17] Data downloaded from http://eca.knmi.nl/dailydata/predefinedseries.php.

[18] http://reisi.iset.uni-kassel.de/pls/w3reisiwebdad/www_reisi_page_new.show_page

[19] http://www.nordpool.com/marketinfo/powersystemdata/

[20] http://servicios3.marm.es/BoleHWeb/accion/cargador_pantalla.htm?screen_code=70005&screen_language=&bh_number=31 &bh_year=2010&bh_emb_tipo=3

[21] http://ec.europa.eu/environment/climat/emission/citl_en_phase_ii.htm

the days which represent the 5th and 95th percentiles, representing the coldest and hottest days. Then we measured the deviation of the daily temperature from the long-term average in the period from January 2nd, 2008 until July 31st, 2010. Finally, we aggregated these deviations by weighting the 6 countries according to the allocated carbon emissions in the NAPs.[22] Due to the non-linear influence of temperature on emissions (see Section 2), we summarized this deviation in two statistics: deviation on cold days and on hot days. Consequently, the two variables, hot_dev and cold_dev, contain information on those hot and cold days at which the temperature was higher or lower than expected.

We took daily mean wind speed values from various stations in Germany.[23] The data ranges from May 1st, 1972 until July 31st, 2010. We calculated an average value for daily wind speed by first calculating a simple mean for each federal state and then aggregating these values weighted by installed wind power in each federal state. Following the same approach with the long-term daily average value, we calculated daily deviation from January 2nd, 2008 until July 31st, 2010. In contrast to temperature, the influence of wind speed on emissions is linear (negative), so that we summarized the deviation in one variable (wind_dev). Additionally, in order to test for the influence of carbon-free windpower, we also included data on the daily windpower feed in Germany, ranging from January 2nd, 2008 to September 7th, 2010. We included both the daily values (windpower) and the daily deviation from the simple mean (wp_dev).

We used weekly reservoir levels used for hydropower generation in Scandinavia (excluding Denmark) and Spain because both regions together represent about 51 % of the European hydropower market. The data range from February, 26th, 2008 to August, 3rd, 2010. We included variation in reservoir levels by two variables. The first, res_dev_low is a dummy which takes the value of 1 for all days of a week if the weekly reservoir level is below the 10th percentile of all weekly reservoir levels. The second, res_dev_high, is a dummy which takes the value 1 for all days of a week if the weekly reservoir is above the 90th percentile of all weekly reservoir levels.

4.2. Estimation

We estimate four different models, named Theory, Fundamental, Autoregressive, and Best, to test which factors determine EUA price dynamics. The Theory Model is based on the theoretical considerations in Section 2 and tests for the influence of fuel switching, economic activity, and weather variables. In the Fundamental Model we select a parsimonious equation, but limit the set of explanatory variables to the fundamental variables discussed in Table 2. Selection is based only on improvement in explanatory power, as measured by the information criteria, and not on theoretical considerations. Moreover, only variables at the 5 % significance level are included. The Autoregressive Model applies a pure time series equation including only autoregressive and moving average terms. Finally, for the Best Model, we again select a parsimonious equation, but do not limit the set of explanatory variables as before.

[22] Germany, 0.3246; UK, 0.1765; Poland, 0.1498; Italy, 0.1448; Spain, 0.1094; France, 0.0948

[23] In order to represent 60 % of the European wind power market, we should have also taken data from Spain (http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=0&language=en&pcode=ten00093). However, we had problems finding good data for wind speed at a sufficient regional resolution for Spain so that we only used data from Germany.

Therefore, the model also includes autoregressive and moving average terms. For all models, we chose the optimal lag order for the explanatory variables also according to improvement in explanatory power and significance.

The time series for the EUA prices, the fuel prices, and the indices are all stationary in first differences. The time series for the weather variables are stationary in levels. Appropriate tests show that there is no difference in variance between the first difference in EUA Spot and Future Dec2010 prices. Consequently, we chose the latter as the dependent variable because the time series already begins on January 2nd, 2008, whereas the former only begins on June 12th, 2008.

