Price Impact of Block Trades: New Evidence from downstairs trading on the World's Largest Carbon Exchange

Gbenga Ibikunle
Environmental and Energy Finance Group
Norwich Business School
University of East Anglia
Norwich, Norfolk, NR4 7TJ
G.Ibikunle@uea.ac.uk
Tel: +44 (0) 1603 591040

Andros Gregoriou
Corresponding author
Bournemouth Business School
Bournemouth, BH8 8EB
andros.gregoriou@googlemail.com
Tel: +44 (0) 1202 968701

Naresh R. Pandit
Norwich Business School
University of East Anglia
Norwich, Norfolk, NR4 7TJ
N.Pandit@uea.ac.uk
Tel: +44 (0) 1603 592886

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Abstract

We examine the determinants of the price impact of block trades on the European Climate Exchange (ECX) using data from Phase II of the European Union Emissions Trading Scheme (EU-ETS), over the time period 2008-2011. Block trading on the ECX induces less price impact than in equity markets and a large proportion of the effects contradict the previous literature. Wider bid-ask spreads and volatility are characterised by smaller price impact. Larger levels of price impact are more likely to occur during the middle of the trading day than during the first or the final hours. Purchase block trades induce relatively smaller price impact on a price run-up while sell block trades exhibit larger price impact on a price run-up.

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

Keywords: Block trades; Price impact; European Climate Exchange; European Union Emissions Trading Scheme (EU-ETS); Determinants; Liquidity.

1. Introduction

Kraus and Stoll (1972) was the first study to discover that block trades possess price impact. They present several arguments as the cause of this phenomenon: Short-run liquidity effects occurring as a result of price compromise suffered because counterparties are not readily available; price compromise when instruments are not perfect substitutes for each other leading to inefficient trading and hence price impact; and the idea that price concessions are granted in order to execute market order underscores *desperation* to make a trade happen. These factors convey information to markets about the potential value of the order to the counter-parties and hence the order becomes information driving leading to price impact. Holthausen et al. (1990) find evidence of premium payment or price concession for execution of buyer initiated block trades. They hold that premium is paid by buyers prior to a block trade; the premium is incorporated permanently in the price consequently, while no evidence of premium payment is found for block sales. Kraus and Stoll (1972) find that price impact is higher for block purchases than sales because concession or an implicit commission paid are usually higher for purchases than sales suggesting that there is indeed premium paid on block sales. A major contribution from their pioneering work is to establish a positive relationship between block trades and price impact. Chan and Lakonishok (1993) among others provide supporting evidence for this (see for example Barclay and Warner, 1993; Holthausen et al., 1990); they also find a relationship between market capitalisation and price impact (see also Chan and Lakonishok, 1995).

Holthausen et al. (1987) also investigate price impacts due to block trades, and discovers that larger trades induce larger price impact than smaller trades. Barclay and Warner (1993), Chakravarty (2001) and Alzahrani et al. (2010) also provide evidence that order size and subsequent execution potentially results in corresponding trade price impact. In relation to temporary price impact, The first study to witness asymmetry in block trades price effects is Gemmill (1996) on the London Stock Exchange, with significant differences in the magnitude of price impact being reported. Their study reports permanent price impacts due to block trades on the London Stock Exchange; and also find permanent impact equivalent to 33% of the bid-ask spread for block trades that are purchased and 17% for block trades that are sold.

Consistent with Gemmill (1996), most of the studies conducted on price impact of buyer and seller initiated block trades report price impact asymmetry between the two groups (see among others Conrad et al., 2001; Keim and Madhavan, 1996; Chiyachantana et al., 2004; Holthausen et al., 1990). They generally submit that prices appreciate after purchase block trades are executed and depreciate on sales. The depreciation that occurs after sell trades are executed suffers reversion but purchase block trade induced appreciations remains. Chan and Lakonishok (1993) argue the reason for this is that block sales have a higher likelihood of involving a broker (acting as an intermediary) than a block purchase. The temporary impact from sell trades is therefore a reflection of price concession as compensation for the intermediary role played by the broker.

As evidenced from the studies reviewed above, price impact of block trades have been extensively researched for customary markets, however no study to our knowledge has been undertaken for block trade price impacts in permit markets. We therefore attempt an analysis of determinants of price impact in the EU-ETS using data from the scheme's largest platform, the ECX. This study is informed by the increasingly large number of block trades in the EU-ETS. In 2005, approximately 80% of EU-ETS trades occurred OTC, most of these trades meet ECX's definition of block trades. The volume traded OTC progressively decreased to average approximately 70% of total transactions value over the entire course of Phase I. By January 2010, the proportion of exchange based trades in the scheme had reached 50% according to World Bank estimates (see Kossoy and Ambrosi, 2010). This rebalancing is informed by the desire of participants to avoid counterparty risks, an issue that has taken on greater significance in derivative markets as a whole.

Our results show intriguing patterns that largely contradict earlier studies from customary markets. For permanent and temporary effects, we find several instances of price impact asymmetry for block purchases and sales. Contrary to earlier studies, wider spreads lead to smaller price impacts. We attribute our findings to the fact that block trades executed after a price run up induce smaller price impact, as suggested by Saar (2001) and as we find in our sample. The implication here is that liquidity concerns in the EU-ETS play a less prominent role in emissions permits pricing than in customary markets. This is underscored by Ibikunle et al. (2011b) pointing out that small amounts of trading lead to larger proportions of price discovery in the EU-ETS. Short run improvements in liquidity, though an important factor in market efficiency (see Chordia et al., 2008), do not detract from block trade price impact on the world's largest carbon platform. Our findings have implications for compliance traders and policy makers alike. It is important that in designing future phases of the EU-ETS, this and other aspects of our results should be considered.

The remainder of this paper is structured as follows. In section 2 we provide a discussion of the EU-ETS mechanism, the set up of the ECX and review related literature based on permit trading. Section 3 outlines the data and econometric methodology used to analyze our findings. Section 4 discusses the empirical analysis Section 5 concludes.

2. Background to study

2.1. Institutional set-up

The EU-ETS is the largest cap and trade scheme in the world and currently covers about 11,500 installations within the European Union (EU). The initial aim is to fulfil the EU's obligation under the Kyoto protocol. Although the terminal year for the Protocol is 2012, the EU has already agreed to extend the scheme into a third phase. Since its inception in 2005, the scheme has steadily improved in terms of market structure and functioning (see Ibikunle et al., 2011a). The scheme runs as a classic cap and trade with emission permits initially 100% grandfathered in 2005. Subsequently, certain percentages have been allocated for auctioning subject to industrial sectors. In Phase III, auctioning is expected to be the main means of initial allocation (see Daskalakis et al., 2011; Ibikunle et al., 2011a) for an overview of the three phases). In the EU-ETS, the emission permit is known as European Union Allowance (EUA). EUAs are electronically produced only as streams of record on national registries of individual EU countries. Each EUA has a unique code to ensure transparency and forestall fraud. The national registries are all connected to a common central point called the Community Independent Transaction Log (CITL). For every phase of the scheme, member countries submit to the European Commission (EC), a National Allocation Plan (NAP) detailing volume of EUAs to be generated and planned caps for individual installations based in those countries. Every April, the installations submit EUAs equivalent to their verified emissions for the preceding compliance year. Project based permits are also allowed for submission, there are however specified limits to quantity allowed in lieu of EUAs[1] (see Daskalakis et al., 2011 for a financial perspective of the EU-ETS).

[1] 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).

We are not aware of any study on price impact of block trading in the EU-ETS; however, Mizrach and Otsubo (2011), in a general microstructure analysis of the EU-ETS, examine price impact of regular EUA and CER trades. No distinctions were made for the trades based on size or trade sign. They also fail to distinguish between upstairs and downstairs markets trades, which we clearly define in this study.

Benz and Klar (2008), Frino et al. (2010) and Ibikunle et al. (2011a) examine liquidity, price discovery and transactions costs in the EU-ETS. Their results are not directly relevant to this study but do provide an insight into vital microstructure properties of the EU-ETS. Some other studies have examined off-platform variables that can explain price formation in the EU-ETS: Christiansen and Arvanitakis (2004), Mansanet-Bataller et al (2007) and Alberola et al. (2008) all using daily data, investigate the effects of energy fundamentals on daily EUA returns during Phase I of the EU-ETS. Mansanet-Bataller and Pardo (2007) and Miclăuş et al. (2008) employ used event study methodology in investigating the effect of NAP and emissions verification announcements on EUA prices.

2.2. The European Climate Exchange (ECX) and Trading Rules

The ECX, a member of the Climate Exchange Plc group of companies, is the largest carbon exchange in the world by volume and value. Trading rules and procedures on the exchange follow general financial markets practice. Trading commences at 07:00 and lasts till 17:00 hours UK local time. There is a pre-trading period of 15 minutes from 06:45 hours to allow members place orders in preparation for trading start, however almost no orders are executed during this period. The settlement period, which runs from 16:50:00 to 16:59:59 hours UK time, is the third stage of the trading day and is used for determination of the settlement price. The fourth stage of the trading is the after-hours period reserved only for reporting Exchange for Physical/Swaps (EFP/EFS) trades. Ibikunle et al. (2011b) extensively study the contribution of trades reported during this period to price discovery. These trades can be regarded as a form of 'upstairs' trading in the context of the ECX and hence will not be examined in this paper following Frino et al. (2007) and Alzahrani et al. (2010).

