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The Market Microstructure of the European Climate Exchange

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Abstract

This paper analyzes the market microstructure of the European Climate Exchange, the largest EU ETS trading venue. The ECX captures 2/3 of the screen traded market in EUA and more than 90% in CER. Volume growth has averaged 277% in EUA between 2005 and 2009 and 724% in CER since 2007. Spreads range from €0.0188 to €0.0406 for EUA and €0.0276 to €0.0541 for CER. The median proportion of the spread due to adverse selection reaches 76% for EUA and 75% for CER. Realized volatility, bid-ask spreads and adverse selection costs decline with verified emission releases. Market impact estimates imply that an average trade will move the EUA market by 1.05 euro centimes and the CER market 1.44. The ECX is providing between 75% and 88% of price discovery for EUA trading and between 64% and 72% for CER. We find imbalances in the order book help predict returns for up to three days. A simple trading strategy that enters the market long or short when the order imbalance is strong is profitable even after accounting for spreads and market impact.

`Keywords`: carbon; market microstructure; bid-ask spread; information share; order imbalance;

`JEL Classification`: G13, G32, E44;

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1. Introduction

The largest market for carbon trading is the European Union Emissions Trading System (EU ETS), a cap and trade scheme that emerged out of the Kyoto Protocol. European Union Allowances (EUA), the primary compliance instrument, and project based credits called Certified Emission Reductions (CER), are currently traded on eight major exchanges, BlueNext, Climex, the European Climate Exchange (ECX), European Energy Exchange (EEX), Energy Exchange Austria (EXAA), Green Exchange, Gestore del Mercato Elettrico (GME) and Nord Pool.

The ECX has, since the start of carbon exchange trading in 2005, been the leading venue. In 2009, the ECX processed 65.6% of the screen based trading volume in EUA and 91.6% in CER. The current paper analyzes the market microstructure of the ECX and contrasts it with more mature commodity markets. We find that, after less than five years of trading, the ECX has comparable spreads to markets like gasoil and natural gas. Furthermore, the futures market dominates price discovery as in many other commodity markets.

There are very few intra-day analyses of carbon emissions market. Benz and Hengelbrock (2008) is the first market microstructure study of EUA futures. They analyzed the liquidity and price discovery of two EUA futures markets, ECX and Nord Pool for the Phase I 2005-2007. They find that their bid-ask spread estimate in the market has narrowed, and the more liquid ECX dominates the contribution to price discovery. Rittler (2012) studies price discovery and volatility spillovers between the EUA spot and futures market in the first year of Phase II. Conrad, Rittler, and Rotfuß (2012) analyze high-frequency volatility dynamics following EU policy announcements. Medina, Pardo and Pascual (2012) calculate bid ask spreads for Phase I and Phase II EUA.

EUA prices collapsed well before the end of Phase I due to an excess supply of credits, and allowances could not be banked. These obstacles inhibited market liquidity. The total volume of EUA futures trading during 2005-2007 was approximately $1,500$ million metric tonnes of CO2 equivalent (MMtCO2e), which is less than half of the volume traded in the single year 2009. EUA prices have stabilized in the Phase II compliance period, 2008-2012. For these reasons, we believe that a comprehensive market microstructure analysis of Phase II carbon trading is needed.

We extend the carbon pricing literature by analyzing market impact as well as spreads, using the structural Madhavan, Richardson and Roomans (MRR, 1997) model. While previous studies focused only on the EUA market, we also explore the CER market. We examine the price discovery contribution across spot and futures markets. Finally, we examine the predictive content of order

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imbalances for future EUA returns.

Our tick data from the ECX includes only trade prices, volumes, and the direction of trade initiation. To estimate the bid-ask spreads, we use the MRR (1997) GMM approach. Median spreads on the most liquid December 2009 expiry contracts are €0.0188 for EUA and €0.0276 for CER. Spreads decline with the release of European Commission data about allowances in April and accumulating information about the economy. The spreads rise with realized volatility and decline with trade frequency. The more illiquid 2010 to 2012 expiries are from 40% to nearly 200% larger.

The model allows us to examine the contents of the spread, the adverse selection cost and the cost of supplying liquidity. The median proportion of the EUA spread due to adverse selection is 76% which is consistent with a highly institutional market like the ECX. The model also provides a measure for market impact. We find a median market impact of €0.0106 for EUA and €0.0145 for CER.

We then examine the cointegration between ECX futures and the spot market which is dominated by BlueNext. From these estimates, we compute information shares using Hasbrouck's (1995) approach and an alternative decomposition based on Gonzalo and Granger (1995). Using either measure, we find that the ECX is providing between 75% and 88% of price discovery for EUA trading. The information dominance of the ECX in CER trading is not as strong as EUA, with about 64% and 72% of price discovery coming from the futures. These estimates support the model of Figuerola-Ferretti and Gonzalo (2010) in which the more liquid market should lead price discovery.

Our final section examines return predictability when there is an imbalance between buyer and seller initiated trading volumes. We find persistence in returns lasting up to three days. We then devise a simple, profitable trading strategy that enters at the close on days of large imbalances and exits at the next day's open.

We begin with a description of the competitive environment faced by the ECX in Section 2. Then we analyze trading activity in EUA and CER in Section 3. We estimate spreads and market impact for EUA and CER futures in Section 4. Section 5 contains our information share analysis. Section 6 looks at return predictability and trading profits from order book imbalances. Section 7 concludes.

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2. Market Share

The two major instruments traded in the EU ETS are European Union Allowances (EUA) and Certified Emission Reduction (CER) credits. Each security offsets one metric tonne of CO2 equivalent. Demand and supply are determined from national allocations distributed at the individual facility level.[1] We examine market share in each, starting with EUA.

2.1 EUA

The top panel of Table 1 contains estimates of the ECX screen market share in EUA from 2005-09. The ECX has 65.59% of screen trading activity.[2] Volumes are in millions of metric tonnes of CO2 equivalent (MMtCO2e). Volume growth has averaged 277% in EUA between 2005 and 2009 and 724% in CER since 2007.

[Insert Table 1: EUA and CER Market Shares in Screen Trading]

The primary competition in EUA for the ECX is coming from BlueNext which was acquired by NYSE/Euronext in late 2007. They have steadily increased market share, reaching 32.8% in 2009, primarily through a dominance in spot trading.[3] Nord Pool, which sold its clearing operation to Nasdaq OMX in October 2008, continues to erode.[4] The EEX, peaked in 2006 with a 6.87% market share, but it has less than a 1% market share in 2009.[5]

2.2 CER

The primary market for Certified Emission Reductions (CER) is project based. Article 12 of Kyoto created the Clean Development Mechanism (CDM) which enables developed countries to produce offsets through projects outside of Kyoto. There is now a well-established procedure for registering

[1] There were 12,242 installations in the EU registry which were allocated 1,966 $MMtCO_2e$ in 2009.
[2] There is also a substantial volume of trading in an over-the-counter (OTC) market that clears through the exchanges. In 2009, the ECX processed 2,114.4 MMtCO2e in EUA, representing a 98.85% market share.
[3] In December 2012, the BlueNext spot market closed following a series of permit thefts from the EU registry. While ECX offers a "daily futures" contract as a substitute, the volume has remained very small. As of July 5, 2013, only 43,115 daily contracts have traded this year, only 1% of the 4.229 million longer term EUA futures contracts.
[4] Nasdaq's acquisition of Nordpool has not increased trading activity on the exchange. In the past year, July 2012-June 2013, the re-branded Nasdaq OMX Commodities Europe has traded only 15,276 EUA and 2,652 CER futures contracts.
[5] The EEX is primarily an emissions auction market. In 2012 though, the combined volumes of screen and auction based trading were, according to Bloomberg June 11, 2013, "European Energy Exchange Approves New Carbon-Market Subsidiary," was less than 4% of the volumes traded on the ECX.

