The Market Microstructure of the European Climate Exchange

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Revised: April 2012

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

JEL Classification: G13, G32, E44;

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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 €0.06 for EUA and from €0.07 to €0.18 for CER. Market impact estimates imply that an average trade will move the EUA market by 1.08 euro centimes and the CER market 4.29. Both Granger-Gonzalo and Hasbrouck information shares imply that approximately 90% of price discovery is taking place in the ECX futures 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.

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 150-year old markets like cotton. 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.

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.

The paper makes a contribution to the microstructure literature by implementing an enhanced version of Hasbrouck's (2004) bid-ask spread estimator for transaction prices. 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 two approaches. We begin with a standard estimator from the commodities literature, the Thompson and Waller (1998) estimator. We then produce alternative estimates using Hasbrouck's (2004) Bayesian approach. Using the trade direction indicator improves the Hasbrouck estimates considerably. Spreads on the most liquid contracts are a little more than twice the minimum tick increment, with December 2009 expiry spreads averaging €0.0221 for EUA and €0.0695 for CER. The more illiquid 2011 and 2012 expiries are two to three times as large.

For market impact, we use Hasbrouck's (1991) vector autoregressive model. We find a median peak market impact of €0.0108 for EUA and €0.0429 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.

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

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.

[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

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

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. 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.

Our main difficulty in estimating spreads is that we only have information on trades but not quotes. This is quite typical in commodities markets, and a number of approaches have been taken to estimate spreads in this context.

5.1 Thompson-Waller

The Thompson and Waller (1988) spread estimate is given by,

$$S_t^{TW} = \sum_{i=1}^{T} \left| p_i - p_{i-1} \right|^+ / T^+. \tag{1}$$

$T^+$is the number of non-zero changes in the transactions prices on day t.

Bryant and Haigh (2004) compare a number of different estimators for commodity futures to data where they have quotes. The Thompson-Waller estimates have the lowest root mean squared errors.

5.2 Hasbrouck

The second estimation method we used to obtain the bid-ask spread is the Bayesian method of Hasbrouck (2004). The underlying structural model is based on the Roll (1984) model.

The model starts from the description of efficient price. "Efficient" means that the price reflects all current information, and the model assumes the price m_t follows a random walk process,

$$m_t = m_{t-1} + u_t \quad \text{where } u_t \text{ are } i.i.d.N(0, \sigma_u^2). \tag{2}$$

u_t is the new information which is not incorporated in m_t yet.

In a competitive market, traders will set the bid p_t^b and ask p_t^a quotes wide enough to cover their execution cost, c. Namely,

$$\begin{aligned} p_t^b &= m_t - c, \\ p_t^a &= m_t + c. \end{aligned} \tag{3}$$

The log bid-ask spread is $p_t^a - p_t^b = 2c$, and c can be interpreted as the half-spread.

Transactions occur at either the inside bid or ask. Denoting the trade direction by x_t, the log transaction price p_t can be represented as,

$$p_t = \begin{cases} p_t^b & \text{if } \; x_t = -1 \\ p_t^a & \text{if } \; x_t = +1 \end{cases} \tag{4}$$

where trade direction of the incoming order is given by the Bernoulli random variable $x_t \in \{-1, +1\}$. -1 indicates a sell order and $+1$ indicates a buy order. Orders are assumed to arrive with equal probability. It is also assumed that the trade direction arrival is independent of the efficient price innovation u_t. From (2) to (4), the log transaction price process is,

$$\Delta p_t = m_t + c x_t - (m_{t-1} + c x_{t-1}) = c \Delta x_t + u_t. \tag{5}$$

Parameters to be estimated in this model are c and σ_u. In his work, due to data constraints, Hasbrouck also estimated the T latent values, $x = \{x_1, x_2, ..., x_T\}$. Since our data contains the information on trade direction, it is not necessary to estimate those values. However, in order to see how the additional information can improve the estimation results, we start our empirical analysis by estimating the series of x.

While sampling theory considers parameters as unknown fixed constants, Bayesian inference views parameters as random variables. In Bayesian inference, we update our prior beliefs about the parameters after observing the data, and obtain the marginal posterior probability density function (pdf) for each parameter. The pdf can be obtained by integrating out "nuisance parameters." If analytical integration is available, the derivation is done analytically. If not, then it is done by numerical integration.

In Bayesian inference, the numerical integration typically relies on the Gibbs sampler. Let the posterior pdf of c, σ_u and x be given by $F(c, \sigma_u, x_1, ..., x_T \mid p)$.To obtain the marginal pdf's $f(c \mid p), f(\sigma_u \mid p), f(x_1 \mid p), ..., f(x_T \mid p)$, the Gibbs sampler algorithm takes the following steps:

1. Choose the initial values, $\sigma_u^{(0)}$ and $x^{(0)}$.
2. Draw c from $f(c \mid \sigma_u^{(0)}, x^{(0)}, p)$ and set c so drawn as $c^{(1)}$.
3. Draw σ_u from $f\left(\sigma_u \mid c^{(1)}, x^{(0)}, p\right)$ and set σ_u so drawn as $\sigma_u^{(1)}$.
4. Draw x from $f(x \mid c^{(1)}, \sigma_u^{(1)}, p)$ and set q so drawn as $x^{(1)}$.
5. Repeat steps 2-4 n_r times and collect $(c^{(j)}, \sigma_u^{(j)}, x^{(j)})$, $j = 1, ..., n_r$.
6. Burn the first n_b draws and keep the rest.

The Gibbs sampler ensures that the limiting distribution of the n_rth draw for any parameter is distributed in the corresponding marginal pdf. The half spread c is then obtained as the sample mean of the $c^{(j)}$.

