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. 2009 Trading volumes total €22 billion and are growing, with EUA transactions doubling, and CER volume up 61%. Spreads range from €0.02 to €0.04 for EUA and €0.04 for actively traded CER. Market impact estimates imply that an average trade will move the EUA market by 1.06 euro centimes and the CER market 1.45. The proportion of the EUA spread due to adverse selection reaches 76%. Our findings of highly autocorrelated trade direction and short time interval between trades imply evidence of strategic trading by informed institutional traders. Both Granger-Gonzalo and Hasbrouck information shares imply that approximately 90% of price discovery is taking place in the ECX futures market compared to the BlueNext spot market. 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;

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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 is now as liquid as markets like cocoa and gasoil. 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 (2009) studies price discovery and volatility spillovers between the EUA spot and futures market in the first year of Phase II. Medina, Pardo Tornero 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. 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, a question which is not addressed by Benz and Hengelbrock (2008). Finally, we examine the predictive content of order 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 spreads, we use Madhavan, Richardson and Rooman's (1997) GMM approach. Spreads on the most liquid contracts are a little more than twice the minimum tick increment, with December 2009 expiry spreads averaging €0.0210 for EUA and €0.0435 for CER. The more illiquid 2011 and 2012 expiries are as one-and-a-half times as large.

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 extremely large compared to the 36% for the spread of NYSE-listed stocks documented by Madhavan et al (1997). The autocorrelation of the trade direction is around 0.6 through year, which is again much higher than that of NYSE-listed stocks of 0.37.

Our findings, 1. highly positively autocorrelated trade direction, 2. short time interval between trades, and 3. large proportion of adverse selection component, jointly imply evidence of strategic trading by informed institutional traders. And in fact, ECX is an institutional market. Our findings give additional empirical support to Chung, Li and McInish (2005) which document that 1. serial correlation in trade direction are positively and significantly related to the probability of information-based trading and 2. shorter intervals between trades induces stronger positive serial correlation in trade direction.

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 Granger and Gonzalo (1995). Using either measure, we find that the futures market is providing about 90% of 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 Sections 3 and 4. We estimate spreads for EUA and CER futures in Section 5. Section 6 models market impact for the most liquid EUA and CER contracts. Section 7 contains our information share analysis. Section 8 looks at return predictability and trading profits from order book imbalances. Section 9 concludes.

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

Table 1 contains estimates of the ECX market share in EUA from 2005-09. Volumes in are millions of metric tonnes of CO2 equivalent (MMtCO2e), and at this stage, we do not distinguish between spot, options and futures trading.

[Insert Table 1: EUA Market Shares in Screen and OTC 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. The ECX has responded with a "daily" futures contract that was introduced in late 2008, but the new instrument has not taken back any share. Nord Pool, which sold its clearing operation to Nasdaq OMX in October 2008, continues to erode. Nasdaq's acquisition of the rest of Nord Pool's power and derivatives business may reverse this.

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 these credits through the United Nations. Mizrach (2010) 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 Table 2.

[1] There were 12,242 installations in the EU registry which were allocated 1,966 $MMtCO_2e$ in 2009.

[Insert Table 2: CER Market Shares in Screen and OTC Trading]

The dominance of the ECX is even clearer from this table. The ECX has 91.63% of screen trading activity and 99.42% of OTC trading. The trend for BlueNext is upward though. Their spot CER trading has established a market niche.

3. EUA Futures Trading

As shown above, ECX is the leading market for both EUA and CER trading. Because the futures contracts are the most liquid, we focus primarily on the futures market, beginning with EUA. Table 3 describes some features of the derivative securities traded on the ECX.

[Insert Table 3: ECX EUA Contract Specifications]

The ECX trades EUA 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. Options contracts turn into futures contracts on expiry and use the December futures are the underlying.

3.1 Screen trading

About 87% of trades are screen based. We turn to this first and will devote most of our analysis of spreads and price impact on this part of the market. Summary measures of trading volume are reported in Table 4.

[Insert Table 4: ECX EUA Futures Screen Trading Summary Statistics]

The ECX lists contract months in a quarterly cycle up to 2020. We report the five most active expiries which are all in December. The most active contract, the near-to-expiry December 2009 EUA, generated more than $238,000$ trades. That is nearly $1,000$ per trading day and is about 80% of the all EUA futures screen trading. The yearly average trade price of December 2009 expiry is €13.26, €13.84 for 2010, €14.27 for 2011, and €15.33 for 2012. Total transaction volume is nearly €15 billion the December 2009 expiry and more than €21 billion across all expiries.

3.2 OTC trading

Trades can be entered into the ECX system by more than 100 ICE Futures Europe members or order routing through 42 energy clearing firms.[2] We report these trading volumes in Table 5.

[Insert Table 5: ECX EUA Futures OTC Trading Summary Statistics]

Screen trading and OTC trading share similar features: the most active contract is the near-to-expiry December 2009. OTC trades are characteristically larger than screen trades. The annual average of the number of contracts per trade through OTC trading is about 46 contracts, compared to under 5 for screen trading. Although only 13% of trades are OTC, the market value of over-the-counter trades is €27.5 billion compared to €21.4 billion through screen trading.

4. CER Futures Trading

We now turn to the CER trading on the ECX. Contract specifications are listed in Table 6.

[Insert Table 6: ECX CER Contract Specifications]

As with EUA futures trading, the CER futures market is continuous, operated between 7:00-17:00 GMT and follows the same rules. Furthermore, 68% of trades are screen based. Spreads between EUA and CER are slightly above €1 on average.

4.1 Screen trading

We summarize 2009 trading activity in the four most active expiries in Table 7. The most liquid contract is the December 2009 CER, the near-to-expiry contract as in EUA futures trading.

[Insert Table 7: ECX CER Futures Screen Trading Summary Statistics]

Since so much of CER activity is project based, trading volumes are much smaller than EUA futures. $9,036$ trades are generated by the December 2009 CER, which is about half of all CER futures screen trading. 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.

The annual average price of the CER futures is around €12 for all the four active contracts.

