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FROM FUNDAMENTALS TO FINANCIAL ASSETS: THE
EVOLUTION OF UNDERSTANDING PRICE FORMATION IN THE
EU ETS

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Abstract

Now in its third compliance period, we can look back at more than 12 years of existence of the emissions trading system (ETS) in the European Union. The focus of this paper is to review the empirical literature on price formation in the EU ETS. As a reoccurring concept, we draw on a simple theoretical model of price formation that we subsequently extend to accommodate three different strands of literature. First, we gather evidence based on empirical papers which look at the role of fundamental price drivers. Second, we review the event study literature, where political and regulatory uncertainty is the main topic. Third, we devote a major part to finance literature in this market. In every section, we pay special attention to the challenges that arise when empirically modeling allowance prices in this complex market. We emphasize that there is a need for more evidence and possibly alternative approaches due to the complex interplay of compliance and finance trading motives. As a result, the findings of this review provide important lessons about price formation in the EU ETS, which can also inform the design of such programs in other countries.

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1 Introduction

The EU Emissions Trading System (ETS) is the world’s largest and most long lived cap-and-trade scheme to regulate greenhouse gas (GHG) emissions (World Bank, 2017), and the flagship instrument of the EU’s climate policy (EC, 2017). As such, it is an important experiment to find out if such schemes can indeed achieve the intended objectives. Yet in the past, concerns were raised about both the environmental effectiveness and efficiency of the scheme, and thus its general functioning. An important indicator for the functioning of the EU ETS in that respect is the price of allowances (European Emission Allowances, EUAs), whose evolution is shown in Figure 1. Two important developments stand out: a considerable decline of prices between early 2011 and early 2013, and the upward trend that started in mid 2017. The period of low prices raised concerns that the EU ETS might not work as intended and is in need of reform (e.g. Edenhofer (2014)). This is not least because both the plunge and the recent rise came as a surprise. In 2008, when the EU’s 2020 climate target was adopted, 2013 EUA futures prices were at a level of around 30€/t (Ellerman et al., 2016). Furthermore, the accompanying regulatory impact assessment pointed to a price of around 40€/t in 2020 (Delbeke et al., 2009; Capros et al., 2011). All that suggested that prices would rise rather than decline. The recent upward trend of the price was probably less unanticipated, and many observers tie it to the ETS reform which was passed into law in 2018. Nevertheless, it remains controversial if this implies that the ETS is now functioning well or if it is just a temporary effect that may subside in the future.

![Figure 1: EUA price development since 2008 (Data from ICE via Quandl)](image)

Against this background, we review the empirical literature on price formation in the EU ETS with a methodological focus. As a reoccurring concept, we draw on a simple theoretical model of...
price formation giving us a price path equation which we subsequently update and extend. The empirical studies we review are integrated into this framework in each of our three sections. In the first section, we look at studies investigating abatement-related fundamental price drivers. Second, we review the literature studying the impact of political and regulatory uncertainty as, for example, debates about revisions of the ETS on allowance prices. Subsequently, we devote a third part to the finance literature in this market. Figure 2 underlines our division into the three different strands of literature. In addition, a list of the main papers we review can be found in Figure 3. It also gives a timeline for the different compliance phases of the market and categorizes the sample periods used in the empirical studies accordingly.

**Figure 2: General structure of the review**

Since there exists a vast amount of empirical literature in this direction, the papers we cover do not constitute a complete list. Rather than trying to be exhaustive, we select three main papers in each section. For each paper, we spend time on carefully summarizing the methodology before presenting the results in order to make the insights accessible to a broader readership. The selected papers are, in our opinion, well written and representative for this particular strand of the literature. By including the most recent research and putting a certain emphasis on the growing finance literature, we complement excellent previous work in this direction by Zhang and Wei (2010), Chevallier (2011), Bertrand (2013), Zhang (2016) and Hintermann et al. (2016).

Moreover, our review differs from previous research because of the simple theoretical model
we consider. It can be seen as starting point of each section against which we review the related empirical literature. We assess, if feasible, if the underlying theory is supported by empirical evidence, paying special attention to methodological limitations. Step by step, we extended the model to reflect additional theoretical considerations that are beneficial to explaining price formation. The review thus develops an incremental understanding of price formation leading the reader up to the current frontier - inspired by Shiller (2014), who takes a similar approach in his Nobel Prize Lecture on speculative asset pricing. We chose this path because in our view, there is a strong link between the structure and evolution of the EU ETS, on the one hand, and the challenges faced by empirical researchers and the underlying theory, on the other hand. Accordingly, we are convinced that organizing this review in the above way is best suited to shed light on the co-evolution of theoretical understanding and empirical validation of price formation in the EU ETS.

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Figure 3: Timeline of sample periods used for empirical analysis

2 Fundamental price drivers

We take as a starting point the seminal paper on price formation in intertemporal permit systems by Rubin (1996). In this paper, the allowance price at time $t$ is given by

$$p_t = p_0 e^{rt},$$

(2.1)

which establishes that the price is determined by an initial price $p_0$ and the interest rate $r$. As long as there is a positive bank, the allowance price increases with a growth rate given by the interest rate.
The initial price $p_0$ is implicitly determined by the intertemporal market balance equation:

$$\int_{\tau=0}^{T} x(p_0 e^{r\tau}) d\tau = \bar{G}, \quad (2.2)$$

where $x$ are emissions and $\bar{G}$ is the overall cap which is set by the regulator. As long as the cap is binding, i.e. equation (2.2) holds, the price is positive at all times and equal to the marginal costs of abatement relative to baseline emissions ($\pi$): $p = c'(\pi - x)$. Since the price is uniquely determined by $c'$ and $\bar{G}$, they are called the demand and supply side market fundamentals, respectively. These fundamentals, however, are unobservable in practice. Consider, for example, that the current allowance price depends on future abatement costs and baseline emissions which are not observable today. Empiricist therefore need to rely on observable information variables $I_t$ to analyze the impact of fundamentals on the allowance price.

On the demand side, which is the focus of this section, these variables include the coal and the gas price as main factors. Since electricity generation from coal is emission intensive, the coal price has, in theory, a negative impact on the allowance price. Using gas is cleaner which leads to a positive impact of the gas price through the possibility of fuel switching. Two other frequently considered demand-side price drivers are economic activity and weather variables. Economic activity is the main driver of baseline emissions. Higher economic growth has a positive impact on production and emissions, leading to increasing demand for allowances. In addition, factors such as weather conditions including hot or cold periods, wind speed or precipitation can also have an impact. The latter two variables affect generation from renewables which has implications for emissions.

The above theoretical considerations constitute both the existence and direction of the effect of market fundamentals - as observed through information variables - on allowance prices. Empirical studies yield, however, ambiguous results. The remainder of this section will elaborate this in detail based on six selected papers, which we discuss in light of their methodological approaches and the kind of insights for price formation that come with it. Each paper differs in the applied methods and/or the set of information variables it considers. First, we focus on linear regression approaches.

