ESSAYS ON EMPIRICAL MARKET MICROSTRUCTURE

by

YOICHI OTSUBO

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ABSTRACT OF THE DISSERTATION

Essays on Empirical Market Microstructure

By YOICHI OTSUBO

Dissertation Director:
Professor Bruce Mizrach

The first essay analyzes the market microstructure of the European Climate Exchange (ECX), the largest European Union Emissions Trading Scheme trading venue. Spreads range from 2 to 6 times the minimum tick increment on European Union Allowances (EUA) futures. Market impact estimates imply that an average trade will move the EUA market by 1.08 euro centimes. 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.

The second essay provides a case that the Thompson-Waller (TW) estimator would have downward bias, which has not been carefully discussed in the literature. Such case is that (i) the buy (sell) order tends to follow buy (sell) order and (ii) the price changes associated to such orders are small. The upward bias of the TW estimator would be canceled out by the downward bias, and in such case the estimator would perform better than the other absolute price change methods. The application to the EUA futures contract trading implies that its trading pattern and the price change provide the conditions that reduce the bias of the TW estimator. The Madhavan, Richardson and Roomans model is applied to examine the spread component of the market. A dominance of asymmetric information component in the spread is found. The fraction of the spread attributable to that component increases gradually during the observation period.

The final essay examines price discovery of Japanese companies' Tokyo-New York cross-listed shares. Kalman filter is utilized to estimate partial price adjustment model. By employing Kalman filter, the present research can deal with missing values problem researchers has to confront in order to analyze non-overlapping markets such as Tokyo and New York. I find that events with larger magnitude of efficient price change occur during Tokyo opening hours. Dynamic measure shows that New York Stock Exchange is more efficient in price discovery.

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Dedication

To My Parents and My Fiancée

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Chapter 1

Introduction

Market microstructure is the branch of financial economics. It is the study of the trading mechanisms used for financial securities. The term market microstructure first appeared as the title of the paper by Mark Garman (1976). His work attempts to "depart from the usual approaches of the theory of exchanges by ... adopting a viewpoint which treats the temporal microstructure, i.e., moment-to-moment aggregate exchange behavior, as an important descriptive aspect" of markets.

Market microstructure provides useful approaches for answering questions such as: How are prices formed? How liquid is the market? How is new information incorporated? Empirical market microstructure studies are distinctive in that they use high-frequency intra-day data that can be measured by the hour, minute, or even the second.

This work contributes in the study of empirical market microstructure by (i) employing the methods to a newly established market, (ii) discussing a potential bias of the widely used spread estimation method, and (iii) providing a methodology for measuring a market's contribution in price discovery.

Chapter 2 analyzes the market microstructure of the European Climate Exchange (ECX) and contrasts it with more mature commodity markets. We find that, after less than five years of trading, 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.

The essay extend the carbon pricing literature by analyzing market impact as well as spreads. While previous studies focused only on the European Union Allowances (EUA) market, the Certified Emission Reduction (CER) market is also explored. The study examines the price discovery contribution across spot and futures markets, a question which has not been addressed. Finally, the predictive content of order imbalances for future EUA returns is examined.

One of the popular methods to estimate the spread is the Thompson-Waller (TW) estimator. The TW estimate usually consists of two components, the bid-ask spread and the magnitude of true price changes, and it would be biased upward. While the upward bias due to the change in the true price has been pointed out in the literature, the potential downward bias has not been carefully discussed.

Chapter 3 provides a case that the TW estimator would have downward bias. Such case is that (i) the buy (sell) order tends to follow buy (sell) order, and (ii) the price change associated to such orders are small. Furthermore, the upward bias of the TW estimator would be canceled out by the downward bias, and in such case the estimator would perform better than the other absolute price change methods which suppose to modify the TW estimator.

The empirical finding from the application to the EUA futures contract trading implies that its trading pattern and the price change provide the conditions that reduce the bias of the TW estimator. The study also applies Madhavan-Richardson-Roomans (MRR) model to examine the components of the spread and the price impact. In the EUA futures market, information component dominates the bid-ask spread. The immediate price impact of a typical trade is almost the half of the tick in January, and falls to less than one third of the tick in December.

Chapter 4 examines an approach which provides a way to study price discovery of two markets which do not open simultaneously, in the case as Tokyo Stock Exchange (TSE) and New York Stock Exchange (NYSE). The two widely used methods for measuring contributions to price discovery, Information share (IS) and Gonzalo-Granger portfolio weights (GG), require two markets to be open simultaneously. The estimated efficient prices produced by Kalman filter can be used to generate the price series assuming that two markets' opening hours are overlapped.

The method applied in the study is a structural approach suggested by Yan and Zivot (2006). They proposed a measure based on impulse response function. With their structural approach, information innovation and microstructural noise are distinguished explicitly. In the present work, partial price adjustment model suggested by Amihud and Mendelson (1987) is used for the structural model.

To estimate the model, Kalman filter is utilized. It enables us to estimate not only the parameters but also the efficient prices, information shocks and noises. By modifying the partial price adjustment model to allow different variance on information shock for each market's opening hours, the work finds that the magnitude of the shocks are larger during Tokyo opening hours. Price discovery impulse response function shows that NYSE is more efficient in price discovery, but values of IS and GG vary significantly across stocks.

Chapter 2

The Market Microstructure of the European Climate Exchange

2.1 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.

2.2 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.

2.2.1 EUA

Table 2.1 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.

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.

2.2.2 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.

[1] There were $12,242$ installations in the EU registry which were allocated $1,966$ MMtCO$_2$e in 2009.

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 2.2.

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.

2.3 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 2.3 describes some features of the derivative securities traded on the ECX.

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.

2.3.1 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 2.4.

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.

2.3.2 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 2.5.

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.

2.4 CER Futures Trading

We now turn to the CER trading on the ECX. Contract specifications are listed in Table 2.6.

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.

2.4.1 Screen trading

We summarize 2009 trading activity in the four most active expiries in Table 2.7. The most liquid contract is the December 2009 CER, the near-to-expiry contract as in EUA futures trading.

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

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

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

2.4.2 OTC trading

We summarize OTC trading activity in the active December contracts in Table 2.8.

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.

2.5 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.

2.5.1 Thompson-Waller

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

$$S_t^{TW} = \sum_{i=1}^{T} \left| p_i - p_{i-1} \right|^+ / T^+. \tag{2.1}$$

$T^+$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.

2.5.2. 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,

$$m_t = m_{t-1} + u_t \quad \text{where } u_t \text{ are } i.i.d.N(0, \sigma_u^2). \tag{2.2}$$

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,

$$\begin{aligned} p_t^b &= m_t - c, \\ p_t^a &= m_t + c. \end{aligned} \tag{2.3}$$

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,

$$p_t = \begin{cases} p_t^b & \text{if } \; x_t = -1 \\ p_t^a & \text{if } \; x_t = +1 \end{cases} \tag{2.4}$$

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 (2.2) to (2.4), the log transaction price process is,

$$\Delta p_t = m_t + cx_t - (m_{t-1} + cx_{t-1}) = c\Delta x_t + u_t. \tag{2.5}$$

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 $F\left(c, \sigma_u, x_1, ..., x_T \mid p\right)$.To obtain the marginal pdf's $f\left(c \mid p\right), f\left(\sigma_u \mid p\right), f\left(x_1 \mid p\right), ..., f\left(x_T \mid p\right)$, 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.

2.5.3 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 2.1 plots the TW spread estimates for the four expiries. 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.

[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.

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 2.2. 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 2.3 compares the TW and Hasbrouck spread estimates of December 2009 expiry. The two dotted lines are a 99% empirical confidence interval for the Hasbrouck estimates constructed from the MCMC draws.

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 2.4 and 2.5, 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.

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.

Figure 2.6 shows that the 99% confidence interval for the Hasbrouck estimates still lie below the TW in every month. However, it seems clear that utilizing trade direction generates plausible estimates.

2.6 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

$$\begin{aligned} p_t^b = p_t,\, p_t^a = p_t + c, &\quad \text{if } x_t = -1 \\ p_t^a = p_t,\, p_t^b = p_t - c, &\quad \text{if } x_t = 1. \end{aligned} \tag{2.6}$$

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,

$$r_t = a_{r,0} + \textstyle\sum_{i=1}^{5} a_{r,i} r_{t-i} + \sum_{i=0}^{5} b_{r,i} x_{t-i} + \varepsilon_{r,t}, \tag{2.7}$$

[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.

$$x_t = a_{x,0} + \sum_{i=1}^{5} a_{x,i} r_{t-i} + \sum_{i=1}^{5} b_{x,i} x_{t-i} + \varepsilon_{q,t}. \quad (2.8)$$

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

Market impact is a dynamic process

$$\partial r_{t+j} / \partial x_t \quad (2.9)$$

which we will now compute for both EUA and CER.

2.6.1 EUA market impact

We graph in Figure 2.7 the May 2009 market impact of the liquid 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 2.9. 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.

2.6.2 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 2.9. 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.

2.7 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.

2.7.1 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,

$$\Delta \boldsymbol{p_t} = \boldsymbol{\Psi}(L)\boldsymbol{e_t}, \tag{2.10}$$

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

$$\boldsymbol{p_t} = \boldsymbol{\Psi}(1)\sum_{j=1}^{t} \boldsymbol{e}_j + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t. \tag{2.11}$$

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 (2.11) to be expressed as

$$\boldsymbol{p_t} = \boldsymbol{\iota} m_t + \boldsymbol{\Psi}^*(L)\boldsymbol{e}_t, \tag{2.12}$$

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

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

$$IS_i = \frac{\psi_i^2 \sigma_{ei}^2}{\boldsymbol{\psi}'\boldsymbol{\Omega}\boldsymbol{\psi}} = \frac{\psi_i^2 \sigma_{ei}^2}{\psi_1^2 \sigma_{e1}^2 + \psi_2^2 \sigma_{e2}^2}, i = 1, 2 \tag{2.13}$$

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

$$IS_i = \frac{([\boldsymbol{\psi}'\boldsymbol{C}]_i)^2}{\boldsymbol{\psi}'\boldsymbol{\Omega}\boldsymbol{\psi}}, \tag{2.14}$$

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

$$\mathbf{p}_t = \mathbf{A}_1 \mathbf{g}_t + \mathbf{A}_2 \mathbf{h}_t, \tag{2.15}$$

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,

$$GG_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1} + \alpha_{\perp,2}}, i = 1, 2. \tag{2.16}$$

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

$$\Delta\mathbf{p}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{p}_{t-1} + \textstyle\sum_{j=1}^{k}\mathbf{B}_j\Delta\mathbf{p}_{t-j} + \mathbf{e}_t, \tag{2.17}$$

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 (2.17). For Ω diagonal,

$$IS_i = \frac{\alpha_{i\perp}^2\sigma_{ei}^2}{\alpha_{1\perp}^2\sigma_{e1}^2 + \alpha_{2\perp}^2\sigma_{e2}^2}, \qquad i = 1, 2 \tag{2.18}$$

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

$$IS_i = \frac{([\boldsymbol{\alpha}'_{\perp}\boldsymbol{C}]_i)^2}{\boldsymbol{\alpha}'_{\perp}\boldsymbol{\Omega}\boldsymbol{\alpha}_{\perp}}, \tag{2.19}$$

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

$$GG_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, GG_2 = \frac{-\alpha_1}{\alpha_2 - \alpha_1}. \tag{2.20}$$

[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.

2.7.2 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 2.10, we report the relative volumes, in numbers of trades, for the futures and the spot market. 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 (2.17). We verify in Table 2.11 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, $\alpha_2 > 0$.

Table 2.11 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 2.8 plots the monthly information shares from January to December 2009. 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.

2.8 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,

$$r_t = a + \sum_{k=1}^{10} b_k OIB_{t-k} + e_t \tag{2.21}$$

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,

$$OIBX_t = \sum_{j=1}^{t} x_j / \sum_{j=1}^{t} |x_j|\,; \tag{2.22}$$

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

$$OIBV_t = \sum_{j=1}^{t} x_j p_j v_j / \sum_{j=1}^{t} p_j v_j. \tag{2.23}$$

We find, in Table 2.12, 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. 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 2.13 reports the gain in Euros of trading a single contract using this strategy.

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.

2.9 Concluding Remarks

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.

2.10 Tables of Chapter 2

Table 2.1
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 2.2
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 2.3
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 2.4
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 2.5
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 2.6
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 2.7
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 2.8
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 2.9
Monthly Peak Market Impact EUA and CER Trades

Month	EUA	CER
January	0.0118	-0.0163
February	0.0103	0.0201
March	0.0168	0.1552
April	0.0113	0.0870
May	0.0123	0.1301
June	0.0066	-0.0066
July	0.0087	0.0335
August	0.0086	0.0524
September	0.0049	-0.0024
October	0.0118	0.1148
November	0.0045	0.0025
December	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 2.10
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 2.11
Cointegration and Information Shares

	Cointegration		Johansen Test		Granger causality		Information Share		
Month	α_1	α_2	$r=0$	$r=1$	Spot	Futures	GG	H_{low}	H_{high}
January	-0.494**	0.039	63.73**	4.19*	0.475	12.872**	92.67	26.68	99.83
	(0.114)	(0.112)			(0.623)	(0.000)			
February	-0.897*	0.020	26.89**	0.50	0.860	8.169**	97.78	18.66	99.99
	(0.402)	(0.414)			(0.509)	(0.000)			
March	-0.336**	0.216*	68.12**	0.58	0.864	12.336**	60.87	13.35	94.23
	(0.103)	(0.101)			(0.423)	(0.000)			
April	-0.844**	-0.125	208.78**	0.96	3.509*	174.979**	117.43	95.77	99.18
	(0.044)	(0.071)			(0.032)	(0.000)			
May	-0.771**	0.055	153.42**	0.02	1.568	91.322**	93.39	82.22	99.79
	(0.055)	(0.076)			(0.211)	(0.000)			
June	-0.691**	0.039	116.87**	2.26	1.088	52.204**	94.63	70.22	99.84
	(0.066)	(0.078)			(0.339)	(0.000)			
July	-0.777**	0.079	230.89**	0.20	0.455	180.663**	90.74	89.48	99.66
	(0.040)	(0.067)			(0.635)	(0.000)			
August	-0.801**	0.130	191.33**	1.10	1.259	120.759**	86.07	80.60	98.95
	(0.050)	(0.071)			(0.286)	(0.000)			
September	-0.908**	0.061	132.23**	1.32	1.913	43.511**	93.67	43.08	99.86
	(0.097)	(0.116)			(0.151)	(0.000)			
October	-0.992**	0.099	46.50**	0.79	0.882	60.789**	90.95	66.66	99.62
	(0.174)	(0.229)			(0.476)	(0.000)			
November	-0.728**	0.053	97.50**	1.93	0.191	13.811**	93.16	13.95	99.92
	(0.176)	(0.174)			(0.826)	(0.000)			
December	-0.846	0.077	13.31*	1.22	0.892	6.139**	91.64	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.

Table 2.12
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 (2.21) using daily EUA December 2009 futures. We measure the imbalance in number of transactions (OIBX) as defined in (2.22) or in € volume (OIBV) as defined in (2.23).