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these credits through the United Nations. Mizrach (2012) estimates that, as of November 2010, 2,463 projects have been approved which produce an annual average of 389.3 million CERs.

Once registered, credits can be traded in the secondary market to third parties. All of the exchanges which publicly report data also trade CERs. We tabulate trading volumes in spot, futures and options in the bottom panel of Table 1. The dominance of the ECX is even clearer from this table. The ECX has 91.63% of screen trading activity[6].

3. EUA and CER Futures Trading

As shown above, ECX is the leading market for both EUA and CER trading. About 87% (68%) of EUA (CER) trades on ECX are screen based. Because the futures contracts are the most liquid, we focus primarily on the futures market. As such, our analysis of spreads and price impact will be devoted on this part of the market.

The ECX trades both EUA and CER futures continuously from 7:00 GMT to 17:00 GMT. EUA contracts clear through ICE Europe and physical delivery is made in any national registry. Traders in ECX can open a position with one contract which is equivalent to 1,000 MtCO2e. Prices reported by ECX are in Euros per metric tonne and tick size is €0.01 per tonne, i.e. €10 per contract. The BlueNext contract features were similar, and trades cleared through LCH Clearnet. BlueNext harmonized its trading hours with ECX in July 2009.

Summary measures of trading volume are reported in Table 2.

[Insert Table 2: EUA and CER Futures and Spot Screen Trading Summary Statistics]

The ECX lists contract months in a quarterly cycle. We report the four most active expiries which are all in December. The most active contract, the near-to-expiry December 2009 generated more than 238,000 and 9,000 trades for EUA and CER, respectively. That is nearly 1,000 per trading day and is about 80% of the all EUA futures screen trading. On the other hand, it is about half of all CER futures screen trading. CER traders spread their activity along the yield curve more than with EUA, with 24.8% of volume in the December 2010, 11.1% in the December 2011, and 15.2% in the December 2012.

Based on the number of trades in the on-the-run December 2009 expiry, the ECX has, compared to BlueNext, an 88.77% market share in EUA and 83.67% in CER.

[6] The majority of CER trading still takes place over-the-counter. In 2009, the ECX processed 610.0 MMtCO2e in CER, representing a 99.42% market share.

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The yearly average trade price of EUA December expiry is €13.26 for 2009, €13.84 for 2010, €14.27 for 2011, and €15.33 for 2012. The annual average price of the CER futures is around €12 for all the four active contracts. Spreads between EUA and CER are slightly above €1 on average.[7] The slope of the CER futures curve is much less steep than with EUA; average prices range from €11.97 to €12.16. Total transaction volume of EUA is nearly €15 billion for the December 2009 expiry and more than €21 billion across all expiries.

4. MRR Model Estimation

The bid-ask spread is one of the important measures of market liquidity. Narrower spreads facilitate trades and lower transaction costs. Main difficulty in estimating spreads in commodity markets is that we usually have information on trades but not quotes. The ECX transaction data include the trade indicator variables which is not common in other commodity markets. Hence it is natural to implement the estimation method suggested by Madhavan, Richardson and Roomans (MRR, 1997) which makes the use of the trade indicator variables. The MRR model also has the benefit of delivering the spread decomposition and market impact in a single stage estimation.[8]

4.1 Madhavan-Richardson-Roomans model

The MRR model studies the transitory deviations of transactions prices from fundamental prices. The true price m_t is interpreted as the post-trade expected value of the asset conditional upon public information, u_t, and the trade initiation variable, x_t. We assume that u_t is an independent and identically distributed random variable with mean zero and variance σ_u^2. The revision in beliefs is the sum of the change in beliefs due to new public information and order flow innovations, so that

$$m_t = m_{t-1} + \theta \left(x_t - E[x_t | x_{t-1}] \right) + u_t, \tag{1}$$

where $x_t - E[x_t|x_{t-1}]$ is the surprise in order flow and $\theta > 0$ measures the degree of information asymmetry or the permanent impact of the order flow innovation. Higher values of θ indicate larger revisions for a given innovation in order flow.

The transaction price can expressed as $p_t = m_t + \phi x_t + u_t$, where ϕ is the costs of supplying

[7] Mizrach (2012) notes that political uncertainties have kept EUA and CER prices from being cointegrated.
[8] Glosten and Harris (1988) and Huang and Stoll (1997) both utilize the trade initiation variable as well, but the MRR model fits better on average, a pseudo $\widetilde{R}^2$ of 17.39% for MRR, vs. 16.81% for Glosten-Harris and 15.55% for Huang-Stoll.

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liquidity. It follows that the ask and bid price are

$$\begin{aligned} p_t^a &= m_{t-1} + \phi + \theta\left(1 - E[x_t|x_{t-1}]\right) + u_t \\ p_t^b &= m_{t-1} - \phi - \theta\left(1 + E[x_t|x_{t-1}]\right) + u_t \end{aligned} \tag{2}$$

The bid-ask spread is $p_t^a - p_t^b = 2\left(\phi + \theta\right)$.

In general, the transaction price p_t is

$$p_t = m_{t-1} + \theta\left(x_t - E[x_t|x_{t-1}]\right) + \phi x_t + u_t + \varepsilon_t \tag{3}$$

where ε_t is an independent and identically distributed random variable with mean zero and variance σ_ε^2. The term ε_t includes microstructural noise, such as stochastic rounding errors. Thus, the change in the transaction price is

$$\Delta p_t = \left(\phi + \theta\right) x_t - \phi x_{t-1} + \theta E[x_t|x_{t-1}] + u_t + \varepsilon_t - \varepsilon_{t-1}. \tag{4}$$

A general Markov process is assumed for the trade initiation variable x_t. The probability that a transaction at the ask (bid) follows a transaction at the ask (bid) is

$$\gamma = \Pr\left(x_t = +1|x_{t-1} = +1\right) = \Pr\left(x_t = -1|x_{t-1} = -1\right). \tag{5}$$

The first-order autocorrelation of the trade initiation variable $\rho = E[x_t, x_{t-1}]/Var[x_{t-1}] = 2\gamma - 1$. Then the conditional expectation of the trade initiation variable given public information are computed as

$$\begin{aligned} E[x_t|x_{t-1} &= +1] = \gamma - (1 - \gamma) = \rho \\ E[x_t|x_{t-1} &= -1] = (1 - \gamma) - \gamma = -\rho, \end{aligned} \tag{6}$$

thus the conditional expectation $E[x_t|x_{t-1}] = \rho x_t$. Given this, (4) can be transformed into

$$\Delta p_t = \left(\phi + \theta\right) x_t - \left(\phi + \rho\theta\right) x_{t-1} + \xi_t, \tag{7}$$

where $\xi_t = u_t + \varepsilon_t - \varepsilon_{t-1}$ is a composite of public information and microstructural noises. We assume that ξ_t is an independent and identically distributed random variable with mean zero and variance σ_ξ^2.