2.1 Empirical evidence and challenges using linear models

To empirically investigate the relations identified by economic theory, linear regression analysis is a great starting point. It identifies the effects that the main determinants have on allowance prices and shows whether the theoretical considerations hold in practice. Not only can we establish that a relationship exists but also look at its magnitude and sign. For this to work, we need a well specified model that fits the data. Economic theory gives us potentially powerful explanatory variables to include in our regression model. However, the empirical literature shows that it is not a trivial task to find a good model for allowance prices.

The carefully conducted empirical analysis by Hintermann (2010) is representative for the problem encountered by many authors. As one of the most influential papers in this field, it first develops a theoretical model of marginal abatement costs. Subsequently, it turns out to be difficult to find
empirical evidence for the model using data from Phase I. The set of information variables in this paper contains potentially important factors, such as the coal price, economic activity and weather variables. They are not all statistically significant in explaining the allowance price. Initially, merely the year-ahead gas futures price is a significant factor in a regression along the following lines

\[ EUA_t = \beta_0 + \beta_1 \text{Gas}_t + \beta_2 \text{Coal}_t + \beta_3 \text{Temp}_t + \beta_4 \text{Prec}_t + \beta_5 \text{Reservoir}_t + \beta_6 D_{\text{crash}} + \epsilon_t, \]

where \( D_{\text{crash}} \) is a dummy variable capturing the effect of the crash occurring in April 2006, \( \text{Temp}_t \) is weighted temperature by population over different measurement locations in Europe, \( \text{Prec}_t \) is precipitation and \( \text{Reservoir}_t \) are Nordic reservoir levels. As dependent variable, Hintermann (2010) uses daily over-the-counter EUA price changes. A link between market fundamentals, other than gas prices, and allowance prices can only be established after splitting the sample into sub-periods (pre- and post-crash) and including lagged dependent and explanatory variables as well as multiplicative interaction terms. In the final specification, gas and coal prices as well as precipitation and Nordic reservoir levels as indicator for renewables production show significant effects in the anticipated direction.

While some might argue that the market was simply not mature enough in Phase I, Koch et al. (2014) find similar evidence of such challenges for Phase II. They initially find limited explanatory power of fundamentals, although the set of information variables considered as explanatory factors used in this paper is quite extensive. It consists of month-ahead coal and gas futures, the European stock index STOXX Europe 600, renewables generation from two production types (hydro as well as wind and solar) and the number of issued Certified Emission Reductions (CERs). Accordingly, the main specification reads

\[ EUA_t = \beta_0 + \beta_1 \text{Gas}_t + \beta_2 \text{Coal}_t + \beta_3 \text{Econ}_t + \beta_4 \text{Wind/Solar}_t + \beta_5 \text{Water}_t + \beta_6 \text{CER}_{t-1} + \epsilon_t \]

As alternative to coal and gas prices, they include a fuel-switching price. Additionally, the Economic Sentiment Indicator instead of the stock index is used as a forward-looking measure of economic activity. Sampled with monthly frequency, they consider December EUA futures as their allowance price series. From this set, the gas price and economic activity can be identified as clear price drivers. Surprisingly, the coal price does not significantly affect allowance prices. Although the significant factors show the anticipated effect, the overall explanatory power of the models is low. They increase the model fit by accounting for the effect of major policy events using dummy variables. This implies that certain observations disturb or change the estimated relationship such that taking them out improves the findings of a linear model.

Another interesting paper along these lines is Rickels et al. (2014). The paper differentiates itself from previous work by paying special attention to the multitude of data series that we can choose from. Starting with the choice of allowance price data, the researcher already has various options: over-the-counter, spot and futures prices from different sources. Once this decision is made, the variety continues with the choice of information variables, in particular, coal and gas prices. Rickels et al. (2014) show that empirical papers, whose conclusions regarding the role of
fundamentals differ, often use different price series. They point out that, particularly, the coal price can differ quite substantially and it is not obvious which series to choose, because the market lacks transparency. In their own empirical study, they carefully select each price series. They run auxiliary regressions of each candidate series on the allowance price, to get a feeling for the explanatory power of the series. In the final model specification,

$$EUA_t = \beta_0 + \beta_1 Switch_t + \beta_2 Stocks_t + \beta_3 Oil_t + \beta_4 Wind_t + \beta_5 Hydro_t + \epsilon_t,$$

they find a significant and positive effect of fuel switching, a very limited effect of renewables and a positive effect of economic activity as measured by the oil price and the STOXX 50 index. Rickels et al. (2014) also consider a detailed cointegration analysis to study possible long-term relationships. We will discuss Creti et al. (2012) as an example for this approach in the next section.

These are merely three examples of challenges faced by economists and econometricians who want to study the price determinants of allowance prices in the EU ETS. They show that the relationship between allowances prices and their fundamentals need to be modeled with care. Since the dummy variables in Koch et al. (2014) are associated with major policy events, we can see the importance of controlling for political uncertainty, which will be discussed in Section 3. The extensive analysis of different price series in Rickels et al. (2014) further shows that the choice of time series and data source matters. This section is not exhaustive. Similar approaches and results can be found in e.g. Alberola et al. (2008), Mansanet-Bataller et al. (2011) and Aatola et al. (2013).

In addition, all three papers discussed above find that the residuals of their models are not well behaved in a sense that they are correlated and have a non-constant variance. These problems are addressed by the authors in different ways. Hintermann (2010) uses a GARCH specification and lagged dependent variables to account for this. Koch et al. (2014) and Rickels et al. (2014) rely on Newey-West robust standard errors. Both phenomena, autocorrelation and heteroskedasticity, are frequently encountered in empirical studies. Particularly, the presence and severity of heteroskedasticity are common in studies of financially traded assets. In general, we can see that the allowance price series show several characteristics of financial data. This is discussed in more detail in the last section.

2.2 Alternative approaches

In the previous section, we saw that standard econometric approaches need to be adapted to account for time-varying volatility, outliers related to news events as well as possible nonlinear or time-varying relations. While the importance of new events will be discussed in the next section, here we present papers that focus on the last aspect: time-variation, nonlinearity and instability of the relation between allowance prices and fundamentals.

The first paper is Lutz et al. (2013). It investigates possible nonlinearities in the relationship between the EUA price and its fundamentals during Phase II. They distinguish two different pricing regimes - one applies during periods of high volatility and the other during periods of low volatility. The model allows for two distinct sets of coefficients. The idea that fundamentals have potentially different effects in turbulent times than in quiet times is interesting and intuitive. It is applied to
EU ETS data with daily sampling frequency. The non-switching model is

\[ EUA_t = \beta_0 + \beta_1 \text{Oil}_t + \beta_2 \text{Coal}_t + \beta_3 \text{Gas}_t + \beta_4 \text{Stocks}_t + \beta_5 \text{Commodity}_t + \beta_6 \text{Default}_t + \beta_7 \text{Temp}_t + \epsilon_t \]

As allowance price series, Lutz et al. (2013) consider the popular December futures series from ICE. Their set of information variables is composed of coal and gas futures prices with matching maturity, oil prices, the STOXX 50 European stock price index, a commodity price index and deviation from average temperature. In addition, they include a default spread to account for default risk in credit markets.

