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By *Gbenga Ibikunle, Andros Gregoriou, Andreas G. F. Hoepner and Mark Rhodes*

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**Gbenga Ibikunle**
*Corresponding Author*
University of Edinburgh Business School
University of Edinburgh
29 Buccleuch Place
Edinburgh, EH8 9JS
Gbenga.Ibikunle@ed.ac.uk
Tel: +44 (0) 1316515186

**Andros Gregoriou**
Hull University Business School
University of Hull
Hull, HU6 7RX
a.gregoriou@hull.ac.uk

**Andreas G. F. Hoepner**
School of Management
University of St. Andrews
St Andrews, KY16 9RJ
ah445@st-andrews.ac.uk

**Mark Rhodes**
Hull University Business School
University of Hull
Hull, HU6 7RX
m.rhodes@hull.ac.uk

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## Abstract

We apply Chordia et al.'s (2008) conception of short-horizon return predictability as inverse indicator of market efficiency to the analysis of instruments on the world's largest carbon exchange, ICE's ECX. We find strong relationship between liquidity and market efficiency such that when spreads narrow, return predictability diminishes. This is more pronounced for the highest trading carbon futures and during periods of low liquidity. Since the start of trading in the Kyoto commitment period of the EU Emissions Trading Scheme (EU-ETS) prices continuously moved nearer to unity with random walk benchmarks, and this improves from year to year. Overall, our findings suggest trading quality in the EU-ETS has improved markedly and matures over the 2008-2011 compliance years. These findings are significant for global climate change policy.



**JEL Classifications: G12, G13, G14, G15, G18**

**Keywords:** Liquidity; Order flow; Market efficiency; Return predictability; High frequency data; EU Emissions Trading Scheme (EU-ETS); Carbon futures; Climate change

## 1. Introduction

As market participants require time to incorporate new information into their trading strategies, a market deemed efficient over a daily horizon does not necessarily translate into a market that is efficient at every point during the day (see for example Fama, 1970; Epps, 1979; Hillmer and Yu, 1979; Patell and Wolfson, 1984; Chordia et al., 2008). Confirmation of this notion is available in the contributions of Cushing and Madhavan (2000) and Chordia et al. (2005) showing that short-run returns can be predicted from order flows. However Chordia et al. (2008) find that this predictability diminishes with improving market liquidity and across different tick size regimes on the NYSE. Similarly Chung and Hrazdil (2010a) confirm the diminishing predictability proposition in a large sample analysis of NASDAQ stocks. These two studies thus provide evidence of strong relations between liquidity and market efficiency through the impact of liquidity on the predictability of returns from order flows.

Instead of using order imbalance, a separate group of studies examine the connection between liquidity and returns through the demand for *premia* when transacting in illiquid instruments. Pástor and Stambaugh (2003) find a positive cross-sectional relationship between stock returns and liquidity risks. Their results are underscored by similar findings from Datar et al. (1998) and Acharya and Pederson (2005). Similarly, Amihud (2002) document evidence supporting the hypothesis that expected market liquidity provides an indication of stock excess return in the time series, implying that the excess return to some extent typifies an illiquidity premium. Chang et al. (2010) also find a consistent narration on the Tokyo Stock Exchange.

Chordia et al. (2008) make an insightful argument for the relatedness of market efficiency to market liquidity. Consider market makers in a hypothetical market struggling to sustain liquidity supply. This may be as a result of financial difficulties or over-exposure to untenable positions. Market makers may be relatively sensitive to significant buy orders for example, or an imbalance between buy and sell orders may imply that trading is taking place on the basis of private information. In any case, when such a scenario exists, pricing strain caused by arriving order flows potentially forces a brief deviation of prices from their underlying worth (hence inefficiency; see Fama, 1970). Thus order flow can give an indication of instrument returns, at least over short intervals (see also Stoll, 1978; Chordia and Subrahmanyam, 2004). Experienced and vigilant market participants (perhaps trading with algorithms during a significant proportion of the time) are likely to notice at least some of these deviations from random walk benchmarks. They are likely to tender market orders with the aim of profiting from the arbitrage. The choice of market orders is informed by the need to quickly profit before the arbitrage opportunity disappears, as this would most likely be fleeting. Strangely enough, the submitted orders from the arbitrageurs, assuming they are made in ample volumes and on time, are the ones that would lead to relieving the pressure on the market makers inventories. This then leads to the rapid correction of the asset prices. According to Chordia et al. (2005), the correction in asset prices decreases return predictability. Since arbitrage traders are more likely to tender these orders when the spreads are narrow (see for example Peterson and Sirri, 2002; Brennan and Subrahmanyam, 1998 for the influence of liquidity on trading tactics), one would expect reduced return predictability when the market is more liquid and experiences more activity of arbitrage traders than otherwise.

We investigate this hypothesis in a unique market created as a result of climate change policy, the EU Emissions Trading Scheme (EU-ETS).[1] The EU-ETS is the largest compulsory pseudo-cap and trade scheme in the world and its success will significantly inform the direction of global climate policy and the expansion of the emission-constrained economies already created in Europe, New Zealand, Australia and parts of the United States, Canada, China and Japan.[2] Understanding the EU-ETS's microstructure therefore goes a long way in helping inform global climate change policy. The contribution this paper makes to global policy, when viewed in this light, can therefore be considered important. The EU-ETS platforms operate very much like regular financial platforms and hence provide the avenue for assessing the relevant microstructure issues by employing established methodology from the finance literature.

Based on the foregoing hypothesis, we examine the links between liquidity and market efficiency on the largest emissions trading platform in the world, the European Climate Exchange in London, using mainly the short horizon order imbalance and return predictability regressions methodology of Chordia et al. (2008). We find as follows: (i) Intraday return predictability is significantly reduced when the traded instruments are relatively more liquid, hence short horizon market efficiency is incontrovertibly associated with daily liquidity, robustness tests also contribute to this conclusion; (ii) instrument trading efficiency and by extension market

[1] Our approach is clearly different from the spot-futures relationship approach usually adopted for measuring futures market efficiency (see for example Kellard et al., 1999).

[2] It is also noteworthy that the effect of EU-ETS legislation is now felt in every part of the world as airlines doing business in the EU are now subject to EU-ETS regulations, this came into effect in January 2012.

efficiency improves as the market evolves/matures over a forty month period; (iii) the ECX instruments tested show improvement in terms of conformity with random walk benchmarks with each successive compliance period. Overall, this paper concludes that the carbon market has achieved a comparable informational efficiency in relation to long established financial markets.

The remainder of the paper is arranged as follows: In the next section we provide the background to the study by discussing the EU-ETS and summarizing the literature on market efficiency and transaction costs in the EU-ETS. Section 3 discusses sample selection and describes the data. Section 4 reports our econometric methodology and the empirical findings, and finally Section 5 concludes.

## 2. Background to this study

### 2.1. The EU Emissions Trading Scheme (EU-ETS)

The Kyoto Protocol, an international accord on climate change, came into force in January 2005 and provides mechanisms through which participating countries can achieve their emissions reduction targets. Under the treaty, the EU undertakes to reduce its emissions to 8% below the 1990 levels, mainly by employing the International Emissions Trading (IET) mechanism which is designed as the EU-ETS. Details of this are described further below. The greenhouse gas permit trading market has since grown into a multi-billion dollar market with Europe leading the charge. The European emissions permit market has accounted for more than 95% of market share for any given year since 2006[3] (see Kossoy and Ambrosi, 2010; Linacre et al., 2011). This is however set to change as New Zealand, municipal and state governments in Japan and the United States have all in recent years commenced operating similar schemes and Australia is set to start in 2015 after the adoption of its own climate change legislation in 2011. The Australian scheme will be linked with EU-ETS as from 2015.

The EU-ETS is divided into three phases; the first phase, the so-called Phase I (2005-2007) was a largely inefficient trial period (see Montagnoli and de Vries, 2010 for example) before the commencement of the actual Kyoto commitment period (Phase II; 2008-2012). Phase II forms the basis of our investigations. The EU has recently commenced a post-Kyoto phase (Phase III,

[3] The concept of permit trading is not novel to the Kyoto Protocol or the EU-ETS however, the most prominent example of emissions trading until recently has been the United States Acid Rain programme. The Environmental Protection Agency (EPA) has employed emissions trading as a policy tool to achieve emissions reductions since 1992.

2013-2020). This commitment is supported by a global climate agreement reached in Durban in December 2011. The Durban meeting also raises expectations with respect to the achievement of future global climate change agreements (see Ranson and Stavins, 2012). The EU-ETS operates as a cap and trade while allowing the use of certain external emissions permit instruments through the EU Linking Directive 2004/101/EC (see Flåm, 2007). This is the main driver for the EU's emissions reduction target of 8% below 1990 levels over the Kyoto commitment years. The EU adopts a 'burden sharing agreement' (Council Decision 2002/358/CE) allowing it to *re-allocate* emissions reduction targets within its member states so as to allow emissions growth in less developed EU countries. Within its Kyoto target, the EU thus allocates individual targets to its constituent nations. This means more demanding targets for the larger European economies such as Germany than for the smaller ones. It then falls on the member countries to identify the installations affected within their borders under the aggregated reduction target. The additional ten countries (the so-called ascension nations) as well as Iceland, Liechtenstein and Norway (non-EU European countries) also participate in the EU-ETS (see Williams and Kittel, 2004).