The parameters of the model can be estimated by the generalized method of moments (GMM) with the moment conditions implied in the model:

$$m\left(\phi, \rho, \theta\right) = E\begin{pmatrix} x_t x_{t-1} - x_t^2\rho \\ \xi_t \\ \xi_t x_t \\ \xi_t x_{t-1} \end{pmatrix} = 0, \tag{8}$$

where $\xi_t = \Delta p_t - \left(\phi + \theta\right) x_t - \left(\phi + \rho\theta\right) x_{t-1}$. The Madhavan-Richardson-Roomans (MRR) spread

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estimate is

$$S^{MRR} = 2\left(\widetilde{\phi} + \widetilde{\theta}\right), \tag{9}$$

where $\widetilde{\phi}$ and $\widetilde{\theta}$ are GMM estimates of (7).

4.2 GMM estimation

We first analyze the intra-day prices for the most liquid December 2009 expiries for EUA and CER from the ECX. The transaction data contains a record of each trade price, trade direction (whether the trade falls on the best bid or ask), trade volume and trade type (screen or OTC). The sample begins on January 2, 2009 and ends on December 14, 2009 (244 trading days).

Table 4 reports the monthly parameter estimates of the model for EUA December 2009 Expiry and Table 5 does the same estimation for CER December 2009.

[Insert Table 4: The MRR Model Parameter Estimates for EUA]

[Insert Table 5: The MRR Model Parameter Estimates for CER]

All three parameters θ, ϕ, ρ and the spread estimates for each month are statistically significant at 1% level for EUA. As the model is over-identified, it allows us to test whether the model's moment conditions match the data well by the J-test. The null hypothesis of the test is that the model fits the data well, i.e., $m(\theta, \phi, \rho) = 0$. The fifth column of the table reports the J-statistics and corresponding p-values between the parentheses. We do not reject the null hypothesis for all twelve cases at 5% level. The sixth column of the table reports the pseudo R-squared, $\widetilde{R}^2$, computed as the square of the correlation between the estimated Δp_t from (7) and their actual values. The explanatory power of the model ranges from 12.96% to 21.28%.

The model's moment conditions also match the CER data well for all twelve cases at 5% level. The model explains 3.53% to 18.41% of the CER price change.

4.3 Spread estimates

The spread estimates for both EUA and CER are all statistically significant at 1% level.[9] Figure 1 plots the MRR spread estimates for EUA and CER.

[Insert Figure 1: ECX 2009 Futures Monthly Spreads for EUA and CER]

[9] The standard errors of the spread are computed using a method suggested by MRR.

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The median MRR spread estimates of the most liquid December 2009 EUA contract are €0.0188, less than twice the minimum quote increment of €0.01. Our finding is consistent with Medina et al (2012) who estimate MRR spreads of €0.0209 in 2009.[10] This is less than 53% of the the yearly average spread of the near-December EUA contract in 2007, €0.0356, estimated by Benz and Hengelbrock (2008). The spread is 0.14% of the average 2009 transaction price. This number is comparable to the quoted spread of other energy futures markets such as gasoil (0.14%).[11]

Second, the spread estimates tend to narrow gradually through time. This pattern is typical empirical regularity in futures markets (e.g., Bryant and Haigh 2004). The monthly MRR spread decreases 57%, from €0.0367 to 0.0158, between January and December.

As we have seen above, CER futures markets are less active than EUA futures markets. Hence we expect wider spread estimates for CER in Figure 1. The median MRR spreads for the December 2009 expiry are €0.0276, 0.23% of its 2009 average price, which is comparable to the effective spread of natural gas (0.19%) estimated by Marshall et al (2012).

MRR spread estimates for CER also tend to narrow over time, consistent with our finding in the analysis of EUA. The spread shrinks roughly 80% from €0.1236 to 0.0234 between January and December.

To determine what observable characteristics explain the declining bid-ask spreads, we estimate the regression,

$$S_t^{MRR} = c + b_1 \ln Vol_t + b_2 \ln RV_t + e_t \tag{10}$$

where S_t^{MRR} represents the market's monthly average spread and Vol_t is the monthly volume measured by the number of trades. RV_t is the monthly realized volatility in basis points, based on hourly return. We anticipate that a greater trading activity should contribute to a smaller bid-ask spread, $b_1 < 0$. We further assume that greater volatility reduce the market liquidity, hence we expect that $b_2 > 0$. We estimate (10) for the EUA and CER December 2009 contract.

[Insert Table 3: Determinants of the Spread for EUA and CER]

Table 3 shows that volume and volatility explain the EUA and CER bid-ask spread estimates. For both EUA and CER, an increase in the realized volatility increases the spread in all four

[10] The 2009 annual average spread is caluculated based on the quartely estimates reported in Table VIII of Medina et al (2012).

[11] Marshall, Nguyen and Visaltanachoti (2012) calculate effective and quoted spreads of the 24 major commodities during the period January 1996 to August 2009. The average median effective and quoted spreads across all sample commodities are 0.16% and 0.18%.

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regressions. The CER future's bid-ask spread significantly narrows with its trading frequency. For EUA, trading frequency does not have a significant effect on its bid-ask spread. The adjusted R^2s show that trading volume and realized volatility explain up to 58.7% of the change in bid-ask spread for EUA and 61.7% for CER.

The realized volatility of the two markets decreases during the year. The declining trend of the volatility may be due to the decrease in market uncertainty. The key information in the market is the end-user demand for emissions allowances. The actual emissions from the previous year are reported by firms at the end of March, and the European Commission (EC) releases verified emissions data to the public at the beginning of April. The realized volatility in April declines to 52.61% and 53.23% of its March level respectively for EUA and CER, which is consistent with the EC's information release procedure. As more economic information is released throughout the year, there is less uncertainty about the annual demand for emissions allowances. Realized volatility in November falls to 14.82% and 18.16% of the March level for EUA and CER.

4.4 Adverse selection

We further consider the informational aspect of the market by examining the adverse selection component θ of the bid-ask spread estimates from the MRR model. The median proportion of the EUA and CER spread due to adverse selection is 75.90% and 75.18%, respectively. Our finding indicates that information component highly dominates the bid-ask spread in the ECX. Its proportion is large compared to the 36% for the spread of NYSE-listed stocks documented by Madhavan et al (1997). The high adverse information component implies that the presence of relatively more informed traders increases the probability that a market maker would end up trading with an informed trader. Hence, market makers set relatively higher margins to compensate losses induced by adverse selection.