In both regimes, they find the same set of relevant price drivers. Coal and gas prices, oil prices and the stock index are statistically significant determinants of the EUA price. In Regime 2, which is characterized by low and constant volatility, all significant price drivers show the anticipated sign. It is the gas price that has the largest effect. This is in line with previous research and economic theory. Regime 1, however, shows high uncertainty and time-varying volatility. The results on price drivers are similar in this regime, except for the effect of the coal price, which is now positive. This goes against economic considerations that predict, as in the second regime, a negative effect of the coal price on allowance prices. The paper shows that the role of one of the fundamental drivers, coal prices, can reverse in times of high volatility and that this induces a significant difference between calm periods and periods of uncertainty. A recent paper by Jiao et al. (2018) follows the idea of different regimes by looking at EUA return distributions in two regimes defined by economic states. However, they do not investigate the impact of fundamentals on prices, but use predictions of future economic states together with the past return behavior for Value at Risk forecasting.

Another interesting approach to look at the relation between EUA prices and its fundamentals is taken by Creti et al. (2012). They investigate the question whether this relation has been stable over the course of Phases I and II and might be evolving towards a long-term equilibrium relationship. Their approach is different from the ones discussed so far. Rather than working with stationary data by transforming integrated price series into return series, they analyze the non-stationary price data using cointegration techniques. Previous work finds evidence of a cointegration relationship in Phase II, while evidence for Phase I is mixed. For more information on previous evidence, we refer to Rickels et al. (2007) and Bredin and Muckley (2011).

Creti et al. (2012) use daily EUA futures prices, and as information variables a calculated switching price, oil price data as well as the Euro STOXX 50 index. The relationship they investigate thus reads as

\[ EUA_t = \beta_0 + \beta_1 \text{Oil}_t + \beta_2 \text{Stocks}_t + \beta_3 \text{Switch}_t + \epsilon_t \]

They consider their whole sample period (2005-2010) as well as two sub-periods corresponding to the different compliance phases. They find a clear cointegration relationship in Phase II with positive and significant coefficients for all fundamentals. However, for Phase I, they can only find a relationship if they allow for a structural break in 2006. The break corresponds to the time of discovery of the over-allocation in Phase I. The nature of the relationships differ between Phase I
and II. They find a negative effect of the stock price variable in Phase I and an insignificant effect of the fuel-switching variable. Overall, these findings indicate an increasing role of fundamentals. Nevertheless, there is no clear evidence for a stable relationship which is also confirmed by the cointegration analysis of Rickels et al. (2014).

Further evidence can be found in Keppler and Mansanet-Bataller (2010). They use yet another approach than the ones already presented. Keppler and Mansanet-Bataller (2010) analyze the interplay between daily CO2, electricity, gas and coal prices based on a Granger causality analysis. We would like to stress two points from their analysis. First, they address the commonly observed endogeneity problem researchers face when attempting to include electricity prices in their model. Electricity prices should have an effect on EUA prices, but the reverse is likely to be true, as well. Further evidence of potential endogeneity concerns can be found in Aatola et al. (2013). Second, Keppler and Mansanet-Bataller (2010) use the concept of Granger causality, which is different from the cointegration analysis performed in Creti et al. (2012). A time series \( \{ x_t \}_{t=1}^n \) Granger causes another time series \( \{ y_t \}_{t=1}^n \), if the past of \( x \) has an effect on the present of \( y \). This is a fundamentally different approach that does not look at long-term relationships, but investigates if a variable has explanatory power in predicting the future of another. Moreover, cointegration analysis is performed on integrated data, while Granger causality tests generally require stationary time series.

Keppler and Mansanet-Bataller (2010) include both EUA spot and futures prices from 2005 to 2008, as well as gas and coal futures, spot and futures electricity prices for both peak and base load, the clean dark and spark spread (CDS, CSS) as well as a stock index (STOXX 600) and several temperature variables. Since the pairwise tests can run in either direction (\( x \) can Granger cause \( y \), and \( y \) can Granger cause \( x \)), there is a great number of possible tests from the above variables. They split the analysis into Phase I and Phase II, which introduces even more pairs to consider. Here, we only point out the main findings.

For Phase I, Keppler and Mansanet-Bataller (2010) find that futures EUA returns Granger cause spot returns, while spot returns do not Granger cause futures. Both time series have a correlation of 0.999. In addition, EUA futures are Granger caused by CSS and CDS for peak-load electricity as well as by the temperature index, but not by gas, coal or electricity returns. Conversely, EUA futures Granger cause electricity futures for peak and base load, which, in turn, Granger cause the stock index. Based on the previous causality analysis, the authors decide to run a regression with electricity futures as dependent variable and not the allowance price.

\[
feleb_t = \beta_0 + \beta_1 EUA_t + \beta_2 CSS_t + \beta_3 Gas_{t-1} + \epsilon_t,
\]

where \( feleb_t \) stands for the futures price for base load electricity. The allowance price, which is usually the dependent variable, enters as a regressor together with the CSS and the gas price. They find positive and significant effects of all regressors.

Results are different for Phase II (2008). The main difference is that now electricity futures Granger cause EUA futures and not vice versa. Hence, EUA futures are the dependent variable in their Phase II model, electricity spot prices for peak load, electricity futures prices for base load, CDS, temperature index and the stock index as well as a lag of the gas price are now the regressors.
Consider

\[ EUA_t = \beta_0 + \beta_1 selep_{t-2} + \beta_2 felep_{t-4} + \beta_3 CDS_{t-1} + \beta_4 Temp_{t-3} + \beta_5 Stocks_t + \beta_6 Gas_{t-1} + \epsilon_t, \]

where \( selep_t \) denotes the spot price for peak load electricity. All regressors have a significant and positive effect. Again, the paper adds evidence that there has been change in the relationship of allowance prices and its fundamentals over time which has to be taken into account by analysts. From a methodological point of view, the preceding two papers introduce two popular and frequently used econometric tools - cointegration analysis and Granger causality - which will come back in the section on market frictions, where both are applied to study the relationship between EUA spot and futures prices.

The papers reviewed in this section establish a clear link to the upcoming two sections. A first potential explanation for the difficulties in modeling allowance prices might lie in the fact that the market has been created as a policy tool. Political decisions were responsible for introducing the EU ETS. Therefore, political decisions are likely to have a substantial effect on prices - possibly even more so in this market than in other commodity markets, which are also strongly affected by political uncertainty. There is clear evidence pointing in this direction in the papers discussed in this section and we will discuss the literature that emerged on this topic in the next section. Additionally, the fact that emission allowances are traded as a financial asset as well as the existence of various derivatives of this asset both lend itself to a second potential explanation. As trading becomes more frequent and volumes increase, this aspect of the EU ETS as a financial market cannot be disregarded. It is reflected in significant heteroskedasticity found by the reviewed studies on fundamentals. There is a whole strand of the literature available that only focuses on this aspect and it will be reviewed in the last section.