[2] https://www.theice.com/publicdocs/futures/ICE_ECX_presentation.pdf

The slope of the futures curve is much less steep than with EUA; average prices range from €11.97 to €12.16.

4.2 OTC trading

We summarize OTC trading activity in the active December contracts in Table 8.

[Insert Table 8: ECX CER Futures OTC Trading Summary Statistics]

There are features shared by screen trading and OTC trading: the most actively traded expiry is the December 2009 CER; volume is more evenly distributed across expiries than with EUA; and the slope of the futures curve is flatter.

OTC trades have large lot sizes. On average, 72 contracts are exchanged in each OTC transaction, while through screen trading, there are only 9 contracts per trade. The market value of OTC trading activity is €3.2 billion, compared to €0.9 billion for screen trades.

As our emphasis shifts to measuring spreads and liquidity, we focus on the screen traded markets for the remainder of the paper.

5. Spread 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 (1997) which makes the use of the trade indicator variables.

5.1 Madhavan-Richardson-Roomans

The first estimation approach we used to obtain the bid-ask spread is the method proposed by Madhavan, Richardson and Roomans (1997). Their trade indicator model allows us to study the components of the spread.

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 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:

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

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

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

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

5.2 Spread Estimates

The intra-day prices used here are transaction prices from the ECX for the December 2009, 2010, 2011 and 2012 futures contract of EUA and CER. The 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) for December 2009 expiry, or on December 31, 2009 December (255 trading days) for the other expiries. We use all of the observations to compute the estimates.

Figure 1 plots the MRR spread estimates for the four expiries.

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

First, the spread estimates tend to narrow gradually through time. The monthly MRR spread on the December 2009 contract, for instance, decreases 57%, from €0.0367 to 0.0158, between January and December. Yet the spread of the contract widens more than 20% from November to December, which can be expected from observing the decrease in number of trades from $14,711$ to $4,234$.

The monthly spread on the December 2010 contract decreases 80% from €0.0810 to 0.0164, falling at the similar level as the spread of the 2009 contract as it reaches expiry. Traders roll into the 2010 contract, making $9,427$ trades, versus only $4,234$ trades in the December 2009.

Second, the yearly average of MRR spread estimates of the most liquid December 2009 contract are around €0.02, 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.[3] This is less than 60% of the the yearly average spread of the near-December EUA contract in 2007, €0.0356, estimated by Benz and Hengelbrock (2008). The spread of €0.02 is 0.15% of the average 2009 transaction price. This number is comparable to the quoted spread of other commodity futures markets such as cocoa (0.16%) or gasoil (0.14%).[4]

Third, for the further expiries, MRR spread estimates tend to rise. The average MRR spreads of the 2011 and 2012 expiries rise to almost 4 centimes. This finding is consistent with Benz and Hengelbrock (2008). They report that the spread of the 2008 expiry in year 2007 rise almost 2 centimes from the nearest 2007 expiry.

In Figures 2, we repeat the spread estimates for CER. Here we focus on December 2009 expiry, since the further expiry are only thinly traded. As we have seen above, CER futures markets are less active than EUA futures markets. Hence we expect wider spreads to be found for CER.

[Insert Figure 2: ECX 2009 CER Futures Monthly Spreads December 2009 Expiry]

CER spreads are roughly twice as wide as EUA futures. The yearly average MRR spreads of €0.0435 is 0.36% of its yearly average price. MRR spread estimates tend to narrow over time consistent with our finding in the analysis of EUA. The spread for the December 2009 expiry shrinks roughly 80% during the year which is greater than we observed from EUA.

The MRR model allows us to examine further aspects of the market. Table 9 reports the monthly parameter estimates of the model for EUA December 2009 Expiry.

[Insert Table 9: The MRR Model Parameter Estimates: EUA Futures 2009 December Expiry]

All three parameters θ,ϕ,ρ and the spread estimates for each month are statistically significant at 5% level. 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

[3] The 2009 annual average spread is caluculated based on the quartely estimates reported in Table VIII of Medina et al (2012).
[4] Marshall, Nguyen and Visaltanachoti (2011) 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%.

cases at 5% level.[5]

The parameters θ and ϕ can be interpreted as the adverse selection cost and the cost of supplying liquidity, respectively. Figure 3 plots the estimated spread components for each month.

[Insert Figure 3: ECX 2009 EUA Futures Monthly Spread Components]

Both the costs of liquidity supply and the adverse selection costs tend to decrease from January to December. The median proportion of the EUA spread due to adverse selection is 76% which ranges from 61% of January to 84% of October. Our finding indicates that information component highly dominates the bid-ask spread in the ECX. Its proportion is extremely 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 a market maker set relatively higher margin so that she can compensate her loss induced by adverse selection.

The autocorrelation of the trade direction ρ is around 0.6 through year as we can see in Table 9. This autocorrelation is much higher than that of the NYSE-listed stocks of 0.37 (Madhavan et al. 1997). Furthermore, we find that the 85% of the time intervals between trades were less than one minute and 37% was less than one second. These findings, 1. highly positively autocorrelated trade direction, 2. short time interval between trades, and 3. large proportion of adverse selection component, jointly imply evidence of strategic trading by informed institutional traders (Kyle 1985, Covrig and Ng 2004, Kelly and Steigerwald 2003). In fact, 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.[6] The annual fee of $4500 and €2500 for ICE membership and ECX emissions trading privilege respectively, effectively rules out the retail participation.[7] Our findings give additional empirical support to Chung, Li and McInish (2005) which document that 1. serial correlation in trade direction are positively and significantly related to the probability of information-based trading and 2. shorter intervals between trades induces stronger positive serial correlation in trade direction.

[5] We do not reject the null hypothesis for all months of the further expiry contracts of EUA and 2009 expiry CER, except for one case.
[6] ICE member list availabe at https://www.theice.com/FuturesEuropeMembers.shtml
[7] The documented ICE membership fee is for *trade participants* who are limited to trade on own account. The annual fee for *general participants* who is able to trade on behalf of their clients is $11,500.

6. 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

$$\theta\left(x_t - E[x_t|x_{t-1} = -1]\right) = \theta\left(1 + \rho\right). \tag{10}$$

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.