The adverse selection costs tend to decrease from January to December. In April, the adverse selection cost for EUA and CER respectively declines to 74.72% and 58.90% from its level in March. Adverse selection in November falls to 44.82% and 51.76% of the March level. These are consistent with the declines in realized volatility, the EC's April emissions data release, and economic information accumulating through the calendar year.

The autocorrelation of the trade direction ρ for EUA is around 0.6 through year, higher than that for CER which ranges from 0.11 to 0.48, as we can see in Tables 4 and 5. EUA's autocorrelation is much higher than that of the NYSE-listed stocks of 0.37 (MRR, 1997). Chung, Li and McInish

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(2005) document that serial correlation in trade direction is positively and significantly related to the probability of information-based trading.[12]

In later section we will provide empirical evidence that the market's order imbalance is able to predict the market returns. The real time order flow is unlikely to be available for retail traders. Therefore the market's order flow would be a source of private information which benefits the institutional traders.

4.5 Price impact

Another measure of market liquidity is the price impact. The MRR model provides a measure for the price impact of a typical buyer initiated trade, which is

$$\theta \left(x_t - E[x_t | x_{t-1} = -1] \right) = \theta \left(1 + \rho \right). \tag{11}$$

The magnitude of the MRR price impact measure is determined by two parameters, the degree of information asymmetry θ and the auto correlation of trade indicator variables ρ. Higher θ implies larger revisions in public belief, i.e. larger price impact of the order flow. If $x_{t-1} = -1$, highly positive ρ increases the magnitude of revision in public beliefs of asset value, i.e. the price impact, induced by an arrival of a buy order at time t.

The last column in Table 4 reports the price impact of a typical buyer initiated trade estimated from MRR model for EUA. The standard errors are obtained by a bootstrapping procedure. The median impact for an EUA trade is €0.0106, with a range from €0.0079 for November to €0.0179 for January. The monthly price impact declines for 43.73% throughout the trading year.

The last column in Table 5 reports the price impact of a CER trade. The median price impact of a CER trade is €0.0145, which is 36.79% larger than that of a EUA trade. The impact ranges from €0.0047 for June to €0.0305 for March. The monthly price impact diminishes for 48.70% during the year.

The larger price impact of a CER trade can be explained by the thinner market activity. Furthermore, the difference in typical trade size may also contribute to the difference in the size of the impact between the two markets. The mode and median size of contract per trade for EUA are both 1. In contrast, those statistics for CER trading are 10 and 5 respectively.

[12] Chung, Li and McInish (2005) also show that shorter intervals between trades induces stronger positive serial correlation in trade direction. We find that the 85% of the time intervals between EUA trades were less than one minute and 37% were less than one second.

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4.6 Longer term expiries

In this section, we examine the MRR model for the 2010, 2011 and 2012 futures contracts of EUA and CER.[13] We estimate the model over the period January 2 to December 31, 2009 December (255 trading days).

Apart from September 2009 for the December 2011 EUA expiry, the J-test fails to reject the MRR model. Spreads are also statistically significant at the 1% level apart from that one contract month.

The median monthly spreads for EUA are €0.0291 for December 2010, €0.0406 for Dec. 2011, and €0.0347 for Dec. 2012. These are from 55% to 116% higher than the near December contract. For CER, the estimated annual spreads are €0.0384, €0.0663 and €0.0796, which are from 39% to 189% higher than the December 2009 CER contract. The rise in spreads for the more distant expiries is consistent with Benz and Hengelbrock (2008). They report that the spread of the EUA 2008 expiry in year 2007 rose almost 2 centimes from the nearest 2007 expiry.

We plot the evolution of the EUA bid-ask spreads over the calendar year in Figure 1. The spreads display the same downward slope over the year as the December 2009 expiry. The monthly spread on the December 2010 contract decreases from €0.0810 to 0.0164, December 2011 falls from €0.0435 to 0.0215, and December 2012 falls from €0.0549 to 0.0247.

5. Information Share

A growing share of EUA and CER trading volume in 2009 took place in the BlueNext spot market. We now ask in which market, futures or spot, is price discovery taking place? To answer this question, this section computes the Hasbrouck and Gonzalo-Granger information shares of the spot market in Paris with the futures market in London. Figuerola-Ferretti and Gonzalo (2010) demonstrate a link between the Gonzalo-Granger information share and the futures-spot price discovery model developed by Garbade and Silber (1983). Garbade and Silber establish that price discovery takes place in the market with the highest liquidity. In Table 2, we report the relative numbers of trades for the futures and the spot market in EUA and CER. For all of 2009, there are 238,172 trades of EUA and 9,036 trades of CER in both markets for the December 2009 contract. Given that 88.8% and 83.7% of those trades occur in the futures market, respectively, we anticipate

[13] We were only able to compute annual estimates for CER because of limited data. For example, there are only 5 trades in the December 2011 expiry in March 2009.

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that the ECX should lead price discovery.

5.1 Concepts

Hasbrouck (1995) proposes a measure for one market's contribution to price discovery. Let $p_{1,t}$ and $p_{2,t}$ denote log observed spot and futures market prices, respectively. Since $p_{1,t}$ and $p_{2,t}$ are for the same underlying, they are assumed not to drift far apart from each other, i.e. the difference between them should be $I(0)$. And, each price series is assumed to be integrated of order one. The price changes are assumed to be covariance stationary. This implies that they have a Wold representation,

$$\Delta \boldsymbol{p_t} = \boldsymbol{\Psi}(L)\boldsymbol{e_t}, \tag{12}$$

where $\boldsymbol{e_t}$ is a zero-mean vector of serially uncorrelated disturbances with covariance matrix $\boldsymbol{\Omega}$, and $\boldsymbol{\Psi}$ is the polynomial in the lag operator. Applying the Beveridge-Nelson decomposition yields the levels relationship,

$$\boldsymbol{p_t} = \boldsymbol{\Psi}(1)\sum_{j=1}^{t}\boldsymbol{e}_j + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t. \tag{13}$$

The matrix $\boldsymbol{\Psi}(1)$ contains the cumulative impacts of the innovation $\boldsymbol{e}_t$ on all future price movements and $\boldsymbol{\Psi}^*(L)$ is a matrix polynomial in the lag operator. Then, a random walk assumption for the efficient price and the common stochastic trend representation suggested by Stock and Watson (1988) enable (13) to be expressed as

$$\boldsymbol{p_t} = \boldsymbol{\iota} m_t + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t, \tag{14}$$

$$m_t = m_{t-1} + v_t,$$

where $\boldsymbol{\iota}$ is a row vector of ones.

