Could Market Making be Profitable in The European Carbon Market?

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ABSTRACT

We investigate when market making can be profitable in the European Carbon Futures market, by developing an order type selection rule, based solely on transaction level data. We employ a granular approach that uses an observable variable, i.e. trading intensity, to extract the liquidity and information price components and we investigate their impact on spreads, volatility and ultimately on the profitability of different order types. We find that market orders are always less profitable than limit orders. In addition, market makers are expected to derive most of their profits in a low trading intensity environment, mainly due to higher liquidity commissions and a lower probability of dealing with better informed agents. In contrast, an unconditional limit order submission strategy from an off-floor trader should not be preferred, apart from a medium trading intensity environment, where information and liquidity premia adequately compensate them for execution and information risk.

Keywords: EUA Futures, UHF Trading, Intraday Price Discovery, Market Making

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1. INTRODUCTION

Investors, every time they enter the market, need to make a decision about the type of order, i.e. limit order versus market order, that better serves their economic interests. When they submit a market order, they face no execution risk, because their order is executed immediately at the opposite side quote. This means, though, that they are exposed to price risk, since their trades might be executed at a price that is not the most favourable, especially when market depth is shallow (e.g. Biais et al., 1995). In contrast, if they submit a limit order, they reduce price risk, because they declare the maximum (minimum) price they are willing to buy (sell) the asset for, but they cannot be sure whether their order will be executed, since prices might move away from their quote.

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Previous literature (e.g. Handa and Schwartz, 1996; Handa et al., 1998) recognizes that market conditions affect the suitability of each order type and suggests that price formation and its impact on volatility and spreads determines the relative merits of each order type to gain economic significance. Intraday price formation is driven by liquidity and information (O'Hara, 1995). Prices are affected temporarily by increasing demand on one side of the spread and therefore, market makers increase the price of liquidity in order to deal with persistent order imbalances (Madhavan, 2000). This would increase the price of liquidity and thus, spreads, which would increase investors' preference for limit orders (e.g. Chung et al., 1999), so they can charge for liquidity and earn the spread. In the opposite case, when the price for liquidity is low and spreads are narrower, investors seem to prefer to consume it and therefore, they reduce the use of limit orders (Biais et al., 1995).

In parallel, the arrival of information affects prices permanently. Market makers, in fear of trading with better informed agents, charge a fee associated with adverse selection (Kyle, 1985; Glosten and Milgrom, 1985), but they generally lose when they trade with informed agents and recover their losses when they trade with uninformed agents. Limit orders would be rather inappropriate in a market setting where a higher presence of informed agents is expected, because they have option features. Copeland and Galai (1983) suggest that a buy (sell) limit order is like a put (call) option because if prices move against the trader who submitted the limit order, the order will be executed, most frequently at the trader's losses, especially if the order is mispriced (Bae et al., 2003). If prices move in the opposite direction, the order will not be executed. This is clearly an unfavourable condition for limit orders and, although market orders (which face a higher price risk (Peterson and Sirri, 2002)) should be less preferable upon higher volatility (e.g., Foucault, 1999), the literature makes a clear distinction between liquidity (transitory) and information-driven volatility. Higher transitory volatility seems to attract more limit orders (e.g. Handa and Schwartz, 1996; Handa et al., 1998), while limit orders upon a high information component of volatility seem to be associated with informed agents whose information advantage decays slowly (Keim and Madhavan, 1995).

Consequently, the literature recognizes that order type suitability is not a static concept and it depends on changing market conditions. Empirical market microstructure literature (e.g., Cohen et al., 1981; Chakravarty and Holden, 1995; Harris and Hasbrouck, 1996) elaborates on this and introduces additional factors, e.g. trade initiation and order size, that might affect the performance of limit orders. All empirical studies use order by order data, i.e. the submission of all limit and market orders, and approach the issue from a fully empirical perspective, by counting the frequency or by measuring the relative costs associated with different order types across different levels of price change volatility, implied spread, order size and direction (buy or sell). This approach, although it uses all the information available (all orders), it is rather agnostic and descriptive in its nature. It derives some empirical conclusions based on unconditional statistics of limit orders, and therefore, it is not able to provide a trading rule, conditional on some (model) predictions.

This is the primary concern of our study, which focuses on a transaction-by-transaction – rather than on an order-by-order – basis, trying to provide an order-type selection rule based solely on transaction level data (e.g. Kalaitzoglou and Ibrahim, 2017). Transactions, as opposed to limit orders, are realized commitments to trade and therefore they convey vital information with regards to realized and expected price changes (Hasbrouck, 1991). We suggest using this information to condition the selection of a suitable order type, based on informed agents' identification and the estimation of time-variant price components, extracted solely by observable transaction data. First, we recognize that the presence of better informed agents might deter investors from submitting limit orders. We classify market transactions into three categories according to their link to private information, namely uninformed, fundamental and informed agents, based on the deviations of the arrival rate of their trading from (a data-driven estimate of) normal levels. Second, we also recognize the impact of liquidity and information price components of intraday formation and their impact on spreads, variance and ultimately, on the selection of order type. Our major difference from previous literature is that we employ an intraday pricing model that estimates time-variant price and variance components based solely on transaction level data. Using these estimates we then develop an order-type selection rule based on the theoretical and empirical propositions of previous literature. Finally, we test the relevance of our conditional predictions by testing their economic performance. Our approach is relevant to investors who want to condition their orders on expected market conditions.

The second contribution of our study refers to the investigation of the suitability of the order-type selection rule we develop in a market with an increasing importance for the global emission reduction targets (e.g. MacCracken et al., 1999; Klepper and Peterson, 2006), where no prior study exists. We focus our interest in the European Carbon Futures market and especially its most liquid venue; the European Climate Exchange (ECX) in London. This market has undergone a significant development in terms of overall liquidity and maturity (Kalaitzoglou and Ibrahim, 2013a) and previous literature (e.g. Benz and Hengelbrock, 1998) reports that spreads and price-change volatility, identified as the main determinants of the suitability of different order types, exhibit persistent patterns and considerable predictability, mainly due to the cap-and-trade system (e.g. Daskalakis et al., 2009), regulatory announcements (Mansanet-Bataller and Pardo, 2009) and the relative illiquidity (Mizrach and Otsubo, 2014). This predictability could increase execution certainty, which would be beneficial for limit orders, but could also reduce price risk, which would be beneficial for market orders. In general, increased predictability would provide a better estimate of the presence of private information and of price components and, therefore, could render the conditional selection of order type more profitable. All these would lead to a more mature price discovery, which would assist the market in achieving emission reduction targets by assigning a more “faire” price on Carbon; a rather complex task due to the uncertainty about the fundamentals of Carbon emissions (e.g. Manne and Richels, 1991; Alberola and Chevallier, 2009).

The order selection is an intrinsic issue of intraday trading and the development of a trading rule requires a pricing model with time-variant components. Previous literature in the Carbon Market recognizes liquidity and order flow as the main drivers of intraday price formation. Several studies (e.g. Bredin et al., 2014; Mizrach and Otsubo, 2014) trading intensity, i.e. duration and/or transaction size, as a major element of intraday price formation. They report an increasing price impact of higher trading intensity and, therefore, a stronger predictability of returns. Along the same lines, Kalaitzoglou and Ibrahim (2013b, 2015) report that higher trading intensity is associated with a higher presence of information and, therefore, it induces price uncertainty and thus, trading patterns. These patterns are also observed in order-flow dependency (e.g. Ibikunle et al., 2013; Medina et al., 2014) and higher trading intensity is also found to increase (decrease) the information (liquidity) price and volatility component (Ibrahim and Kalaitzoglou, 2016).

Following previous literature, we consider trading intensity as a major driver of intraday price formation in the European Carbon Futures market and we use it to identify different agent types, to extract the price components and to generate some conditional predictions for the suitability of the different order types.[1] The empirical findings identify an increasing impact of trading

1. In this study, in consistency with previous literature (e.g. Harris and Hasbrouck, 1996; Foucault, 1999; Peterson and Sirri, 2002), we consider a major classification of order types into market and limit orders. The first prioritizes execution time, while the second execution price. The EU ETS has gained complexity over the years, especially in Phase III, and different order types of increasing complexity have been introduced in order to facilitate trading. For example, in the early stages of

intensity on the information price component due to a stronger link to information, but a decreasing impact on the liquidity component, due to a higher execution probability/lower inventory risk. Consequently, the overall impact on price formation, and subsequently on the profitability of the different order types, depends on the relative magnitude of each effect. When trading intensity is expected to be low, the information price component is also low, but the liquidity component is at its highest level. We find that these are the market conditions that market makers, who prioritize liquidity gains and not execution risk, would prefer to derive their profits from. In contrast, when trading intensity is high, the price of liquidity is low, while a higher information price component indicates a higher presence of informed agents. These are the market conditions that would deter investors from placing limit orders. Finally, a limit-order submission strategy of an off-floor investor, who cannot compete with market makers on liquidity provision or with better informed agents on information advantages, appears to be more competitive only at medium levels of trading intensity, where information and liquidity premia adequately compensate them for execution and information risk. Overall, however, limit orders perform consistently better than market orders.

2. DATA SAMPLE AND INITIAL OBSERVATIONS

Sample

Our data consist of all transactions and best-quote revisions of EUA Futures contracts with December duration, traded on the European Climate Exchange (ECX) and it is collected solely from the Thomson Reuters Tick History (TRTH) database. The information on this database about the contracts traded during the first phase of the EU ETS, i.e. 2005–2007, as well as the first year of phase II, i.e. 2008, is rather sporadic and cannot be used for the purposes of this study. Our dataset covers a period from 29/9/2008 until 30/04/2016. This period covers almost the whole phase II, 29/9/2008–17/12/2012, and the first 3.25 years of phase III, 29/9/2008–30/4/2016. For the best-quote revisions TRTH provides the best bid and the best ask prices and the associated volume at level one of each side of the spread. For transactions we collect the price and the volume. For each event we have the time stamp at millisecond accuracy. We consider the bid-ask spread reported immediately before each transaction, as the prevailing spread at the time of the transaction and in the case of multiple transactions we keep the last quote revision.