We expect that the thinner CER market will have a much larger trade impact. Table 10 reports the price impact of a typical buyer initiated trade estimated from MRR model for both EUA and CER. The standard errors are obtained by bootstrapping procedure.

[Table 10: Monthly Average Price Impact EUA and CER Trade: MRR model estimation]

The median impact for an EUA trade is €0.0106, with a range from €0.0079 for November to €0.0179 for January. As with the spreads, market impact generally falls during the trading year until the expiry month. The median impact for an CER trade is 1.4 times larger than for the EUA, €0.0145. The impact ranges from €0.0047 for June to €0.0305 for March.

7. Information Share

A growing share of EUA trading volume is being conducted in the spot market by BlueNext. We now ask in which market, futures or spot, is price discovery taking place? To answer this question, this section computes the Hasbrouck and Granger-Gonzalo information shares of the spot market in Paris with the futures market in London.

7.1 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,

$$\Delta \boldsymbol{p_t} = \boldsymbol{\Psi}(L)\boldsymbol{e_t}, \tag{11}$$

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,

$$\boldsymbol{p_t} = \boldsymbol{\Psi}(1)\textstyle\sum_{j=1}^{t} \boldsymbol{e}_j + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t. \tag{12}$$

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 (12) to be expressed as

$$\boldsymbol{p_t} = \boldsymbol{\iota} m_t + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t, \tag{13}$$

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

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 $\boldsymbol{\psi}'\boldsymbol{\Omega}\boldsymbol{\psi}$, and if $\boldsymbol{\Omega}$ is diagonal, i.e. e_t are mutually uncorrelated, then market i's information share is defined as

$$IS_i = \frac{\psi_i^2 \sigma_{ei}^2}{\boldsymbol{\psi}'\boldsymbol{\Omega}\boldsymbol{\psi}} = \frac{\psi_i^2 \sigma_{ei}^2}{\psi_1^2 \sigma_{e1}^2 + \psi_2^2 \sigma_{e2}^2}, i = 1, 2 \tag{14}$$

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

$$IS_i = \frac{\left([\boldsymbol{\psi}'\boldsymbol{C}]_i\right)^2}{\boldsymbol{\psi}'\boldsymbol{\Omega}\boldsymbol{\psi}}, \tag{15}$$

where $\left[\boldsymbol{\psi}'\boldsymbol{C}\right]_i$ is the ith element of the row matrix $\boldsymbol{\psi}'\boldsymbol{C}$. 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

$$\mathbf{p}_t = \mathbf{A}_1\mathbf{g}_t + \mathbf{A}_2\mathbf{h}_t, \tag{16}$$

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,

$$GG_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1} + \alpha_{\perp,2}}, i = 1,2. \tag{17}$$

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

$$\Delta\mathbf{p}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{p}_{t-1} + \textstyle\sum_{j=1}^{k}\mathbf{B}_j\Delta\mathbf{p}_{t-j} + \mathbf{e}_t, \tag{18}$$

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[8] from (18). For Ω diagonal,

$$IS_i = \frac{\alpha_{i\perp}^2\sigma_{ei}^2}{\alpha_{1\perp}^2\sigma_{e1}^2 + \alpha_{2\perp}^2\sigma_{e2}^2}, \qquad i = 1,2 \tag{19}$$

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

$$IS_i = \frac{\left([\boldsymbol{\alpha}'_\perp \boldsymbol{C}]_i\right)^2}{\boldsymbol{\alpha}'_\perp\boldsymbol{\Omega}\boldsymbol{\alpha}_\perp}, \tag{20}$$

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

$$GG_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, GG_2 = \frac{-\alpha_1}{\alpha_2 - \alpha_1}. \tag{21}$$

[8] Rittler (2009) reports the Hasbrouck information share and the common factor weights, $CFW_1 = \frac{|\alpha_2|}{|\alpha_2|+|\alpha_1|}$, $CFW_2 = \frac{|\alpha_1|}{|\alpha_2|+|\alpha_1|}$. This measure would provide misleading results when α has unfavorable sign. In some cases, it could give more weight to the price which moves away from the equilibrium.

7.2 Estimates

We estimate both information shares using hourly returns from the ECX EUA December 2009 futures expiry and the BlueNext EUA spot contract. We analyze the active seven hour overlap from 9:00 to 16:00 UK time for the two markets. After sampling every 60 minutes from the data set, we have a sample of $1,880$ observations.

In Table 11, we report the relative volumes, in numbers of trades, for the futures and the spot market.

[Insert Table 11: EUA Futures and Spot Monthly Trading Volumes]

For all of 2009, there are $268,893$ trades in both markets. 88.5% of those trades are futures trades. Figuerola-Ferretti and Gonzalo (2010) show theoretically that relative liquidity determines the error correction representation, and this leads us to anticipate that the futures market should lead price discovery.

We start with the cointegration test and the estimation of (18). We verify in Table 12 that 11 out of 12 months are cointegrated with a statistically significant error correction, $\alpha_1 < 0$, of the spot market to the futures contract. In every month but April 2009, there is some modest adjustment of the futures to the spot, $\alpha_2 > 0$.

[Insert Table 12: Cointegration and Information Shares]

Table 12 also reports Granger causality test results. We find unidirectional causality from the futures market to the spot market in every month but April. This could be a result of accounting procedures in the EU ETS. As noted by Ellerman, Convery and De Perthuis (2010), firms report their actual emissions from the previous year at the end of March, and at the end of April, they have to surrender the previous year allowances. This seasonality may explain why the spot market contributes more to price discovery during the month of April.

Figure 4 plots the monthly information shares from January to December 2009.

[Insert Figure 4: Futures Market Information Shares]

The average IS estimate for 2009 is 75.2%. The GG share is between the Hasbrouck upper and lower bound over the year, and averages 89.6%.

Average IS estimates of the futures market information share never fall below 50%. Except for March 2009, the GG share never falls below 86%. Both IS and GG exhibit the lowest share in

March. That may also be explained by the EU ETS verification procedures.

The monthly proportions of trading volumes are also plotted in Figure 8. There is a positive relationship between the ratio of futures volume and the average IS share 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. This result is consistent with the literature on commodity price discovery.

