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Why do carbon prices and price volatility change?

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ABSTRACT

An asymmetric information microstructural pricing model is proposed in which price responses to information and liquidity vary with every transaction. bid-ask quotes and price components account for learning by incorporating changing expectations of the rate of transacted volume (trading intensity) and the risk level of incoming trades. Analysis of European carbon futures transactions finds expected trading intensity to simultaneously increase the information component and decrease the liquidity component of price changes, but at different rates. This explains some conflicting results in prior literature. Further, the expected persistence in trading intensity explains the majority of the autocorrelations in the level and the conditional variance of price change; helps predict hourly patterns in returns, variance and the bid-ask spread; and differentiates the price impact of buy versus sell and continuing versus reversing trades.

1. Introduction

A number of papers have analysed the microstructure of the European carbon market that started in January 2005 with the implementation of the European Union Emission Trading System (EU ETS). We initially focus on a selection that relates to intraday price formation, and one that provides a coverage of the main microstructural models used to analyse this market. Benz and Hengelbrock (2008) analyse price leadership and discovery using the Madhavan et al. (1997) microstructure model (henceforth 'the MRR') and a vector error correction (VECM) model. Rittler (2012) analyses price leadership between futures and spots using the common factor weights of Schwarz and Szakmary (1994) and the information shares of Hasbrouck (1995). Ibikunle et al. (2013, 2016) investigate adverse selection components using the portfolio trading pressure version of the basic Huang and Stoll (1997) model, and price discovery and impact of trades using return ratios and non-structural regressions. Mizrach and Otsubo (2014) analyse market impact and spreads using the MRR, price discovery contribution across futures and spots using Hasbrouck's (1995) and Gonzalo and Granger's (1995) information shares, and the predictive content of order imbalances using a regression. Medina et al. (2013, 2014) analyse price discovery contribution between European Union Allowances (EUAs) and Certified Emission Reductions (CERs) using a VECM, and the evolution of the spread, risk and market-making profits between the first two phases of the market using the MRR and the models of Roll (1984) and Hasbrouck (1993). Bredin et al. (2014) analyse the volume-(absolute) return-duration relationship using a vector autoregression. Rannou (2014) analyses return, volatility and return autocorrelation predictability of order book measures (aggregated to 30-min intervals) using regressions. Schultz and Swieringa (2014) analyse market friction catalysts for price discovery (at 5-min intervals) on a number of fungible assets using the information shares of Hasbrouck (1995) within a VECM. The structural models used in these studies, namely the models of Roll (1984) and Hasbrouck (1993), the portfolio trading pressure version of Huang and Stoll (1997), and Madhavan et al. (1997), are quite useful in providing preliminary analyses, especially of average or aggregate measures. However, they are rather generic, have highly static features, and each fails to account for at least one of a number of stylised facts that have recently emerged about the microstructure of the carbon market.

The most prominent of these stylized facts are: a significant autocorrelation of order flow (e.g., Benz and Hengelbrock, 2008); a generally low, but increasing, trading activity and liquidity

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(e.g., Mizrach and Otsubo, 2014); the presence of different types of agent with distinctly different trading behaviour (e.g., Kalaitzoglou and Ibrahim, 2013a); the occurrence of price, liquidity and volatility jumps, mainly due to regulatory announcements, release of relevant data on installation emissions and the over-allocation by national governments of carbon emission permits or allowances (e.g., Mansanet-Bataller and Pardo, 2009; Alberola et al., 2008; and Ellerman et al., 2014); and the presence of liquidity and information related intraday patterns in trading activity (e.g., Ibikunle et al., 2016; Kalaitzoglou and Ibrahim, 2013b).

These facts are likely to have direct implications on price formation and, hence, the choice of model used to analyse it. First, the significant autocorrelation in order flow ought to preclude the use of the model of Roll (1984), used by Medina et al. (2014), and the portfolio trading pressure model of Huang and Stoll (1997), used by Ibikunle et al. (2013), as these models assume zero autocorrelation of order flow. Models that make this assumption when order flow is autocorrelated are likely to overestimate some price components (e.g., asymmetric information) and underestimate others (e.g., public information and liquidity). Second, the presence of different agents, identifiable through trade characteristics, such as size and speed, emphasises that both volume and time between trades (duration) are important in price formation. For example, transaction size or dollar volume have been found to affect the liquidity component (e.g., Huang and Stoll, 1997) and the information component (e.g., Easley and O'Hara, 1987) of price changes. There is also evidence of a time dimension to price changes (e.g., Glosten and Milgrom, 1985; and Diamond and Verrecchia, 1987). Third, price, volatility and liquidity shocks and intraday patterns in these measures are likely to affect inventory risk, order execution risk and, in the short term, the type of trader that instigates subsequent trades. In particular, the MRR, used by Benz and Hengelbrock (2008) and Medina et al. (2014) to analyse the carbon market, accounts for autocorrelation of order flow but ignores trade size or duration, as it assumes unit quantity and equally-spaced trades. It also does not allow for time varying liquidity or volatility shocks, and assumes a constant price response to surprises in order flow (private information) and to variations in liquidity costs. It is unable, therefore, to differentiate between the price impact of small versus large trades, slow versus fast trades, trades instigated by different classes of agents, or low versus high liquidity trading times. Thus, it provides constant average estimates of bid-ask spreads and price volatility. To identify intraday patterns in these measures one needs to estimate the MRR, or the Roll (1984), Hasbrouck (1993) and Huang and Stoll (1997) models, as many times as intervals in which the trading day, month or year is dissected, as do Madhavan et al. (1997) and the carbon market intraday studies reviewed above.

