



# Why do carbon prices and price volatility change?



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## ABSTRACT

An asymmetric information microstructural pricing model is proposed in which price responses to information and liquidity vary with every transaction. bid-ask quotes and price components account for learning by incorporating changing expectations of the rate of transacted volume (trading intensity) and the risk level of incoming trades. Analysis of European carbon futures transactions finds expected trading intensity to simultaneously increase the information component and decrease the liquidity component of price changes, but at different rates. This explains some conflicting results in prior literature. Further, the expected persistence in trading intensity explains the majority of the autocorrelations in the level and the conditional variance of price change; helps predict hourly patterns in returns, variance and the bid-ask spread; and differentiates the price impact of buy versus sell and continuing versus reversing trades.

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## 1. Introduction

A number of papers have analysed the microstructure of the European carbon market that started in January 2005 with the implementation of the European Union Emission Trading System (EU ETS). We initially focus on a selection that relates to intraday price formation, and one that provides a coverage of the main microstructural models used to analyse this market. Benz and Hengelbrock (2008) analyse price leadership and discovery using the Madhavan et al. (1997) microstructure model (henceforth 'the MRR') and a vector error correction (VECM) model. Rittler (2012) analyses price leadership between futures and spots using the common factor weights of Schwarz and Szakmary (1994) and the information shares of Hasbrouck (1995). Ibikunle et al. (2013, 2016) investigate adverse selection components using the portfolio trading pressure version of the basic Huang and Stoll (1997) model, and price discovery and impact of trades using return ratios and non-structural regressions. Mizrach and Otsubo (2014) analyse market impact and spreads using the MRR, price discovery contribution across futures and spots using Hasbrouck's (1995) and Gonzalo

and Granger's (1995) information shares, and the predictive content of order imbalances using a regression. Medina et al. (2013, 2014) analyse price discovery contribution between European Union Allowances (EUAs) and Certified Emission Reductions (CERs) using a VECM, and the evolution of the spread, risk and market-making profits between the first two phases of the market using the MRR and the models of Roll (1984) and Hasbrouck (1993). Bredin et al. (2014) analyse the volume-(absolute) return-duration relationship using a vector autoregression. Rannou (2014) analyses return, volatility and return autocorrelation predictability of order book measures (aggregated to 30-min intervals) using regressions. Schultz and Swieringa (2014) analyse market friction catalysts for price discovery (at 5-min intervals) on a number of fungible assets using the information shares of Hasbrouck (1995) within a VECM. The structural models used in these studies, namely the models of Roll (1984) and Hasbrouck (1993), the portfolio trading pressure version of Huang and Stoll (1997), and Madhavan et al. (1997), are quite useful in providing preliminary analyses, especially of average or aggregate measures. However, they are rather generic, have highly static features, and each fails to account for at least one of a number of stylised facts that have recently emerged about the microstructure of the carbon market.

The most prominent of these stylised facts are: a significant autocorrelation of order flow (e.g., Benz and Hengelbrock, 2008); a generally low, but increasing, trading activity and liquidity

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(e.g., Mizrahi and Otsubo, 2014); the presence of different types of agent with distinctly different trading behaviour (e.g., Kalaitzoglou and Ibrahim, 2013a); the occurrence of price, liquidity and volatility jumps, mainly due to regulatory announcements, release of relevant data on installation emissions and the over-allocation by national governments of carbon emission permits or allowances (e.g., Mansanet-Bataller and Pardo, 2009; Alberola et al., 2008; and Ellerman et al., 2014); and the presence of liquidity and information related intraday patterns in trading activity (e.g., Ibikunle et al., 2016; Kalaitzoglou and Ibrahim, 2013b).

These facts are likely to have direct implications on price formation and, hence, the choice of model used to analyse it. First, the significant autocorrelation in order flow ought to preclude the use of the model of Roll (1984), used by Medina et al. (2014), and the portfolio trading pressure model of Huang and Stoll (1997), used by Ibikunle et al. (2013), as these models assume zero autocorrelation of order flow. Models that make this assumption when order flow is autocorrelated are likely to overestimate some price components (e.g., asymmetric information) and underestimate others (e.g., public information and liquidity). Second, the presence of different agents, identifiable through trade characteristics, such as size and speed, emphasises that both volume and time between trades (duration) are important in price formation. For example, transaction size or dollar volume have been found to affect the liquidity component (e.g., Huang and Stoll, 1997) and the information component (e.g., Easley and O'Hara, 1987) of price changes. There is also evidence of a time dimension to price changes (e.g., Glosten and Milgrom, 1985; and Diamond and Verrecchia, 1987). Third, price, volatility and liquidity shocks and intraday patterns in these measures are likely to affect inventory risk, order execution risk and, in the short term, the type of trader that instigates subsequent trades. In particular, the MRR, used by Benz and Hengelbrock (2008) and Medina et al. (2014) to analyse the carbon market, accounts for autocorrelation of order flow but ignores trade size or duration, as it assumes unit quantity and equally-spaced trades. It also does not allow for time varying liquidity or volatility shocks, and assumes a constant price response to surprises in order flow (private information) and to variations in liquidity costs. It is unable, therefore, to differentiate between the price impact of small versus large trades, slow versus fast trades, trades instigated by different classes of agents, or low versus high liquidity trading times. Thus, it provides constant average estimates of bid-ask spreads and price volatility. To identify intraday patterns in these measures one needs to estimate the MRR, or the Roll (1984), Hasbrouck (1993) and Huang and Stoll (1997) models, as many times as intervals in which the trading day, month or year is dissected, as do Madhavan et al. (1997) and the carbon market intraday studies reviewed above.

To analyse the carbon market, or other markets with similar characteristics, this paper addresses these shortcomings by formulating a new asymmetric information microstructure model of price changes that incorporates these features. Unlike many prior microstructure models, the responsiveness of price changes to surprises in order flow (private information) and signed liquidity costs (liquidity) are dynamically updated with every transaction. This updating is based on the trader's expectations of the information content of the next trade, and the degree of risk that this trade is expected to represent. Specifically, the trader extracts information from the volume and duration of previous trades, through one liquidity measure of trading intensity (duration-weighted volume), and uses this information to formulate expectations of the level of trading intensity of the next trade. The trader also extracts information from the recent evolution in the proportion of informed traders and price volatility and formulates expectations on the level of risk he might face with the next trade. The trader then sets bid and ask price quotes given this process of learning from trading

activity, trade characteristics and market risk conditions. Price quotes, therefore, are conditional on, or regret-free of, the sign (buy or sell) as well as the expected information content and liquidity characteristics of the next trade. In contrast, the MRR, that of Hasbrouck (1993), which nests the model of Roll (1984), and the basic version of Huang and Stoll (1997) assume constant price responsiveness to information and liquidity variations, and their price quotes are regret-free with respect to the sign of the next trade only.

Beside its formulation for the analyses of the carbon market, or similar relatively shallow markets, the model contributes by combining and extending in a unified setting features that have appeared separately in the general microstructure literature. It nests the models of Roll (1984), Glosten and Harris (1988), Madhavan et al. (1997), and Angelidis and Benos (2009) (which adds contemporaneous volume to the MRR), and reduces to a version of the volume-enhanced specification of Huang and Stoll (1997) but with updated expectations. It contributes to Dufour and Engle's (2000) extension of Hasbrouck's (1993) vector autoregressive model of prices and trades by incorporating the time series features of volume, duration and a jump risk process into a structural model of prices. Such structural models relate price, volatility and spread components to underlying economic parameters on a one-to-one basis. In contrast, not all time series models have structural reducible forms, especially with regard to the interpretation of the error terms (see Hasbrouck, 2007, p.82).<sup>2</sup> Further, the model contributes to Grammig et al. (2011) by incorporating the information embedded in volume, to Angelidis and Benos (2009) by incorporating the information embedded in duration, and to all the aforementioned studies by formulating expectations based on volume, duration and the risk of trading with the more informed. Moreover, the non-price based pure time-series procedure of Kalaitzoglou and Ibrahim (2013a) to identify agent classes in the carbon market is incorporated here in a structural model of prices to dissect return, volatility, bid-ask spread, and the autocorrelations of returns and volatility by agent type. Thus, in the new pricing model the structural variables of trading frictions involved in setting regret-free price quotes and, hence, in price formation, are based on expectations and are agent specific.

We use this model to analyse price formation throughout the entire history (to 30 April 2015) of EUA futures carbon trading at the European Climate Exchange (ECX). This market is an appropriate test bed as it is the main venue for trading carbon allowances (although see Medina et al., 2013, for the growing role of CERs), and is characterised by: relatively low, but increasing, liquidity; price and volatility variations, especially during its early development period; information and liquidity trading episodes; and phases with different structural and regulatory features creating different liquidity and pricing environments (phases).<sup>3</sup> We use the model to study price components, the autocorrelations and hourly patterns of transaction returns (change in price), conditional variance of returns, bid-ask spreads, and order submission choice of the most heavily traded EUA futures in each of the three market phases.

The remainder of the paper is organised as follows. Section 2 provides a brief motivation of the focus on the carbon market, Section 3 introduces the new microstructure pricing model and compares its features to a number of prior models, Section 4

<sup>2</sup> Time series models, however, can accommodate more dynamic interactions even if they lose some structural interpretations with inappropriate lag lengths. Causality in structural models is usually one-way, from trades to prices (see Manganello, 2005 and Hasbrouck, 2007). Huang and Stoll's (1997) volume extended model allows volume to affect estimates of the probability of continuation (and, hence, autocorrelation of order flow).

<sup>3</sup> See the cited literature, references therein, and, e.g., Point Carbon reports at [www.pointcarbon.com](http://www.pointcarbon.com).

presents the data, Section 5 presents estimation results and a comparison with the MRR, Section 6 discusses the results, and Section 7 concludes.