8. Return Predictability

In many markets, there is a robust finding that order imbalances can predict future returns. Evans and Lyons (2002) first demonstrated this for foreign exchange, Chordia, Roll, and Subrahmanyam (2002) for stock returns, and in Treasury bonds, Brandt and Kavajecz (2004).

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,

$$r_t = a + \sum_{k=1}^{10} b_k OIB_{t-k} + e_t \tag{22}$$

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,

$$OIBX_t = \sum_{j=1}^{t} x_j / \sum_{j=1}^{t} |x_j|\,; \tag{23}$$

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

$$OIBV_t = \sum_{j=1}^{t} x_j p_j v_j / \sum_{j=1}^{t} p_j v_j. \tag{24}$$

We find, in Table 13, 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 13: Return Predictability]

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 $OIB_t = \sum_{j=1}^{t} x_j$. 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 14 reports the gain in Euros of trading a single contract using this strategy.

[Insert Table 14: 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 €0.0221 to the strategy though, this removes all the profits, leaving us with a loss of −€6.16.

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 54 days, but paying the spread on entry and exit still leaves a profit of €1.79.

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 €6.32.

As a final exercise, we explore how well the strategy might scale up using our market impact estimates of €0.0108 per contract. Profits peak at 3 contracts, totaling €8.46. If impacts are smaller at the open or close, this strategy could potentially scale further.

9. Conclusion

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

Screen trading has come to dominate OTC transactions, and transactions have at least doubled in every year since trading began in 2005.

Exchange competition is vigorous between important global players, but at the moment a duopoly between the Intercontinental Exchange which bought the ECX in March 2010 and NYSE/Euronext (BlueNext) could be the equilibrium.

Competition appears to be keeping the spreads quite low, with Madhavan-Richardson-Roomans spreads on the most active EUA contracts about twice the minimum tick of €0.01. These estimates are two-thirds of the average spread on the most liquid 2007 contracts estimated by Benz and Hengelbrock (2008). The yearly average spread of the December 2009 contract is 0.15%, which is comparable to the quoted spreads of cocoa and gasoil.

We find 1. highly positively autocorrelated trade direction, 2. short time interval between trades, and 3. large proportion of adverse selection component, 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 on average for EUA and about one-and-a-half ticks for CER.

Information shares confirm the trading volume figures, with approximately 90% of the price discovery taking place on the ECX futures market compared to the BlueNext spot market. This confirms the model of Figuerola-Ferretti and Gonzalo (2010) that the more liquid market leads price discovery.

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 Market Shares in Screen and OTC Trading

	Screen Market Share					OTC Market Share		
	Volume	**ECX**	**Nordpool**	**BlueNext**	**EEX**	**Volume**	**ECX**	**Nordpool**
2005	55.8	63.57%	23.63%	7.81%	4.66%	66.7	77.88%	22.12%
2006	233.9	72.33%	7.41%	13.27%	6.87%	319.5	86.78%	13.22%
2007	451.0	83.30%	5.92%	5.26%	5.46%	717.0	91.25%	8.75%
2008	1,180.9	70.42%	2.03%	20.87%	6.68%	1,368.5	93.45%	6.55%
2009	3,293.6	65.59%	0.63%	32.79%	0.98%	2,114.4	98.85%	1.15%

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

Table 2
CER Market Shares in Screen and OTC Trading

	Screen Market Share					OTC Market Share		
	Volume	**ECX**	**Nord Pool**	**BlueNext**	**EEX**	**Volume**	**ECX**	**Nordpool**
2007	5.7	0.00%	100.00%	0.00%	0.00%	24.5	0.0%	100.0%
2008	185.4	91.43%	4.23%	3.02%	1.32%	432.0	88.41%	11.59%
2009	298.4	91.63%	0.57%	7.58%	0.22%	610.0	99.42%	0.58%

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

Table 3
ECX EUA Contract Specifications

Features	**EUA Futures**	**EUA Options**
Unit of Trading	1,000 $CO2$ EUA	One ICE ECX EUA Options Contract
Minimum size	1 contract	1 contract
Price quotation	Euros (€.cc) per metric tonne	Euros (€.cc) per metric tonne
Tick size	€0.01 per tonne (€10 per contract)	€0.01 per tonne (€10 per contract)
Contract months	Quarterly expiry cycle up to 2020	Quarterly expiry cycle up to 2020
Expiry Day	Last Monday of the contract month.	3 days before futures
Trading system	ICE electronic platform or ISV	ICE electronic platform or ISV
Trading model	Continuous trading	Continuous trading
Trading hours	07:00 to 17:00 hours UK Time	07:00 to 17:00 hours UK Time
Settlement prices	Trade wtd. avg. 16:50 to 16:59	Trade wtd. avg. 16:50 to 16:59
Delivery	Physical delivery in natl. registry	Turn into futures contracts at expiry
Clearing	ICE Clear Europe	ICE Clear Europe
Margin	ICE Clear Europe margins	ICE Clear Europe margins

Source: https://www.theice.com/productguide/ProductDetails.shtml?specId=197. Independent Software Vendors (ISVs) offer software compatible with the ICE platform.

Table 4
ECX EUA Futures Screen Trading Summary Statistics

Volumes	**Dec-09**	**Dec-10**	**Dec-11**	**Dec-12**	**Dec-13**	**Total**
# of trades	238,172	34,911	10,231	17,248	180	300,858
# of contracts	1,125,509	229,083	73,874	142,858	1,980	1,574,463
€(millions)	14,924.77	3,170.93	1,054.27	2,190.31	29.43	21,383.88

The table reports trading activity on screen traded EUA futures contracts from January to December 2009. We have excluded expiries with less than 500 contracts, although these are included in the totals.

Table 5
ECX EUA Futures OTC Trading Summary Statistics

Volumes	**Dec-09**	**Dec-10**	**Dec-11**	**Dec-12**	**Dec-13**	**Total**
# of trades	35,598	5,128	1,270	2,337	98	44,492
# of contracts	1,398,671	311,180	104,843	206,412	7,202	2,040,304
€(millions)	18,292.19	4,294.14	1,507.05	3,182.77	116.11	27,528.78

The table reports trading activity on OTC EUA futures trades that clear on the ECX from January to December 2009. We have excluded expiries with less than 500 contracts, although these are included in the totals.