Trading occurs both directly on the platform and bilaterally off the platform, then registered on the platform for on-screen registration. By virtue of this, the exchange maintains three trading mechanisms: trades occur on the ICE platform; by EFP/EFS trades; or through the Block Trade Mechanism. A mobile version of the ETS has been made available through smart phone application called mobile ICE. Although, the large values of trades occur off the platform as OTC trades, higher number of trades is executed on the platform. Trading on the ICE platform is open only to ICE Futures Europe members with Emissions trading privilege and have also previously listed a minimum of one trading personnel with the ECX. This person is known to the exchange as a *Responsible Individual (RI)*[2]. The RI is the trader known to the exchange and must conform to exchange set rules as well as attain a level of trading competence before admission. Non-members[3] of the exchange can however be involved in order routing by using the ICE Platform's front end application called WebICE and through other similar applications provided by Independent Software Vendors (ISVs) accredited by the exchange.

Orders are submitted by participants by entering it into the ETS, the trades executed as a consequence of orders are deemed to be anonymous by exchange rules. The executed trades

[2] For institutional traders with General and Trade Participant memberships, there is no limit to the number RIs registered with the exchange, however Individual Participant members must register only one RI.

[3] These non-members must be clients of members who have already gained their consent to use the application for order routing.

go via the trade registration system (TRS) for account allocation. Price transparency is ensured by the availability of real-time prices made available on ICE Platform screens and vendor sources. These vendors include Bloomberg, CQG, E-Signal/FutureSource, Reuters, IDC and ICE Live. The exchange also sets reasonability limits for purchase and sale orders. A purchase (sale) order above (below) the limit is rejected. Sale (purchase) order above (below) the limit is accepted without being executed except the market shifts to alter the reasonability limits and hence places it within the limit. The exchange also maintains a 'no cancellation range' within which trades reported as mistakes may not be cancelled. This rule enhances market confidence and reduces noise trades. Clearing is provided by Ice Clear Europe which charges transaction fees (in addition to annual subscription fees for various participant categories) on behalf of the exchange. Transaction fees are not placed on the exercise of an option or on physical delivery of futures contracts. Minimum tick has been held constant at €0.01 per tonne of CO_2 since 27th March 2007 from its previous €0.05 at commencement in 2005.

Trading in contracts cease on the last trading Monday of the expiry month and the underlyings are thus eligible for delivery within 72 hours of trading cessation. Since Ice Clear Europe acts as the clearing agent, physical delivery of contracts' underlyings are effected through them. By nature of the EU-ETS, Clearing members are required to own a Person Holding Account (PHA) with a country registry within the EU-ETS. The transfer of EUAs and CERs are made from the PHA account of the selling Clearing member onto the PHA of Ice Clear Europe, then from theirs to the buying party's PHA. All 27 EU registries are currently eligible for physical deliveries under this arrangement. All registries operate on a continuous basis and are connected to the CITL. Transfer of permit rights are done online real time hence CITL usually confirms receipt of transfer requests within 60 seconds. However, CITL must conduct further checks to confirm the authenticity of the request and validity of the permits being traded and this can take up to 24 hours. The need for these robust checks has assumed a larger dimension since January of 2011 when more than €30 million worth of permits were stolen from registries across the EU. The ECX has a defined minimum lot quantity for block trades. Each block trade must be a minimum of 50 lots/contracts (50,000 EUAs or CERs).

3. Data and Methodology

3.1. Data

We obtain two sets of data; the first is high frequency data from the ICE Futures Europe detailing intraday transactions to the nearest second. The dataset covers from the start of Phase II EU-ETS (1st January, 2008) until the 9th May, 2011. The use of the dataset ensures that this study provides the longest time period analysis of Phase II EU-ETS trading till date. The second dataset contains end of day (EOD) variables, it is also from ICE Futures Europe and covers the same time span and provides daily computations of our intraday data.

We select only the December expiry contracts because they are the only ones for which official exchange index data is available[4]. This selection is also based on volume considerations. All trades executed within the initial pre-open period and during the after-hours market are excluded. All other trades executed off market and in upstairs market which include mainly EFP/EFS trades are also excluded. These steps are taken to provide a basis for comparing our results with previous studies, also to ensure robustness and consistency. The final dataset consists of a total of 961,131 trades over the period. We follow ECX's definition

[4] The selected December maturity contracts are for 2008, 2009, 2010, 2011, 2012, and 2013.

of block trade as any trade with a minimum lot size of 50 contracts (50,000 EUAs). This definition yields a sample size of 16,715 block trades (excluding EFP/EFS trades). This is about 1.74% of the total number of trades in the cleaned dataset. The absolute quantity is comparable to the 16,951 NYSE downstairs block trades analysed by Madhavan and Cheng (1997) for 30 Dow Jones stocks and larger than the sample of 5987 from the London Stock Exchange investigated by Gemmill (1996). We adopt the trade signs allocated to each trade by ECX in our data set[5].

3.2. Methodology

We begin our inquiry by computing three types of price impacts generally recognised in the literature. These are the total, permanent and price impact measures. Microstructure literature acknowledges permanent price impacts as those occasioned by trades with private information and temporary price impacts as those resulting from noisiness in trading leading to reversal of price (see Glosten and Harris, 1988; Chan and Lakonishok, 1995; Easley et al., 2002). We follow Holthausen et al. (1990), Gemmill (1996), Frino et al. (2007) and Alzahrani et al. (2010) in using the five-trade standard to compute the price impact measures. We ensure comparability by calculating all three measures as percentage returns according to equations (1), (2) and (3):

$$\text{Total Impact} = \frac{(P_t - P_{t-5})}{P_{t-5}} \quad (1)$$

$$\text{Temporary Impact} = \frac{(P_{t+5} - P_t)}{P_t} \quad (2)$$

[5] We also use the tick rule (see Lee and Ready, 1991) with very similar trade sign classification results.

$$\text{Permanent Impact} = \frac{(P_{t+5} - P_{t-5})}{P_{t-5}} \quad (3)$$

The total price impact is the percentage return from the block trade to five trades before the block trade. The permanent price impact is the percentage return from five trades before the block transaction to five trades after the block transaction. Finally, the temporary price impact is measured as the percentage return from the block transaction to five trades after the execution of the trade. We use transaction prices in the absence of direct quotes. We adopt the model of Frino *et al.* (2007), thereafter employed by Alzahrani *et al.* (2010) in examining some likely determinants of block trade impact on the ECX. Accordingly, we estimate the following time series regression with EUA contracts-specific variables:

$$\mathrm{Pr}\,ice\,\mathrm{Im}\,pact = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \varepsilon$$
(4),

where price impact corresponds to one of three price impact measures: total price impact, permanent price impact and temporary price impact. The explanatory variables are computed as follows:

Size represents the natural logarithm of volume of contracts contained in the block transaction. Based on the assumption that trade size corresponds to information content (see Kraus and Stoll, 1972; Easley and O'Hara, 1987; Chan and Lakonishok, 1993 among others), we adopt trade size as a proxy for information content of the block trade. When investors have private information on an instrument, they act based on the new belief developed as a result. Hence, they place a sell order if the belief is that the instrument is overpriced or purchase if the instrument is underpriced (see also Madhavan et al., 1997).

Volatility represents the standard deviation of trade to trade on the trading day prior to the block trade[6]. Volatility is representative of intraday fluctuation in trading prices; it shows the pattern of trading belief over the course of a trading session, and can therefore be regarded as an implicit proxy of adverse selection costs of trading. The higher the level of volatility of an instrument, the greater the risk associated with it, thus leading to wider spreads as compensation for trading (see Sarr and Lybek, 2002). The onset of larger spreads on account of volatility suggests that volatility will lead to price impacts. It is expected that volatility of the futures contracts will be positively related to price impact as a result (Domowitz et al., 2001).

Turnover represents the natural logarithm of total Euro value of contracts traded on the trading day prior to the block divided by the prevailing Euro volume of open interest. Turnover has been regularly employed as a measure of trading activity and market liquidity (see among others Lakonishok and Lev, 1987; Hu, 1997; Frino et al., 2007). Further, open interest has been established as a good measure of market liquidity in futures markets. Using open interest as proxy for market depth (liquidity) follows after Bessembinder and Seguin (1993; 1992) and Fung and Patterson (1999). Open interest is a reflection of order flow of trades and readiness of traders to risk their funds and therefore has similar levels of correlation with volatility that spreads have. Price impact is expected to be lower with improvements in liquidity; hence we anticipate a negative relationship with price impact.

Momentum is computed as the lagged cumulative daily return for each contract on five trading days prior to the trading day of the block trade. This expresses the trading trend for

[6] We also use standard deviation of trade to trade in line with Alzahrani et al. (2010). The results are quantitatively similar and are available from the authors upon request.

the specific instrument. Higher returns will indicate a purchasing trend and lower returns, a selling trend. Saar (2001) submits that price performance history of an instrument is related to its expected price impact asymmetry. Specifically, block trades that are executed on the back of decreasing price performance will manifest higher positive asymmetry, and block trades executed after a strong run of price appreciation should exhibit less impact or possibly negative asymmetry. Since the transitioning to Phase II in the EU-ETS, the market has experienced stronger liquidity and market efficiency as earlier stated and hence has largely been on a run up in terms of price performance. Based on this, we anticipate momentum will have predominantly negative price impact coefficients.

