Carbon Price Formation in Phase III of the EU ETS

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Abstract

In recent years, carbon price formation was increasingly driven by a various set of fundamentals from compliance sectors as well as speculative expectations of longer-term developments. I propose a model that assumes the traded emissions allowance returns to depend on short- and long-term horizons of price expectations based on supply and demand, which are composed of the discounted long-term balance and short-run demand from physical compliance demand and speculative traders' expectations. Applying an empirical model which proxies changes in long-term expectations using sentiment indices constructed on relevant news headlines and short-term returns from fuel returns and stock returns, I find statistical evidence that EUA returns depend on a combination of both time horizons with expected signs of estimated elasticities.

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Abbreviations

API2: API #2 Coal Price Index published in the Argus/McCloskey Coal Price Index Report (delivered into Amsterdam, Rotterdam, Antwerp)
Btu: British thermal unit
CCGT: Combined-cycle gas turbine
CDS: Clean Dark Spread
CI: Confidence interval
CIF: Carbon intensity factor
CO2: Carbon dioxide
coef.: Coefficient
CSI: Carbon sentiment index
CSS: Clean Spark Spread
Dec: December
ECF: Energy conversion factor
EEX: European Energy Exchange
EU: European Union
EU ETS: European Union Emission Trading Scheme
EUA: European Emission Allowance
FEF: Fuel efficiency factor
GDP: Gross domestic product
MAC: Marginal abatement cost
MSR: Market Stability Reserve
MWh: Megawatt hour
NCG: NetConnect Germany
OLS: Ordinary least squares
p-val.: P-value
RSI: Renewable sentiment index
std. err.: Standard error
t, mt: (Metric) ton
TP3 (1, 2, 4): Trading Phase 3 (1, 2, 4) of the EU ETS

1. Introduction

The European Union's Emission Trading Scheme (EU ETS) is widely recognized as a core instrument of the Union for implementing its emission reduction targets, namely carbon neutrality by 2050. Introduced in 2005 as a so-called cap-and-trade regulation, it aims to reduce aggregate emissions within a legally binding framework to reduce overall emissions from covered sectors at least cost. After years of limited significance in practice, partly due to issues of (inelastic) oversupply, major revisions - such as the so-called Market Stability Reserve (MSR) - expressed the Union's commitment to more ambitious supply reductions, driving the price to levels where marginal carbon reductions were incentivized. As a notable example, the EU ETS periodically incentivized fuel-switching from coal to less polluting gas in electricity generation. In parallel, related policy developments implying more strict emission reduction targets additionally contributed to market participants' increasing expectation of expected supply tightenings and started an era of increased credibility of such measures. With the continuous inflow of speculative money and new classes of investors, EU ETS allowances (EUAs) increasingly developed from a compliance tool to a recognized commodity with characteristics of a financial asset [1]. While the effect of power generating fuels traditionally is an important branch of EUA pricing research and gained practical relevance under fuel-switching market environments, it remains a challenge to objectively integrate emerging price drivers, such as longer-term supply signals, which extend the planning time horizon of market participants expectations. Recently, new branches of literature propose concepts from financial market research, e.g. from asset pricing theory, to the topic, often applying data-driven methods. While contributing with descriptively valuable observations, these often omit bottom-up economical explanations. Those remain important for EUAs being a supply and demand driven asset with characteristics of a commodity. From a fundamental view, it is however not a straightforward endeavour to model longer-term policy expectations objectively, which have become highly relevant for price formation.

With this study, I contribute to existing research with an empirical study on price formation under long- and short-term horizons in recent years, based on a formal economical framework. By doing so, I empirically answer the question whether both long- and short-term price expectations have influenced price formation, as my theoretical model of myopic and speculative type horizons would predict. Utilizing data of fuel returns, stock returns and news headlines, I estimate the magnitude of effects on EUA returns as elasticities. By considering both short-term and long-term price drivers from compliant sectors and financial speculators, I contribute an integrative approach to the increasingly heterogenous landscape. I find empirical evidence that short-term compliance demand varies with the state of fuel margins and is generally related to stock returns while some changes in long-term expectations continuously contribute to EUA returns. The result therefore contributes to the holistic understanding of EUA price formation in times of dynamically developing drivers.

The remainder is organized as follows. Chapter 2 provides some backgound on the EU ETS and market evidence. Chapter 3 derives a theoretical model of short-term and long-term price drivers. Chapter 4 explains the empirical methodology and presents empirical results. Chapter 5 provides a discussion of results and concludes.

2. The European Emissions Market

2.1. Design

The European Union's Emission Trading Scheme (EU ETS) is the European Union's flagship instrument for achieving least-cost reductions of carbon emissions. Being a cap-and-trade system, it limits the total volume of greenhouse gas emissions from covered sectors, which currently respond to approximately 50% of total greenhouse gas emissions in Europe [2]. It started in 2003, aiming to incentivize the reduction of greenhouse gases within covered sectors in a cost-effective and economically efficient manner [3]. Currently covered sectors are energy activities (electricity generation with capacities exceeding 20 megawatts except municipal waste installations, mineral oil refineries and coke ovens) and energy-intensive industrial processes (involving metals, minerals, pulp and paper). Besides emissions from aluminium production and other chemical processes, carbon dioxide currently is the main emission covered, therefore the European emissions trading scheme is often referred to as a *carbon market*[1]. [2]
One allowance within the scheme is called one European Union Allowance (EUA) and entitles the holder to emit one ton of carbon dioxide in a specified period [3]. The period in which the producer of the emission has to comply with the scheme by surrendering the equivalent number of allowances is called the *compliance cycle* or *compliance period*, with a one year duration each and a subsequent, clearly defined phase of reporting and delivering. The reference product is the front December future.

[1]Since this study focuses on the (mainly carbon-emitting) energy sector as a primary driver of demand in the current phase of the scheme, I use the terms *emissions* and *carbon* equivalently for the benefit of simplicity.

Depending on the phase of the scheme, allowances are distributed to market participants via free allocations (based on "industry benchmarks", rewarding emission efficiency) and scheduled national auctions through energy exchanges. The supply of certificates is per definition inelastic, since the amount of allowances allocated to the market is externally set by the EU and not the result of a market mechanism. There is, however, some flexibility to the amount and distribution of supply, both through policy innovations, which affected both market characteristics and price formation in the past. Being temporally divided into "trading phases", the scheme is reviewed and innovated regularly. One of the first major additions was the introduction of "banking and borrowing" of certificates at the start of the second phase in 2008, allowing market participants to optimize their consumption over time and to increase their planning horizon, thus strengthening market stability [2].

More ambitious reduction targets can, for example, be implemented by applying a more strict linear reduction factor (i.e. the decreasing amount of allowances allocated each year), which is legally set. The balance is also tightened implicitly through the introduction of a major instrument being the so-called *market stability reserve* (MSR)[4], which is active since January 2019 mainly to increase market resilience but also as a de-facto tool to absorb potential oversupply. After a periodic calculation of the total number of allowances in circulation, the MSR takes in a set amount of EUAs above a defined threshold from scheduled auctions. These are only to be released if the number of certificates in circulation subsequently falls below another threshold. [5] From 2023 onwards, the maximum amount of certificates in the MSR will be linked to the previous year's auction volumes, with a potential surplus to be removed by a cancellation mechanism, which is recognized as a policy instrument to raise carbon prices and to incentivize renewable investment. Being a multi-dimensional instrument, it is not trivial to estimate the compound price effect resulting from its different channels of action. It even seems to produce counter-intuitive effects, such as increasing price volatility. [6]

Noteworthy, alongside the introduction of the MSR, a defined share of scheduled allocations was conditionally postponed to subsequent years - but not cancelled - using so-called *backloading* - arguably being a signal for a willingness to stabilize prices rather than a result of purely economic reasoning.

2.2. Market Data

Changing policy circumstances and demand situations are reflected in historical prices. Figure 2.1 depicts daily closing price history of rolling front December futures as the reference product. The left hand section depicts the whole history when this paper was written (01.01.2005 - 07.05.2021). The middle section shows price history for the dataset that was available for baseline regressions (05.01.2010 - 07.05.2021), while the right hand side reduces the historical time frame to the most restrictive data in the most comprehensive model (18.03.2018 - 07.05.2021).
Certificates from the first trading phase (TP1, 2005 - 2007) expired practically worthless since inter-phase banking and associated transfers of certificates was only allowed from TP2 onwards. TP2 (2008 - 2012) was characterized by signficant oversupply, resulting in a low-price environment where carbon abatement incentives hardly existed. TP3 (2013 - 2020) experienced some reforms, including a revised auctioning scheme for distributing EUAs, postponing some of the auction volume in order to reduce oversupply ("backloading"), defining a "linear reduction factor" of supply (-1.74% per year) and the introduction of the MSR. With increased signalling for a willingness to achieve price levels that would incentify carbon abatement (initially through low hanging fruit such as "fuel switching" from coal to gas in electricity generation), prices began to react more sensitively to (announced) policy innovations. Notable landmarks are the EU's "green recovery" package [7] after the early Covid crisis (which itself is visible with a price drop due to demand uncertainties) and general discussions implying strong supply cuts with various rule changes for the start and during TP4.
After years of limited relevance, the market probably priced increasingly credible signalling from the EU to utilize the ETS as a core instrument for achieving her climate targets.