## 2. The European carbon market

As various aspects of the market have been amply described in the academic literature and reports of world organisations we focus in this section on introducing relevant terminology and microstructure issues. The cap-and-trade EU ETS started in 2005 with the implementation of the Kyoto Protocol. The resulting spot and futures market of emission allowances and credits, each permitting the emission of 1000 tonnes of carbon dioxide, or equivalent in greenhouse gases, has since grown rapidly. Most trading occurs in European Union Allowance (EUA) futures at the European Climate Exchange (ECX) (e.g., [Benz and Hengelbrock, 2008](#); and [Ellerman et al., 2014](#)). Despite its growth, however, the market has been beleaguered with accumulated excess supply of allowances due, in part, to initial over-allocation of permits by member states to their emitting industrial installations.<sup>4</sup> Together with associated regulatory and news announcements of implications of the ‘banking’ prohibition to carry allowances forward from Phase I (2005–2007) to Phase II (2008–2012), and the depressed demand for energy products instilled by the economic downturn following the 2007 financial crisis, this has caused a number of price shocks and depressed trading.<sup>5</sup> For example, when 2005 emissions data was released in April 2006, the revealed excess supply of allowances caused EUA prices to drop by nearly 70% from a peak of €32 per tonne (e.g., [Point Carbon, 2009](#)). In 2005 trading was almost negligible for lengthy periods, and from June 2008 prices started dropping from €28.7 to €8.8 by February 2009. Considerable price spikes occurred intermittently throughout the market history (see, e.g., [Alberola et al., 2008](#), and the price and volume graph in the [online Appendix D](#)). Bid-ask spreads have also varied considerably (e.g., [Mizrach and Otsubo, 2014](#)) though generally followed a declining trend. Thus, the history of the market contained intermittent shocks and shallow episodes where liquidity rather than information may have been the overriding concern. The degree to which the time-varying interplay of liquidity and information affected price formation during this period is central to the formulation of our microstructure model, which we present next.

## 3. A dynamic joint expectation model

Consider the initial setup of the MRR. Let  $\tilde{v}_t$  denote the ‘true’ value of a risky asset at event time  $t$ , and  $\mu_t = E[\tilde{v}_t | H_t]$  its post-trade expectation given the available information set  $H_t \subseteq \Psi_t$ , where  $\Psi_t$  is the full information set at time  $t$ . Denote by  $q_t$  a trade sign indicator variable that takes a value of +1 (–1) if trade  $t$  is buyer (seller) initiated.<sup>6</sup> This indicator is assumed to follow a Markov process, which implies  $E[q_t | q_{t-1}] = \rho q_{t-1}$ , where  $\rho$  is the first-order autocorrelation of  $q_t$ .<sup>7</sup> In contrast with the MRR, we consider a time varying asymmetric information parameter,  $\theta_t$ , in

the formulation of the revision in post-trade beliefs, and a time-varying liquidity cost parameter,  $\varphi_t$  in the formulation of the transaction price. The revision in beliefs is, therefore,

$$\mu_t - \mu_{t-1} = \theta_t(q_t - E[q_t | q_{t-1}]) + \varepsilon_t, \quad (1)$$

and the transaction price is

$$p_t = \mu_t + \varphi_t q_t + \xi_t, \quad (2)$$

where  $(q_t - E[q_t | q_{t-1}])$  is the surprise in order flow, which captures private information;  $\varepsilon_t \sim iid(0, \sigma_\varepsilon^2)$  is the innovation in beliefs between time  $t - 1$  and time  $t$  due to public information;  $\varphi_t q_t$  is signed liquidity cost; and  $\xi_t \sim iid(0)$  captures errors due to time-varying returns or price discreteness. Bid and ask price quotes will be discussed in Section 6.5.1. Using Eqs. (1) and (2), we have the following formulation of transaction price:

$$p_t = \mu_{t-1} + \theta_t(q_t - E[q_t | q_{t-1}]) + \varphi_t q_t + \varepsilon_t + \xi_t, \quad (3)$$

where  $\theta_t(q_t - E[q_t | q_{t-1}])$  is the ‘asymmetric information’ effect of surprises in order flow. Using this and Eq. (2) for  $t - 1$ , Eq. (3) can be expressed in terms of intraday price movements:

$$\Delta p_t \equiv p_t - p_{t-1} = (\theta_t + \varphi_t)q_t - (\rho\theta_t + \varphi_{t-1})q_{t-1} + \varepsilon_t + (\xi_t - \xi_{t-1}). \quad (4)$$

The dynamics of  $\theta_t$  and  $\varphi_t$  are specified next. In revising their beliefs, following the transaction at time  $t - 1$ , market makers or traders expect the post trade ( $t$ ) value of the asset to be affected by the expected characteristics of the transaction at time  $t$ . To be able to set regret-free prices, they need to take into account expected post-trade effects. There is strong evidence in the literature that trade characteristics such as size and timing are correlated with intraday prices, volatility and spreads (e.g. [Glosten and Milgrom, 1985](#); [Diamond and Verrecchia, 1987](#); [Easley and O'Hara, 1992](#)). Accordingly, it is reasonable to assume that in formulating price quotes, traders incorporate expected (size and timing) characteristics of the next trade, as well as post wider spreads if they expect sudden changes to market risk conditions. This latter aspect is incorporated by assuming traders are averse to two main types of risk: price volatility and the proportion of informed traders present in the market. As these usually accompany each other during bouts or episodes of intense trading (e.g., [Admati and Pfleiderer, 1988](#)), we conjecture that both types of risk can be approximated by the proportion of informed traders. We further conjecture that the expectations of trade characteristics and risk conditions affect *both* the degree of impact that surprises in order flow have on the revision in beliefs ( $\theta_t$ ) and the size of the liquidity cost ( $\varphi_t$ ) has on prices. In our model, and in contrast with the MRR, these two parameters are formulated as functions of expected trading intensity (also used to detect the type of agent expected to instigate the next trade) and expected shifts in the proportion of informed traders.<sup>8</sup> We define trading intensity as the rate of transacted volume, or duration-weighted volume,  $s_t = v_t/d_t$ , where  $v$  is the volume (size) of trade  $t$  and  $d$  is its duration. The sudden shift in the proportion of informed trades at event  $t$  is approximated by a Poisson random variable,  $P_t$ , with mean  $\lambda$ , which is assumed to be independent of order flow ( $q_t$ ) and trading intensity ( $s_t$ ). Formally,

$$\theta_t = \theta_1 + \sum_{\pi}^3 (\theta_{2,\pi} I_{\pi,t}) E[s_t | H_{t-1}] + \theta_3 E[P_t | H_{t-1}], \quad (5)$$

$$\varphi_t = \varphi_1 + \sum_{\pi}^3 (\varphi_{2,\pi} I_{\pi,t}) E[s_t | H_{t-1}] + \varphi_3 E[P_t | H_{t-1}], \quad (6)$$

<sup>8</sup> The type of agent is detected through regimes of duration as in [Kalaitzoglou and Ibrahim \(2013a\)](#), who analyse duration in the carbon market to end of 2008 but not price formation. See [Appendix C in the online supplement](#).

<sup>4</sup> However, [Ellerman et al. \(2014\)](#) argues that the ‘over allocation’ in the first ‘pilot’ period was small and the main problems were difficulties in setting emission caps and the compressed time schedule.

<sup>5</sup> Phase I was a pilot period modelled according to the acid rain experience of the USA. Phase II is the Kyoto commitment period where installations have to register and match emissions to allowances. Phase III (2013–2020) is a regulatory enhanced trading period (see [Ellerman et al., 2014](#), for more detail on phases).

<sup>6</sup> MRR include a third possibility of a value of 0 for trades that may occur within the best bid and ask (the touch). In the carbon market, however, the trade sign (buys or sells) is indicated, and trades occur either at the best bid or the best ask. Accordingly,  $q_t$  is either +1 or –1.

<sup>7</sup> The probability of continuation, i.e. a buy (sell) follows a buy (sell), is  $\equiv \Pr(q_t = 1 | q_{t-1} = 1) = \Pr(q_t = -1 | q_{t-1} = -1)$ . Thus,  $\rho = 2\gamma - 1$ . See [Appendix B](#).



where  $I_{\pi,t} = (I_{uninformed,t}, I_{fundamental,t}, I_{informed,t})'$ ;  $I_{uninformed,t} = 1$  if  $E[s_t|H_{t-1}] \leq s_1$  and zero otherwise;  $I_{fundamental,t} = 1$  if  $s_1 < E[s_t|H_{t-1}] \leq s_2$  and zero otherwise; and  $I_{informed,t} = 1$  if  $E[s_t|H_{t-1}] > s_2$  and zero otherwise.  $I_{\pi,t}$  is a set of binary variables that indicates the type of agent expected to instigate the next trade, whether *uninformed*, *fundamental* (discretionary liquidity traders) or *informed*, according to the specific regime ( $\pi = (uninf, fund, inf)'$ ) of trading intensity that is expected to exist at event/time  $t$ . Estimates of the threshold values  $s_1$  and  $s_2$  that identify the three regimes, are obtained by estimating a Smooth Transition Mixture of Weibull Autocorrelated Duration (STM-ACD) model.<sup>9</sup> To complete the formulation we next specify the expectations of intensity,  $E[s_t|H_{t-1}]$ , and expected risk conditions,  $E[P_t|H_{t-1}]$ . Since trading intensity is expected to be autocorrelated we describe its dynamics by an autoregressive process of order  $m$ ,  $AR(m)$ .<sup>10</sup> Accordingly, its conditional expectation is:

$$E[s_t|H_{t-1}] = s_t - e_t = c_0 + c_1 s_{t-1} + c_2 s_{t-2} + \dots + c_m s_{t-m}, \quad (7)$$

where  $c_i, i = 0, \dots, m$  are AR coefficient parameters and  $e_t \sim iid(0, \sigma_e^2)$  is an error term that is assumed to be uncorrelated with  $\varepsilon_t$ . Finally, in application, the conditional expectation of the Poisson risk variable is measured by the proportion of over-the-counter (OTC) transactions that occur during the 15-min interval that includes and precedes trade  $t-1$ .<sup>11</sup> Formally,  $E[P_t|H_{t-1}] = (1/N) \sum_{n=1}^N I_{OTC,t-n}$ , where  $I_{OTC,t-n} = 1$  if trade  $t-n$  is an OTC trade and zero otherwise, and  $N$  is the total number of transactions that occur during the 15-min interval.