Overall, about 12,000 installations with a minimum heat excess of 20 megawatts (MW) in a number of sectors within the EU (accounting for 40% of the EU's total greenhouse gas emissions) are brought under the EU-ETS.[4] A total of 2.2 billion $tCO_2$ were distributed to the affected installations in Phase I (see Dodwell, 2005; Zhang and Wei, 2010; Capoor and Ambrosi, 2008; Hawksworth and Swinney, 2009). European Union Allowance (EUA) is the trading permit unit (currency) in the EU-ETS, project based instruments are however permitted for submission to a specified degree, depending on the phase.[5] EUAs are generated electronically as instruments on national registries of participating EU countries. Each EUA is assigned a distinctive code to ensure transparency and forestall fraud.[6] A central Community Independent Transaction Log (CITL) connects all the national registries. A National Allocation Plan (NAP) containing the allocable quantity of EUAs is prepared by participating countries for every phase. Every April, the installations are required to submit EUAs equal to their verified net emissions for the

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[4] The sectors affected are electricity generators, mineral oil refineries, coke ovens, ferrous metals, glass, ceramic products and cement manufacturers to glass and pulp producers. Electricity generators are however the leading $CO_2$ emitters. By Council decision, in 2012 the aviation sector was brought into the EU-ETS (Directive 2008/101/EC). A few other sectors are to be included from 2013 onwards.

[5] Project based permits include Certified Emission Reduction Units (CER) and Emission Reduction Units (ERU) from Clean Development Mechanism and Joint Implementation (JI) respectively (see Daskalakis et al., 2011).

[6] Nevertheless, significant fraud was identified in the scheme resulting in the brief suspensions of the EU-ETS, most recenty in January 2011. Futures' trading was not suspended however, we present results separately for the different compliance periods, including the last part of our sample commencing in January 2011.

preceding calendar (compliance) year (see Daskalakis et al., 2011 for a detailed financial overview of the EU-ETS).

### 2.2. Trading on the ECX

The ECX is the largest carbon platform in the EU-ETS and by extension the world. In 2010, EUA carbon permits constituted more than 84% of global carbon market value with approximately 73% traded as futures contracts (see Kossoy and Ambrosi, 2010; Linacre et al., 2011). The ECX platform is the market leader in EU-ETS exchange-based carbon trading with more than 92% market share. It is a derivatives platform and most of the trading activities have consistently occurred in its December maturity contracts, Ibikunle et al. (2013) estimates that since 2009, at least 76% of the trading has occurred in the December contracts. The regular futures contracts are marketed on a quarterly expiry cycle: March, June, September and December. The underlying for each ECX EUA contract is 1,000 EUAs. The trading system is electronic and continuous. Official trading starts at 7:00hrs and ends at 17:00hrs UK local time from Monday to Friday. There is however, a pre-opening trading period of 15 minutes to allow for participants to place early orders in planning for the trading day. The market thus opens for an initial period between 6:45am and 7:00am, with virtually no executed orders. The maturity date for the contracts is the last Monday of the traded month with physical settlement occurring within three days following expiry. Carbon Financial Instruments (CFI) trading on the ICE ECX platform[7] is done electronically on the ICE platform. ICE Futures Europe platform is accessible only to members for order placement. All valid orders and their corresponding executions are anonymous. The electronically executed trades pass through the so-called Trade Registration System (TRS) for account allocation.

### 2.3. Review of EU-ETS Literature on market efficiency and liquidity

To the best of our knowledge, no study has been undertaken on the contemporaneous linkages between market efficiency and liquidity in the EU-ETS. Ibikunle et al. (2013) infer market efficiency from informational efficiency (the effectiveness of incorporating available information) on the ECX. They show that intraday evolution of market efficiency is contingent on trading activity, stopping short of linking long-term market efficiency to market liquidity. Their methodological approach is also different to ours. Several studies have made contributions to the understanding of microstructure properties of the EU-ETS instruments using various

[7] ICE ECX and ECX are used interchangeably in this paper.

approaches. Joyeux and Milunovich (2010) examine issues related to market efficiency and price discovery during Phase I of the EU-ETS; they find inter-temporal links between the spot and two futures contracts. Daskalakis and Markellos (2008) find that the market in Phase I did not conform to weak-form efficiency. The authors suggest that the lack of efficiency could be due to banking restrictions and immaturity of the market in Phase I. Montagnoli and de Vries (2010) also show that Phase I was an inefficient experiment, with thin trading leading to huge bias for EMH; the study goes on to examine trading in the early period of the second phase and report significant improvements in market efficiency.

Benz and Klar (2008) provide the first insights into price discovery for the European carbon futures market. Using intraday data with the Engle and Granger (1987) VECM framework, they investigate estimated transaction costs in the now agreed inefficient Phase I (2005-2007) of the EU-ETS. In a study using identical methodologies, Rittler (2012) examines price discovery and information transmission in the early part of Phase II. The study aims to identify the price leader between the spot traded from Bluenext, Paris and futures contracts traded on the ECX, London. The two studies are similar not only in methodologies, but also in the direction of investigation. Benz and Klar (2008) focus on price leadership between two platforms (ECX and NordPool) in the EU-ETS; while Rittler (2012) on price leadership between two instruments (spot and futures contracts). The former concludes that the ECX leads price discovery and the latter concludes that futures leads price discovery. Mizrach and Otsubo (2011) also investigate the initiation of price discovery between the Bluenext spot market in Paris and the ECX futures market in London using Hasbrouck (1995) and Gonzalo and Granger (1995) information share estimation approaches. They report that the ECX is responsible for about a 90% share of combined price discovery for the two platforms.

On liquidity, Frino et al. (2010) investigate liquidity and transaction costs in the EU-ETS using intra-day data from the ECX, they find that aggregate long-term liquidity improves over the course of Phase I and the early months of Phase II. Ibikunle et al. (2011) also examine liquidity evolution in Phase II. Using event study methodology with the market model, they show that liquidity and trading quality improve on account of new regulations at the start of Phase II.

## 3. Data

In this paper, we compute all of order imbalance, liquidity and futures returns measures on an instrument-specific basis.[8] The use of instrument-specific variables for the examination of market efficiency is grounded in the microstructure literature (see for example Brennan et al., 1993; Lo and MacKinlay, 1990). Serial dependence between days is approximately zero for dynamic instruments (see Chordia et al., 2005), which are too heavily traded for anomalies to exist for very long. An examination of connections between liquidity and market efficiency on a platform such as the ECX, with actively traded instruments, should therefore be centred on intraday trading. The carbon futures order imbalance analysis of Mizrach and Otsubo (2011) using daily measures therefore will unlikely suffice. Since they focus on daily order imbalance, the results have no relevance for our research questions. We use 15-minute intervals as the focus of this study rather than the five-minute intervals used by other studies (see as examples Chordia et al., 2008; Chung and Hrazdil, 2010a; Chung and Hrazdil, 2010b) based on two conditions:

1. Concerns about non-trading for less actively traded instruments on ECX. Since on EU-ETS derivative trading platforms, the nearest maturity contracts usually account for about 80% of trades in emission permits, non-trading therefore is taken into account by extending the interval to 15 minutes.

2. Theoretically, a predictive connection between order imbalances and returns should not endure for more than minutes, since market inefficiencies create arbitrage opportunities. Trading activities on account of this in turn leads to regained market efficiency. Hence, while non-trading remains an issue, the time interval chosen must be short enough to capture the inefficiencies in trading activity. This informs the decision not to extend the interval beyond 15 minutes.

Based on the foregoing and the problem of determining serial dependence in the presence of non-trading, we restrict our analysis to instruments that are traded relatively frequently for a specific compliance year.[9] We also follow Chordia et al. (2001) in excluding instruments with differing trading characteristics to the major CFIs traded on the exchange. Thus we exclude EUA Daily futures and EUA spreads. Ultimately, only five EUA futures contracts with varying

[8] We employ this approach for all analyses unless otherwise stated.
[9] If we applied 5 minute-intervals as the basis for the measures, we would have been forced to examine only one contract per year for the period under consideration, thus we use 15-minute intervals.

trading years are retained in the sample, these are the December expiry contracts for 2008, 2009, 2010, 2011 and 2012. The December maturity contracts account for more than 76% of daily trading volume on the ECX for the period under investigation. The dataset obtained directly from the ICE/ECX London comprises of all intra-day tick-by-tick ECX EUA futures contracts on-screen trades on the ECX platform from January 2008 through April 2011. The dataset contains date, timestamp, market identifier, product description, traded month, order identifier, trade sign (bid/offer), traded price, quantity traded, parent identifier and trade type. The dataset is split into four compliance periods of Phase II, the 2008, 2009, 2010 and 2011 compliance years. Tick size for the entire period is €0.01 having been changed from €0.05 on 27th March 2007 (during Phase I). The division based on regulatory compliance periods is exogenous and provides for a practical basis to examine the effect of liquidity on return predictability.