To use Gibbs sampler, we need to have fully conditional posterior pdf. The conditional posterior pdf of c given σ_u and x is a normal distribution and that of σ_u^2 given c and x is an inverted gamma distribution. x_t is assumed to be distributed as Bernoulli. We generate $n_r = 10,000$ sequences and burn $n_b = 2,000$ draws.

5.3 Results

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 TW spread estimates for the four expiries.

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

The TW spread estimates tends to narrow gradually through time. The monthly spread on the December 2009 contract, for instance, decreases 42%, from €0.0345 to 0.0201, between January and December.

On the other hand, the monthly spread on the December 2010 contract decreases 70% from €0.0654 to 0.0193, falling below 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. This pattern is commonly observed in futures markets.

The yearly average spread of the December 2009 contract is €0.0221, slightly more than twice the minimum quote increment of €0.01. This is two-thirds of the the yearly average spread of the near-December EUA contract in 2007 estimated by Benz and Hengelbrock (2008).

The spread of €0.0221 is 0.17% of the average 2009 transaction price. This number is comparable to the quoted spread of other commodity futures markets such as cotton (0.16%) or gasoline (RBOB, 0.15%).[3]

For the more illiquid 2011 and 2012 expiries, spreads rise to almost 6 centimes. These spreads are 0.41% and 0.34% of the average trade prices for the year. This finding is consistent with Benz and Hengelbrock (2008). They report that the spread of the more illiquid 2008 expiry in year 2007 spread rise almost 2 centimes from the 2007 expiry.

We first calculated Hasbrouck estimates assuming random trade assignments x. We eventually ruled out these estimates on a priori grounds. With the exception of the December 2011 expiry, the yearly average spread was smaller than the minimum tick size. This is similar to the results of Frank and Garcia (2006) who find that the Hasbrouck estimates are below the minimum tick size for 6 commodity futures they analyze.

We then modified the Gibbs sampler to use the observed x's.

1. Choose the initial values, $\sigma_u^{(0)}$.
2. Draw c from $f(c \mid \sigma_u^{(0)}, p)$ and set c so drawn as $c^{(1)}$.
3. Draw σ_u from $f\left(\sigma_u \mid c^{(1)}, p\right)$ and set σ_u so drawn as $\sigma_u^{(1)}$.
4. Repeat steps 2-3 $n_r$times and collect $(c^{(j)}, \sigma_u^{(j)})$ $j = 1, ..., n_r$.
5. Burn the first n_b draws and keep the rest.

Hasbrouck spread estimates with observed trade direction are wider than that with drawn direction. However, by using the observed x, all of the monthly average estimates except two (July and November of December 2010 expiry) are greater than the minimum tick. The additional information of trade direction would help the Hasbrouck method have reasonable estimates.

Hasbrouck spread estimates with observed x are plotted in Figure 2.

[Insert Figure 2: ECX 2009 EUA Futures Monthly Spreads: MCMC Estimates]

The Hasbrouck spread estimates also decrease during the sample period. For the December 2009 contract, they fall from €0.0326 to €0.0129 for an average of €0.0181 for the year. The other expiries have spreads that are from 47% to 62% higher.

Figure 3 compares the TW and Hasbrouck spread estimates of December 2009 expiry. The two

[3] Marshall, Nguyen and Visaltanachoti (2010) calculate effective and quoted spreads of the 24 major commodities during the period April 2008 to August 2009. The median percentage effective spread is 0.09% and 0.12% for quoted spreads.

dotted lines are a 99% empirical confidence interval for the Hasbrouck estimates constructed from the MCMC draws.

[Insert Figure 3: ECX 2009 EUA Futures Monthly Spreads December 2009 Expiry]

The Hasbrouck estimates are statistically smaller than the TW in every trading month, but the estimates show a similar pattern over the sample.

In Figures 4 and 5, we repeat these spread estimates for CER. 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 4 and 5: ECX 2009 CER Futures Monthly Spreads]

CER spreads are roughly three times as wide as EUA futures. The yearly average TW spreads for the December expiries rise from €0.0695 for the 2009 to €0.1778 for the 2011. The €0.0695 spread for the 2009 expiry is 0.57% of its yearly average price.

The Hasbrouck estimates are substantially smaller, ranging from €0.0354 for the December 2009 expiry to €0.0596 for December 2012. Both TW and Hasbrouck spread estimates tend to narrow over time as with EUA. Their contraction is greater than that of EUA, shrinking 73% and 87% respectively for the December 2009 expiry.

[Insert Figure 6: ECX 2009 CER Futures Monthly Spreads December 2009 Expiry]

The 99% confidence interval for the Hasbrouck estimates still lie below the TW in every month, but it seems clear that utilizing trade direction generates plausible estimates.

6. Price Impact

Another measure of market liquidity is the price impact. We estimate it using Hasbrouck's (1991) vector autoregressive model[4] of intra-day quote and trade evolution. The application was fairly straightforward, even though we lack quotes for the bid and ask. Since we have trade direction, we assume

[4] We first approached the question using the structural model of Sandas (2001). We estimated the model using both OLS and Hasbrouck's (2004) MCMC procedure. In both cases, we found market impacts that were unreasonably small. In either case, trading volumes of more than 1,000 contracts were required to move the price €0.01.

$$p_t^b = p_t,\, p_t^a = p_t + c, \quad \text{if } x_t = -1$$
$$p_t^a = p_t,\, p_t^b = p_t - c, \quad \text{if } x_t = 1. \tag{6}$$

This method assumes a constant bid ask spread, but we think this is not likely to effect the long-run estimates of the market impact.