The fuel price series includes various prices for the same fuel, but at different maturities, e.g. spot, one month forward, and six month forward for the gas price. As these prices are related, a multicollinearity problem can arise. Consequently, in Table C.3 in Appendix C we show auxiliary regressions between the fuel prices in order to check for multicollinearity. The results show that a multicollinearity problem would only arise if oil prices of different maturities were included in the regressions. In contrast, the variations in prices of different maturities for gas and coal seem to entail distinct information. In Table C.3 we also show the auxiliary regressions for the fuel prices included in the Fundamental and Best model. The adjusted R^2 indicates that the variation in the coal and oil price is, to some extent, explained by the other fuel prices. But they also indicate that the variance inflation factors are sufficiently below 10 and also remain below the corresponding R^2s of the mean equations.

Estimating the four models in a first run, an ARCH-LM test reveals the existence of autoregressive conditional heteroscedasticity in the residuals. Therefore, we specified the variance equations for the four equations as GARCH(1,1). Without any knowledge of the real distribution, we kept the assumption of a Gaussian Error distribution, but used Bollerslev-Wooldridge robust standard errors and covariances to obtain heteroscedasticity consistent covariance.[24]

Table 3 shows the regression results of the mean and variance equation for the four models. For all equations the sample size is 688. L^x indicates the lag order x, D indicates first differences. The Table also shows the regression statistics: the adjusted R^2, the general R^2,[25] the Akaike info criterion, and the Schwarz criterion. Additionally, it shows the Ljung-Box Q(4) statistic for serial correlation, where a lag order of 4 is chosen by $\leq [2\sqrt{689}]$, and the ARCH-LM (1) statistic for remaining heteroscedasticity in the residuals. The Ljung-Box statistic indicates that the first two equations still show serial correlation, whereas it disappears in the second two equations due to the inclusion of autoregressive and moving average terms. The ARCH-LM statistic reveals that heteroscedasticity is removed by the GARCH(1,1) specification of the variance.

[24] By quasi maximum likelihood theory the maximization of a misspecified Gauss log-likelihood function due to non-normal innovations is justified.

[25] $R_g^2 = 1 - exp[-\frac{2}{n}(l(\hat{\beta}) - l(0))]$, where $l(\hat{\beta})$ and $l(0)$ are the log likelihoods of the fitted and the 'null' model, and n is the sample size (Nagelkerke, 1991).

Table 3: Regression results

	Theory	Fundamental	Autoregressive	Best
		Mean equation: D_EUA_dec2010		
L^0D_gas_spot	——	-0.0214*** [0.008]	——	-0.0217*** [0.006]
L^0D_gas_f1	——	0.0351*** [0.000]	——	0.0332*** [0.000]
L^0D_gas_f6	0.0113 [0.275]	——	——	——
L^0D_coal_f1	——	0.1413*** [0.000]	——	0.1440*** [0.000]
L^0D_oil_spot	——	0.0482*** [0.000]	——	0.0520*** [0.000]
L^0D_switch_spot	-0.0090*** [0.006]	——	——	——
L^0D_switch_f1	0.0156*** [0.001]	——	——	——
L^0D_index_og	0.0217*** [0.000]	0.0128*** [0.000]	——	0.0134*** [0.000]
L^0hot_dev	-0.0647*** [0.006]	-0.0628** [0.011]	——	-0.0550** [0.031]
L^0cold_dev	-0.0043 [0.687]	——	——	——
L^{-1}wp_dev	-0.0001* [0.077]	——	——	——
L^0res_high	-0.0426 [0.414]	——	——	——
L^0res_low	0.0584** [0.049]	——		
AR(1)	——	——	-0.5719*** [0.005]	——
MA(1)	——	——	0.6653*** [0.000]	0.1949*** [0.000]
		Variance Equations: $Resid^2$		
CONST	0.0021 [0.18]	0.0022 [0.15]	0.0024 [0.19]	0.0022 [0.13]
$RESID(-1)^2$	0.0932*** [0.00]	0.1039*** [0.00]	0.1045*** [0.00]	0.1069*** [0.00]
GARCH(-1)	0.8961*** [0.00]	0.8836*** [0.00]	0.8870*** [0.00]	0.8799*** [0.00]
adjusted R^2	0.1650	0.2470	0.0136	0.2675
general R^2	0.1525	0.2269	0.0089	0.2491
Akaike	0.7905	0.6889	0.9270	0.6625
Schwarz	0.8697	0.7482	0.9600	0.7284
Q(4)	15.827 [0.003]	25.099 [0.000]	4.594 [0.101]	5.822 [0.120]
ARCH_LM(1)	0.4422 [0.506]	0.167 [0.683]	1.6198 [0.204]	0.645 [0.422]