BAS is a second measure of liquidity in the model. Relative bid-ask spread is the corresponding relative bid-ask spread just before the block transaction is executed. High price impact is expected to be characterised by wider spreads than lower price impact. We follow the standard market microstructure literature by compute relative bid-ask spread as:

$$\text{Relative Spread} = \frac{(P_a - P_b)}{(P_a - P_b)/2} \tag{5}$$

Marketreturn is a more robust measure that represents the contract-specific daily return on ECX EUA index for each contract. By adopting contract specific return we emulate Frino et al. (2007) in using a more refined measure of market return.

Time dummy variables are created to capture the time of day effects. Alzahrani et al. (2010) and Frino et al. (2007) report intraday differences in level of block trade asymmetry effects. For consistency and completeness, we introduce time of day dummy variables to test for these effects on block trades on the ECX. Analogous to previous studies, the trading day is split into three intervals. On the ECX, the normal trading day is from 07:00 hours to 17:00 hours UK local time. *TimeDum 1* takes the value of one if the block trade occurs between 07:00 and 08:00 hours and value 0 otherwise. *TimeDum 2* takes the value of one if the block trade occurs during the middle of the trading day (08:01-16:00 hours UK time) and 0 otherwise. The third interval of the day which is the final hour of trading day (16:01-17:00 hours) is not represented in the regression results because it is the reference group of block trades and takes the value of 0.

4. Empirical Results and Discussion

4.1. *Descriptive Statistics*

Panel A of Table 1 shows descriptive statistics based on the volume of trade classification. Of the 16,715 block trades in our final sample, 8356 are buyer initiated and 8359 seller initiated. Total volume of block trades to the total number of trades in the sample is 1.74%. In comparison, trading in a permit market like the ECX seems to be less dependent on institutional activity. This is however, only if we equate block trading activity to institutional activity. The nature of the EU-ETS is such that emissions are capped and traded in the upstream; hence trading in EU-ETS permits is dominated primarily by both installations trading for compliance purposes and other institutional investors such as Barclays Capital. The current situation is that most of these institutional activities are not exchange based, they occur mainly on OTC basis. While forming only a small portion of EUA trades on the ECX, they account for a far higher proportion of Euro volume of trades (see Mizrach and Otsubo, 2011; Ibikunle et al., 2011b).

0.869% of all the trades in the final sample are identified as buyer initiated block trades while a slightly higher percentage of 0.87% are seller initiated block trades. This trend while conforming to some previous studies (for example Frino et al. (2007)), contrasts with others (see for example Gregoriou (2008)). The average values of price impact for both classes of trades are -0.036% for purchases and 0.038% for sales. The direction of the impacts, while in contrast with Alzahrani et al. (2010), is the first suggestion of the existence of price impact asymmetry in the sample. Although, having a higher number of seller initiated block trades conform to a number of previous studies, the higher average level of price impact for block sales suggest that there should be a higher volume of purchase trades since less price impact occurs on purchase trades. This argument only holds if the price impact is positive for purchases and negative for sales as is usually the case in most studies of equity classes.

[INSERT TABLE 1 HERE]

Further descriptive characteristics are provided in Panel B of Table 1. This table shows description using trading activity and liquidity (relative bid-ask spread) measures. After removal of the high volume EFP/EFS trades from the on-screen block trades, we have a total of 16,715 block trades with a combined value of approximately €21 million. For all block trades, the average number of contracts per trade is more than 13 times the value for all trades combined. The average number of trades (transaction value) for block purchases is higher than sales at 80.21 (€1258.03) and 77.67 (€1207.4) respectively. This trend is consistent with previous studies. The average relative bid-ask spread value is 0.067% for purchases and 0.056% for sales. The average relative bid-ask spreads for *all trades* compare favourably with those of all block trades. In fact, with the exception of block purchases, the spread for all trades is higher than all classes in Panel B of Table 1. For more developed markets and traditional asset classes, the expectation would be to have reduced spreads for all trades and larger spreads for block trades since they are more likely to be influenced by private information rather than search for liquidity. A number of microstructure studies suggest that large sized trades are more likely to contain higher level of information than smaller ones (see Easley and O'Hara, 1987 for further details). Investors have however been known to fragment trades over a course of time to take advantage of private information rather than make an abnormally large trade in order to avoid revealing the privately held information before they can take advantage. Information content can however still be inferred by direction of trade over time (see Easley et al., 1996). To some extent, the results in Panel B of Table 1 showing block purchases with higher average number of contracts per trade seem to confirm this intuition. However, it is also noted that all trades that are approximately 11 times smaller average trade size than block trades has slightly higher average relative spread. A possible explanation is the noisy nature of price discovery during the trading day on the ECX. Noise in price discovery and information asymmetry on the ECX has been documented by Ibikunle et al.(2011b).

4.2. Regression Results and Discussion

Table 2 reports the estimation results of equation (4) for the whole block trades sample without the time of day dummy variables. Panel A shows the mean price impact of the three types of price asymmetry impacts employed as independent variables: temporary, permanent and total price impacts. All values are positive but none are significant at any conventional level (1%, 5%, and 10%). Results show higher levels of price impact for permanent effects than temporary effects at 0.001152 to 0.00098. Although both values are low in comparison to previous studies and also statistically insignificant, the result still suggest that informed trades are likely to leave higher impacts on price than liquidity driven trades.

Panel B reports the regression coefficient estimates for the independent variables. Total impact coefficient estimates for all of Marketreturn, momentum and relative bid-ask spread variables are significant at all conventional significance levels. Trade size has a direct negative relationship with price impact, the estimates are however not significant at any of the tested levels of significance. For this variable, the permanent and temporary effects are very similar; the standard error estimates are also similar. The volatility coefficient estimates show that there is a positive relationship with price impact for all three types of effects. The permanent effects coefficient is significant at 10% level and the temporary effects estimate at the 5% level. Again the estimates and standard errors are similar; however the temporary effects estimate is higher than the permanent effects estimate. This indicates that a higher proportion of price impact due to volatility is temporary.

Turnover estimates are positive but none are statistically significant. The very low positive estimates suggest that liquidity improvements do not reduce block trade price impact and may actually aid it. However, this is far from certain as the estimates do not even border on significance. Marketreturn is the only variable to be statistically significant across the full range of effects. We observe statistically significant positive effects on price impact for both permanent and temporary effects and negative effect on price impact for total effects; this is also significant at the 1% level. Positive Marketreturn estimates mean the price impact for block purchases is higher than that of block sales. The significant negative total effects estimate however calls this conclusion into question and will be examined more closely in succeeding analyses when we identify trade signs in the results. As expected, based on the returns trend on the ECX, momentum has negative effects on price impact for the full range of effects tested. The total effects estimate is significant at the 1% level. Wider spreads are expected to lead to a positive relationship with price impact and narrow spreads are representative of high levels of liquidity (negative relationship with price impact). Only the total effects coefficient estimate (-0.05176) is significant at 1% level and it shows a negative effect on price impact. Alzahrani et al. (2010) report identical results with temporary effects having a positive relationship with BAS and permanent effects, possessing a negative relationship. The results imply that wider spreads are positively related with only temporary price impact. When the price impact is permanent, it is characterised by narrow spreads.

[INSERT TABLE 2 HERE]

A general observation in Table 2 is that block trades have generally low impact on price on the ECX as majority of the coefficient estimates are not statistically significant. Our inferences from the results are tempered by this realisation. Notwithstanding, we present sufficient evidence to suggest that there is a reduced price impact when the price return is on a run-up and that wider spreads lead to temporary price impact. We also have evidence indicating that higher volatility and positive Marketreturn drive up premium leading to larger price impact when block trades are executed.

4.2.1. Price impact and trade sign

Consistent with previous studies, we investigate the determinants of price impact of block trades for purchase and sell transactions separately in this section, and the results are displayed in Table 3.

Mean permanent price impact for sell block trades in Table 3 is 0.00153 and this is statistically significant at the 1% level, the mean temporary price effect is 0.000693 and is statistically significant at the 10% level. The estimates indicate that the average permanent price impact is more than twice the temporary price impact, further cementing the proposition that the ECX is more reactive to informed block sell trades execution than liquidity induced ones. Informed block trades have a higher likelihood of inflicting permanent price shifts. The mean total effects on price impact for sell block trades is also statistically significant at the 1% level, the estimate is 0.00084. For purchase trades, none of the coefficient estimates are significantly different from zero. Coefficient estimates for sell block trade size are all highly statistically significant and negative, with the permanent and temporary effects being significant at 1% level. The coefficients confirm that larger sell block trades have both permanent and temporary impacts on price of carbon futures on the ECX. Volume of executed trades is therefore a function of price impact for sell block trades. The relationship is significantly negative.

With regards to volatility, two of the coefficient estimates for purchase block trades are positive with one of them, temporary effects being statistically significant at the 5% level, the total effect is however negative and also significant at the same level. Total effects coefficient estimate for sell trades is statistically significant at the 1% level. This, along with the negative purchase trades estimate, contrasts with existing literature based on investigations from more traditional financial platforms. The positive permanent and (significant) temporary effects estimates for the purchase trades are however consistent with current literature (see for example Alzahrani et al., 2010; Chiyachantana et al., 2004). Volatility as a measure of variation in belief held by market participants is a proxy for the level of participatory risk in the market, hence the higher the volatility, the stronger the block trade price impact. The estimates for volatility provide evidence to both support and contradict this belief. Results provide evidence that higher volatility is a significant and positive function of temporary price impact for block purchases. The total effects estimate is a contradiction of this reasoning. The permanent effects coefficient estimate is not significant but it is positive. Using the total effects estimate (the only significant volatility estimate), for sell block trades, volatility is positively related with price impact.