### 3.1. Order Imbalance and Return Measures

We begin our enquiry by computing the variables employed for most of this paper. In the dataset, all the trades are labelled as either buyer initiated or seller initiated, hence we do not need to algorithmically allocate trade classifications. We use two order imbalance methods based on nominal trades and the euro weight of trades respectively. Nominal order imbalance ($OIBQ_t$) for each CFI and for each 15-minute interval is calculated using equation (1), while the euro order imbalance ($OIB€_t$) is simply the weighing of (1) with euro trading value of the trades as shown in equation (2).[10] The nominal order imbalance is non-weighted and thus fails to account for the economic significance of the trades unlike the euro order imbalance measure, for most of the analysis; we therefore employ the latter measure of order imbalance.

$$OIBQ_t = {}^{BUY_t - SELL_t}/_{BUY_t + SELL_t} \qquad (1)$$

$$OIB€_t = {}^{€BUY_t - €SELL_t}/_{€BUY_t + €SELL_t} \qquad (2)$$

For each CFI, the measures are calculated for every 15-minute interval in a trading day.

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[10] We also examine the possibility that our order imbalance measures may reflect exogenous shocks by computing absolute values for liquid and low liquidity periods as described in page 259 of Chordia et al. (2008) for robustness.

In computing the 15-minute returns variable, we use the last transaction prices for every 15-minute period.[11] Although returns are viewed as being less biased when computed from quotes than from transaction prices, we face two challenges in computing from quotes. First, heterogeneities exist for trading rates of occurrence for CFIs on the ECX as a result of the high level of differing trading frequencies. Potentially, the results will be extremely biased and contradictory since the method could result in returns computed over various spans for different CFIs. One needs to also be mindful that computing returns with transaction prices could be affected by bid-ask bounce. However, the summary statistics of trading prices for each of the four compliance periods suggests that this is not a significant source of concern in the ECX dataset. Also, since our analyses are based on contract-specific measures, we mitigate the problem of non-synchronicity. In addition, when a contract fails to trade at $t_{-1}$, we do not use it in constructing market aggregate measure at time $t$. We therefore employ the transaction prices for computing the return variable for each fifteen-minute period such that the return for 10.15am is computed using the last trade at 10:00am and the last trade at 10:15am. For all analyses utilising lagged estimates, the earliest 15-minute interval for each trading session/day is removed since it is connected to the lagged interval of the foregoing trading session.

### 3.2. Liquidity Measures

We adopt two measures of short-term liquidity constructed using transaction prices at regular 15-minute intervals. Relative spread, which is the main measure of liquidity used, is given as the as the best/highest traded bid price minus the best/lowest traded ask price, then divided by the average of the best traded bid and best traded ask price for every 15-minute period. *Traded spread*, the second measure of liquidity employed, is defined as the best traded bid price minus the best traded ask price over the same interval.[12] The traded spread is computed for use in robustness analysis and most of the results for it are not presented in this paper.

Contract-specific daily bid-ask spread measures are first computed, and then aggregated cross-sectionally across the CFI samples to obtain a market-wide liquidity value. Four exogenous liquidity periods are identified based on compliance periods available in Phase II of the EU-ETS. The sample thus span forty months of trading based on available data. Period (i) runs from 2nd January 2008 until December 31st 2008; period (ii) from 2nd January 2009 until December 31st

[11] We also use the mid-point of the last bid and ask transaction prices for every 15-minute period with similar outcomes.

[12] We also compute the measures with traded bid and ask prices at the stroke of each 15-minute period, the results are very similar with no material variation in value.

2009; period (iii) from 4th January 2010 until December 31st, 2010 and period (iv) from 3rd January 2011 until April 29th 2011. Period (iv) is restricted by data availability for this study. The four periods correspond to Phase II-Year I, Phase II-Year II, Phase II-Year III and Phase II-Year IV respectively. Since they jointly represent two-thirds of Phase II, they have a good degree of representativeness.

## 4. Results and Discussion

### 4.1. Summary statistics

Table 1 shows summary statistics for traded spread, relative spread, market returns and the two order imbalance measures. The samples are representative of values for all the contracts examined in the assigned periods, with the exclusion of those missing observations (i.e. when no trading occurs). The statistics clearly show a strong improvement in liquidity over the four compliance periods. The mean traded and relative spread measures for Phase II-Year I are €0.1197 and €0.0043 respectively. These decrease substantially by 74% and 56% to €0.031374 and €0.001918 in Year IV for the traded and relative spreads respectively. Order imbalance measures generally increase in magnitude, progressing from negative territory (-0.005787, €-0.08279) in Year I to positive values in the Year IV (0.02042, €0.002767) for $OIBQ_t$ and $OIB€_t$ respectively. The statistics are somewhat similar to those of Chordia et al. (2008) and thus show a market with increasing ratio of bid trades to ask trades. Most efficient markets record more bid than ask trades, since arbitrage traders operate from neutral positions, from which they bid for opportunities. The data thus imply an improvement in level of market efficiency for the ECX with each progression to a different compliance year. We further test this hypothesis in subsequent sections of this paper. Another interesting observation that serves to underscore this suggestion, as well as further cementing findings of other studies on the improving returns on the ECX (see for example Ibikunle et al., 2012), is the marked improvements in the returns from Year I to Year IV.

**[TABLE 1 ABOUT HERE]**

### 4.2. Correlations

Table 2 shows correlation coefficients for lags of the two order imbalance measures and the futures returns. The order imbalance measures, as one would expect are clearly highly correlated except for in Year I, however all are statistically significant at 1% level. The return is not as highly correlated with the order imbalance measures; in fact we record statistically significant negative correlations for Year II, which is surprising. For other periods and for the $OIBQ_t$ measure, the correlation coefficients are positive and also statistically significant. For $OIB€_t$, only the Year III returns a coefficient that is not statistically significant at all levels tested. The initial expectation here is that of high correlation of returns with the order imbalance measures. Although this is not the case, the correlation analysis results are by no means conclusive evidence of the link between returns and order imbalance on the ECX. It is very important to understand that while there are already several investment vehicles on the carbon trading platform, the main aim of the market is not for wealth creation, but rather to establish an emission-constrained economy. This simple fact complicates the picture for the relationship (market efficiency and liquidity) we are investigating.

**[TABLE 2 ABOUT HERE]**

4.3. Predictive Regressions, Market efficiency and Liquidity

We employ Chordia et al.'s (2008) returns predictability model (3) to estimate the level of short-horizon efficiency. If $Ret_t$ is the contract return and $OrderImbalance_t$ corresponds to either of $OIBQ_t$ or $OIB€_t$, then;

$$Ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \varepsilon_t \tag{3}$$

Based on results of the correlation analysis, the expectations for the predictive regressions are not very clear. Table 3 reports results for the predictive regressions of 15-minute returns on lag order imbalance measures. Panel A shows the results for regressions run with the $OIBQ_t$ measure and Panel B for the $OIB€_t$ measure. The results are not stable across the various periods for both regressions. For the regressions run with the entire sample, the results suggest that on the ECX, lagged order imbalance is not a significant predictor for short-run returns and this is consistent for both order imbalance measures. However, different findings are obtained for the period-based results. For example, in Panel A: for Years I, III and IV the $OIBQ_t$ coefficients (levels of statistical significance) are 0.000325 (10%), 0.000368 (5%) and 0.000441 (5%) respectively. The $R^2$ for the two periods are respectively 0.025%, 0.022% and 0.0054% respectively. Similarly, and more significantly, in four of the periods considered using the $OIB€_t$ measure, Panel B reports statistically significant coefficients for three of the periods. In Years I, II and IV of Phase II trading, the $OIB€_t$ coefficients (significance levels) are 0.000582(5%), 0.000547(10%) and 0.000436 (10%) respectively. The $R^2$ values for the three periods are respectively 0.023%, 0.02%

and 0.009%. Thus, if the overall estimates for the forty-month period examined are not considered, we can see the influence of order imbalances in the determination of market returns. It is evident that this explanatory power decreases with each passing period, which is consistent with Chordia et al. (2008). These results indicate that the market efficiency improves over the period under examination.

**[TABLE 3 ABOUT HERE]**

Considering the trading frequency on the ECX and the intervals of 15-minutes examined, these values are substantial and provide a basis to explore further the hypothesis that lagged order imbalance influences short-run returns. Since there is a suggestion of period dependency to the estimates, we examine next how market efficiency has evolved over the four periods. We run monthly predictive regressions for the forty months under observation, starting with January 2008 and ending with April 2011. We use the $OIB€_t$ as the sole order imbalance measure, since it represents the economic significance of the trading imbalance and its results in Table 3 are more significant. From this point on, for consistency, we focus on the use of only $OIB€_t$. We expect that as market efficiency improves, the power of order imbalance in predicting short-run returns diminishes; hence $R^2$ values are expected to drop progressively over the entire period. Figure 1 shows a plot of the monthly regressions $R^2$ values and t-statistics for the entire period. The plot shows the $R^2$, decreasing from a height of 1.4831% in September of 2008 to 0.0004% in February, 2011. The t-statistic values have remained largely stable within the positive territory, especially over the April 2009-April 2011 period. The values hit the peak of 3.81 in February 2008 and ends with 1.08 in April 2011. The t-statistics and the $R^2$ values have a Spearman's correlation estimate of 0.38.