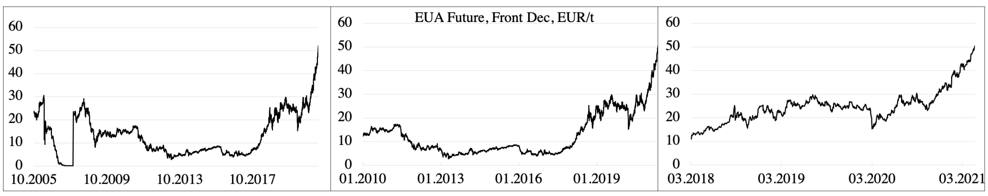

Figure 2.1.: EUA price history. Left: Total data. Middle: Baseline data. Right: Combined model data. (Own depiction, EEX data)

In these higher price environments, traders and compliance firms were forced to consider the EUAs as a serious commodity far more strongly than before. Figure 2.2 depicts the EUA price together with examplatory coal, gas and electricity rolling front year futures contracts as well as the EuroStoxx 50 blue chip stock price index. Intuitively, it sketches how EUA prices slowly claimed their place within financial market and energy complex correlations.

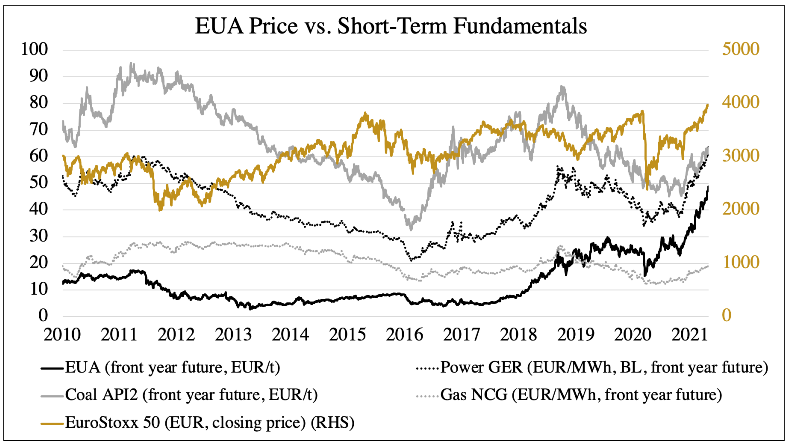

Figure 2.2.: EUA price vs. fuels, electricity and stock index prices. (Own depiction, EEX and Sharecast data)

Figure 2.3 illustrates the emerging impact of EUAs on compliance players from the electricity sector. Relying on traded energy derivatives screen prices, the so-called clean dark spread (CDS) and clean spark spread (CSS) mimic the profit margin of a coal-fired or gas-fired power plant respectively, based on profits from (forward) sold power minus short-run marginal cost (fuel and emission certificates). In principle, a unit would then only produce electricity when its spread is positive. The presented curves are calculated using baseload contracts for electricity, meaning that a full hour generation profile is sold - peakload contracts for hours of peak demand only are usually priced higher. Gas plants (usually tied to lower fixed cost and higher variable cost, often producing peakload) have a typical fuel efficency of around 50%, whereas coal plants historically sold baseload and tend to vary more in this aspect - therefore, I provide three different levels of efficiencies (35%, 38%, 41%) to illustrate the variations in modelled profitabilities. The figure provides a graphical intuition of market evidence regarding EUAs' developing impact: As prices began to rise to new levels with increased policy commitment, this had a direct impact on electricity generation as the main compliance sector. EUAs periodically drove low-efficiency coal-firing power plants out of the money and allowed efficient gas-firing (and less polluting) gas plants to generate baseload electricity.

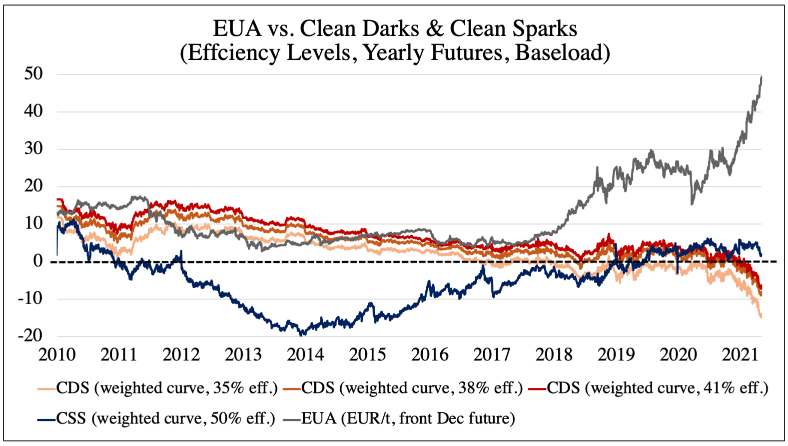

Figure 2.3.: EUA price vs. fuel spreads in EUR (gas: 50% eff., coal: 35, 38, 41% effs.) (Own depiction and calculations, EEX data)

2.3. Previous Research on EU ETS Price Formation

Explaining EUA price drivers is not straightforward and has motivated research from different perspectives over time. Initially, there has been some controversy whether the system - mostly producing prices too low to incentivize abatement - worked as intended in early phases or not. In 2010, Hintermann studied price drivers in the pilot phase of the EU ETS. Focusing on marginal abatement cost as an economical price explanation, he finds that the necessary condition for achieving the ETS' main goal (carbon reduction at least cost) was only satisfied towards the end of the first phase. Since banking was not allowed in the first phase, he finds that in this environment, weather shocks had a significant impact on EUA prices since the daily abatement decision was binding instead of cumulative decisions under banking and borrowing, which is allowed only since TP2 onwards [8]. Multiple researchers agree that low prices were a result of general oversupply, since the overall cap in the late first, second and earlier third phase was not binding [9] [10]. Following up on the initally low price environment, some focused on discussing market functioning [11]. Some emphasize policy recommendations, e.g. making cases for price floors, even recently [12].
Given that the EU ETS is to a large extent still driven by demand from

electricity generation, many studies focus on energy-related commodities as price drivers for EUAs. Reviewing the literature during mid - TP3, Hintermann and Rickels (2016) find that among the studies focusing on energy system fundamentals in context of EUA pricing, some results are often confirmed and others tend to vary across time horizons and methodologies, which may partly be due to oversimplifications of the energy landscape [9]. For example, the gas price is mostly found to have a positive impact on allowance prices, while the impact of coal prices is not clear. Aatola, Ollikainen and Toppinen (2013) run various regression models on stationary energy time series, including storage levels and electricity prices and find a negative impact of coal in the years before 2010 [13]. Lutz, Pigorsch and Rotfuß (2013) apply a Markov regime switching model with an extensive selection of energy related variables and find a positive relationship during certain states of market volatility. Koch et al. (2014) with a GARCH model and Fell, Hintermann and Vollebergh (2015) find no significant relationship between coal and EUAs [14] [15]. Schumacher et al. (2012) investigate mainly TP2, focus on short-term price drivers from the energy sector and economic activity and apply multiple empirical specifications and find signifcant fuel elasticities among mixed results. [16].

While there is no clear opinion on whether EUAs and fuels are cointegrated [17] [14] [18], there appears to be a robust cointegrated relationship between EUAs and electricity prices (and also Nordic hydro reservoir levels), which are tricky to model due to cross-border restrictions within the European energy system [19] [15].

In a working paper, Bai and Okullo (2020) manually consider major historical information events and find that electricity generators completely passed through costs of EUAs, which they only partly reduced using certificate banking, while also finding evidence for the presence of a volatility premium [20].

Bayer and Aklin (2020) contribute to the literature with a dimension of future expectations: They employ a method to compute synthetic controls based on GDP for estimating counterfactual emissions to show that firms cut emissions already today, even though prices are low, as long as there is credible signalling for stricter regimes in the future [21]. Quemin (2020) argues that rolling finite planning horizons of compliance firms can explain past annual prices and that raising ambition through an indirect supply cut (i.e. the MSR) has under bounded foresight not the same effect as a direct cut [22]. Deeney et al. (2016) study the effect of European Parliament decisions on daily EUA prices from 2010 to 2014, using GARCH style volatility clustering. They find that those decisions reduced carbon prices and increased volatility during specific circumstances, such as phases of low market attention, low (broad energy market and financial market) sentiment or being non-party-political decisions [23].