2.3 Insights and implications

The section on fundamental price drivers gives an insight into the findings and methods of six empirical papers, representative of this strand of the literature on the EU ETS. The first part reveals that, although economic theory has clear predictions, they are not always easy to verify in practice. In the second part, we see that the relation between allowance prices and their fundamental drivers is not stable over time implying that there might be time variation and structural changes in this relationship which need to be taken into account. Even when allowing for time variation with the help of a regime-switching model, the explanatory power of abatement-related fundamentals remains low. This underlines the need for alternative concepts which we turn to in the next sections.

3 Political and regulatory uncertainty

The previous section alluded to regulatory uncertainty as another factor influencing price formation, which has recently gained more attention in face of the low EUA prices and the difficulty of explaining the price development with the help of fundamentals.

Regulatory uncertainty can be accommodated in the standard model of price formation in many
ways. One way is to assume that, if there is a regulatory intervention, the price will either jump up with probability $\varphi$ or jump down with probability $(1 - \varphi)$. This idea is formally introduced in Salant (2016). The new expected price $p^A$ is then given by:

$$p^A = \varphi p^H + (1 - \varphi) p^L,$$

where $p^L \geq 0$ and $p^H \geq p^L$ denote the lower and higher price after a jump, respectively. The risk for a regulatory intervention which causes such a jump is ongoing and it is determined by the hazard rate $\alpha > 0$. In this case Salant (2016) shows that no arbitrage considerations cause the price change in anticipation of the jump to be:

$$\frac{dt}{dt} = (\alpha + r)p_t - \alpha p^A$$

which implies that the growth rate of prices in this new situation changes from $r$ to (3.2). This is a first order differential equation with solution

$$p_t = p_0 e^{(r+\alpha)t} - \frac{\alpha p^A}{r + \alpha} \left(e^{(r+\alpha)t} - 1\right),$$

which adds the two new factors ($\alpha$ and $p^A$) to the price equation (2.1) from the previous section. The old price equation is recovered when letting $\alpha = 0$. A news announcement leads market participants to adapt the probability of a jump, either downward or upward depending on the type of announcement. This, in turn, leads to a change in the allowance price path.

Alternatively, one could also represent regulatory uncertainty by assuming that the cap will be changed with a certain probability. This implies that the standard intertemporal market balance equation (2.2) would change to:

$$\int_{\tau=0}^{T} x(p_0 e^{r\tau}) d\tau = \mathbb{E}(\mathcal{G})$$

Again, a news announcement gives market participants new information from which they infer an abrupt change of $\mathbb{E}(\mathcal{G})$. This leads the price to jump in the respective direction. Such price jumps are in practice reflected by abnormal returns which is the basis for the empirical studies we discuss in the remainder of this section.

The selected papers focus on the impact of different types of regulatory announcements on allowance prices. They look at announcements of realized emissions as well as political or regulatory decisions. While many papers discussed in the previous section already incorporated some aspects related to political decisions by splitting the sample into sub-samples or by including dummy variables, the papers discussed here take a more direct approach. Two of them perform an event study and one uses a dummy variable approach to detect news related price changes.

In general, event studies can uncover price changes caused by a specific event. The main idea relies on a comparison of the price change that would be expected in the absence of the event - the normal return - to the actual change in prices. If the difference aggregated over a pre-specified event window is large enough, there has been a significant price effect caused by the studied event. This
difference between actual and normal returns is called the abnormal return. Formally, the abnormal return at time $t$ can be defined as

$$AR_t = r_t - E_t(r_t),$$

where $r_t$ denotes the actual return and $E_t(r_t)$ is the expected normal return at time $t$. If the event window ranges from $t_1$ to $t_2$, cumulative abnormal returns are obtained as

$$CAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} AR_t.$$

Those returns are the main quantity of interest and they need to be carefully estimated. Since actual returns are an observed quantity, it is the estimation of normal returns that is crucial. We do not know what the price would have been if the event had not taken place. To obtain estimates of normal returns, the following papers use different approaches. They also look at different types of events.

3.1 Realized emissions

The first paper we present is Hitzemann et al. (2015). The authors look at the effect of emission announcements on EUA returns. Once a year, in April, the quantity of realized emissions are publicly announced. Comparison of these figures with the cap reveals whether there has been a shortage or surplus of allowances. Information about realized emissions will directly affect the supply side of allowances. The demand side will be affected, as well, since the announcement provides information on future emissions and affects expectations of future supply. They are expected to have an impact on the current EUA price. If the actual emissions match the expectations of market participants, the effect should be negligible, as the corresponding information will already be reflected in current prices. However, if the number of realized emissions differs from expectations, its announcement carries a surprise factor which will affect EUA prices. They also investigate how these announcements affect trading volumes and intra-day volatilities of EUA futures.

In order to capture the news related effect, Hitzemann et al. (2015) define five dummy variables for each announcement. They are designed to capture the effect on the day of the announcement as well as the period before and after the event. The dummy variables are used as explanatory variables in a regression on absolute abnormal returns of EUA futures. This procedure provides an estimate of the immediate effect as well as the effect directly prior to and after the announcement. Similar to the remaining two papers that use event studies, abnormal returns play an important role in this paper. They are calculated as the difference between actual returns and the overall average return:

$$AR_t = r_t - \bar{r},$$

with $\bar{r} = T^{-1}\sum_{t=1}^{T} r_t$. Using absolute abnormal returns, $AAR_t = |AR_t|$, the dummy variable
regression reads

\[ AAR_t = \beta_0 + \beta_1 D_{[-4,-2]} + \beta_2 D_{-1} + \beta_3 D_0 + \beta_4 D_{+1} + \beta_5 D_{[+2,+4]} + \epsilon_t, \]

where \( D_{[t_1,t_2]} \) is a dummy variable which equals 1 during the indicated day(s) and 0 otherwise. The same regression are carried out with trading volumes and implied as well as realized volatility, the latter two being a measure of intra-day volatility. As a robustness check, Hitzemann et al. (2015) also calculate abnormal returns using average returns over a rolling window, which yields similar results as using the total average.

Overall, the authors find significant abnormal returns on the event day. They also find increased trading volumes and intra-day volatility on the same day. The return response is particularly high in 2008 and 2012. There is no significant effect on abnormal returns before or after the announcement day. Neither of the other dummy variables has a significant effect. This finding shows an immediate market response. The market seems to incorporate new information efficiently into prices. Additionally to these findings, they observe low trading volumes and low intra-day volatility prior to the announcement. Hitzemann et al. (2015) interpret this as a "calm-before-the-storm" effect. The results are in line with findings from other energy and commodity markets.

### 3.2 Backloading and cap-updating

A second paper we highlight is Koch et al. (2016). The paper investigates two types of policy events: backloading and updating of the cap. Backloading refers to the decision to postpone the auctioning of allowances. While updating of the long-term cap should lead to a price reaction, backloading is cap-neutral and should not affect allowance prices. However, if market participants have a short foresight horizon, then backloading can have an effect. In addition, incorporating regulatory risk into the theoretical framework, as in Salant (2016), says that both types of announcements should affect the probability of price jumps, which leads to a different expected price after the announcement. A price effect due to an announcement related to backloading can therefore confirm this theoretical argument.