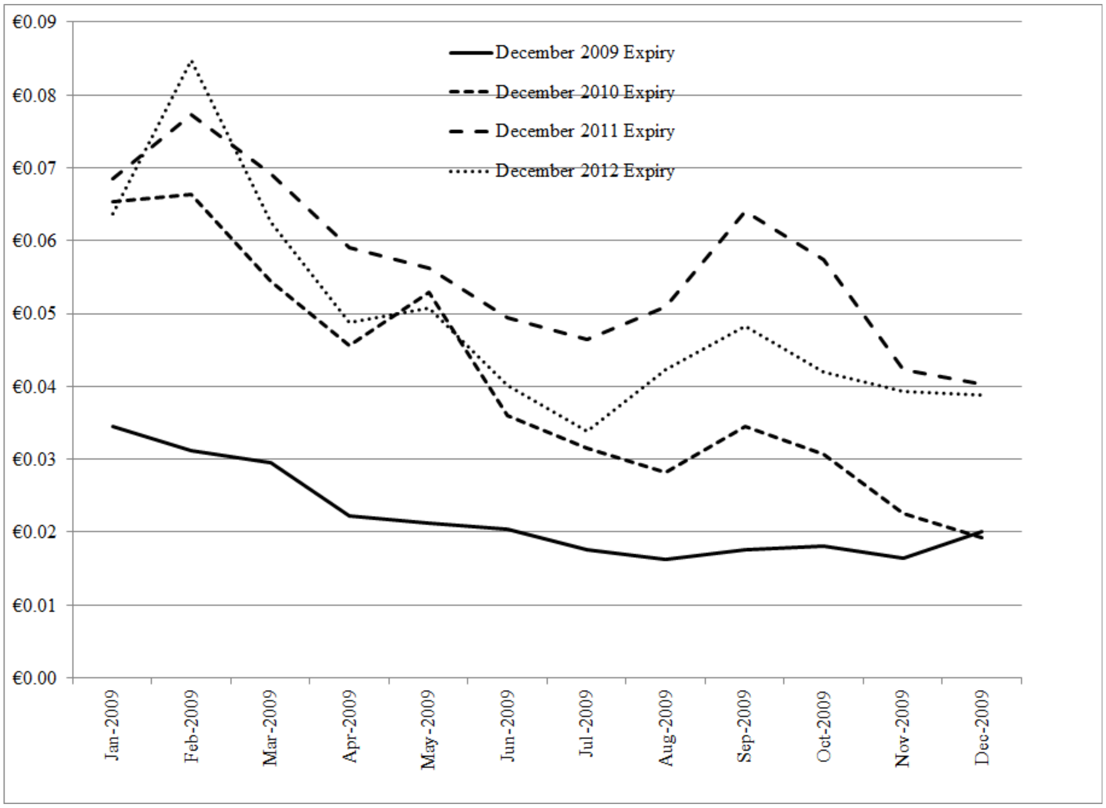
Table 2.13
Trading Strategies

Entry at Close	Exit at Open	|Threshold|	Trade Size	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.

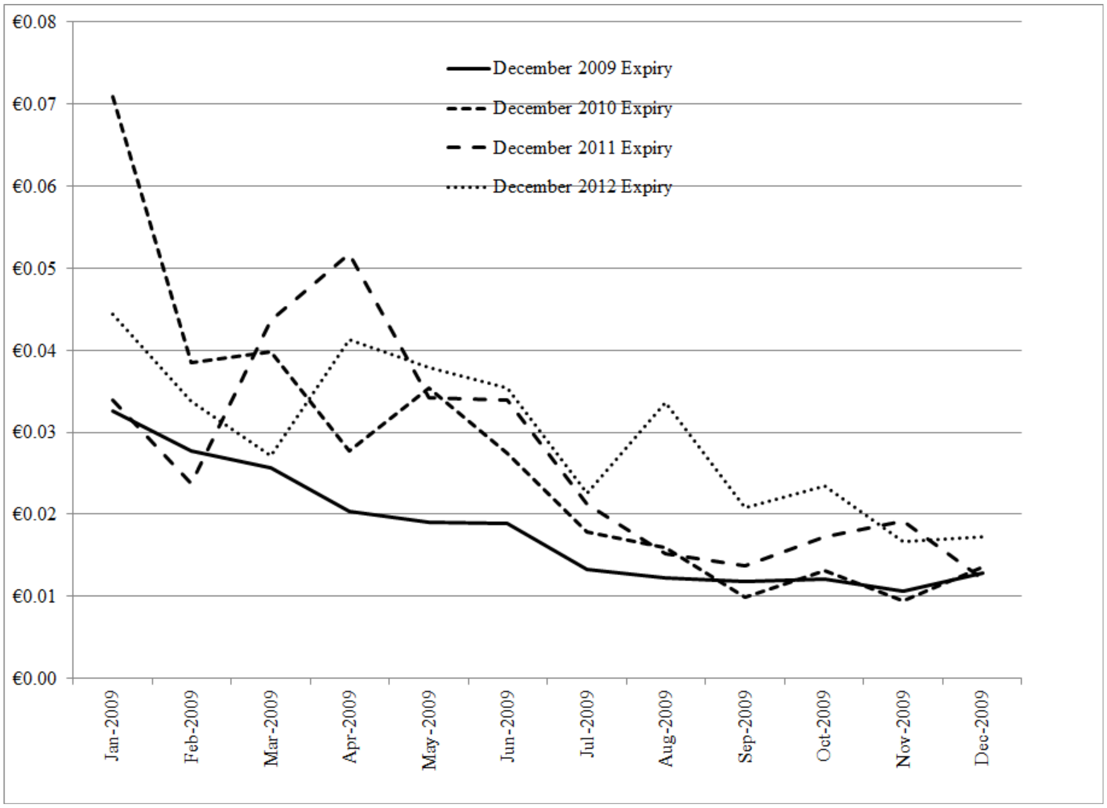
2.11 Figures of Chapter 2

Figure 2.1
ECX 2009 EUA Futures Monthly Spreads: Thompson-Waller Estimates



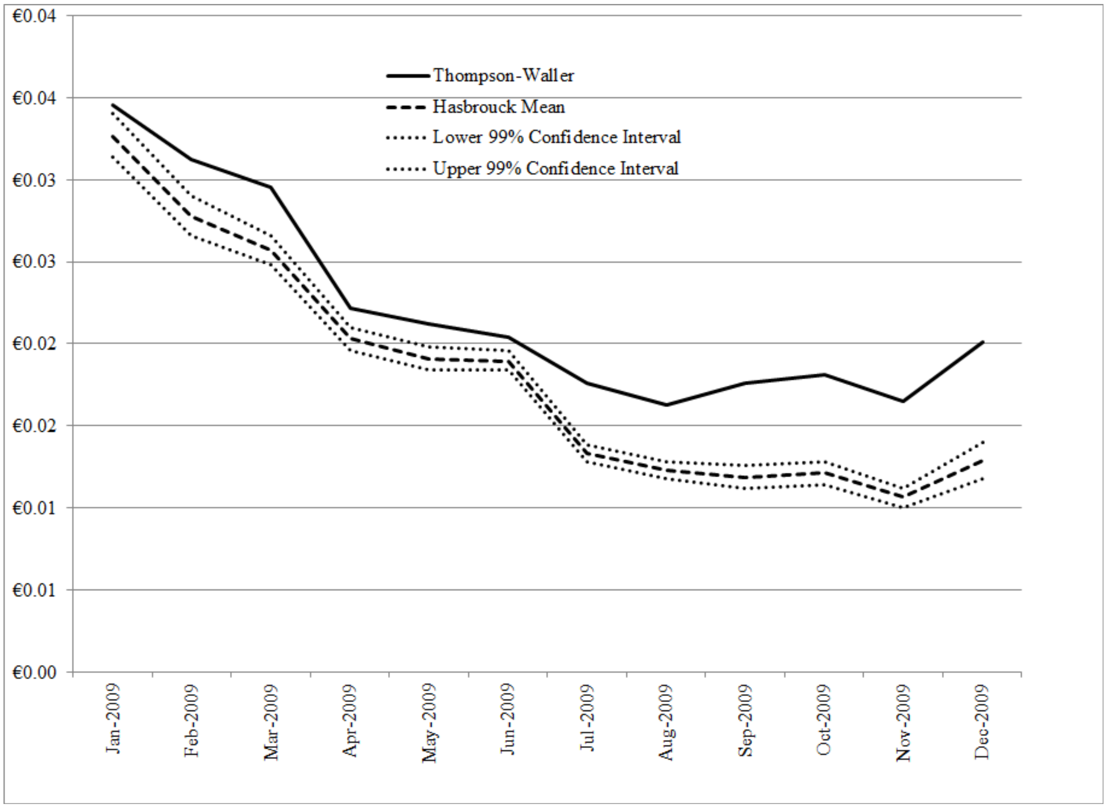
The figure displays monthly average bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Thompson-Waller estimator, (2.1).

Figure 2.2
ECX 2009 EUA Futures Monthly Spreads: Hasbrouck MCMC Estimates



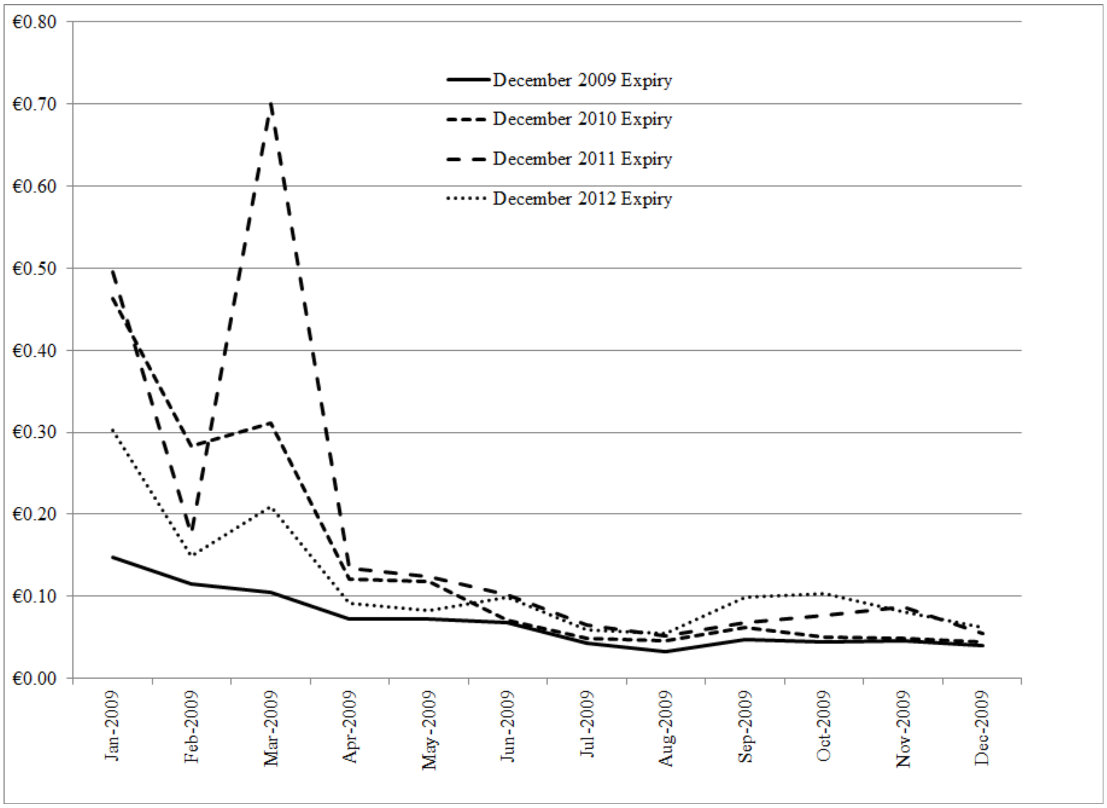
The figure displays bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Hasbrouck Markov Chain Monte Carlo (MCMC) estimator modified to use the observed trade initiation x.

Figure 2.3
ECX 2009 EUA Futures Monthly Spreads: December 2009 Expiry



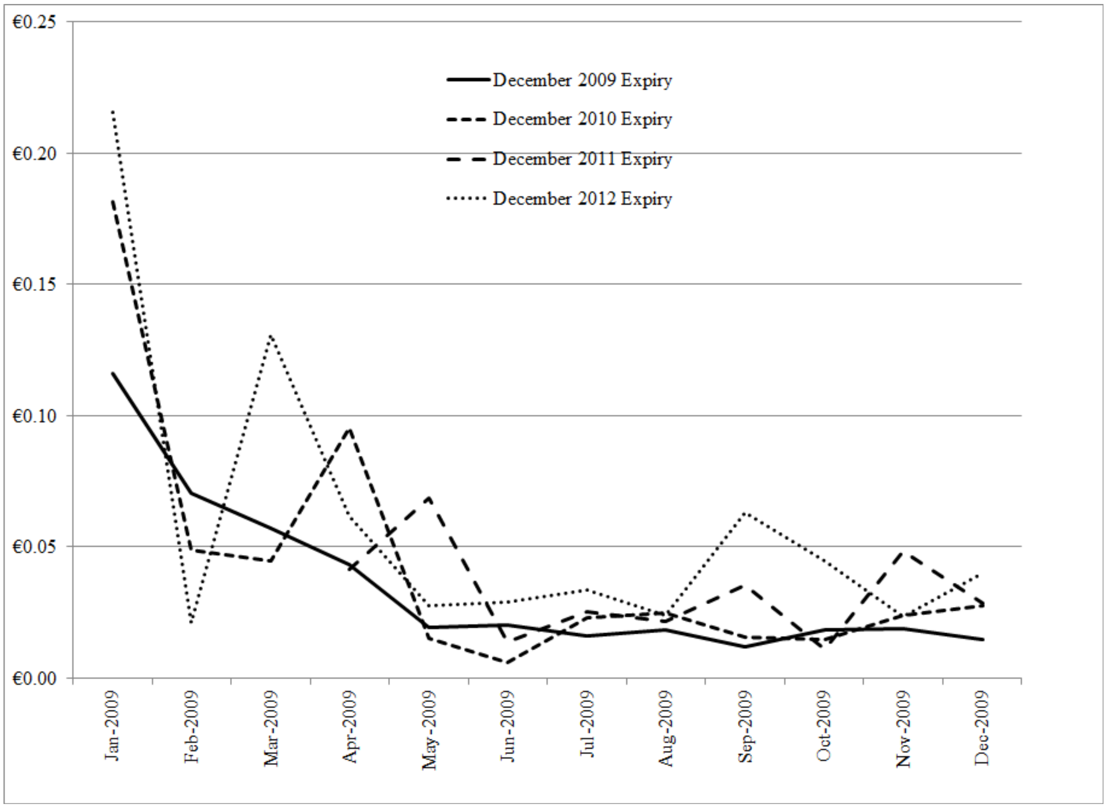
The figure compares bid-ask spread estimates of EUA December 2009 expiry futures from the European Climate Exchange. We report: (1) Thompson-Waller monthly averages and (2) Modified Hasbrouck MCMC estimates, where we report the average and empirical 99% confidence intervals.