**[FIGURE 1 ABOUT HERE]**

In keeping with Chordia et al. (2008) and Chung and Hrazdil (2010a), we next examine the connections between liquidity and market efficiency which is the main object of this study. We employ $OIBQ€_t$ and the relative spread measure. First, we examine the evolution of liquidity over the entire period. Figure 2 presents the time series plot of relative spread over the forty-month period under observation.[13] Conspicuously, there is a sustained narrowing of the market spread over the entire period, suggesting that liquidity improves with time on the ECX. Further, there seems to be a blip noticeable about the start of trading for each period. This shows a temporary loss of liquidity, perhaps present as a result of some form of calendar effect.[14]

**[FIGURE 2 ABOUT HERE]**

For robustness, we employ two other measures of liquidity based on price impact ratios, these measures are taken based on the argument that, for any given volume of trading, the price response will be greater in illiquid markets. We employ both the Amihud (2002) and the Florackis et al. (2011) measures of long term illiquidity. The Amihud (2002) and Florackis et al. (2011) ratios are given as equations (4) and (5) below respectively:

$$Amihud_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{V_{itd}} \tag{4}$$

$$Florackis_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}} \quad (5),$$

where $R_{itd}$, $V_{itd}$ and $TR_{itd}$ are the return, euro volume and turnover ratio of EUA futures contract $i$ on day $d$ at month $t$ and $D_{it}$ is the number of trading days in month $t$ for EUA futures $i$; therefore larger values indicate that the market is less liquid The results for the long-term evolution of liquidity using (4) and (5) are presented in Figure 3. It can be seen that the evolution is consistent with Figure 2.

**[FIGURE 3 ABOUT HERE]**

In reference to Blume et al. (1989) and Cox and Peterson (1994), the impact of illiquidity is more significant during periods of very low liquidity. In view of this and in order to maintain consistency with Chordia et al. (2008), we split the days in our sample based on those that are considered liquid and those that are relatively illiquid. The illiquid days are defined as those

13 The traded spread yields a similar plot. Further, we employ the traded spread in all other sections of this paper for robustness examinations. In all instances, the results yielded are not materially different from the ones yielded by our use of the relative spread. The results presented in this paper are thus robust to substitute liquidity proxies.

14 Ibikunle et al. (2011), using the market model (Brown and Warner, 1985), examine calendar effects on the European Energy Exchange (EEX) carbon platform and find no significant effect. We nevertheless apply several dummy regressions to capture effects of specific dates in further analyses.

whose average relative spread for that day is at least one standard deviation above the mean relative spread for a surrounding period over (-30, +30).[15]

In Table 4, we present descriptive statistics for relative spreads on high and low liquidity days over the 40-month period. The general trend is that the number of illiquid days as a proportion of the total number of trading days in the respective periods decreases from year to year. In Phase II-Years I, II, III and IV[16] for example, the proportion of illiquid days as percentages of total number of trading days are 13.58%, 12.89%, 10.87% and 9.33% respectively. The gradual improvement evident here is consistent with Figures 2 and 3. If considered in tandem with Figure 1, provides evidence for the hypothesis that market efficiency improves when the market is more liquid.[17] The next logical step is to empirically examine the foregoing hypothesis on the ECX, which is examining the impact of liquidity on market efficiency.

**[TABLE 4 ABOUT HERE]**

In order to empirically analyse the effect of liquidity on the evolution of market efficiency, we interact the $OIB€_t$ variable (in Table 3) with a low-liquidity day dummy. For every day when the average relative spread is at least one standard deviation above the mean relative spread for a surrounding period over (-30, +30), the dummy takes on the value of 1 and 0 otherwise. If $ILD_t$ corresponds to the low liquidity dummy on day t, then model (3) becomes;

$$Ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \beta_1 OrderImbalance_{t-1} * ILD_t + \varepsilon_t \tag{6}$$

15 We also employ the (-60, +60) window as used by Chung and Hrazdil (2010a), with no substantial differences in the number of liquid and illiquid days. For robustness, we econometrically estimate effective half-spread for days in a randomly selected month in each year using the Huang and Stoll (1997) spread decomposition model. The distribution of liquid/illiquid days observed is not qualitatively dissimilar to the one we use above.

16 In Year IV, the 7 illiquid days have lower spread values than the liquid days. This underscores the limitations to our definition of illiquid days, which we control for by using another window and seeing very small qualitative difference in the distribution of illiquid days. Suppose we have a period of low spreads leading to April (when compliance traders must submit emission permits) as a result of perceived increase in trading activity, and suppose most of our illiquid days are around this period. Then we are likely to obtain 'illiquid' days with lower average spread than the average of the vastly larger number of liquid days. This is plausible since our definition of illiquidity is relative to only a given number of surrounding days in the year for every illiquid day. Moreover, the differences in the values are so small that they are not statistically different from one another, even at the 10% level. The same case is made for the mean values in Year III.

17 The percentage proportion of median relative spread on illiquid days to liquid days for Years I, II, III and IV are 119%, 125%, 101% and 90% respectively. These values (except for Year IV for which we have data for only 1/3 of the year) square with the expectation that the average spread for low liquidity days will be higher than that of liquid days.

The regression model (6) is thus run such that on low liquidity days, the lagged $OIB€_t$ variable with the dummy interaction becomes $OIB€_{t-1}$ and 0 on other days.[18] In Table 5, we present the results for the regression analysis. In this analysis, we focus on the significance of the interaction variable. As in Panel B of Table 3, the Phase II-Year III period does not conform to the general trend observed for the other periods. The coefficients for three of the examined periods are positive and statistically significant.  For Phase II-Year I, the coefficient (t-statistic) is 0.003341(4.05) and significant at 1% level. Also for Phase II-Year II, the coefficient (t-statistic) is 0.003313 (3.80) and significant at 1% level. The trend holds also for the final year under consideration, Phase II-Year IV, with coefficient (t-statistic) at 0.0021 (2.23) and statistically significant at 5% level. The highest coefficient value is recorded for Year I, it decreases from then on until a slight rise in Year IV. One reason that could be advanced for the deviation of Year III (2010) from other periods is that 2010 was the post Copenhagen year. 2010 was a year of big disappointment after the UN Conference Parties failed to reach an agreement on a successor to the Kyoto Protocol, as was widely expected in the build-up to the December 2009 Copenhagen conference.

**[TABLE 5 ABOUT HERE]**

The coefficients on lagged order imbalance are all statistically insignificant.  This implies that where lagged order imbalance is found to affect / predict returns, it does so only when the market is illiquid.  Results in Table 5 show that this finding on illiquidity and lagged order flow explains a greater proportion of variation in returns.  The $R^2$ values decrease from Year I to Year IV. For example, in Year I, the $R^2$ is 0.0038, but by Year IV, this has diminished to 0.000451. This decline observed in the explanatory power of the periodic models and their significance is consistent with the gradual improvement in liquidity reported in Figures 2, 3 and in Table 1. Adjustments in liquidity thus affect levels of market efficiency.

Exogenous impacts can lead to extreme order imbalances which can in turn result in a loss of liquidity. Thus in our analysis, using the low liquidity dummy on $OIB€_t$ to determine impact of liquidity, instead of capturing the effect of liquidity in improving market efficiency, we may well have been picking up the impact of exogenous shocks. We therefore construct absolute order

[18] We also carry out robustness tests by including dummies for specific day-after events such as the submission of annual emission reports, NAP and annual emission results announcements. We also include dummies for days preceding specific holidays in the U.K. The resultant coefficients show that the events are not significant to our investigations on intraday basis; also our earlier results are not materially altered.

imbalances for liquid and illiquid periods following the method of Chordia et al. (2008) in order to examine this possibility. We construct these measures for all the four periods and find only minimal variations across both the liquid and illiquid days. This result, along with several other checks mentioned in the footnotes, implies that our results indeed capture the real role of liquidity in improving market efficiency. In any case, as Chordia et al. (2008) point out, it is illogical to assume that illiquidity is jointly determined with signed order imbalances. If an illiquidity-inducing event that is exogenous to the market does occur, one should expect to see as less of buy orders as sell orders.

### 4.4. Granger Causality Analyses

As an additional check of robustness and to further explore the notion that narrowing spreads on day $t$ results in improved market efficiency on day $t_{+1}$, we carry out Granger causality tests (see Granger, 1969). We thus examine the hypothesis that past values of the liquidity proxy are able to explain variation in current market efficiency. This is undertaken by estimating a vector autoregressive model (VAR), in this case with two dependent variables. The first, $\varphi$, is the daily relative spread liquidity proxy. The second, $\delta$, denotes the daily mean of the 15-minute Euro order imbalance measure for each EUA futures contract traded.[19] The lag length, $l$, is chosen to purge autocorrelation.[20] This results in a model of the following form:

$$\begin{aligned} \varphi_t &= \alpha_0 + \alpha_1\varphi_{t-1} + \cdots + \alpha_l\varphi_{l-1} + \beta_1\delta_{t-1} + \cdots + \beta_l\delta_{l-1} + \epsilon_t \\ \delta_t &= \alpha_0 + \alpha_1\delta_{t-1} + \cdots + \alpha_l\delta_{l-1} + \beta_1\varphi_{t-1} + \cdots + \beta_l\varphi_{l-1} + \mu_t \end{aligned} \tag{7}$$

The equations in model (7) are estimated simultaneously for each of the four periods. The statistics presented in Table 6 are the Wald statistics for the joint hypothesis:

$$\beta_1 = \beta_2 = \cdots = \beta_l = 0 \tag{8}$$

for each of the equations in (7). The null tested is that $\delta$ does not Granger-cause $\varphi$ in the top equation and that $\varphi$ does not Granger-cause $\delta$ in the bottom equation. We run these estimates on a contract-specific basis for each period; the results are presented in Panel A of Table 6.