This model encompasses a number of models that appeared in the literature: if  $\rho = \theta_3 = \varphi_3 = 0$ ,  $I_\pi = d_t = 1$ , and  $E[s_t|H_{t-1}] = s_t$ , the model reduces to that of [Glosten and Harris \(1988\)](#); if  $\theta_{2,\pi} = \theta_3 = \varphi_{2,\pi} = \varphi_3 = 0$ , it reduces to the MRR; if the autocorrelation of order flow is restricted to zero ( $\rho = 0$ ), it reduces to a special case of the version of [Huang and Stoll \(1997\)](#) but with changing expectations<sup>12</sup>; and if  $\theta_{2,\pi} = \theta$ ,  $\varphi_{2,\pi} = \varphi$ ,  $I_\pi = d_t = 1$ ,  $E[s_t|H_{t-1}] = s_t$ , and  $\theta_1 = \theta_3 = \varphi_3 = 0$ , the model simplifies to that of [Angelidis and Benos \(2009\)](#).<sup>13</sup>

The model is estimated using an iterative generalised method of moments procedure with an appropriate set of moment conditions (see [Appendix A in the online supplement](#)).

The model in Eqs. (4) to (7) incorporates a number of effects. The revision in beliefs parameter ( $\theta$  in the MRR) is now decomposed into trading intensity and risk effects. In particular, the coefficient vector  $\theta_{2,\pi} = (\theta_{2,uninf}, \theta_{2,fund}, \theta_{2,inf})'$  measures price responsiveness to innovations in order flow related to dealers' expectations of the trading intensity of the next trade. According to [Dufour and Engle \(2000\)](#), a shorter duration leads to higher price revisions due to the higher informational content of trades. [Karpoff \(1987\)](#) and others also highlight a strong link between volume and

the absolute value of price changes. Consequently, when dealers expect higher trading intensity, they should expect higher price revisions for a given surprise in order flow. Therefore, the sum of  $\theta_1$ , which statistically is the long-term trend of price responsiveness, and the product of  $\theta_{2,\pi}$  and expected trading intensity, should be positive and higher in the informed regime compared to the other two regimes. A positive  $\theta_{2,\pi}$  would indicate an increased price effect of larger and faster transactions and would be consistent with the propositions of [Easley and O'Hara \(1992\)](#) and [Dufour and Engle \(2000\)](#).<sup>14</sup>

The model also decomposes the liquidity cost parameter ( $\varphi$  in the MRR) into trading intensity and risk effects. In particular, the coefficient vector  $\varphi_{2,\pi}$  measures the transitory price impact of trading intensity. Evidence of economies of scale effects presented in the literature (e.g., [Karpoff, 1987](#)), together with [O'Hara's \(2003\)](#) argument that liquidity has to be time varying or at least be systematic in some sense to affect the risk of holding an asset, lead us to expect a negative sign for these parameters.<sup>15</sup> Since some costs are fixed, a higher trading volume should decrease the per-unit cost. Considering that the carbon market is relatively less liquid than other markets, larger and faster transactions are expected to improve dealers' inventory positions and, hence, should contribute to lower trading costs. These parameters, then, should account for the liquidity component of the spread. Importantly, this effect opposes the permanent informational impact of trading intensity, and the net impact on prices and the spread is determined by the relative magnitude of the terms containing  $\theta_{2,\pi}$  and  $\varphi_{2,\pi}$ . This flexibility of considering opposing effects should provide at least a partial explanation of the conflicting results in previous studies concerning transaction size, time and price and the role of liquidity in asset pricing.<sup>16</sup>

The model also incorporates risk effects. Risk-averse traders should require higher compensation if they expect the next trade to expose them to higher levels of risk, hence they may post wider spreads. First, dealers are assumed to observe the market, update themselves continuously, and interpret information signals according to the  $AR(m)$  process for intensity and the STM-ACD model for intensity thresholds. They can, therefore, form expectations on whether the incoming trade is informed, fundamental or uninformed. However, during the early development period of the carbon market there were price and information jumps that may have reflected in shifts in the proportion of informed traders or market volatility. Allowing for such shifts would account for the risk-aversion component of the spread. The last term in Eqs. (5) and (6) is a dual measure of risk not revealed in trading intensity, because it is uncorrelated with trading intensity by construction. This term allows regret-free price quotes to incorporate expectations of possible sudden shifts in market risk conditions

<sup>9</sup> See [Table C1, Appendix C, in the online supplement](#). These threshold values are used here to dissect expected trading intensity into three regimes: low ( $E[s_t|H_{t-1}] \leq s_1$ ), which indicates uninformed trades; medium ( $s_1 < E[s_t|H_{t-1}] \leq s_2$ ), which indicates fundamental trades; and high ( $E[s_t|H_{t-1}] > s_2$ ), which indicates informed trades. These regimes indicate the type of agent who instigates the trade based on an association between the shape of the hazard function of duration (i.e., instantaneous transaction rate) in each trading intensity regime and expected trading behaviour of informed, uninformed and discretionary liquidity traders.

<sup>10</sup> The minimum volume for automatic matching is one and time in our dataset is measured in seconds. This discreteness, therefore, is alone sufficient to induce autocorrelations in these measures. [Palao and Pardo \(2014\)](#) also provide evidence that carbon trades are clustered in sizes of one to five contracts and in multiples of five.

<sup>11</sup> OTC trades are large trades and hence are expected to carry information.

<sup>12</sup> [Huang and Stoll's \(1997\)](#) extended model ignores changing expectations even though they suggest a way by which it can be incorporated (see footnote 6 in their paper).

<sup>13</sup> [Angelidis and Benos \(2009\)](#) incorporate volume contemporaneously with price, but volume is not known prior to trade  $t$ . Accordingly, their model is partially retrospective and cannot be used to set regret-free quotes.

<sup>14</sup> [Easley and O'Hara \(1992\)](#) maintain that increased volume has a larger price impact due to the increased presence of informed traders. [Dufour and Engle \(2000\)](#) argue that price variations are larger upon increased trading frequency. A positive  $\theta_2$  would indicate larger price variations for a unit change in order flow innovation when trade size and frequency are expected to be higher. Such a result would empirically support both studies.

<sup>15</sup> [O'Hara \(2003\)](#) argues that liquidity is akin to a tax or a cost borne by investors and predicts a negative effect on asset prices if these costs are large enough. By allowing liquidity costs to vary with every transaction and be affected by the type of agent expected for the next trade and by the proportion of informed traders present in the market our model incorporates this concept. The estimation results presented below strongly support this.

<sup>16</sup> [Stoll \(1978\)](#), for example, reports a U-shaped relation between volume and spread. [Glosten and Harris \(1988\)](#) report an increasing relationship between volume and adverse selection costs, and [De Jong et al. \(1995\)](#), [Huang and Stoll \(1997\)](#) and [Ahn et al. \(2002\)](#) report a decreasing effect of volume on spreads. [Angelidis and Benos \(2009\)](#) confirm a decreasing relationship, but only for the liquidity component of price changes. The model proposed in this study conjectures that these differences could be explained by the dual and opposing effect of trading intensity on the information and liquidity cost components of price change.

arising from an increased or decreased presence of informed traders. The parameters  $\theta_3$  and  $\varphi_3$  measure the response of price changes that these shifts might have on asymmetric information and liquidity, respectively. Expected positive signs would indicate higher price variations for a given surprise in order flow.

#### 4. Data

We examine price discovery in EUA December futures contracts (most heavily traded) on the European Climate Exchange (ECX) trading on the Intercontinental Exchange (ICE) Futures Europe electronic platform. The trade data used spans the entire initial 'pilot period' of Phase I (2005–2007), the entire 'trade period' of Phase II that coincided with the 'Kyoto commitment period' (2008–2012), and two years and four and half months of Phase III (2013–2020) to 30 April 2015. The intraday dataset, obtained from ICE-ECX, consists of date, timestamp (in seconds), price, volume, trade sign (buy or sell) and trade type (block, Exchange for Physical (EFP), Exchange for Swap (EFS), screen, screen-cross, screen-cross-contra and screen-cross-non-contra) indicators for all reported transactions.<sup>17</sup> We define as OTC trades that are block, EFP or EFS. The rest are grouped as 'non-OTC' trades. Main session trading hours are 07:00 to 17:00 h UK local time from Monday to Friday.

To represent prices in the different phases, and for comparability with prior literature (e.g., Medina et al., 2014), we use volume rollover to construct a continuous series for each phase. Phase I series is constructed from December contracts maturing during Phase I only. Phase II and III series are constructed similarly. As some contracts are issued in a phase but mature in another, the sample periods covered by the three continuous series are 22/4/2005–17/12/2007, 10/1/2006–17/12/2012 and 4/1/2010–30/4/2015.<sup>18</sup> The following treatment is applied to the data. First, the timestamp is adjusted for daylight savings. Second, we analyse trades that occurred during the official trading hours only, since after-hours trades are OTC trades that are reported with a delay of up to 30 min, and their inclusion would contaminate duration measurement due to untimely reporting. Third, all trades prior to 1/1/2006 (124 trades) are omitted from the Phase II series due to very infrequent trading (e.g., there were only 3 trades in June and 40 in November). The same is applied to trades prior to 1/1/2010 for the Phase III series (307 trades). Fourth, there are 28, 30 and 21 trades in the constructed series for Phase I, II and III, respectively, with a change in price (return) greater than twenty times the standard deviation of the return distribution of the series in each phase (a change beyond the known price crashes that are well documented for the carbon market). Some of these trades appear to be contra cancelling trades because they appear in pairs, one showing a certain increase in price followed by another showing an equal decrease in price. We strive to model 'normal' market conditions (including large volatility and risk jumps), but these are extreme observations, cancellations or entry errors that are likely to affect model parameter estimates disproportionately, thus distorting the description of the

market as a whole, including the known price crashes. Over ninety percent of these trades are screen trades and represent only 0.09%, 0.002% and 0.002% of the number of trades in each phase series, respectively. We, therefore, omit them as outliers, cancellations or recording errors.<sup>19</sup> Fifth, 9%, 29% and 45% of the total number of trades in each of the continuous series, respectively, have the same time stamp, price and trade sign indicator as the preceding trade. These zero-duration trades are considered as possible strategic trades (large broken up trades) and, since they cause no change in price or order flow, their volume is aggregated with that of the previous trade. Other zero duration trades that show either a change in price or in trade sign are not aggregated and left as unique trades. This aggregation represents the largest reduction in the number of observations of each series. The number of trades for each series prior to volume aggregation and removal of outliers is 29,746, 1,462,248, and 1,202,377 trades, respectively. The final sample after volume aggregation and removal of outliers contains 26,928, 1,043,514 and 660,138 trades, respectively. Sixth, the duration and trading intensity of the final series are then diurnally adjusted, as in Engle (2000), and seasonally adjusted by annual dummies to remove heteroskedasticity of a known form. Finally, in the final series for Phase I, II and III, the standard deviation of price change of (unique) trades with the same time stamp is 0.9824, 0.0729 and 0.0211, respectively, while that of trades of different time stamps is 0.7190, 0.1661, and 0.0247, respectively. Thus, unique (included) zero duration trades contribute to volatility of price change, but the disparity is largest in Phase II. Accordingly, a constant of one is added to all durations to enable model estimation (Dufour and Engle, 2000, adopt a similar practice).