Figure 2.4
ECX 2009 CER Futures Monthly Spreads: Thompson-Waller Estimates



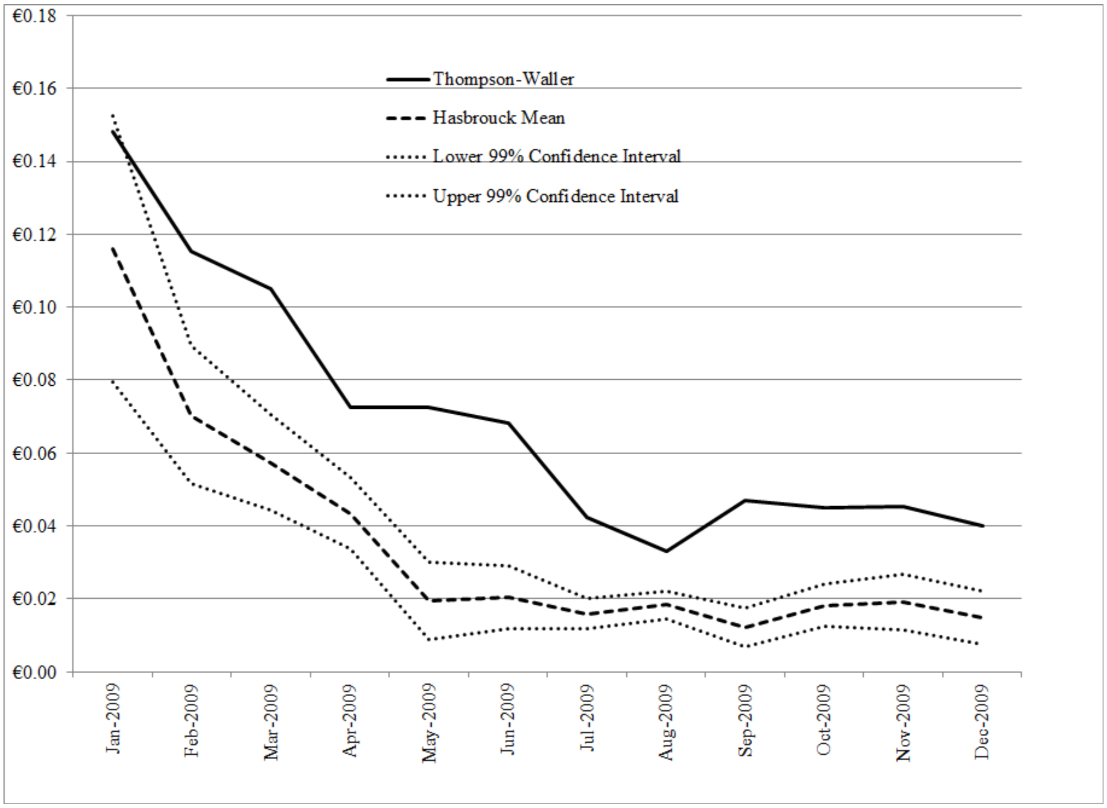
The figure displays monthly average bid-ask spread estimates of CER December expiry futures from the European Climate Exchange. Estimates are computed using the Thompson-Waller estimator, (2.1).

Figure 2.5
ECX 2009 CER Futures Monthly Spreads: Hasbrouck MCMC Estimates



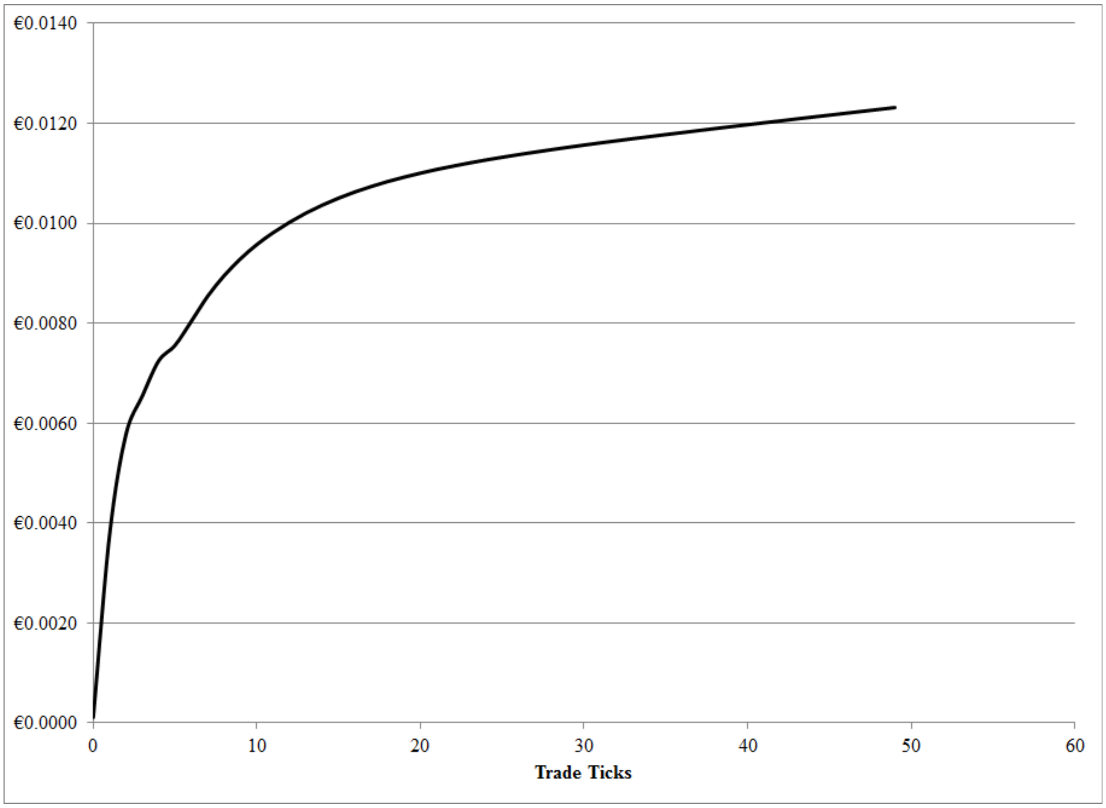
The figure displays bid-ask spread estimates of CER December expiry futures from the European Climate Exchange. Estimates are computed using the Hasbrouck Markov Chain Monte Carlo (MCMC) estimator modified to use the observed trade initiation x.

Figure 2.6
ECX 2009 CER Futures Monthly Spreads: December 2009 Expiry



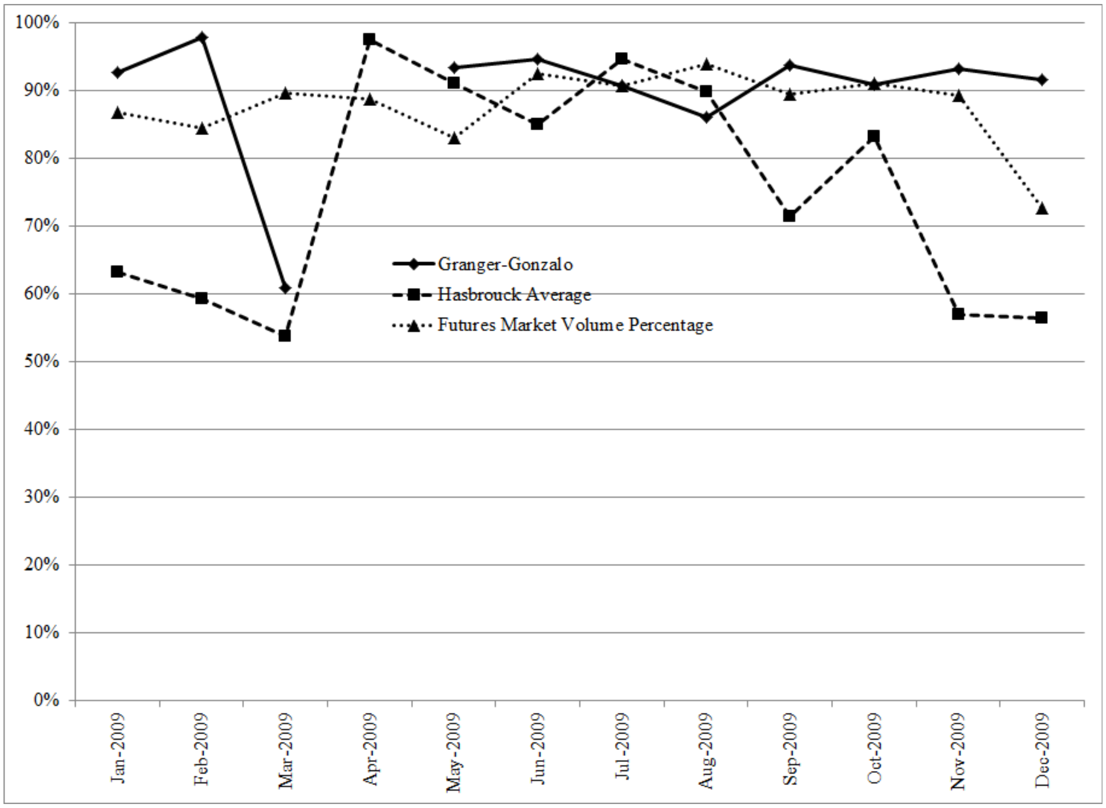
The figure compares bid-ask spread estimates of CER December 2009 expiry futures from the European Climate Exchange. We report: (1) Thompson-Waller monthly averages; and (2) Modified Hasbrouck MCMC estimates, where we report the average and empirical 99% confidence intervals.

Figure 2.7
Dynamic Price Impact in Hasbrouck VAR Model
December 2009 EUA Futures



The figure plots the dynamic impulse response (2.9) of a buy order on the mid-quote return for the December 2009 expiry EUA futures contract. The VAR model (2.6) is estimated on data from May 2009 with quotes derived from Thompson-Waller spread estimates.

Figure 2.8
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 (2.19) is plotted. The Granger-Gonzalo information share is given by (2.20). For comparison, we include the monthly percentage of trading activity occurring in the ECX futures market.

Chapter 3

Measuring the Bid-Ask Spreads: Application to the European Union Allowances Futures Market

3.1 Introduction

The bid-ask spread is one of the important measures of market liquidity. Narrower spreads facilitate trades and lower transaction costs. The main difficulty in estimating spreads in futures market is that the information on quotes are usually not provided. A number of approaches have been taken to estimate spreads.

One of the popular methods to estimate the spread is the Thompson-Waller (TW) estimator. Applications of the measure are found in Thompson and Waller (1988), Thompson, Eales and Seibold (1988), Ma, Peterson, and Sears (1992), and Bryant and Haigh (2004) for example. The TW estimate equates to the average bid-ask spread if the expected true price change and the variance of true price change are both zero. Under the violation of this condition, it consists of two components, the bid-ask spread and the magnitude of true price changes, and it would be biased upward.[6] While the upward bias due to the change in the true price has been pointed out in the literature, the potential downward bias has not been carefully discussed.

This study provides a case that the TW estimator would have downward bias. Such case is that (i) the buy (sell) order tends to follow buy (sell) order, and (ii) the price change associated to such orders are small. Furthermore, the upward bias of the TW estimator would be canceled out by the downward bias, and in such case the estimator would perform better than the other absolute price change methods such as the Wang-Yau-Baptiste (1997) which suppose to modify the TW estimator.

The empirical finding from the application to the European Union Allowances (EUA) futures contract trading implies that its trading pattern and the price change provide the conditions that reduce the bias of the TW estimator. The TW estimates are not remarkably different to the estimates provided by the trade indicator model approach such as Roll (1984)

[6]This upward bias in the TW estimator has been pointed out in the literature, Smith and Whaley (1994) for example.

and Madhavan, Richardson and Roomans (1997).

The statistical significance of the Madhavan-Richardson-Roomans (MRR) parameter estimates implies that the assumptions on the trade indicator variables in the Roll model would be rejected. The MRR model estimation results report that the fraction of the spread attributable to adverse selection costs increases gradually. In the EUA futures market, information component dominates the bid-ask spread. The immediate price impact of a typical trade is almost the half of the tick in January, and falls to less than one third of the tick in December.

The application of EUA futures trading on MRR model estimation provides additional perspectives in the study of the carbon emissions market, which is a relatively new research area in the market microstructure.[7]

The remaining part of this paper is organized as follows. Section 2 describes the spread estimation methods and discuss the possible bias of the estimators. Section 3 discusses the bias of the spread estimators from the empirical findings. Section 4 provides the estimation results and the implications of the Madhavan-Richardson-Roomans model parameters. Finally, section 5 summarizes our findings.

3.2 Spread Estimation Methods

This section presents methodologies for bid-ask spread estimation. These methods considered in the present study can be categorized in two types: the absolute price change measures and the trade indicator model parameter estimation.

3.2.1 Absolute Price Change

I start with describing the three absolute price change measures. All of the methods are variants of average absolute change in the transaction price. The potential bias of the estimators are discussed at the last subsection.

[7] Research on the market microstructure of the European carbon emissions market are done by Benz and Hengelbrock (2008) and Mizrach and Otsubo (2011) for example.

Thompson-Waller

The idea of measuring the bid-ask spread by the average of absolute price change is first applied by Thompson and Waller (1987). The change in transaction price, Δp_t, can be expressed as

$$\Delta p_t = \frac{S}{2} I_t + \Delta m_t \tag{3.1}$$

where S is the spread, Δm_t is the change in the true price, and I_t is the indicator variable, $I_t = 2$ if a buy order follows a sell order, $I_t = -2$ if a sell order follows a buy order, and $I_t = 0$ otherwise. Then the TW spread estimate is given by,

$$S^{TW} = \textstyle\sum_{t^+=1}^{T^+} \left|\Delta p_{t^+}\right|^+ / T^+. \tag{3.2}$$

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

Modified Thompson-Waller

If the trade initiation of the executed transaction, I_t, are observable, the TW estimator can be modified as

$$S^{MTW} = \textstyle\sum_{t'=1}^{T'} \left|\Delta p_{t'}\right| / T' \tag{3.3}$$

where $\Delta p_{i'}$ is the price change that moves from bid to ask (or ask to bid) and $T'$is the number of such changes in the transactions prices.

The estimates S^{TW} and S^{MTW} equate to the average bid-ask spread if the expected true price change and the variance of true price change are both zero. Under the violation of this condition, as we can see from (3.1), they consist of two components, the bid-ask spread and the magnitude of true price changes, and it would be biased upward.

Wang-Yau-Baptiste

Wang, Yau, and Baptiste (1997) attempt to reduce the bias of the TW estimator by discarding any price change that follows another price change of the same sign.[8] The Wang-

[8] This estimator was applied in Bryant and Haigh (2004), Tse and Zabotina (2004) and Chou and Chung (2005) for example.

Yau-Baptiste (WYB) estimator is given as

$$S^{WYB} = \sum_{t''=1}^{T''} |\Delta p_{t''}| / T'' \tag{3.4}$$

where $\Delta p_{t''}$ is the price change that moves in a different direction from the previous change and $T''$is the number of such changes in the transactions prices.