[19] Sufficient trading of the instrument must have taken place for it to enter the sample.
[20] We use various lag lengths ranging from 3 to 17.

**[TABLE 6 ABOUT HERE]**

Panel A shows that the hypothesis that *liquidity improvements on a given day do not inform market efficiency formation during the next* is strongly rejected for all tested contracts for the first three periods. For the fourth period, which includes trading data for only 82 days of trading, we cannot reject this hypothesis. There is also evidence of two-way causation in respect to the Dec-2009 (Year II), Dec-2010 (Year III), Dec-2011 (Year III) and the Dec-2012 (Year III) EUA futures contracts. Broadly therefore, the evidence of two-way causation cannot be conclusively established since it affects contracts only in specific periods. Further, the same contracts are not affected uniformly across all the periods in which they are tested. In order to explore further the possibility of bi-directional causality in futures contracts, we also run the VAR on contract-specific basis without recourse to periods. The results are presented in Panel B of Table 6. Again, there is substantial evidence of Granger causality running from liquidity to order imbalance; however two-way causation is only observed in the case of the Dec-2012 contract. Thus, the evidence in Table 6 confirms further our overriding hypothesis that liquidity on emissions permit trading platforms results in more efficient trading.

### 4.5. Variance Ratios: Measuring randomness of returns

The main premise of this paper is that the predictability of intraday (short-run) return from order imbalances (order flow) is an inverse measure of market efficiency. Chordia et al. (2008) propose another procedure involving the measuring of randomness of returns series. This requires the comparison of variance ratios over short and long horizons. The variances of long-horizon returns are divided by the variance estimated for returns over shorter intervals. For a market in harmony with the random walk process, the variance of returns measured over longer horizons is equal to the sum of variances of shorter horizon returns as long as the summation of the shorter horizons are equal to that of the longer horizon. Thus, variance of the longer horizon returns is $\eta$ times the variance of returns measured over shorter horizons, if $\eta$ is the number of short horizon periods in the longer horizon. Based on our earlier results, we maintain the hypothesis that during liquid spells, there will be fewer deviations from random walk benchmarks, i.e. the variance ratios will be closer to one for each instrument. We concede the point made by Grossman and Miller (1988) that divergence from random walk can be induced by inventory related issues due to return serial correlation, however in a largely efficient market; arbitrage opportunities created by this deviation will lure participants into providing the required liquidity. Hence the divergence from a random walk will be very much temporary, even if market makers cannot absorb orders.

**[TABLE 7 ABOUT HERE]**

For each instrument within each period, we compute 15-minute returns as described in section 3 and also for open to close for all trading days. We then compute the variance ratio by multiplying the 15-minute return variance by the number of 15-minute periods in a trading day. In a market conforming to the random walk process, the variance ratio values will be close to one. Table 7 presents the results of the Variance ratio analysis for contracts traded in each period as well as value weighted variance ratios for each period. The weight employed is the total trading value per instrument. As expected, consistent with Figure 2 and Table 1, the overall variance ratio values decrease progressively from 3.74 in Phase II-Year I to 1.39 in Year III and picked up slightly to 1.42 in first four months of Year IV. It is therefore evident that as the market becomes more liquid and the EUA futures contracts are traded faster with minimal impact on their prices, the market approaches a variance ratio of unity i.e. conforms more to the random walk process. The hypothesis that liquidity contributes to an efficient market in emission permit trading markets is therefore once again not rejected. Another interesting trend in Table 7 is the propensity for the least traded contracts during a specific period to have the highest variance ratios. For example, in Year I, the Dec-2010 contract is the least traded and has a ratio of 16.61, more than seven times the value for the most traded contract in Year I (Dec-2008). The ratio disparity is however less severe in later years, for example the Dec-2012 ratio in Year III is only about twice the value of that of the Dec-2010 contract. The results all therefore support the expectation that divergence from random walk benchmarks is less severe if markets are liquid.

## 5. Conclusions

The EU-ETS represents the largest emissions trading experiment in the world. Although there are now a few other compulsory schemes elsewhere, the success of the ETS second phase would still provide a strong impetus in the formation of a truly global climate change policy. Our work contributes to the understanding of this market and provides evidence of its workability, in this paper we focus on efficiency. Returns predictability on an efficient market should be momentary, infrequent and in the event it occurs, arbitrageurs should provide the necessary pool for order absorption. In this paper, we investigate the predictability of returns from intraday order flows across forty months of trading on the world's largest emissions trading platform. We provide evidence that while return predictability occurs on the platform; this has significantly decreased since the start of Phase II in 2008 and continues to decline over the entire period investigated. The prices of each instrument are thus closer to the random walk benchmark as the scheme evolves. Taking the assumption that loss of market efficiency leads to arbitrage openings, one can then conclude that arbitrage activities, especially in periods of high liquidity, lead to more efficient markets. Inherently we provide the first evidence that for emission permit trading platforms, liquidity enhances market efficiency. The importance of our study is further underscored by the fact that the cost of hedging increases when efficiency decreases in futures markets (see Krehbiel and Adkins, 1993).

The ECX is the most liquid platform in the EU-ETS and in the world. For future research, it would therefore be interesting to examine return predictability in relation to liquidity on the less liquid platforms as well.

**Table 1: Descriptive statistics**

This table shows descriptive statistics for liquidity and order imbalance measures computed from trading data for the ECX. Traded spread is the difference of best traded bid and ask prices for every 15-minute period; relative spread is defined as the best traded bid minus the best traded ask price, then divided by the average of the best traded bid and best ask over the same intervals. The spreads are averaged across the day for each instrument and cross-sectionally across all instruments. $OIBQ_t$ is the difference between the number buyer initiated trades and seller initiated trades, divided by total trades over every 15-minute interval in a trading day. $OIB€_t$ is given as the Euro value of buyer initiated trades less Euro value of seller initiated trades, then divided by the total Euro value of trades over the same interval. *T* is the total number of days during a trading period/year; *t* is the aggregate number 15 minute intervals for all the instruments. The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The data includes December maturity EUA futures contracts traded during the period.

| | | **Traded Spread (€)** | **Relative Spread** | $OIBQ_t$ | $OIB€_t$ |
|---|---|---|---|---|---|
| Entire sample | Mean | 0.069 | $3.45*10^{-03}$ | $-1.89*10^{-02}$ | $-2.87*10^{-02}$ |
| T= 847 | Median | 0.054 | $2.88*10^{-03}$ | $2.35*10^{-04}$ | $-2.14*10^{-02}$ |
| t= 58,836 | Std. Dev. | 0.051 | $2.10*10^{-03}$ | 0.21 | 0.20 |
| Phase II, Year I | Mean | 0.120 | $4.31*10^{-03}$ | $-5.79*10^{-03}$ | $-8.28*10^{-02}$ |
| T= 256 | Median | 0.103 | $3.75*10^{-03}$ | $6.12*10^{-03}$ | $-8.95*10^{-02}$ |
| t= 14,125 | Std. Dev. | 0.058 | $2.17*10^{-03}$ | 0.33 | 0.25 |
| Phase II, Year II | Mean | 0.065 | $4.26*10^{-03}$ | $-3.02*10^{-02}$ | $-1.25*10^{-02}$ |
| T= 254 | Median | 0.060 | $3.70*10^{-03}$ | $-1.41*10^{-02}$ | $1.48*10^{-02}$ |
| t= 18,550 | Std. Dev. | 0.029 | $2.34*10^{-03}$ | 0.18 | 0.21 |
| Phase II, Year III | Mean | 0.034 | $2.28*10^{-03}$ | $-2.69*10^{-02}$ | $-1.42*10^{-02}$ |
| T= 255 | Median | 0.031 | $2.10*10^{-03}$ | $-2.09*10^{-02}$ | $-1.57*10^{-02}$ |
| t= 21,239 | Std. Dev. | 0.011 | $8.01*10^{-04}$ | 0.14 | 0.17 |
| Phase II, Year IV | Mean | 0.031 | $1.92*10^{-03}$ | $2.04*10^{-02}$ | $2.77*10^{-03}$ |
| T= 82 | Median | 0.025 | $1.55*10^{-03}$ | $1.90*10^{-03}$ | $7.77*10^{-03}$ |
| t= 4,922 | Std. Dev. | 0.017 | $9.42*10^{-04}$ | 0.09 | 0.13 |