Furthermore, Hintermann and Rickels (2016) state that additional to the literature that focuses on fundamentals-based approaches, a rich literature emerged that applies methods from analyzing prices of financial assets on EUAs, often focusing on empirical methodology and data exploration. While the results are often not easy to interpret conceptually, this landscape of literature indicates that EUA markets seem to work similar to other commodity markets, even though certificate scarcity is policy-induced and artificial [9]. Alongside these recent developments in the literature, Friedrich et al. (2020) review the literature and find that EUAs tend to increasingly show characteristics of a "financial asset". They divide the existing literature into three subcategories (focusing on "demand-side fundamentals", "regulatory intervention" and "finance"). Noting that the two latter challenge the widespread view that EUA prices purely reflect marginal abatement cost, they call for research that unifies the "complex interplay" of "compliance, regulatory uncertainty and financial trading" [1]. By considering aggregate effects from compliance demand and speculative expectations regarding longer-term policy changes, I contribute an integrating approach in this direction.

3. Theory

I model EUA prices and returns to be partly driven from short-term energy system demand and industrial demand and partly driven from (mutual) expectations of longer-term supply and demand factors.
Supply and demand determine the price discovery for certificates. While supply is set by the policy maker, I assume demand to be created by two types of investors, which are either compliance buyers or speculators. These types define characteristic behavior and not necessarily individual restrictions, thus market participants can be a mix of both types.
I assume a sum of profit-maximizing rational market participants in need for certificates. They are an individually unknown combination of types (long- and short-term horizons) regarding their assessment of future price developments. Participants demand certificates either to fulfill their compliance obligations or their speculative demand or both.
In the long run, the EUA price is a function of expected demand, given that supply is exogenously set by the policy maker and inelastic towards demand. Assuming that supply depends on rules, an expectation of possible changes is reflected in the long-term price expectation as well. Among expected production of goods in the covered sectors, long-term demand depends on the speed of decarbonization and/or carbon abatement capacities, thus influencing the long-term equilibrium price expectation.
Main channels of supply and demand for certificates can be thought of as environments of certainty (historical and current state) and uncertainty (future developments), see Table 3.1.

Descriptive variables	**Demand side**	**Supply side**
Complete sets of information:	Unit margins, industrial activity	Current ETS rules
Expectations under uncertainty:	Renewables and abatement cost	Policy innovations

Table 3.1.: Candidates for desciptive variables.

Expectations regarding near-term supply and demand shocks are reflected in market prices of liquid maturities. Individual planning horizons may be strongly limited for various reasons. Employing the two types of behavior, I propose a combined model of short- and long-term price expectations driving the price and thus, returns. Instead for deriving analytical solutions, the model serves as a theoretical justification for the devision in short- and long-term horizons and what to expect from it.

3.1. Market Participants

Demand for certificates is created by compliance and speculative types. In combination, these types form price expectations both with long-term and short-term time horizons, although reasons are different. Compliance buyers primarily plan their demand based on short- to near-term signals, which are fuel futures prices for electricity generators and expected economic activity for industrial producers. This behavior is due to their hedging horizon (which is usually done for the front 1-5 years in a decreasing manner), budget planning restrictions and anchoring effects of currently valid policies (advanced analysis regarding potential policy changes would be speculation).

Speculators primarily focus on long-term supply and demand balances in order to buy or sell the scarce commodity against their equilibrium price expectation for a given time horizon, which they achieve through comprehensive research.

These types are a stylized separation and overlap in practice, which the theoretical specification allows for: Compliance buyers try to optimize their long-term costs through applying a long-term view, although the horizon is restricted by research cost and balance-sheet restrictions, such as budget planning horizons which are limiting the possibilities for certificate banking. Speculators focus on long-term fundamental research, yet they know that short-term horizons exist among other participants. Thus, short-term price movements based on short-term demand and fixed supply are anticipated and considered as well. Therefore the boundaries of short- and long-term horizons between the types blur: Actually, both investor classes are a combination of both types. Intermediary institutions, such as broker-dealers, advisors or other kinds of service providers, bring the types further together by acting as market makers and knowledge transmitters.

Thus, the consequence is a contiuum of types. In combination, both time horizons together drive the price in an unknown combination, but with universally applicable dynamics which are able to theoretically explain short- and long-term price drivers.

3.2. Long-Term Fundamentals

The total balance of certificates depends on cumulative supply and demand over time.

Demand for certificates is determined by a subset of components. Mainly, these include:

- the sectors covered, currently and in the future
- the physical demand per sector
- both speculative and hedging demand (financial demand)

Supply, on the other hand, is inelastic in the short run, since its amount is fixed by the rules of the EU as the law-making institution and the distribution of additional allowances (such as in auctions) is independent of market dynamics. However, as fundamental rules can change (and have changed over time), future supply of certificates is not certain in the long run and expecations of variation in future supply are possibly reflected in market prices.

Information regarding these future developments are public knowledge, although subjective expectations may differ due to individual interpretations and opinions. For emission markets to achieve emission reductions at least cost, allowance prices must equal marginal abatement cost [8]. Given unlimited planning horizons with certificate banking and borrowing, market participants should plan their demand based on long-term expectations, corrected by their cost of capital. When more strict policies are expected, firms should bank allowances, while they should borrow when they expect the opposite [24]. Since the long-run equilibrium price is capped by marginal abatement cost, the long-run equilibrium price depends on marginal abatement cost as well as expected supply and demand risk, depending on publicly available information sets. In such a situation

where all participants behave that way and there is no uncertainty (or all uncertainty is judged identically), prices would instantaneously jump to their new equilibrium level as new information becomes available.
The amount of available certificates (i.e. the supply and demand balance) at a long-term future T expected at today's time t results from the accumulated supply (sup) and accumulated demand (dem) at time T:

$$SD_T = \sum_{t=0}^{T} sup_t - \sum_{t=0}^{T} dem_t \tag{3.1}$$

More generally, at any time t before T, the balance SD is generated as:

$$SD_t = \sum_{t=0}^{t} sup_t - \sum_{t=0}^{t} dem_t \tag{3.2}$$

The price of an allowance at time t functionally depends on the balance at time t and a function of the expected future balance, discounted by a discount rate d:

$$p_t{}^{\mathrm{EUA}} = f\left(SD_t, SD_T{}^{\text{-d}}\right) \tag{3.3}$$

Since long-term supply depends on policy rules and long-term demand depends on long-term carbon intensity, long-term marginal abatement cost, long-term supply rules and covered sectors, the relationship can be written as:

$$p_t{}^{\mathrm{EUA}} = f\left(SD_t, (rule_T, MAC_T, CIF_T)^{\text{-d}}\right) \tag{3.4}$$

In equation 3.4, MAC_T denotes the marginal abatement cost in the long run (at time T) and CIF_T denotes the carbon intensity factor of both electricity generation and industrial production at time T, which depend on renewable capacities and industry efficiency. $rule_T$ stands for the supply rules and covered sectors at time T. d is the discount rate, reflecting both cost of capital and the risk that $\mathrm{SD_T}$ changes.
Applying the discount rate on long-term balance expectations and assuming a no-arbitrage condition for the functional link between present prices and discounted future prices, 3.4 can be expressed as:

$$p_t{}^{\mathrm{EUA}} = (E_t(P_T{}^{\mathrm{EUA}}))^{\text{-d}} \tag{3.5}$$

The long-term upper cap in the form of marginal abatement cost (MAC_T) is not ambiguous, but the state of research on the topic at time t is public information at time t, so the expected price floats between zero and long-term marginal abatement cost.

$$p_t^{\mathrm{EUA}} \in [0, MAC_T] \tag{3.6}$$

Note that long-term T is not uniquely defined, but marks the (rolling) end of a given long-term planning horizon.
The allowance price is updated over time within the range in 3.6 over time as $rule_T$, MAC_T or CIF_T from 3.4 change. Log returns r_t^{EUA} are defined by this updating dynamic. The discount rate d in equation 3.7 manifests for every t depending on given uncertainty expectations and cost of capital. Note that I abbreviate the natural logarithm (ln) as *log* throughout this paper for simplicity and readability.

$$\begin{aligned} r_t^{\mathrm{EUA}} &= \\ log(p_t^{\mathrm{EUA}}) - log(p_{\mathrm{t\text{-}1}}^{\mathrm{EUA}}) &= \\ log[(E_t(p_T^{\mathrm{EUA}}))^{\mathrm{\text{-}d}})] - log[(E_{\mathrm{t\text{-}1}}(p_T^{\mathrm{EUA}}))^{\mathrm{\text{-}d}})] \end{aligned} \tag{3.7}$$

This simple model offers multiple benefits. First, it serves as a straightforward link for explaining how future expectations should affect today's prices under rational behavior. Second, it allows expectations to contain speculative elements under uncertainty. Third, by relying on supply and demand fundamentals, it allows for changes in rules, such as covered sectors or changing proportions of rational expectations and pure speculation.