Then we focus solely on transactions and we record the number of quote revisions between two consecutive transactions. We apply the following data manipulation process in order to create continuous series and to account for various microstructure phenomena. First, we omit observations

the market, when liquidity had been rather low, larger trades would cause adverse price movements and therefore, block trade facilities where introduced in the form of Exchange For Physical (EFP) and Exchange for Swap (EFS) orders. These created an upstairs market of negotiated trades, which may have a significant impact on the organized market (e.g. Kalaitzoglou and Ibrahim, 2013) but is not the primary focus of this study and therefore not examined. The focus of this study is the organized market of screen trades, where limit order and market making strategies can be developed and therefore, negotiated trades are not considered as part of such a strategy. However, there are also other types of orders that are being used in the organized market, either related to liquidity (e.g. iceberg orders) or to execution price (e.g. stop limit orders and stop limit orders with protection). These order types can be largely classified as different types of market or limit orders with secondary characteristics. For example, iceberg orders are similar to market orders, but with a hidden liquidity part, while stop limit orders are similar to limit orders but only for a price improvement. The objective of our analysis is to introduce a tradable order-type selection rule, focusing on either execution or price risk. In this context, what is more important is the primary characteristics of order types (i.e. immediate execution versus requested price) and not the secondary characteristics (i.e. volume or price improvement). Of course, they would affect the profitability of a trading strategy, but they would constitute a refinement, rather than an integral part, of the trading rule.

with no or erroneous inputs, such as a 0 price, or with a bid price higher than the ask price. Second, we consider only the contracts with the highest trading volume and we roll over from one maturity to the next when the new contract exhibits higher daily volume for at least two consecutive days. The rollover days are 9/12/2008, 4/12/2009, 16/12/2010 and 14/12/2011 for phase II and 13/12/2013, 12/12/2014, 11/12/2015 for phase III. This produces two datasets, namely ECX II and ECX III, with 1,206,114 and 1,517,191 transactions, respectively. Third, a significant number of trades are reported with the same time stamp and with the same price, differing only at the transacted volume. These trades are likely to be a large trade being met by different, smaller, orders from the opposite side of the spread. In addition, the high frequency of zero waiting times, i.e. durations, between these transactions would introduce significant bias in our analysis below, where we try to derive the price premia and identify different trade types based on their conditional arrival rate. Therefore, we consolidate these transactions' aggregating volume. This thinning process results in two datasets of 864,368 and 835,289 transactions, for ECX II and ECX III, respectively. Fourth, TRTH does not provide a trade initiation variable and therefore, we need to extract it from the bid-ask quotes and transaction prices. We follow the 'EMO' rule (Ellis et al., 2000) to assign a +1 (–1) to buyer- (seller)-initiated trades. We also test the robustness of our findings with two different algorithms; the 'tick' (Harris, 1989) and the 'LR' (Lee and Ready, 1991) rules.

Initial Observations

Table 1 presents the descriptive statistics of the two rolling series; ECX II and ECX III. The first notable observation is that the main asset traded in each phase is the contracts with the maturity in the same phase. Until the end of 2012, the number of trades in the ECX II series is far superior to ECX III. In addition, the number of observations before 2012 for ECX III accounts for about 10% of the total trades, but with an increasing number every year. Consequently, the price discovery for EUA Futures is expected to occur in the contracts with the closest maturity. The large difference in overall liquidity between the two series is also observed in the decreasing duration over the trading years. In both phases, the duration in the early trading period is significantly higher compared to the main trading period of each asset. For example, the average duration in 2010 for ECX III is 2,752 seconds and it drops to 35.61 seconds in 2013 – comparable to 40.74 seconds in 2012 for ECX II – when Phase III contracts become the main asset. The transaction size does not change significantly, so the differences are observed due to a higher number of transactions.

In addition, prices consistently decrease over the years due to macroeconomic factors (Conrad et al., 2012), and this pattern is also followed by price volatility, price change volatility and implied spreads. Average prices move from 18.92 in 2008 to 5.68 in 2016, while price change volatility decreases from 0.03 in ECX II and 0.07 in ECX III to 0.01, when the contracts are most actively traded. The most notable variation is observed in implied spreads, which are significantly larger when the contracts are not the main asset, e.g. 0.12 in ECX III in 2010, and they drop to 1 tick, i.e. 1 cent, in the most active periods, e.g. ECX II in 2012 and ECX III in 2016. They too confirm that the main price discovery occurs when the contracts with the closest maturity are traded.

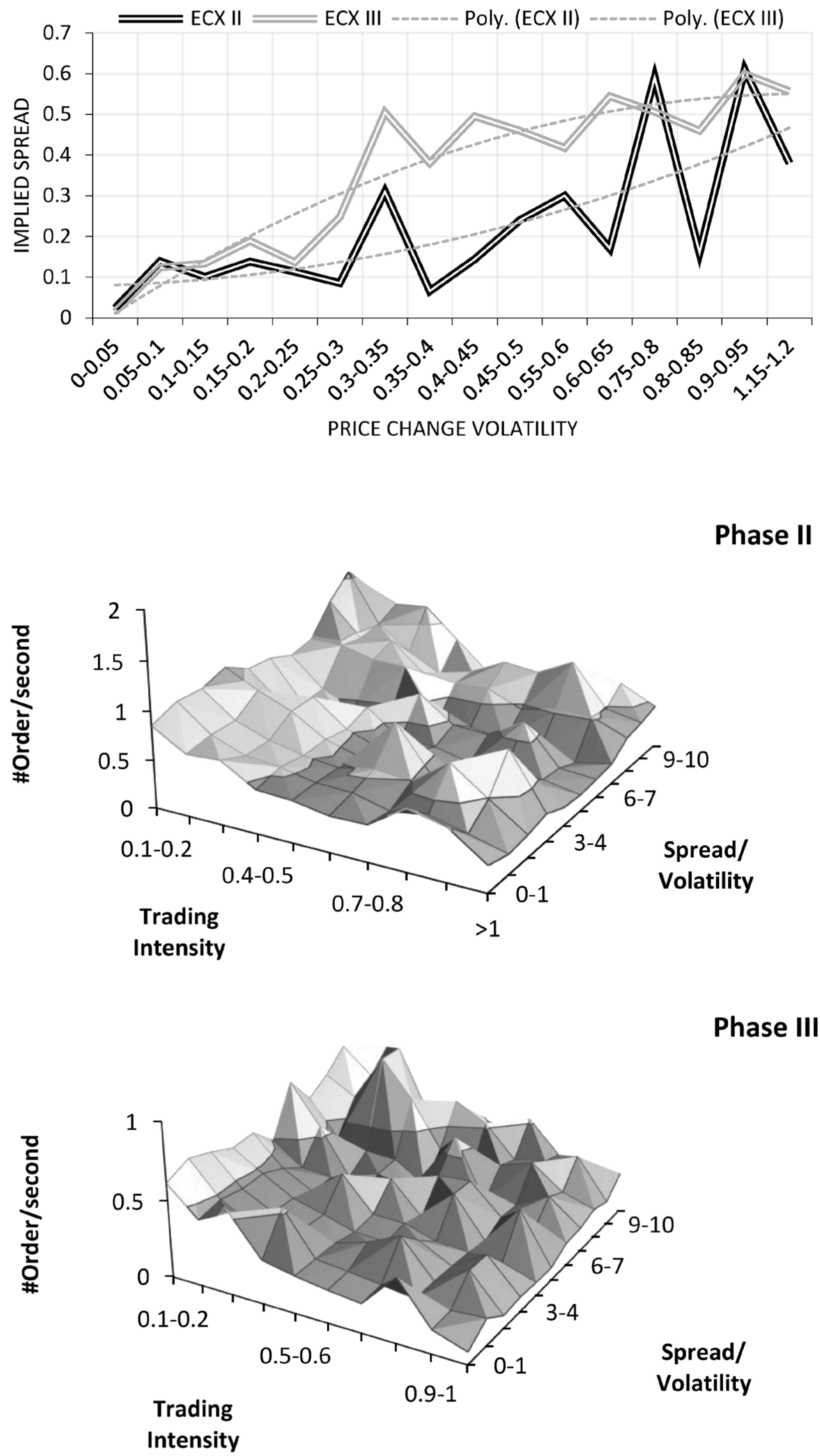
Furthermore, the first panel in Figure 1 plots the average actual spread across different levels of price change volatility. It shows that the two are positively correlated in both markets. Higher spreads increase the liquidity proceeds of limit orders (Biais et al., 1995), but higher volatility decreases the pay-offs of their put-option characteristics (Copeland and Galai, 1983). Therefore, we speculate that since they are positively correlated, what might be more important for limit orders is their relative rate of change. We compute the ratio of implied spread to price-change volatility and, following Ibrahim and Kalaitzoglou (2016), we consider that trading intensity affects both. In order

Table 1: Descriptive Statistics

		Dur	Vol	P	ΔP	S	#Order	Dur	Vol	P	ΔP	S	#Order
Total	Avg	44.90	10.09	12.27	0.00	0.02	10.03	68.04	15.51	6.16	0.00	0.02	6.94
ECXII	Med	6.51	4.00	13.12	0.00	0.02	2.00	5.46	5.00	5.83	0.00	0.01	3.00
#864,368	Max	24878	2000	24.39	0.95	1.92	71467	35742	5000	20.22	0.64	4.56	50990
ECXIII	Min	0.00	1.00	5.61	–1.09	0.01	0.00	0.00	1.00	2.46	–0.95	0.01	0.00
#835,289	Std	129.26	21.81	3.56	0.02	0.02	214.25	430.22	44.58	2.08	0.01	0.02	116.60
	Avg	64.27	4.76	18.92	0.00	0.05	12.58						
2008	Med	8.20	2.00	18.25	0.00	0.05	3.00						
ECXII	Max	23901	216	24.39	0.92	1.82	7471						
#36,645	Min	0.00	1.00	13.50	–1.09	0.01	0.00						
	Std	223.24	7.37	2.79	0.03	0.04	96.36						
	Avg	45.39	6.03	13.24	0.00	0.03	9.69						
2009	Med	6.06	2.00	13.54	0.00	0.03	3.00						
#202,288	Max	24878	478	16.04	0.95	1.92	22643						
	Min	0.00	1.00	8.05	–0.95	0.01	0.00						
	Std	134.29	9.99	1.63	0.02	0.02	117.74						
2010	Avg	48.31	10.73	14.56	0.00	0.02	24.77	2572.65	19.90	16.57	0.00	0.12	472.69
ECXII	Med	7.03	4.00	14.80	0.00	0.02	3.00	174.05	10.00	16.63	0.00	0.06	19.00
#190,012	Max	19584	995	16.73	0.27	0.38	71467	35742	995	19.19	0.64	4.56	50990
ECXIII	Min	0.00	1.00	12.25	–0.26	0.01	0.00	0.00	1.00	14.53	–0.59	0.01	0.00
#3,108	Std	137.95	21.30	1.02	0.01	0.01	437.88	5254.79	40.81	0.91	0.07	0.32	1826.05
2011	Avg	42.36	11.56	13.03	0.00	0.02	3.90	383.07	14.28	13.60	0.00	0.03	30.68
ECXII	Med	6.55	5.00	12.91	0.00	0.02	2.00	25.95	5.00	13.73	0.00	0.03	4.00
#216,302	Max	18002	689	18.18	0.51	0.64	1721	24783	995	20.22	0.61	1.24	2753
ECXIII	Min	0.00	1.00	6.73	–0.88	0.01	0.00	0.00	1.00	7.26	–0.79	0.01	0.00
#23,912	Std	116.73	22.34	2.99	0.01	0.02	12.08	1069.67	28.19	3.37	0.03	0.03	99.62
2012	Avg	40.74	12.72	7.53	0.00	0.02	3.19	156.28	17.13	7.88	0.00	0.02	10.86
ECXII	Med	6.16	5.00	7.51	0.00	0.02	2.00	18.60	5.00	7.83	0.00	0.02	3.00
#219,121	Max	3744	2000	9.63	0.24	0.43	565	17448	2000	10.45	0.39	0.43	1507
ECXIII	Min	0.00	1.00	5.61	–0.21	0.01	0.00	0.00	1.00	5.93	–0.32	0.01	0.00
#58,973	Std	104.29	29.31	0.76	0.01	0.01	5.99	378.51	47.92	0.85	0.02	0.01	25.61
	Avg							35.61	14.81	4.46	0.00	0.02	3.62
2013	Med							4.60	4.00	4.47	0.00	0.01	2.00
ECXIII	Max							11755	5000	6.84	0.43	0.72	390
#258,745	Min							0.00	1.00	2.46	–0.95	0.01	0.00
	Std							104.29	44.83	0.71	0.01	0.01	5.65
	Avg							38.16	15.56	5.90	0.00	0.01	3.50
2014	Med							4.78	5.00	5.93	0.00	0.01	2.00
ECXIII	Max							5102	5000	7.57	0.43	0.25	1116
#241,635	Min							0.00	1.00	3.71	–0.42	0.01	0.00
	Std							109.11	47.09	0.69	0.01	0.01	6.89
	Avg							55.44	16.75	7.56	0.00	0.01	4.32
2015	Med							5.99	5.00	7.49	0.00	0.01	3.00
ECXIII	Max							5088	3685	8.71	0.15	0.16	352
#166,877	Min							0.00	1.00	6.28	–0.18	0.01	0.00
	Std							151.36	47.38	0.58	0.01	0.01	4.70
	Avg							33.80	14.11	5.68	0.00	0.01	5.48
2016	Med							5.29	5.00	5.37	0.00	0.01	4.00
ECXIII	Max							2130	2000	8.33	0.17	0.20	277
#82,039	Min							0.00	1.00	4.62	–0.17	0.01	0.00
	Std							81.74	29.08	0.89	0.01	0.01	4.95