Existing literature suggests increased depth (turnover) reduces block trade price impact. Results in Table 3 indicate that the ECX supports this trend. The table reports positive coefficient estimates for permanent effects and temporary effects on price impact for purchase trades and negative estimates for block sell trades. All four estimates are significant at varying levels. This result contradicts Frino et al. (2007), but is consistent with Alzahrani et al. (2010) on the Saudi Stock Market (SSM). They suggest that huge block sell trades in actively traded instruments may signal adverse information on intent of the trades. This is seemingly because they indicate moves of informed participants and consequently lead to increase in instrument sales. This can lead to intensification of price impact of the block trades involved.

Positive Marketreturn coefficient estimates indicate larger price impacts for purchase block trades and reduced impact for block sell trades. The results are largely in keeping with this. Marketreturn estimates for five of the coefficients are statistically significant at the 1% level. Consistent with Frino et al. (2007) and Alzahrani et al. (2010), they are positive for the full range of price effects for the block sell trades. The permanent effects and temporary effects estimates for the purchase trades are positive as well with the temporary effect estimate also being significant at the 1% level.

According to Chiyachantana et al. (2004), institutional block trades executed on the back of several days of positive price appreciation lead to lesser permanent price impact. This corroborates Saar (2001) who reports that block trades executed following a recent price run-up generate smaller price impact. The results in Table 3 mirror that in Panel B of Table 2 and therefore for the most part remain consistent with this argument. Of the three types of effects tested, only the total effects coefficient estimates show statistically significant results. The total effects coefficient estimate for purchase block trades is negative and statistically significant at the 1% level, indicating lesser price impact as a result of price run-up. The negative and significant sell coefficient (total effects) implies the opposite trend is true for sell block trades.

The BAS coefficient estimates are positive and significant at 1% level for permanent and total effects for sell block trades. The total effects BAS estimate for purchase block trades is also significant at the 1% level but otherwise negative. Other coefficient estimates are statistically insignificant. The significant BAS estimates convey the impression that with wider spreads there is reduced price impact for both purchase and sell trades and therefore with narrower spreads there is greater price impact. This contradicts previous studies (see for example Aitken and Frino, 1996; Gemmill, 1996) but is consistent with results earlier reported in Table 2. The ECX is a platform created for trading emission permits unlike equity markets aimed at trading stocks. Emission permits are for submission only once a year but the market has been very liquid all year round since the commencement of Phase II of the EU-ETS (see Montagnoli and de Vries, 2010; Ibikunle et al., 2011a; 2011b). Trading in emission permit instruments when they are not immediately needed for submission to the regulatory authorities may indicate a level of informed trading. Based on this reasoning, high levels of liquidity may lead to increased price impact for both purchase and sell block trades. This result corroborates the estimates obtained for the turnover variable.

[INSERT TABLE 3 HERE]

Buyer and seller initiated block trades on the ECX induce both temporary and permanent price impacts. Increased liquidity also generates larger price impacts. The dissimilarities in market properties between the EU-ETS cap and trade scheme and traditional financial markets is underscored by the differences in the impact of the two liquidity measures used in the model. The estimates of the volatility coefficients are unclear in respect to the distinctive impact of volatility on block trade price impact. Further evidence confirms the prediction that there is reduced price impact for both purchase and sell block trades when an instrument is experiencing a price run-up leading to the block trade execution. Based on the Marketreturn coefficients, we provide evidence in line with previous studies citing larger price impact for block purchases and smaller price impact for block sales.

4.2.2. Intraday Variations in Price Impact

In traditional markets, spreads have been reported to conform to a U shaped pattern over the trading day. However, little has been reported on intraday variations in the EU-ETS. Rotfuβ (2009) reports a roughly U shaped pattern of intraday volatility on the ECX using ECX data from first year of trading in Phase II. Ibikunle et al. (2011b) report a slightly different intraday pattern of volatility and traded volumes with 2009 data from the same platform. The authors show an inverted S shaped pattern for both trading activity measures. Indeed the pattern reported by Rotfuβ (2009) is closely similar to the inverted S shaped pattern in the former's study. To our knowledge, the only available evidence of intraday variations in estimated spread pattern available for the EU-ETS is the work of Ibikunle et al. (2011b). The authors, using the Huang and Stoll (1997) spread decomposition model obtain half-spread estimates for six trading intervals on the ECX. The estimates suggest that spreads are highest during the opening two hours of the trading day and decreases throughout the trading day. The sixth interval is the after-hours trading period; the study shows a marked rise in the spread estimates during this interval. This shows a U shaped pattern, confirming the reports of studies carried out on traditional trading platforms. Figure 1 shows intraday variations in average relative bid-ask spread computed by using our entire dataset (including non-block trades). There is a discernible suggestion of a U shaped pattern emerging.

[INSERT FIGURE 1 HERE]

In order to examine the presence of intraday variations in the intensity of block trade price impact for the ECX, we divide the trading day into three intervals in line with previous studies. The intervals are the first trading hour of the day (7:00-8:00 hours UK local time), the mid-trading day interval (08:01-16:00 hours UK local time) and the final trading interval is the final trading hour of the day (16:01-17:00 hours UK local time). We allocate for each interval a dummy variable that takes on the value of 1 if a block trade is executed during that interval and otherwise takes a value of 0. *TimeDum 1* and *TimeDum 2* respectively stand for the first and second intervals and are represented in the equation (6) (other variables have been defined in section 3). The final trading interval is employed as the reference category and therefore is excluded from the actual regressions. The coefficient estimates obtained for the first two categories is representative of the price impact conduct in comparison to the reference category *TimeDum 3*:

$$\text{Price Impact} = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \beta_7 TimeDum1 + \beta_8 TimeDum_2 + \varepsilon \quad (6)$$

Table 4 shows the results of equation (6) for *all*, purchase and sell block trades. We estimate the regression using all three price impact variables individually as dependent variables. For purchase and all block trades the *TimeDum 2* dummy variables are statistically significant for all price impact measures. Block trades executed during the first hour of the trading day encounter price impact which are not significantly different from those executed during the last hour of the day. For purchase trades, there are significant differences between trades executed during the middle of the day and those executed in the last hour of the normal trading day. The coefficient estimates suggest that the greater price impact generally occurs during the middle interval of the trading day[7]. For all block trades combined the *TimeDum 1* coefficients are statistically insignificant while all *TimeDum 2* estimates are significant. This is consistent with the purchase trades trend. Most of the sell block trade coefficient estimates show that sell block trades during the first two intervals do not induce price impact significantly different from those induced by trades in the last hour of the trading day. The permanent effects *TimeDum 2* coefficient is significant at the 10% level. The estimate suggests that for sell block trades, trades executed during the middle of the trading day induce higher price impact than those during the first hour of trading day. The difference in the effect of intraday trading activity patterns on the ECX and other traditional financial platforms is underscored by this behaviour. For a number of studies, the first hour of the trading has been reported as the period when block trades induce the largest price impact (see Frino et al. 2007 as an example). Earlier in this section, we report that wider spreads in fact

[7] As a robustness test, we also use other time intervals as controls with similar conclusions: price impact during the first hour is not significantly different from the last hour of the trading day but the two intervals are largely significantly different from the middle of the trading day. The results (not reported) are available from the authors upon on request.

characterise less price impact on the ECX contrary to earlier studies, this result is therefore the only logical outcome of our investigation of end of day effect. This is because Figure 1 shows that the lowest spreads are experienced during the middle of the day and the highest spread intervals are during the first hour of the trading day.

[INSERT TABLE 4 HERE]

4.2.3. Trade Size Dependencies on Price Impact

Microstructure studies suggest that liquidity influenced trades are usually characterised by small orders and informed trades, larger orders (see Glosten and Harris, 1988 as an example). Analyses of the large orders dominated after hours trading market on the ECX by Ibikunle et al. (2011b) indicate a confirmation of this proposition in the European carbon futures market. If different types of trades are characterised by differing sizes of trades, it is suspected that block trades will not uniformly cause price impact. To determine how block trades of different sizes can affect price functioning, we adopt the approach of Alzahrani et al. (2010) and Madhavan and Cheng (1997) in dividing block trades in our sample into three different trade size categories. We divide block trades into three groups as follows: 50-100 contracts, 101-200 contracts, and more than 200 contracts. We estimate equation (6) for each of the groups using all three measures of price impact already identified.

[INSERT TABLE 5 HERE]

Table 5 reports the results for purchase block trades. The first observation we make is the very high proportion of the lower end block trades. Approximately 90% of executed trades in the sample are for the smallest trade size category (50-100 EUA Futures contracts). Another observation is the dearth of estimates significantly different from zero. What this implies is that although there may be variations in the range of price impact induced by block trades of different sizes (as evidenced by coefficient estimates), these variations are not significant.