The analysis in Koch et al. (2016) is a classical event study approach, but instead of simply using average returns as an estimate of normal return, they rely on model predictions. As we saw in the previous section, there is not one preferred model for EUA returns. This complicates the question of model choice. To solve this problem, Koch et al. (2016) rely on a flexible procedure called Dynamic Model Selection. From a vast amount of different models, including potentially different sets of regressors at different time periods, the procedure selects the one with the best fit. For each event, this model is used to predict normal returns for a 7-day event window. Although the general idea is similar, this approach is substantially more involved than the dummy variables in the previous paper.

Koch et al. (2016) apply their approach to EUA futures price data from 2008 to 2014. The set of possible regressors consists of oil, coal, electricity, commodity and stock prices, interest rates, corporate bond spread, CER prices and a volatility index.

They find that events related to backloading explain many jumps in the data. Four backloading
events cause a significant price drop and two a significant price increase, while only two events related to long-term cap changes trigger a statistically significant price effect. The latter are the agreement on 2020 targets and the Green Paper on 2030 targets - both having a positive effect. In summary, they conclude that policy events can explain the existence and timing of jumps in EUA prices. However, many events do not cause an effect in the anticipated direction. The goal to increase the price by backloading has not been achieved, because there is an overall negative effect on prices. Koch et al. (2016) argue that expectations about the degree of commitment plays an important role in allowance pricing.

3.3 Decisions by the European Parliament

The third and final paper in this section is Deeney et al. (2016). The authors look at the effect of announcements of the European Parliament (EP) on EUA returns. The EP holds legislative authority over the EU ETS which makes its decisions a crucial event to study. Deeney et al. (2016) select 29 relevant events from October 2007 to February 2014. They categorize events according to three main criteria. First, they distinguish between “party-political” and “non-party-political”. Party-political decisions concern resolutions put forward by the seven political groups of the EP. Non-party-political decisions come from the European Commission or the European Council. Second, they construct a measure of EUA market sentiment and label events as high or low sentiment according to the resulting index. Third, they measure market attention, or news exposure, which leads to the third and final category. The events are divided between high and low news exposure.

After dividing the 29 events into categories, they are left with 10 party-political and 19 non-party-political events, 12 high sentiment and 17 low sentiment as well as 14 high news exposure and 15 low news exposure events. The event window is chosen to consist of 11 days, the day of the Decision by Parliament as well as five days before and after this day. To calculate abnormal returns, they use a zero log return model as well as a constant log return model. As the name suggests, in the first model, normal returns are assumed to be zero during the event window, \( E_t(r_t) = 0 \). In this case, \( AR_t = r_t \). In the second model, normal returns are constant and equal to the mean return during the estimation window, which consists of the 20 days before the start of the event window:

\[
E_t(r_t) = \frac{1}{20} \sum_{i=t-25}^{t-6} r_i.
\]

Both models are easy to implement and yield very similar results in this application. In addition, the authors investigate volatility effects using a GARCH model equipped with dummy variables for the period before the event, the event day itself and the period after the event.

Deeney et al. (2016) find significant negative abnormal returns as well as an increase in volatility due to the announcements related to EP decisions. Looking at the different categories, these findings seem driven by non-party-political events. Most party-political events have no significant effect. A possible explanation according to Deeney et al. (2016) is that party-political decisions get more media coverage and attract more attention in advance than non-party-political resolutions. This
suggests that the party-political decision does not come as a surprise and that prices already reflect this information. Additionally, they find the same effects after events in times of low market sentiment and when market attention is low. When market attention is high, there is no significant abnormal return, but a decrease in volatility after the announcement. Both findings are relevant for the timing and extent to which political decisions are revealed to market participants.

3.4 Other related papers

Other studies in this direction are e.g. Mansanet-Bataller and Pardo (2009), Mansanet-Bataller and Sanin (2014) and Fan et al. (2017). The latter paper looks at a wide range of announcements regarding regulatory updates in an event study using adjusted mean returns as a measure of normal returns. They find 24 out of the 50 events they consider to have caused significant abnormal returns. Another recent contribution is Cretí and Joëts (2017) who also use an event study. However, before the event study, they test for periods of exuberance in the allowance price data and find evidence for several short periods of explosive behavior. Events that offer possible explanations for these episodes are then used in an event study in which no abnormal returns are found.

In addition, we would like to mention Sanin et al. (2015) as a last paper in this section. The authors apply a different approach which is, in essence, a combination of methods used by papers in the previous section on fundamentals. Sanin et al. (2015) use an ARMA model for allowance prices with fundamentals as exogenous regressors and a GARCH component. To the GARCH model they add a jump component that allows for sudden jumps in volatility which they relate to supply announcements by the European Commission. The fact that their focus lies on volatility dynamics rather than prices emphasizes the financial market aspect of the EU ETS. This is where we turn to in the next section: the financial economics and econometrics literature of the EU ETS.

3.5 Insights and implications

Event studies are a powerful tool to establish a direct link between price behavior and certain events, which is extremely valuable in the EU ETS literature, given its tight link to political decisions. However, in event studies, all revolves around the notion of abnormal returns and there exists a plurality of ways how to estimate them. Our discussion shows that methods to obtain this crucial quantity can differ substantially. From simply using zero or constant returns, the approach can get as complex as the Dynamic Model Selection used in Koch et al. (2016). The results will depend on the applied method. In addition, the selected papers show that many events do not show the anticipated price effect. This leaves us with the final strand of the literature we consider: methods from financial economics applied to explain allowance price formation.

4 Emission allowances as a financial asset

Besides its role as a (physical) compliance market, the EU ETS is also a financial market. The main purpose of such a financial commodity market is risk reduction (hedging), speculation and price
discovery. Moreover, a financial market introduces new agents to the ETS: financial traders or speculators who aim to make profit from trading allowances or derivatives such as options and futures. This raises the question in how far speculation, hedging and (in)efficient price discovery affect the price formation in the EU ETS. Analyzing the EU ETS from a financial market perspective, where EUAs or corresponding derivatives are traded as financial assets, thus offers useful insights into the functioning of the market.

We focus on two different aspects. The first strand of literature considers market frictions and the price discovery processes. Financial economic theory suggests that markets are efficient if prices reflect all available information such that there are no arbitrage opportunities. Typical inefficiencies which impair information transmission are transaction costs. Other market frictions are convenience yields and risk premia that may lead to under- or overvalued prices, compared to the idealized first best market solution. In this case, deviations from the optimal EUA price can, for example, be due to shocks on the availability of (physical) EUAs and the hedging demand of regulated firms.

The second strand of literature that we discuss in this section is on behavioral aspects of the EU ETS. By now, non-regulated actors make up a large share of the overall trading volume in the market. Given that trading accounts held by financial actors tend to be more active than those of compliance traders (Berta et al., 2017; Betz and Schmidt, 2016), their behavior is potentially an important factor for price formation. Consequently, during the last years, the behavior of these actors and possible differences in their trading strategies have become a major interest in the literature.