Table 1 presents the descriptive statistics of Duration (*Dur*) in seconds, Volume (*Vol*) in number of contracts per transaction, Price (*P*) in £, Price change (ΔP) in £, Actual Spread (*S*) in £ and number of orders per trade (*#Order*), for the full sample and for each year.

Figure 1: Spread, Variance and Limit Orders



The first panel of Figure 1 presents the average implied spread across different levels of price-change volatility. The bold lines represent the actual figures for ECX II and ECX III, while the dotted lines represent a second order polynomial smoothing. The bottom two panels present the average number of orders per second across different levels of trading intensity and the ratio of implied spread over price-change volatility.

to get an idea of the frequency of limit orders, we compute the number of quote revisions per second, #Order/second, in between trades as a proxy for the intensity of limit-order submissions. The second and the third panels of Figure 1 show the average number of quote revisions, across different levels of trading intensity and the ratio of implied spread/price change volatility. Both markets exhibit similar patterns with more limit orders being preferred when trading intensity is low and when spreads are relatively higher than price-change volatility. This primary finding is the main focus of the following sections, where we try to decompose prices, spread and volatility into their liquidity and information price components, based on time variations of trading intensity.

3. TRADING INTENSITY AND INFORMED AGENTS

Methodology

Market makers face an information-related risk when dealing with better informed agents. The same applies to investors who might also become liquidity suppliers on one, or both sides of the spread, by submitting limit orders. They have the discretion to select the most suitable order type and therefore, these off-floor traders can time the submission of limit orders to minimize the risk of being picked up by informed agents. Following previous literature (e.g. Easley and O'Hara, 1992) that associates fluctuations in trading activity with information, we identify three types of traders: uninformed, fundamental and informed; based on the conditional intensity of their trading.

More specifically, we consider the waiting time for a contract to be traded, i.e. $S_i = x_i * K(u_i)$, measured as the product between the waiting time for a transaction i, i.e. $x_i = t_i - t_{i-1}$, where t_i is the time stamp, and the scaling factor $K(u_i) = exp(-(v_i - \overline{v})/2\sigma_v)$ that measures the transaction volume v_i, relative to its sample mean, $\overline{v}$, and variance, σ_v^2.[2] S_i is a natural measure of 'trading intensity' and its arrival rate could be also associated with the arrival of information (e.g. Kalaitzoglou and Ibrahim, 2015). The arrival rate of purely liquidity-motivated trades should be time invariant (Hujer and Vuletić, 2007) and therefore, the conditional intensity, i.e. 'hazard' function, of S_i should be a horizontal line. In contrast, because private information arbitrage opportunities decay with time, better informed agents should have the incentive to act closer to the arrival of new information; a trading behaviour that could be captured by a downward slope hazard function. Finally, we recognize a third group of agents, who continuously observe the market and time their trades according to extracted signals. They trade with a lag to the arrival of private information and therefore, their hazard function should exhibit an upward slope. We derive the hazard functions from S_i, according to a Smooth-Transition-Mixture (of distributions) Autoregressive-Conditional-Weighted-Duration (STM-ACWD) model (Kalaitzoglou and Ibrahim, 2015):

$$S_i = \Theta_i \varepsilon_i, where\, \Theta_i = E(S_i | F_{i-1}; \varphi)\, and\, \varepsilon_i | J_i \sim i.i.d. \tag{1}$$

Θ_i is the conditional expected trading intensity; F is the publicly available information set, and $\varepsilon_i = S_i / \Theta_i$ is the standardized trading intensity with density $f(\varepsilon_i | J_i; \varphi_2)$ and $E(\varepsilon_i | J_i; \varphi_2) = E(\varepsilon_i) = 1$. $\Theta_i = E(S_i | F_{i-1}; \varphi) = \Theta(S_{i-1}, \ldots, S_1; \varphi_1)$ is modelled using a linear ARMA specification. Finally, f is assumed to be a smooth transition mixture of Weibull distributions:

$$f(S_i | J_i; \tau) = (\gamma_i / S_i)\left[S_i \Gamma(1 + 1/\gamma_i)/\Theta_i\right]^{\gamma_i} exp\left(-\left[S_i \Gamma(1 + 1/\gamma_i)/\Theta_i\right]^{\gamma_i}\right) \tag{2}$$

2. Durations are computed in milliseconds and diurnally and annually adjusted (e.g. Ibrahim and Kalaitzoglou, 2016).

where $\Gamma(\because)$ is the gamma function. The overall shape parameter of the Weibull distribution, $\gamma_i = \gamma(J_i : \boldsymbol{\tau}) = \gamma_1 + (\gamma_2 - \gamma_1) * G_1(J_i : g_1, j_1) + (\gamma_3 - \gamma_2) * G_2(J_i : g_2, j_2)$, is a function of a threshold variable, J_i, represented by S, and a vector of parameter coefficients $\boldsymbol{\tau} = (\gamma_1, \gamma_2, \gamma_3, g_1, g_2, j_1, j_2)$. γ_i, is the weighted average of γ_1, γ_2 and γ_3, i.e. the shape parameters in the respective three regimes determined by the threshold variable J_i, and the weights are determined by the smooth transition functions, $G_k(S_i : g_k, j_k) = (1 + exp\{-g_k * (J_i - j_k)\})^{-1}$, with smoothness parameters $g_k, k = 1, 2$. This specification provides a time-variant estimate of the hazard function $\lambda_i \equiv \frac{f(S_i | J_i; \tau)}{1 - F(S_i | J_i; \tau)}$, where $F(S_i | J_i; \tau)$ is the conditional CDF of S. When $\gamma_i = 1$ the Weibull distribution reduces to Exponential, which exhibits a flat hazard function that we associate with uninformed trading. In contrast, when $\gamma_i < 1$ ($\gamma_i > 1$) the Weibull distribution exhibits a(n) downward (upward) slope hazard function, which we associate with informed (fundamental) trading. Consequently, market participants can have an estimate of the probability of the next trade to be into one of the three categories, by estimating Θ_i and using j_1. and j_2.

Furthermore, intraday price formation is also affected by liquidity. The use of S_t as a threshold variable also distinguishes between three levels of liquidity; when $S_t < j_1$ ($S_t > j_2$) we identify a period of relatively high (low) or medium ($j_1 < S_t < j_2$) relative liquidity.

Empirical Findings

The empirical findings in the first two columns of Table 2 confirm previous findings in the literature, with higher trading intensity being associated more with informed trading (e.g. Kalaitzoglou and Ibrahim, 2013b) and a higher intensity of subsequent trading (e.g. Kalaitzoglou and Ibrahim, 2013a, 2015). High trading intensity, i.e. $S_t < 0.3508$ in ECX II, is associated with a decreasing hazard function ($\gamma_1 = 0.0838$) and thus, these trades are more likely to be instigated by better informed agents. In contrast, low trading intensity, i.e. $S_t > 0.5801$ in ECX II, exhibits a flat hazard function ($\gamma_3 \approx 1$) and thus, these trades are more likely to be liquidity rather than information motivated. Finally, medium trading intensity, i.e. $0.3508 < S_t < 0.5801$ in ECX II, is associated with an increasing hazard function ($\gamma_2 = 4.083$) and thus, with traders who discretionarily place their trades following information signals. In general, these findings confirm that increased trading intensity is associated with a higher presence of information and, therefore, should be expected to be associated with higher informational volatility and, thus, fewer limit orders (e.g. Peterson and Sirri, 2002), as is also observed in Figure 1. In the following sections we investigate the impact of trading intensity on price components, price premia and ultimately on the selection of order type.

4. TRADING INTENSITY AND INTRADAY PRICING

Methodology

We consider a market-wide price formation that is regret-free from both information and liquidity effects, using the following structural pricing model (Ibrahim and Kalaitzoglou, 2016) with time-variant information, θ_i, and liquidity, φ_t, price components.

$$\Delta p_i = \theta_i (q_i - \rho q_{i-1}) + \Delta \varphi_i q_i + u_i \tag{3}$$

where Δp_i is the change in price, p, from previous transaction; q_i is the order flow variable that takes a value of +1 if trade i is buyer-initiated and –1 if it is seller-initiated (this variable is assumed to follow a simple Markov process with ρ being the first order autocorrelation of q_i); ($q_i - \rho q_{i-1}$) is the