3.3. Short-Term Fundamentals

From a short-term perspective, supply is exogenously set by the policy maker. Short-term demand depends on compliance demand, determined by fuel prices and expected economic activity and upon speculative demand, which is a function of compliance demand as a result of speculators' expectations of the compliance type's behavior.
As research from other financial markets puts it, "[m]yopic investors fo-

cus on short-run price changes rather than long-term fundamental value, resulting in an overweighting of public information and a slow diffusion of fundamental news" [25]. I apply this concept to explain short-term price dynamics for both compliance and speculative types of EUA investors. By proposing short-term compliance demand as an informational anchor, positive speculative feedback loops reinforce the short-term dynamic in the fashion of a iterative mutual expectations, creating a component of temporary momentum as is regularly observed and discussed for assets in general [26]. Inspired by evidence of market price phenomena, resulting from limited time horizons of market participants ("myopia") on other markets such as equity markets, explained e.g. by principal-agent relationships [25], I derive a short-term model. Instead of principal-agent relationships, my model builds on short-term physical demand combined with speculative anticipation due to EUAs' nature as a commodity.

3.3.1. Limited Time Horizons: Myopic Compliance Demand

Given the fact that EUAs are a scarce commodity with returns driven by (expected) supply and demand, also for the short run, I start by focusing on short-term demand rather than prices directly.
The demand for certificates from the **electricity sector** is implicitly given by the expected generation of fossil fuel technologies, implied through their expected profit margins. These short-term margins frequently modelled in the energy trading industry imitate a typical unit's profit by replicating revenue from the sale of power (for all hours, i.e. "baseload") minus the cost from input fuels. They are called the *Clean Spark Spread (CSS)* for gas-fired plants and the *Clean Dark Spread (CDS)* for coal-firing plants. Units will typically run when their margin is positive, covering their short-run marginal cost. Therefore, the spreads are well suitable for modelling expected bidding behavior based on market prices and the associated expected fundamental demand for certificates.

$$CDS = p_{\text{power}} - C_{\text{coal}} \tag{3.8}$$

$$CSS = p_{\text{power}} - C_{\text{gas}} \tag{3.9}$$

p_{power} is the price of one unit of baseload electricity, which, assuming that bidding plants are price takers, is set by the market, and C_{coal} and C_{gas} are the short-term cost of coal and gas units, which depend on individual unit characteristics. How many emissions certificates are needed for producing one unit of power depends on fuel-specific energy conversion factors (converting units), fuel efficiency factors (how much power can be generated with one unit of fuel) and carbon intensity factors (how much emissions are released from using one unit of the fuel). A usual specification of the concept therefore is [27]:

$$CDS = p_{\text{power}} - \left(\frac{p_{\text{coal}}}{ECF_{\text{coal}} * FEF_{\text{coal}}} + (p_{\text{emissions}} * CIF_{\text{coal}}) \right) \quad (3.10)$$

with p_{power} being one unit of the baseload electricity contract (for the location and time horizon of interest), p_{coal} being the relevant coal contract price (converted to local currency) and $p_{\text{emissions}}$ the relevant contract price for emissions. ECF_{coal} is the energy conversion factor for coal, FEF_{coal} the (average) fuel efficiency factor for coal and CIF_{coal} the carbon intensity factor for coal. The CSS for gas units is calculated equivalently:

$$CSS = p_{\text{power}} - \left(\frac{p_{\text{gas}}}{ECF_{\text{gas}} * FEF_{\text{gas}}} + (p_{\text{emissions}} * CIF_{\text{gas}}) \right) \quad (3.11)$$

with corresponding factors and prices for gas, as described for 3.10. Generation units are incentivized to generate electricity when their margins are positive. They demand EUAs as an input factor based on fuel efficiency and carbon intensity. Typically, $CIF_{gas} < CIF_{coal}$ and $FEF_{gas} > FEF_{coal}$, meaning that gas generation units demand less EUAs for one unit of electricity due to the fuel's nature. The demand for EUAs from fossil generation therefore depends on these two measures.
Selecting contract maturities m of the input fuel then allows for computing a specific time horizon for the CDS and CSS, respectively.

$$Demand^{\text{Elec}}{}_{\text{t}} = f(CDS^{\text{m}}{}_{\text{t}}, CSS^{\text{m}}{}_{\text{t}}) \quad (3.12)$$

Electricity price impacts from weather variation should not be relevant in the long run, as neither power prices nor fuel demand are able to price in a weather period that far away in the future. Instead, market participants apply a recurring normal weather pattern for judgement - perhaps with a slightly increasing temperature trend - which is beyond the scope of this study and its needs for detail.

When considering log returns instead of levels for power, coal and gas, this affects the fuel spreads as follows when applying the natural logarithm and transforming (refer to Appendix A.1 for a comprehensive calculation):

$$\begin{aligned} log\, CDS = log\, p_{\text{power}} + log \left[1 + \frac{-\frac{p_{\text{coal}}}{ECF_{\text{coal}} * FEF_{\text{coal}}}}{p_{\text{power}}} \right] \\ + log \left[1 + \frac{-p_{\text{emissions}} * CIF_{\text{coal}}}{p_{\text{power}} + (ECF_{\text{coal}} * FEF_{\text{coal}})} \right] \end{aligned} \tag{3.13}$$

$$\begin{aligned} log\, CSS = log\, p_{\text{power}} + log \left[1 + \frac{-\frac{p_{\text{gas}}}{ECF_{\text{gas}} * FEF_{\text{gas}}}}{p_{\text{power}}} \right] \\ + log \left[1 + \frac{-p_{\text{emissions}} * CIF_{\text{gas}}}{p_{\text{power}} + (ECF_{\text{gas}} * FEF_{\text{gas}})} \right] \end{aligned} \tag{3.14}$$

which serves as an illustration how log returns of fuels influence log changes of short-run profit margins.

Demand also comes from **energy-intensive industries**. Assuming that their activity correlates with overall economic activity, the expected industrial demand for certificates may be approximated as a function of a broad stock price index, reflecting expected future discounted cash flows of the industry, under the assumption that demand correlates with these industry cash flows.

$$\begin{aligned} E(Demand^{\text{Ind}}{}_{\text{t}}) = g(p^{\text{stocks}}{}_{\text{t}}) \\ E(\Delta Demand^{\text{Ind}}{}_{\text{t}}) = g(log\, p^{\text{stocks}}{}_{\text{t}}) \end{aligned} \tag{3.15}$$

It is important to note that the model does not consider price endogeneity, i.e. it considers the effect of fuel prices on EUA prices, but not a hypothetical vice versa effect. For stock markets, the effect is with very high probability negligible due to the large difference in trading volumes.

3.3.2. Information Processing: Iterated Expectations

As described in section 3.1, speculative types also have a short-term planning component. It mainly consists of anticipating the other type's myopia and exploiting short-term movements in prices, explained by the myopic type's informational inputs (CDS, CSS, stocks).
Allen, Morris and Shin (2006) find for financial markets that asset prices today depend on the average expectation of tomorrow's price, given that traders are risk averse and short lived and prices are noisy [26]. The associated behavior, where traders form their price expectations based on their expectation of what the others expect (and so on), is described as a "beauty contest" by Keynes (1936) [28].
I use the concepts of iterated mutual expectations as a theoretical explanation how speculators confirm and amplify the short-term price dynamics created by myopic compliance types.

Remembering from equations 3.13 and 3.14 that fuel prices feed into ${CDS^m}_t$ and ${CSS^m}_t$ with negative sign, it must be that:

$$\begin{aligned} E\left[\frac{\partial\, Demand^{\mathrm{Elec}}{}_{\mathrm{t}}}{\partial\, log\; coal_{\mathrm{t}}} \mid {CDS^{\mathrm{m}}}_{\mathrm{t}} > 0\right] < 0 \\ E\left[\frac{\partial\, Demand^{\mathrm{Elec}}{}_{\mathrm{t}}}{\partial\, log\; gas_{\mathrm{t}}} \mid {CSS^{\mathrm{m}}}_{\mathrm{t}} > 0\right] < 0 \end{aligned} \tag{3.16}$$

where expectations regarding the effect of changes in fuel prices are conditioned on the fuel spread's current relevance for market demand (i.e. actively creating demand under positive short-run margins).

When comparing both expectations in 3.16, it is important to note that the expected difference in effects on returns should depend (among fuel efficiency factors and energy conversion factors) on carbon intensity factors of coal and gas, which differ in magnitude. The exact sensitivity of expectations would then depend on how positive ${CDS^m}_t$ and ${CSS^m}_t$ exactly are.

Applying iterated expectations, this generalizes among market participants (and especially speculators) to expectations of expectations, that are expected, and so on. This generates momentum and lets the short-run effect persist aside from long-term price drivers.

By definition, a similar statement is appropriate for changes in expected industry demand, proxied by stock returns, although it does not need to be conditioned, since expected industry demand contributes to expected short-term demand continuously. In this case, the expected effect on demand is positive, since rising stock prices serve as proxy for higher expected industrial activity (unlike fuels, which make electricity generation *less* profitable).

$$E\left[\frac{\partial\, Demand^{\mathrm{Ind}}{}_{\mathrm{t}}}{\partial\, log\, p^{\mathrm{stocks}}{}_{\mathrm{t}}}\right] > 0 \tag{3.17}$$

Also here, expectations of expectations stabilize the instant effect, although since stock price themselves are discounted long-term expectations, the categorization of being a short-term effect is not as clear. Additionally, note that $p^{\mathrm{stocks}}{}_{\mathrm{t}}$ serves two functions. First, it is a proxy for expected industry demand for certificates. Second, it may serve as a "risk-on" proxy for periods of speculative money inflows in EUA markets alongside broader asset price appreciation, which is an effect of positive impact on returns as well.