Table 1 presents descriptive statistics of the final series for all trades and OTC trades separately (a further breakdown by other types of trade is available from the authors). Prices decrease from Phase I to Phase III, and OTC trades have higher prices on average than those of other trades. Average returns are near zero with a high kurtosis and a slight skewness (negative in Phase I). The median of the order flow variable (not reported in Table 1, as only the median is meaningful) is –0.35, –0.08 and 0.03 over the phases, for both screen and OTC trades. Average trade duration across all transactions decreases substantially from 873.89 s, to 60.89 s to 73.23 s over the phases (after deducting 1 s). The median duration decreases monotonically, indicating increasing trading activity and perhaps market depth. Average volume and duration of all trades are lower than those of OTC trades in all phases, and hence screen orders are smaller and executed faster on average. The average volume of OTC trades increases substantially over the phases (in Phase III the median is nine times that of Phase I). The median volume of all trades decreases from 10 in Phase I to 5 in Phases II and III, but that of OTC trades diverges considerably and increases from 10 in Phase I to 90 in Phase III. Thus, large and block trades got larger and traded faster in Phases II and III than Phase I, but slightly slower in Phase III than Phase II. The latter effect is perhaps due to their larger size. The median diurnally adjusted duration, however, decreases considerably from Phase I to Phase III for all trades, but increases for OTC trades,

<sup>17</sup> EFP, EFS and most block are OTC trades registered through a special ICE Block facility. The Exchange allows reporting of these trades after trading and up to 18:00 h (Ibikunle et al., 2016). Although a quarterly cycle of contracts is available, trading concentrates on the December contracts, which have been the focus of most prior analyses in the carbon market. Every futures contract, 'lot', corresponds to 1000 European Union Allowances (EUAs), and every EUA carries the right to emit 1 tonne of CO<sub>2</sub> equivalent in greenhouse gases (see [www.ecx.eu](http://www.ecx.eu)). Prices are in Euros and Euro cents per tonne. Also see Thomson Reuters Point Carbon reports at [www.pointcarbon.com](http://www.pointcarbon.com).

<sup>18</sup> We rollover when daily volume of the nearest contract exceeds that of the maturing contract consistently for two days. The rollover dates from one December contract to another (starting with the December 2005 contract and ending with the December 2015 contract) for Phase I are 21/11/2005 and 23/11/2006; for Phase II are 9/12/2008, 4/12/2009, 17/12/2010 and 14/12/2011; and for Phase III are 13/12/2013 and 12/12/2014.

<sup>19</sup> These trades do not detract from the ability of the model to incorporate shocks and from providing a proper description of the market including the price crashes that occurred in Phase I. The graph in the online Appendix D, which plots the final sample, clearly shows the inclusion of the main price crashes of the market. Further, most microstructure studies, especially those analysing duration, impose filters on the data to eliminate outliers or recording errors. Madhavan et al. (1997), for example, omit overnight trades as they are likely to come from a different distribution, trades below \$1 or above \$200, trades more than 50% away from the previous quote or trade price, trades more than \$5 from the mid-quote, for stock priced \$10 or above any quote with a spread greater than 20%, and for low priced stocks any quote implying a spread above \$2. Medina et al. (2014), Benz and Hengelbrock (2008), Rannou (2014) and Mizrach and Otsubo (2014) consider only 'normal' screen trades. Ibikunle et al. (2013) analyse after hours trades only, and Ibikunle et al. (2016) analyse on-screen block trades (only) and exclude December trades (close to maturity).

**Table 1**  
Descriptive statistics.

		Price (€) (p)	Return ( $\Delta p$ )	Duration ( $x_t$ )	Volume ( $v_t$ )	D-a Duration	D-a Tr. intensity
Phase I							
All trades	Mean	15.60	0.00	874.89	13.13	1.00	1.00
	Median	16.20	0.00	210	10	0.24	0.08
	Maximum	31.00	9.95	62055	600	79.44	553.16
	Minimum	0.01	−9.80	1	1	0.00	0.00
	Std. Dev.	8.84	0.73	2467.34	19.08	2.85	5.54
	Skewness	−0.23	0.26	9.80	9.37	10.44	43.90
	Kurtosis	1.95	67.98	140.36	149.72	163.26	3799.24
OTC	Mean	16.71	0.06	903.63	19.27	1.05	0.89
	Median	16.50	0.00	241	10	0.31	0.09
	Maximum	31.00	9.95	62055	600	79.44	553.16
	Minimum	0.03	−9.80	1	1	0.00	0.00
	Std. Dev.	8.07	1.03	2390.68	28.56	2.75	7.89
	Skewness	−0.40	1.35	11.32	7.25	12.03	44.12
	Kurtosis	2.29	33.29	190.62	82.35	224.90	2849.33
Phase II							
All trades	Mean	13.79	0.00	61.89	13.06	1.00	1.00
	Median	13.70	0.00	10	5	0.17	0.17
	Maximum	33.70	5.85	50101	28952	849.29	400.16
	Minimum	2.82	−5.69	1	1	0.01	0.00
	Std. Dev.	5.03	0.16	320.62	49.90	5.16	3.62
	Skewness	0.64	0.02	53.01	213.34	53.01	21.56
	Kurtosis	3.11	149.02	4703.64	110358.81	4734.62	1153.60
OTC	Mean	16.06	0.01	164.01	44.04	2.58	1.56
	Median	14.99	0.00	50	25	0.79	0.20
	Maximum	33.50	5.85	50101	28952	849.29	373.89
	Minimum	2.82	−5.60	1	1	0.01	0.00
	Std. Dev.	5.24	0.41	822.33	150.37	13.06	6.55
	Skewness	0.36	−0.04	26.19	87.80	26.65	18.28
	Kurtosis	2.42	21.80	1004.66	15176.90	1048.23	622.22
Phase III							
All trades	Mean	5.97	0.00	74.23	18.86	1.00	1.00
	Median	5.60	0.00	7	5	0.09	0.13
	Maximum	20.22	0.98	54113	25000	743.64	1320.06
	Minimum	2.46	−0.98	1	1	0.01	0.00
	Std. Dev.	2.21	0.02	497.40	102.59	6.57	5.54
	Skewness	2.81	−0.21	38.07	101.57	37.11	79.86
	Kurtosis	14.75	265.63	2262.27	19042.88	2194.03	12787.64
OTC	Mean	6.84	0.00	299.67	221.96	3.90	4.87
	Median	6.00	0.00	60	90	0.80	0.33
	Maximum	19.70	0.98	47768	25000	650.64	1320.06
	Minimum	2.48	−0.98	1	1	0.01	0.00
	Std. Dev.	3.35	0.12	1344.90	735.18	17.69	34.01
	Skewness	2.04	−0.29	16.34	17.90	16.76	21.40
	Kurtosis	7.09	15.43	381.42	479.73	407.24	600.11

In this table descriptive statistics of transaction price (in Euro cents), return (change in price), duration (seconds), volume (# of contracts) and diurnally adjusted (D-a) duration and trading intensity are presented for all trades and OTC (EFPs, EFP and block) trades in the continuous series for each phase.

indicating a clear slowing down of OTC trades and a speeding up of screen trades. The median diurnally adjusted trading intensity for all trades doubles in Phase II but decreases slightly in Phase III, while that of OTC trades increases monotonically over the phases. Thus, although OTC trades are slowing, their increasing size indicates increasing intensity, while screen trades show decreasing intensity. These descriptive statistics reveal quite different liquidity and trading environments across phases, which partly motivates the choice of market for analysis.

## 5. Estimation

### 5.1. The MRR

To aid comparison, we first estimate the MRR. Parameter estimates presented in Table 2 are, in general, comparable to those reported in prior studies. However, they are slightly different from those estimated by the three carbon studies of Benz and Hengelbrock (2008), Medina et al. (2014), and Mizrach and Otsubo (2014). They report contract, quarterly or monthly estimates, but

on comparable (annual) grounds their estimates of  $\theta$ ,  $\rho$  and  $\varphi$  are smaller. This is found to be mainly due to their analysis of screen trades only.<sup>20</sup> In Table 2, average estimates of the degree of asymmetric information ( $\theta$ ) are considerably larger and more significant than those of the transitory liquidity component ( $\varphi$ ) in all phases.<sup>21</sup> This indicates that changes in beliefs about true values are more sensitive

<sup>20</sup> Considering only screen trades we are able to replicate Medina et al.'s (2014) quarterly estimates for Phase I (which are similar to those reported in Benz and Hengelbrock, 2008). For example, we estimate  $\theta$ ,  $\varphi$  and  $\rho$  to be 0.0420, 0.0021, and 0.4416, respectively, for 2006 Q1, which are almost identical to those reported by Medina et al. (2014). (Benz and Hengelbrock, 2008, provide estimates for  $\theta$  and  $\varphi$  only, and for the same quarter are 0.0412 and 0.0036.) In contrast, our estimates for the three parameters in that quarter using all trades are 0.0733, 0.0155, and 0.4577, respectively. Thus, including OTC trades gives different estimates of the asymmetric information component of price change ( $\theta$ ), the autocorrelation of order flow ( $\rho$ ), and the liquidity cost component ( $\varphi$ ). A more detailed comparison of quarterly and annual estimates is available from the authors.

<sup>21</sup> Benz and Hengelbrock (2008) report very small and, sometimes, insignificant estimates for the transitory component. However, as Medina et al. (2014), they too estimate the MRR for calendar quarters and exclude OTC trades (see previous footnote). Our dynamic model, discussed below, reveals more detail on this aspect.