Since $\boldsymbol{\beta}'\mathbf{p_t} = 0$, where $\boldsymbol{\beta} = (1, -1)'$, is assumed to be stationary, $\boldsymbol{\beta}'\boldsymbol{\Psi}(1) = 0$. And this implies that the rows of $\boldsymbol{\Psi}(1)$ is identical. Hence denoting $\boldsymbol{\psi} = (\psi_1, \psi_2)'$ as the common row vector of $\boldsymbol{\Psi}(1)$, v_t can be decomposed into $\psi_1 e_{1,t}$ and $\psi_2 e_{2,t}$. $\psi_i e_{i,t}$ can be interpreted then as "part of the information v_t reflected in $p_{i,t}$". The variance of v_t is $\boldsymbol{\psi}^0\boldsymbol{\Omega}\boldsymbol{\psi}$, and if $\boldsymbol{\Omega}$ is diagonal, i.e. e_t are mutually uncorrelated, then market i's information share is defined as

$$IS_i = \frac{\psi_i^2\sigma_{ei}^2}{\boldsymbol{\psi}^0\boldsymbol{\Omega}\boldsymbol{\psi}} = \frac{\psi_i^2\sigma_{ei}^2}{\psi_1^2\sigma_{e1}^2 + \psi_2^2\sigma_{e2}^2}, i = 1, 2 \tag{15}$$

where ψ_i is the ith element of $\boldsymbol{\psi}$, and σ_{ei}^2 is the ith diagonal element in $\boldsymbol{\Omega}$. Hence, information share suggested by Hasbrouck measures the proportion of the information attributed to two different observed prices. And he interprets this proportion as the contribution to the price discovery.

If $\boldsymbol{\Omega}$ is non-diagonal, the information share measure has the problem of attributing the covari-

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ance terms to each market. Hasbrouck suggests to compute the Cholesky decomposition of $\mathbf{\Omega}$ and measure the information share using the orthogonalized innovations. Let $\boldsymbol{C}$ be a lower triangular matrix such that $\boldsymbol{C}'\boldsymbol{C} = \mathbf{\Omega}$. Then the information share for the ith market is

$$IS_i = \frac{\left([\boldsymbol{\psi}^0\boldsymbol{C}]_i\right)^2}{\boldsymbol{\psi}^0\mathbf{\Omega}\boldsymbol{\psi}}, \tag{16}$$

where $\left[\boldsymbol{\psi}^0\boldsymbol{C}\right]_i$ is the ith element of the row matrix $\boldsymbol{\psi}^0\boldsymbol{C}$. The resulting information share depends on the ordering of price variables. In the bivariate case, the upper (lower) bound of the IS_i is obtained by computing the Cholesky factorization with the ith price ordered first (last).

Harris, McInish and Wood (2002) employ permanent-transitory component decomposition introduced by Gonzalo and Granger (1995) to measure price discovery. The Gonzalo-Granger common factor approach decomposes market prices as

$$\mathbf{p}_t = \mathbf{A}_1\mathbf{g}_t + \mathbf{A}_2\mathbf{h}_t, \tag{17}$$

where $\mathbf{g}_t$ is the permanent component, $\mathbf{h}_t$ is the transitory component, and $\mathbf{A}_1$ and $\mathbf{A}_2$ are factor loading matrices. As in Hasbrouck information shares setup, price series are assumed to be cointegrated. Thus, both price series are $I(1)$, the error correction term is $I(0)$ and $\mathbf{g}_t$ is $I(1)$. $\mathbf{h}_t$ is $I(0)$ and does not Granger cause $\mathbf{g}_t$ in the long run. Gonzalo and Granger define $\mathbf{g}_t = \boldsymbol{\gamma}'\mathbf{p}_t$ where $\boldsymbol{\gamma} = (\boldsymbol{\alpha}'_\perp\boldsymbol{\beta}_\perp)^{-1}\alpha'_\perp$, $\boldsymbol{\alpha}$ is the error correction coefficient vector, and $\boldsymbol{\beta} = (1, -1)'$ the cointegrating vector such that $\boldsymbol{\alpha}'_\perp\boldsymbol{\alpha} = 0$ and $\boldsymbol{\beta}'_\perp\boldsymbol{\beta} = 0$. The permanent component is then a weighted average of market prices with component weights $\boldsymbol{\gamma}_i = \boldsymbol{\alpha}_{\perp,i}/(\boldsymbol{\alpha}_{\perp,1} + \boldsymbol{\alpha}_{\perp,2})$ for $i = 1, 2$. As a result, Harris, McInish and Wood (2002) suggest an alternative measure of price discovery,

$$GG_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1} + \alpha_{\perp,2}}, i = 1, 2. \tag{18}$$

In order to obtain IS and GG, the first step is to estimate the following vector error correction (VEC) model,

$$\Delta\mathbf{p}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{p}_{t-1} + \textstyle\sum_{j=1}^{k}\mathbf{B}_j\Delta\mathbf{p}_{t-j} + \mathbf{e}_t, \tag{19}$$

where $\boldsymbol{\alpha}$ is error correction vector, $\boldsymbol{\beta} = (1, -1)'$ is cointegrating vector and $\mathbf{e}_t$ is a zero mean vector of serially uncorrelated innovations with covariance matrix Ω. Baillie, Booth, Tse and Zabotina (2002) shows that IS and GG can be obtained by utilizing estimated parameters from (19). For Ω diagonal,

$$IS_i = \frac{\alpha^2_{i\perp}\sigma^2_{ei}}{\alpha^2_{1\perp}\sigma^2_{e1} + \alpha^2_{2\perp}\sigma^2_{e2}}, \qquad i = 1, 2 \tag{20}$$

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where $\alpha_{i\perp}^2$ is the ith element of $\alpha_\perp$. If the e_t are correlated, we use the Cholesky factorization,

$$IS_i = \frac{\left([\boldsymbol{\alpha}_?^0 \, \boldsymbol{C}]_i\right)^2}{\boldsymbol{\alpha}_?^0 \, \boldsymbol{\Omega} \boldsymbol{\alpha}_?}, \tag{21}$$

where $\left[\boldsymbol{\alpha}_?^0 \, \boldsymbol{C}\right]_i$ is the ith element of the row matrix $\boldsymbol{\alpha}_?^0 \, \boldsymbol{C}$, and

$$GG_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, GG_2 = \frac{-\alpha_1}{\alpha_2 - \alpha_1}. \tag{22}$$

5.2 Estimates

We estimate both information shares using hourly returns of the EUA and CER ECX December 2009 futures expiry, and the BlueNext EUA and CER spot contracts. We analyze the active seven hour overlap from 9:00 to 16:00 GMT time for the two markets. After sampling every 60 minutes from the data set, we have a sample of $1,936$ observations.

We start with the cointegration test and the estimation of (19) with EUA. We verify in Table 6 that the EUA futures and the spot prices are cointegrated with a statistically significant error correction, $\alpha_1 < 0$, of the spot market to the futures contract. There is some modest adjustment of the futures to the spot, $\alpha_2 > 0$.

[Insert Table 6: Cointegration and Information Shares: EUA and CER Futures vs. Spot]

The IS estimate for 2009 is 74.63%. The GG share is between the Hasbrouck upper and lower bound 88.25%. The ratio of futures trading frequency is very close to the GG share and within the Hasbrouck upper and lower bounds , which is supportive of Figuerola-Ferretti and Gonzalo's (2010) relative liquidity model. From those findings, we can conclude that the efficient price of EUA is discovered first in the futures market, and the spot price follows. The essential role of the ECX is also supported by Granger causality test results in Table 6 which show unidirectional causality from the EUA futures market to the spot market.