Let r_t be the change in the midpoint of the bid-ask spread, $(p_t^b + p_t^a)/2 - (p_{t-1}^b + p_{t-1}^a)/2$. We follow Hasbrouck in making the identifying assumption that the current trade can effect the current quote, but not vice versa,

$$r_t = a_{r,0} + \textstyle\sum_{i=1}^5 a_{r,i} r_{t-i} + \sum_{i=0}^5 b_{r,i} x_{t-i} + \varepsilon_{r,t}, \tag{7}$$

$$x_t = a_{x,0} + \textstyle\sum_{i=1}^5 a_{x,i} r_{t-i} + \sum_{i=1}^5 b_{x,i} x_{t-i} + \varepsilon_{q,t}. \tag{8}$$

We use 5 lags in the VAR. The estimates are not sensitive to this choice.

Market impact is a dynamic process

$$\partial r_{t+j} / \partial x_t \tag{9}$$

which we will now compute for both EUA and CER.

6.1 EUA market impact

We graph in Figure 7 the May 2009 market impact of the liquid December 2009 EUA futures.

[Figure 7: Market Impact December 2009 EUA Futures]

The impact accumulates quickly at first, reaching €0.01 after 12 trades. The impact plateaus after 50 ticks, with a cumulative effect of €0.0123.

We compare May to the other months in Table 9.

[Table 9: Monthly Peak Market Impact for EUA and CER]

The median peak impact for an EUA trade is €0.0108, with a range from €0.0045 for November 2009 to €0.0225 for December 2009. As with the spreads, market impact generally falls during the trading year until the expiry month.

6.2 CER market impact

We expect that the thinner CER market will have a much larger trade impact. We report all the monthly peak impacts in the second column of Table 9. We do confirm that the median impact is four times larger than for the EUA, €0.0429.

The imprecision of our estimates though is reflected in the range. There are months with so few trades though that we get some negative market impact estimates. January 2009, with only 260 screen trades, is one of them. For the positive estimates, market impact ranges from €0.0025 for November 2009 to €0.1552 for March 2009.

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,

$$\Delta \boldsymbol{p_t} = \boldsymbol{\Psi}(L)\boldsymbol{e_t}, \tag{10}$$

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,

$$\boldsymbol{p_t} = \boldsymbol{\Psi}(1)\textstyle\sum_{j=1}^{t} \boldsymbol{e}_j + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t. \tag{11}$$

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 (11) to be expressed as

$$\boldsymbol{p_t} = \boldsymbol{\iota} m_t + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t, \tag{12}$$

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

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

$$IS_i = \frac{\psi_i^2\sigma_{ei}^2}{\boldsymbol{\psi}^0\boldsymbol{\Omega}\boldsymbol{\psi}} = \frac{\psi_i^2\sigma_{ei}^2}{\psi_1^2\sigma_{e1}^2 + \psi_2^2\sigma_{e2}^2}, i = 1, 2 \tag{13}$$

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

$$IS_i = \frac{\left([\boldsymbol{\psi}^0\boldsymbol{C}]_i\right)^2}{\boldsymbol{\psi}^0\boldsymbol{\Omega}\boldsymbol{\psi}}, \tag{14}$$

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

$$\mathbf{p}_t = \mathbf{A}_1\mathbf{g}_t + \mathbf{A}_2\mathbf{h}_t, \tag{15}$$

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,

$$GG_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1} + \alpha_{\perp,2}}, i = 1, 2. \tag{16}$$

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

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{p}_{t-1} + \textstyle\sum_{j=1}^{k} \mathbf{B}_j \Delta \mathbf{p}_{t-j} + \mathbf{e}_t, \tag{17}$$

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[5] from (17). For Ω diagonal,

$$IS_i = \frac{\alpha_{i\perp}^2 \sigma_{ei}^2}{\alpha_{1\perp}^2 \sigma_{e1}^2 + \alpha_{2\perp}^2 \sigma_{e2}^2}, \qquad i = 1, 2 \tag{18}$$

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

$$IS_i = \frac{\left(\left[\boldsymbol{\alpha}_?^0\, \boldsymbol{C}\right]_i\right)^2}{\boldsymbol{\alpha}_?^0\, \boldsymbol{\Omega}\boldsymbol{\alpha}_?}, \tag{19}$$

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

$$GG_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, GG_2 = \frac{-\alpha_1}{\alpha_2 - \alpha_1}. \tag{20}$$

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

[Insert Table 10: 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

[5] 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.

lead price discovery.

We start with the cointegration test and the estimation of (17). We verify in Table 11 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 11: Cointegration and Information Shares]

Table 11 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 8 plots the monthly information shares from January to December 2009.

[Insert Figure 8: 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,

$$r_t = a + \sum_{k=1}^{10} b_k OIB_{t-k} + e_t \tag{21}$$

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,

$$OIBX_t = \sum_{j=1}^{t} x_j / \sum_{j=1}^{t} |x_j|\,; \tag{22}$$

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

$$OIBV_t = \sum_{j=1}^{t} x_j p_j v_j / \sum_{j=1}^{t} p_j v_j. \tag{23}$$

We find, in Table 12, 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 12: 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 13 reports the gain in Euros of trading a single contract using this strategy.

[Insert Table 13: 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 Thompson-Waller spreads on the most active EUA contracts about twice the minimum tick of €0.01. By using the trade direction indicator in our sample, the Hasbrouck MCMC models generates similar estimates. 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 0.17%, which is comparable to the quoted spreads of cotton and gasoline.

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 four ticks for CER.

Information shares confirm the trading volume figures, with approximately 90% of the price discovery taking place on the ECX futures 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.

References

Benz, Eva A. and Jördis Hengelbrock (2008). "Liquidity and Price Discovery in the European CO2 Futures Market: An Intraday Analysis," 21st Australian Finance and Banking Conference 2008 Paper. Available at SSRN: http://ssrn.com/abstract=1143923.