Table 6
ECX CER Contract Specifications

Features	**CER Futures**	**CER Options**
Unit of Trading	1,000 CER Units.	One ICE ECX CER Options Contract
Minimum size	1 contract	1 contract
Price quotation	Euros (€.cc) per metric tonne	Euros (€.cc) per metric tonne
Tick size	€0.01 per tonne (€10 per contract)	€0.01 per tonne (€10 per contract)
Contract months	Quarterly expiry cycle up to 2013	Quarterly expiry cycle up to 2013
Expiry Day	Last Monday of the contract month.	3 days before futures
Trading system	ICE electronic platform or ISV	ICE electronic platform or ISV
Trading model	Continuous trading	Continuous trading
Trading hours	07:00 to 17:00 hours UK Time	07:00 to 17:00 hours UK Time
Settlement prices	Trade wtd. avg. 16:50 to 16:59	Trade wtd. avg. 16:50 to 16:59
Delivery	Physical delivery in natl. registry	Turn into futures contracts at expiry
Clearing	ICE Clear Europe	ICE Clear Europe
Margin	ICE Clear Europe margins	ICE Clear Europe margins

Source: https://www.theice.com/publicdocs/circulars/11018%20attach.pdf. Independent Software Vendors (ISVs) offer software compatible with the ICE platform

Table 7
ECX CER Futures Screen Trading Summary Statistics

			Expiry		
Volumes	**Dec-09**	**Dec-10**	**Dec-11**	**Dec-12**	**Total**
# of trades	9,036	3,732	2,145	2,255	17,873
# of contracts	76,817	38,584	17,342	23,764	157,172
€(millions)	919.65	469.05	209.49	288.11	1,892.89

The table reports trading activity on screen traded EUA futures contracts from January to December 2009. We have excluded expiries with less than 500 contracts, although these are included in the totals.

Table 8
ECX CER Futures OTC Trading Summary Statistics

	Expiry				
Volumes	**Dec-09**	**Dec-10**	**Dec-11**	**Dec-12**	**Total**
# of trades	4,260	1,492	972	1,454	8,272
# of contracts	272,497	117,799	75,990	114,108	593,094
€(millions)	3,218.89	1,375.36	892.04	1,359.71	6,985.87

The table reports trading activity on screen traded EUA futures contracts from January to December 2009. We have excluded expiries with less than 500 contracts, although these are included in the totals.

Table 9
The MRR Model Parameter Estimates: EUA Futures 2009 December Expiry

	θ	ϕ	ρ	S^{MRR}	$Jtest$
January	0.0112	0.0072	0.6049	0.0367	2.7081
	(0.0006)	(0.0006)	(0.0062)	(0.0008)	(0.6078)
February	0.0097	0.0060	0.6172	0.0313	0.5711
	(0.0005)	(0.0005)	(0.0055)	(0.0008)	(0.9662)
March	0.0108	0.0041	0.5960	0.0298	0.0009
	(0.0004)	(0.0004)	(0.0052)	(0.0005)	(1.0000)
April	0.0081	0.0036	0.5948	0.0234	8.0138
	(0.0003)	(0.0003)	(0.0045)	(0.0004)	(0.0911)
May	0.0086	0.0024	0.6225	0.0219	0.0465
	(0.0003)	(0.0003)	(0.0049)	(0.0005)	(0.9997)
June	0.0068	0.0040	0.6113	0.0217	1.7178
	(0.0002)	(0.0003)	(0.0046)	(0.0004)	(0.7875)
July	0.0060	0.0020	0.6149	0.0159	1.2246
	(0.0002)	(0.0002)	(0.0050)	(0.0003)	(0.8740)
August	0.0056	0.0017	0.6103	0.0147	0.0590
	(0.0002)	(0.0002)	(0.0057)	(0.0003)	(0.9996)
September	0.0059	0.0011	0.6196	0.0140	0.5594
	(0.0003)	(0.0003)	(0.0061)	(0.0004)	(0.9675)
October	0.0062	0.0012	0.6004	0.0147	2.9444
	(0.0003)	(0.0003)	(0.0065)	(0.0004)	(0.5672)
November	0.0048	0.0014	0.6308	0.0125	0.0682
	(0.0003)	(0.0003)	(0.0063)	(0.0003)	(0.9994)
December	0.0064	0.0014	0.5624	0.0158	2.2278
	(0.0005)	(0.0005)	(0.0127)	(0.0006)	(0.6939)

The table reports the GMM parameter estimates of the Madhavan-Richardson-Roomans model (7) for each month with EUA December 2009 expiry. Figures between parentheses in the 1st to 4th columns are the standard error The bid-ask spread estimates S^{MRR} are $2\,(\phi+\theta)$. The 5th column reports the J-statistics and corresponding p-values between the parentheses.

Table 10
Monthly Average Price Impact EUA and CER Trade

	EUA	CER
January	0.0179	0.0257
	(0.0010)	(0.0145)
February	0.0156	0.0118
	(0.0009)	(0.0090)
March	0.0173	0.0305
	(0.0007)	(0.0047)
April	0.0129	0.0215
	(0.0004)	(0.0047)
May	0.0139	0.0145
	(0.0005)	(0.0048)
June	0.0110	0.0047
	(0.0004)	(0.0036)
July	0.0096	0.0144
	(0.0004)	(0.0018)
August	0.0091	0.0114
	(0.0004)	(0.0022)
September	0.0095	0.0094
	(0.0005)	(0.0025)
October	0.0099	0.0193
	(0.0005)	(0.0025)
November	0.0079	0.0193
	(0.0004)	(0.0030)
December	0.0101	0.0132
	(0.0008)	(0.0043)

GMM estimates of the Madhavan-Richardson-Roomans model, (7), are reported. The price impact of a typical buyer initiated trade is obtained by $\theta(1+\rho)$. Bootstrap standard errors are reported between the parentheses.