**Table 2**  
Estimation results.

	Phase I			Phase II			Phase III		
	MRR	DJM-F	DJM-S	MRR	DJM-F	DJM-S	MRR	DJM-F	DJM-S
$\theta_1$	0.0798 (5.40)	0.0054 (0.16)		0.0209 (33.19)	−0.0007 (−0.39)		0.0042 (73.09)	0.0002 (0.33)	
$\theta_{2,unif}$		0.0793 (2.76)	0.0836 (2.62)		0.0352 (3.66)	0.0363 (5.83)		0.0055 (3.25)	0.0068 (3.91)
$\theta_{2,fund}$		0.0779 (5.47)	0.0808 (5.32)		0.0332 (5.23)	0.0327 (5.89)		0.0043 (3.89)	0.0044 (5.76)
$\theta_{2,inf}$		0.0750 (6.95)	0.0790 (7.44)		0.0316 (7.12)	0.0309 (6.97)		0.0016 (7.77)	0.0041 (7.34)
$\theta_3$		0.0183 (3.33)	0.0127 (3.54)		−0.0003 (−1.21)			0.0011 (1.27)	
$\rho$	0.4628 (65.35)	0.4631 (65.43)	0.4628 (65.39)	0.4221 (302.10)	0.4222 (302.21)	0.4219 (302.02)	0.3178 (167.20)	0.3194 (168.20)	0.3177 (167.15)
$\varphi_1$	0.0019 (2.70)	0.0970 (5.00)	0.1019 (3.12)	0.0019 (4.82)	0.0413 (3.58)	0.0426 (7.28)	0.0021 (25.25)	0.0035 (9.41)	0.0069 (14.86)
$\varphi_{2,unif}$		−0.0858 (−2.18)	−0.0928 (−2.75)		−0.0317 (−2.72)	−0.0397 (−3.69)		−0.0043 (−3.99)	−0.0076 (−2.37)
$\varphi_{2,fund}$		−0.0838 (−3.21)	−0.0988 (−3.31)		−0.0291 (−3.36)	−0.0311 (−5.81)		−0.0042 (−5.63)	−0.0056 (−5.56)
$\varphi_{2,inf}$		−0.9621 (−5.16)	−0.1060 (−5.36)		−0.0345 (−5.97)	−0.0371 (−7.18)		−0.0032 (−7.07)	−0.0047 (−7.20)
$\varphi_3$		0.0092 (2.14)	0.0170 (2.59)		0.0010 (0.97)			0.0021 (1.18)	
$\lambda$		0.3199 (16.00)	0.3197 (16.42)		0.0878 (28.05)			0.0130 (27.44)	
$\sigma_\epsilon^2$	0.1530 (3.35)	0.1731 (3.13)	0.1707 (2.62)	0.3196 (5.02)	0.3923 (5.69)	0.3613 (3.53)	0.0119 (5.15)	0.0130 (6.91)	0.0112 (8.72)
$\sigma_\xi^2$	0.1614 (7.38)	0.1584 (7.10)	0.1085 (6.69)	1.0567 (9.64)	0.8606 (11.14)	0.7078 (13.55)	0.0229 (7.91)	0.0057 (13.26)	0.0054 (12.74)
# lags		22	17		102	94		37	29
J-stat		3.8914 (0.27)	4.8872 (0.43)		4.7690 (0.19)	3.1098 (0.54)		3.2941 (0.35)	2.6405 (0.62)
$H(0)$									
$\theta_{2,u} = \theta_{2,f}$			8.52			231.63			658.57
$\theta_{2,f} = \theta_{2,i}$			7.69			139.26			147.79
$\varphi_{2,u} = \varphi_{2,f}$			12.55			−470.90			−312.43
$\varphi_{2,f} = \varphi_{2,i}$			16.22			302.89			−339.50

In this table, estimation results of the MRR and the DJM models are presented (DJM-F is full version and DJM-S is significant parameter version). Estimates of  $\sigma_\epsilon^2$  and  $\sigma_\xi^2$  for Phase I are reported as they are, but for Phase II and III are reported multiplied by 100. # lags of trading intensity is determined by the Schwartz Information Criterion (SIC). Values in parenthesis are *t*-statistics, except for *J*-stat where they are *p*-values. Estimates of the autocorrelation coefficients in trading intensity are available from the authors. Values in the hypothesis section  $H(0)$  are two-mean equality *t*-tests (1.96 is 5% sig).

to private information than prices are to changes in liquidity costs. However, estimates of  $\theta$  and  $\rho$  decrease considerably from Phase I to Phase III, while estimates of  $\varphi$  remain roughly constant in the first two phases but increase slightly in Phase III. This indicates that the sensitivity to asymmetric information is decreasing while that to liquidity costs remains roughly the same as the market develops.<sup>22</sup>

The sum of  $\theta$  and  $\varphi$ , which is half the spread according to the MRR, decreases from Phase I (0.0817) to Phase III (0.0063), which is an 87% decrease in spread costs. A similarity with the MRR results on the NYSE is the significant autocorrelation in order flow,  $\rho$ , which decreases monotonically from Phase I (0.4628) to Phase III (0.3178). Accordingly, the probability of order flow continuation ( $\gamma = (1 + \rho)/2$ ) decreases over time and across phases. This reflects less price trends, increasing liquidity, and an early indication that the proportion of price volatility attributable to the bid-ask bounce decreases over time. Both, the variance of public information ( $\sigma_\epsilon^2$ ) and that of price discreteness ( $2\sigma_\xi^2$ ) are significant, and decrease over the phases.<sup>23</sup>

<sup>22</sup> A decreasing estimate of  $\theta$  is consistent with Mizrahi and Otsubo (2014).

<sup>23</sup> Medina et al.'s (2014) estimates of  $\sigma_\epsilon^2$  and  $2\sigma_\xi^2$  for the first two phases are significant and also decrease over time in each phase. Benz and Hengelbrock (2008) and Mizrahi and Otsubo (2014) do not report estimates of the variance components.

This indicates a changing riskiness of the trading environment, decreasing price discreteness and an increasing role of trading frictions.

This preliminary analysis with the MRR across market phases provides initial evidence of changing characteristics of intraday price formation and trading spreads in the carbon market, and hence the need for a more appropriate time-varying model. The narrowing spread, mainly due to a decrease in the asymmetric information component (terms in Eq. (4) involving  $\theta$ ), indicates increasing market liquidity with progress towards market maturity. Dealers seem to reduce the asymmetric information component of the spread in the latter phases either because the risk of transacting with the informed is lower due to a decreased presence of informed trades or that they can earn more by transacting with an increasing number of the uninformed, or both. The narrowing spreads indicate increasing trading activity, the lower autocorrelation of order flow indicates less price trends and higher probability of reversals, and the decreasing variance of public information ( $\sigma_\epsilon^2$ ) and that of price discreteness ( $2\sigma_\xi^2$ ) indicate lower price uncertainty and perhaps higher price 'accuracy'. Thus, the market is becoming increasingly vibrant and the characteristics of price discovery have evolved over the phases.



**Table 3**

Summary statistics of GMM model parameter estimates and spread and variance components.

Panel A												
Phase	Model	$\hat{\theta}$	TI	E.TI	AS	RA-I	THETA	$\hat{\phi}$	LIQ	RA-L	PHI	IS
I	DJM							0.1019				
	Uninf	0.0836	0.0278	0.0290	0.0024	0.0042	0.0066	−0.0928	0.0992	0.0056	0.1048	0.2227
	Fund	0.0808	0.1957	0.1785	0.0144	0.0044	0.0189	−0.0988	0.0843	0.0059	0.0902	0.2182
	Inf	0.0790	2.4340	3.4913	0.2757	0.0035	0.2793	−0.1060	−0.2678	0.0047	−0.2631	0.0323
	All		0.9983	0.9976	0.0789	0.0040	0.0793		−0.0032	0.0054	0.0019	0.1624
	MRR						0.0793				0.0019	
II	DJM							0.0426				
	Uninf	0.0363	0.0800	0.1505	0.0055		0.0055	−0.0397	0.0367		0.0367	0.0843
	Fund	0.0327	1.0133	1.0593	0.0346		0.0346	−0.0311	0.0097		0.0097	0.0887
	Inf	0.0309	2.0285	3.9845	0.1213		0.1213	−0.0371	−0.1158		−0.1158	0.0112
	All				0.0209		0.0209		0.0059		0.0059	0.0536
	MRR						0.0209				0.0059	
III	DJM							0.0069				
	Uninf	0.0068	0.0183	0.0306	0.0002		0.0002	−0.0076	0.0067		0.0067	0.0138
	Fund	0.0044	0.2694	0.2915	0.0013		0.0013	−0.0056	0.0053		0.0053	0.0131
	Inf	0.0041	2.4286	4.0538	0.0166		0.0166	−0.0047	−0.0122		−0.0122	0.0089
	All		1.0001	1.0001	0.0042		0.0042		0.0021		0.0021	0.0125
	MRR						0.0042				0.0021	
Panel B												
Phase		Trade	AS	LIQ	RA	Interactions	C.VAR	A.Var				
I	Uninf		0.0000	0.0077	0.00010	0.0053	0.4008	0.3154				
	Fund		0.0002	0.0056	0.00011	0.0060	0.3996	0.6830				
	Inf		0.6215	1.0664	0.00013	−1.2317	0.8440	0.7850				
	All		0.1678	0.2930	0.00010	−0.3284	0.5258	0.5258				
II	Uninf		0.0001	0.0016		0.0003	0.0197	0.0249				
	Fund		0.0011	0.0002		0.0004	0.0195	0.0249				
	Inf		0.0788	0.1399		−0.1762	0.0603	0.0425				
	All		0.0098	0.0183		−0.0213	0.0246	0.0249				
III (×100)	Uninf		0.0000	0.0061		0.0002	0.0283	0.0588				
	Fund		0.0002	0.0039		0.0011	0.0271	0.0563				
	Inf		0.2189	0.4072		−0.4812	0.1668	0.1062				
	All		0.0478	0.0928		−0.1045	0.0581	0.0586				

In this table, Panel A presents parameter estimates and calculations of adverse selection, liquidity, risk aversion and implied spread costs. DJM stands for the dynamic joint model presented in this paper. MRR is the model of [Madhavan et al. \(1997\)](#). *Uninf*, *Fund*, *Inf*, and *All* stand for uninformed, fundamental, informed and all transactions.  $\hat{\theta}$  and  $\hat{\phi}$  are GMM 'DJM' estimates ([Table 2](#)). *TI* is trading intensity. *E.TI* is expected trading intensity estimated by the  $AR(m)$  embedded in the DJM pricing model. *AS*, *LIQ*, and *RA* are adverse selection, liquidity and risk aversion components of price change. *RA-I* and *RA-L* are the information and liquidity related risk aversion components (in Eqs. (5) and (6)).  $THETA = AS + RA-I$  and  $PHI = LIQ + RA-L$  across transactions in a regime  $\pi$ . *IS* is the implied spread =  $2(THETA + PHI)$ . Panel B presents components of conditional variance as in Eq. (10). *Interactions* are all the interaction terms in Eq. (10) between adverse selection, liquidity and risk aversion. *RA* exists and is reported only when  $\hat{\theta}_3$  or  $\hat{\phi}_3$  are significant (Phase I).  $\sigma_e^2$  and  $\sigma_c^2$  components are not reported, but are included in the conditional variance (C. VAR) and are plotted as proportions in [Fig. 2](#). *A.Var* is the realised variance. All entries for Phase III in Panel B are reported multiplied by 100.