For Marketreturn, the total effects estimates are statistically significant for the first two categories. Negative Marketreturn estimates for all three categories of trade sizes indicate lower price impact for purchase block trades across all examined trade sizes. The coefficient estimates for the 101-200 contracts category is nearly a third smaller than that of the smallest size category, suggesting in effect that price impact diminishes by a third with larger orders. The Marketreturn estimates for the largest category are insignificant. The negative and significant bid-ask spread estimates indicate lower price impact with increasing trade sizes as well. The negative estimates for Marketreturn are consistent with results obtained for total effects of purchase block trades in Tables 3 and 4. Temporary and permanent Marketreturn estimates for the smallest sized category of trades (50-100 contracts) are however positive and statistically significant at the 1% and 10% levels respectively. They imply larger price impact for purchase block trades of size 50-100 EUA futures contracts especially for temporary effects. The temporary effects coefficient is more than two and half times the value of the permanent effects coefficient indicating that most of the price impact as a result of Marketreturn is temporary. This result is consistent with temporary effects estimates of purchase block trades in Tables 3 and 4. This is expected since the 50-100 contracts category account for nearly 90% of block trades in the sample.

We also observe that larger sized block trades, especially the 101-200 contracts category, potentially induce higher price impact than smaller sized ones. For example, for the size (volume) variable, we find that for each of permanent, temporary and total effects, the 101-

200 contracts size range has positive coefficients that are larger than the other two groups. The positive values indicate a positive relationship with price impact across all three effects. For volatility, which measures the dispersion of participants' belief, the total effects estimates for all three trade sizes are statistically significant. Coefficient of the mid-range sized block trades is positive and statistically significant at the 1% level and higher than the other groups with coefficient of more than one reported (1.364). This means for this group, increasing volatility leads to higher price impact. The negative and statistically significant coefficients for the lowest and largest volume size categories imply that increased volatility does not necessarily imply higher price impact, it instead signals the opposite. This is consistent with earlier total effects coefficient estimates for purchase block trades from Tables 3 and 4. Since these two trade groups account for more than 93% of the sample size, the consistency with earlier results on purchase trades is not surprising. The total effects coefficient estimates for momentum are statistically significant for all three categories; again the results suggest that the middle group induce higher price impact on a price run-up while the other two categories confirm the argument of Saar (2001). The negative and statistically significant coefficients confirm that less price impact is induced on a price run up.

The permanent effects estimates for *TimeDum 2* are positive and statistically significant and they show the 101-200 contracts category having a coefficient of 0.00898, which is more than seven times the value of the closest estimate (greater than 200 contracts). The permanent effects time dummy variables also confirm earlier suggestion in Table 4 that purchase block trades executed in the middle of the day marginally induce larger price impact than those executed in the first hour of the trading day. Most of the *TimeDum 2* estimates are statistically significant and confirm the earlier findings; the only exception is the total effects estimate for the largest trade size category. *The TimeDum 1* estimate at 0.0047 (statistically significant at 5% level) is more than three times the value of the *TimeDum 2* estimate (0.00126) which is significant at 10% level. This is the only indication that the largest trades' size group may encounter higher price impact during the first hour of trading than during the middle of the day.

Differentiation and in some cases, dominance of the block size category of 101-200 contracts from (over) the largest size contracts category is though unexpected, not entirely unusual. This is consistent with the hypothesis and evidence presented by Barclay and Warner (1993), after testing block trade impacts on stock price NYSE firms. In their sample, most of the cumulative stock price change is due to medium sized trades. Here, the interesting pattern evolving may be an indication of the 101-200 contracts category becoming the starting point of price impact effects. Already we show estimates indicating that the 50-100 group trades induce more temporary price impact than permanent price impact, suggesting most of the trades in this group is liquidity seeking. This coupled with the large volume of block trades of 50 contracts trade sizes suggest a gradual erosion of the market's view of 50 contracts as a block trade. The ECX sets the standard for what is regarded as block trade and currently it stands at 50 contracts according to exchange rules. Markets have however been known to induce structural shifts in response to emerging trading *culture*. The ECX as an EU-ETS platform, though a market entity, is a product of political action and may not be subject to the same expectations as regular markets developed as engines of wealth creation. Even then, the market seems to be taking a life of its own gradually. This however does not explain why the largest contract size category shows less price impact effects than the middle size category.

Barclay and Warner (1993) argue that under certain conditions, informed traders, rather than trade in large sizes, would usually split up their trades into smaller chunks falling into the medium sized category, hence the asymmetric phenomenon. Also, we suggest as follows: The frequency of on-screen buyer initiated block trades greater than 200 contracts on the ECX (3.45%) over three years and four months is very low. The low frequency levels may be a contributing factor to the low coefficient estimates. Perhaps infrequent trade sizes are likely to elicit less price reaction than those that are fairly regular. Further, in our dataset, more than 98% of the greater than 200 block trades occur outside of the first hour of normal trading day. Total effects coefficient for the greater than 200 contracts category indicates that greater price impact occurs during the first hour of the trading day for this group of trades. Therefore, since trades during the other periods in the day are less likely to induce price impact in comparison to those executed during the first hour, the effects of the greater than 200 contracts category block trades may have been consequently muted by general reduced price reaction to greater than 200 trades during these periods of the normal trading day.

The R^2 values for the equation estimations range from 2.13% to 19.32% for total effects estimates which is an indication of the significant explanatory power of the model.

[INSERT TABLE 6 HERE]

Table 6 shows the results for sell block trades. We observe trends similar to Table 5 with approximately 91% of executed trades in the sample made up of the smallest trade size category (50-100 EUA contracts). Also, as in the purchase block trades estimates; there is a dearth of coefficients significantly different from zero.

The total effects coefficient estimates for the volatility variable are all statistically significant. The negative and statistically significant value of the greater than 200 contracts category shows that increased volatility results in higher price impact for sell trades of 200 contracts or more on the ECX. The opposite is the case for smaller sized trades. Size shows a positive relationship with price impact as evidenced by the negative total effects coefficient estimates. Consistent with Alzahrani et al. (2010), the statistically significant coefficient for the lowest sized contract groups is larger than the two other groups. This indicates that smaller sized sell block trades are more informative than larger ones. Professional traders have long been known to split large block trades into smaller trades to avoid early detection of the information content of the trades (see Barclay and Warner, 1993; Chakravarty, 2001). Although microstructure studies show that informed trades are discernible also from the direction and frequency of trades, trades fragmentation potentially mutes the price impact of block trades (Keim and Madhavan, 1996). Marketreturn coefficient estimates for total effects are all positive and estimates for the smallest and largest groups are statistically significant at the 1% level. The trend shown by the Marketreturn coefficients is consistent with that of size coefficients; there is larger price impact for the smaller sized trades as they are perceived as being more informative.

For the greater than 200 contracts category, the total effects and permanent effects coefficient estimates for the momentum variable is negative and statistically significant at the 5% level indicating that there is indeed higher price impact on a price run-up contrary to the effect for purchases. This confirms the sell coefficient estimates in Tables 3 and 4 as well as the submission of Frino et al. (2007). Viewed in tandem with the block purchase estimates in previous tables, we can submit that block purchase trades behaviour on the ECX are consistent with Saar (2001) and sell block trades with Frino et al. (2007). The BAS estimates are all statistically significant for both permanent and total effects. There is an interesting scenario playing out with both effects' estimates however. Only the 101-200 contracts category has negative coefficients which is consistent with Frino et al. (2007). The other two categories are positive, reinforcing the conclusions we draw from Tables 3 and 4 that on the ECX, widening spreads leads to reducing price impact. As previously explained, the negative coefficients of the middle group, which is in keeping with previous studies' results, represents an asymmetric relationship among the different trade sizes. This norm may not be unconnected with a structural shift in the market's definition of block trade and other reasons we already allude to above. Also, the dummy variable coefficients are largely statistically insignificant and hence very little inferences can be drawn from them.

The R^2 values for total effects estimates are 2.75%, 8.74% and 10.52% respectively for the smallest sized to the largest sized sell block trade categories. Temporary effects are 0.4%, 2.05% and 10.46%. And permanent effects values are 1.6%, 2.80% and 6.69% respectively.

The general pattern of behaviour exhibited in Table 6 suggests that sell block trades executed on the ECX on the whole are less likely to induce price impact than purchase block trades.

5. Conclusion

In this paper, we investigate the determinants of price impact for block trades executed on the world's largest carbon trading platform by analysing tick data on 16,715 block trades over a three year period. While price impact of block trades has been considerably studied in traditional international markets, there has been no study carried out on what determines price impact of block trades in permit markets. Block trades increasingly constitute large Euro volumes of trades in the EU-ETS as more installations try to avoid counter-party risks by trading on platforms rather than OTC.

We conduct our empirical analysis by estimating regression models used to determine price impact of block trades in previous market microstructure studies on traditional equity markets. We conducted the analysis on all block trades and for block purchases and sales in isolation in order to investigate the possibility of price impact asymmetry in the carbon markets. Results show that most of the block trades on the ECX occur at the minimum quantity for the exchange sanctioned block trade size of 50 contracts. This is consistent for both buyer and seller initiated block trades. This indicates that traders on either side of block trades on the ECX employ identical trading tactics in terms of order placing. The evidence shows that stealth trading may be a trading strategy of choice for most block traders on the platform. The low volume of block trades of 16,715 (1.74%) out of a total of 961,131 trades also suggest that block trades may be commonly split into quantities below the block trade threshold. This suggestion is reinforced by the nature of the EU-ETS, where most participants are either big compliance traders or institutional investors.