Table 11
EUA Futures and Spot Monthly Trading Volumes

	# of trades		
Month	**Futures**	**Spot**	**Proportion (%)**
January	16,690	2,554	86.73
February	20,744	3,840	84.38
March	23,488	2,715	89.64
April	31,400	4,007	88.68
May	25,067	5,135	83.00
June	29,237	2,348	92.57
July	24,589	2,539	90.64
August	19,154	1,236	93.94
September	13,722	1,602	89.55
October	15,136	1,482	91.08
November	14,711	1,762	89.30
December	4,234	1,591	72.69

The table reports EUA screen trading activity in the ECX December 2009 futures and BlueNext spot market. Proportion is the relative number of trades in the futures market.

Table 12
Cointegration and Information Shares

Month	Cointegration α_1	α_2	Johansen Test $r = 0$	$r = 1$	Granger causality Spot	Futures	Futures information share GG	$H_{avg.}$	H_{low}	H_{high}
January	-0.494**	0.039	63.733**	4.190*	0.475	12.872**	92.67	63.25	26.68	99.83
	(0.114)	(0.112)			(0.623)	(0.000)				
February	-0.897*	0.020	26.890**	0.503	0.860	8.169**	97.78	59.32	18.66	99.99
	(0.402)	(0.414)			(0.509)	(0.000)				
March	-0.336**	0.216*	68.116**	0.583	0.864	12.336**	60.87	53.79	13.35	94.23
	(0.103)	(0.101)			(0.423)	(0.000)				
April	-0.844**	-0.125	208.777**	0.955	3.509*	174.979**	117.43	97.48	95.77	99.18
	(0.044)	(0.071)			(0.032)	(0.000)				
May	-0.771**	0.055	153.420**	0.018	1.568	91.322**	93.39	91.00	82.22	99.79
	(0.055)	(0.076)			(0.211)	(0.000)				
June	-0.691**	0.039	116.872**	2.257	1.088	52.204**	94.63	85.03	70.22	99.84
	(0.066)	(0.078)			(0.339)	(0.000)				
July	-0.777**	0.079	230.885**	0.196	0.455	180.663**	90.74	94.57	89.48	99.66
	(0.040)	(0.067)			(0.635)	(0.000)				
August	-0.801**	0.130	191.333**	1.095	1.259	120.759**	86.07	89.77	80.60	98.95
	(0.050)	(0.071)			(0.286)	(0.000)				
September	-0.908**	0.061	132.233**	1.315	1.913	43.511**	93.67	71.47	43.08	99.86
	(0.097)	(0.116)			(0.151)	(0.000)				
October	-0.992**	0.099	46.502**	0.785	0.882	60.789**	90.95	83.14	66.66	99.62
	(0.174)	(0.229)			(0.476)	(0.000)				
November	-0.728**	0.053	97.501**	1.933	0.191	13.811**	93.16	56.94	13.95	99.92
	(0.176)	(0.174)			(0.826)	(0.000)				
December	-0.846	0.077	13.313*	1.222	0.892	6.139**	91.64	56.36	12.84	99.89
	(0.701)	(0.687)			(0.491)	(0.000)				

α_1 and α_2 are the error correction coefficients. Standard errors are in parentheses. They are statistically significant at *5%,and **1%, respectively. The Johansen test is the trace test. The null hypothesis r is the number of cointegration relations at most. For $r = 0$ and $r = 1$, the *5% critical values are 12.53 and 3.84 respectively; **1% critical values are 16.31 and 6.51 respectively. The Granger causality test is an F-test for whether spot (futures) prices Granger cause futures (spot) prices. We reject the null hypothesis at *5%,and **1%, respectively. 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.

Table 13
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

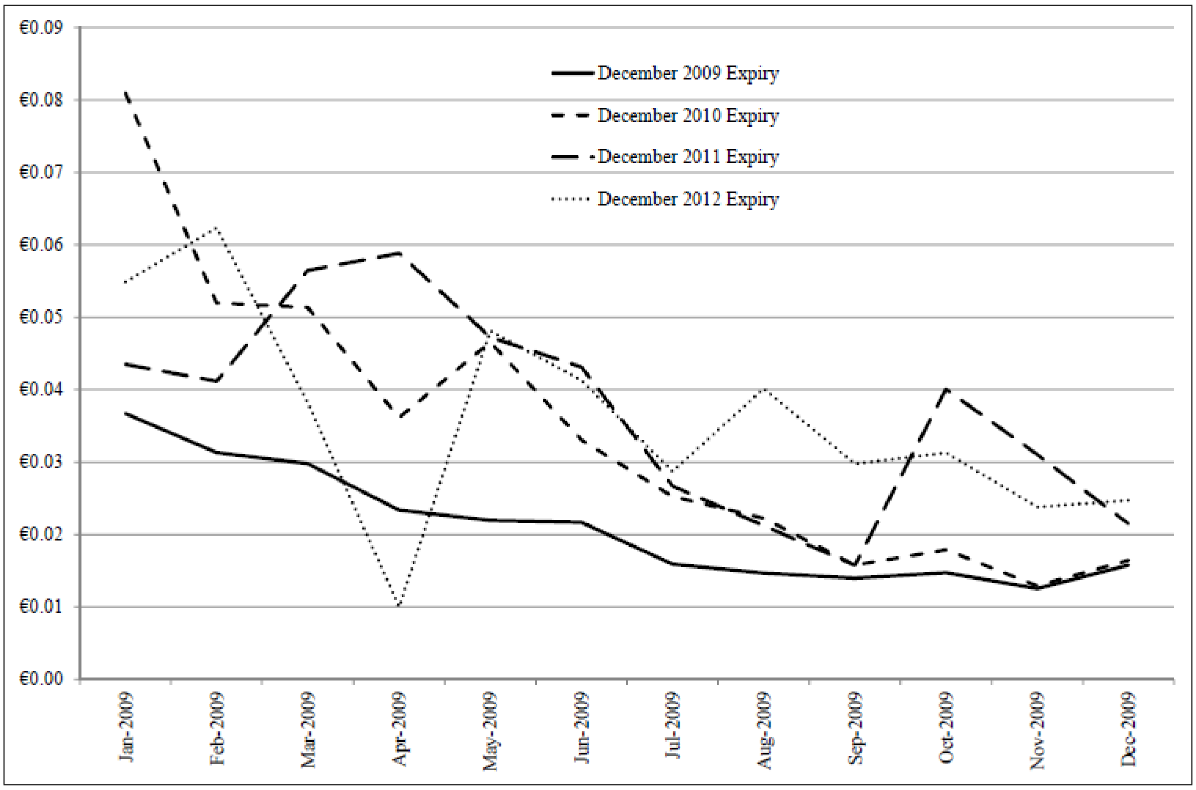
The table reports estimates of the order imbalance regression (22) using daily EUA December 2009 futures. We measure the imbalance in number of transactions (OIBX) as defined in (23) or in € volume (OIBV) as defined in (24).