Table 2: Estimation Results

	Phase II	Phase III		Phase II	Phase III
ω	0.0647	0.0543	θ_{2un}	0.0053	0.0029
	(19.11)	(14.49)		(17.61)	(17.14)
α	0.2926	0.2975	θ_{2fun}	0.0026	0.0016
	(32.66)	(26.98)		(23.19)	(24.25)
β	0.7074	0.7025	θ_{2inf}	0.0014	0.0008
	(132.66)	(138.73)		(28.03)	(27.30)
g_1	1.0153	0.9976	ρ	0.5074	0.4567
	(13.50)	(15.50)		(382.45)	(314.93)
g_2	1.0146	0.9972	φ_3	0.0066	0.0039
	(12.07)	(11.51)		(8.65)	(8.27)
s_1	0.3508	0.3067	φ_{2un}	–0.0035	–0.0018
	(28.26)	(26.93)		(–4.62)	(–3.43)
s_2	0.5801	0.5776	φ_{2fun}	–0.0015	–0.0010
	(34.87)	(36.33)		(–17.14)	(–8.59)
γ_1	0.0838	0.1932	φ_{2inf}	–0.0009	–0.0004
	(18.21)	(18.85)		(–23.77)	(–8.83)
γ_2	4.0983	3.9613	$100 \text{ x } \sigma_\varepsilon^2$	0.0083	0.0030
	(21.02)	(20.16)		(18.06)	(8.22)
γ_3	0.9612	0.9718	$100 \text{ x } \sigma_\xi^2$	0.0050	0.0019
	(17.22)	(17.02)		(12.59)	(17.05)
L	–253632.3	–101825.2	J	5.73	3.38
$\gamma_1=1$	405105.64	249339.3	p	(0.08)	(0.18)
	(0.00)	(0.00)			
$\gamma_2=1$	2525874.8	1434944.8			
	(0.00)	(0.00)			
$\gamma_3=1$	5.76	3.12			
	(0.03)	(0.06)			

The first panel of Table 2 presents the estimation results for the STM-ACWD model in Eq. (1) and the pricing model in Eq. (3). The values in () are *t*-statistics. The bottom panel presents the Log-Likelihood value, *L*, the *J*-statistic and hypothesis-testing for the shape parameters of the Weibull distribution. The values in () are *p*-values

surprise in the order flow, which captures the revelation process of private information; u_i is the error component that captures bot public information and price discreteness. The price responses to information and liquidity, θ_i and φ_i, are updated after every transaction according to the revision in expectations: $\theta_i = \sum_{\pi}^{3}\left(\theta_\pi I_{\pi,i}\right)\Theta_\iota^{-1}$ and $\varphi_\iota = \varphi_1 + \sum_{\pi}^{3}\left(\varphi_{2,\pi} I_{\pi,i}\right)\Theta_\iota^{-1}$, where, Θ_ι^{-1} is an increasing function of trading intensity, θs and φs and parameters to be estimated and $I_{\pi,i}$ is a set of binary variables that indicates the type of agent expected to instigate the next trade, according to the specific regime $\pi = (uninformed, fundamental \text{ or } informed)'$ of trading intensity that is expected to exist at event/time i. This model is estimated with an iterative GMM procedure using an appropriate set of moment conditions (see Ibrahim and Kalaitzoglou, 2016).

This model provides a conditional estimate of the components of the implied spread

$$C.IS = 2\left(\underbrace{\theta_i}_{\text{Information Component}} + \underbrace{\varphi_\iota}_{\text{Liquidity Component}} \right) \tag{4}$$

as well as a decomposition of conditional variance to its structural components: asymmetric information, *AS*; liquidity, *LIQ*; interactions between information and liquidity, *INT*; and errors such as public information, *PI*; and price discreteness, *PD*. This decomposition is:

$$C.Var\left[\Delta p_i\right] = \underbrace{\left(1-\rho^2\right)\left[\theta_i^2\right]}_{AS_i} + \underbrace{2\left(1-\rho\right)\left[\varphi_i^2\right]}_{LIQ_i} + \underbrace{2\left(1-\rho^2\right)\left[\theta_i\varphi_i\right]}_{Int_i} + \underbrace{u^2}_{PI\ \&PD} \tag{5}$$

Empirical Findings

The last two columns of Table 2 present the estimation results for the market wide pricing model we use in eq. (3), which confirm the previous literature with respect to the impact of trading intensity on intraday price formation (e.g. Dufour and Engle, 2000; Bredin et al., 2014; Ibrahim and Kalaitzoglou, 2016). In brief, we find trading intensity to have a dual impact, mainly driven by information and liquidity concerns. Higher trading intensity is found to increase price changes due to private information concerns, with a decreasing sensitivity to surprise in order flow, e.g. low trading intensity, θ_{un}, in ECX II is 0.0053, while high trading intensity, θ_{inf}, in ECX II is 0.0014. In contrast, higher trading intensity is also found to decrease price changes due to liquidity concerns, with also a decreasing sensitivity to order-flow changes, e.g. low trading intensity, φ_{un}, in ECX II is –0.0035, while high trading intensity, φ_{inf}, in ECX II is –0.0009. The relative magnitude of each effect, as well as the autocorrelation of order flow, i.e. 0.5074 in ECX II and 0.4567 in ECX III, determine the width of the implied spread and the magnitude of variance, eq. (5), but not necessarily with the same magnitude. Therefore, different market conditions, here captured by different levels of trading intensity, might exhibit different implied spread and price change volatility variations, which might favour the submission of a different type of order.

The first line of Figure 2 shows that our estimates of the implied spread and the price change variance follow closely the actual variations and both are found to be higher at the extremes of trading intensity. According to our estimates, volatility and implied spreads are higher when expected trading intensity is low due to a higher liquidity-price component, which also increases the transitional component of variance. In parallel, when trading intensity is high, the information price component is higher, which increases the information (*AS*) component of variance. Consistent with the literature, more limit orders per second are observed when the transitory variance component is high. This is an empirical finding that we analyse in the following sections.

5. LIMIT VERSUS MARKET ORDERS: DECISION CRITERIA AND MODEL PREDICTIONS

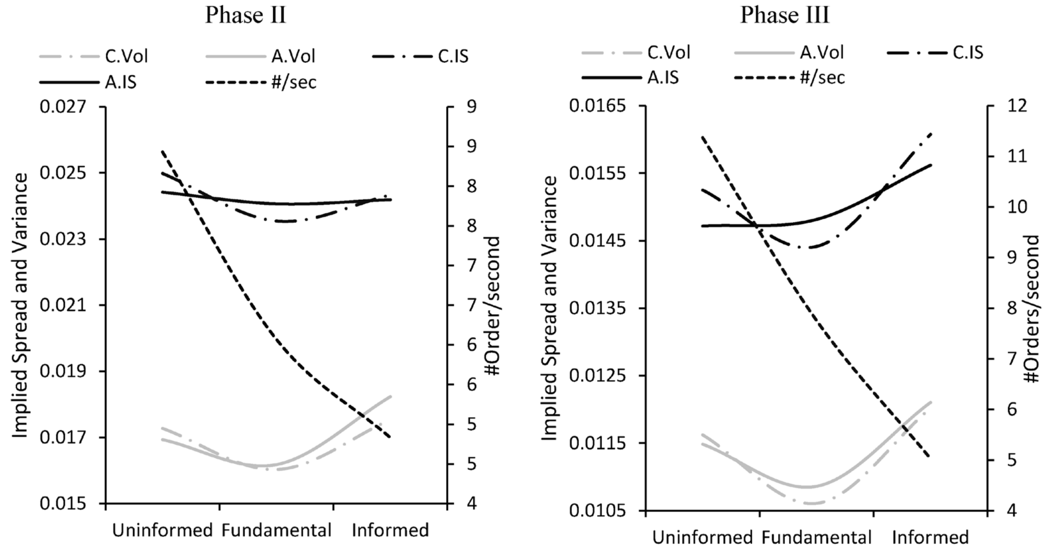
Decision Criteria

The decompositions of conditional spreads and variance can be used to develop some selection rules, with respect to the suitability of the type of order, conditional on market-wide expectations. We consider two types of investors, with respect to limit-order submissions. The first is the market makers, who have the obligation to provide liquidity, always quoting bid and ask prices, in exchange for reduced fees and other types of trading benefits. The second is all other, off-floor, investors who are assumed to select the submission of a market or a limit order at every event.

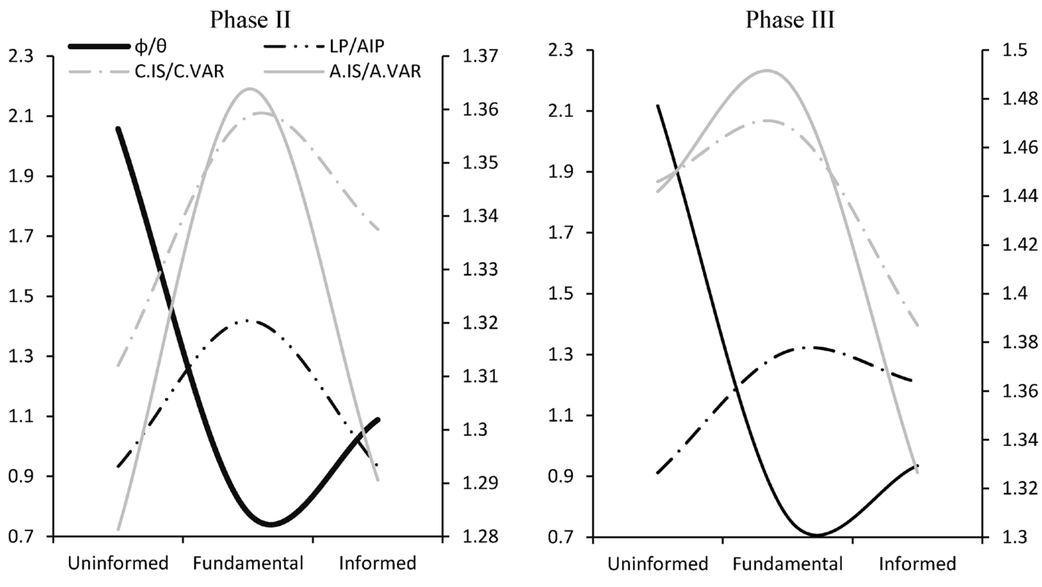
According to the literature (e.g. Harris and Hasbrouck, 1996) market makers are mostly exposed to information risk and not to execution risk. A market maker is supposed to submit regret-free prices that take into consideration both information and liquidity concerns, but under competition there might be a maximum spread that they could charge and therefore, the information premium might not be sufficient when trading with better-informed agents. Consequently, they should derive most of their profits from (and prefer) transactions when the commission they charge for liquidity (price of liquidity) is at its highest level with respect to their commission for information risk. Our price decomposition accounts for both liquidity and information and market makers should prefer market conditions when φ / θ is maximized. This would maximize proceeds from immediacy (higher φ) and minimize the risk of being picked up by better-informed agents (lower θ).

Figure 2: Conditional and Unconditional Spread, Volatility and their components

A. Conditional and Unconditional Spreads and Volatility



B. Decision Criteria



The first row of Figure 2 presents the actual and the conditional implied spread and price change volatility, as well as the number of orders per second, for both phases across different agent types. The second row presents the ratio of actual and conditional implied spread over price-change volatility (right axis) and the ratio of price components, φ/θ, and risk premia LP/AIP (left axis) for both phases across different agent types.

On the other hand, discretionary submission of limit orders from off-floor traders should not be expected to be unconditionally optimal (Bae et al., 2003), because they are less competitive on liquidity than market makers since they do not get their discounts and the benefits, while they are still exposed to the execution risk on top of the risk of being picked up by better-informed agents. Therefore, their choice should depend on the price for liquidity and information, but also on the risk they need to bear for their orders to be competitive but also regret-free from liquidity and information concerns. If their prices, being regret-free, are beyond the best bid and ask they might not be executable, while if they are executable, they might not be regret-free. Consequently, off-floor traders should also consider risk in their selection of order type. Our model provides estimates of information and liquidity risk (variance components), as well as estimates of the equivalent price components. We postulate that off-floor traders should prefer a limit order when their commission for every unit of risk they are exposed to is the highest possible. Therefore, we suggest using the ratio of conditional spread over conditional volatility as an index for the suitability of a limit order. Higher levels would indicate a higher reward for every unit of risk.