Brandt, Michael W. and Kenneth A. Kavajecz (2004). "Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve," *Journal of Finance* 59, 2623-54.

Bryant, Henry and Michael Haigh (2004)."Bid-Ask Spreads in Commodity Futures Markets," *Applied Financial Economics* 14, 923-936.

Chordia, Tarun and Avanidhar Subrahmanyam (2004). "Order imbalance and individual stock returns: Theory and evidence," *Journal of Financial Economics* 72, 485-518.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam (2002). "Order Imbalance, Liquidity, and Market Returns," *Journal of Financial Economics* 65, 111-30.

Ellerman, Denny, Frank Convery, and Christian De Perthuis (2010). *Pricing Carbon*, New York: Cambridge U. Press.

Evans, Martin D. D. and Richard K. Lyons (2002). "Order Flow and Exchange Rate Dynamics," *Journal of Political Economy* 110, 170-80.

Figuerola-Ferretti, Isabel and Jesus Gonzalo (2010). "Modelling and Measuring Price Discovery in Commodity Markets," *Journal of Econometrics* 158, 95-107.

Frank, Julieta and Philip Garcia (2006). "Estimating Liquidity Costs in Agricultural Futures Markets using Bayesian Methods," U. of Illinois Working Paper.

Gonzalo, Jesus and Clive Granger (1995). "Estimation of common long-memory components in cointegrated systems," *Journal of Business and Economic Statistics* 13, 27-35.

Harris, Frederic,Thomas McInish, and Robert Wood (2002). "Security price adjustment across exchanges: An investigation of common factor components for Dow stocks," *Journal of Financial Markets* 5, 277-308.

Hasbrouck, Joel (1991). "Measuring the information content of stock trades," *Journal of Finance* 46, 179-207.

Hasbrouck, Joel (1995). "One security, many markets: determining the contribution to price discovery," *Journal of Finance* 50, 1175-99.

Hasbrouck, Joel (2004). "Liquidity in the Futures Pits: Inferring Market Dynamics from Incomplete Data," *Journal of Financial and Quantitative Analysis* 39, 305-326.

Marshall, Ben, R., Nhut H. Nguyen, and Visaltanachoti Nuttawat (2010). "Commodity Liquidity Measurement," Working Paper, http://ssrn.com/abstract=1603683

Mizrach, Bruce (2010). "Integration of the Global Emissions Trading Markets," Rutgers University Working Paper, http://papers.ssrn.com/sol3/ papers.cfm?abstract_id=1542871.

Rittler, Daniel (2009). "Price Discovery, Causality and Volatility Spillovers in European Union

Allowances Phase II: A High Frequency Analysis," University of Heidelberg Discussion Paper Series, No. 492.

Roll, Richard (1984). "A Simple Implicit Measure of the Effective Bid-ask Spread in an Efficient Market," *Journal of Finance* 23: 1127-1139.

Sandas, Patrick (2001). "Adverse Selection and Competitive Market Making: Empirical Evidence from a Limit Order Market," *Review of Financial Studies* 14, 705-34.

Thompson, Sarahelen and Mark Waller (1988). "The Intraday Variability Of Soybean Futures Prices: Information and Trading Effects," *Review of Futures Markets* 7, 110-126.

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

Volumes	**Dec-09**	**Dec-10**	**Expiry** **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
Monthly Peak Market Impact EUA and CER Trades

Month	EUA	CER
Jan-09	0.0118	-0.0163
Feb-09	0.0103	0.0201
Mar-09	0.0168	0.1552
Apr-09	0.0113	0.0870
May-09	0.0123	0.1301
Jun-09	0.0066	-0.0066
Jul-09	0.0087	0.0335
Aug-09	0.0086	0.0524
Sep-09	0.0049	-0.0024
Oct-09	0.0118	0.1148
Nov-09	0.0045	0.0025
Dec-09	0.0225	0.0861
Median	0.0108	0.0429

We report the monthly peak market impact in Euros for EUA and CER trades of the December 2009 futures contract.

Table 10
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 11
Cointegration and Information Shares

	Cointegration		Johansen Test		Granger causality		Futures information share			
Month	α_1	α_2	$r=0$	$r=1$	Spot	Futures	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 12
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

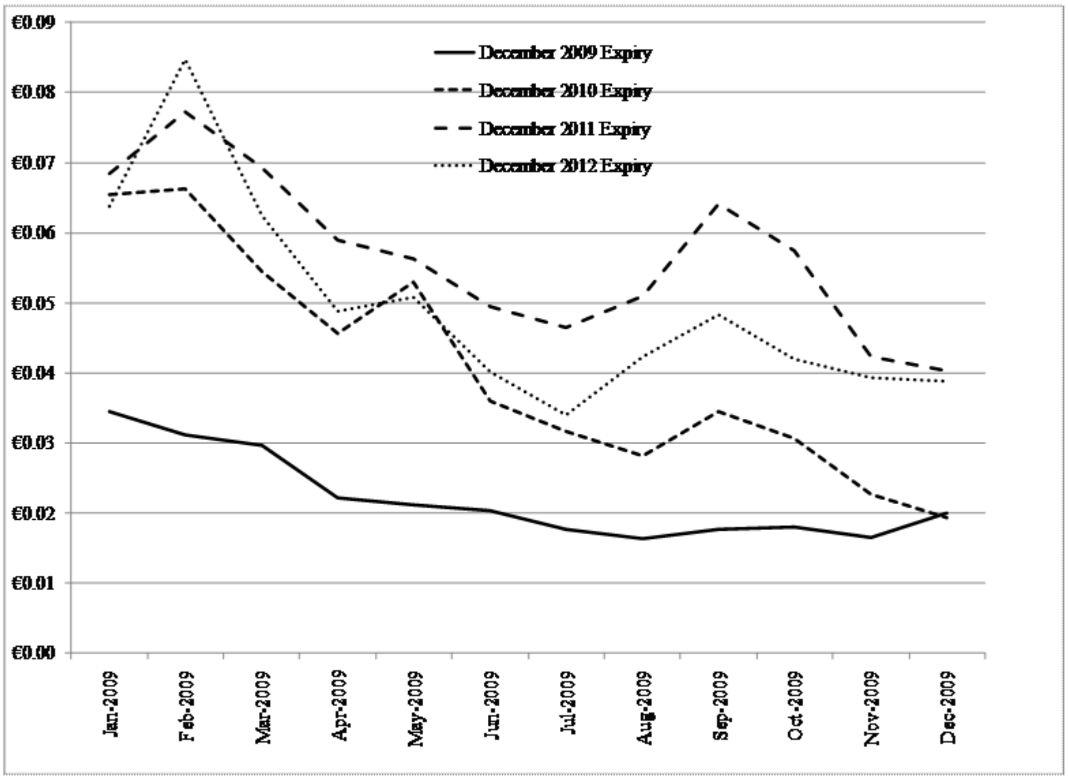
The table reports estimates of the order imbalance regression (21) using daily EUA December 2009 futures. We measure the imbalance in number of transactions (OIBX) as defined in (22) or in € volume (OIBV) as defined in (23).