In comparison with customary instruments, the price impact of carbon futures on the ECX is small and largely statistically insignificant. Lack of price reaction to large trades can be viewed as a possible consequence of thin trading (see Ball and Finn, 1989). Although trading has advanced in the EU-ETS, this is still very low in comparison to established markets. Since there is little price reaction, there is very little opportunity of benefitting from price impact asymmetry before and after block trades. We find some proof of price impact asymmetry for buyer and seller initiated block trades. For sell trades the permanent effect is 0.00153 and 0.000949 for purchases. The purchase trade estimate borders on significance while the sell trade estimate is highly significant at 1% level. The result suggests higher premium is paid by sellers rather than buyers, which is a clear contradiction with many studies. It is not surprising that premium is paid on the ECX by sellers rather than buyers when the market structure is considered. The ECX is a derivatives exchange for emission permits which are required for submission only once a year; hence for most trading days the permits are largely hedging instruments. Compliance buyers do not need to hold on to the underlying instruments all year round and therefore only needs to take long positions in the market to ensure they are insulated against penalties for non-compliance. In the event that they are in possession of excess instruments, they can undertake a short position. Considering the fact that the permits hold little value to a compliance trader unless it is being submitted, many will willingly make concessions to sell them.

This paper provides evidence that lower price impact is characterised by wider spreads. For buyer initiated block orders, trade execution induces larger price impact in the ECX during the middle of the trading day than during the first and last trading hours. We also find evidence in support of positive price run-up leading to both lower price impact and higher price impact depending trade sign. For block purchases, there is smaller price impact when a trade occurs after a price run-up, while for block sales, there is greater price impact. There is however also a block trade size dependency to this.

The recent enactment of emissions trading legislation in Australia, the country with the highest per capita emission levels, once again underscores the growing significance of carbon emissions trading. Australia's ETS will become the second largest in the world when it comes online in 2015. Along with the EU-ETS and the New Zealand ETS, a platform for inter-regional emissions' trading is being set, therefore continued focus must be placed on the evolution of emissions markets. Our results shed some more light on several microstructure issues relating to block trading on the ECX, for instance there is evidence of sophisticated trading techniques now in play in the market. We find that in many cases, the most information laden trades are not the largest ones, but the medium (for most buys) and the small trades (for most sells). Policy makers must therefore ensure that regulations in the emissions markets keep pace with trading innovations.

Table 1

Summary statistics for Block Trades

The table shows descriptive statistics for block trades of December maturity EUA Futures executed on the European Climate Exchange (ECX) platform between January 2008 and April 2012. Panel A reports the proportion of trades and trading activity measures. Panel B also reports trading activity measures with mean average bid-ask spread estimates. Standard deviation measures the standard deviation of percentage price impact.

Panel A

	Number of trades	**% of total number of trades**	**% Price impact**	**Standard deviation**
All trades	961131			
Block trades	16715	1.73909696	0.0012113	0.004648943
Block purchases	8356	0.869392414	-0.0356055	0.005818786
Block sales	8359	0.869704546	0.0380149	0.00301713

Panel B

	Number of trades	Average number of contracts/trade	Average transaction Value/trade (€)	Average Relative Spread (€)
All trades	961131	6.793	108.4	0.000657745
Block trades	16715	78.939	1232.711	0.000616625
Block purchases	8356	80.205	1258.03	0.000673899
Block sales	8359	77.67	1207.4	0.000559373

Table 2

Determinants of Price Impact of Block Trades

The table reports regression results and price impact estimates for block trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The following regression is estimated:

$$Price\,Impact = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \varepsilon$$

Where Price Impact corresponds to permanent, total and temporary price impacts. Size represents the natural logarithm of the number of December maturity futures contracts for each block trade; Volatility is the standard deviation of trade to trade returns prior to the block trade on the trading day; Turnover is the natural logarithm of the futures contracts turnover on the trading day prior to the block trade, turnover is calculation as a ratio of total trade volume prior to the block to the prevailing open interest estimates; Marketreturn is the return of EUA Futures contract specific index computed by the ECX; Momentum corresponds to the cumulative return on the specific EUA Futures contract in the five days prior to the block trade; BAS is the prevailing relative bid-ask spread at the time the block trade is executed, BAS is measured as the last ask price prior to the block trade minus the last bid price before the block trade divided by the average of both prices. Panel A reports the price impact estimates and Panel B, the regression results.
One EUA Futures contract has an underlying of 1000 EUAs.
*** indicates statistical significance at 1% level, ** indicates statistical significance at 5% level and * indicates statistical significance at 10% level.

Panel A: Price impact estimates

Variables	Permanent effects	Total effects	Temporary effects
Mean estimates	0.001152	0.000188	0.00098

Panel B: Regression Results

Variables	Permanent effects	Total effects	Temporary effects
Size	-2.23E-04 (0.000207)	-1.55E-05 (7.11E-05)	-2.04E-04 (0.00021)
Volatility	**0.123101*** (0.06778)	0.013629 (0.023224)	**0.13624**** (0.068748)
Turnover	0.000101 (8.40E-05)	2.22E-05 (2.88E-05)	9.41E-05 (8.52E-05)
Marketreturn	**0.01379***** (0.005088)	**-0.00634***** (0.001744)	**0.02001***** (0.005161)
Momentum	-0.00313 (0.002388)	**-0.00265***** (0.000818)	-0.00068 (0.002422)
BAS	-0.03604 (0.058404)	**-0.05176***** (0.020012)	0.02749 (0.059238)
Observations	**16715**	**16715**	**16715**
R-Squared	0.000816	0.002439	0.001405

Table 3

Determinants of Price Impact of Buyer and Seller Initiated Block Trades

The table reports regression results for buyer and seller initiated block trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The following regression is estimated:

$$\Pr ice \operatorname{Im} pact = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \varepsilon$$

Where Price Impact corresponds to permanent, total and temporary price impacts. Size represents the natural logarithm of the number of December maturity futures contracts for each block trade; Volatility is the standard deviation of trade to trade returns prior to the block trade on the trading day; Turnover is the natural logarithm of the futures contracts turnover on the trading day prior to the block trade, turnover is calculation as a ratio of total trade volume prior to the block to the prevailing open interest estimates; Marketreturn is the return of EUA Futures contract specific index computed by the ECX; Momentum corresponds to the cumulative return on the specific EUA Futures contract in the five days prior to the block trade; BAS is the prevailing relative bid-ask spread at the time the block trade is executed, BAS is measured as the last ask price prior to the block trade minus the last bid price before the block trade divided by the average of both prices. One EUA Futures contract has an underlying of 1000 EUAs.
*** indicates statistical significance at 1% level, ** indicates statistical significance at 5% level and * indicates statistical significance at 10% level.

	Permanent effects		**Total effects**		**Temporary effects**	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
Variables						
Size	-8.11e-05	**-0.00038*** **	0.000166	**-1.53E-04** **	-0.00024	**-0.00023*** **
	(0.000396)	(0.000103)	(0.000125)	(6.15E-05)	(0.000407)	(8.19E-05)
Volatility	0.127959	0.082493	**-0.09767** **	**0.0877*** **	**0.27752** **	-0.00599
	(0.125606)	(0.035296)	(0.039672)	(0.020987)	(0.129103)	(0.027956)
Turnover	**0.000311***	**-7.42E-05***	6.10E-05	1.68E-05	**0.000278***	**-9.1E-05*** **

	(0.000165)	(4.08E-05)	(5.20E-05)	(2.43E-05)	(0.000169)	(3.23E-05)
Marketreturn	0.007473	**0.01535*** **	**-0.0262*** **	**0.01013*** **	**0.03362*** **	**0.00523*** **
	(0.009791)	(0.002529)	(0.003093)	(0.001504)	(0.010064)	(0.002003)
Momentum	-0.00476	-0.00146	**-0.0044*** **	**-0.00121***	-0.0007	-0.00024
	(0.004538)	(0.001195)	(0.001433)	(0.00071)	(0.004664)	(0.000946)
BAS	-0.12295	**0.2152*** **	**-0.13429*** **	**0.19294*** **	0.027107	0.020282
	(0.09387)	(0.038715)	(0.029648)	(0.02302)	(0.096484)	(0.030664)
Constant	0.000949	**0.00153*** **	-0.00057	**0.00084*** **	0.001554	**0.000693***
	(0.001821)	(0.000466)	(0.000575)	(0.000277)	(0.001872)	(0.000369)
Observations	**8356**	**8359**	**8356**	**8359**	**8356**	**8359**
R-squared	0.000815	0.01515	0.016926	0.023723	0.002306	0.003079

Table 4

Determinants of Price Impact and Time of Day Effects

The table reports regression results for all, buyer and seller initiated block trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The following regression controlling for time of day effect is estimated:

$$Price\,Impact = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \beta_7 TimeDum1 + \beta_8 TimeDum_2 + \varepsilon$$

Where Price Impact corresponds to permanent, total and temporary price impacts. Size represents the natural logarithm of the number of December maturity futures contracts for each block trade; Volatility is the standard deviation of trade to trade returns prior to the block trade on the trading day; Turnover is the natural logarithm of the futures contracts turnover on the trading day prior to the block trade, turnover is calculation as a ratio of total trade volume prior to the block to the prevailing open interest estimates; Marketreturn is the return of EUA Futures contract specific index computed by the ECX; Momentum corresponds to the cumulative return on the specific EUA Futures contract in the five days prior to the block trade; BAS is the prevailing relative bid-ask spread at the time the block trade is executed, BAS is measured as the last ask price prior to the block trade minus the last bid price before the block trade divided by the average of both prices. TimeDum 1equals 1 if the block trade occurs in the first hour of the trading day and 0 otherwise, TimeDum 2 takes the value of 1if the trade occurs between 8:00hours and 16:00hours London local time. One EUA Futures contract has an underlying of 1000 EUAs.