***/**/* Significance at the 1%/5%/10% level; p-value in parenthesis

5. Discussion

In order to test which factors influence EUA price dynamics, we estimate four different regression models: Theory, Fundamental, Autoregressive, and Best. The estimation results are presented in Table 3. As mentioned above, the model Theory includes all variables that should influence the EUA price according to the theoretical considerations in Section 2. Fuel prices (gas and coal) enter the model via the switching price, which is included once based on a spot and once on a one month forward price. The oil price is not included because there is only a weak theoretical foundation for fuel switching towards oil-fired power plants. The oil price might also serve as a proxy for the economic activity or as predictor for natural gas price development, but we capture the former effect by including a stock market price index, measuring economic activity, and the latter effect by including the six month forward price for natural gas. Additionally, we include variables to measure the influence of weather variation.

The regression results in Table 3 show that the two switching prices (i.e. the one based on spot and the one based on forward prices) influence the EUA price with an opposite sign. The forward switching price has a positive influence, but the spot switching price has a negative influence. The sign for the forward switching price is in line with theory, indicating that fuel switching from gas to coal takes place. The negative coefficient of the spot price is not in line with theory. Note however that the variation in the spot switching price is mainly driven by variation in the spot gas price as the spot coal price shows a very low daily variation. Therefore, the negative effect is mainly the result of variations in the spot gas price, which suggest that a demand effect might dominate the switching effect in the very short run, since a higher (lower) gas price also provides incentives for lower (higher) electricity supply and, in turn, lower (higher) energy demand. The influence of the six month forward gas price is not significant, however the sign is in line with theory and would also suggest fuel switching. Also, the influence of the stock market price index is in line with theory, confirming that higher economic activity leads to higher energy demand and carbon emissions and, hence, to a higher carbon price.

Among the weather variables, only the deviation of temperature on hot days, the deviation of wind power feed in Germany and the dummy for lower deviation of average reservoir levels in Spain and the Nordic countries is significant. The negative sign for temperature is not in line with theory because higher temperatures are expected to *increase* energy demand for cooling purposes. One explanation for the opposite sign could be the fact that higher temperatures are the consequence of higher solar radiation (e.g., Bristowa and Campbella, 1984). Continuous high solar radiation is particularly present on hot days in the summer season, providing ideal conditions for carbon-free solarpower production. Consequently, the negative influence of temperatures on EUA prices might indicate that a carbon-free energy effect dominates the initially expected energy demand effect. To confirm this result, solar radiation should be included as a variable and not just approximated by temperature deviation on hot days. Unfortunately, the available data does not allow us to do that. However, our speculation about an increasing importance of renewable energy provision is confirmed by the two other significant weather variations, which are both in line with theory. Although the influence of the deviation of windpower feed is only significant at a 10 % level, it has to acknowledged that the variable only captures the windpower feed in Germany (see Section 4.2 above), but is used for a prediction at the European level. Consequently, the inclusion of European data might lead to a higher significance level. The influence of reservoir levels has already been shown by previous studies (e.g., Hinterman, 2010). However, the significance of just the negative deviation confirms that hydropower is mainly used for base load provision but not for peak load provision because a positive deviation would rather be stored and used for base load supply later on.