Bias of the Absolute Price Estimators

If the assumptions of the true price changes are violated, S^{TW} and S^{MTW} would have upward bias. While the literature has pointed out this bias due to the true price changes, the possibility of the TW estimator having downward bias has not been carefully discussed.

Suppose that a buyer initiated trade follows a buyer initiated trade. In such case, the absolute price change captured by S^{TW} is not the spread, but it is the change in the best ask price. If the two consecutive trades are executed in a short period, it is likely that the change in the lowest ask price is small. When these changes are smaller than the average spread, S^{TW} would be biased downward.

It is most likely that the unrealistic assumptions of the true price changes are violated and therefore TW estimator suffers from upward bias. However, if a market observes many trades in such a manner discussed above, the upward bias caused by the variance of the true price changes would be canceled out by the downward bias.

To calculate S^{MTW}, change in the price between two consecutive buyer (seller) initiated trades are discarded. Thus, the price changes which potentially offset the upward bias of the estimator are filtered out. The modified TW estimator is, because of the modification, would have greater bias than S^{TW}.

The WYB estimator discards the price changes that followed by another change with same direction. It is likely that a positive (negative) price change is caused by the placement of a buy (sell) order. Hence, the price changes discarded to compute S^{WYB} would be similar to those discarded to calculate S^{MTW}. Thus, although the WYB estimator discards such price changes in order to reduce the bias, it would have greater bias than S^{TW}.

Therefore, although the assumptions which TW estimator is based on are unrealistic and would have bias, it would perform better than the other absolute price change estimators in practice. Applying those methods to the ECX data, further discussions are done with the empirical findings in later section.

3.3.2 Trade Indicator Model

In this section, two models of bid, ask and transaction prices are introduced. Both models describe the trade direction by trade indicator variables.

Roll

Roll (1984) assumes an informationally efficient market, and assumes that the true price m_t follows a random walk process,

$$m_t = m_{t-1} + u_t. \tag{3.5}$$

where the u_t are i.i.d. zero-mean random variables with variance σ_u^2. 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,

$$\begin{aligned} p_t^b &= m_t - c, \\ p_t^a &= m_t + c. \end{aligned} \tag{3.6}$$

The bid-ask spread is $p_t^a - p_t^b = 2c$, and c can be interpreted as the half-spread. Denoting the trade direction by x_t, the transaction price p_t can be represented as,

$$p_t = \begin{cases} p_t^b & \text{if } \ x_t = -1 \\ p_t^a & \text{if } \ x_t = +1 \end{cases} \tag{3.7}$$

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, serially independent. It is also assumed that the trade direction arrival is independent of the efficient price innovation u_t.

The Roll model has two parameters, c and σ_u^2. These are estimated from the variance and first-order autocovariance of the price changes, Δp_t. The variance is

$$\begin{aligned} Var\left(\Delta p_t\right) &= E[(\Delta p_t)^2] \\ &= E\left[x_{t-1}^2 c^2 + x_t^2 c^2 - 2x_{t-1}x_t c^2 - 2x_{t-1}u_t c + 2x_t u_t c + u_t^2\right] \\ &= 2c^2 + \sigma_u^2. \end{aligned} \tag{3.8}$$

The last equality follows because in expectation, all of the cross-products vanish except for those involving x_t^2, x_{t-1}^2, and u_t^2. The first order covariance is

$$\begin{aligned} Cov\left(\Delta p_t, \Delta p_{t-1}\right) &= E[\Delta p_{t-1}\Delta p_t] \\ &= E[c^2\left(x_{t-2}x_{t-1} - x_{t-1}^2 - x_{t-2}x_t + x_{t-1}x_t\right) \\ &\quad +c\left(x_t u_{t-1} - x_{t-1}u_{t-1} + u_t x_{t-1} - u_t x_{t-2}\right)] \\ &= -c^2. \end{aligned} \tag{3.9}$$

It is easily verified that all autocovariances of order 2 or higher are zero. From the above, the spread, S^{Roll}, is estimated as

$$S_t^{Roll} = 2\sqrt{-Cov\left(\Delta p_t, \Delta p_{t-1}\right)} \tag{3.10}$$

and $\sigma_u^2 = Var\left(\Delta p_t\right) + 2Cov\left(\Delta p_t, \Delta p_{t-1}\right).$

Roll OLS

From (3.5) to (3.7), the transaction price process is,

$$\Delta p_t = m_t + cx_t - \left(m_{t-1} + cx_{t-1}\right) = c\Delta x_t + u_t. \tag{3.11}$$

If one can observe the trade initiations, the above model can be estimated by usual ordinary least squares (OLS) regression. Hence the Roll OLS spread estimate is

$$S_t^{ROLS} = 2\widehat{c} \tag{3.12}$$

where $\widehat{c}$ is the OLS estimate of (3.11). Note that the OLS does not require the trade initiation variable to be serially uncorrelated.

Madhavan-Richardson-Roomans

Madhavan, Richardson and Roomans (1997) proposed an alternative trade indicator model which allow us to study the components of the spread.

The true price m_t is interpreted as the posttrade expected value of the asset conditional upon public information, u_t,and the trade initiation variable, x_t. The revision in beliefs is the sum of the change in beliefs due to new public information and order flow innovations, so that

$$m_t = m_{t-1} + \theta\left(x_t - E[x_t|x_{t-1}]\right) + u_t, \tag{3.13}$$

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 so-called 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

$$\begin{aligned} p_t^a &= m_{t-1} + \phi + \theta\left(1 - E[x_t|x_{t-1}]\right) + u_t \qquad (3.14) \\ p_t^b &= m_{t-1} - \phi - \theta\left(1 + E[x_t|x_{t-1}]\right) + u_t \end{aligned}$$

The bid-ask spread is $p_t^a - p_t^b = 2\left(\phi + \theta\right)$. Note that if $\theta = 0$, it is the same as in Roll's setup.

In general, the transaction price p_t is

$$p_t = m_{t-1} + \theta\left(x_t - E[x_t|x_{t-1}]\right) + \phi x_t + u_t. \tag{3.15}$$

Thus, the change in the transaction price is

$$\Delta p_t = \left(\phi + \theta\right) x_t - \phi x_{t-1} + \theta E[x_t|x_{t-1}] + u_t \tag{3.16}$$

Similar to Roll, their model assumes that buys and sells are unconditionally equally likely, so that $E[x_t] = 0$ and $Var[x_t] = 1$. Unlike Roll, however, they allow for serial dependence, 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

$$\gamma = \Pr\left(x_t = +1 | x_{t-1} = +1\right) = \Pr\left(x_t = -1 | x_{t-1} = -1\right). \tag{3.17}$$

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

$$\begin{aligned} E[x_t | x_{t-1} &= +1] = \gamma - (1-\gamma) = \rho \\ E[x_t | x_{t-1} &= -1] = (1-\gamma) - \gamma = -\rho, \end{aligned} \tag{3.18}$$

thus the conditional expectation $E[x_t | x_{t-1}] = \rho x_t$. Given this, (3.15) can be transformed into

$$\Delta p_t = (\phi + \theta)\, x_t - (\phi + \rho\theta)\, x_{t-1} + u_t. \tag{3.19}$$

The parameters of the model can be estimated by the generalized method of moments (GMM). The MRR spread estimate is

$$S_t^{MRR} = 2\left(\widetilde{\phi} + \widetilde{\theta}\right) \tag{3.20}$$

where $\widetilde{\phi}$ and $\widetilde{\theta}$ are GMM estimates of (3.18). If θ is not statistically significantly different from zero, the spread consists only by the direct liquidity costs. And if ρ is statistically significantly different from zero, that is an indication of serial correlation of the trade initiation, and the Roll estimate, S_t^{Roll}, is probably biased.[9]

[9] Hasbrouck (2007) shows that if $0 < \rho < 1$, the Roll spread estimate is biased downward and if $0 < corr(x_t, u_t) < 1$, it is biased upward.

3.3 Empirical Application: The European Union Allowances Futures Market

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. EUA is traded on the European Climate Exchange (ECX). 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.

The intra-day prices used here are transaction prices from the ECX for the December 2009 futures contract of EUA. The data contains a record of each trade price, trade direction (whether the trade falls on the best bid or ask) and volume. The sample begins on January 2, 2009 and ends on December 14, 2009 (244 trading days). All of the observations are used to compute the estimates.

Firstly, the bid-ask spreads of the market are estimated by the absolute price change methods. The empirical findings imply that the EUA futures market would provide the conditions which reduces the bias of the TW estimator.

Secondly, the GMM estimation for the MRR model parameters are conducted and the components of the spread are examined.

3.3.1. Spread Estimation

Figure 3.1 plots the TW, the modified TW and the WYB spread estimates. All the spread estimates tend to narrow gradually through time. The TW, WYB and modified TW spread decrease $42\%, 47\%$ and 50% between January and December, respectively.

The yearly average spreads computed by three methods are €0.0221, €0.0258 and €0.0287. The spread estimate of the first six months varies greatly by method. In particular, the modified TW spreads are €0.0075 to €0.0110 wider than the TW spreads.

The WYB and modified TW spreads are consistently wider than the TW spread. This result is expected from our discussion in section 3.2. The TW estimates seem to be less upward biased. The continuous execution of orders in the same side, which is discarded to calculate S^{MTW} and S^{WYB} would reduce the bias of S^{MTW}.

Table 3.1 reports the number of such orders. On average, 65% of the observations used in the TW estimation are the orders continuously traded in the same side. If the price change of such continuous orders are significantly smaller than the price change of the other cases, TW estimates are considered to have downward bias, which would offset the upward bias due to the change in the true price.

Figure 3.2 compares the monthly average of the absolute price change of the orders discarded to calculate S^{MTW}, and S^{MTW} themselves. The size of price changes from buyer (seller) initiated to buyer (seller) initiated are remarkably smaller than the other case. As we have seen above, notable size of the observations used in the TW estimation are such small price changes. The wider spread of WYB and the modified TW spreads would be explained by the elimination of those small price changes. Thus, the gap between the modified TW and the TW spreads would be considered as the magnitude of the downward bias of TW estimates.

Although the modified TW spreads would not suffer from the downward bias, it would suffer from the upward bias due to the change in the true price. Prior to get into that discussion, we examine the results of the Roll spread estimates.

Figure 3.3 plots the Roll covariance estimates and the Roll OLS estimates. The Roll covariance estimates and the Roll OLS estimates for the first four months are remarkably different. The Roll model assumes that the trade initiations are serially uncorrelated and are also uncorrelated with changes in the efficient price. We already confirmed that the first assumption is not appropriate with our data, from the observation that the 65% of the order is followed by the same side of the order. Those two assumptions are tested later on with the MRR model estimation.

The Roll OLS estimation does not require the serial uncorrelation of the trade directions. Hence, we expect that the Roll OLS estimate would be a better estimate than the Roll covariance estimates. Furthermore, by analyzing the Roll OLS residuals, $\widehat{u}_t$, we examine the factor of upward bias in the absolute price change methods.

Figure 3.4 reports the modified TW spread, the Roll OLS and the standard deviation of its residuals. The standard deviation of the Roll OLS residuals, $\sqrt{Var(\widehat{u}_t)}$ is considered as an ad-hoc estimates of the size of the change in the true price. The figure indicates that the larger the variances of the changes in the true price, the greater the gap between the estimates. That would be an empirical evidence of the upward bias in the modified TW caused by the magnitude of the true price change.

All the three estimates, S^{TW}, S^{MTW} and S^{WYB} would be upward biased due to the true price change. Our discussion in section 3.2 provide a possible case that the upward bias of S^{TW} would be canceled out, while the bias of S^{MTW} and S^{WYB} would not. The findings in the pattern of the order arrivals, the change in transaction price, and the change in the true price suggest that the ECX is such a case. Thus, although the assumptions for the TW estimator are obviously violated, since buy (sell) order tends to follow buy (sell) order and the corresponding price change are relatively small in the ECX, the TW estimator would provide better estimate than the other two absolute price change estimators for this particular market.

3.3.2 Spread Components and Price Impact

Figure 3.5 plots the TW, Roll OLS and the MRR estimates. As the TW and Roll OLS estimates, the MRR estimates express the narrowing trend of the spread in the ECX. The yearly average spread of the EUA futures December 2009 contract is €0.0208. This confirms the conclusion of Mizrach and Otsubo (2011) that the annual average spread of the near-December EUA contract in year 2009 is two-thirds of that in 2007 estimated by Benz and Hengelbrock (2008). Benz and Hengelbrock used the MRR estimates.

While its spread estimates are not remarkably different to the other methods, the MRR model allows us to examine further aspects of the market. Table 3.2 reports the MRR parameter estimates. The results enable us to examine the two assumptions made in the Roll model. First, the consistent statistical significance of θ estimates implies that, from (3.13), the trade initiation variable, x_t is a factor of the change in the true price, Δm_t. Hence, this would reject the assumption that the trade initiation and the change in the true price are not correlated. Second, the autocorrelation of the trade initiation variables, ρ, is strongly significant. The annual average of 0.6027 of the auto correlation implies that the probability of a buy (sell) order follows a buy (sell) order is $\gamma = 0.8014$. Thus, obviously the non serial correlation assumption of the trade directions is rejected.

Mizrach and Otsubo (2011) applied the Hasbrouck's Bayesian method (2004) assuming the Roll model. The unreasonable estimates found in their study would be due to the high serial correlation of the trade directions.[10]

The parameters θ and ϕ can be interpreted as the degree of asymmetric information and the direct cost of supplying liquidity, respectively. Figure 3.6 shows the spread components. The costs of liquidity supply tend to decrease from January to December. Its size is not statistically significant during the second half of the year. The adverse selection costs also tend to fall over the year. However, the fraction of the spread attributable to asymmetric information increases gradually, from 73% to 83%. In the ECX, information component dominates the bid-ask spread. This finding would fit with the fact that the transactions observed in this study are all traded electronically.

Lastly, the MRR model provides us an estimate of the immediate price impact of a typical trade. The price impact is almost the half of the tick in January, and falls to less than one third of the tick in December. This finding is consistent with Mizrach and Otsubo (2011). The last three columns of Table 3.2 provides benchmarks for the volume of a typical trade. Although the mean volume are 4 to 10 contracts, the order usually arrives with one contract as the mode volume suggests.

3.4 Concluding Remarks

This study provides a case that the TW estimator would have downward bias. Such case is that (i) the buy (sell) order tends to follow buy (sell) order and (ii) the price change associated to such orders are small. While the upward bias due to the change in the true price has been pointed out in the literature, the downward bias has not been carefully discussed. Furthermore, the upward bias of the TW estimator would be canceled out by the downward bias, and in such case the estimator would perform better than the other absolute price change methods.

The empirical finding from the application to the EUA futures contract trading implies that its trading pattern and the price change provide the conditions that reduce the bias of the TW estimator. The TW estimates are not remarkably different to the estimates

[10] We generate the trade direction under the assumption of non serial correlation. The results would be improved by generating the trade initiation variables assuming a two state Markov process.

provided by the trade indicator model approach, Roll OLS and MRR.

The statistical significance of the MRR parameter estimates implies that the assumptions on the trade indicator variables in the Roll model would be rejected. The MRR model estimation results report that the fraction of the spread attributable to adverse selection costs increases gradually. In the ECX, information component dominates the bid-ask spread. The immediate price impact of a typical trade is almost the half of the tick in January, and falls to less than one third of the tick in December.