## 5.2. The dynamic joint expectation pricing model

[Table 2](#) also presents the estimation results of the dynamic joint expectation microstructure model (dubbed DJM).<sup>24</sup> We focus description on the DJM-S estimates. The only significant asymmetric information parameters are those associated with expected trading intensity ( $\hat{\theta}_{2,\pi}$ ), which are positive in all three market phases. There is no constant long-term average value for this component ( $\hat{\theta}_1$  are insignificant). This highlights the time varying nature of the DJM and provides evidence that information asymmetry changes on a trade-by-trade basis and is inextricably linked to trading intensity (liquidity). Estimates  $\hat{\theta}_2$  are significantly lower for higher trading intensity (see *H(0)* section of [Table 2](#):  $\hat{\theta}_{2,uninformed} > \hat{\theta}_{2,fundamental} > \hat{\theta}_{2,informed}$ ) which indicates that price changes are less sensitive to surprises in order flow when trades are expected to be of higher intensity. The total effect of trading intensity on price changes, however,

is captured by the product  $(\hat{\theta}_{2,\pi} I_{\pi,t})E[S_t|H_{t-1}]$ , and not by  $\hat{\theta}_{2,\pi}$  alone. [Table 3](#) Panel A tabulates this product in the column entitled 'AS'. The increasing degree of information asymmetry with trading intensity is clear in all phases. Thus, although estimates of the parameter theta are lower for higher intensity, and hence prices are less sensitive to incremental information, the total impact of the informed on the magnitude of the asymmetric information price component is higher, and that of the fundamentals is higher than that of the uninformed. Accordingly, the impact on price changes of surprises in order flow is greater if the next trade is expected to be of higher volume, lower duration, or both. This confirms expectations drawn from separate prior analyses. It is consistent with [Dufour and Engle \(2000\)](#) who show that more frequent trading carries higher information content, and with [Easley and O'Hara \(1987\)](#), [Hausman et al. \(1992\)](#) and [Angelidis and Benos \(2009\)](#) who argue that larger trading volume indicates the presence of informed trading and, consequently, the expectation of a higher price impact. Our model reveals that the degree of information asymmetry is agent specific, and is directly related to expectations of trading intensity. Thus, for a given surprise in order flow, transactions that are expected to be instigated by different agents will have different intensity of impact on prices. All else equal, the informed affect prices more than the fundamentals, and the latter more than the uninformed. In the carbon market the asymmetric component of the informed is many

<sup>24</sup> A full-parameter specification is estimated first and is tabulated as DJM-F. Insignificant parameters are then dropped and a restricted version re-estimated and tabulated as DJM-S. In estimating the restricted version the moment conditions in lines 9 and 10 of [Eq. A1 in Appendix A](#) are dropped since  $\hat{\theta}_3$  and  $\hat{\phi}_3$  are insignificant. The *J*-statistics reported in [Table 2](#) are all insignificant, which indicate a reasonable model specification. STM-ACD estimates that determine the intensity thresholds are in [Appendix C of the online supplement](#).



multiples that of the uninformed (115, 22 and 23 times in Phases I, II and III, respectively).

However, there is a simultaneous counter effect on price changes through the liquidity component. 'DJM-S' estimates  $\hat{\phi}_1$  and  $\hat{\phi}_{2,\pi}$  reported in Table 2 are significant in all phases. Unlike the asymmetric information component, the liquidity (transaction costs) component has a positive constant element ( $\hat{\phi}_1$ ), which is much larger in magnitude than its MRR estimate. The MRR, therefore, underestimates the magnitude of fixed transaction costs. In addition, estimates  $\hat{\phi}_{2,\pi}$  are all significantly negative. The DJM model, therefore, reveals that there is a high fixed transaction cost when trading intensity is zero (no trades) which decreases with expectations of higher trading intensity, but this rate of decrease differs across phases. In Phase I,  $\hat{\phi}_{2,\pi}$  decreases monotonically as intensity rises from the uninformed to the informed, but in Phase II it exhibits a U-shape, and in Phase III it rises monotonically (Table 2,  $H(0)$ , reports these differences as statistically significant). Thus, price changes in each phase have different sensitivities to variations in liquidity costs. However, the total effect of trading intensity on the liquidity component of price changes, excluding risk effects, is captured by the sum  $\hat{\phi}_1 + \hat{\phi}_{2,\pi} I_{\pi,t} E[S_t | H_{t-1}]$  and not by  $\hat{\phi}_{2,\pi}$  alone. Table 3 Panel A tabulates this sum in the column entitled 'LIQ'. It is highest in magnitude for uninformed trades and lowest for informed trades in all three phases (i.e., there is a consistently negative relationship between total liquidity costs and the expected ratio of trade size to duration). Accordingly, liquidity costs too vary by agent type, and expected trading intensity has a negative effect on these costs. This is consistent with O'Hara's (2003) assertion that "if liquidity affects the risk of holding an asset then liquidity would have to be time varying," and with her expectation that liquidity costs "negatively affect asset prices because of their negative effect on asset returns". Thus, expected trading intensity increases the asymmetric information component and decreases the liquidity component of price change, but at different rates.<sup>25</sup>

Note that 'LIQ' for each agent, whether uninformed, fundamental or informed, decreases in magnitude over time from Phase I to Phase III. This highlights the relative liquidity cost components across market phases – higher (fixed and variable) costs in the least liquid Phase I and lower in the most liquid Phase III.

With regard to the risk component, 'DJM' estimates of the mean parameter of the Poisson risk variable ( $\hat{\lambda}$ ) are positive and significant in all three phases, but decrease substantially from Phase I to Phase III. Thus, there were sudden shifts in the number of OTC trades, especially during the pilot period, that did not reflect in expectations of trading intensity. The highest estimate in Phase I indicates riskier trading conditions in that less liquid phase. The presence of such risk, however, seems to have a permanent information and a temporary liquidity effect on price discovery only in Phase I ( $\hat{\theta}_3$  and  $\hat{\phi}_3$  are significant only in Phase I). Thus, on average, there were positive liquidity cost shifts that were priced in Phase I but not in the subsequent two phases. The link between these costs and the more volatile environment of Phase I is highlighted in the higher standard deviation of returns in Phase I reported in Table 1. Thus, the proportion of OTC trades during the 15-min interval that precedes a transaction was a significant risk factor that necessitated an increase in transaction costs only in Phase I, while the degree to which the next trade is expected to be more informed (higher trading intensity)

causes a statistically significant reduction in the transaction cost component in all phases. Accordingly, the dual and opposing role of trading intensity (liquidity) on information and liquidity costs is prevalent.<sup>26</sup> This role cannot be readily shown using the MRR, Roll (1984) or the Huang and Stoll (1997) models.

The role of public information and price discreteness (estimates of  $\sigma_e^2$  and  $\sigma_\xi^2$  in Table 2) decreases across the phases. In general, this seems to be in line with the higher trading activity across phases and frequency of release of regulatory announcements and emissions data particularly in Phase II (Mansanet-Bataller and Pardo, 2009; and Ellerman et al., 2014). Trading intensity is highly autocorrelated and the number of significant lags is large (# lags in Table 2 reports the number of significant lags, and is 17, 94 and 29 in Phase I, II and III, respectively, under the DJM-S estimation). Finally, the insignificant  $J$ -statistics confirm the proper estimation of the DJM and the appropriateness of the moment conditions in exactly identifying the parameters.

## 6. Discussion of Results

### 6.1. Autocorrelations of returns and return volatility

One of the primary goals of allowing the adverse selection component ( $\theta_t$ ) and the liquidity costs ( $\varphi_t$ ) to vary with every transaction, and be functions of expected trading intensity and the changing risk environment, is to test the degree to which these factors are able to explain the prevalent autocorrelations in returns ( $\Delta p_t$ ) and in return volatility (realised volatility  $(\Delta p_t)^2$ ). The evidence of high autocorrelation in trading intensity in the DJM estimation shows that the model incorporates the characteristic autocorrelation in volume and duration.<sup>27</sup> The degree to which this explains the autocorrelations in returns and volatility, through changes in beliefs and signed liquidity costs, is an empirical question that we answer next.

Table 4 Panel A reports Ljung–Box  $Q$ -statistics at lags one and ten for the level and the square of returns, and for the level and the square of the components of the MRR and the DJM models that are not related to trading frictions (i.e.,  $\varepsilon_t + \xi_t - \xi_{t-1}$  in Eq. (4), henceforth referred to by 'residuals'). The reported values for both the level and the square of returns are very high, and increase from Phase I to Phase III, which testify to the prevalent high autocorrelation in returns and in realised volatility in this market.<sup>28</sup> The

<sup>26</sup> Note that this role is revealed by the DJM model through the time varying responsiveness of price change to information and liquidity variations (i.e., through time varying  $\theta_t$  and  $\varphi_t$ ). Huang and Stoll's (1997) volume extended model is a linear dissection, through dummies, over a pre-determined trichotomy of volume. Accordingly, their model still produces average estimates of structural parameters within each trichotomy and is, thus, unable to detect liquidity variations on a trade-by-trade basis. The DJM, therefore, presents a substantial improvement, especially in its usefulness in setting regret-free price quotes during trading.