In the Fundamental Model, we fit a parsimonious model for the explanation of EUA price dynamics, but restrict the set of regressors to the fundamental variables. The regression results show that including the fuel prices directly, and not in the aggregated form of the implied switching price, significantly increases the explanatory power. The coefficients of the spot and one month forward gas price underpin the result from the Theory regression: fuel switching dominates for the one month forward prices, but the demand effect dominates for immediate (spot) price changes. The effect of temperature also remains robust and unchanged in sign. However, the theoretical considerations are somehow rebutted by the positive coefficient of the coal price. This result is neither in line with the switching effect nor with the demand effect. In fact, for fuel switching, the *relative* coal price (and not the stand-alone price) should matter so that the estimated positive coefficient does not necessarily imply that fuel switching does not take place. Nevertheless, it remains puzzling to observe this influence, in particular because of the rather large effect size as well as the fact that previous studies found opposite or insignificant results.

The effect of the oil price is positive and including it significantly improves the model fit. Yet, as mentioned above, a theoretical foundation for the positive influence is lacking. The oil price should not matter for fuel switching, primarily because the share of electricity production based on oil is very low. Nevertheless, the sign suggests fuel switching from oil to coal. The positive coefficient could also result from the oil price strongly correlating with overall economic activity. However, we rule out this explanation as the coefficient of the other proxy for economic activity (the stock price index) also remains significant. Therefore, only the explanation stating that the oil price is a good predictor for gas price development still stands. However, even though the *sign* of the coefficient of the six month forward price for gas underpins this argument, gas price formation seems to internalize this information only with a lag because it is not significant.

Overall, the unexpected effects of the coal and oil prices suggest that something is missing from our regressions. In particular, there seems to be some development which is positively correlated with both the demand for energy (and thereby affecting the EUA price) and for coal (thereby affecting the coal price). In this case, the variation in coal prices would reflect the effect of the omitted variable and mistakenly suggest a positive effect of coal prices on EUA prices. The Q-test statistic of the Fundamental Model supports our suspicion of an omitted variable bias. It indicates that autocorrelation is still present, implying some sort of inertia in the EUA price series that is not picked up by our explanatory variables. In order to deal with the autocorrelation problem, it is necessary to introduce lagged dependent variables. However, Hinterman (2010) argues that lagged terms should not be included in a regression trying to explain past developments, but only for forecasting purposes. Nevertheless we also estimate a pure autoregressive model in order to compare its explanatory power to a model including fundamentals.

The regression results of the Autoregressive Model show that both explanatory lagged terms are statistically significant. However, the adjusted R^2 conveys that the explanatory power is extremely low. Hence, a model including fundamentals strongly outperforms a pure autoregressive approach. Yet, the regression statistics show that autocorrelation is now removed.

Thus, the Best Model includes both the fundamental explanatory variables from the second model and a moving average term from the third model in order to remove autocorrelation. We specify the Best Model based on the usual information criteria. Even though the inclusion of the moving average term slightly improves the model fit, the coefficients of the fundamental variables are almost identical to those in the Fundamental Model. Yet, the significance of the moving average term indicates that an important variable seems to be missing from the model. The violation of the Markov property indicates that there are still inefficiencies in the EUA market.