The application of EUA futures trading on MRR model estimation provides supplements of the recent study in the market microstructure of the carbon emissions market.

3.5 Tables of Chapter 3

Table 3.1
Number of Observations used in the Spread Estimation:
Thompson-Waller, Modified Thompson-Waller, and Wang-Yau-Baptiste Estimates

Month	T^+	T'	T''	$T^+ - T'$
January	7073	2614	2784	4459
February	8746	3270	3227	5476
March	10483	3752	3864	6731
April	14988	5055	5825	9933
May	11658	3672	4347	7986
June	13306	4480	5106	8826
July	10186	3374	3507	6812
August	8051	2685	2937	5366
September	6493	2213	2061	4280
October	6163	2083	1877	4080
November	5004	1831	1333	3173
December	1516	618	408	898

T^+, T' and T'' are the number of observations used in estimating the the Thompson-Waller estimator, (3.2), the modified Thompson-Waller estimator, (3.3), and the Wang-Yau-Baptiste estimator, (3.4), respectively. $T^+ - T'$ is the number of continuous arrivals of orders in the same side.

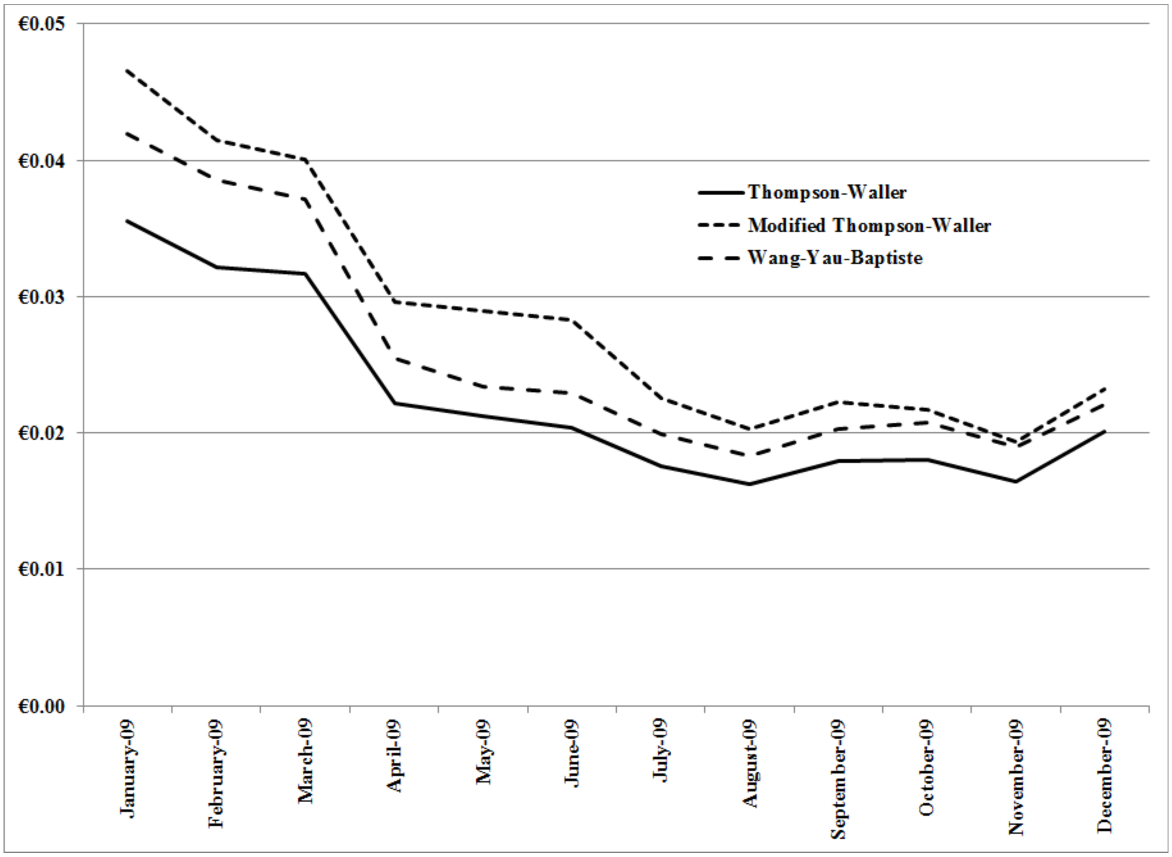
Table 3.2
ECX 2009 EUA Futures Monthly Spreads:
The Madhavan-Richardson-Roomans Model Estimation

	Parameter Estimates			Spread	Price Impact	Volume of a Typical Trade		
Month	θ	ϕ	ρ	S^{MRR}	$\theta(1-\rho)$	Mean	Median	Mode
January	0.0113	0.0068	0.5985	0.0362	0.0046	4.28	1.33	1.00
	(5.3245)	(2.7663)	(15.6134)					
February	0.0098	0.0054	0.6202	0.0304	0.0037	4.67	1.95	1.00
	(5.6303)	(2.7187)	(19.6160)					
March	0.0108	0.0041	0.5881	0.0298	0.0045	5.42	2.32	1.00
	(6.2744)	(2.0337)	(18.7422)					
April	0.0083	0.0032	0.5967	0.0231	0.0034	3.85	1.00	1.00
	(8.0332)	(2.7600)	(23.0085)					
May	0.0089	0.0024	0.6205	0.0227	0.0034	4.14	1.00	1.00
	(7.5504)	(1.7841)	(22.1724)					
June	0.0071	0.0034	0.6114	0.0211	0.0028	3.93	1.00	1.00
	(7.4906)	(2.9868)	(21.4333)					
July	0.0063	0.0015	0.6091	0.0156	0.0024	4.29	1.04	1.00
	(7.2377)	(1.5539)	(20.7204)					
August	0.0059	0.0012	0.6025	0.0144	0.0024	4.14	1.00	1.00
	(6.6080)	(1.3306)	(18.5398)					
September	0.0057	0.0013	0.6138	0.0140	0.0022	5.75	2.76	1.00
	(5.5347)	(0.9177)	(17.6084)					
October	0.0062	0.0011	0.5987	0.0146	0.0025	6.46	3.23	1.18
	(5.4784)	(0.7868)	(16.5301)					
November	0.0048	0.0014	0.6217	0.0125	0.0018	6.45	3.05	1.00
	(5.0195)	(1.3847)	(17.7620)					
December	0.0065	0.0013	0.5510	0.0155	0.0029	10.02	5.80	5.40
	(4.5817)	(0.9949)	(11.6166)					

GMM estimates of the parameters θ, ϕ and ρ of the Madhavan-Richardson-Roomans model, 3.19, are reported. The t-statistics are in parentheses. The spread is $S^{MRR} = 2(\phi + \theta)$, and the price impact of a typical buyer initiated trade is obtained by $\theta(1-\rho)$. The last three columns are benchmarks for the number of contracts in a typical trade: monthly mean, median and the mode of number of contracts per trade.

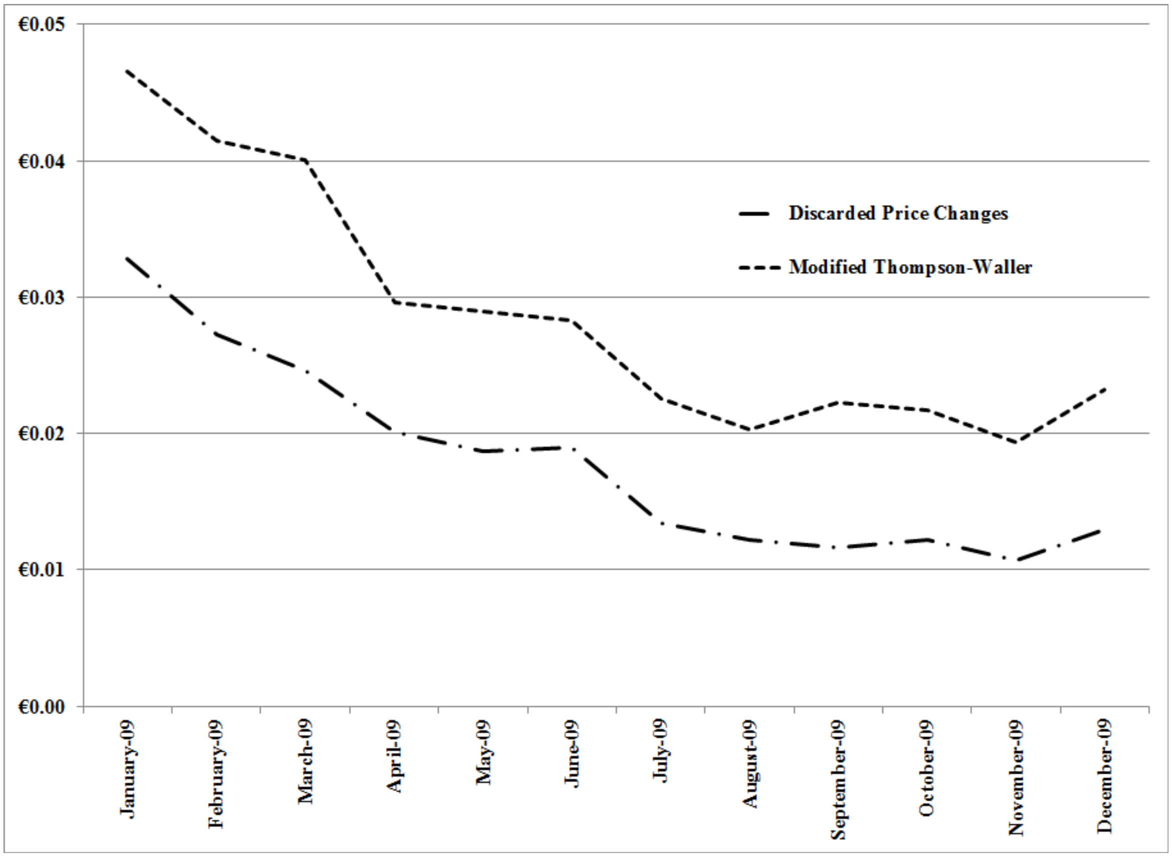
3.6 Figures of Chapter 3

Figure 3.1
ECX 2009 EUA Futures Monthly Spreads:
Thompson-Waller, Modified Thompson-Waller, and Wang-Yau-Baptiste Estimates



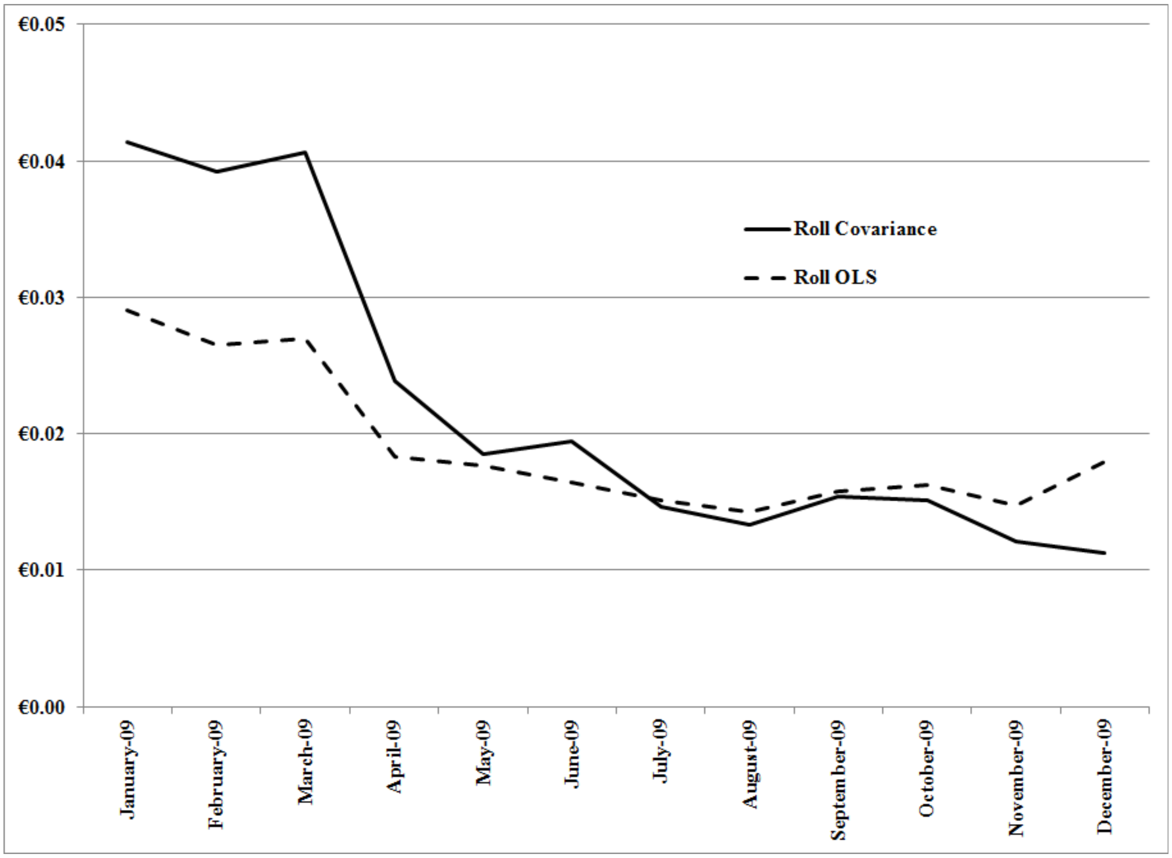
The figure displays monthly average bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Thompson-Waller estimator, (3.2), the modified TW estimator, (3.3) and the Wang-Yau-Baptiste estimator (3.4).