We replicate the same exercise with CER. The CER futures and spot prices are cointegrated with a statistically significant error correction, $\alpha_1 < 0$, of the spot market to the futures contract. Moreover we observe a statistically significant error correction, $\alpha_2 > 0$, of the futures to the spot. We find bidirectional Granger causality between the CER futures market and the spot market. Consistent to the finding in our causality test, the information dominance of CER futures market is moderate. The IS estimate for 2009 is 72.39%. The GG share of 63.54% and the ratio of futures trading frequency are both between the Hasbrouck upper and lower bound.

The information share estimates demonstrate the dominance of the ECX futures market in

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price discovery.

6. Return Predictability

Our analysis of the EUA futures market found (i) highly positively autocorrelated trade direction, (ii) short time interval between trades, and (iii) large adverse selection component of the bid-ask spread. These jointly imply evidence of strategic trading by informed institutional traders (Kyle 1985, Covrig and Ng 2004, Kelly and Steigerwald 2003).[14] These stylized facts are similar to other, more liquid markets where order imbalances have been shown to be useful in predicting returns. Evans and Lyons (2002) and Rime, Sarno and Sojli (2010) demonstrated this for foreign exchange, Chordia, Roll, and Subrahmanyam (2002) for stock returns, and in Treasury bonds, Brandt and Kavajecz (2004). As these markets are much bigger and more liquid, we expect that the order flow in ECX can predict the market returns.

In this section, we study the return predictability in EUA December 2009 futures expiry. To determine whether order imbalances can predict future returns, we estimate the regression,

$$r_t = a + \sum_{k=1}^{10} b_k OIB_{t-k} + e_t \tag{23}$$

where r_t denotes the overnight returns on date t. We initially use the last trade tick of the day and the opening tick of the next day to calculate the overnight return series. OIB_t is the scaled order imbalance on day t. We measure it two ways: the daily number of buyer-initiated less seller-initiated trades, scaled by the total number of trades,

$$OIBX_t = \sum_{j=1}^{t} x_j / \sum_{j=1}^{t} |x_j| \,; \tag{24}$$

we also weight trades by dollar volume $p_t v_t$,

$$OIBV_t = \sum_{j=1}^{t} x_j p_j v_j / \sum_{j=1}^{t} p_j v_j. \tag{25}$$

We find, in Table 7, that there are up to three days of return predictability from the closing tick to the opening price t days later. The persistence of order imbalances on returns is somewhat shorter than the five days found by Chordia and Subrahmanyam (2004) in NYSE stocks.

[Insert Table 7: Return Predictability]

[14] The ECX is an institutional market. There are 111 members active in ECX emissions contracts trading, and most of the members are large sized institutions. The annual fees are $\$4,500$ and $€2,500$ for ICE membership and ECX emissions trading privilege respectively. The ICE member list available at https://www.theice.com/FuturesEuropeMembers. shtml

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Order imbalance measured as either trades or Euro volume explains about 7% of subsequent returns.

We find a very simple profitable trading strategy using the raw order imbalance,

$$OIB_t = \sum_{j=1}^{t} x_j. \tag{26}$$

. Our baseline is the case where you enter the market long (short) at the close if the imbalance in the order book for the day is positive (negative). You then exit the position at the next day's open. The first column of Table 8 reports the gain in Euros of trading a single contract using this strategy.

[Insert Table 8: Trading Strategies]

Entering every day at the last tick and exiting at the next day's first tick, the strategy returns €4.36, with profits on 54.4% of the trading days. If we add average spreads of €0.021 to the strategy though, this removes all the profits, leaving us with a loss of −€5.77.

We next explore more selective entries based on a threshold of 1,000 trade (in absolute value) order imbalance. This strategy only enters the market on 55 days, but paying the spread on entry and exit still leaves a profit of €2.03.

The ECX does provide a facility to trade at the open and settlement prices. Entering and exiting here avoids the spread and raises the profit to €6.45.

As a final exercise, we explore how well the strategy might scale up using our market impact estimates of €0.0121 per contract. Profits peak at 10 contracts, totaling €34.44. If impacts are smaller at the open or close, this strategy could potentially scale further.

7. Conclusion

Carbon trading is a relatively new activity, but it already resembles the trading patterns of other more mature instruments.

Spreads on the most active EUA contracts are less than twice the minimum tick of €0.01. These estimates are about half of the average spread on the most liquid 2007 contracts estimated by Benz and Hengelbrock (2008). The median spread of the December 2009 contract is 0.14%, which is comparable to the quoted spread of gasoil. CER median spreads are 0.23%, which is comparable to the quoted spread of natural gas. Bid-ask spreads and adverse selection costs decline with the release of European Commission data about allowances in April and accumulating

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information about the economy.

We find highly positively autocorrelated trade direction, a short time interval between trades, and a large adverse selection component of the bid-ask spread. These jointly imply evidence of strategic trading by informed institutional traders. Our findings give additional empirical support to Chung, Li and McInish (2005).

Market impact estimates also suggest a highly liquid market. A trade moves the market a little bit more than a tick for EUA and about one-and-a-half ticks for the less liquid CER.

Information shares are consistent with market shares, with between 75% and 88% of EUA price discovery taking place on the ECX futures market compared to the BlueNext spot market. Between 64% and 72% of price discovery in CER occurs in the futures markets. Both the EUA and CER results confirm the model of Figuerola-Ferretti and Gonzalo (2010) that the more liquid market leads price discovery. While the carbon offset market has continued to evolve, particularly with the closure of BlueNext, the dominance of the ECX has increased.

Order imbalances provide information about returns up to three days later, and we utilize a simple strategy that generates profits at modest trade sizes.

Carbon trading may soon be a global activity, and our microstructure analysis suggests that this market is likely to absorb and benefit from this additional liquidity.

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Table 1
EUA and CER Market Shares in Screen Trading

		Market Share			
	Volume	**ECX**	**Nordpool**	**BlueNext**	**EEX**
EUA					
2005	55.8	63.57%	23.63%	7.81%	4.66%
2006	233.9	72.33%	7.41%	13.27%	6.87%
2007	451.0	83.30%	5.92%	5.26%	5.46%
2008	1,180.9	70.42%	2.03%	20.87%	6.68%
2009	3,293.6	65.59%	0.63%	32.79%	0.98%
CER					
2007	5.7	0.00%	100.00%	0.00%	0.00%
2008	185.4	91.43%	4.23%	3.02%	1.32%
2009	298.4	91.63%	0.57%	7.58%	0.22%

The market shares and volume are based on 2009 traded totals of EUA and CER futures, spot and options transactions in MMtCO2e. We exclude EXAA from the table for space reasons. The data were collected directly from the exchanges.