Table 14
Trading Strategies

Entry at Close	Exit at Open	|Threshold|	Trade Size	Market Impact	Trades	Profits €
Last Tick	First Tick	None	1	0	237	4.36
Cross Spread	Cross Spread	None	1	0	237	-6.16
Cross Spread	Cross Spread	1,000	1	0	54	1.79
Settlement	Open	1,000	1	0	54	6.32
Settlement	Open	1,000	3	0.0108	54	8.46

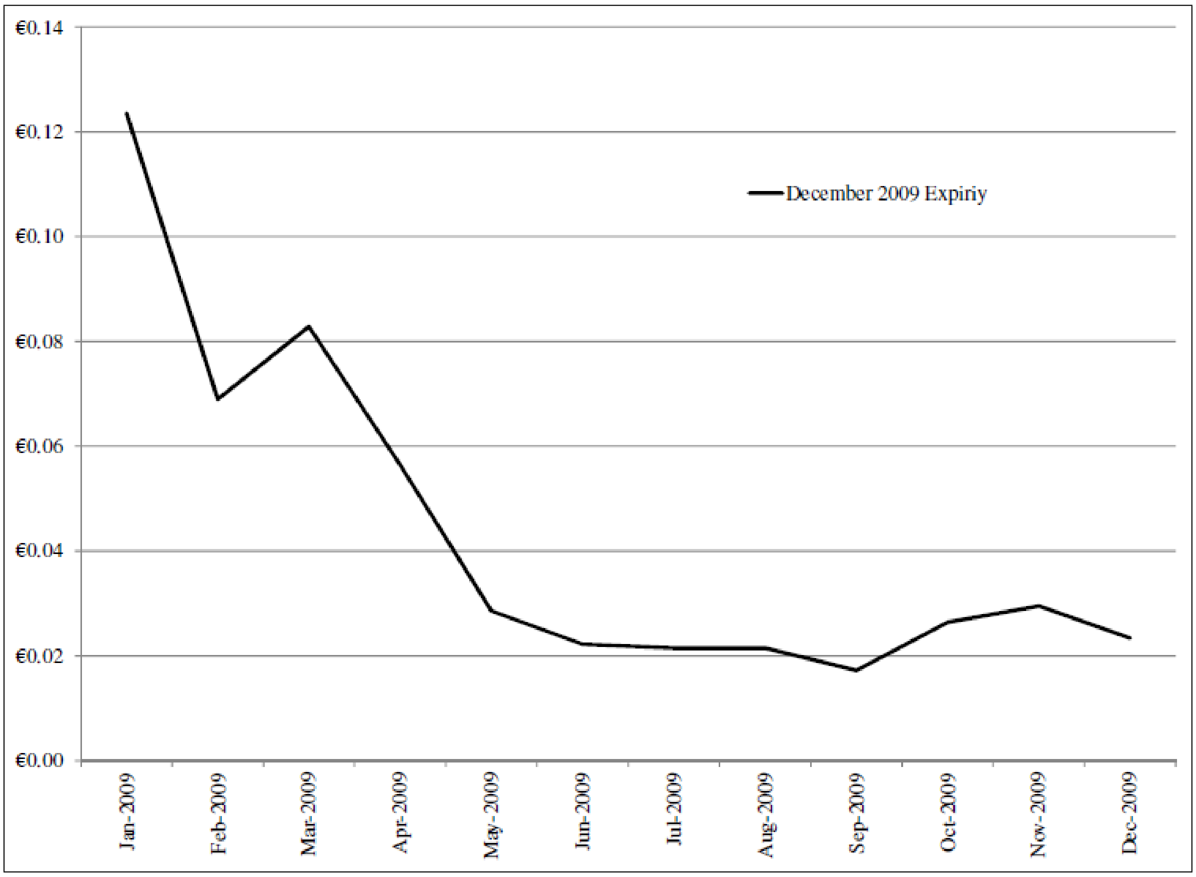
The table explore trading strategies using the order book imbalance, $OIB_t = \sum_{j=1}^{t} x_j$, under different assumptions about entry and exit prices, the threshold order imbalance required for entry, trade size and market impact. x_j is a binary variable indicating whether the trade is buyer (+1) or seller (-1) initiated.