Figure 3.2
The Monthly Average of the Discarded Absolute Price Change and the Modified Thompson-Waller Estimates



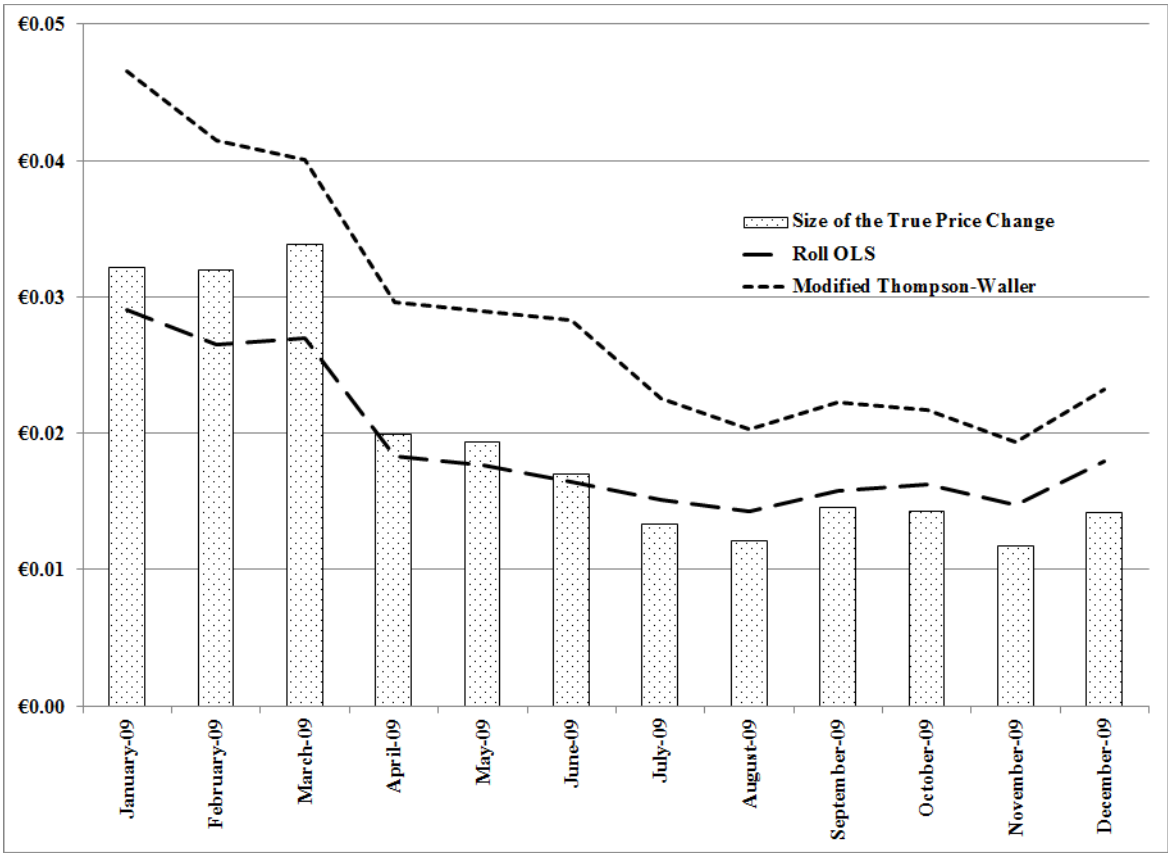
The figure displays the monthly average of the discarded absolute price changes to compute the modified Thompson-Waller estimates, and the modified Thompson-Waller estimates, (3.3).

Figure 3.3
ECX 2009 EUA Futures Monthly Spreads:
The Roll Covariance and the Roll OLS Estimates



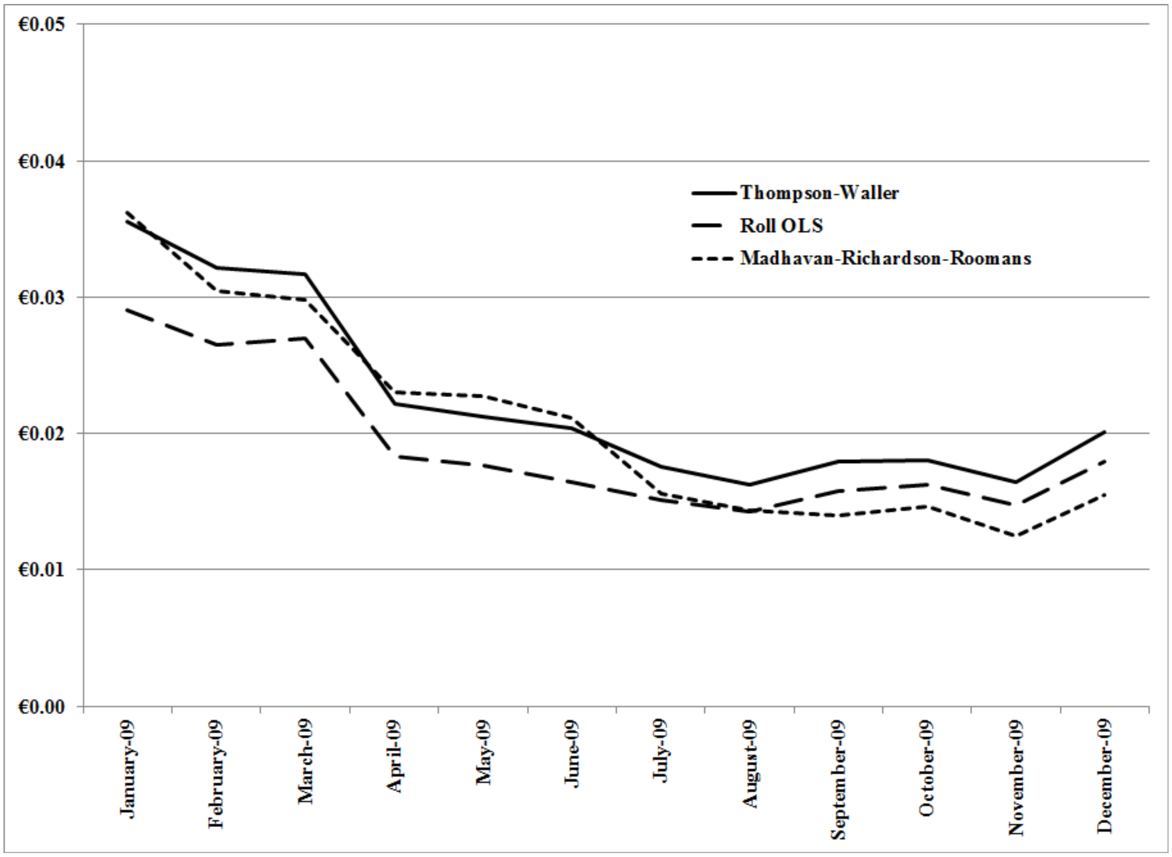
The figure displays monthly average bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the Roll covariance estimator, (3.10), and the Roll OLS estimator, (3.12).

Figure 3.4
ECX 2009 EUA Futures Monthly Spreads:
The Modified Thompson Waller and the Roll OLS Estimates



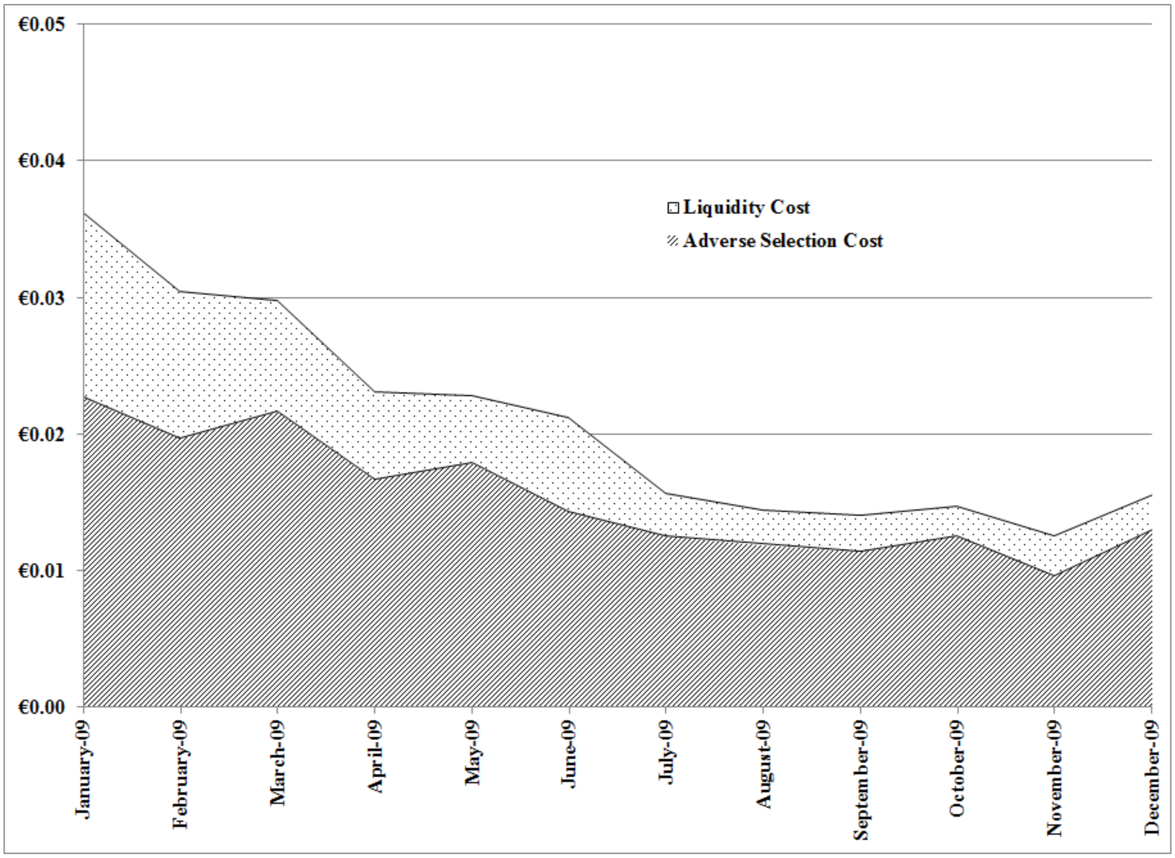
The figure displays monthly average bid-ask spread estimates of EUA December expiry futures from the European Climate Exchange. Estimates are computed using the modified Thompson-Waller estimator, (3.3), and the Roll OLS estimator, (3.12). The monthly average size of the true price change are the standard deviation of the Roll OLS residuals.

Figure 3.5
ECX 2009 EUA Futures Monthly Spreads:
The Thompson-Waller, the Roll OLS and
the Madhavan-Richardson-Roomans 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, (3.2), the Roll OLS estimator, (3.12), and the Madhavan-Richardson-Roomans estimator, (3.20).

Figure 3.6
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, (3.19).

Chapter 4

Price Discovery of Tokyo-New York Cross-Listed Stocks

4.1 Introduction

Recently, securities have been traded not only in their domestic market but also in abroad. Stocks of Toyota Motor Corp. are traded every day in Tokyo Stock Exchange (TSE). However, after the market in Japan is closed, people in U.S. then start trading Toyota stocks in New York Stock Exchange (NYSE). The share in NYSE is not such as "Toyota Motor U.S.," they are exactly the same share of "Toyota" operated in Japan.

Companies which listed their share in US is not only Toyota. There are 29 companies, 18 in NYSE and 10 in Nasdaq, traded as American Deposit Receipts (ADR). The first Japanese cross-listed firm was Sony Corp, in December, 1970. Since then, Japanese companies have been listing their share in US markets. Their motivation to cross-list in New York are based on the idea that doing so might be a good signal to their customers and investors,and ensures or increases their brand.

This study, however, the purpose is not to investigate their motivation of cross-listing. My interest here is in the price discovery process of those cross-listed securities. How efficient is the foreign market in finding cross-listed security's efficient price? What is the degree of contributions to price discovery? International fragmentation (trading identical assets in multiple place) as ADRs may raise concerns about the efficacy of price discovery. As represented by Toyota, Sony, or Mitsubishi UFJ Financial Group, Japanese ADRs are of principal enterprises' stocks. Thus, the process of price discovery of those assets is of concern to many market traders.

Consequently, it is important to determine where the price information and price discovery are being produced. Price discovery is one of the most important function of the market. It incorporates new information on fundamental value into market prices through transactions. These transactions, however, include noise such as transitory liquidity needs and errors in analysis/interpretation on information. Even without these stochastic noises, market participants may strategically over- or under-react to the change in fundamental value. Furthermore, trading mechanism of the market may cause the deviation of transaction prices from intrinsic value of the security. An efficient market is able to reflect the information, affected by noises, onto price quickly.

The method suggested by Yan and Zivot (2006) can measure the dynamic aspect of the price discovery. They proposed a measure based on impulse response function. With their structural approach, information innovation and microstructural noise are distinguished explicitly. In this study, partial price adjustment model suggested by Amihud and Mendelson (1987) is used for the structural model. To estimate the model, Kalman filter is utilized. It enables us to estimate not only the parameters but also the efficient prices, information shocks and noises.

The benefit of this approach is that it provides us a way to study price discovery of two markets which do not open simultaneously, in the case as TSE and NYSE. The two widely used methods for measuring contributions to price discovery, Information share (IS) and Gonzalo-Granger portfolio weights (GG), require two markets to be open simultaneously. The estimated efficient prices produced by Kalman filter can be used to generate the price series assuming that two markets' opening hours are overlapped.

Literatures of price discovery across markets are initiated by studies on U.S. stocks cross-listed in central and regional markets. Articles in that line of studies include Hasbrouck (1995), Harris, McInish, Shoesmith and Wood (1995), Harris, McInish and Wood (2002) for example. Studies of price discovery across international markets have been increasingly shown its presence. Werner and Kleidon (1996) analyze intraday patterns for U.K. and U.S. trading of British cross-listed stocks. They focuses on studying price volatility, volume and liquidity during overlapping period of New York and London market. Menkveld (2008) extend the model of Chowdhry and Nanda (1991) to analyze British and Dutch ADRs. That article employs Hasbrouck IS, and also focuses on overlapping period. Eun and Sebherwal (2003) examine the price discovery of Canadian stocks listed on both the Toronto Stock Exchange and a U.S. exchange. Their approach is reduced model approach, and it is based on the error correction coefficient. Although those studies investigate international cross-listed stocks, their analysis is done for overlapping period and none of them utilize structural approach. Unlike them, this article examine the price discovery during non-overlapping period applying partial price adjustment model.

There are few studies employing structural approach with partial price adjustment model. One is Chelley-Steeley (2003), that paper studies stocks listed on both the Paris Bourse and SEAQ-International in London. It also examine the dynamic aspect of price discovery process, but does not use Yan and Zivot measure. Besides, Paris and London are overlapped. The study applying the most similar approach to the present research is done by Menkveld, Koopman and Lucas (2007). Based on partial price adjustment model, they investigate around-the-clock price discovery for Amsterdam-New York cross-listed stocks. Their study includes non-overlapping period, and Kalman filter is used to deal with missing values. However, that article does not examine the dynamics of price discovery, but devotes spaces to investigate the change in efficient price variation.

The methods proposed in this work would give ideas for future research in price discovery of U.S. vs. Asian emerging markets whose operation hours are not overlapped. By modifying the partial price adjustment model to allow different variance on information shock for each market's opening hours, we find that the magnitude of the shocks are larger during Tokyo opening hours. PDIRF shows that NYSE is more efficient in price discovery, but values of IS and GG vary significantly across stocks.

The rest of this paper is organized as follows. Section 2 introduce the model and methods to measure price discovery. Estimation methods are introduced in section 3. Section 4 describes the applied data and section 5 presents the estimation results. Section 6 concludes.