Although the relationship of interest is different, it is interesting to see that many of the methods which we saw in Section 2 reappear in this section. Previously, they were applied to analyze the allowance price and its relationship to fundamentals. In particular, cointegration analysis, Granger causality tests and (variations of) GARCH models are popular also in this strand of the literature. The main difference is that the methods are applied to different data series. Studies in the section analyze, for example, the price volatility, bank volume or the duration of trades.

4.1 Financial market frictions

Financial market frictions are typically analyzed by the relationship between ETS spot and futures prices. There are two (non-exclusive) theoretical views on this relationship (e.g. Fama and French (1987)). First, according to the theory of storage, price differences should reflect the forgone interest due to investing in a commodity, its storage costs and a convenience yield (Kaldor, 1939; Working, 1949; Brennan, 1958). Since storage costs for EUAs are virtually zero, price differences should be only due to the interest rate and the convenience yield. The latter arises because of a potential benefit of holding EUAs rather than futures. This benefit could exist due to potential stock-outs (i.e. a zero bank) in the future which can lead to positive price shocks because firms cannot borrow from future compliance periods. The second view on the relationship between spot and futures prices is the hedging pressure theory (e.g. Keynes (1923, 1930), Hicks (1939), Hirshleifer (1990)). In this case, futures prices consist of the expected spot price and a risk premium. The latter has to be paid by producers to financial traders or speculators that take the contrary position in the market.
The risk premium reflects the producers’ demand for risk reduction (due to risk aversion). They thus accept a lower return which is the profit of speculators. Both theories can be incorporated in a standard cost-of-carry model implying no-arbitrage between spot and futures prices. Specifically, the futures price is

\[ p_{fut}^t = p_t e^{(r - \gamma + \lambda)(T - t)} \]  

(4.1)

where \( p_t \) is the ETS spot price, \( T \) is the expiry date of the futures contract, \( \gamma \) is a convenience yield and \( \lambda \) is a risk premium. Due to arbitrage this relationship holds for allowances prices in general and thus we can write the allowance price path as

\[ p_t = p_0 e^{(r - \gamma + \lambda)t}. \]  

(4.2)

Hence, similar as the hazard rate in the previous section, the risk premium and the convenience yield change the price path and enter the original equation (2.1) through an additional term in the exponential function. A positive risk premium leads to a steeper price path with prices lower than optimal, initially, and higher than optimal in later periods. A negative risk premium and the convenience yield, in contrast, have opposing effects since they flatten the price path.

In addition, deviations from the cost-of-carry model can also be explained by other market frictions that prevent a perfect arbitrage. An example for this could be transaction costs. Such frictions may lead to inefficient information transmission between spot and futures markets and distort the price discovery process.

The first paper we consider in this regard is Rittler (2012). The paper focuses on the price discovery process between spot and futures markets. In a first step, he derives the theoretical futures prices from observed spot prices based on the cost-of-carry model given by equation (4.1) assuming no convenience yields and risk premiums, \( \gamma = \lambda = 0 \). Theoretical and observed futures prices are then used to estimate a vector error correction model (VECM) to analyze cointegration of long-run prices based on Engle and Granger (1987). Subsequently, Rittler (2012) computes common factor weights as price discovery measures for the markets (Hasbrouck (1995), Schwarz and Szakmary (1994)) and conduct Granger causality tests for the short-term relationship. He uses tick-by-tick spot and futures prices with maturities in December 2008 and 2009 from BlueNext and ECX, respectively, for the period of May 2008 to December 2009. Data are transformed to 10 and 30 minutes frequencies. To make his results comparable to previous literature, which commonly used daily data for this exercise, he also uses daily data.

Using daily data, the author finds no cointegration between prices, indicating the absence of a stable long-run relationship. This confirms the result by Chevallier (2010a) who also finds no cointegration for similar data. It is also consistent with Joyeux and Milunovich (2010), who provide results for Phase I. In contrast, Uhrig-Homburg and Wagner (2009) find evidence of a long-run relationship with daily data for Phase I. More recent studies by Charles et al. (2013) and Bredin and Parsons (2016) also conduct conintegration tests with daily data. The former find a significant relationship between spot and futures prices using data from March 2009 to January 2012. Bredin
and Parsons (2016) use data from 2005 to 2014, and find only cointegration between observed and theoretical cost-of-carry futures in Phase I, while for Phases II and III, there is no cointegration.

Overall, the results for the relationship between daily spot and futures prices are mixed and suggest some frictions preventing a perfect arbitrage. However, when using 10 or 30 minutes intraday data, Rittler (2012) finds strong support for cointegrated prices. He suggests that markets are indeed closely linked but this can only be observed when exploiting information in high frequency rather than daily data. Furthermore, Rittler (2012) finds common factor weights of about 70% for the futures market, which means that it contributes more to the price discovery process than the spot market. Regarding short-term causality, he finds a bidirectional impact based on the Granger causality tests. Rittler (2012) concludes that the price discovery process is similar to other mature markets. This result is confirmed by Schultz and Swieringa (2014) who also use high frequency data. In addition, Schultz and Swieringa (2014) find that transaction costs are an important market friction that prevents faster price adjustments for some EU ETS securities. The study by Mizrach and Otsubo (2014) confirms the cointegration between EUA futures and spot prices, where the more liquid futures market leads the price discovery. They also identify a profitable trading strategy that exploits the predictive power of order imbalances with regard to returns of the next trading days.

Also concerned with the microstructure of the carbon futures market, we choose Ibrahim and Kalaitzoglou (2016) as a second paper. They propose an asymmetric information microstructural model of intraday price changes in order to analyze the effect of expected trading intensity on intraday price changes. Their dynamic joint-expectations model incorporates stylized facts about the EU ETS that have emerged in the literature, such as autocorrelation in the order flow and the existence of trading patterns associated with information and liquidity. In their model, the price responds dynamically to information and liquidity with every transaction, as traders form their expectations about subsequent trades based on trading activity and trade characteristics of previous trades. Specifically, when formulating price quotes, traders take into account trading intensity, information content, and volatility of previous trades. The authors find that the autocorrelations in returns and in the volatility of returns observed in the EU ETS can be explained to a large extent by the predictability in the persistence of trading intensity.

While Charles et al. (2013) find cointegration between spot and futures prices (see above), they reject the cost-of-carry model with zero convenience yield. They interpret this as market inefficiency due to transaction costs that prevent perfect arbitrage. Other studies take a different perspective in this regard. One example is the third paper we consider. Trück and Weron (2016) also start with the theoretical cost-of-carry model but allow for a positive or negative convenience yield which includes the risk premium as well in their case. Specifically, they calculate the implied convenience yield based on observed spot and futures prices based on equation (4.1), yielding

\[
\gamma = r - \frac{\ln(p_{fut}^t) - \ln(p_t)}{(T - t)}
\]  

(4.3)

where \(\gamma\) may also include a risk premium \(\lambda\). For this purpose, they use daily spot and futures (December contracts 2009 to 2015) price of Phase II (2008 to 2012). They find that after a short period of a positive convenience yield in 2008, the convenience yield turns highly negative between
and -7% thereafter. In a second step, Trück and Weron (2016) regress the implied convenience yields on several factors by applying a pooled OLS regression. Among others they use the allowance surplus in the market and risk measures (variance and skewness of EUA prices) as independent variables. They find that a higher allowance surplus decreases the convenience yield. They interpret this result as consistent with the theory of storage since generally more allowances (a higher stock), should lead to lower risk of a stock-out and therefore holding allowances has a lower additional value. In addition, they find a negative effect of the EUA price variance on the convenience yield. This is seen as evidence for the impact of the hedging demand: firms are willing to pay higher prices for futures in order to reduce their risk exposure.