*** indicates statistical significance at 1% level, ** indicates statistical significance at 5% level and * indicates statistical significance at 10% level.

	Permanent effects			**Total effects**			**Temporary effects**		
	All	Purchase	Sell	All	Purchase	Sell	All	Purchase	Sell
Variables									
Size	-2.12E-04	-7.12E-05	**-0.0004*** **	-1.56E-05	0.000163	**-0.00015** **	-1.93E-04	-0.00023	**-0.0002*** **
	(0.00021)	(0.000396)	(0.000104)	(7.1E-05)	(0.00013)	(6.16E-05)	(0.00021)	(0.000407)	(8.20E-05)
Volatility	**0.12965***	0.140498	**0.081464** **	0.013028	**-0.1014** **	**0.08805*** **	**0.143456** **	**0.293964** **	-0.007381
	(0.06787)	(0.125857)	(0.035329)	(0.02325)	(0.03976)	(0.021003)	(0.068834)	(0.12933)	(0.027986)

Turnover	**0.000159***	**-0.00042****	**-7.61E-05***	1.89E-05	2.87E-05	2.78E-05	**0.000156***	**0.00042****	**-0.0001*****
	(9.09E-05)	(0.000178)	(4.42E-05)	(3.1E-05)	(5.6E-05)	(2.63E-05)	(9.22E-05)	(0.000183)	(3.50E-05)
Marketreturn	**0.014*****	0.00706	**0.01533*****	**-0.006*****	**-0.026*****	**0.01001*****	**0.01963*****	**0.03391*****	**0.0053*****
	(0.00509)	(0.00979)	(0.002534)	(0.00174)	(0.00309)	(0.001506)	(0.005163)	(0.01006)	(0.002007)
Momentum	-0.003358	-0.005145	-0.001492	**-0.003*****	**-0.004*****	**-0.001298***	-0.000901	-0.001205	-0.000177
	(0.00239)	(0.004543)	(0.001222)	(0.00082)	(0.001435)	(0.000712)	(0.002427)	(0.004668)	(0.000949)
BAS	-0.031604	-0.112778	**0.21514*****	**-0.053*****	**-0.137*****	**0.193584*****	0.032823	0.040245	0.019585
	(0.058437)	(0.093939)	(0.038723)	(0.020021)	(0.029673)	(0.023021)	(0.059264)	(0.096531)	(0.030675)
TimeDum 1	0.00071	0.001221	5.32E-05	3.77E-05	-0.00037	0.000217	0.000681	0.001611	-1.62E-04
	(0.000514)	(0.001006)	(0.00025)	(0.000176)	(0.000318)	(0.000149)	(0.000522)	(0.001034)	(0.000198)
TimeDum 2	**0.00055****	**0.001243*****	**-0.000192***	**-0.0002****	**-0.0004****	-8.36E-05	**0.000752*****	**0.001595*****	-0.000107
	(0.000248)	(0.000476)	(0.000123)	(8.50E-05)	(0.00015)	(7.29E-05)	(0.000252)	(0.000489)	(9.72E-05)
Constant	0.00898	0.000362	**0.001662*****	0.000324	-0.000405	**0.000919*****	0.00059	0.000808	**0.000744****
	(0.000955)	(0.001841)	(0.000472)	(0.000327)	(0.00581)	(0.00028)	(0.000969)	(0.001892)	(0.000374)
Observations	**16715**	**8356**	**8359**	**16715**	**8356**	**8359**	**16715**	**8356**	**8359**
R-squared	0.001139	0.001678	0.015592	0.002927	0.017613	0.024505	0.001971	0.003651	0.003249

Table 5

Determinants of Price Impact and Block Trade Sizes (Purchases)

The table reports regression results for buyer initiated block trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The following regression controlling for time of day effect is estimated:

$$\Pr ice\,\mathrm{Im}pact = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \beta_7 TimeDum1 + \beta_8 TimeDum_2 + \varepsilon$$

Where Price Impact corresponds to permanent, total and temporary price impacts. Size represents the natural logarithm of the number of December maturity futures contracts for each block trade; Volatility is the standard deviation of trade to trade returns prior to the block trade on the trading day; Turnover is the natural logarithm of the futures contracts turnover on the trading day prior to the block trade, turnover is calculation as a ratio of total trade volume prior to the block to the prevailing open interest estimates; Marketreturn is the return of EUA Futures contract specific index computed by the ECX; Momentum corresponds to the cumulative return on the specific EUA Futures contract in the five days prior to the block trade; BAS is the prevailing relative bid-ask spread at the time the block trade is executed, BAS is measured as the last ask price prior to the block trade minus the last bid price before the block trade divided by the average of both prices. TimeDum 1equals 1 if the block trade occurs in the first hour of the trading day and 0 otherwise, TimeDum 2 takes the value of 1if the trade occurs between 8:00hours and 16:00hours London local time. One EUA Futures contract has an underlying of 1000 EUAs.

*** indicates statistical significance at 1% level, ** indicates statistical significance at 5% level and * indicates statistical significance at 10% level.

	Permanent effects			**Total effects**			**Temporary effects**		
	50-100	101-200	>200	50-100	101-200	>200	50-100	101-200	>200
% Proportion	(89.92%)	(6.63%)	(3.45%)	(89.92%)	(6.63%)	(3.45%)	(89.92%)	(6.63%)	(3.45%)
Variables									
Size	0.00045	0.00415	0.00061	-0.0002	0.000137	-0.0002	0.00069	0.00409	0.00081
	(0.00055)	(0.00913)	(0.00063)	(0.00022)	(0.00121)	(0.00077)	(0.00057)	(0.0092)	(0.00091)
Volatility	0.10824	0.58599	-0.1827	**-0.2042*** **	**1.36374*** **	**-0.4455** **	**0.3632*** **	-0.6891	0.28285
	(0.10295)	(1.30361)	(0.1463)	(0.04143)	(0.172751)	(0.17831)	(0.1073)	(1.31408)	(0.21186)

Turnover	**0.0005*****	-0004	-0.0003	2.34E-06	0.000357	0.00017	**0.00053*****	-0.0007	-0.0004
	(0.000145)	(0.0019)	(0.00022)	(5.82E-05)	(0.000252)	(0.00027)	(0.00015)	(0.00192)	(0.00032)
Marketreturn	**0.01545***	-0.141	0.00765	**-0.0225*****	**-0.0722*****	-0.0125	**0.03816*****	-0.0715	0.01952
	(0.00795)	(0.10907)	(0.01201)	(0.0032)	(0.014454)	(0.01464)	(0.00829)	(0.10995)	(0.01739)
Momentum	**-0.006***	-0.0032	-0.003	**-0.0068*****	**0.0375*****	**-0.0239*****	0.00035	-0.0388	**0.01993****
	(0.00368)	(0.04991)	(0.006)	(0.00148)	(0.006614)	(0.00732)	(0.00383)	(0.05031)	(0.00869)
BAS	-0.0936	-0.7974	-0.2368	**-0.1146*****	**-0.4928****	-0.0351	0.03819	-0.3243	-0.2096
	(0.07416)	(1.45393)	(0.23141)	(0.02985)	(0.19267)	(0.28204)	(0.0773)	(1.4656)	(0.33511)
TimeDum 1	-0.0008	0.00786	0.00052	-0.0004	-0.00081	**0.0047****	0.00124	0.00866	-0.0042
	(0.00081)	(0.01233)	(0.00194)	(0.00032)	(0.001557)	(0.00236)	(0.00084)	(0.01243)	(0.00281)
TimeDum 2	**0.00063***	**0.00898***	**0.00134****	**-0.0004****	-0.00025	**0.00126***	**0.00108*****	**0.0092****	8.41E-05
	(0.00039)	(0.00477)	(0.00058)	(0.00016)	(0.000632)	(0.000711)	(0.00041)	(0.00481)	(0.00084)
Constant	-0.0008	-0.0317	-0.0055	0.00133	-0.00059	0.00135	-0.0021	-0.0314	-0.0069
	(0.00235)	(0.04569)	(0.00379)	(0.00094)	(0.006054)	(0.00462)	(0.00245)	(0.04605)	(0.00549)
Observations	**7514**	**554**	**288**	**7514**	**554**	**288**	**7514**	**554**	**288**
R-squared	0.00293	0.01228	0.04803	0.02125	0.193243	0.09498	0.0069	0.01124	0.05165

Table 6

Determinants of Price Impact and Block Trade Sizes (Sales)

The table reports regression results for buyer initiated block trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The following regression controlling for time of day effect is estimated:

$$Price\,Impact = \alpha + \beta_1 \ln(size) + \beta_2 Volatility + \beta_3 \ln(Turnover) + \beta_4 Marketreturn + \beta_5 Momentum + \beta_6 BAS + \beta_7 TimeDum1 + \beta_8 TimeDum_2 + \varepsilon$$

where Price Impact corresponds to permanent, total and temporary price impacts. Size represents the natural logarithm of the number of December maturity futures contracts for each block trade; Volatility is the standard deviation of trade to trade returns prior to the block trade on the trading day; Turnover is the natural logarithm of the futures contracts turnover on the trading day prior to the block trade, turnover is calculation as a ratio of total trade volume prior to the block to the prevailing open interest estimates; Marketreturn is the return of EUA Futures contract specific index computed by the ECX; Momentum corresponds to the cumulative return on the specific EUA Futures contract in the five days prior to the block trade; BAS is the prevailing relative bid-ask spread at the time the block trade is executed, BAS is measured as the last ask price prior to the block trade minus the last bid price before the block trade divided by the average of both prices. TimeDum 1equals 1 if the block trade occurs in the first hour of the trading day and 0 otherwise, TimeDum 2 takes the value of 1if the trade occurs between 8:00hours and 16:00hours London local time. One EUA Futures contract has an underlying of 1000 EUAs.