**Table 2: Correlations for 15-minute trading intervals on the ECX**

The table shows correlations values for three variables. $OIBQ_t$ is the difference between number buyer initiated trades and seller initiated trades, divided by total trades over every 15-minute interval in a trading day. $OIB€_t$ is given as the Euro value of buyer initiated trades less Euro value of seller initiated trades, then divided by the total Euro value of trades over the same interval. The return is computed for every 15-minute interval using the last trade at every interval. *t* is the aggregate number 15 minute intervals for all the instruments. The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The data includes December maturity EUA futures contracts traded during the period. ***, ** and * represents statistical significance at 1%, 5% and 10% levels respectively.

| | | Return | $OIB_{Qt-1}$ |
|---|---|---|---|
| Whole Sample (2008-2011) | $OIBQ_{t-1}$ | 0.006 | |
| t= 58,836 | $OIB€_{t-1}$ | 0.002 | 0.53*** |
| Phase II, Year I | $OIBQ_{t-1}$ | 0.02* | |
| t= 14,125 | $OIB€_{t-1}$ | 0.02* | 0.39*** |
| Phase II, Year II | $OIBQ_{t-1}$ | -0.007* | |
| t= 18,550 | $OIB€_{t-1}$ | -0.014* | 0.80*** |
| Phase II, Year III | $OIBQ_{t-1}$ | 0.02** | |
| t= 21,239 | $OIB€_{t-1}$ | 0.01 | 0.64*** |
| Phase II, Year IV | $OIBQ_{t-1}$ | 0.02 | |
| t= 4,922 | $OIB€_{t-1}$ | 0.03** | 0.55*** |

**Table 3: Predictive regressions of 15-min returns on lagged Order Imbalance**
Panel A shows results for 15-min predictive regressions for EUA Futures contracts on the ECX. $OIBQ_{t-1}$ is the difference between number buyer initiated trades and seller initiated trades, divided by total trades over the 15-minute interval, *t-1*. The $Ret_t$, computed for every 15-minute interval using the last trade at every interval is the return at interval, *t*. Panel B shows results for 15-min predictive regressions for EUA Futures contracts on the ECX. $OIB€_{t-1}$ is given as the Euro value of buyer initiated trades less Euro value of seller initiated trades, then divided by the total Euro value of trades over the 15-minute interval, *t-1*. The $Ret_t$, computed for every 15-minute interval, using the last trade at every interval, is the return at interval, *t*. The following regression is thus estimated:

$$Ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \varepsilon_t$$

The data used is for Phase II of the EU-ETS, and spans 2nd January 2008-29th April 2011. The data includes December maturity EUA futures contracts traded during the period.

**Panel A**

| **Dependent Variable: $Ret_t$** | | | | |
|---|---|---|---|---|
| Whole Sample (2008-2011) | **Coefficient** | **t-Statistic** | **Probability** | |
| Intercept | $3.47*10^{-06}$ | 0.13 | 0.90 | |
| $OIBQ_{t-1}$ | $1.81*10^{-04}$ | 1.46 | 0.14 | |
| R-squared | | | | $3.60*10^{-05}$ |
| Phase II, Year I | | | | |
| Intercept | $-5.09*10^{-05}$ | -0.84 | 0.40 | |
| $OIBQ_{t-1}$ | $3.25*10^{-04}$ | 1.77 | 0.08 | |
| R-squared | | | | $2.53*10^{-04}$ |
| Phase II, Year II | | | | |
| Intercept | $-1.23*10^{-05}$ | -0.19 | 0.85 | |
| $OIBQ_{t-1}$ | $3.56*10^{-06}$ | 1.00 | 0.32 | |
| R-squared | | | | $2.44*10^{-04}$ |
| Phase II, Year III | | | | |
| Intercept | $2.69*10^{-05}$ | 1.19 | 0.23 | |
| $OIBQ_{t-1}$ | $3.68*10^{-04}$ | 2.32 | 0.02 | |
| R-squared | | | | $2.22*10^{-04}$ |
| Phase II, Year IV | | | | |
| Intercept | $7.54*10^{-05}$ | 2.08 | 0.04 | |
| $OIBQ_{t-1}$ | $4.41*10^{-04}$ | 2.10 | 0.03 | |
| R-squared | | | | $5.40*10^{-05}$ |

**Panel B**

| | Dependent Variable: $\boldsymbol{Ret_t}$ | | | |
|---|---|---|---|---|
| Whole Sample (2008-2011) | **Coefficient** | **t-Statistic** | **Probability** | |
| Intercept | $-1.74*10^{-06}$ | -0.07 | 0.95 | |
| $OIB€_{t-1}$ | $5.90*10^{-05}$ | 0.46 | 0.65 | |
| R-squared | | | | $4.00*10^{-06}$ |
| Phase II, Year I | | | | |
| Intercept | $-8.28*10^{-05}$ | -2.34 | 0.02 | |
| $OIB€_{t-1}$ | $5.82*10^{-06}$ | 2.07 | 0.04 | |
| R-squared | | | | $2.29*10^{-04}$ |
| Phase II, Year II | | | | |
| Intercept | $-8.39*10^{-06}$ | -0.14 | 0.89 | |
| $OIB€_{t-1}$ | $5.47*10^{-04}$ | 1.84 | 0.07 | |
| R-squared | | | | $1.83*10^{-04}$ |
| Phase II, Year III | | | | |
| Intercept | $1.96*10^{-05}$ | 0.88 | 0.38 | |
| $OIB€_{t-1}$ | $1.82*10^{-04}$ | 1.36 | 0.18 | |
| R-squared | | | | $8.70*10^{-05}$ |
| Phase II, Year IV | | | | |
| Intercept | $-1.67*10^{-05}$ | -0.26 | 0.79 | |
| $OIB€_{t-1}$ | $4.36*10^{-04}$ | 1.80 | 0.07 | |
| R-squared | | | | $8.68*10^{-05}$ |

**Table 4: Distribution of liquid and illiquid days on the ECX (2008-2011)**

The table shows distribution of liquid and illiquid days on the ECX. The daily relative spread, measure of liquidity is computed using December maturity EUA futures contracts. The relative spread is defined as the best traded bid minus the best traded ask price scaled by the average of the best traded bid and ask prices over 15-minute intervals, then averaged for each trading day. For every day when the daily relative spread is at least one standard deviation above the mean relative spread for the surrounding period over (-30, +30), we define the day as illiquid and when it is not, liquid. The data is for Phase II of the EU-ETS, and spans 2[nd] January 2008-29[th] April 2011. The data includes December maturity EUA futures contracts traded during the period

| | | Relative Spread on liquid days | Relative Spread on illiquid days |
|---|---|---|---|
| Phase II, Year I | Mean | $4.31*10^{-03}$ | $4.37*10^{-03}$ |
| | Median | $3.74*10^{-03}$ | $4.45*10^{-03}$ |
| | Std. Dev. | $2.22*10^{-03}$ | $8.52*10^{-04}$ |
| | Sample days, T | 223 | 33 |
| Phase II, Year II | Mean | $4.17*10^{-03}$ | $4.98*10^{-03}$ |
| | Median | $3.61*10^{-03}$ | $4.51*10^{-03}$ |
| | Std. Dev. | $2.36*10^{-03}$ | $2.08*10^{-03}$ |
| | Sample days, T | 225 | 29 |
| Phase II, Year III | Mean | $2.29*10^{-03}$ | $2.22*10^{-03}$ |
| | Median | $2.09*10^{-03}$ | $2.10*10^{-03}$ |
| | Std. Dev. | $8.24*10^{-04}$ | $5.49*10^{-04}$ |
| | Sample days, T | 230 | 25 |
| Phase II, Year IV | Mean | $1.94*10^{-03}$ | $1.65*10^{-03}$ |
| | Median | $1.59*10^{-03}$ | $1.42*10^{-03}$ |
| | Std. Dev. | $9.70*10^{-04}$ | $5.24*10^{-04}$ |
| | Sample days, T | 75 | 7 |

**Table 5: Predictive regressions of 15-minute returns on lagged $OIB€_t$ and lagged $OIB€_t$ interacted with an illiquidity dummy**

The table shows results for 15-min predictive regressions for EUA Futures contracts on the ECX. $OIB€_{t-1}$ is given as the Euro value of buyer initiated trades less Euro value of seller initiated trades, then divided by the total Euro value of trades over the 15-minute interval, *t-1*. The $Ret_t$, is computed for every 15-minute interval using the last trade at every interval is the return at interval, *t*. The dummy ILD is 1.0 for every day when the daily relative spread is at least one standard deviation above the mean relative spread for the surrounding period over (-30, +30) and 0 otherwise. The following regression is thus estimated:

$$Ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \beta_1 OrderImbalance_{t-1} * ILD_t + \varepsilon_t$$

The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The data includes December maturity EUA futures contracts traded during the period.