Other papers that empirically consider risk premia are Chevallier (2010b, 2013), Kamga and Schlepper (2015) and Pinho and Madaleno (2011). They find on average positive risk premia and suggest that this indicates that investors want to hedge against rising prices. Similar to Trück and Weron (2016), Chevallier (2010b, 2013) and Pinho and Madaleno (2011) also find that the price variance affects the risk premia. The role of hedging is also confirmed by Hintermann (2012). He derives an option pricing formula in which the price depends on the penalty for non-compliance and the probability of a non-binding cap. He applies it to Phase I data and finds that it can explain large parts of the price development. Therefore, he concludes that hedging against paying the penalty was an important price driver in Phase I.

4.2 Behavioral aspects

This section sheds light on how the behavior of different market actors might play a role for ETS prices. Behavioral aspects covered here comprise the existence of different trading types, non-rational behavior such as herding, and the use of trading strategies aiming at exploiting price patterns. Two important theoretical papers in this context are Barberis et al. (1998) and De Long et al. (1990). Both derive price formulas for assets in which they distinguish between the fundamental value of the asset and an additional term due to mispricing.

Barberis et al. (1998) ask how market participants form beliefs about the probability of future changes – or rather how these beliefs are updated in response to new information. Standard models implicitly assume that updating happens instantaneously and with full confidence about the effect on prices in equilibrium. Yet it is known that there is both overreaction and underreaction of stock prices to new information. Barberis et al. (1998) propose a model of investor sentiment based on psychological evidence to explain this behavior. While earnings from the asset follows a random walk, the investor believes that they switch between two regimes: a mean reverting regime and a trending regime. Although the probability is higher that we stay in one regime, the investor updates his beliefs about the current regime with every new information. Barberis et al. (1998) show that their framework which is built on this formal model of investor sentiment can explain both under- and overreaction. For both phenomena Barberis et al. (1998) give a link to concepts from psychology (conservatism and representativeness).

De Long et al. (1990) analyze the effect of noise traders in financial markets. They assert two types of traders in the market: sophisticated investors and noise traders, whereby the latter falsely
believe they have special information about the future price of the risky asset and in consequence misperceive the true expected price. This misperception leads to persistent irrational trading behavior that distorts prices (first-order effect). This in turn creates a noise-trading induced risk for sophisticated traders, which even further distorts prices (second-order effect).

Formally, this can be put into the framework of the previous sections as follows. If we denote by $p^F_t$ the original price path that is determined by fundamentals, the previous equations (2.1), (3.2) and (4.2) can all be seen as different representations of $p^F_t$. In this section, however, the allowance price can deviate from this fundamental value:

$$p_t = p^F_t + \mathcal{B}, \quad (4.4)$$

where $\mathcal{B}$ is a general additive term representing any changes from $p^F_t$ which are due to behavioral aspects such as herding behavior, different trading strategies or even speculative bubbles. The presence of noise traders as in De Long et al. (1990) can also be captured as well as false updating of beliefs as in Barberis et al. (1998). The latter two papers both give an exact specification of the term $\mathcal{B}$ with mathematical derivations given their respective model framework.

While, in theory, the concepts are intuitive and clear-cut, it is challenging to empirically distinguish the two parts in equation (4.4) in the case of the EU ETS. This is because, as we have seen in Section 2, the part of $p^F_t$ is difficult to determine due to the low explanatory power of abatement-related fundamentals. The remainder of this section summarizes three papers which empirically investigate behavioral aspects by looking at trading strategies and herding behavior.

A first paper we consider is Kalaitzoglou and Ibrahim (2013), which illuminates trading behavior by identifying different types of agents active in the EU ETS futures market. Instead of focusing on returns or volatility, their unit of analysis is the time that passes between trades, i.e. the duration of trades. Thereby, they examine in how far clustering of duration characteristics correlates with the trading behavior of market participants and how many types of agents can be identified.

The duration between single transactions is modeled with a smooth transition mixture autocorrelated duration (STM-ACD) model. By incorporating smooth transitions into the model, the dynamics between two regimes (where a regime is dominated by a certain type of trader) can be captured. The data comprises the time, price, volume, and trade direction of all transactions on the ECX from 2005 to 2008. In addition, an over-the-counter (OTC) dummy is included in order to determine whether OTC trades are associated with a specific type of trader. The presence of three different trader types in the market is examined: The informed traders receive private information to which they react by trading in large volumes. The uninformed have no access to this information and hence initiate their trades randomly. Lastly, while the fundamentals are also uninformed, they are able to extract information from the market by examining past trades.

The empirical analysis suggests that differentiating between three regimes indeed improves the explanatory power of the model. The trader types associated with these regimes are identified by analyzing the shape of the hazard rate, which measures the probability of a trade being initiated after the arrival of exogenous information as a function of time. In the case of the informed traders, the hazard rate is decreasing, for the uninformed it is flat, while for the fundamental traders,
who extract information with a delay by analyzing informed trades, the hazard rate is increasing. Regarding the smooth transition mechanism included in the model, the findings suggest smoother transitions between the informed and the fundamental regime in Phase II compared to Phase I. This implies that learning by the uninformed happened faster in later stages of the EU ETS and, as a result, greater market depth.

Balietti (2016) as well considers the presence of different trading behaviors. Specifically, the author estimates in how far the relation between trading activity and volatility varies with different trader types. In contrast to Kalaitzoglou and Ibrahim (2013), the author differentiates between different trader types according to the specific design of the EU ETS as a compliance market. This market is characterized by actors who are regulated by the EU ETS, and hence obliged to participate, and financial actors, who participate either as intermediaries or to make profit from speculation. Moreover, actors are exposed to different (product) markets depending on whether they are active in the energy, industry, or financial sector. The initial endowment of certificates relative to their baseline emissions (i.e. whether they are over- or underallocated) is also taken into account.

In order to examine how the specific characteristics of the market actors translates into differences in their trading behavior, Balietti (2016) regresses the volatility on the trading activity of the different participants. The data is derived from the EU Transaction Log (EUTL), where every single transaction within the EU ETS is stored. The trading activity-volatility relation is estimated by simultaneously estimating returns and volatility. Therefore, two equations are iterated: Equation 1 estimates the price changes conditional on autoregressive terms and lagged volatilities, while equation 2 estimates the conditional standard deviation based on lagged volatilities, lagged price changes, and trading activity. As a proxy for trading activity, Balietti (2016) uses both the daily transferred EUA volumes (fitted by an ARIMA process) and the number of daily permit transfers.