Taken altogether, our findings highlight two problems of the EUA market in Phase II: the presence of serial correlation and the positive coefficient of the coal price, contradicting theoretical considerations. One reason for these phenomena could be that the market again turned into a long position due to the economic crisis in fall 2008. Whereas verified emissions exceeded allocated emissions by around 8% in 2008, they fell behind allocated emissions by 5% in 2009.[26] In order to test whether the results are in line with theory when the market is short, we estimated the regressions on subsamples before and after the economic crisis separately. The signs of the coefficients, in particular the one of the coal price, did not change. Nevertheless, the strategic behavior of market participants might be influenced by the long position of the market in Phase II. According to Grubb et al. (2009, p.12), “the allowance price is now sustained mainly by the prospect of banking allowances forward into the much tougher Phase III of the scheme”, indicating potentially missing variables in our model.

We would like to end this discussion with a short comparison of the performance of our models to previous attempts by the other authors. Even with our Best model we obtain much smaller values for the explanatory power as measured by the adjusted R^2 and general R^2 than Mansanet-Bataller et al. (2007), Alberola et al. (2008), and Hinterman (2010). The higher adjusted R^2 in Alberola et al. (2008) can to some extent be explained by the inclusion of the electricity price, which we left out due to the cointegration issue that involves many theoretical considerations with respect to the European energy market. As we were were looking for just a simple explanation for short-term EUA price dynamics, this was beyond scope of our paper. The higher general R^2 in Hinterman (2010) can to some extent be explained by the inclusion of the non-linear terms, which assume e.g. interactions between fuel and weather variables. We did not follow this approach because could not find a sound theoretical foundation, even though this approach might be promising with respect to forecasting. Overall, we wonder that the previous studies, in particular Mansanet-Bataller et al. (2007), find such high explanatory power in their models, considering that they try to explain first differences of daily market data in an even more immature market than Phase II. In comparison to Rickels et al. (2007), we find a clear improvement in the model’s explanatory power.

[26] http://ec.europa.eu/environment/climat/emission/citl_en_phase_ii.htm

6. Conclusion

In this paper, we analyze whether fundamental factors, i.e. fuel prices, economic activity, and weather, can adequately explain EUA price dynamics during Phase II of the EU-ETS. Understanding the impact of fundamentals on price dynamics in the world's largest market for emission allowances is not only important for an efficient design of such allowance markets in other regions of the world, but also in order to learn more about carbon abatement cost. Even though our results show that fundamentals explain price dynamics reasonably well, the market still shows signs of immaturity and inefficiency because the Markov property is violated. An empirical model based on fundamental variables still displays autocorrelation and can be improved by adding autoregressive terms. Most importantly, we estimate a positive influence of the coal price on the EUA price, which weakens the theoretical considerations on fuel switching as a major carbon abatement mechanism within the EU-ETS.

A further interesting observation is suggested by our estimate for the influence of unusually hot days on the EUA price. We estimate a negative influence of such extreme weather events on the EUA price, even though theory would predict a positive impact because more cooling is required on hot days, raising energy demand and, consequently, the EUA price. A possible solution for this puzzle is that higher solar radiation on unusually hot days allows more solarpower to be fed into the grid. Power producers can then use electricity generated by this carbon-free source for the provision of peak load, and do not have to rely on coal- or gas-based sources. It would be interesting to include appropriate data for solarpower provision in the regression in order to give more substance to this idea. In general however, we find notable evidence for an increasing influence of carbon-free renewable energy on the EUA price: unusually high wind speed in Germany, which implies a higher amount of wind power in the grid, is associated with a declining EUA price. Furthermore, unusually low reservoir levels in Spain and the Nordic countries, which imply lower amounts of hydropower in the grid, are associated with a increasing EUA price.

Further research on EUA price dynamics should solve the puzzle of the positive coal price effect and answer the question of what drives both energy demand and coal price, therefore also testing the relevance of fuel switching for carbon abatement. Additionally, it should include better data representing the provision of renewable energy (e.g., daily solar radiation). Our empirical results also suggest that further theoretical work with respect to an efficient design of cap-and-trade systems is needed. In particular it should explore a possible implementation of a more flexible supply mechanism in order to react to unexpected variations in economic activity. Nonetheless, even though the EUA market still shows signs of inefficiencies, it is noteworthy that the EU-ETS has already achieved real emission reductions between 120–300 Mt CO_2 throughout Phase I despite the over-allocation of EUAs (Ellerman and Buchner, 2008; Grubb et al., 2009). Moreover, these reductions have been achieved at costs significantly lower than those projected (Grubb et al., 2009).