This selection criterion, although parsimonious in its construct, does not take into consideration the relative balance between information and liquidity, at least not in the way our criterion for market makers does. Consequently, we estimate the information-risk premium (*AIP*) and the liquidity-risk premium (*LP*), separately, as the component of transaction price change attributed to each type of risk, divided by the contribution of each type of risk to the total variance (e.g., Kalaitzoglou and Ibrahim, 2017). This way, *LP* and *AIP* measure the monetary reward required for every unit of a specific type of risk:

$$LP_i = \varphi_i \,/\, LIQ_i \tag{6}$$

$$AIP_i = \theta_i \,/\, AS_i \tag{7}$$

We use the ratio of $LP \,/\, AIP$ as a stricter version of the previous selection criterion, i.e. $C.IS \,/\, C.Var$, suggesting that a discretionary submission of a limit order by an off-floor investor should be preferable when the reward for liquidity is at the highest level with respect to the reward for information, accounting also for exposure to the different types of risk. This criterion implies that discretionary submission of limit orders should be preferred when the reward for every unit of liquidity risk is high and, therefore, either when the cost of liquidity is high (high φ) or when execution risk is lower (reflected on a lower *LIQ*), especially when this coincides with a low reward for exposure to information risk (reflected in a low *AIP*). The underlying implicit assumption is that off-floor traders cannot beat market makers in liquidity rewards and, therefore, their quotes might not be competitive and liquidity regret-free at the same time, while they cannot beat better-informed agents either. Therefore, they need to bear a higher information risk than the market makers, but up to a level that their reward for liquidity is higher than their exposure to information risk. They should prefer to submit limit orders when the market conditions allow a high liquidity reward without rendering their quote-setting non-marketable or non-regret-free.

In general, the suggested order-type selection rule is based on risk aversion and it can be conceptually extended in order to accommodate the needs of different investment strategies. For example, a hedging motivated trading strategy would be more sensitive to anticipated uncertainty and, therefore, it would place more weight on expected variance, i.e. *LIQ* or *AS*. Furthermore, the distinction between information and liquidity premia could also be further refined in order to take into account speculative trading, which would be more sensitive to directional price changes and price momentum and therefore, it should place a greater weight on anticipated permanent price changes, i.e. *AIP*.

Model Predictions

The second row of Figure 2 summarizes the empirical predictions of the conditional criteria derived from the pricing model we use. The first notable observation refers to the relationship between the price for liquidity, captured by φ_i and the price for information, captured by θ_i. The ratio of φ / θ consistently reaches its highest point when trading intensity is expected to be low. This would result in a high price for liquidity, a higher φ in our estimation, which should be expected because lower trading intensity means longer waiting times and, thus, higher immediacy costs. At the same time, low trading intensity is associated with a low presence of information (e.g. Easley and O'Hara, 1992; Ibrahim and Kalaitzoglou, 2016) and, therefore, the information price component, θ, should be low. This, according to our decision criteria, should be the ideal environment for market makers and it is partially confirmed by the fact that most limit orders per second (first row Figure 2) are observed in this regime (uninformed). However, when trading intensity is expected to be higher, the ratio of φ / θ decreases and we purport that this should not be a desirable market condition for market makers, which is partially consistent with the findings in Figure 1 and Figure 2. More precisely, according to the estimation results liquidity (information) costs decrease (increase) with higher trading intensity, i.e. φ_{fun} and φ_{inf}, but the lowest point of the ratio of φ / θ is observed in the fundamental regime. At this level of trading activity, θ takes its maximum value with respect to φ and it presents a high(er) information cost compared to a low(er) liquidity cost. This should be less desirable for market makers who, not facing an execution risk (e.g. Harris and Hasbrouck, 1996), should prioritize proceeds from liquidity and minimize exposure to information risk.

However, the relatively higher reward for information might be an opportunity for the second group of traders we consider, the off-floor discretionary limit-order traders, who need to undertake some risk (but not too much), because they cannot compete with either the market makers on liquidity basis or with better-informed agents on information advantages. Therefore, this middle ground might present exploitable opportunities. In fact, at this level of trading activity the implied spread and the price change variance are found to be at their minimum levels (first row of Figure 2), but their ratio, for conditional *C.IS* / *C.VAR* and actual *A.IS* / *A.VAR* estimates, reaches its maximum (second row of Figure 2), because the variation of the spread is lower in magnitude than the variation of the variance. Both criteria we consider for discretionary limit-order investors reach their pick in this regime, i.e. when trading intensity is expected to be medium, a level that we associate with fundamental traders. We postulate that this level of anticipated trading activity is the zone where limit-order submission should become more desirable for investors who do not enjoy liquidity or private information benefits. At this level of trading activity, liquidity concerns and the cost of liquidity should be lower and, therefore, not the primary objective of market makers. In parallel, the increased trading activity might be the result of a higher presence of price-unresolved information, which results in a higher cost for information. However, compared to even higher levels of trading intensity, which are linked to private information through the decreasing hazard function, it seems to be associated not with informed agents, but with other fundamentals. Consequently, in a high trading-intensity regime, off-floor discretionary limit-order traders would lose to better-informed agents, while in a low trading intensity regime they might not be able to compete with market makers. This middle regime presents them with sufficient spreads, compared to price-change variance, so they can benefit from the submission of limit orders. We anticipate their financial performance to be better in this regime.

Finally, the preference of market orders, for a non-informed agent, should be a decreasing function of the anticipated presence of private information (e.g. Peterson and Sirri, 2002) and it should, therefore, decrease with higher expected trading intensity.

6. LIMIT VERSUS MARKET ORDERS: PERFORMANCE

Methodology

In order to investigate whether these conditional propositions developed in the previous section have any practical implication we test the relative performance of each order type. We consider transactions as a realized commitment to trade and we compare the performance of limit and market orders as two options for investors that might come at a different immediate or long-term cost. The first measure focuses on the relative gains of each order type, with a submitted price $p^{ask/bid,submitted}$, actual or generated by the pricing model (see Madhavan et al., 1997) compared to an immediate execution at the opposite side of the prevailing spread at the time of each transaction, $p^{ask/bid}$. This is comparable to the immediate trading cost, which constitutes the source of revenue for investors who choose to act as liquidity providers. Following Harris and Hasbrouck (1996) we define our measure of ex-ante performance, $P^{ex-ante}$:

$$P_i^{ex-ante} = \begin{cases} p_i^{ask} - p_i^{bid,submitted} & \text{for a buy} \\ p_i^{ask,submitted} - p_i^{bid} & \text{for a sell} \end{cases} \tag{8}$$

Higher values indicate higher performance. This measure, although indicative of the transaction costs involved in realising a commitment to trade, prioritizes execution over price risk. In order to account for the time dimension of performance we employ an ex-post measure of performance; the cost of a 5-minute round trip (Harris and Hasbrouck, 1996) as:

$$P_i^{ex-post} = \begin{cases} p_{i+5}^{bid} - p_i^{bid,submitted} & \text{for a buy} \\ p_i^{ask,submitted} - p_{i+5}^{ask} & \text{for a sell} \end{cases} \tag{9}$$

where, p_{i+5} is the last prevailing same-side quotes within a 5' time interval. In the case of market orders, submitted prices are replaced by the transaction prices. $P_i^{ex-post}$ measures the proceeds/costs of a 5-minute round trip, e.g. buying the asset now and selling it after 5 minutes; if the subsequent bid price is lower (higher) than the current bid (quote) then this would incur a loss (profit). This measure of ex-post performance is more relevant to a passive trader, e.g. limit orders, because it considers the time dimension of performance, i.e. 5 transactions. It is also particularly relevant to an unconditional limit-order submission strategy, especially when execution risk does not incur losses, such as in the case of a market maker, because the profits of a market maker depend on adverse price movements and the strategy to reverse the trades (Harris and Hasbrouck, 1996). A higher figure would indicate a more profitable order type.

Performance measures and trader types

Ideally, in order to investigate the performance of different order types for the different trader types we consider, i.e. market makers who are liquidity providers, always quoting bid and ask prices, versus off-floor traders who can submit discretionary market or limit orders, we would focus on the submission of each order. However, first, our dataset includes only best bid and ask quote revisions, and second, a major objective of our study is to develop an order-type selection rule based solely on transaction data. Our model can generate some conditional predictions with regards to the suitability of different order types according to the criteria we discuss above, but in order to check the validity of these predictions, we need to test them on the available (transaction) data. For this purpose, we operate under the following assumptions, trying to map the types of traders we consider solely on transaction level data. These assumptions are only used for validation purposes and they do not affect the conditional predictions of our approach.

For market makers we consider the actual quote revisions as their limit-order submissions. Our dataset includes best quote revisions, which might be a quote revision made by a market maker or a limit order submitted by a discretionary limit-order investor. We have no way to distinguish between the two and we make the explicit assumption that the pricing of the market makers does follow the market-wide pricing formation we consider above, but their pricing might differ from this, due to reduced costs and other benefits they get as a reward for providing liquidity. Based on this assumption we make the distinction between the model-generated implied spread, conditional on liquidity and information concerns, as the regret-free pricing that a discretionary limit-order investor would use.[3] A wider (narrower) spread might be more (less) regret-free, but with higher (lower) execution risk. Therefore, we assume that a rational off-floor limit-order investor would not deviate from the regret-free prices generated by the model. In contrast, market makers, who are less exposed to execution risk and their pricing might include discounts, might deviate from this pricing and therefore the actual spread might deviate from its conditional estimate. The conditional and the actual implied spread are expected to have a high correlation and the same sample mean, but they should be not expected to be the same at every transaction. Deviations might be due to the (hypothesized) balancing of liquidity and information risk, necessary for the off-floor limit-order investors, which is what we primarily want to investigate here; whether the actual versus conditional spread deviations (market maker versus off-floor limit-order investor) render different order types relatively preferable for different types of traders.