Table 13
Trading Strategies

Entry at Close	Exit at Open	$\vert$Threshold$\vert$	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

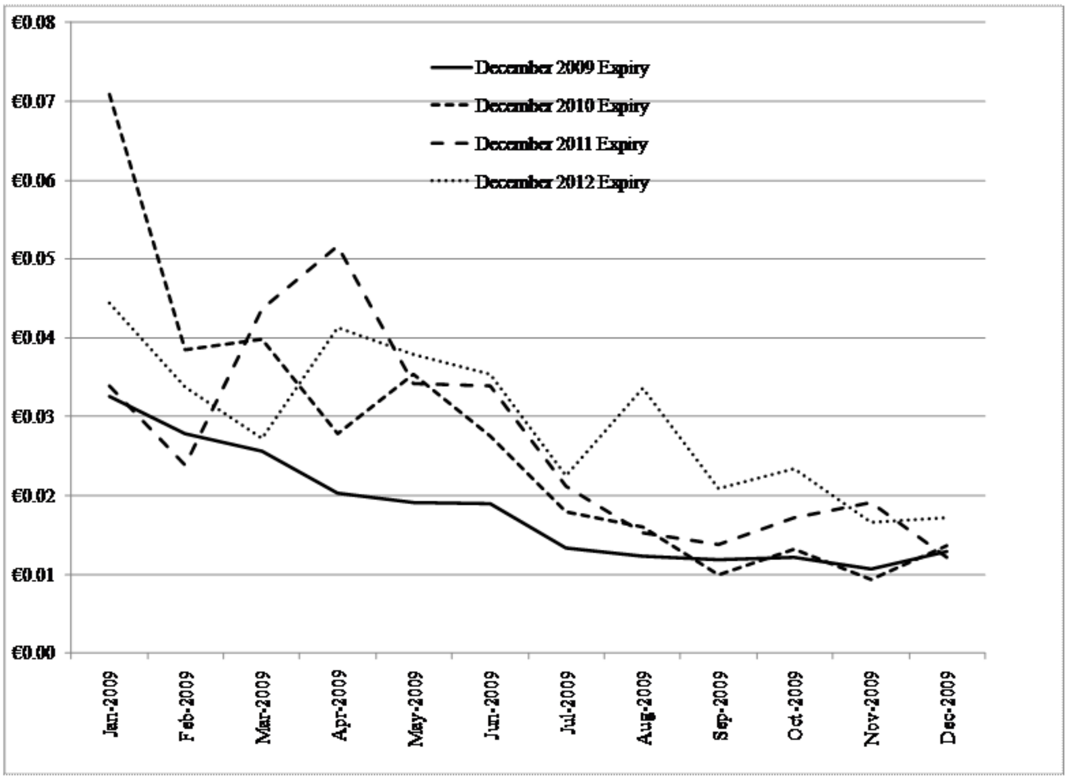
The table explore trading strategies using the order book imbalance, $OIB_t = \sum_{j=1}^{t} x_j$, under different assumptions about entry and exit prices, the threshold order imbalance required for entry, trade size and market impact. x_j is a binary variable indicating whether the trade is buyer (+1)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