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



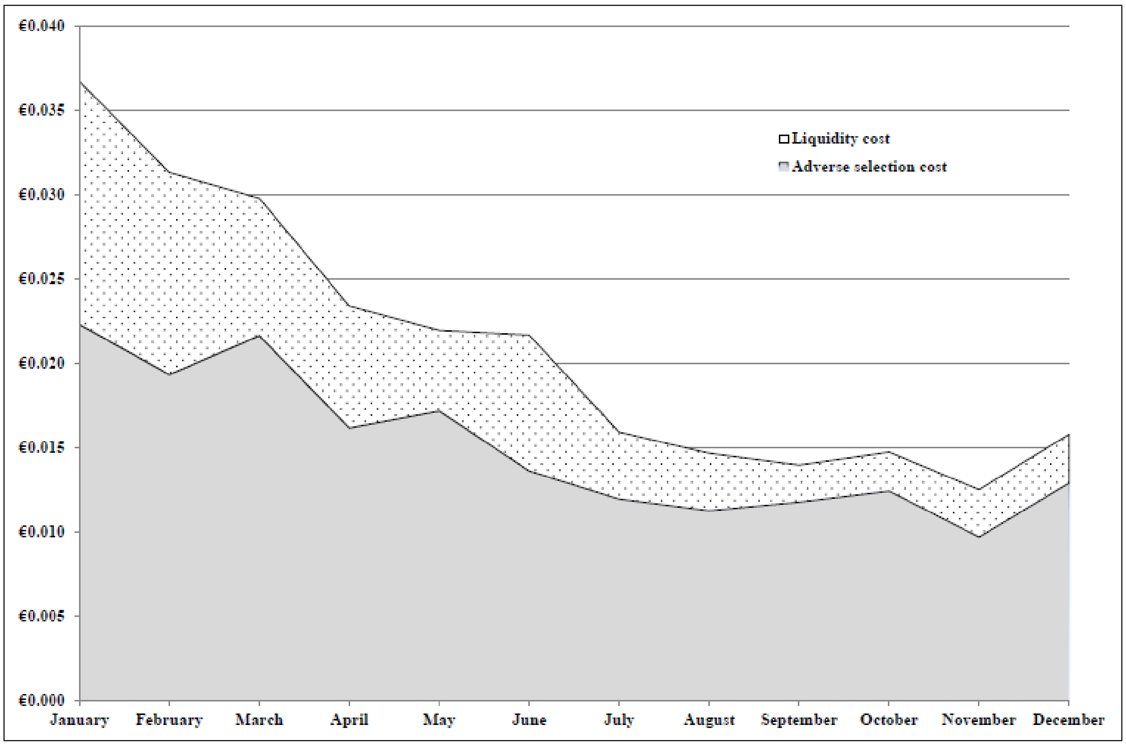
The figure displays bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Madhavan Richardson Roomans model with Generalized Method of Moments.

Figure 2
ECX 2009 CER Futures Monthly Spreads: December 2009 Expiry



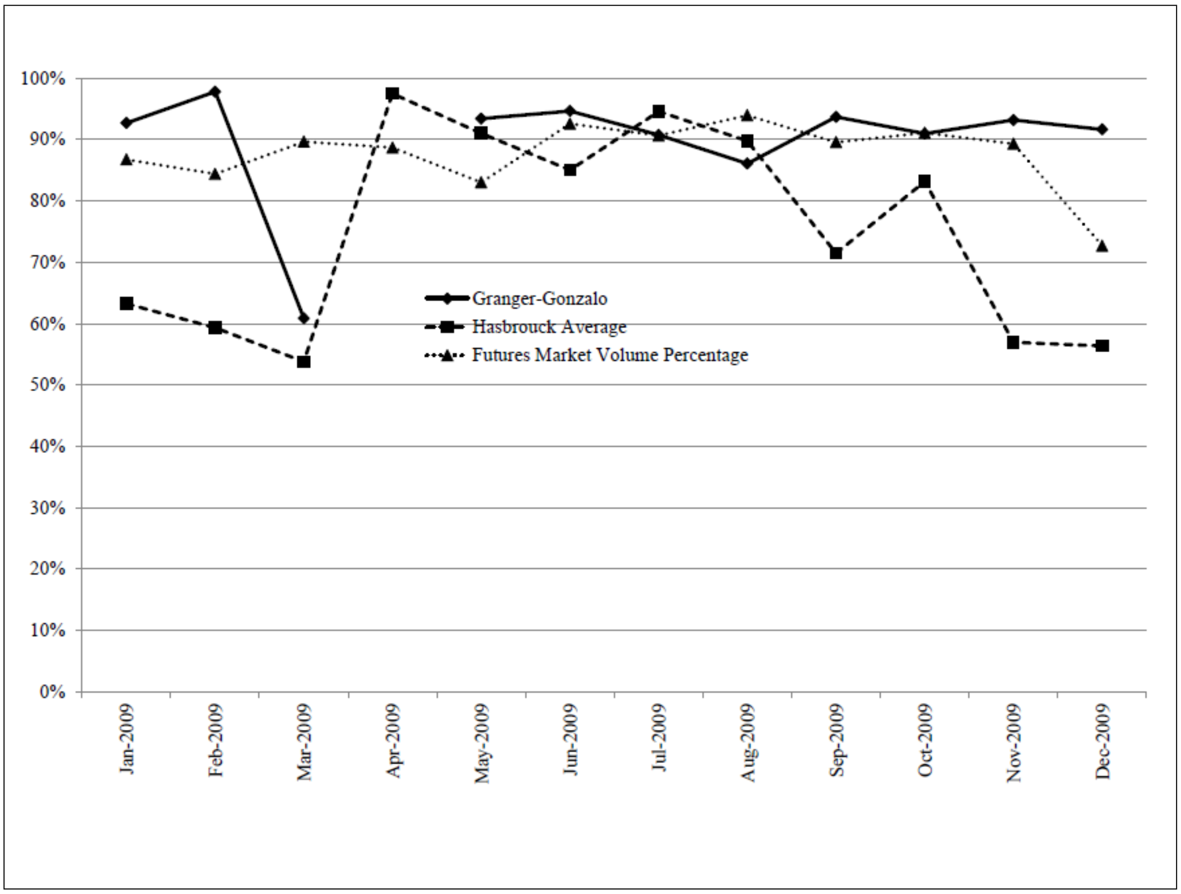
The figure displays bid-ask spread estimates of CER December 2009 expiry futures from the European Climate Exchange. Estimates are computed using the Madhavan Richardson Roomans model with Generalized Method of Moments.

Figure 3
ECX 2009 EUA Futures Monthly Spread Components



The figure displays monthly average bid-ask spread estimate components of EUA December expiry futures from the European Climate Exchange. Liquidity costs are 2ϕ and adverse selection costs are 2θ, where ϕ and θ are GMM parameter estimates of the Madhavan-Richardson-Roomans model.

Figure 4
Futures Market Information Shares, January-December 2009



The figure shows the monthly information share estimates for the December 2009 futures expiry. We use 60-minute returns. The average of upper-bound and lower-bound Hasbrouck information share (20) is plotted. The Granger-Gonzalo information share is given by (21). For comparison, we include the monthly percentage of trading activity occurring in the ECX futures market.