Remembering demand equations 3.16 and 3.17, expected EUA returns follow expected changes in demand:

$$log\, p_t{}^{\mathrm{EUA}} = f(log\, CDS^{\mathrm{m}}{}_{\mathrm{t}}, log\, CSS^{\mathrm{m}}{}_{\mathrm{t}}, log\, p^{\mathrm{stocks}}{}_{\mathrm{t}}) \tag{3.18}$$

with short-term drivers influencing EUA returns in the following directions:

$$\begin{aligned} \frac{\partial f}{\partial\, log\, CDS^{\mathrm{m}}{}_{\mathrm{t}}} &< 0 \\ \frac{\partial f}{\partial\, log\, CSS^{\mathrm{m}}{}_{\mathrm{t}}} &< 0 \\ \frac{\partial f}{\partial\, log\, p^{\mathrm{stocks}}{}_{\mathrm{t}}} &> 0 \end{aligned} \tag{3.19}$$

3.4. The Integrated Model: Price Formation

Using equations 3.7 and 3.18, returns of EUA futures can be written as a function of the expected discounted future supply and demand balance along with the short-term effect, where ${r_t}^{EUA}$ is the return component resulting from changes in long-term expectations derived in equation 3.7:

$$log\, {p_t}^{\mathrm{EUA}} = f({r_t}^{\mathrm{EUA}},\ log\, {CDS^{\mathrm{m}}}_{\mathrm{t}},\ log\, {CSS^{\mathrm{m}}}_{\mathrm{t}},\ log\, {p^{\mathrm{stocks}}}_{\mathrm{t}}) \qquad (3.20)$$

While the term structure of EUA futures was found to have quite varying characteristics in earlier stages [29], more recent market data indicate that with a more developed EUA futures market, futures prices reflect expected spot prices plus a convenience yield with a small contango (reflecting interest or the opportunity cost of capital) quite as expected.

4. Analysis

As derived in the previous chapter, long- and short-term dynamics in combination drive the traded EUA price and daily returns. In order to test the theoretical predictions, I set up an empirical analysis utilizing recent market data. I start with estimating effects from short-term certificate demand from the energy sector and manufacturing industries with an ordinary least squares (OLS) linear regression. From there, I gradually start refining the setup. To account for new information sets regarding long-term supply and demand entering the market and influencing price expectations, I derive sentiment indices from energy news headlines and include them into the model. Due to data availability, this narrows the analyzed time frame from >10 years of available market data down to >3 years, albeit with a relatively high resolution of news headline data for this subperiod, which is also characterized by strong price reactions to increasing political commitment.

	Near Term	**Long Term**
Supply	current rule set (common knowledge)	supply rule changes
Demand	fuels forward curves, stock returns	expected speed of decarbonization

Table 4.1.: Sources of EUA return dynamics. Near term demand is estimated using a fuels & stocks regression; long term supply and demand expectations are approximated using sentiment indices.

The direction of the long-term influencing factors are expected to behave as follows.
Increased renewable generation depresses - ceteris paribus - electricity returns by increasing (sometimes only partly elastic, since stochastic) supply. By suppressing fossil margins, this extra supply then should depress demand for certificates as well. Therefore, the sign of these long-term effects of renewable capacity increases is expected to be negative on EUA returns today.

An expected negative supply shock in form of a rule change reducing total supply should, on the other hand - ceteris paribus - positively impact EUA returns by reducing supply, which is priced in today (with varying degrees of uncertainty). This cost would then be passed through to electricity returns, too, as long as fossil technologies are, at least periodically, price setting. Due to endogeneity concerns, returns of electricity products are not analyzed in the model, but are implicitly considered through state-identifying fuel spread dummy variables. For independent estimates, I analyze fuel coefficients instead of the spreads directly (which depend directly on the EUA price level). To mitigate collinearity issues, I do not include temperatures (heating and cooling degree days) and seasonal dummies in this analysis, since both effects should indirectly feed into the model through fuels returns.
Expected coefficients of the fuels returns are positive for gas and negative for coal: As a previous study puts it, "[a]n increase in the price of gas (coal) leads to a higher (lower) switching price and hence to an increase (decrease) in coal use and a higher (lower) demand for EUAs" [16].
In contrast, when analyzing fuel returns individually in states of high fuel significance (in interaction with both fuel spread dummies), the direction of the fuels' coefficients is expected to be both negative. Higher fuel returns make units gradually unprofitable, depending on their location in the efficiency distribution of the power plant park - the more units are cancelled out of production, the less certificate demand there should be.
Changes in long-term effects are expected to be positive on EUA returns with expected policy-induced certificate supply tightening and negative on EUA returns with negative changes in expected carbon intensity through expected renewable capacity increases (see Figure 4.1).

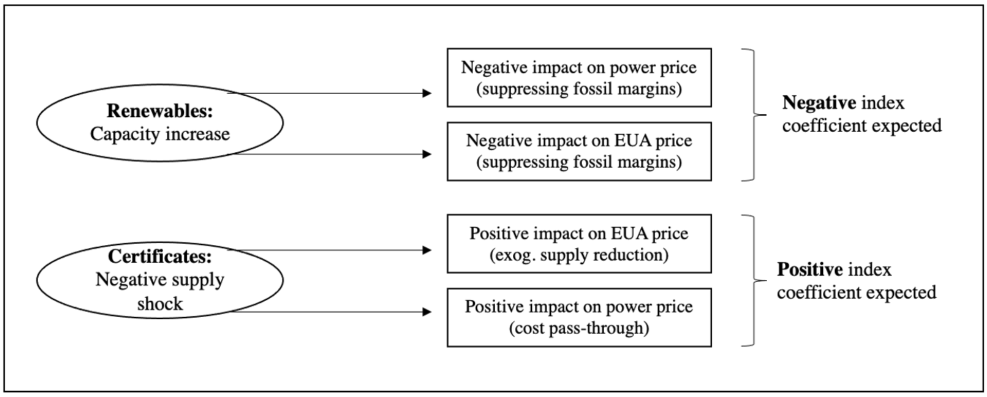

Figure 4.1.: Expected signs of long-term proxies.

4.1. Empirical Methodology

A crucial decision is whether prices or returns should be considered in the analysis. Remembering theoretical foundations of the model, the relationships between movements of the EUA price and short-term reflect changes in input fuel prices, changes in economic activity and changes in long-term fundamental expectations in the form of news. These types of relationships call for a relative model in principle, favoring (log) returns over prices as model variables. Such a model would practically be able to model the relative effect of new information entering the market, either via changes in prices or new information. A main benefit of this approach is that a direct interpretability of the index is preserved and a clear foundation for further specifications is provided, while generally the coefficients may be intuitively interpreted as return elasticities. A key difficulty is identifiying when which relative impact is relevant for EUA returns and to account for that, which I do by definining fuel spread dummy variables and let the fuel returns interact with them. Another challenge is to grasp an objective interpretation of new information regarding long-term developments, which I estimate using news-based sentiment indices.

Remembering that coal and gas substitute each other in fossil-based electricity generation depending on market prices, a statistical link to relevant price levels is still needed. In failing to do so, one would indirectly assume that fuel returns are always relevant for EUA returns to the same extent, which is far from being realistic. To solve this issue, while preserving the intuitive and technical benefits of a log return model, I integrate fuel spread dummies into the model in order to identify relevant states of fuel usage, as the theory would expect.

Additional to economic reasoning, I applied statistical tests to diagnose the properties of the empirical model from a technical perspective as well. When using log returns, the Durbin-Watson test finds no substantial first-order autocorrelation. Additionally, checking for heteroskedasticity in the comprehensive model residuals using an augmented Dickey-Fuller test revealed that the null hypothesis of residual heteroskedasticity can be rejected on a 1 % significance level. Therefore it can be assumed that the log return series are stationary, which is important for robust results (since it can be ruled out that the residuals depend on each other, which would mean that there is an important aspect which the model is missing

- resulting in an overestimated goodness-of-fit and biased test statistics). The same hypothesis cannot be rejected for the given price series. Thus, also statistical properties call for analysing returns instead of prices. Refer to Appendix A.2 for detailed test statistics.

Short term demand originating from the electricity sector is modelled using generation input fuel price curves and taking log returns. The part of short-term demand that is created from the energy-intensive industry sectors covered by the ETS, whose expected activity is aproximated by the broadly traded European stock index EuroStoxx 50. Future expectations are, to some degree, reflected in the price data: Stock prices reflect discounted future cash flows of the companies given current information, which are affected by their operative activity and thus, correlate with expected certificate demand. Stock returns then reflect, among other factors, changes in this expectation. The stock index data is obtained from Sharecast [30]. Fuel and EUA price series are obtained from EEX [31].