Figure 1
ECX 2009 EUA Futures Monthly Spreads: Thompson-Waller Estimates



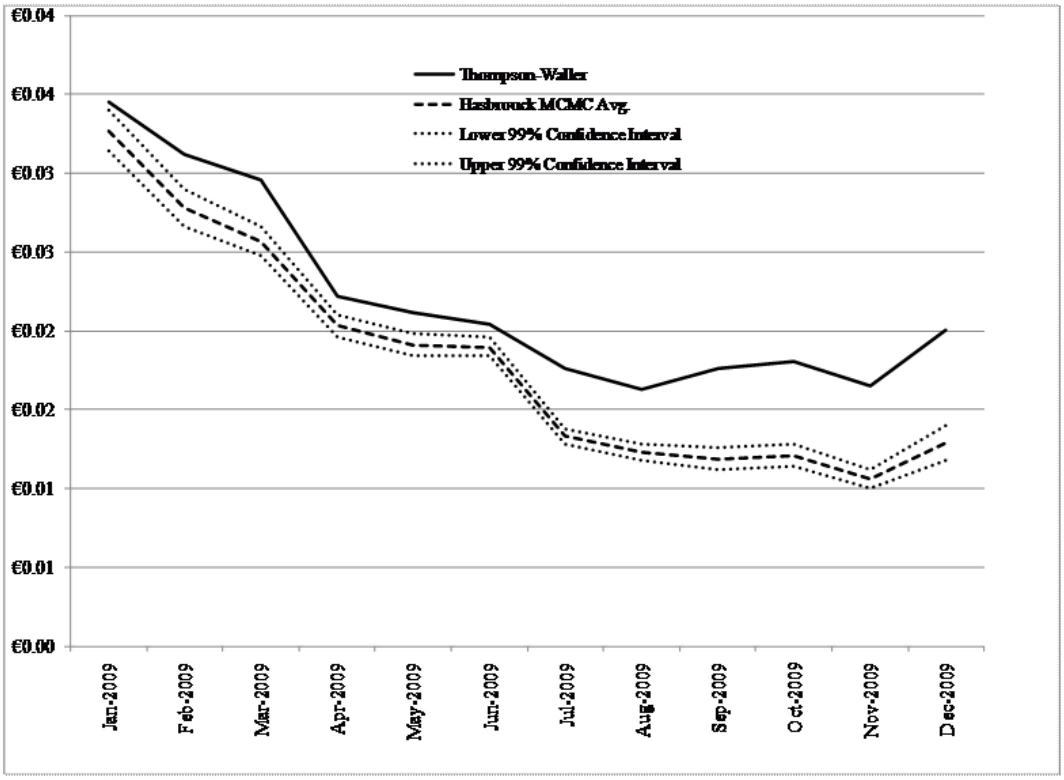
The figure displays monthly average bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Thompson-Waller estimator, (1).

Figure 2
ECX 2009 EUA Futures Monthly Spreads: Hasbrouck MCMC Estimates



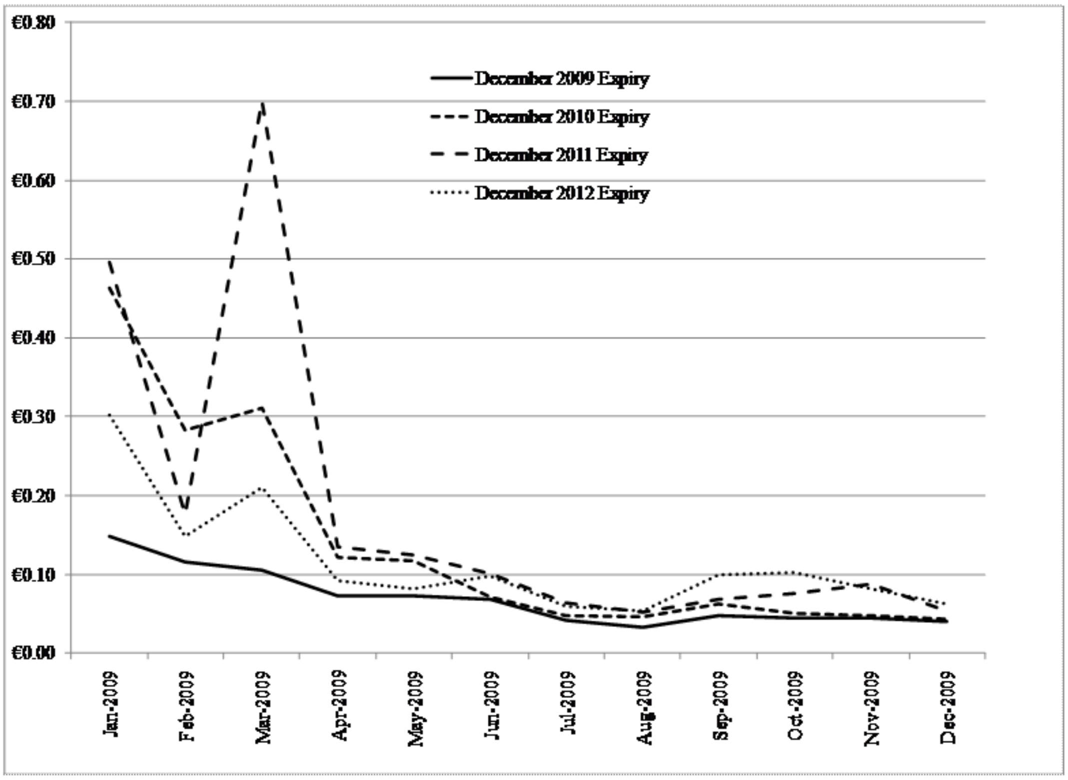
The figure displays bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Hasbrouck Markov Chain Monte Carlo (MCMC) estimator modified to use the observed trade initiation x.