*** indicates statistical significance at 1% level, ** indicates statistical significance at 5% level and * indicates statistical significance at 10% level.

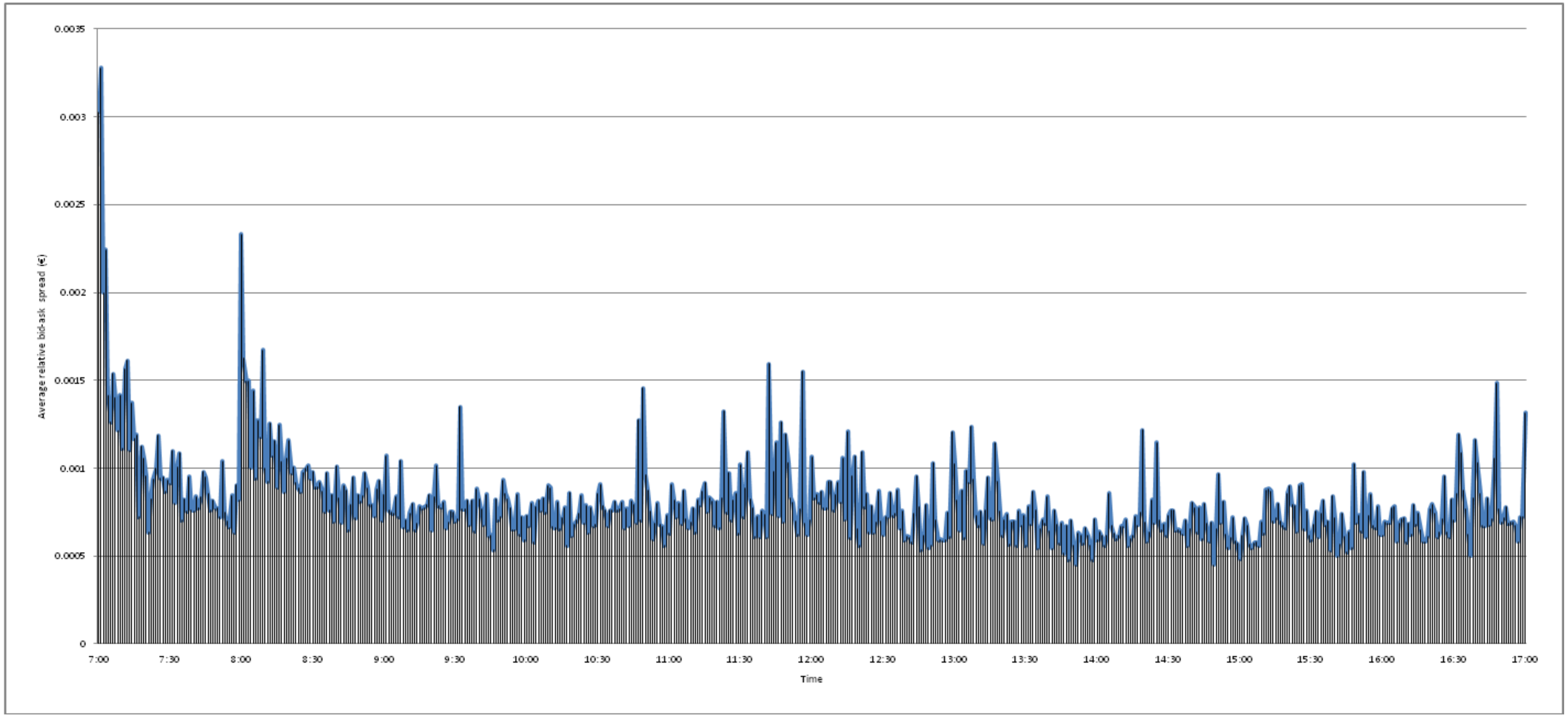
	Permanent effects			**Total effects**			**Temporary effects**		
	50-100	101-200	>200	50-100	101-200	>200	50-100	101-200	>200
	(90.85%)	(5.91%)	(3.24%)	(90.85%)	(5.91%)	(3.24%)	(90.85%)	(5.91%)	(3.24%)
Variables									
Size	**-0.0006*** **	0.000208	6.11E-06	**-0.0003*** **	-6.93E-05	-0.000284	**-0.00034** **	0.000281	0.000291
	(0.000184)	(0.00074)	(0.000563)	(0.000109)	(0.00044)	(0.000372)	(0.000146)	(0.00055)	(0.000426)
Volatility	**0.07243** **	0.149375	0.219073	**0.079*** **	**0.3850*** **	**-0.3131** **	-0.007511	**-0.2344** **	**0.5352*** **
	(0.037281)	(0.13468)	(0.197052)	(0.022083)	(0.07887)	(0.12992)	(0.029643)	(0.09889)	(0.149093)

Turnover	**-8.22E-05***	-0.000197	**0.000307***	3.52E-05	**-1.6E-04***	0.000131	**-1.2E-04*****	4.16E-05	0.00017
	(4.75E-05)	(0.00014)	(0.000168)	(2.81E-05)	(8.35E-05)	(0.00011)	(3.78E-05)	(0.00011)	(0.000127)
Marketreturn	**0.01571*****	0.014257	0.005785	**0.0098*****	0.006089	**0.0210*****	**0.006*****	0.008196	**-0.01531****
	(0.002705)	(0.00891)	(0.010015)	(0.001602)	(0.00522)	(0.00660)	(0.002151)	(0.00654)	(0.007577)
Momentum	-0.001109	-0.002535	**-0.0120****	-0.001126	0.000802	**-0.008****	3.47E-05	-0.00333	-0.004076
	(0.001272)	(0.00431)	(0.005642)	(0.000753)	(0.00252)	(0.00374)	(0.001011)	(0.00316)	(0.004269)
BAS	**0.24239*****	**-0.386*****	**0.309398***	**0.2246*****	**-0.353*****	**0.22181****	0.015639	-0.034031	0.08854
	(0.041112)	(0.14524)	(0.162059)	(0.024352)	(0.08505)	(0.10685)	(0.032689)	(0.10664)	(0.122616)
TimeDum 1	1.23E-05	0.000365	-0.000867	0.000244	-1.71E-05	-0.00122	-0.00023	0.000385	0.000354
	(0.000265)	(0.00092)	(0.001236)	(0.000157)	(0.00054)	(0.00082)	(0.000211)	(0.00067)	(0.000935)
TimeDum 2	**-0.00027****	0.00019	**0.00093****	-1.16E-04	6.44E-05	0.000151	-0.000157	0.000126	**0.000774****
	(0.000132)	(0.00039)	(0.000461)	(7.82E-05)	(0.000229)	(0.000304)	(0.000105)	(0.000287)	(0.000349)
Constant	**0.002675*****	-0.001896	0.000281	**0.00148*****	-0.000379	0.002501	**0.001199****	-0.001531	-0.002227
	(0.00078)	(0.003752)	(0.003324)	(0.000462)	(0.002197)	(0.002191)	(0.00062)	(0.002755)	(0.002515)
Observations	**7594**	**494**	**271**	**7594**	**494**	**271**	**7594**	**494**	**271**
R-squared	0.016866	0.028029	0.066916	0.027449	0.087412	0.105204	0.00352	0.020461	0.104627

Figure 1

Intraday variations in relative bid-ask spread on the ECX

The figure shows intraday relative bid-ask spread pattern for all trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. Average bid-ask spread which is defined for each trade as the last ask price prior to the trade minus the last bid price before the trade divided by the average of both prices is computed for each of the six EUA Futures contracts in our sample and then averaged cross-sectionally across all contracts.



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Appendix

Ice ECX EUA Futures Contract Specifications

Unit of Trading	One lot of 1,000 emission allowances (i.e. 1,000 tonnes of CO_2)
Quotation	Euro (€) and Euro cent (c) per metric tone
Tick	€0.01 (i.e. €10 per lot)
Contract months	Contracts are listed on a quarterly expiry cycle such that March, June, September and December contract months are listed up to December 2012 (Annual contracts with December expiries for 2013 and 2014 as well as March 2013 are available for only EUA contracts)
Contract security	ICE CLEAR EUROPE guarantees the financial performance of ICE Futures Europe contracts registered in the name of its members
Trading system	Trading will occur on the ICE Futures Europe platform accessible via Web ICE, or through a conformed Independent Software Vendor
Trading model	Continuous trading between 07:00 hours to 17:00 hours UK local time
Settlement Prices	Trade weighted average during the daily closing period with Quoted Settlement Prices if low liquidity
Delivery	The Contracts are physically deliverable by the transfer of emissions allowances. There is a delivery period of 3 days after the last day of trading