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Table 2
EUA and CER Futures and Spot Screen Trading Summary Statistics

	Dec-09	**Dec-10**	**Dec-11**	**Dec-12**	**Total**	**Spot**	**Dec-09 vs Spot (%)**
EUA	238,172	34,911	10,231	17,248	300,562	30,140	88.77
CER	9,036	3,732	2,014	2,148	16,930	1,764	83.67

The table reports trading activity on the four most actively screen traded EUA and CER futures contracts on the ECX from January to December 2009. The spot totals are from BlueNext.

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Table 3
Determinants of the Spread for EUA and CER

	EUA	CER
Constant	0.003	0.329*
	(0.029)	(0.105)
Volume	0.001	-0.046*
	(0.003)	(0.016)
RV	0.007**	0.013*
	(0.002)	(0.006)
Adj. R^2	0.587	0.617

The table reports estimates of (10) for January 2 to December 15, 2009. The dependent variable is the MRR spread estimate for the EUA or CER December 2009 futures contract. Volume is the number of trades. RV is the realized volatility based on hourly returns. Standard errors are in parentheses. * and ** indicate significance at the 5%,and 1%, respectively.

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Table 4
The MRR Model Parameter and Price Impact Estimates for EUA

	θ	ϕ	ρ	S^{MRR}	*J-test*	$\widetilde{R}^2$	Price Impact
January	0.0112**	0.0072**	0.6049**	0.0367**	2.7081	0.1977	0.0179**
	(0.0006)	(0.0006)	(0.0062)	(0.0008)	(0.6078)		(0.0010)
February	0.0097**	0.0060**	0.6172**	0.0313**	0.5711	0.1585	0.0156**
	(0.0005)	(0.0005)	(0.0055)	(0.0008)	(0.9662)		(0.0009)
March	0.0108**	0.0041**	0.5960**	0.0298**	0.0009	0.1765	0.0173**
	(0.0004)	(0.0004)	(0.0052)	(0.0005)	(1.0000)		(0.0007)
April	0.0081**	0.0036**	0.5948**	0.0234**	8.0138	0.1888	0.0129**
	(0.0003)	(0.0003)	(0.0045)	(0.0004)	(0.0911)		(0.0004)
May	0.0086**	0.0024**	0.6225**	0.0219**	0.0465	0.1682	0.0139**
	(0.0003)	(0.0003)	(0.0049)	(0.0005)	(0.9997)		(0.0005)
June	0.0068**	0.0040**	0.6113**	0.0217**	1.7178	0.2128	0.0110**
	(0.0002)	(0.0003)	(0.0046)	(0.0004)	(0.7875)		(0.0004)
July	0.0060**	0.0020**	0.6149**	0.0159**	1.2246	0.1842	0.0096**
	(0.0002)	(0.0002)	(0.0050)	(0.0003)	(0.8740)		(0.0004)
August	0.0056**	0.0017**	0.6103**	0.0147**	0.0590	0.1909	0.0091**
	(0.0002)	(0.0002)	(0.0057)	(0.0003)	(0.9996)		(0.0004)
September	0.0059**	0.0011**	0.6196**	0.0140**	0.5594	0.1296	0.0095**
	(0.0003)	(0.0003)	(0.0061)	(0.0004)	(0.9675)		(0.0005)
October	0.0062**	0.0012**	0.6004**	0.0147**	2.9444	0.1495	0.0099**
	(0.0003)	(0.0003)	(0.0065)	(0.0004)	(0.5672)		(0.0005)
November	0.0048**	0.0014**	0.6308**	0.0125**	0.0682	0.1495	0.0079**
	(0.0003)	(0.0003)	(0.0063)	(0.0003)	(0.9994)		(0.0004)
December	0.0064**	0.0014**	0.5624**	0.0158**	2.2278	0.1810	0.0101**
	(0.0005)	(0.0005)	(0.0127)	(0.0006)	(0.6939)		(0.0008)

The table reports the monthly GMM parameter estimates of the Madhavan-Richardson-Roomans model (7) for the EUA December 2009 expiry. GMM standard errors are in parentheses. The bid-ask spread estimates S^{MRR} are $2(\phi+\theta)$. The 5th column reports the J-statistics and corresponding p-values in parentheses. The 6th column reports the pseudo R-squared, $\widetilde{R}^2$,computed as the square of the correlation between the estimated Δp_t from (7) and their actual values. The last column reports the price impact $\theta(1+\rho)$ for a buyer initiated trade with bootstrap standard errors below in parentheses. * and ** indicate significance at the 5%,and 1%, respectively.

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Table 5
The MRR Model Parameter and Price Impact Estimates for CER

	θ	ϕ	ρ	S^{MRR}	*J-test*	$\widetilde{R}^2$	Price Impact
January	0.0208	0.0410**	0.2399**	0.1236**	1.4289	0.1841	0.0257
	(0.0146)	(0.0113)	(0.0614)	(0.0174)	(0.8392)		(0.0145)
February	0.0088	0.0258**	0.3480**	0.0690**	0.0010	0.0821	0.0118
	(0.0093)	(0.0074)	(0.0358)	(0.0108)	(1.0000)		(0.0090)
March	0.0274**	0.0140**	0.1128**	0.0828**	0.6400	0.1571	0.0305**
	(0.0055)	(0.0045)	(0.0383)	(0.0079)	(0.9585)		(0.0047)
April	0.0161**	0.0121**	0.3350**	0.0565**	0.6757	0.1553	0.0215**
	(0.0038)	(0.0036)	(0.0336)	(0.0055)	(0.9543)		(0.0047)
May	0.0111*	0.0032	0.2996**	0.0286**	0.2772	0.0353	0.0145**
	(0.0046)	(0.0043)	(0.0390)	(0.0068)	(0.9912)		(0.0048)
June	0.0035	0.0076*	0.3359**	0.0222**	0.7291	0.0407	0.0047
	(0.0035)	(0.0030)	(0.0337)	(0.0046)	(0.9477)		(0.0036)
July	0.0102**	0.0006	0.4155**	0.0215**	0.6063	0.0775	0.0144**
	(0.0015)	(0.0016)	(0.0243)	(0.0024)	(0.9624)		(0.0018)
August	0.0079**	0.0028	0.4393**	0.0215**	0.0008	0.1360	0.0114**
	(0.0017)	(0.0016)	(0.0318)	(0.0023)	(1.0000)		(0.0022)
September	0.0069**	0.0018	0.3745**	0.0172**	1.5625	0.0412	0.0094**
	(0.0025)	(0.0020)	(0.0295)	(0.0026)	(0.8155)		(0.0025)
October	0.0133**	0.0000	0.4526**	0.0266**	4.7400	0.0961	0.0193**
	(0.0024)	(0.0024)	(0.0304)	(0.0034)	(0.3150)		(0.0025)
November	0.0142**	0.0006	0.3632**	0.0295**	2.0492	0.0954	0.0193**
	(0.0036)	(0.0030)	(0.0398)	(0.0038)	(0.7267)		(0.0030)
December	0.0090**	0.0027	0.4753**	0.0234**	1.7863	0.0598	0.0132**
	(0.0034)	(0.0032)	(0.0369)	(0.0049)	(0.7750)		(0.0043)

The table reports the monthly GMM parameter estimates of the Madhavan-Richardson-Roomans model (7) for the CER December 2009 expiry. GMM standard errors are in parentheses. The bid-ask spread estimates S^{MRR} are $2(\phi+\theta)$. The 5th column reports the J-statistics and corresponding p-values in parentheses. The 6th column reports the pseudo R-squared, $\widetilde{R}^2$,computed as the square of the correlation between the estimated Δp_t from (7) and their actual values. The last column reports the price impact $\theta(1+\rho)$ for a buyer initiated trade with bootstrap standard errors below in parentheses. * and ** indicate significance at the 5%,and 1%, respectively.