Figure 3
ECX 2009 EUA Futures Monthly Spreads: December 2009 Expiry



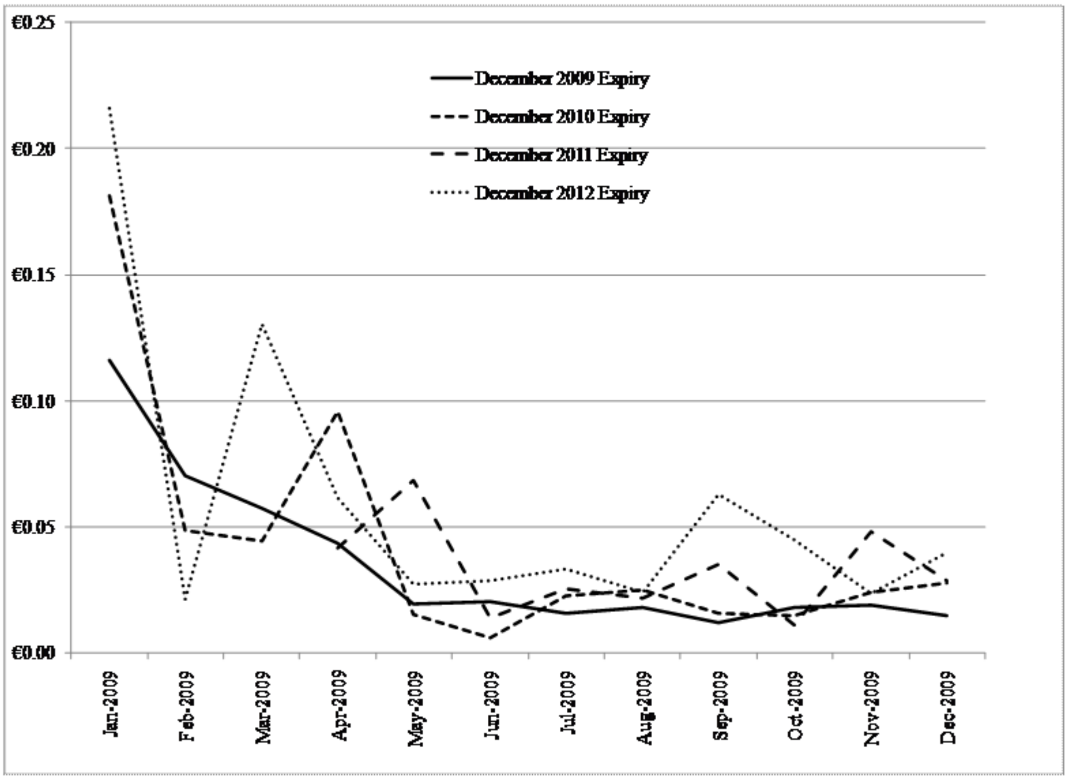
The figure compares bid-ask spread estimates of EUA December 2009 expiry futures from the European Climate Exchange. We report: (1) Thompson-Waller monthly averages and (2) Modified Hasbrouck MCMC estimates, where we report the average and empirical 99% confidence intervals.

Figure 4
ECX 2009 CER Futures Monthly Spreads: Thompson-Waller Estimates



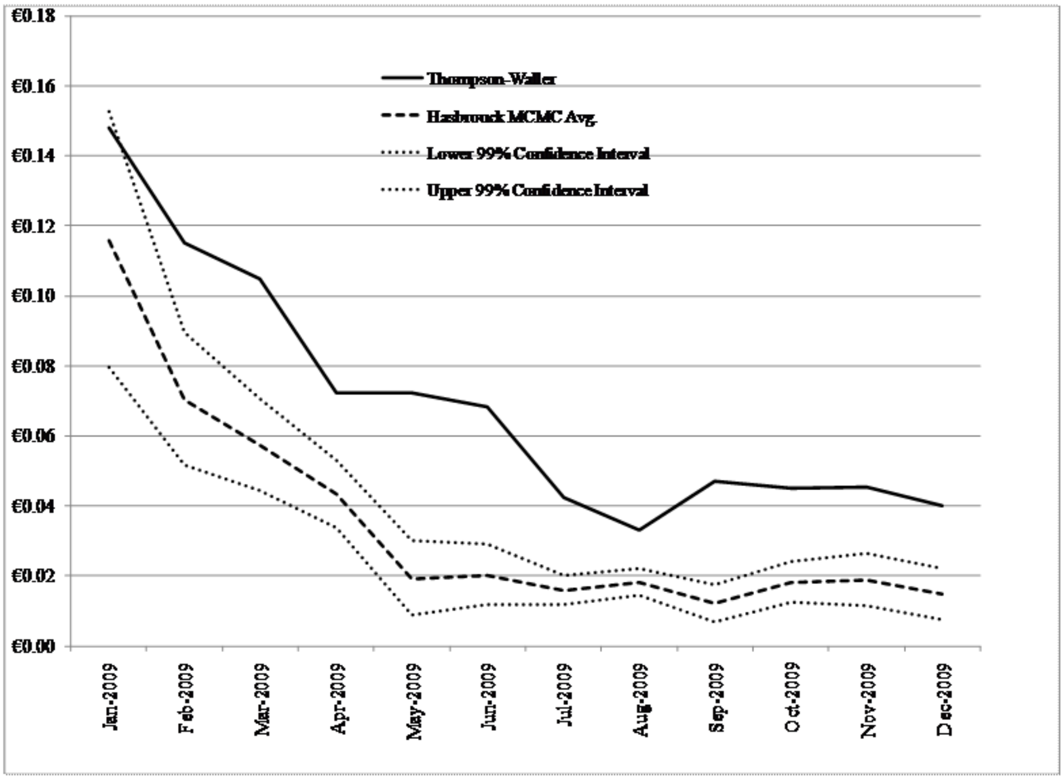
The figure displays monthly average bid-ask spread estimates of CER December expiry futures from the European Climate Exchange. Estimates are computed using the Thompson-Waller estimator, (1).