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Appendices

Appendix A.

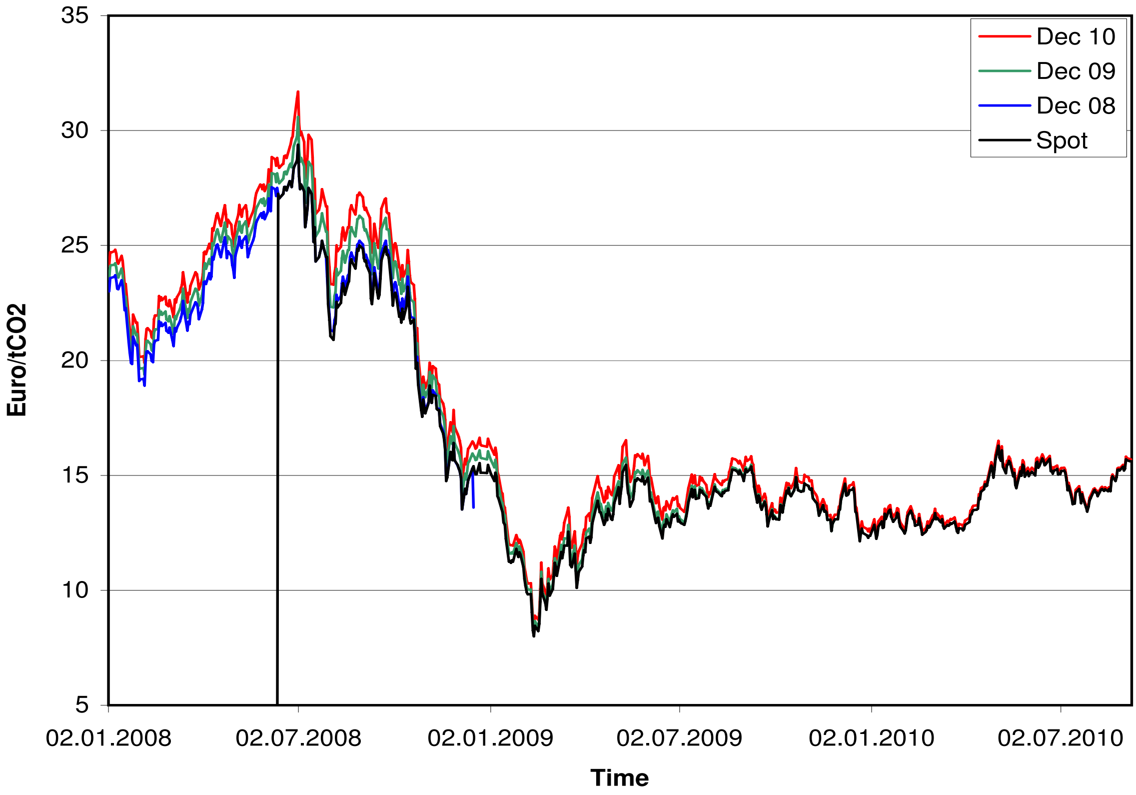

Figure A.4: Price dynamics for EUA spot and forward market for Phase II

Table A.1: 2008 Electricity production profiles

	Germany	Spain	France	Italy	Poland	UK
Total (GWh)	448.6	311.1	579.9	303.8	98.2	380.6
Coal	124.6	48.7	24.4	43.1	83.9	125.3
Gas	75.9	121.6	21.9	172.7	3.2	176.7
Petroleum products	8.6	18.0	5.9	31.5	2.3	6.1
Nuclear	148.5	59.0	439.5	0.0	0.0	52.5
Hydro	27.0	26.1	68.8	47.2	2.7	9.3
Wind	40.6	32.2	5.7	4.9	0.8	7.1
Biomass/Waste	23.5	5.6	13.7	4.5	5.2	3.6

Appendix B.