Most of the analysis is conducted using this distinction of the quotes and the transaction price as market orders. However, focusing solely on the quotes themselves would completely ignore execution risk. In order to take this into consideration, we multiply all performance measures for limit orders by a proxy for the execution probability we develop, under the following propositions: (i) More aggressive pricing, i.e. a lower distance from the opposite side quote, should be expected to be executed faster; (ii) Smaller size orders should be executed faster; (iii) A more liquid market environment, i.e. more contracts traded per unit of time, should increase the probability of execution. Following these we construct a reverse penalty function, *PF* that increases upon greater overall liquidity, $H_{5,i}$, and decreases with higher distance from the opposite quote, $dist_i \equiv P_i^{ex-post}$, and higher order size, $size_i \equiv K(u_i)$:

$$PF_i = \frac{H_{5,i}}{size_i} exp(-dist_i) \tag{9}$$

where, $H_{5,i} = \left(A_i \Gamma(1+1/\gamma_i)/\Theta_i\right)^{\gamma_i}$ is the cumulative hazard function, which measures the expected accumulated number of units of $K(u_i)$, which measures transaction size, relative to its sample moments; A is the diurnally adjusted transformation of 5 minutes. The ratio of $H_{5,i} / size_i$ measures how many times the order size is expected to be covered by total transaction volume over the next 5 minutes. Higher values should make it easier for a larger order to be executed. In contrast, the factor $exp(-dist_i)$ penalizes less competitive pricing, as it should be more difficult to be executed. Consequently, higher values of *PF* should indicate a higher execution probability. We convert *PF* into a probability of execution, $P^{execution}$, where, $P^{execution} : PF \to [0,1]$ is a mapping of *PF* into $[0,1]$, using the following smoothing function:

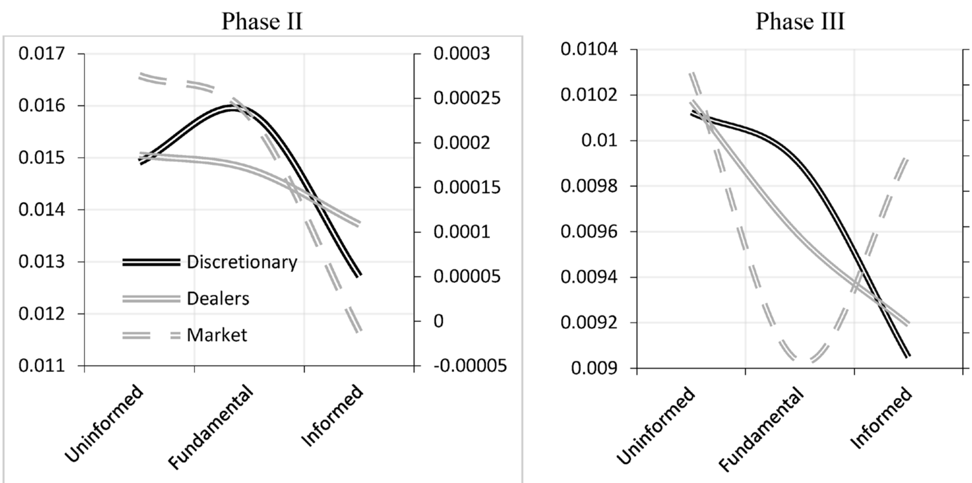
$$P_i^{execution} = \left(1 + exp(-PF)\right)^{-1} \tag{10}$$

3. This is also a potential empirical extension of testing the order-type selection trading rule introduced here in order to accommodate other order types. For example, a stop limit order can only be submitted at a (directional) price improvement. Consequently, a more refined trading rule would be to submit a limit order when the conditional implied spread is wider, but a stop limit order when the conditional implied spread is narrower than the actual implied spread (i.e. the quoted best bid and ask prices).

Empirical Findings

Figure 3 presents the average ex-ante performance, i.e. relative gains over an immediate execution at the opposite quote, for market orders, market makers' quotes and discretionary, off-floor investors' limit orders, across different levels of expected trading intensity, i.e. expected levels of the presence of private information. There are two major observations. First, limit orders, probably due to a higher execution probability, are more profitable when trading intensity is expected to be low. This is consistent with our model predictions, which suggest that these are the market conditions that maximize liquidity gains, with respect to the presence of private information. Second, also in consistency with our initial propositions, although the limit-order gains decrease upon higher trading intensity and thus, with a lower (higher) transitory (informational) volatility component, the

Figure 3: Ex-ante Performance: Relative Transaction Cost



			Un LO	Un D	Un MO	Fun LO	Fun D	Fun MO	Inf LO	Inf D	Inf MO
Phase II	Un	LO	0.00								
		D	-0.71	0.00							
		MO	78.31	788.33	0.00						
	Fun	LO	-1.81	-2.96	-55.99	0.00					
		D	0.46	8.48	-660.62	2.49	0.00				
		MO	49.61	530.89	2.89	35.46	471.29	0.00			
	Inf	LO	4.09	9.21	-49.76	3.90	5.18	-31.59	0.00		
		D	2.53	28.99	-486.01	3.06	20.32	-380.06	-1.56	0.00	
		MO	31.45	332.66	10.95	22.46	291.92	7.39	20.08	230.77	0.00
Phase III	Un	LO	0.00								
		D	-1.30	0.00							
		MO	308.60	218.32	0.00						
	Fun	LO	3.99	2.45	-104.66	0.00					
		D	10.01	5.12	-97.36	3.33	0.00				
		MO	191.31	86.55	1.75	124.09	82.25	0.00			
	Inf	LO	53.78	25.60	-244.44	26.79	11.84	-223.83	0.00		
		D	13.41	12.31	-116.92	3.24	1.76	-41.17	-1.71	0.00	
		MO	452.93	220.56	1.26	231.16	177.83	-2.45	469.28	106.03	0.00

Figure 3 presents the average ex-ante performance of market makers' limit orders (Dealers), of off-floor traders' limit orders (LO) and of market orders (MO, right axis), across different agent types: uninformed (Un), Fundamental (Fun) and Informed (Inf). The table presents the *t*-statistics of the difference of the value indicated by the columns minus the value indicated by the rows.

relative gains of off-floor discretionary limit order investors become statistically superior to those of market makers, this is when trading intensity is expected to be medium. For this range, an increasing hazard function means that an increasing arrival rate of transacted contracts should be expected, while off-floor discretionary limit-order investors' bid and ask prices become more competitive. This combination should be expected to increase the execution probability of their limit orders and, therefore, their realized gains are found to be higher, compared to the gains of market makers.

This difference is statistically significant in both phases and, consistent with our conditional predictions, this is the range of trading intensity that off-floor traders should prefer. In more detail, according to Figure 2, spreads might be higher at the extremes, which would lead the ex-ante performance of the trades, but volatility also increases. The combination of low liquidity costs and high spreads to variance ratios in the middle regime should penalize investors who prioritize liquidity and favour investors who are uninformed, but need a higher information component in order to be able to compete and make relative profits. This range of trading intensity with low spreads, which might be of less interest to market makers, but also low volatility, which might be less associated with information than a high trading intensity regime, seems to create a space for off-floor traders who would like to act as market makers on one or both sides of the spread. According to Figure 4, this range of expected trading intensity seems to lead to a marginally higher ex-post performance for off-floor investors, but the main differences in performance are driven by actual price changes, and not by different quote setting. Consequently, the variance of ex-post performance is considerably higher than the one of ex-ante performance and, therefore, the differences between different types of traders do not appear to be statistically significant.

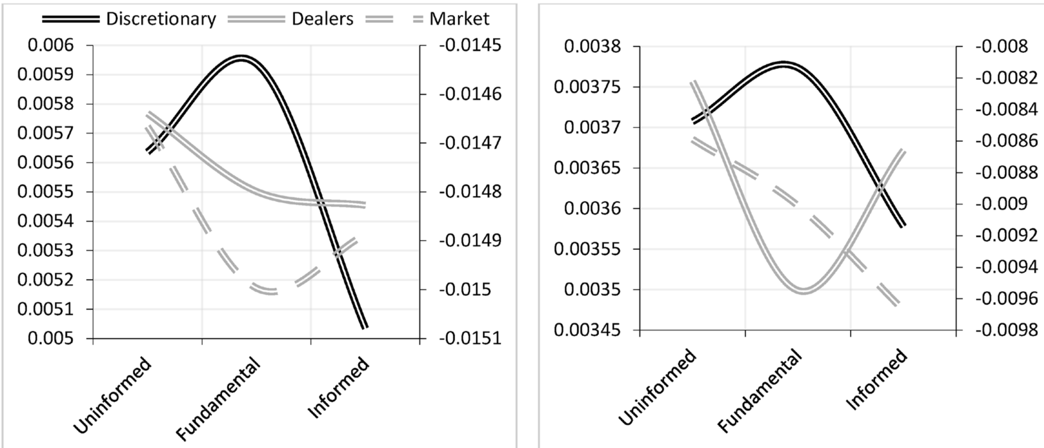
In addition, according to both performance measures we employ, limit orders seem consistently to perform better in the European Carbon market, compared to the market order, i.e. immediate execution. Both the ex-ante and ex-post performance of market orders in Figures 3 and 4 are found to be inferior to limit orders and the difference is always statistically significant. Probably, this is an intrinsic characteristic of the market which is relatively illiquid compared to more established markets. This should be expected to result in wider spreads, even for comparable levels of price-change variance. This should increase the attractiveness of limit orders, especially when spreads are high due to a high price of liquidity, i.e. when trading intensity is low in our sample.

Finally, we test the robustness of our results to a different trade initiation and length of a round trip. The European Carbon market is affected by periodic shifts in fundamentals, such as the announcements of the National Allocation Plans (NAPs), and therefore, demand on one side of the spread might be consistently stronger over a period of time. In Figure 5 we estimate the average ex-ante and ex-post performance of buyer- and seller-initiated trades and we confirm qualitatively our previous findings. The performance of limit orders is superior to market orders and it is found to be a decreasing function of trading intensity for both buying and selling. Furthermore, limit orders submitted by off-floor discretionary investors are consistently found to be superior when trading intensity is expected to be in the middle regime. Figure 6 presents the ex-post performance of the different types of trades when using different durations for a round trip, i.e. 1' and 15'. The results stay qualitatively the same. Our findings should also be robust for order size and spread variations because our setup explicitly considers trading intensity, and its impact on spreads, price-change volatility and their components.