Figure 5
ECX 2009 CER Futures Monthly Spreads: Hasbrouck MCMC Estimates



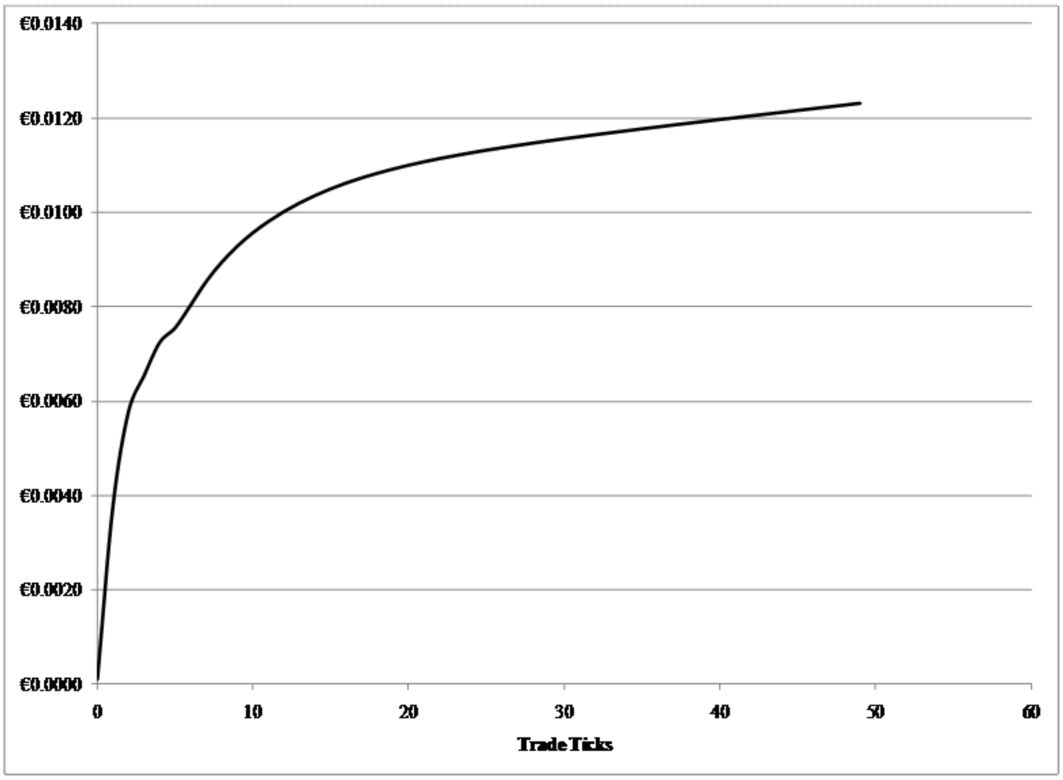
The figure displays bid-ask spread estimates of CER December expiry futures from the European Climate Exchange. Estimates are computed using the Hasbrouck Markov Chain Monte Carlo (MCMC) estimator modified to use the observed trade initiation x.

Figure 6
ECX 2009 CER Futures Monthly Spreads: December 2009 Expiry



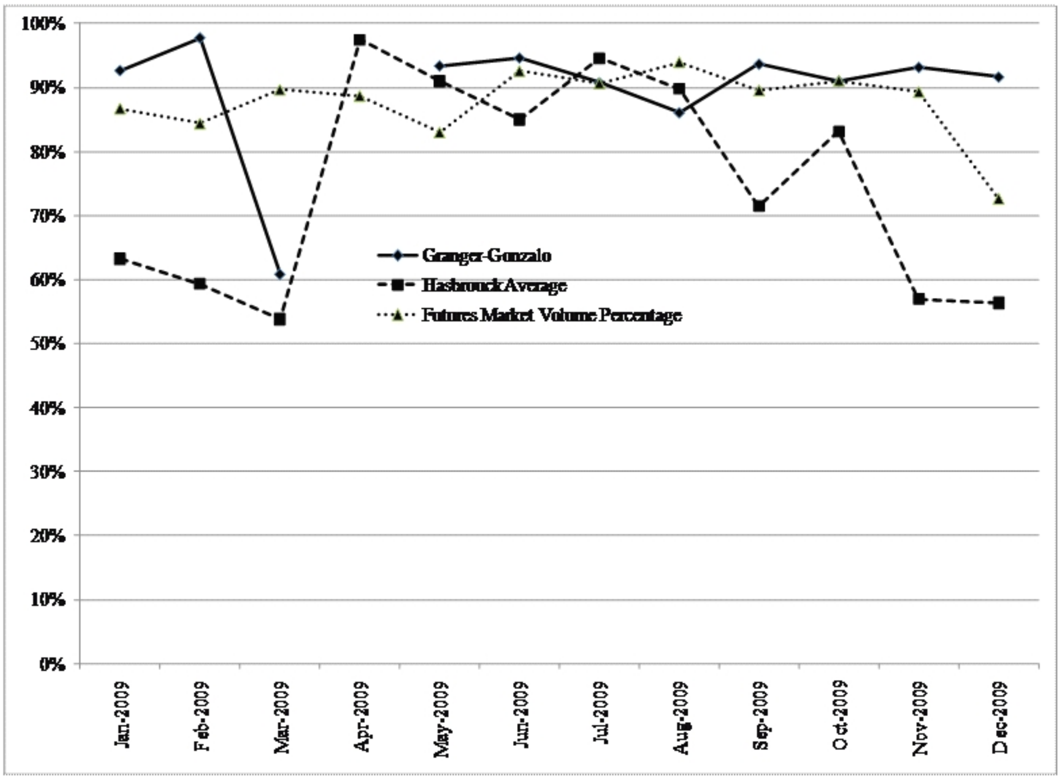
The figure compares bid-ask spread estimates of CER December 2009 expiry futures from the European Climate Exchange. We report: (1) Thompson-Waller monthly averages; and (2) Modified Hasbrouck MCMC estimates, where we report the average and empirical 99% confidence intervals..

Figure 7
Dynamic Price Impact in Hasbrouck VAR Model
December 2009 EUA Futures



The figure plots the dynamic impulse response (9) of a buy order on the mid-quote return for the December 2009 expiry EUA futures contract. The VAR model (6) is estimated on data from May 2009 with quotes derived from Thompson-Waller spread estimates.

Figure 8
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 (19) is plotted. The Granger-Gonzalo information share is given by (20). For comparison, we include the monthly percentage of trading activity occurring in the ECX futures market.