<sup>27</sup> These coefficients are estimated jointly with the other parameters of the DJM. They are not reported in Table 2 to conserve space, but are available from the authors. There are a number of possible reasons for the autocorrelation in trading intensity. The main participants in the carbon market are energy brokers and large emitting installations such as coal power stations and cement factories. These usually submit medium to large orders driven by their business needs and compliance requirements. Such behaviour formed by the 'nature of their business,' as well as by regulation, is sufficient to induce autocorrelation in trade volume. Other reasons related to the trading mechanism and order submission strategies and specifications, such as strategic trading, round lots and the non-divisibility of assets (i.e., fractions of one contract are not traded), are also possible. Time, however, is an unlikely culprit since trading clocks are recorded in milliseconds, though some data providers report coarser granularity in seconds (as is in our dataset), which would contribute to discreteness and, hence, to sequential persistence in time measures. See Palao and Pardo (2014) for clustering of size and prices.

<sup>28</sup> Note that the reported values for  $Q(10)$  do not differ much from those of  $Q(1)$ . Studying autocorrelations at lags longer than ten is unlikely, therefore, to result in different conclusions.

<sup>25</sup> Angelidis and Benos (2009), who do not consider trade duration, report a monotonically decreasing transaction cost component with higher (contemporaneous) volume in the Athens Stock Exchange. Our results that incorporate expected volume and duration support this general conclusion but reveal that the effects of volume and duration on information and liquidity occur at different rates. The MRR, and the carbon studies that use it, ignores these effects as it assumes unit quantity, equally spaced trades and constant price responses.

Table 4

Autocorrelations and proportion explained of returns and variance.

	Phase I		Phase II		Phase III			
	Level	Square	Level	Square	Level	Square		
Panel A								
Q(1)								
Returns	3940.1 (0.00)	3839.8 (0.00)	225963.6 (0.00)	258429.6 (0.00)	128527.3 (0.00)	165204.3 (0.00)		
MRR	3916.4 (0.00)	3797.6 (0.00)	184194.4 (0.00)	258413.9 (0.00)	123671.2 (0.00)	165170.8 (0.00)		
DJM	719.5 (0.00)	0.04 (0.83)	25842.7 (0.00)	39140.8 (0.00)	18499.8 (0.00)	23596.1 (0.00)		
MRR%	0.60%	1.10%	18.48%	0.01%	3.78%	0.02%		
DJM%	81.74%	100.00%	88.56%	84.85%	85.61%	85.72%		
Q(10)								
Returns	4099.9 (0.00)	10800.7 (0.00)	227746.0 (0.00)	341340.2 (0.00)	128920.0 (0.00)	166860.2 (0.00)		
MRR	4077.3 (0.00)	10702.8 (0.00)	186428.6 (0.00)	340545.6 (0.00)	123071.8 (0.00)	166809.6 (0.00)		
DJM	736.9 (0.00)	0.13 (1.00)	31975.0 (0.00)	49102.8 (0.00)	19037.6 (0.00)	25198.7 (0.00)		
MRR%	0.55%	0.91%	18.14%	0.23%	4.54%	0.03%		
DJM%	82.03%	100.00%	85.96%	85.61%	85.23%	84.90%		
			Phase I		Phase II		Phase III	
			MRR	DJM	MRR	DJM	MRR	DJM
Panel B								
Proportion of returns due to trading frictions		All Tr.	0.5641	0.6481	0.5719	0.6045	0.5214	0.5959
		Uninf		0.6197		0.6374		0.6816
		Fund		0.6256		0.6086		0.6612
		Inf		0.6762		0.5844		0.5038
Proportion of variance due to trading frictions		All Tr.	0.0951	0.1926	0.0241	0.2747	0.0152	0.6164
		Uninf		0.0125		0.0556		0.0461
		Fund		0.0052		0.0105		0.0308
		Inf		0.1750		0.2086		0.5396

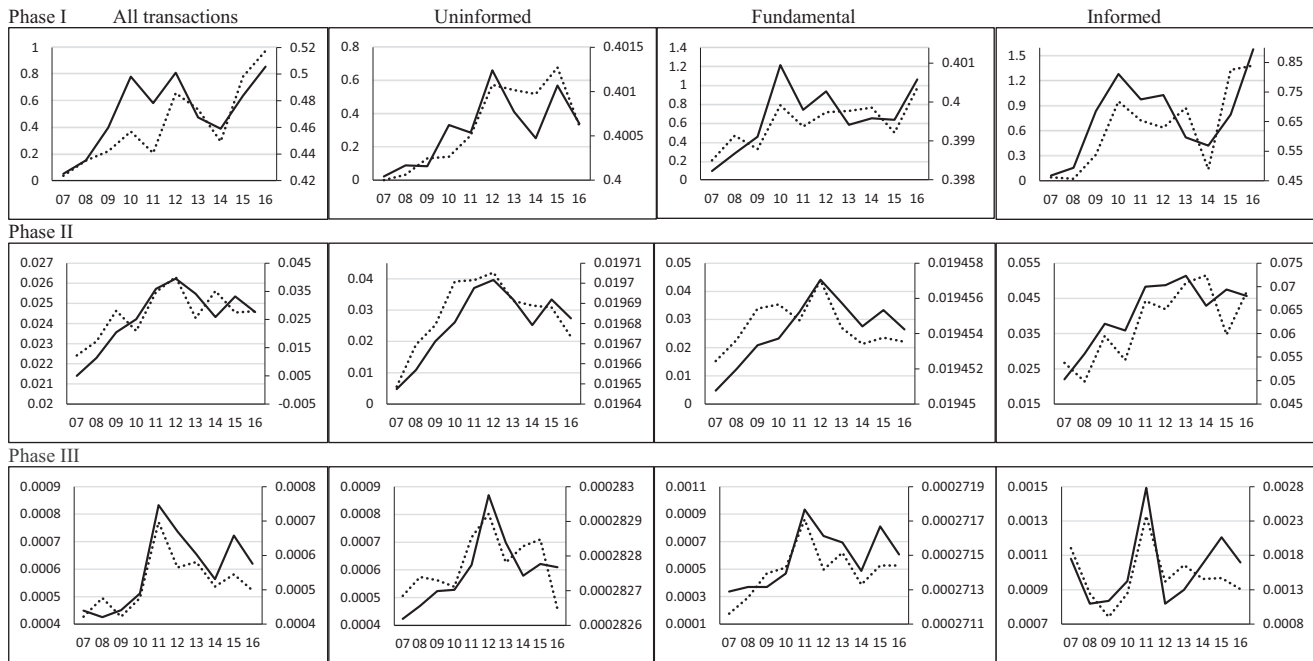
In this table, Panel A presents the Ljung–Box Q-statistic of lag orders 1 and 10,  $Q(1)$  and  $Q(10)$ , on the level and the square of actual (realised) returns (change in price,  $\Delta p_t$ ) and on the level and square of the components of the MRR and the DJM models not related to trading frictions ('residuals').  $MRR\%$  and  $DJM\%$  are the ratios  $(1 - Q_{MRR}/Q_{Returns})$  and  $(1 - Q_{DJM}/Q_{Returns})$ , respectively. They measure the percentage of autocorrelation explained by the trading friction components of these models.  $p$ -values are in parenthesis. Panel B presents the average across transactions of the proportion of realised returns and of realised variance explained by trading frictions in the MRR and DJM models. These are presented separately for all transactions (*All Tr.*), uninformed (*Uninf*), fundamental (*Fund*) and informed (*Inf*) transactions. The proportion of realised returns explained by trading frictions is  $1 - |\Delta p_t - E[\Delta p_t | H_{t-1}]| / |\Delta p_t|$ , and the proportion of variance explained by trading frictions for all trades is  $1 - (\Delta p_t - E[\Delta p_t | H_{t-1}])^2 / (\Delta p_t)^2$ , where  $|\cdot|$  denotes the absolute value operator and  $(\Delta p_t)^2$  is realised variance (the square of actual returns). The proportion of variance explained by trading frictions for *Uninf*, *Fund* and *Inf* is each agent's share of the value for *All Tr.*

values for the residuals of the MRR are lower, but still are very high and significant, which indicates that trading frictions in the MRR do not account for the majority of autocorrelations in returns and the volatility of returns. However, values for the residuals of the DJM model are far lower (even though still significant, except for the square of returns in Phase I). The percentage reduction in the Q-statistics after modelling returns with the MRR and the DJM models are reported in the rows entitled  $MRR\%$  and  $DJM\%$ . These show that trading frictions in the MRR explain only between 0.60% and 18.48% of the first-order autocorrelation, and between 0.55% and 18.14% of the tenth-order autocorrelation in the level of returns. In contrast, the structural components of the DJM model explain between 81.74% and 88.56% and between 82.03% and 85.96%, respectively. With regard to realised volatility, the MRR only explains 0.01% to 1.10% of the first-order autocorrelations and 0.03% to 0.91% of the tenth-order autocorrelations, while the DJM model explains 84.85% to nearly 100% and 84.90% to nearly 100%, respectively.

These results are striking. The structural DJM model is capable of explaining the majority of the direction of both returns and volatility at transaction level. While in pure time-series contexts such autocorrelations have traditionally been modelled in residuals by ARMA, GARCH and other stochastic volatility specifications, they, however, are trading-related structural features inherent in the DJM pricing model. Thus, the degree to which expected autocorrelations in trading intensity (volume over duration) induce autocorrelations in returns and the volatility of returns, through

time-variation in the response to surprise in order flow ( $\theta_t$ ) and liquidity costs ( $\varphi_t$ ), is substantial. This is evidence supporting the earlier conjecture that these parameters vary with every trade and are agent specific. Moreover, the fact that different agents respond at different rates upon the arrival of information, as reflected in their different trade timing and size (captured by trading intensity), seems to be persistent, and expectations in this persistence induces autocorrelations in returns and return volatility. The DJM model shows that this induced effect is sufficient to explain the majority of the characteristic autocorrelation in returns and volatility. It can be argued, therefore, that the main cause of the characteristic autocorrelations in returns and in the volatility of returns at transaction level is not so much the discreteness in prices ( $\sigma_\epsilon^2$ , though significant, is not a trading friction) or the autocorrelation or surprises in order flow (MRR does not explain as much as the DJM), but rather the predictability in the persistence of the rate of transacted volume (liquidity).<sup>29</sup> This is a main contribution of this paper.