Table B.2: Empirical studies about influence of fundamental factors in Phase I of the EU ETS: data sources and econometric approach

	Mansanet-Bataller et al. (2007)	Rickels et al. (2007)	Alberola et al. (2008)	Hinterman (2010)
Energy price data	daily energy forward prices from the International Petroleum Exchange (brent oil and natural gas) and from Tradition Financial Services (coal TFS API 2 Index)	daily spot energy prices from the Sachverständigenrat zur Begutachtung der Gesamtwirtschaftlichen Lage (brent oil), from the Financial Times London (euro gas traded in Zeebrugge) and the global coal RB Index.	daily brent crude futures Month ahead price negotiated on the Intercontinental Futures Exchange, daily futures Month Ahead natural gas price negotiated on Zeebrugge Hub, the daily coal futures month ahead price CIF ARA, the price of electricity Powernext is the contract of futures Month Ahead Base. The spreads and the switching price include the peak electricity price.	ICE month-ahead futures and Zeebrugge spot prices for UK natural gas, TTF year-ahead contracts for natural gas in continental Europe. McCloskey coal marker for North-Western Europe.
Weather price data	German weather data from the Deutscher Wetterdienst and European weather index from Powernext	Weather indices were calculated by the HSH N Financial Markets Advisory AG	European weather from Powernext and European temperature indices from Tendance Carbone.	Temperature and Precipitation from the European Climate Assessment and Dataset and weekly nordic reservoir levels from Nordpool exchange.
Econometric approach	OLS with Newey-West covariance matrix estimator	OLS with variance equation specified as GARCH (1,1), where the covariance matrix is adjusted with the BHHH algorithm	OLS with a Newey-West Heteroscedastic-Consistent Covariance Matrix	Auto-regressive Conditional Heteroskedasticicy (ARCH) term of order 1

Appendix C.

Table C.3: Auxiliary regressions results for fuel prices

gas Prices					
	d_gas_spot	d_gas_f1	d_gas_f6		adjusted. R^2
d_gas_spot	—-	-0.049 (0.407)	0.203 (0.000)		0.007
d_gas_f1	0.058 (0.209)	—-	0.146 (0.156)		0.011
d_gas_f6	0.120 (0.176)	0.103 (0.019)	—-		0.022
Coal prices					
	d_coal_spot	d_coal_f1			adjusted. R^2
d_coal_spot	—-	-0.218 (0.057)			-0.005
d_coal_f1		—-	0.0211 (0.323)		-0.004
oil prices					
	d_oil_spot	d_oil_f1	d_oil_f3		adjusted. R^2
d_oil_spot	—-	1.462 (0.000)	-0.192 (0.000)		0.995
d_oil_f1	-0.214 (0.000)	—-	1.251 (0.000)		0.989
d_oil_f3	-0.214 (0.000)	1.252 (0.000)	—-		0.989
implied switching prices					
	d_switch_spot	d_switch_f1			adjusted. R^2
d_switch_spot	—-	-0.046 (0.457)			-0.002
d_switch_f1	0.008	—-			-0.000
fuel prices					
	d_gas_spot	d_gas_f1	d_coal_f1	d_oil_f1	adjusted. R^2
d_gas_spot	—-	-0.068 (0.260)	0.120 (0.393)	0.077 (0.113)	-0.001
d_gas_f1	0.017 (0.674)	—-	0.768 (0.000)	0.068 (0.138)	0.058
d_coal_f1	0.010 (0.290)	0.059 (0.000)	—-	0.081	0.141
d_oil_f1	0.047 (0.064)	0.007 (0.855)	0.752 (0.000)	—-	0.119