| | | Coefficient | t-Statistic | Probability | |
|---|---|---|---|---|---|
| Phase II, Year I | Intercept | $-9.05*10^{-06}$ | -0.14 | 0.89 | |
| t= 13,869 | $OIB€_{t-1}$*ILD | $3.34*10^{-03}$ | 4.05 | 0.00 | |
| | $OIB€_{t-1}$ | $1.62*10^{-04}$ | 0.64 | 0.52 | |
| | R-squared | | | | $3.80*10^{-03}$ |
| Phase II, Year II | Intercept | $-7.49*10^{-06}$ | -0.12 | 0.91 | |
| t= 18,296 | $OIB€_{t-1}$*ILD | $3.31*10^{-03}$ | 3.80 | 0.00 | |
| | $OIB€_{t-1}$ | $3.08*10^{-04}$ | 0.98 | 0.33 | |
| | R-squared | | | | $1.39*10^{-03}$ |
| Phase II, Year III | Intercept | $1.98*10^{-05}$ | 0.89 | 0.37 | |
| t= 20,984 | $OIB€_{t-1}$*ILD | $4.38*10^{-04}$ | 1.12 | 0.26 | |
| | $OIB€_{t-1}$ | $1.23*10^{-04}$ | 0.86 | 0.39 | |
| | R-squared | | | | $1.45*10^{-04}$ |
| Phase II, Year IV | Intercept | $8.15*10^{-05}$ | 2.31 | 0.02 | |
| t= 4,840 | $OIB€_{t-1}$*ILD | $2.07*10^{-03}$ | 2.23 | 0.03 | |
| | $OIB€_{t-1}$ | $1.91*10^{-04}$ | 0.64 | 0.52 | |
| | R-squared | | | | $4.51*10^{-04}$ |

**Table 6: Liquidity and market efficiency dynamics: Granger causality**

The Table shows results for the Granger (1969) causality analysis. A model of the following form is estimated:

$$\varphi_t = \alpha_0 + \alpha_1\varphi_{t-1} + \cdots + \alpha_l\varphi_{l-1} + \beta_1\delta_{t-1} + \cdots + \beta_l\delta_{l-1} + \epsilon_t$$
$$\delta_t = \alpha_0 + \alpha_1\delta_{t-1} + \cdots + \alpha_l\delta_{l-1} + \beta_1\varphi_{t-1} + \cdots + \beta_l\varphi_{l-1} + \mu_t$$

is estimated for the likely pairings of ($\delta$, $\varphi$) series in the set. $\delta$ denotes the daily mean of the 15-minute Euro order imbalance measure, $\varphi$ is the daily relative spread liquidity proxy and $l$ is the lag length. F-statistics in the table are the Wald statistics for the joint hypothesis:

$$\beta_1 = \beta_2 = \cdots = \beta_l = 0$$

for each of the bivariate equations. The null tested is that $\delta$ does not Granger-cause $\varphi$ in the top equation and that $\varphi$ does not Granger-cause $\delta$ in the bottom equation. Panel A shows contract-specific (year/period-dependent) results, while Panel B shows contract-specific results with no breaks. The *p-values* are shown in parenthesis. The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The variables are computed from December maturity EUA futures contracts traded during the period.

**Panel A. Daily contract-specific (year-dependent) liquidity and market efficiency dynamics**

| | | Order Imbalance does not cause Relative Spread | Relative Spread does not cause Order Imbalance |
|---|---|---|---|
| **Phase II, Year I** | Dec-2008 Futures | 1.48 (0.12) | 2.40 (0.00) |
| | Dec-2009 Futures | 0.97 (0.49) | 2.93 (0.00) |
| | Dec-2010 Futures | 0.78 (0.54) | 2.04 (0.09) |
| **Phase II, Year II** | Dec-2009 Futures | 1.98 (0.02) | 2.63 (0.00) |
| | Dec-2010 Futures | 5.24 (0.00) | 2.77 (0.00) |
| | Dec-2011 Futures | 1.56 (0.16) | 2.88 (0.01) |
| **Phase II, Year III** | Dec-2010 Futures | 1.06 (0.37) | 2.44 (0.07) |
| | Dec-2011 Futures | 1.70 (0.05) | 1.71 (0.04) |
| | Dec-2012 Futures | 4.69 (0.00) | 2.54 (0.03) |
| **Phase II, Year IV** | Dec-2011 Futures | 0.19 (1.00) | 0.14 (1.00) |
| | Dec-2012 Futures | 0.30 (0.99) | 0.98 (0.50) |

**Panel B. Daily contract-specific liquidity and market efficiency dynamics**

| | Order Imbalance does not cause Relative Spread | Relative Spread does not cause Order Imbalance |
|---|---|---|
| Dec-2008 Futures | 1.48 (0.12) | 2.40 (0.00) |
| Dec-2009 Futures | 1.50 (0.10) | 4.76 (0.00) |
| Dec-2010 Futures | 1.68 (0.06) | 4.45 (0.00) |
| Dec-2011 Futures | 0.65 (0.63) | 3.39 (0.01) |
| Dec-2012 Futures | 2.83 (0.00) | 2.26 (0.01) |

**Table 7: Daily variance ratios**

This Table shows contract-specific ratio of 15-minute return variance to open-to-close return variance, scaled by the number of 15-minute intervals in a trading day on the ECX. The final row in the table is the trading value-weighted aggregate variance ratio per period. Data is as defined as Table 1. ***, ** and * denote values which are significantly different from the previous compliance year's value at 1%, 5% and 10% levels respectively. The data used is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The variables are computed from December maturity EUA futures contracts traded during the period.

| | **Year I** | **Year II** | **Year III** | **Year IV** |
|---|---|---|---|---|
| Dec-2008 | 2.18 | | | |
| Dec-2009 | 9.47 | 3.46*** | | |
| Dec-2010 | 16.61 | 3.13*** | 1.08*** | |
| Dec-2011 | | 5.68 | 1.96*** | 1.43* |
| Dec-2012 | | | 2.44 | 1.37 ** |
| Value weighted overall | **3.74** | **3.22** | **1.39** | **1.42** |

**Figure 1: Market Efficiency measured by 15-minute return predictions with 15-minute lagged Euro Order Imbalance**

The figure shows the plot of predictive $R^2$s and corresponding t-statistics obtained from monthly regressions using 15-min predictive regressions for EUA Futures contracts on the ECX. *OrderImbalance€$_{t-1}$* is given as the Euro value of buyer initiated trades less Euro value of seller initiated trades, then divided by the total Euro value of trades over the 15-minute interval, *t-1*. The *Ret$_t$* computed for every 15-minute interval using the last trade at every interval is the return at interval, *t*. The following regression is thus estimated:

$$Ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \varepsilon_t$$

The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The data includes December maturity EUA futures contracts traded during the period. Note that none of the $R^2$ values is actually zero.

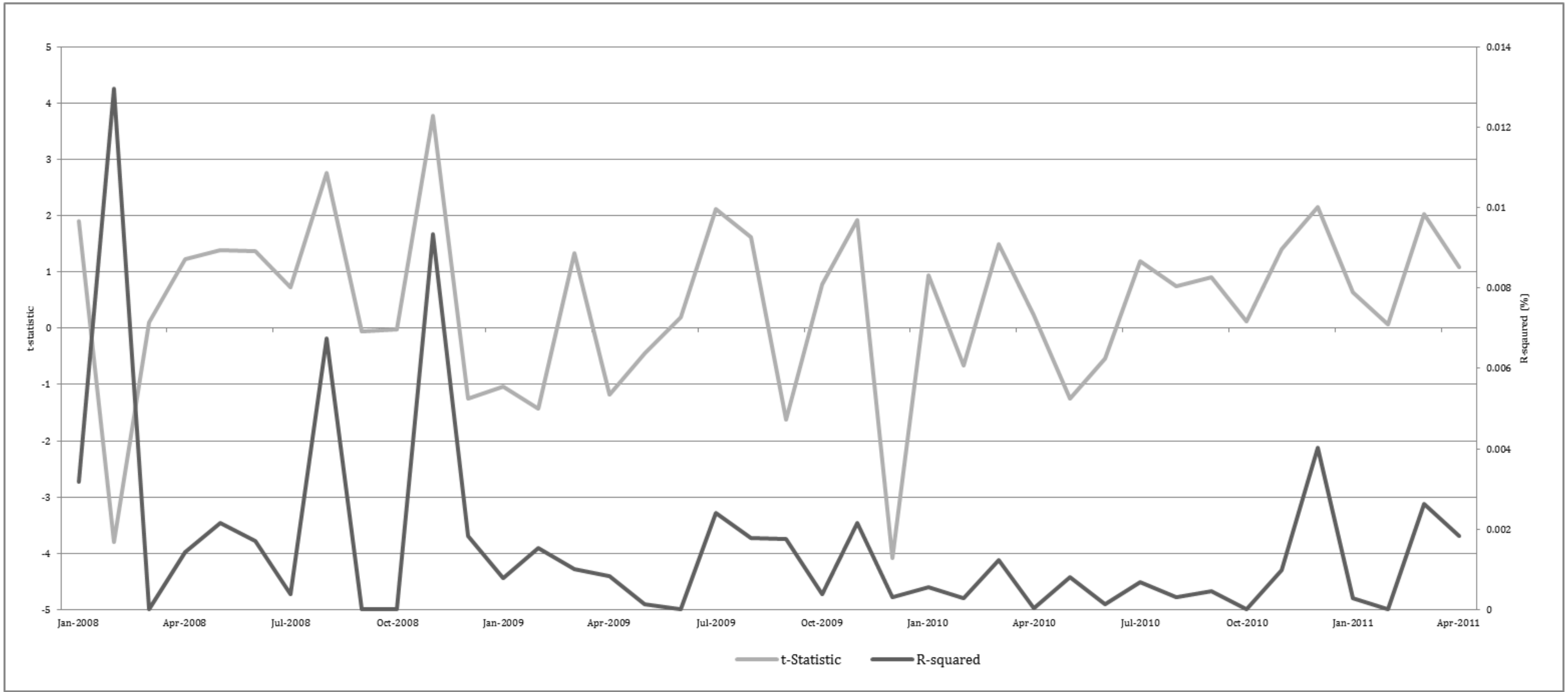


**Figure 2: Daily Average Traded spread and Relative spread for ECX, 2008-2012**

The Figure shows the plot of daily average of liquidity measures: traded spread and relative spread. Traded spread (TSPR) is the difference of best traded bid and ask prices for every 15-minute period; relative spread (RSPR) is defined as the best traded bid minus the best traded ask price, then divided by the average of the best traded bid and best ask over the same intervals. The spreads are averaged across the day for each instrument and cross-sectionally across all instruments. The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The data includes December maturity EUA futures contracts traded during the period.