To analyse the carbon market, or other markets with similar characteristics, this paper addresses these shortcomings by formulating a new asymmetric information microstructure model of price changes that incorporates these features. Unlike many prior microstructure models, the responsiveness of price changes to surprises in order flow (private information) and signed liquidity costs (liquidity) are dynamically updated with every transaction. This updating is based on the trader's *expectations* of the information content of the next trade, and the degree of risk that this trade is expected to represent. Specifically, the trader extracts information from the volume and duration of previous trades, through one liquidity measure of trading intensity (duration-weighted volume), and uses this information to formulate expectations of the level of trading intensity of the next trade. The trader also extracts information from the recent evolution in the proportion of informed traders and price volatility and formulates expectations on the level of risk he might face with the next trade. The trader then sets bid and ask price quotes given this process of learning from trading activity, trade characteristics and market risk conditions. Price quotes, therefore, are conditional on, or regret-free of, the sign (buy or sell) as well as the expected information content and liquidity characteristics of the next trade. In contrast, the MRR, that of Hasbrouck (1993), which nests the model of Roll (1984), and the basic version of Huang and Stoll (1997) assume constant price responsiveness to information and liquidity variations, and their price quotes are regret-free with respect to the sign of the next trade only.

Beside its formulation for the analyses of the carbon market, or similar relatively shallow markets, the model contributes by combining and extending in a unified setting features that have appeared separately in the general microstructure literature. It nests the models of Roll (1984), Glosten and Harris (1988), Madhavan et al. (1997), and Angelidis and Benos (2009) (which adds contemporaneous volume to the MRR), and reduces to a version of the volume-enhanced specification of Huang and Stoll (1997) but with updated expectations. It contributes to Dufour and Engle's (2000) extension of Hasbrouck's (1993) vector autoregressive model of prices and trades by incorporating the time series features of volume, duration and a jump risk process into a structural model of prices. Such structural models relate price, volatility and spread components to underlying economic parameters on a one-to-one basis. In contrast, not all time series models have structural reducible forms, especially with regard to the interpretation of the error terms (see Hasbrouck, 2007, p.82).[2] Further, the model contributes to Grammig et al. (2011) by incorporating the information embedded in volume, to Angelidis and Benos (2009) by incorporating the information embedded in duration, and to all the aforementioned studies by formulating expectations based on volume, duration and the risk of trading with the more informed. Moreover, the non-price based pure time-series procedure of Kalaitzoglou and Ibrahim (2013a) to identify agent classes in the carbon market is incorporated here in a structural model of prices to dissect return, volatility, bid-ask spread, and the autocorrelations of returns and volatility by agent type. Thus, in the new pricing model the structural variables of trading frictions involved in setting regret-free price quotes and, hence, in price formation, are based on expectations and are agent specific.

We use this model to analyse price formation throughout the entire history (to 30 April 2015) of EUA futures carbon trading at the European Climate Exchange (ECX). This market is an appropriate test bed as it is the main venue for trading carbon allowances (although see Medina et al., 2013, for the growing role of CERs), and is characterised by: relatively low, but increasing, liquidity; price and volatility variations, especially during its early development period; information and liquidity trading episodes; and phases with different structural and regulatory features creating different liquidity and pricing environments (phases).[3] We use the model to study price components, the autocorrelations and hourly patterns of transaction returns (change in price), conditional variance of returns, bid-ask spreads, and order submission choice of the most heavily traded EUA futures in each of the three market phases.

The remainder of the paper is organised as follows. Section 2 provides a brief motivation of the focus on the carbon market, Section 3 introduces the new microstructure pricing model and compares its features to a number of prior models, Section 4

[2] Time series models, however, can accommodate more dynamic interactions even if they lose some structural interpretations with inappropriate lag lengths. Causality in structural models is usually one-way, from trades to prices (see Manganelli, 2005 and Hasbrouck, 2007). Huang and Stoll's (1997) volume extended model allows volume to affect estimates of the probability of continuation (and, hence, autocorrelation of order flow).

[3] See the cited literature, references therein, and, e.g., Point Carbon reports at www.pointcarbon.com.