Fuel returns, as constructed in this study, contain information regarding the present and nearer future, which is achieved by calculating weighted averages of futures prices, with decreasing weights for the respective three front contracts. I chose yearly futures contracts, since they tend to be relatively liquid, roughly match the maturity of the reference EUA futures and reflect a nuanced compromise of current and near-future information (see Table 4.2).

Maturity	Year +1	Year +2	Year +3
Assigned weight	60%	30%	10%

Table 4.2.: Modelling a weighted price using a weighted futures curve. Subsequently, log returns are taken from calculated prices.

This is also reflecting common practice since many generators are "hedged along the curve", meaning that a decreasing amount of planned generation is sold on the forward and future markets in order to lock in profits.

Short-term supply is fixed by EU rules. Both the mode of allocation and amount of supply over time is common knowledge.

Long-term demand depends on covered sectors and realized emissions.

Covered sectors are assumed to remain a part of the supply rule set until public information changes. Realized emissions depend on the degree of decarbonization (i.e. renewable development) in both the electricity sector and the industry as well as expected long-term economic growth, as derived in the theoretical section.
Long-term supply depends on changes in the ETS rule set, which is periodically reviewed, discussed and updated. Market evidence has proven that, being a "political commodity", news regarding rule changes have induced movements in prices and trends.
There is existing research constructing sentiment indices based on market characteristics, such as various volatility measures, open interest, and others (including keyword presence in media) [23]. In the interest of isolating the long-term sentiment against shorter-term market characteristics, which probably correlate strongly with the short-run elements of the analysis, I focus purely on energy news media headlines and try to extract a meaningful sentiment score from the language contents.
To account for such new information (with various degrees of certainty) regarding these long-term drivers entering the public information set, I employ publicly visible headlines of Montel News, a key information provider for European energy markets [32] [33] and derive sentiment scores using the pre-trained Vader lexicon [34] using the NLTK package for Python [35].

The CDS and CSS, where emprically needed, are parametrized with assumptions that are common in the industry [27], see Appendix A.3 for details. I assume the CSS to run on 50% fuel efficiency and the CDS on 35% (low), 38% (mid) and 41% (high) efficiency, reflecting the heterogeneity of Europe's coal plant landscape.

4.1.1. Baseline Regressions: Short-Term Demand Fundamentals

The observed time span in the baseline regression reaches from 04.01.2010 to 07.05.2021, making maximum use of the available data at the time of analysis. The baseline is afterwards restricted to the subperiod of subsequent refinement.

The baseline regression model (short-term demand drivers) takes the following form:

$$log\,EUA = \alpha + \beta_1(log\,coal) + \beta_2(log\,gas) + \beta_3(log\,stoxx) + \epsilon \quad (4.1)$$

where the daily log return of EUA futures is explained by daily log returns of yearly coal futures (API2), natural gas futures (NCG) and the EuroStoxx 50 index. API2 is the leading European coal price index for power plant coal with a certain quality (based on the Argus/McCloskey Coal Price Index Report, pricing coal delivered into the Amsterdam, Rotterdam, Antwerp Region) [36]. NCG futures "are for physical delivery through the transfer of rights in respect of Natural Gas at the NetConnect Germany (NCG) Virtual Trading Point" [37] and represent the exchange reference futures price for the German price area, which I use to approximate European prices as a historically fossil-heavy location.

4.1.2. Long-Term Fundamentals: Processing of News Inflow

News headline data was selected using category tags provided by the source [32]: The tags 'carbon' and 'carbon policy' were used as an input filter for constructing the carbon sentiment index (CSI), which serves as a proxy for information regarding policy developments. Accordingly, the tags 'renewables' and 'renewable policy' were used to construct the renewables sentiment index (RSI), which proxies changes in expectations in long-term renewable capacities (affecting expected carbon intensities). It is important to note that these indices are time horizon naive, but include a long-term horizon by definition. Random qualitative checks ensured that long-term information is strongly represented in the sample and that the applied lexicon generally interprets sentiment in the expected direction. To ensure objectivity, no further manual adjustments were applied to the sample or to the sentiment methodology. Manually adding industry-specific vocabulary to the lexicon was tested, but did not substantially better the model precision, so the original lexicon was used in the interest of maximum objectivity. The pre-trained VADER lexicon together with the NLTK methodology assesses language elements that are detected to inhibit positive, negative or neutral sentiment and assigns scores. The result is aggregated and normalized as a compound score with a possible minimum of -1 (most negative) and a maximum of 1 (most positive) [34]. I subsequently take daily averages as an input for regression. Being a subjective score, it is not directly interpretable, unlike prices or returns. It serves as a relative continuous measure to proxy a typical interpretation of changes in public information.

The fuel spread dummies (CDS_{low}, CDS_{mid}, CSS_{low}, CSS_{mid}) code days when medium and low efficiency units (running on each fuel) are in the money, i.e. generating positive short-run profits. The "low" subscript implies that even low-efficiency units are profitable, implying that the respective fuel spread is strongly positive. This means that in those cases, most units of the technology are running and the demand for the respective input fuel and efficiencies is high, which again implies a high temporary relevance of the fuel for certificate demand. Taking a value of zero or one, these dummies indicate whether most ("low" efficiency spread) or some ("mid" efficiency spread) units procuring the respective fuel are in active demand for certificates.
By letting these dummies interact with the short-term generation fuels, a specific statement can be made regarding their influence in states when their respective fuel returns should be relevant for certificate demand. Put differently, the associated hypothesis is that their coefficients should be insignificant in other states.

The combined regression model (short-term baseline together with the sentiment indices and the fuel spread dummies and interaction terms) takes the following form:

$$\begin{aligned}
&log\ EUA = \alpha + \beta_1(log\ coal) + \beta_2(log\ gas) + \beta_3(log\ stoxx) \\
&+ \beta_4(CSI) + \beta_5(RSI) \\
&+ \beta_6(CDS_{\text{low}}) + \beta_7(CDS_{\text{mid}}) + \beta_8(CSS_{\text{low}}) + \beta_9(CSS_{\text{mid}}) \\
&+ \beta_{10}(CDS_{\text{low}} * log\ coal) + \beta_{11}(CDS_{\text{mid}} * log\ coal) \\
&+ \beta_{12}(CSS_{\text{low}} * log\ gas) + \beta_{13}(CSS_{\text{mid}} * log\ gas) + \epsilon
\end{aligned} \tag{4.2}$$

where CSI and RSI are the sentiment index values for carbon and renewables (on a daily scale from -1 to 1), the CDS and CSS variables are fuel spread dummy variables for identifying time spans when fuel prices are relevant and the other variables are daily log returns of fuels.

4.1.3. Data Sample

I use daily price data from the European Energy Exchange [31] for EUA, coal (API2 price marker) and natural gas (NCG price zone) to derive returns and for calculating baseload CDS and CSS. Price data available for this study (05.01.2010 - 07.05.2021) was cleaned to match EUA price data: In cases when there was no price of a fuel on an EUA trading day, the previous closing price was considered. In cases of a fuel price signal on a EUA non-trading day, the interim price change was ignored.
Stock index data (EuroStoxx 50) is taken from the publicly accessible website ShareCast [30]. The time horizon and frequency of the sample matches the fuels and EUA data.
Daily news headline data used to construct sentiment indices was obtained from the public news section of Montel News' website [32] and filtered applying relevant category tags for the long-term developments of interest (carbon and renewables). Due to technical limitations and limits to public availability, this data set is significantly shorter (18.03.2018 - 07.05.2021). The number of headlines after filtering is n = 2991. To account for these differences in available data and to maximize perspective within the context of TP3, I compute a baseline (short-term only) regression for both the whole horizon and the headline data restricted horizon before computing the combined short- and long-term model for the restricted period only. I rely on this twofold baseline analysis mainly in order to gain a better understanding of the result, especially since the restricted subperiod partly coincides with a bullish market environment on the back of regular inflow of policy innovation. In order to assess the model's explanatory power, this indirect comparison of the baseline analysis is essential. Furthermore, it may serve to deliver interesting insights how effects may or may not have changed over the years.

4.2. Results

I compare the empirical results from the (short-term only) baseline model with the combined model by discussing regression outputs for the different data lengths.