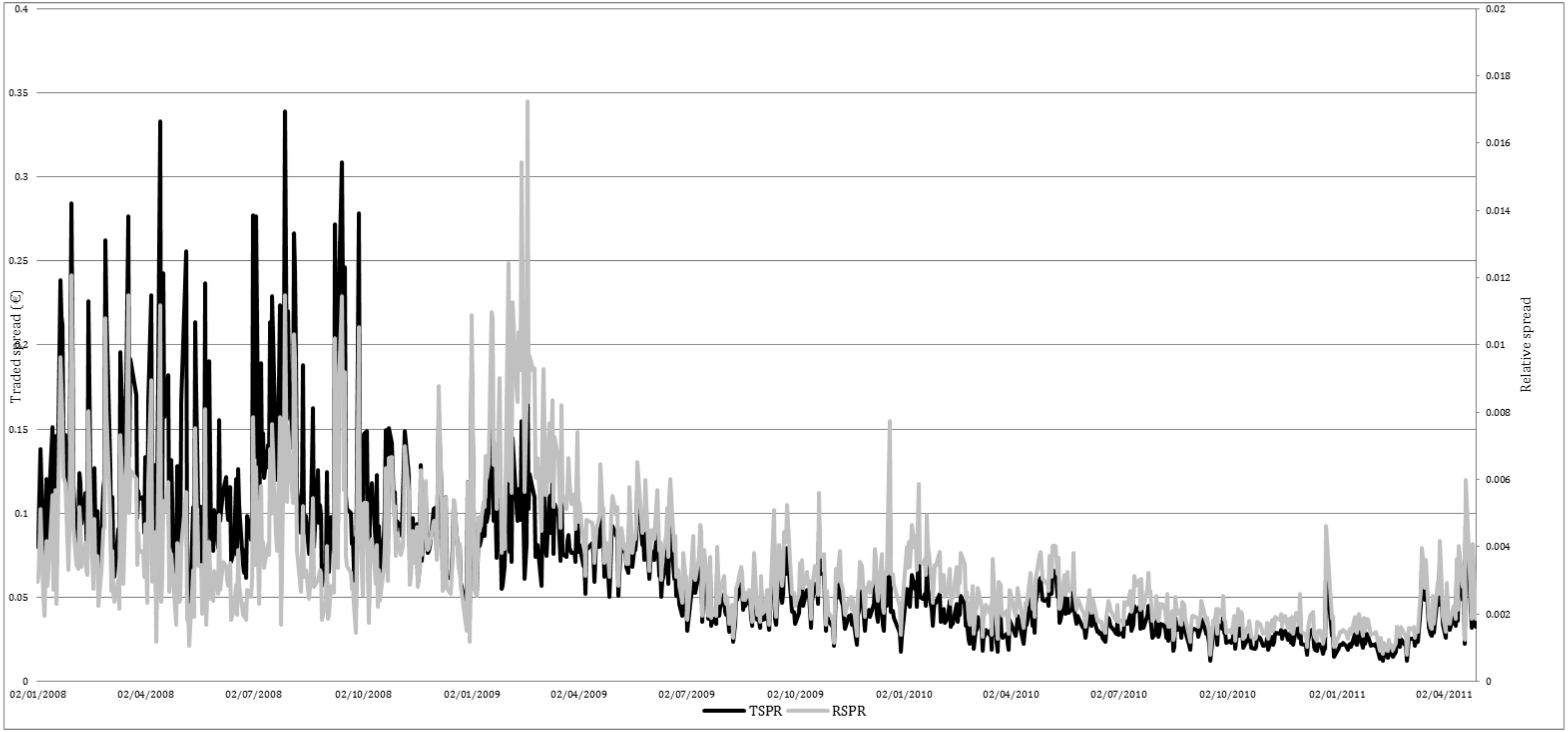


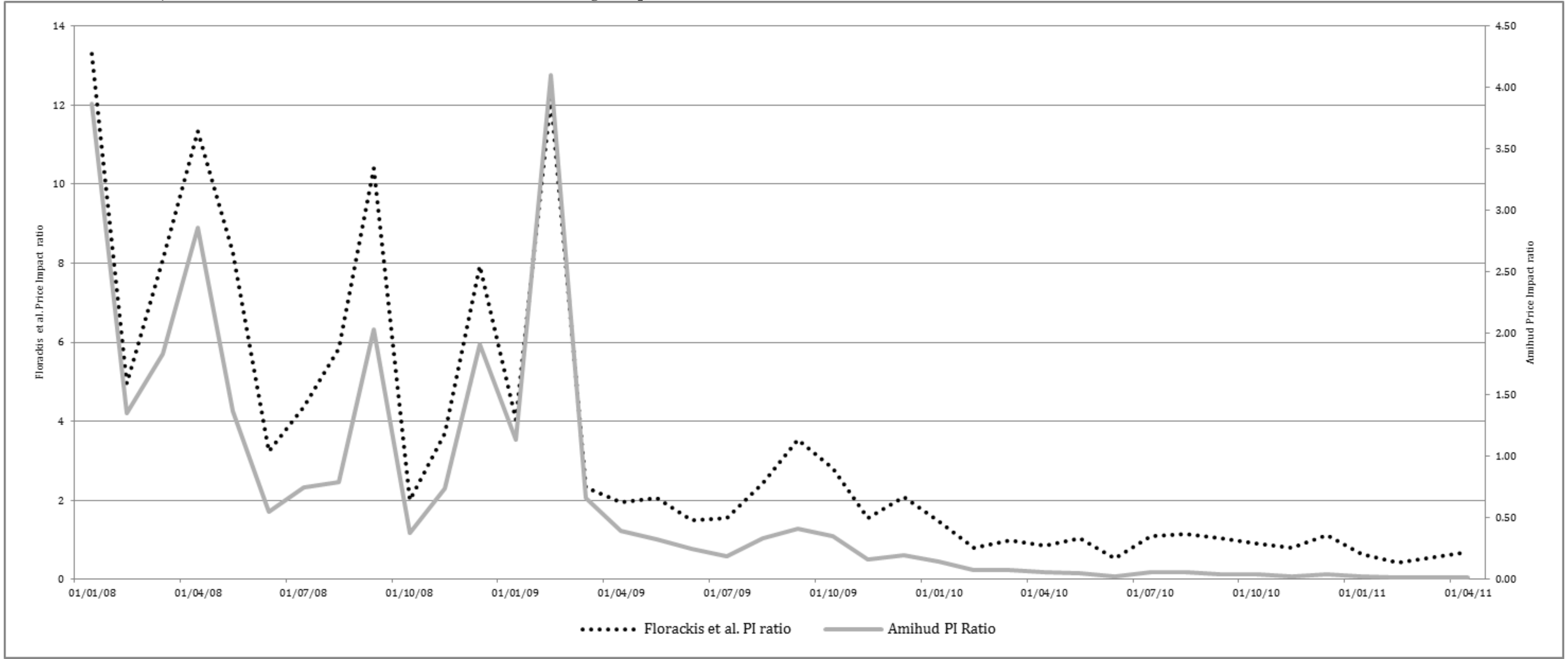
**Figure 3: Monthly Illiquidity/Price Impact Ratios**

The figure shows the plot of monthly computed illiquidity ratios of Amihud (2002) and Florackis et al. (2011), respectively given below as (i) and (ii):

$$Amihud_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{V_{itd}} \quad \text{(i)}$$

$$Florackis_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}} \quad \text{(ii)},$$

where $R_{itd}$, $V_{itd}$ and $TR_{itd}$ are the return, euro volume and turnover ratio of EUA futures contract *i* on day *d* at month *t* and $D_{it}$ is the number of trading days in month *t* for EUA futures *i*. The ratios are averaged cross-sectionally across all instruments. The data is for Phase II of the EU-ETS, and spans 2nd January, 2008-29th April, 2011. The data includes December maturity EUA futures contracts traded on the ECX during the period.



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