The regression on the daily spot price differences hints at a lack of market efficiency in Phase I of the EU ETS: The coefficients of the lagged price differences are significant and negative, i.e. large price differences in the past come along with smaller price changes in the present. The regression on price volatility and permit trading shows that when distinguishing between the three sectors (energy, industry, finance), the trading activity-volatility relation differs with trader type. While the energy sector trades more when volatility is high, the industry sector tends to be more active when volatility levels are low. The financial sector seems to act as a flexible counterpart, trading more with the energy sector when volatility is high and more with the industry sector when volatility is low. However, all in all, many actors seemed to have remained inactive during Phase I especially when volatility was high, suggesting that a large share of actors was unwilling to trade when a lot of information arrived in the market.

The presence of herding behavior in the European Carbon Futures Market is analyzed by Palao and Pardo (2017). Herding behavior can be observed in many fields of human decision making but also in financial markets, where the term captures the tendency of traders to imitate the behavior of others. Their analysis comprises three parts: (i) detecting herding behavior in the futures market, (ii) identifying factors that influence herding behavior and (iii) analyzing the impact of herding behavior on the market.
Herding behavior can be detected by looking for persisting upward and downward runs in the price development, i.e. sequences of buy or sell trades. Palao and Pardo (2017) use the Herding Intensity Measure developed by Patterson and Sharma (2006) to identify the occurrence of such runs in the European Carbon Futures Market. More specifically, this statistic tests for runs that persist longer than what would be expected in the case where market participants base their trades only on their own information.

To identify herding patterns, Palao and Pardo (2017) test for the significance of the impact of time (trend) and price clustering on herding behavior. They find that the herding effect decreases over time but is higher on days where price clustering is strong. Moreover, herding increases during speculative periods and when ETS-related news are published. Similarly, herding is positively correlated with trading frequency, uncertainty (as measured by intraday volatility) and the occurrence of extreme returns.

A related strand of literature considers the presence and profitability of trading strategies exploiting price patterns. Daskalakis (2013) examines the EUA futures market and analyzes the relative performance of different trading strategies that aim at identifying price trends by looking at past prices. This is inconsistent with the efficient market hypothesis and thus should not result in positive returns in an efficient market. The results, indeed, hint both at the failure of the efficient market hypothesis in the period from 2008 to 2009 as well as at an increase in efficiency from 2010 onwards. However, even for 2011, the trading strategies were successful as they produced positive returns, although these were lower than those of the reference sell and hold strategy. This implies that the market became more mature over the years and thus closer to being in line with weak market efficiency. Crossland et al. (2013) consider the daily EUA spot prices in Phase II and analyze the presence of profitable trading strategies based on momentum (price trend continuing) and overreaction (price trend reversing). They find the occurrence of momentum in the short-term and overreaction in the medium-term, both phenomena that contradict the efficient market hypothesis. Related to this, Narayan and Sharma (2015) find that given the predictability of spot prices through forward prices, investors are able to make significantly higher profits using forecasts based on a forward returns model than on a constant returns model.

4.3 Insights and implications

The reviewed literature shows that by analyzing the EU ETS as a financial market further price drivers can be identified. Several papers find evidence for violations of the idealized cost-of-carry model which in turn implies that EUAs and/or its financial derivatives are not optimally priced. These deviations can be explained by different market frictions such as transaction costs and the hedging demand of firms implying risk premia. Another possible price driver is the behavior of traders in the EU ETS. Studies identify the presence of different trading types with distinct trading strategies, possibly non-rational behavior such as herding and the profitability of trading strategies that exploit price patterns.
5 Conclusions

Covering three different strands of empirical literature on the EU ETS, the structure of our review mirrors the increasing complexity associated with understanding what drives prices in the EU ETS. The main papers we reviewed together with a summary of the methods used in the empirical analysis are given in Table 1. The first section, building on basic theory of emissions trading, focuses on the role of market fundamentals on the demand side. Many papers, however, find that the overall explanatory power of the models is low. Important variables do not show a significant effect on the allowance price, or, in some cases, the effect is opposite to what is predicted by basic theory. In addition, it has been shown that the results seem to depend on the specific data series used. Another finding which adds to this is that the relationship does not seem to be stable over time. The main insight of this first part is thus that although fundamentals should have a major effect on allowance prices according to basic theory, the link is less evident in practice.

In view of the insufficient explanatory power of fundamentals as the sole price drivers, the second strand of literature focuses on the implications of the EU ETS being created and affected by political decisions. Accordingly, political announcements and events emerged as a potential explanation of the long period of low prices from around 2013 to around 2017, because regulatory interventions may considerably influence price formation. Such interventions include revisions of the future cap, structural reforms and the uncertainty surrounding these decisions more broadly. The papers reviewed in the respective section provide evidence that related announcements cause significant abnormal returns of allowance prices, and bring additional volatility into the market. Although most of the interventions investigated aimed at strengthening the ETS, no or negative price effects were much more likely than positive ones. This may reflect the low credibility associated with the reforms and the long-term cap as such, as market actors often do not react to announcements or even lower their price expectations if discussed reforms are considered as too weak. To go even further, the political debates and announcements may merely reflect the difficulty to implement an ambitious long-term cap and thus increase overall regulatory uncertainty. Hence, the major insight of this second part is that regulatory interventions of many sorts tend to depress prices, presumably because they undermine the credibility of long-term targets.

The third part acknowledges that the EU ETS is not only a physical compliance market, but also a financial market which allows for hedging, speculation and price discovery. The literature generally finds that the EU ETS market functions similar as other commodity markets in these regards. Several studies focus on the relationship between spot and futures prices to test arbitrage opportunities, which should be fully exploited according to theory. Yet, they find that this is typically not the case because of market frictions. Specifically, transaction costs and risk premia due to the hedging demand of firms seem to play an important role and thus affect the ETS price. It is also shown that the allowance bank volume affects the ETS price, which is often ignored in the ETS literature. Finally, a still nascent literature focuses on behavioral aspects of emissions trading. Studies hint at the presence of different trader types and irrational behavior such as herding. In view of the steep price increase since mid 2017, which is still in need of explanation, a better understanding of the financial market aspects of emissions trading can be particularly useful.
Against this background, and echoing the call by Hintermann et al. (2016), future research in this field is very promising. In particular, we would like to highlight the following two aspects. Firstly, in all strands of the empirical literature, it is evident that findings heavily depend on the method used and its specific restrictions. The fact that the market is maturing together with the existing empirical evidence calls for more flexible methods in the analysis of classical price drivers which may better capture potential (long-term) structural changes. So far, the analysis often keeps the relationship constant over time or relies on restrictive assumptions which limit the form of the transition. Secondly, different trading behaviors by different types of traders in the market stand in contrast to the theoretical approach typically pursued in environmental economics, namely, the assumption of a single representative agent. In the theoretical finance literature, the relevance and implications of different trader types, such as noise traders (e.g. De Long et al. (1990)) or hedgers (e.g. Hirshleifer (1990)), have long been acknowledged. In both areas of research, price formation is an interesting topic to investigate. Weaving these insights into the analysis of emissions trading systems also promises to shed light on the transitional price phenomena observed in the last years, and can further pave the way for refined empirical research.

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Table 1: Paper overview per section, with methods