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Table 6
Cointegration and Information Shares: EUA and CER Futures vs. Spot

	Cointegration		Johansen Test		Granger causality		Futures information share			
	a_1	a_2	$r=0$	$r=1$	Spot	Futures	GG	H_{avg}	H_{low}	H_{high}
EUA	-0.102**	0.014	98.413**	0.202	3.238	167.488**	88.25	74.63	50.07	99.19
	(-0.014)	(0.015)			(0.072)	(0.000)				
CER	-0.103**	0.059**	220.455**	0.060	43.875**	181.688**	63.54	72.39	56.82	87.97
	(0.009)	(0.011)			(0.000)	(0.000)				

α_1 and α_2 are the error correction coefficients. Standard errors are in parentheses. * and ** indicate significance at the 5%,and 1%, respectively. Critical values for the Johansen trace test for $r = 0$ are at the 5% and 1% level, 12.32 and 16.36; for $r = 1$, 4.12, and 6.94. The Granger causality test is an F-test for whether spot (futures) prices Granger cause futures (spot) prices. GG is the Granger-Gonzalo information share for the futures market, $GG = -\alpha_1/(-\alpha_1 + \alpha_2)$. The Hasbrouck shares are the upper and lower bounds and the average.

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Table 7
Return Predictability

Variable	OIBX	OIBV
C	0.0023	0.0022
	(0.001)	(0.001)
OIB_{t-1}	0.0142	0.0142
	(0.006)	(0.006)
OIB_{t-2}	0.0134	0.0135
	(0.006)	(0.006)
OIB_{t-3}	0.0134	0.0134
	(0.006)	(0.006)
OIB_{t-4}	-0.0067	-0.0067
	(0.006)	(0.006)
OIB_{t-5}	-0.0017	-0.0018
	(0.006)	(0.006)
OIB_{t-6}	-0.0017	-0.0017
	(0.006)	(0.006)
OIB_{t-7}	-0.0018	-0.0018
	(0.006)	(0.006)
OIB_{t-8}	0.0039	0.0040
	(0.006)	(0.006)
OIB_{t-9}	0.0017	0.0017
	(0.006)	(0.006)
OIB_{t-10}	0.0036	0.0037
	(0.006)	(0.006)
R^2	0.0697	0.0694

The table reports estimates of the order imbalance regression (23) using daily EUA December 2009 futures. We measure the imbalance in number of transactions (OIBX) as defined in (24) or in € volume (OIBV) as defined in (25).

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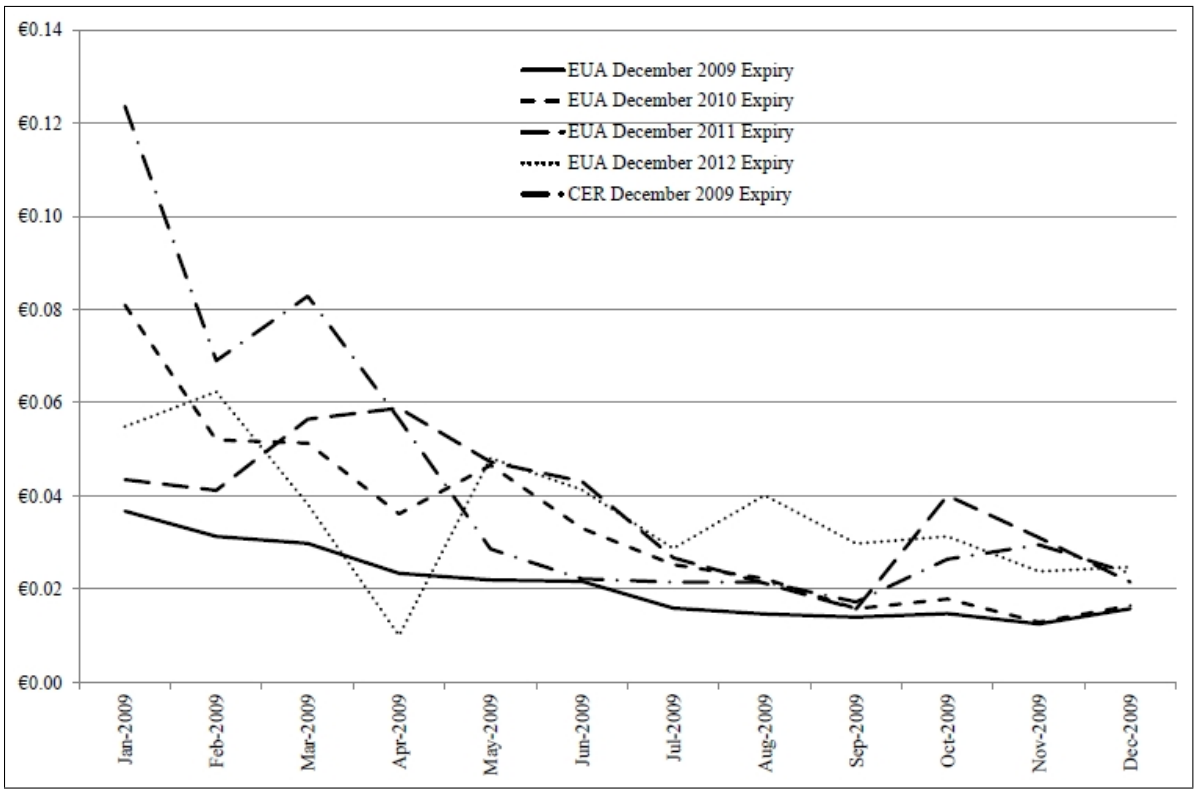
Table 8
Trading Strategies

Entry at Close	Exit at Open	|Threshold|	Trade Size	Market Impact	Trades	Profits €
Last Tick	First Tick	None	1	0	238	4.36
Cross Spread	Cross Spread	None	1	0	238	-5.77
Cross Spread	Cross Spread	1,000	1	0	55	2.03
Settlement	Open	1,000	1	0	55	6.45
Settlement	Open	1,000	3	0.0121	55	34.44

The table explores trading strategies using the raw order book trade imbalance (26), under different assumptions about entry and exit prices, the threshold order imbalance required for entry, trade size and market impact.

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Figure 1
ECX Futures Monthly Spreads: MRR GMM Estimates for 2009



The figure displays bid-ask spread estimates of EUA December 2009 to 2012 expiry futures and CER December 2009 futures from the European Climate Exchange. Estimates are computed using the Madhavan Richardson Roomans model with generalized method of moments.

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