7. CONCLUSION

On a transaction-by-transaction basis, investors face an order-type selection dilemma each time they enter the market. They can either prioritize minimizing execution risk by submitting a market order, or they can prioritize minimizing price risk by submitting a limit order. Each type of

Figure 4: Ex-post Performance: Relative Cost of a Round Trip



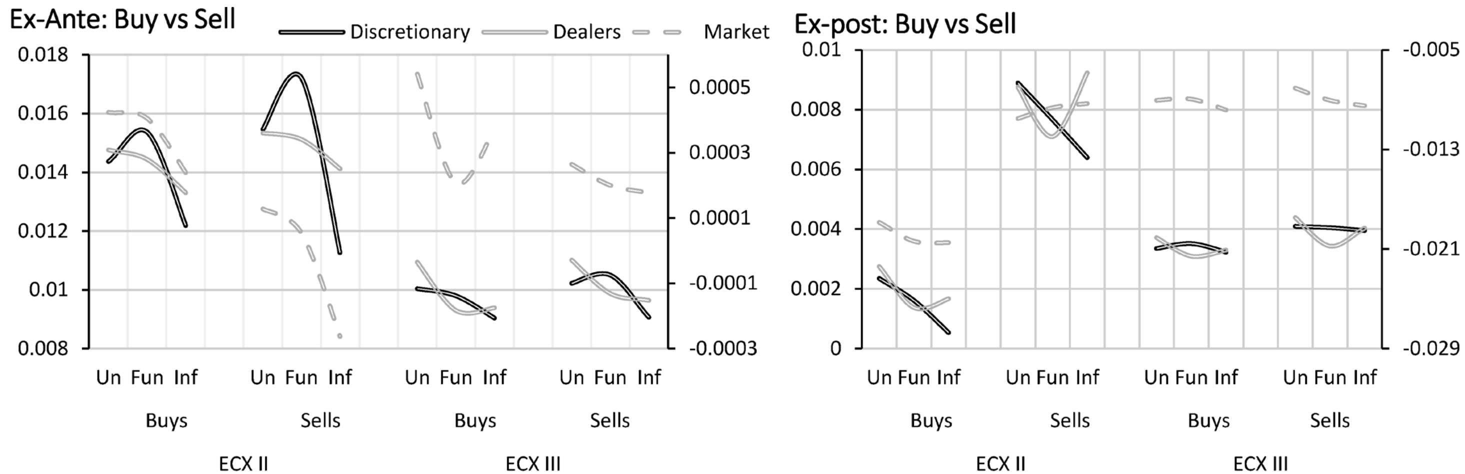
			Un LO	Un D	Un MO	Fun LO	Fun D	Fun MO	Inf LO	Inf D	Inf MO
Phase II	Un	LO	0.00								
		D	-0.36	0.00							
		MO	44.97	49.69	0.00						
	Fun	LO	-0.39	-0.32	-30.91	0.00					
		D	0.25	0.59	-33.31	0.58	0.00				
		MO	34.77	40.34	0.50	24.76	28.42	0.00			
	Inf	LO	0.73	1.10	-21.11	0.81	0.54	-18.62	0.00		
		D	0.23	0.51	-22.37	0.46	0.06	-20.42	-0.41	0.00	
		MO	24.63	30.12	0.23	18.21	22.68	-0.10	15.67	18.43	0.00
Phase III	Un	LO	0.00								
		D	-0.67	0.00							
		MO	98.63	95.91	0.00						
	Fun	LO	-0.30	-0.09	-32.97	0.00					
		D	1.01	1.12	-30.47	0.58	0.00				
		MO	76.60	65.29	1.12	48.72	25.38	0.00			
	Inf	LO	1.67	2.06	-81.01	1.12	-0.33	-68.84	0.00		
		D	0.35	0.78	-74.68	0.37	-0.54	-45.07	-0.78	0.00	
		MO	131.88	123.45	6.62	48.91	41.51	2.37	110.81	92.31	0.00

Figure 4 presents the average ex-post performance of market makers' limit orders (Dealers), of off-floor traders' limit orders (LO) and of market orders (MO, right axis), across different agent types: uninformed (Un); Fundamental (Fun); and Informed (Inf). The table presents the *t*-statistics of the difference of the value indicated by the columns minus the value indicated by the rows.

order exhibits its relative merits and previous literature suggests that the order selection depends on market conditions. Several studies (e.g. Biais et al., 1995) identify the cost of liquidity and consequently, the width of the spread as a major determinant of limit-order suitability. Limit orders appear to be preferred when spreads are wide because investors can earn the spread, while they prefer to consume liquidity when it is cheap and the spreads are narrow. However, spreads consist of a liquidity as well as an information component (O'Hara, 1995), which constitutes the compensation of market makers for the probability of trading with better informed agents. A high probability of trading with better-informed agents is an undesirable condition for limit orders due to their option features (Copeland and Galai, 1983), especially when these orders are mispriced (Bae et al., 2003).

These two price components are also the main drivers of intraday volatility (e.g. Madhavan et al., 1997), which is also found to have a significant impact on order-type selection. Although

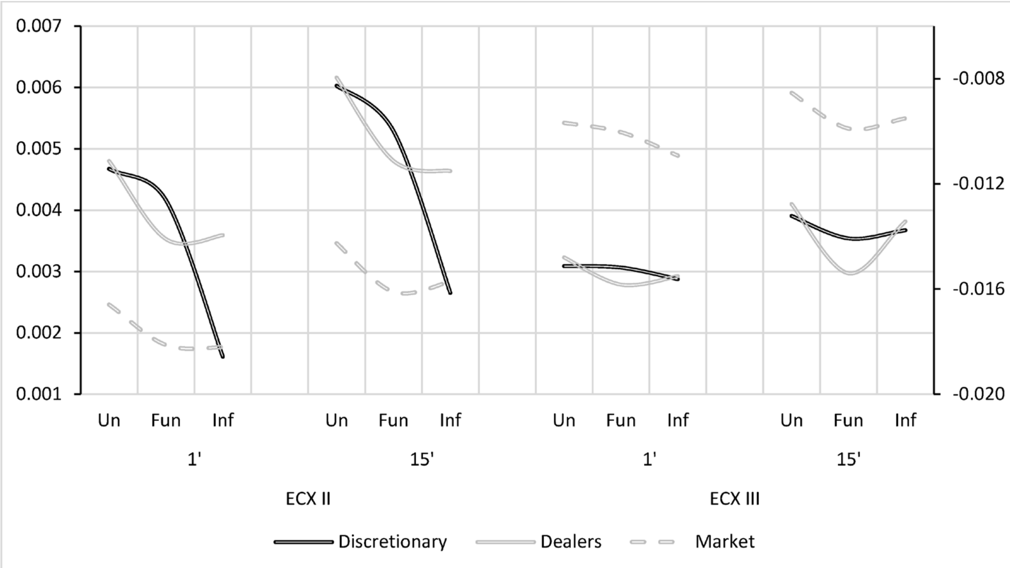
Figure 5: Ex-ante and Ex-post Performance: Buying versus Selling



			Phase II L.O vs D	Phase II L.O vs M.O	Phase II D vs M.O	Phase III L.O vs D	Phase III L.O vs M.O	Phase III D vs M.O
Ex-ante	Buy	Uninformed	-10.96	448.49	536.69	-23.52	187.82	208.47
		Fundamental	12.66	224.77	327.76	3.94	67.81	50.86
		Informed	-12.16	128.77	147.19	-15.57	426.63	364.49
	Sell	Uninformed	0.34	41.38	578.57	-5.73	437.92	77.07
		Fundamental	2.38	19.54	338.87	1.96	179.23	30.51
		Informed	-2.26	9.12	181.72	-6.62	149.97	93.60
Ex-post	Buy	Uninformed	-0.83	35.37	36.05	-3.27	60.78	62.40
		Fundamental	0.30	22.52	22.31	2.26	50.69	48.52
		Informed	-1.09	14.72	15.52	-0.54	73.02	73.80
	Sell	Uninformed	0.23	28.78	34.20	-1.79	85.69	63.17
		Fundamental	0.45	12.55	15.75	0.64	27.62	12.70
		Informed	-1.59	7.47	11.02	-0.59	90.50	79.18

Figure 5 presents the average ex-ante and ex-post performance of market makers' limit orders (Dealers or D), of off-floor traders' limit orders (LO) and of market orders (MO, right axis), across different agent types: uninformed (Un), Fundamental (Fun) and Informed (Inf), separately for Buying and Selling. The table presents the t-statistics of the difference of the value indicated by the columns minus the value indicated by the rows

Figure 6: Ex-post Performance: 1' and 15' round trip



		Phase II			Phase III		
		L.O vs D	L.O vs M.O	D vs M.O	L.O vs D	L.O vs M.O	D vs M.O
Ex-ante 1'	Uninformed	-0.35	49.48	55.26	-1.64	118.96	101.68
	Fundamental	0.84	25.02	27.98	0.63	55.43	26.77
	Informed	-1.68	14.34	17.74	-0.57	139.62	129.93
Ex-ante 15'	Uninformed	-0.35	43.14	47.28	-1.42	96.13	86.26
	Fundamental	0.72	26.34	30.62	1.74	25.59	22.59
	Informed	-1.87	14.90	19.22	-0.36	79.14	77.30

Figure 6 presents the average ex-post performance of market makers' limit orders (Dealers), of off-floor traders' limit orders (LO) and of market orders (MO, right axis), across different agent types: uninformed (Un), Fundamental (Fun) and Informed (Inf), for different lengths of a round trip: 1' and 15'. The table presents the *t*-statistics of the difference of the value indicated by the columns minus the value indicated by the rows

market orders are generally accepted not to be suitable during periods of high volatility (Peterson and Sirri, 2002), the literature makes a distinction between the liquidity (transitory) and information (permanent) components of variance, suggesting that a higher transitory volatility should attract more limit orders (e.g. Handa and Schwartz, 1996), while higher information-related volatility would only attract limit orders from informed agents with information advantages that decay slowly (Keim and Madhavan, 1995). Consequently, previous literature recognizes spreads and variance to be the main determinants of the suitability of different order types.

Previous literature (e.g. Harris and Hasbrouck, 1996) confirms empirically the impact of spreads and volatility on order selection, but this is mostly done in a descriptive way, e.g. identifying under what conditions limit orders are mostly submitted, considering spreads and variance as two separate factors. This is the primary concern of our study, in which we try to unify the impact of spreads and variance on order selection, by focusing on a more granular level, modelling the liquidity and information-price components, their impact on spread and variance and ultimately on order selection. In more detail, we employ an observable variable, i.e. trading intensity, in order to identify how informative each trade is and to extract the liquidity and information-price components. Then we use these components to develop an order-selection rule, which is derived solely by realized price changes and has the evident advantage of being tradable and conditional on committed market conditions and publicly available information.

Considering the importance of the Carbon market for meeting global emission reduction targets, as well as the strong patterns in return (e.g. Benz and Hengelbrock, 2008), volatility (e.g. Kalaitzoglou and Ibrahim, 2013a) and order flow (e.g. Medina et al., 2014), which could render a discretionary limit-order strategy profitable, we develop and apply our order-selection rule in the European Carbon Futures market. We observe that the economic performance of limit orders is consistently superior to market orders in all market conditions. However, we find that market makers should prefer to derive their profits when trading intensity is low and, therefore, the price of liquidity is high and the probability of informed trading is low. In contrast, an off-floor discretionary limit-order strategy, which cannot compete with the liquidity advantages of market makers or the information advantages of informed agents, would only be competitive when trading intensity is at a medium level and, therefore, the balance between information and liquidity premia can adequately compensate execution and price risk.

These findings are consistent with previous literature on other asset classes and provide an ex-ante view that more limit orders might be observed following certain events. For example, we find that limit orders are consistently less costly than market orders in the Carbon market, a feature common with equities in NYSE (e.g. Harris and Hasbrouck, 1996). However, unconditional limit order placement strategies by non-designated market makers cannot always be profitable; a common characteristic with NYSE (e.g. Harris and Hasbrouck, 1996; Peterson and Sirri, 2002). In addition, we report that trading in the Carbon market exhibits a higher intensity of limit orders during wider spreads, but they become increasingly more profitable, when liquidity costs and transitory volatility are higher. Especially, when they are higher than adverse selection and asymmetric information induced volatility. This finding is supported theoretically (e.g. Foucault, 1999), but also empirically (e.g. Bae et al., 2003) in equity markets, where previous research suggests that limit orders appear to be preferred when spreads are larger (e.g. Peterson and Sirri, 2002) and when information-related costs are low (e.g. Foucault, 1999). Finally, in consistency with previous studies we confirm that order-type placement strategies depend on market conditions (e.g. Peterson and Sirri, 2002) and especially that liquidity can be a major determinant of whether an order type is more economically relevant (e.g. Biais et al., 1995).