4.2.1. Baseline Regression: Short-Term Effects

log EUA	coef. (p-val.)		std. err.		CI [0.025		0.975]	
	daily	weekly	daily	weekly	daily	weekly	daily	weekly
Intercept	0.0004 (0.414)	0.0004 (0.417)	0.001	0.001	-0.001	-0.001	0.002	0.002
log coal	-0.0065 (0.885)	-0.0411 (0.68)	0.045	0.1	-0.094	-0.237	0.081	0.155
log gas	0.8084*** (<0.001)	0.5326*** (<0.001)	0.05	0.097	0.711	0.343	0.906	0.722
log stoxx	0.2959*** (<0.001)	0.3699*** (<0.001)	0.042	0.093	0.213	0.187	0.378	0.552

Daily / weekly:
Model: OLS / OLS - Observations: 2879 / 592 - adj. R^2: 0.12 / 0.09 - Durbin-Watson: 1.95 / 1.96

*** significant at 0.1%, ** significant at 1%, * significant at 5%
green font: sign as expected. yellow font: sign weakly as expected. red font: sign unlike expected

Table 4.3.: Baseline results: Short-term effects.
Daily and weekly data (05.01.2010 - 07.05.2021)

Table 4.3 depicts baseline regression results for short-term effects as a reference. Considering the data quality of coal prices (which are regularly moving slower than other commodities in the energy complex), the baseline regression for short-term demand was run both on daily resolution and weekly averages. While the weekly analysis confirmed the direction of coefficients, magnitudes came closer together and the coal coefficient remained insignificant, there was no increase in robustness from resorting to weekly data instead of daily data to be found.
Running the baseline regression for the subperiod (i.e. the period where sentiment data for the main model was available) mainly confirmed the result of the large time sample.
All short-term demand coefficients show the expected signs for returns: Coal is insignificant, but a positive gas coefficients hints the trade-off

between the two polluting generators, with gas in the less-certificate-demanding role, although no relevant fuel-switching levels are considered yet. The gas coefficient is much larger on a daily basis, implying intra-week gas volatility may play a role for certificate returns. Stock returns drive EUA returns through updated expectations of industrial demand.

log EUA	coef. (p-val.)		std. err.		CI [0.025		0.975]	
	daily	weekly	daily	weekly	daily	weekly	daily	weekly
Intercept	0.0016 (0.077)	0.0017 (0.073)	0.001	0.001	0	0	0.003	0.004
log coal	-0.0809 (0.236)	-0.0647 (0.716)	0.068	0.177	-0.215	-0.415	0.053	0.285
log gas	0.9059*** (<0.001)	0.4385*** (0.001)	0.067	0.131	0.775	0.181	1.037	0.696
log stoxx	0.4547*** (0.001)	0.4557** (0.003)	0.07	0.149	0.317	0.162	0.592	0.749

Daily / weekly:
Model: OLS / OLS - Observations: 801 / 165 - adj. R^2: 0.28 / 0.15 - Durbin-Watson: 1.95 / 2.22

*** significant at 0.1%, ** significant at 1%, * significant at 5%
green font: sign as expected. yellow font: sign weakly as expected. red font: sign unlike expected

Table 4.4.: Baseline results: Short-term effects. Subperiod.
Daily and weekly data (18.03.2018 - 07.05.2021)

Table 4.4 presents the same baseline results, but for the reduced time horizon resulting from the data restriction imposed by the long-term sentiment indices in the comprehensive model. The baseline result for the subperiod may serve to provide vague confidence that there are no large structural issues for the validity of the integrated approach in general outside of the specific subperiod.

4.2.2. Combined Model: Including Long-Term Expectations

Table 4.5 depicts the comprehensive regression result. Dummy variables are marked with a light grey background while interaction terms are marked with a darker grey. Time resolution is kept daily, matching the resolution of the sentiment indices, the limited time span of the subset

log EUA	coef. (p-val.)			std. err.			CI [0.025			0.975]		
	(1) sent. sub	(2) sub	(3) long	(1) sent. sub	(2) sub	(3) long	(1) sent. sub	(2) sub	(3) long	(1) sent. sub	(2) sub	(3) long
Intercept	0.0007 (0.404)	0.0005 (0.518)	0.0002 (0.912)	0.001	0.001	0.002	-0.001	-0.001	-0.004	0.002	0.002	0.004
log coal	-0.0398 (0.249)	-0.0345 (0.318)	0.1018 (0.441)	0.034	0.035	0.132	-0.107	-0.102	-0.157	0.028	0.033	0.361
log gas	**0.9606***** (<0.001)	**0.9712***** (<0.001)	**0.8397***** (<0.001)	0.11	0.11	0.063	0.746	0.755	0.715	1.176	1.187	0.964
log stoxx	**0.4327***** (<0.001)	**0.4423***** (<0.001)	**0.2919***** (<0.001)	0.071	0.071	0.042	0.293	0.302	0.209	0.572	0.582	0.375
CSI	**0.0127**** (0.003)			0.004			0.004			0.021		
RSI	0.0033 (0.574)			0.006			-0.008			0.015		
CDS_{low}	-0.0186 (0.064)	-0.0203* (0.043)	-0.0016 (0.305)	0.01	0.01	0.002	-0.038	-0.04	-0.005	0.001	-0.001	0.001
CDS_{mid}	0.0007 (0.404)	0.0005 (0.518)	0.0017 (0.231)	0.001	0.001	0.001	-0.001	-0.001	-0.001	0.002	0.002	0.004
CSS_{low}	-0.0033 (0.448)	-0.0019 (0.657)	0.0017 (0.54)	0.004	0.002	0.002	-0.012	-0.003	-0.003	0.005	0.005	0.003
CSS_{mid}	0.0008 (0.673)	0.0009 (0.628)	0.000 (0.979)	0.002	0.002	0.002	-0.003	-0.003	-0.003	0.005	0.005	0.003
CDS_{low} : log coal	**-0.9325*** (0.04)	**-0.9588*** (0.035)	-0.0558 (0.58)	0.453	0.455	0.101	-1.822	-1.852	-0.253	-0.043	-0.065	0.142
CDS_{mid} : log coal	-0.0398 (0.249)	-0.0345 (0.318)	-0.1082 (0.345)	0.034	0.035	0.115	-0.107	-0.102	-0.333	0.028	0.033	0.116
CSS_{low} : log gas	**-0.4794*** (0.038)	**-0.4573*** (0.049)	**-0.4*** (0.019)	0.231	0.232	0.171	-0.933	-0.912	-0.735	-0.026	-0.002	-0.065
CSS_{mid} : log gas	-0.058 (0.669)	-0.0357 (0.793)	-0.0264 (0.798)	0.136	0.136	0.103	-0.324	-0.303	-0.176	0.208	0.232	0.229

(1) Model: OLS. Observations: 801. adj. R^2 0.29. Durbin-Watson: 1.97
(2) Model: OLS. Observations: 801. adj. R^2 0.279. Durbin-Watson: 1.962
(3) Model: OLS. Observations: 2879. adj. R^2 0.125. Durbin-Watson: 1.955

*** significant at 0.1%, ** significant at 1%, * significant at 5%

Table 4.5.: Combined results:
(1) Incl. sentiment, daily data, subperiod (18.03.2018 - 07.05.2021)
(2) No sentiment, daily data, subperiod (18.03.2018 - 07.05.2021)
(3) No sentiment, daily data, entire period (05.01.2010 - 07.05.2021)

and the fact that a weekly resolution could not make the coal estimate more robust in the baseline regression. Estimated coefficients of gas and stocks over all days of the subperiod are roughly similar to baseline results, but additional interesting relationships appear.

Comparing the comprehensive analysis of the subperiod including sentiment indices (1) with the superiod analysis without sentiment (2) and the entire period analysis without sentiment (3), three main statements are to be made.

First, the interaction with the fuel spread dummies works well for the subperiod with and without sentiment indices, whereas for the entire period, the approach delivers significant results only for gas. I interpret this as an indication that during the relatively low-certificate-price environment, before fuel switching became relevant and recognized, the majority

of traders did not consider fuel prices as a major driver for EUA prices at all, hence the weak relationship.
Second, while always significant, the stock index coefficient is much larger for the subperiod than for the entire timeframe. I interpret it as a confirmation of EUAs' increasing appeareance on the radar of financial market participants, attracting speculative money and participating increasingly in cross-asset "risk on / risk off" cycles.
Third, the slight contribution of the CSI narrows (increases) the distance of coal (and gas) coefficients in interaction with fuel spread dummies roughly in proportion to the respective fuel's carbon intensity factor. This is intuitively logical: an expectation of certificate supply tightening (triggering a price increase, ceteris paribus) controls for some of the expectation that is priced into coal, while gas suffers a bit in this aspect, being somewhat less "meaningful" to carbon policy observators.

The combined result (1) itself offers multiple relevant insights on its own. First, the coefficient of daily coal returns is still not significant with this advanced model specification. Unlike coal, the gas coefficient is highly significant with a positive sign across the subperiod horizon. It is relatively large and positive, implying that a majority of gas returns is fed through to the emissions return, when controlling for other variables (including the direct trade-off versus more emission-intensive coal).
Similarly, but with a relative effect that is almost half in magnitude, stock returns positively explain the emissions return which is in line with the theoretical requirement for them to serve as a proxy for expected industry demand through amounts of production.

When investigating the fuel variables in interaction with the fuel spread dummies, the picture changes. Remember that the dummy variables code days when medium and low efficiency units generate positive short-run profits. The "low" subscript implies that even low-efficiency units are profitable, implying that the respective fuel spread is strongly positive, meaning that most units of the technology are running and the demand for input fuel and efficiencies is high, which implies a high temporary relevance of the fuel for certificate demand. Indeed, in interaction with these states of high market share of the respective fuel, the impact of their returns on the EUA return is strong and significant, with two important details.