4.2 Partial Price Adjustment Model

In this section I introduce a simple partial price adjustment model used by Amihud and Mendelson (1987) which this study is based on. Suppose that there exists a financial asset traded at two markets. Let m_t denote the log efficient price of that asset and $p_{i,t}$ denote its log observed price at market i,

$$\Delta p_{1,t} = \delta_1(m_t - p_{1,t-1}) + w_{1,t}, \qquad 0 \leq \delta_1 \leq 2 \tag{4.1}$$

$$\Delta p_{2,t} = \delta_2(m_t - p_{2,t-1}) + w_{2,t}, \qquad 0 \leq \delta_2 \leq 2$$

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

where

$$E(v_t v_\tau) = \begin{cases} 0 & t \neq \tau \\ \sigma_v^2 & otherwise \end{cases}$$

$$E(v_t) = 0$$

$$E(w_{i,t} w_{i,\tau}) = \begin{cases} 0 & t \neq \tau \\ \sigma_{wi}^2 & otherwise \end{cases}$$

$$E(w_{i,t}) = 0$$

v_t is the innovation to the efficient price, the information shock. $w_{i,t}$ is the noise innovation, the microstructural shock. This stochastic noise pushes the transaction price of the stock away from its fundamental value. Microstructural noises include errors in analysis or interpretation of information, transitory liquidity needs of traders and asymmetric information. δ is the price adjustment coefficient. It captures the tendency of the reaction of market participants. If $\delta < 1$, transaction prices adjust partially to information, whereas $\delta > 1$ implies overreaction to news. Hence even there is no stochastic noise, by this under- or over-reaction of traders prevent market prices from immediate adjustment on the new information. Strategic trading by informed investors who split their order across time may cause market under-reaction, and liquidity suppliers who are compensated for their services may cause market over-reaction. If price adjust to the fundamental immediately, $\delta = 1$, the adjustment is a full price adjustment.

4.2.1 Hasbrouck Information Shares

Hasbrouck (1995) proposes a measure for one market's contribution to price discovery based on the full price adjustment case of the model introduced above.

Since the prices $p_{1,t}$ and $p_{2,t}$ are for the same underlying asset, 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:

$$\mathbf{\Delta p}_t = \mathbf{\Psi}(\mathbf{L})\mathbf{e}_t \tag{4.2}$$

where $\mathbf{e}_t$ is a zero-mean vector of serially uncorrelated disturbances with covariance matrix $\mathbf{\Omega}$, and $\mathbf{\Psi}$ is the polynomial in the lag operator. And, applying Beveridge-Nelson decomposition to (4.2) yields the levels relationship:

$$\mathbf{p}_t = \mathbf{\Psi}(\mathbf{1})\sum_{j=1}^{t}\mathbf{e}_j + \mathbf{\Psi}^*(\mathbf{L})\mathbf{e}_t. \tag{4.3}$$

The matrix $\mathbf{\Psi}(\mathbf{1})$ contains the cumulative impacts of the innovation $\mathbf{e}_t$ on all future price movements and $\mathbf{\Psi}^*(\mathbf{L})$ is a matrix polynomial in the lag operator. Then, the random walk assumption for the efficient price made at (4.1) and the common stochastic trend representation suggested by Stock and Watson (1988) enable (4.3) to be expressed as:

$$\mathbf{p}_t = \boldsymbol{\iota} m_t + \mathbf{\Psi}^*(\mathbf{L})\mathbf{e}_t \tag{4.4}$$

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

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, $\boldsymbol{\beta}'\mathbf{\Psi}(\mathbf{1}) = 0$. And this implies that the rows of $\mathbf{\Psi}(\mathbf{1})$ is identical. Hence denoting $\boldsymbol{\psi} = (\psi_1, \psi_2)'$ as the common row vector of $\mathbf{\Psi}(\mathbf{1})$, 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 $\boldsymbol{\psi}'\mathbf{\Omega}\boldsymbol{\psi}$, and if $\mathbf{\Omega}$ is diagonal, i.e. e_t are mutually uncorrelated, then market i's information share is defined as:

$$IS_i = \frac{\psi_i^2 \sigma_{ei}^2}{\boldsymbol{\psi}'\mathbf{\Omega}\boldsymbol{\psi}} = \frac{\psi_i^2 \sigma_{ei}^2}{\psi_1^2 \sigma_{e1}^2 + \psi_2^2 \sigma_{e2}^2}, i = 1, 2 \tag{4.5}$$

where ψ_i is the ith element of $\boldsymbol{\psi}$, and σ_{ei}^2 is the ith diagonal element in $\mathbf{\Omega}$. 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 $\mathbf{\Omega}$ 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 $\mathbf{\Omega}$ and measure the information share using the orthogonalized innovations. Let $\mathbf{C}$ be a lower triangular matrix such that $\mathbf{C}'\mathbf{C} = \mathbf{\Omega}$. Then the information share for the ith market is

$$IS_i = \frac{([\boldsymbol{\psi}'\mathbf{C}]_i)^2}{\boldsymbol{\psi}'\mathbf{\Omega}\boldsymbol{\psi}} \tag{4.6}$$

where $[\boldsymbol{\psi}'\mathbf{C}]_i$ is the ith element of the row matrix $\boldsymbol{\psi}'\mathbf{C}$. 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 Cholesky factorization with the ith price ordered first (last).

4.2.2 Gonzalo-Granger Portfolio Wights

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

$$\mathbf{p}_t = \mathbf{A}_1\mathbf{g}_t + \mathbf{A}_2\mathbf{h}_t \tag{4.7}$$

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, (4.7) implies the perfect adjustment case of (4.1) and 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 suggest an alternative measure of price discovery,

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

4.2.3 Price Discovery Impulse Response Function

Unlike those two methods above, the third one is based on general case of partial price adjustment model. Model (4.1) show explicitly that the market has two types of shocks, noise and information. The method suggested by Yan and Zivot (2006) to measure the efficiency of price discovery is based on the idea of impulse response on the latter shock, and they name it "Price discovery impulse response function (PDIRF)." To derive PDIRF, represent the transaction price process as follows[11]:

$$p_{i,t} = \sum_{j=1}^{t} \left\{ (1-\delta_i)^{t-j} \delta_i \sum_{l=1}^{j} v_l \right\} + \sum_{j}^{t} (1-\delta)^{t-j} w_{i,j}, \qquad i = 1,2 \tag{4.8}$$

and then PDIRF is given by

$$f_{i,k} = \frac{\partial p_{i,t}}{\partial v_{t-k}} = \sum_{l=0}^{k} \delta_i (1-\delta_i)^l \qquad i = 1,2, k = 0,1,\cdots . \tag{4.9}$$

Since it is the innovation of intrinsic value of the security, information shock has to be a permanent effect, i.e. the impulse response f_k converges to one:

$$\lim_{k\to\infty} \sum_{l=0}^{k} f_{i,l} = 1 \qquad i = 1,2 \tag{4.10}$$

To suffice this condition we have to restrict δ_i in the range of [0,2]. Hence, a fast convergence of PDIRF means a fast full-incorporation of information shock into the transaction price. PDIRF is function of only one variable, δ_i. And the equation above implies that the closer the δ_i to one, the faster the PDIRF converges to one. Then, we can measure the efficiency of price discovery by how close δ_i is to one. In order to compare price discovery efficiency between two markets, quadratic loss $(1-\delta_i)^2$ can be used:

$$LR_1 = (1-\delta_1)^2/(1-\delta_2)^2. \tag{4.11}$$

[11] See appendix for derivation.

If the loss ratio LR_1 is smaller than one, market 1 is more efficient in incorporating price information into the transaction price.

4.3 Estimation Methods

Recognizing that the partial price adjustment model has state space representation, Kalman filter can be employed to estimate the parameters. Kalman filter also gives estimates for unobserved efficient prices, information shocks, microstructural noises. It naturally deal with missing market prices for closed market, which is the major advantage for the present work. In order to estimate IS and GG, transacted prices for both markets are required. Hence, the estimation strategy will be following. First, using Kalman filter to the state space model, PDIRF and missing values are estimated. As we have shown, PDIRF is a function of only one parameter, δ_i, the partial price adjustment coefficient. Next, using the price series including the estimated missing values, IS and GG are obtained by estimating vector error correction (VEC) model.

4.3.1 Estimating Partial Price Adjustment Coefficient

The partial price model has state space representation. The unobserved efficient prices m_t are states and the observed transacted prices $p_{i,t}$ are observations. By assuming all v_t and $w_{i,t}$ are normally distributed with mean zero, mutually and serially uncorrelated, Kalman filter and its associated algorithm obtains the efficient price series $\{m_t\}_{t=0}^T$, information shocks $\{v_t\}_{t=0}^T$, microstructural noises $\{w_{i,t}\}_{t=0}^T$ and missing values. Parameters δ_i, σ_v and $\sigma_{w,i}$ for $i = 1, 2$ are estimated by numerically maximizing the log-likelihood evaluated by the Kalman filter. Then, PDIRF $f_i = \sum_{l=0}^k \delta_i(1-\delta_i)^l$ and $LR_1 = (1-\delta_1)^2/(1-\delta_2)^2$ can be calculated with estimated δ_i.

In the model, the magnitude of information shock σ_v is assumed to be common in both market's business hours. However, it is natural to consider that information occurred in home market opening period has larger magnitude of change in efficient price.[12] To relax the constraint on the magnitude of information shock, we involve η in the state model to

[12] Menkveld, Koopman and Lucas (2007) found larger efficient price volatility in home market (Amsteldam) opening hours than in foreign market (New York) opening hours.

allow each market's opening period to have different variance of the information shock:

$$m_t = m_{t-1} + \eta v_t \tag{4.12}$$

where $\eta = 1$ when foreign market (New York) is open, and $\eta \neq 1$ when home market (Tokyo) is open. Hence, if $\eta > 1$, information occurred in home market has larger magnitude of change in efficient price and if $\eta < 1$, smaller magnitude.

4.3.2 Estimating IS and GG

In order to obtain IS and GG, the first step is to estimate the following VEC model:

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha}\boldsymbol{\beta}' \mathbf{p}_{t-1} + \sum_{j=1}^{k} \mathbf{B}_j \Delta \mathbf{p}_{t-j} + \mathbf{e}_t \tag{4.13}$$

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. Using the estimated missing values of closed market prices, VEC model (4.13) can be estimated. Baillie, Booth, Tse and Zabotina (2002) shows that IS and GG can be obtained by utilizing estimated parameters as:

for Ω diagonal,

$$IS_i = \frac{\alpha_{i\perp}^2 \sigma_{ei}^2}{\alpha_{1\perp}^2 \sigma_{e1}^2 + \alpha_{2\perp}^2 \sigma_{e2}^2}, \qquad i = 1, 2 \tag{4.14}$$

where $\alpha_{i\perp}^2$ is the ith element of $\alpha_\perp$, for Ω not diagonal

$$IS_i = \frac{\left([\boldsymbol{\alpha}'_\perp \boldsymbol{C}]_i\right)^2}{\boldsymbol{\alpha}'_\perp \boldsymbol{\Omega} \boldsymbol{\alpha}_\perp} \tag{4.15}$$

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

$$GG_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, GG_2 = \frac{-\alpha_1}{\alpha_2 - \alpha_1}. \tag{4.16}$$

4.4 Data

The cross-listed Japanese shares studied in this paper are ADRs. Each ADRs is issued by a U.S. depository bank, the biggest depository bank is Bank of New York Mellon. ADRs are traded in U.S. dollars, pay dividends in US dollars, hence they can be traded like U.S. domestic shares.[13]

This study uses 5 minutes trading prices of 18 Japanese stocks listed both in Tokyo and in New York.[14] Our sample covers from September 17, 2007 to April 7, 2008.[15] Table 4.1 shows the all Japanese ADRs traded in NYSE. While New York uses the symbol, Tokyo uses "meigara-kohdo," which means "trading code" to recognize them. During the observation period Tokyo market had 130 business days and New York had 139 business days. TSE operation hours are 4.5hours, it opens at 19:00 Eastern Standard Time(EST) and closes at 1:00 EST (they have break from 21:00 EST to 22:30 EST) while NYSE operation hours are 6.5hours, opens at 9:30 EST and closes at 16:00 EST.[16] Thus, there is no overlapping period in these two markets. Both markets are continuous, consolidated auction markets and report trade and quote information in real time. The major difference between these two is that NYSE is a hybrid market and TSE is a pure electronic market.

Table 4.2 shows the average daily trading value of each markets and its proportion allocated to Tokyo. Average TSE share is 95.588% and even the smallest share that of SNE is 88.601%. Those numbers show that most of the trades are placed in Tokyo. Table 2 also reports the trade price volatility and its ratio. Trade price volatility is calculated as variance of change in log transacted (observed) price. For most of the stocks, larger fluctuations of change in price are observed in Tokyo. It is noteworthy that trade price volatility of CAJ and NIS in NYSE is larger than that in TSE even the trading value share of them are larger in TSE. Changes in observed prices contain both information and noise. Hence we cannot conclude whether those reported volatilities is attributed to information

[13] I use daily average of Japanese yen-U.S. dollar exchange rates to convert all prices to USD.

[14] Frequency of original data was 1 minute. It includes some missing values in market opening period. To fill in those missing values in opening period, last available values are used.

[15] During that period, there were 19 ADRs listed in NYSE. However, data for NTT DoCoMo was not available.

[16] Japan does not apply Daylight Saving Time (DST). Time difference between Tokyo and New York changes from 14hours to 13hours when DST employed in U.S. We have 7,302 observed prices for TSE and 10,870 for NYSE.

or/and noise. I proceed by decomposing the price changes into information and noise using the partial price adjustment model.

4.5 Estimation Results

First, we estimate the partial price adjustment model as introduced in section 4.3. Table 4.3 shows the estimated parameters of state space model including η, and LR_1. LR_1 is lower than one in almost all of the shares, i.e. the price discovery process is more efficient in New York. Half-lives are computed from Yan-Zivot PDIRF. Except two shares, Cannon (CAJ) and NIS Group (NIS), 50% of an information shock is incorporated into observed price immediately.

For all of the shares, estimated η are greater than 1. Hence, we can conclude that the magnitude of information shock are larger during Tokyo opening hours. This result is consistent with the finding in Menkveld, Koopman and Lucas (2007). They report that variance of efficient price innovation in home market opening hours are larger than foreign market opening hours.

The microstructural noise displayed in Table 4.3 shows that for most of the stocks, noises are larger in Tokyo. And that result is consistent with Chelly-Steeley (2003). In that article, home market has larger noise than in foreign market. Now recall that we observed high trade price volatility of Cannon and NIS Group in New York in section 4.4. Even their trading value are much smaller than in Tokyo, price varies more in New York. By our structural approach, change in prices is decomposed in information innovation and noise. And now we can conclude that these highly volatile trade prices of Cannon and NIS Group observed in New York are attributable to large microstructural noise.

Two interesting results are found by this structural approach. One is that the speed of incorporating the new information into the price, the speed of price discovery, is faster in NYSE. Another is that large changes in efficient price occur in Tokyo opening hours. These results imply that NYSE has not be able to make full use of its ability of price discovery.

Using the estimated $\delta_1(\delta_2)$ and the series of m_t, we generate the series of $p_{1,t}(p_{2,t})$ during Tokyo (New York) closing hours. Now we have two prices $p_{1,t}$ and $p_{2,t}$ simultaneously, assuming that TSE and NYSE operating hours are fully overlapped. Given the estimated

LR_1, we expect that New York would information dominates Tokyo for most of the stocks.

To compute the information shares, we estimate VEC model with these prices. Table 4.4 shows the parameters α_i and σ_{ei} from the VEC model and estimated price discovery measures IS and GG. Values of IS and GG vary significantly across stocks. Although the average Hasbrouck information share is close to the corresponding GG_1, values of these measures are not correlated with LR_1. IS and GG measure the average magnitude of information incorporated in observed price attributable to each market. Hence they could be considered as static measures and would not capture the dynamics of price discovery captured by LR_1.