REFERENCES

Alberola, Emilie, Julien Chevallier. (2009). "European carbon prices and banking restrictions: Evidence from Phase I (2005–2007)." *The Energy Journal* 30(3): 51–79. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol30-No3-3.

Bae, Kee-Hong, Hasung Jang, and Kyung Suh Park. (2003). "Traders' choice between limit and market orders: evidence from NYSE stocks." *Journal of Financial Markets* 6(4): 517–538. https://doi.org/10.1016/S1386-4181(02)00047-2.

Biais, Bruno, Pierre Hillion, and Chester Spatt. (1995). "An empirical analysis of the limit order book and the order flow in the Paris Bourse." *The Journal of Finance* 50(5): 1655–1689. https://doi.org/10.1111/j.1540-6261.1995.tb05192.x.

Benz, Eva A., and Jördis Hengelbrock. (2008). "Liquidity and Price Discovery in the European CO_2 Futures Market: An Intraday Analysis." Available at SSRN: http://dx.doi.org/10.2139/ssrn. 1220389.

Bredin, Don, Stuart Hyde, and Cal Muckley. (2014). "A microstructure analysis of the carbon finance market." *International Review of Financial Analysis* 34: 222–234.

Chakravarty, Sugato, and Craig W. Holden. (1995) "An integrated model of market and limit orders." *Journal of Financial Intermediation* 4(3): 213–241. https://doi.org/10.1006/jfin.1995.1010.

Chung, Kee H., Bonnie F. Van Ness, and Robert A. Van Ness. (1999). "Limit orders and the bid–ask spread." *Journal of Financial Economics* 53(2): 255–287. https://doi.org/10.1016/S0304-405X(99)00022-7.

Cludius, Johanna, and Regina Betz. (2016). "EU Emissions Trading: The Role of Banks and Other Financial Actors: Insights from the EU Transaction Log and Interviews." Available at: https://digitalcollection.zhaw.ch/handle/11475/1144.

Cohen, Kalman J., Steven F. Meier, Robert F. Schwarz and David K. Whicomb. (1981). "Transaction costs, order placement strategy, and existence of the bid-ask spread." *Journal of Political Economy* 89.2 (1981): 287–305. https://doi.org/10.1086/260966.

Conrad, Christian, Daniel Rittler, and Waldemar Rotfuß. (2012). "Modeling and explaining the dynamics of European Union Allowance prices at high-frequency." *Energy Economics* 34(1): 316–326. https://doi.org/10.1016/j.eneco.2011.02.011.

Copeland, Thomas E., and Dan Galai. (1983). "Information effects on the bid-ask spread." *The Journal of Finance* 38(5): 1457–1469. https://doi.org/10.1111/j.1540-6261.1983.tb03834.x.

Cummins, Mark, Deeney, Peter, Dowling, Michael M. and Smeaton, Alan. (2016). "Sentiment Effects in the European Emissions Market". Available at SSRN: https://ssrn.com/abstract=2840375.

Daskalakis, George, Dimitris Psychoyios, and Raphael N. Markellos. (2009). "Modeling CO_2 emission allowance prices and derivatives: evidence from the European trading scheme." *Journal of Banking & Finance* 33(7): 1230–1241. https://doi.org/10.1016/j.jbankfin.2009.01.001.

Dufour, Alfonso, Robert F. Engle. (2000). "Time and the price impact of a trade." *The Journal of Finance*, 55(6): 2467–2498. https://doi.org/10.1111/0022-1082.00297.

Easley, David, and Maureen O'Hara. (1992). "Time and the process of security price adjustment." *The Journal of Finance* 47(2): 577–605. https://doi.org/10.1111/j.1540-6261.1992.tb04402.x.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara. (2000). "The accuracy of trade classification rules: Evidence from Nasdaq." *Journal of Financial and Quantitative Analysis* 35(4): 529–551. https://doi.org/10.2307/2676254.

European Commission. (2011). "Impact Assessment." Staff working paper, accompanying the document proposal for a "Directive of the European Parliament and of the Council on Markets in financial instruments" and the Proposal for a "Regulation of the European Parliament and of the Council on Markets in Financial Instruments". Brussels. Available at: http://ec.europa.eu /internal_market/securities/docs/isd/mifid/SEC_2011_1226_en.pdf.

Financial Conduct Authority, Markets in Financial Instruments. (2015). "Consultation Paper I" (CP15/43), p. 206. Available at: https://www.fca.org.uk/publication/consultation/cp15-43.pdf.

Foucault, Thierry. (1999). "Order flow composition and trading costs in a dynamic limit order market." *Journal of Financial Markets* 2(2): 99–134. https://doi.org/10.1016/S1386-4181(98)00012-3.

Glosten, Lawrence R., and Paul R. Milgrom. (1985). "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders." *Journal of Financial Economics* 14(1): 71–100. https://doi.org/10.1016/0304-405X(85)90044-3.

Handa, Puneet, and Robert A. Schwartz. (1996). "Limit order trading." *The Journal of Finance* 51(5): 1835–1861. https://doi.org/10.1111/j.1540-6261.1996.tb05228.x.

Handa, Puneet, Robert A. Schwartz, and Ashish Tiwari. (1998). "The ecology of an order-driven market." *The Journal of Portfolio Management* 24(2): 47–55. https://doi.org/10.3905/jpm.24.2.47.

Harris, Lawrence. (1989). "A day-end transaction price anomaly." *Journal of Financial and Quantitative Analysis* 24(1): 29–45. https://doi.org/10.2307/2330746.

Harris, Lawrence, and Joel Hasbrouck. (1996). "Market vs. limit orders: the SuperDOT evidence on order submission strategy." *Journal of Financial and Quantitative Analysis* 31(2): 213–231. https://doi.org/10.2307/2331180.

Hasbrouck, Joel. (1991). "Measuring the information content of stock trades." *The Journal of Finance* 46(1): 179–207. https://doi.org/10.1111/j.1540-6261.1991.tb03749.x.

Hujer, Reinhard, and Sandra Vuletić. (2007). "Econometric analysis of financial trade processes by discrete mixture duration models." *Journal of Economic Dynamics and Control* 31(2): 635–667. https://doi.org/10.1016/j.jedc.2005.09.015.

Ibikunle, Gbenga, Andros Gregoriou, and Naresh R. Pandit. (2013). "Price discovery and trading after hours: new evidence from the world's largest Carbon Exchange." *International Journal of the Economics of Business* 20(3): 421–445. https://doi.org/10.1080/13571516.2013.782986.

Ibrahim, Boulis M., and Iordanis A. Kalaitzoglou. (2016). "Why do carbon prices and price volatility change?" *Journal of Banking & Finance* 63: 76–94. https://doi.org/10.1016/j.jbankfin.2015.11.004.

Kalaitzoglou, Iordanis A., and Boulis M. Ibrahim. (2013a). "Trading patterns in the European carbon market: The role of trading intensity and OTC transactions." *The Quarterly Review of Economics and Finance* 53(4): 402–416. https://doi.org/10.1016/j.qref.2013.04.001.

Kalaitzoglou, Iordanis A., and Boulis M. Ibrahim. (2013b). "Does order flow in the European Carbon Futures Market reveal information?" *Journal of Financial Markets* 16(3): 604–635. https://doi.org/10.1016/j.finmar.2012.11.002.

Kalaitzoglou, Iordanis A., and Boulis M. Ibrahim. (2015). "Liquidity and resolution of uncertainty in the European carbon futures market." *International Review of Financial Analysis* 37: 89–102. https://doi.org/10.1016/j.irfa.2014.11.006.

Kalaitzoglou, Iordanis A., and Boulis M. Ibrahim. (2017). "Market Conditions and Order Type Preference" Available at SSRN: https://ssrn.com/abstract=3077907.

Keim, Donald B., and Ananth Madhavan. (1995). "Anatomy of the trading process: empirical evidence on the behavior of institutional traders." *Journal of Financial Economics* 37(3): 371–398. https://doi.org/10.1016/0304-405X(94)00799-7.

Klepper, Gernot, and Sonja Peterson. (2006). "Emissions trading, CDM, JI, and more: the climate strategy of the EU." *The Energy Journal* 27(2): 1–26. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol27-No2-1.

Kyle, Albert S. (1985). "Continuous auctions and insider trading." *Econometrica: Journal of the Econometric Society* 53(6): 1315–1335. https://doi.org/10.2307/1913210.

Lee, Charles, and Mark J. Ready. (1991). "Inferring trade direction from intraday data." *The Journal of Finance* 46(2): 733–746. https://doi.org/10.1111/j.1540-6261.1991.tb02683.x.

MacCracken, Christopher N., James A. Edmonds, Son H. Kim, and Ronald D. Sands. (1999). "The Economics of Kyoto Protocol." *The Energy Journal* (20): 27–71. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol20-NoSI-3.

Madhavan, Ananth. (2000). "Market microstructure: A survey." *Journal of Financial Markets* 3(3): 205–258. https://doi.org/10.1016/S1386-4181(00)00007-0.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans. (1997). "Why do security prices change? A transaction-level analysis of NYSE stocks." *The Review of Financial Studies* 10(4): 1035–1064. https://doi.org/10.1093/rfs/10.4.1035.

Manne, Alan S., and Rihard G. Richels. (1991). "Global CO_2 Emission Reductions. The Impacts of Rising Enrgy Costs." *The Energy Journal* 12(1). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol12-No1-6.

Mansanet-Bataller, Maria, and Angel Pardo. (2009). "Impacts of regulatory announcements on CO_2 prices." *The Journal of Energy Markets* 2(2): 75. https://doi.org/10.21314/JEM.2009.019.

Medina, Vicente, Ángel Pardo, and Roberto Pascual. (2014). "The timeline of trading frictions in the European carbon market." *Energy Economics* 42: 378–394. https://doi.org/10.1016/j.eneco.2014.01.008.

Mizrach, Bruce, and Yoichi Otsubo. (2014). "The market microstructure of the European climate exchange." *Journal of Banking & Finance* 39: 107–116. https://doi.org/10.1016/j.jbankfin.2013.11.001.

O'Hara, Maureen. (1995). *Market microstructure theory*. Vol. 108. Cambridge, MA: Blackwell.

Peterson, Mark, and Erik Sirri. (2002). "Order submission strategy and the curious case of marketable limit orders." *Journal of Financial and Quantitative Analysis* 37(2): 221–241. https://doi.org/10.2307/3595004.

Rannou, Yves. (2017). "Liquidity, information, strategic trading in an electronic order book: New insights from the European carbon markets." *Research in International Business and Finance* 39: 779–808. https://doi.org/10.1016/j.ribaf.2014.09.008.