First, from this more isolated point of view, the coefficient of gas returns becomes negative. This makes sense since when considered alone, a higher gas return should lower certificate demand since units become gradually unprofitable - unlike when analyzed in a trade-off setting with coal (which is even more hurt in a similar situation due to higher carbon intensity and then increases the relative demand for gas). Second, the relative impact of gas returns versus coal returns on EUA returns is lower proportional to the lower emission intensity of the fuel. This confirms and specifies the theory, as stated in equations 3.12 and 3.16.

Accordingly, the null hypothesis that fuel returns are not relevant for EUA returns outside a relevant fuel-switching range can be confirmed: At times when only a share of the respective fleet is running (medium efficiency dummy), the effect evaporates. Therefore, the need for a significant high-efficiency dummy (only a minor share of the fleet is "at the money") can be ruled out.

It is important to emphasize that, while significant at a 5% level, standard errors of the estimated interaction terms appear to be high. This can be intuitively explained by the construction of the dummy variables: While cutting off low efficiency units sharply, coal unit efficiencies are more continuously distributed in reality (and the data-generating process) than in the simplified assumption that there are three classes of efficiencies.

5. Discussion

Following available data, I focused on a late phase of TP3 (Q1 2018 - Q2 2021) with my comprehensive empirical model - a period that is characterized by competition between electricity generation fuels, financial market volatility (Covid crisis) and expectations for policy innovation (new rules for EUA supply including the supply-tightening MSR; upcoming Phase IV) and is therefore well suited for an empirical analysis of recent developments in EUA price dynamics. I compared this model to different model specifications and subperiods to obtain some context of results.

I derived a general theory how certificate prices and associated returns depend on both short-term and long-term dynamics. Short-term effects were assumed to include fuel margin competition in electricity generation as well as expected demand from energy-intensive industries, proxied by a broad stock market index. On the certificate supply side, I composed longer-term effects as expectations of changes in carbon policy - which in the European Union is often implemented via the EU ETS as their flagship instrument for carbon emission mitigation. Longer-term effects on the demand side I assumed to depend on the expected degree of decarbonization in Europe, mainly in the form of capacity increases of renewable electricity generation. Empirically, I approximated changes of those long-term expectations with headline-based daily sentiment indices, integrated into a regression of daily EUA returns together with short-term effects (both fuel returns and fuel returns in interaction with states of high fuel relevance). Assuming efficient processing of public information and sufficient price signals, I imposed no lag to any variable and conducted an OLS estimation on returns, dummies and sentiment indices.

For the short run, the results confirm a strong positive effect of gas in a general specification, which can be interpreted as an expected tradeoff versus coal in a fuel-switching setting. Similar to existing research, I did not obtain a significant estimate for the effect of coal returns over all days. However, interactions with relevant fuel spread dummy variables achieved to raise precision of fuel return coefficient estimates. Specifically, they confirm significant relationships, possibly through demand-decreasing effects with decreasing plant margins for both coal and gas, approximately in the magnitude of their carbon intensity of generation, reflecting marginal demand for EUA certificates.

Changes in long-term supply expecations seem to influence EUA returns, approximated using relative daily sentiment modelled from specific news headlines. I did not find a significant relationship for an equivalently constructed sentiment index of renewable energy policy signals, reflecting changes in long-term demand reductions through expected decarbonization. Since it is a large dataset with no manual adjustments to the headlines, additional effects, such as covered sectors, may affect the carbon sentiment index estimate. Similarly, the renewable sentiment index may contain data which goes too far beyond the scope of carbon markets and therefore, distorts potential effects into insignificance. While it seems promising for upcoming research to refine the underlying methodologies, it should be a priority to ensure the objectivity of the indices, which are a major benefit for model robustness in comparison to qualitatively ex-post defined state dummies. In summary, while the estimated effect is small, I find evidence that changes in long-term supply expectations affect EUA returns through the inflow and processing of new information. This implies that emission abatement and efficiency increases are incentivized already today under credible signalling of future rule changes by the EU, an effect which is probably smoothened even further by speculative activity, as derived in the theory section.

A key limitation to note is the data length of the headline sentiment time series, reducing the length of the comprehensive model to less than what would have been possible with the rest of the data (as shown in the other results). Extending the data set could extend the explanatory power and robustness of the estimated model. Furthermore, together with more data, further refining the sentiment-constructing methodology could potentially reveal a larger effect of long-term expectations that could be estimated with the model of this study. Another key area for potential improvement is the relative unit of the sentiment indices: While other coefficients can be interpreted as direct return elasticities, there is no intuitive interpretation of sentiment scores other than relative (positive and negative) strength to themselves. Further processing of the input, even by applying a utility function of agents, could be beneficial for economically meaningful results in that respect.

As mentioned, standard errors of interaction term estimates are high, potentially due to an oversimplified assumption of relevant generation corridors. Extending the assumption and potentially obtaining demand sensitivity estimates for a more continuous demand interaction could be challenging, but insightful.

As another application of results, backtesting trading strategies based on signals generated in relation to sentiment indices could provide constructive insights for discussing information processing and market efficiency, which might be especially promising in combination with the development of sophisticated sentiment indices.

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A. Appendix

A.1. Deriving Logarithms of Fuel Spreads

Starting from 3.10 and 3.11, I apply natural logarithms as follows:

$$
\begin{aligned}
CDS &= p_{\text{power}} - \frac{p_{\text{coal}}}{ECF_{\text{coal}} * FEF_{\text{coal}}} - p_{\text{emissions}} * CIF_{\text{coal}} \\
log\, CDS &= log\, \left[p_{\text{power}} - \frac{p_{\text{coal}}}{ECF_{\text{coal}} * FEF_{\text{coal}}} - p_{\text{emissions}} * CIF_{\text{coal}} \right]
\end{aligned}
$$

$$
define: \quad x = p_{\text{power}},\ y = \frac{p_{\text{coal}}}{ECF_{\text{coal}} * FEF_{\text{coal}}},\ z = p_{\text{emissions}} * CIF_{\text{coal}}
$$

$$
\begin{aligned}
log\,(x+y+z) &= log\left[(x+y) * \left(1 + \frac{z}{x+y}\right)\right] \\
&= log\,(x+y) + log\left(1 + \frac{z}{x+y}\right) \\
&= log\left[x\left(1 + \frac{y}{x}\right)\right] + log\left(1 + \frac{z}{x+y}\right) \\
&= log\, x + log\left(1 + \frac{y}{x}\right) + log\left(1 + \frac{z}{x+y}\right)
\end{aligned}
$$

$$
then\ substitute\ back\ to\ obtain:
$$

$$
\begin{aligned}
log\, CDS = log\, p_{\text{power}} &+ log\left[1 + \frac{-\frac{p_{\text{coal}}}{ECF_{\text{coal}} * FEF_{\text{coal}}}}{p_{\text{power}}}\right] \\
&+ log\left[1 + \frac{-p_{\text{emissions}} * CIF_{\text{coal}}}{p_{\text{power}} + (ECF_{\text{coal}} * FEF_{\text{coal}})}\right]
\end{aligned}
\tag{A.1}
$$

The same holds for CSS by replacing CDS with CSS, p_{coal} with p_{gas},

ECF_{coal} with ECF_{gas}, FEF_{coal} with FEF_{gas} and CIF_{coal} with CIF_{gas}.

A.2. Augmented Dickey-Fuller Test Statistics

	ADF statistic for the comprehensive model, logs:
crit.	-15.048754199327949
p-value	9.360558470233104e-28
lags	3
obs.	797
t	'1%': -3.438581476199162, '5%': -2.865173218890781, '10%': -2.56870466056054

p-value < |crit.|: H_0 (series is not stationary) can be rejected.

	Reference: ADF statistic for the baseline model (entire period), levels (prices):
crit.	0.6900331651677494
p-value	0.9896368510821241
lags	13
obs.	2866
t	'1%': -3.4326337287557456, '5%': -2.862548995880997, '10%': -2.5673071179733613

p-value > |crit.|: H_0 (series is not stationary) cannot be rejected.

A.3. CDS and CSS Parametrization

To compute the CDS and CSS, I parametrized the formulas with the following values based on Platts' European Power Methodology [27]:

	CDS	**CSS**
ECF	6.978 mt/MWh	3.412141 Btu/MWh
CIF	0.34056 mtCO2/MWh	0.18404 mtCO2/MWh

Eidesstattliche Erklärung

Ich bezeuge mit meiner Unterschrift, dass meine Angaben über die bei der Abfassung meiner Arbeit benützten Hilfsmittel sowie über die mir zuteil gewordene Hilfe in jeder Hinsicht der Wahrheit entsprechen und vollständig sind. Ich habe das Merkblatt zu Plagiat und Betrug gelesen und bin mir der Konsequenzen eines solchen Handelns bewusst.

B. Klotz

Benedikt Klotz
Zürich, den 19.07.2021