4.6 Concluding Remarks

This study has examined price discovery of shares of 18 Japanese companies cross-listed in Tokyo and New York. We analyzed 5-min frequency data over the period September 2007-April 2008.

The model we relied on is partial price adjustment model, suggested by Amihud and Mendelson (1987). Hence it takes the form of state space representation, Kalman filter is the natural tool to estimate the parameters of the model. And by utilizing Kalman filter, we can deal with missing values problem one has to confront in order to study two non-overlapping markets. Hence, methods employed in this paper can be applied to future studies on price discovery such as Asian emerging vs. U.S. market.

By modifying the model to allow different variance on information shock for each market's opening hours, this study shows that the magnitude of change in efficient price is larger during Tokyo opening hours. However the dynamic price discovery measure of Yan and Zivot shows that speed of incorporating information shock into transacted price is faster in NYSE. Thus, NYSE does not make full use of its ability of price discovery, since even its efficiency, much of the large information shocks occur during Tokyo opening hours. The results obtained by IS and GG are not consistent with dynamic approach. Further discussion and studies on structural interpretation of the IS/GG approach are needed.

4.7 Tables of Chapter 4

Table 4.1
NYSE-listed Japanese Stocks

US Symbol	JPN Code	Name
ATE	6857	Advantest Corp.
CAJ	7751	Cannon Inc.
HIT	6501	Hitachi Ltd.
HMC	7267	Honda Motor Co. Ltd.
IX	8591	ORIX Corp.
KNM	9766	Konami Corp.
KUB	6326	Kubota Corp.
KYO	6971	Kyocera Corp.
MC	6752	Matsushita Electric Industrial Co. Ltd.
MFG	8411	Mizuho Financial Group Inc.
MTU	8306	Mitsubishi UFJ Financial Group Inc.
NIS	8571	NIS Group Co. Ltd.
NJ	6594	Nidec Corp.
NMR	8604	Nomura Holdings Inc.
NTT	9432	Nippon Telegraph and Telephone Corp.
SNE	6758	Sony Corp.
TDK	6762	TDK Corp.
TM	7203	Toyota Motor Corp.

The table contains company names of 18 cross-listed stocks. While symbols are used in NYSE, code numbers are used in Tokyo.

Table 4.2
Average Daily Trading Value and Trade Price Volatility

Symbol	Avg. Daily Trading Value			Trade Price Volatility		
	Tokyo	NY	TSE Share	Tokyo	NY	Vol.Ratio
	million dollar	million dollar	%			
ATE	81.18	0.74	99.091	2.73×10^{-5}	1.74×10^{-5}	1.568
CAJ	290.57	26.27	91.710	1.70×10^{-5}	3.38×10^{-5}	0.504
HIT	115.51	4.02	96.641	1.47×10^{-5}	6.42×10^{-6}	2.292
HMC	263.7	19.9	92.983	2.05×10^{-5}	6.49×10^{-6}	3.166
IX	113.83	3.09	97.356	3.42×10^{-5}	2.02×10^{-5}	1.693
KNM	35.26	0.23	99.365	2.63×10^{-5}	2.47×10^{-5}	1.066
KUB	49.27	2.54	95.099	2.17×10^{-5}	9.89×10^{-6}	2.194
KYO	100.44	2.27	97.787	1.20×10^{-5}	4.83×10^{-6}	2.478
MC	159.92	9.29	94.512	1.54×10^{-5}	6.17×10^{-6}	2.502
MFG	675.55	2.33	99.657	2.94×10^{-5}	1.91×10^{-5}	1.542
MTU	542.24	24.17	95.732	2.80×10^{-5}	1.32×10^{-5}	2.129
NIS	7.75	0.11	98.585	7.06×10^{-5}	2.64×10^{-4}	0.267
NJ	26.3	1.1	95.984	1.83×10^{-5}	9.86×10^{-6}	1.856
NMR	217.22	8.19	96.365	2.27×10^{-5}	1.10×10^{-5}	2.065
NTT	135.14	11.5	92.160	1.12×10^{-5}	7.45×10^{-6}	1.507
SNE	410.35	52.79	88.601	1.65×10^{-5}	7.25×10^{-6}	2.271
TDK	92.77	1.23	98.689	1.81×10^{-5}	9.60×10^{-6}	1.885
TM	613.02	66.06	90.272	2.18×10^{-5}	5.56×10^{-6}	3.924
Mean	218.334	13.101	95.588	2.37×10^{-5}	2.65×10^{-5}	1.939
Std.Dev.	208.285	18.885	3.286	1.33×10^{-5}	5.98×10^{-5}	0.860

This table contains average daily trading value and trade price volatility in Tokyo and New York from September 17, 2007 to April 7, 2008. TSE Share is the proportion of average daily trading value attributable to Tokyo. Trade price volatility is the variance of log price change. Vol. Ratio is the ratio of variance in Tokyo on that in New York.

Table 4.3
Partial Price Adjustment Model Estimates

Symbol	σ_v^2 †	η	Tokyo δ_1	σ_{w1}^2 †	$Half_1$	New York δ_2	σ_{w2}^2 †	$Half_2$	LR_1
					min.			min.	
ATE	3.306	5.331	0.034	23.289	100	0.979	0.735	0	2184.39
		(0.616)	(0.005)			(0.007)			
CAJ	2.846	3.229	0.852	3.172	0	0.005	31.122	690	0.02
		(0.433)	(0.052)			(0.003)			
HIT	1.600	3.004	0.034	11.548	100	0.829	1.123	0	31.88
		(0.339)	(0.004)			(0.013)			
HMC	1.532	6.920	0.363	12.265	5	0.727	0.892	0	5.45
		(0.411)	(0.021)			(0.024)			
IX	5.370	3.026	0.056	30.431	60	0.764	4.950	0	16.05
		(0.312)	(0.008)			(0.013)			
KNM	5.244	2.859	0.023	21.191	145	0.975	0.558	0	1573.53
		(0.381)	(0.004)			(0.007)			
KUB	2.326	3.040	0.051	17.731	65	0.877	1.381	0	59.07
		(0.252)	(0.006)			(0.014)			
KYO	2.216	1.414	0.046	9.359	70	1.010	0.072	0	10080.16
		(0.128)	(0.004)			(0.024)			
MC	1.691	3.074	0.006	12.553	575	0.935	0.501	0	232.55
		(0.291)	(0.004)			(0.013)			
MFG	2.754	6.823	0.225	20.633	10	0.970	1.835	0	659.52
		(0.523)	(0.020)			(0.010)			
MTU	3.112	6.390	0.158	21.356	20	0.829	1.463	0	24.15
		(0.562)	(0.014)			(0.024)			
NIS	20.902	3.307	0.010	66.514	340	0.154	212.357	20	1.37
		(0.877)	(0.003)			(0.030)			
NJ	1.908	3.078	0.037	12.867	90	0.926	1.045	0	167.53
		(0.322)	(0.004)			(0.010)			
NMR	3.317	3.021	0.138	17.031	20	1.119	0.000	0	52.09
		(0.335)	(0.025)			(0.008)			
NTT	1.596	2.939	0.043	8.709	75	0.960	0.573	0	571.13
		(0.496)	(0.005)			(0.012)			
SNE	2.505	3.018	0.221	10.646	10	0.860	0.470	0	31.13
		(0.193)	(0.020)			(0.029)			
TDK	2.275	6.302	0.290	11.139	10	0.672	2.783	0	4.67
		(0.454)	(0.021)			(0.014)			
TM	1.562	4.941	0.330	14.243	5	0.810	0.558	0	12.42
		(0.329)	(0.021)			(0.024)			
Mean	3.670	3.984	0.162	18.038	94.4	0.800	14.579	39.4	826.69
Std.Dev.	4.447	1.660	0.208	13.703	144.4	0.285	15.393	162.4	2376.40

The table shows the parameter estimates for the partial price adjustment model (4.1) with (4.13). We use log price, 5-min data. $Half_i$ are half-lives, the expected number of minutes for 50% of a information shock to be incoroprated into observed price, computed from Yan-Zivot price discovery impulse response function (4.10). $\sigma_v^2, \eta, \delta_i, \sigma_{wi}^2$ are the parameters from the state space model. Standard errors are in parentheses. LR_1 is the quadratic loss ratio (4.12).

†Original values are reported values times 10^{-6}.

Table 4.4
Vector Error Correction Model Estimates

Symbol	α_1	α_2	σ^2_{e1} †	σ^2_{e2} †	$IS_{1,U}$	$IS_{1,L}$	GG_1
					%	%	%
ATE	-0.009	0.033	11.200	11.400	94.785	74.642	79.212
	(8.30×10^{-6})	(5.72×10^{-6})			(0.008)	(0.015)	(0.014)
CAJ	-0.003	0.005	6.820	19.900	51.041	46.106	62.373
	(4.23×10^{-5})	(2.36×10^{-4})			(2.459)	(2.477)	(1.190)
HIT	-0.015	0.015	6.340	3.550	71.258	53.320	50.486
	(6.47×10^{-5})	(1.00×10^{-4})			(0.383)	(0.421)	(0.267)
HMC	-0.298	0.093	8.680	4.240	62.018	7.589	23.812
	(1.66×10^{-4})	(1.68×10^{-4})			(0.049)	(0.026)	(0.042)
IX	-0.038	0.019	15.536	15.300	64.122	42.165	51.787
	(1.97×10^{-6})	(1.34×10^{-5})			(0.011)	(0.011)	(0.007)
KNM	-0.007	0.002	10.200	13.900	90.088	75.940	76.349
	(9.43×10^{-6})	(7.78×10^{-6})			(0.022)	(0.032)	(0.024)
KUB	-0.024	0.033	9.220	5.660	71.516	46.350	49.984
	(1.47×10^{-5})	(1.26×10^{-5})			(0.019)	(0.022)	(0.014)
KYO	-0.026	0.044	5.490	3.490	52.918	30.974	39.259
	(2.40×10^{-5})	(2.31×10^{-5})			(0.027)	(0.025)	(0.016)
MC	-0.004	0.006	6.450	3.640	81.401	77.801	60.587
	(7.37×10^{-5})	(1.86×10^{-5})			(0.639)	(0.686)	(0.550)
MFG	-0.168	0.113	12.800	12.600	68.804	14.351	40.238
	(9.65×10^{-5})	(9.60×10^{-5})			(0.034)	(0.024)	(0.034)
MTU	-0.149	0.059	13.100	7.650	46.898	4.941	18.875
	(1.84×10^{-4})	(7.07×10^{-5})			(0.087)	(0.036)	(0.069)
NIS	-0.003	0.032	32.100	158.000	95.039	94.101	90.637
	(1.31×10^{-5})	(2.93×10^{-5})			(0.044)	(0.047)	(0.039)
NJ	-0.016	0.025	7.090	5.500	80.203	63.090	61.118
	(1.50×10^{-5})	(1.09×10^{-5})			(0.014)	(0.017)	(0.012)
NMR	-0.104	0.049	9.890	7.820	54.954	12.766	32.131
	(1.40×10^{-4})	(8.29×10^{-5})			(0.079)	(0.052)	(0.065)
NTT	-0.020	0.023	4.730	4.280	69.223	42.981	52.944
	(2.80×10^{-6})	(3.94×10^{-6})			(0.011)	(0.012)	(0.008)
SNE	-0.166	0.053	6.821	4.178	55.369	7.522	24.317
	(5.91×10^{-5})	(3.95×10^{-5})			(0.023)	(0.012)	(0.020)
TDK	-0.195	0.208	8.293	9.099	74.150	26.883	51.648
	(2.23×10^{-5})	(1.80×10^{-4})			(0.028)	(0.027)	(0.024)
TM	-0.232	0.082	8.228	3.893	65.282	9.063	26.006
	(2.41×10^{-4})	(2.64×10^{-4})			(0.060)	(0.031)	(0.049)
Mean	-0.082	0.049	10.166	16.339	69.393	40.588	49.542
Std.Dev.	0.095	0.050	6.177	35.680	14.635	28.272	20.319

We use log price. $\alpha_1.\alpha_2, \sigma_{e1}$,and σ_{e2} are the parameters from the VEC model (4.13). $IS_{1,U}, IS_{1,L}$ and $IS_{1,AVE}$ are the upper bound, lower bound and average Hasbrouck information share, respectively (4.15). GG_1 is the Gonzalo-Granger portfolio weight (4.16).

† Original values are reported values times 10^{-6}.

Appendix

Derivation of the Price Discovery Impulse Response Function

Start from the equation:

$$\Delta p_{i,t} = \delta_i(m_t - p_{i,t-1}) + w_{i,t} \qquad i = 1, 2 \tag{A.1}$$

and rewrite it in level price form:

$$p_{i,t} = (1-\delta_i)p_{i,t-1} + \delta_i m_t + w_{i,t}. \tag{A.2}$$

Then assuming $p_{i,0} = 0$ and $m_{i,0} = 0$, for $t = 1$:

$$\begin{aligned} p_{i,1} &= (1-\delta_i)p_{i,0} + \delta_i m_1 + w_{i,1} \\ &= \delta_i v_1 + w_{i,1} \end{aligned} \tag{A.3}$$

and for $t = 2$:

$$\begin{aligned} p_{i,2} &= (1-\delta_i)p_{i,1} + \delta_i m_2 + w_{i,2} \\ &= (1-\delta_i)[\delta v_1 + w_{i,1}] + \delta_i(v_1 + v_2) + w_{i,2}, \end{aligned} \tag{A.4}$$

hence recursively, for $t \geq 1$:

$$\begin{aligned} p_{i,t} &= \delta_i v_t + [\delta_i + (1-\delta_i)\delta_i]v_{t-1} + \cdots + \left[\sum_{l=0}^{t-1}(1-\delta_i)^l\delta_i\right] v_1 \\ &\quad +(1-\delta_i)^{t-1}w_{i,1} + (1-\delta_i)^{t-2}w_{i,2} + \cdots + w_{i,t} \\ &= \sum_{j=1}^{t}\left\{(1-\delta_i)^{t-j}\delta_i\sum_{l=1}^{j} v_l\right\} + \sum_{j}^{t}(1-\delta)^{t-j}w_{i,j}. \end{aligned} \tag{A.5}$$

Desired result as in equation is obtained and we have the PDIRF $f_{i,k} = \sum_{l=0}^{k}\delta_i(1-\delta_i)^l$ for $i = 1, 2$.

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Curriculum Vitae

Yoichi Otsubo

Degrees

2011 Ph.D. in Economics, Rutgers University, New Brunswick, New Jersey

2008 M.A. in Economics, Rutgers University, New Brunswick, New Jersey

2006 M.A. in International Political Economy, University of Tsukuba, Tsukuba, Japan

2004 B.A. in International Relations, University of Tsukuba, Tsukuba, Japan

Positions Held

2009-2011 Research Assistant, Department of Economics, Rutgers University

2008-2011 Instructor, Department of Economics, Rutgers University

2007-2010 Teaching Assistant, Department of Economics, Rutgers University

2005-2006 Teaching Assistant, College of International Studies, University of Tsukuba