<sup>29</sup> Note that since the MRR has a VARMA (2,1) representation in returns and trade sign (see Hasbrouck, 2007, p. 92) a time series specification with these lag lengths would not explain the autocorrelations in returns and variance, as shown here. In our model, even with the exogeneity assumed for trading intensity and the absence of feedback effects from prices to duration or to volume, the predictability in trading intensity is found sufficient to explain the majority of autocorrelations in returns and volatility by informing agents' responses to surprise in order flow. Thus, ARMA-GARCH effects in returns are driven mainly by expectations of volume and duration.



**Fig. 1.** Conditional variance and realised variance over the trading day. In this figure model conditional variance (dotted lines and right vertical axes) and actual return variance (solid lines and left vertical axis) are presented by hour of day for each market phase. Graphs for all, uninformed, fundamental and informed transactions are in columns one, two, three and four, respectively. The correlation between conditional and realised variance for all transactions is 0.78, 0.82 and 0.91 for Phase I, II and III, respectively.

## 6.2. Proportion of return and variance explained by trading frictions

Table 4 Panel B presents the proportion of realised returns and variance explained by trading frictions in the MRR and the DJM models in each phase (proportions of variance by agent type are each agent's share of the value for all transactions). Over all transactions, trading frictions in the MRR explain between 52.14% and 57.19% of returns, and between 1.52% and 9.51% of variance, while in the DJM model they explain between 59.59% and 64.81% of returns and 19.26% and 61.64% of variance. Thus, the DJM model explains roughly an additional 7% of returns and 18% to 52% of variance. The incremental improvement is sizable, and highlights the MRR's under estimation of the role of trading frictions in the components of price and, especially, of volatility. Both models, however, perform reasonably well in explaining the magnitude of returns.<sup>30</sup>

Unlike the MRR, the DJM model allows for a decomposition of these proportions by type of agent. These are reported in Table 4 Panel B. Two clear patterns emerge in returns. First, as trading intensity rises from the uninformed to the informed, the proportions of returns explained by trading frictions increase in Phase I but decrease in Phases II and III.<sup>31</sup> This may indicate more market over- or under-reaction in Phase I that is unexplained by trading

frictions. Alternatively, it could be due to ignored determinants of price formation specific to the carbon market, such as alternative fuel prices becoming more important in the latter two phases (which would be consistent with a higher correlation between energy and carbon prices following the financial crisis of 2007). Second, these proportions increase for the uninformed from Phase I to Phase III, but decrease for the informed, and those of the uninformed become higher than those of the informed in Phases II and III. This is an early indication that the impact on returns of asymmetric information decreases over the three phases, and 'informed' actions have lesser of an impact on the level of price changes than 'uninformed' actions as the market develops. Perhaps a sign of increasing competition.

The proportion of variance explained by trading frictions for all transactions increases considerably from Phase I to Phase III. The values reported by agent at the lower part of Panel B, are proportions of the values reported for all transactions. Thus, of the 19.26% of total variance explained by trading frictions for all trades in Phase I, 1.25%, 0.5% and 17.5% was due to uninformed, fundamental and informed trades, respectively. Accordingly, informed trades contribute the most to conditional variance, followed by the uninformed, while fundamental trades contribute the least in all three phases. Note that the contributions of the informed and the fundamentals increase across phases, but that of the uninformed increase in Phase II and decrease slightly in Phase III. In general, therefore, trading frictions, particularly private information, play an increasingly important role in volatility.

## 6.3. Hourly patterns in returns and the variance of returns

An important aspect of microstructural models is to explain variations in returns, volatility and trading costs over the course of the trading day (trading costs will be dealt with in Section 6.5). Admati and Pfleiderer (1988), for example, predict that trading

<sup>30</sup> Medina et al.'s (2014) quarterly MRR estimates in Phase I and II using only screen trades imply proportions of realised variance explained ranging roughly from 4% to 26%. Our MRR estimates with all trades are 9.51% for Phase I and 2.41% for Phase II. Thus, the proportion of variance explained by the MRR is consistently small regardless of the type of trade (screen, as in Medina et al., 2014, versus screen and OTC, as here).

<sup>31</sup> Through an analysis of price differences around block trades in Phase II Ibikunle et al. (2016) note that small amounts of trading lead to large price discovery (percentage price differences). The results of the DJM model for Phase II are consistent and, thus, explain that this phenomenon is linked to the role of trading intensity in price formation. More relevant detail is provided in Section 6.5 on trading costs (price components).

should concentrate at periods during which trading costs are relatively lower. Madhavan et al. (1997) report a U-shaped pattern in implied spreads of NYSE stocks. Does the model presented here predict similar patterns that may exist in the carbon market?

From Eqs. (4) to (7), the conditional variance of price change given by the model is:

$$(1 - \rho^2) \left[ \left( (\theta_1 + \varphi_1) + \sum I_{\pi,t} (\theta_2 + \varphi_2) \mathbf{c}' \mathbf{s} + (\theta_3 + \varphi_3) \lambda \right)^2 + (\theta_3 + \varphi_3)^2 \lambda \right] + \rho^2 \varphi_3^2 \lambda + \sigma_\varepsilon^2 + 2\sigma_\xi^2, \quad (9)$$

$$\begin{aligned} & \underbrace{(1 - \rho^2) \left( \theta_1 + \sum (I_{\pi,t} \theta_2) \mathbf{c}' \mathbf{s} \right)^2}_{\text{Adverse Selection}} + \\ & \underbrace{(1 - \rho^2) \left( \varphi_1 + \sum (I_{\pi,t} \varphi_2) \mathbf{c}' \mathbf{s} \right)^2}_{\text{Liquidity}} + \\ & \underbrace{\left[ \begin{aligned} & \underbrace{\theta_3^2 (1 - \rho^2) (\lambda + 1) \lambda}_{\text{Risk Aversion Related to Information}} + \\ & \underbrace{\varphi_3^2 (\lambda (1 - \rho^2) + 1) \lambda}_{\text{Risk Aversion Related to Liquidity}} + \\ & \underbrace{2\theta_3 \varphi_3 (1 - \rho^2) \lambda}_{\text{Risk Aversion Interaction Related to Information and Liquidity}} \end{aligned} \right]}_{\text{Risk Aversion}} + \\ & 2(1 - \rho^2) \underbrace{\left[ \begin{aligned} & \underbrace{\left( \theta_1 + \sum (I_{\pi,t} \theta_2) \mathbf{c}' \mathbf{s} \right) \theta_3 \lambda}_{\text{Interaction between Adverse Selection and Risk Aversion Related to Information}} \\ & + \underbrace{\left( \varphi_1 + \sum (I_{\pi,t} \varphi_2) \mathbf{c}' \mathbf{s} \right) \varphi_3 \lambda}_{\text{Interaction between Adverse Selection and Risk Aversion Related to Liquidity}} \\ & + \underbrace{\left[ \begin{aligned} & \left( \theta_1 + \sum (I_{\pi,t} \theta_2) \mathbf{c}' \mathbf{s} + \theta_3 \lambda \right) \\ & \times \left( \varphi_1 + \sum (I_{\pi,t} \varphi_2) \mathbf{c}' \mathbf{s} + \varphi_3 \lambda \right) \end{aligned} \right]}_{\text{Interaction between Adverse Selection and Risk Aversion Related to Information and Liquidity}} \end{aligned} \right]}_{\text{Interactions}} + \\ & \underbrace{\sigma_\varepsilon^2}_{\text{Public Information}} + \underbrace{2\sigma_\xi^2}_{\text{Price Discreteness}} \end{aligned} \quad (10)$$

where  $\mathbf{c}$  is a vector of coefficients of the AR( $m$ ) process of trading intensity and  $\mathbf{s}$  is a vector of  $m$  lags of trading intensity (see Appendix B).<sup>32</sup> As trading intensity ( $\mathbf{s}$ ) is the only time-varying element in Eq. (9), conditional volatility varies with every transaction and this variation is driven by changes in expected trading intensity. As such, conditional volatility varies by the type of agent expected to instigate the next trade. Fig. 1 shows average realised volatility and the conditional volatility given by the model during every hour of the day. These are presented separately for all, uninformed, fundamental, and informed transactions. In general, the average realised volatility over all transactions increases substantially towards lunch time (with a dip at 11:00 h in Phase I), a decrease to 14:00 h and either a rise towards the end of the day as in Phase I or a rise at 15:00 h and then a fall towards market close in Phases II and III. These patterns are obviously mirrored in actual returns and are roughly similar across different regimes of trading intensity (or types of agent). Each market phase, however, exhibits a different hourly pattern of returns and volatility. Importantly, the graphed conditional volatility generated by the model exhibits highly similar patterns to those of realised volatility, whether as averages over all transactions or separately by type of agent. The correlation between conditional (model) and realised (actual) volatility over all transactions is 0.78, 0.82 and 0.91 in Phase I, II and III, respectively. These values indicate that the model has a high (and increasing) predictive power of hourly patterns in return and volatility, especially in environments (phases) characterised by different liquidity, activity and regulatory structure (see Ellerman et al., 2014).

#### 6.4. Volatility components

The model provides a rich variety of decompositions of conditional volatility.

In the above decomposition (see Appendix B), the adverse selection, liquidity and the interaction terms vary with every trade and are functions of expected trading intensity. Consequently, they can be decomposed further by the type of agent expected to instigate the next trade.<sup>33</sup> Table 3 Panel B reports these components. First, and as shown in the scale of the axes in Fig. 1, the conditional variance (C.VAR) for all transactions decreases substantially from Phase I to Phase III. Thus, Phase I was most risky and Phase III least risky. In terms of all trades, the largest component of conditional variance due to trading frictions is the interaction of liquidity, information and risk aversion (although risk aversion exists only in Phase I and is three orders of magnitude smaller than the information and liquidity components). This interaction component is negative on average across all trades, while the liquidity, information and risk aversion components are positive. The time varying nature of the DJM and its incorporation of the effects of volume and duration, therefore, reveal the dual and opposing role of trading intensity on information and liquidity as a large negative interaction term that counteracts a sizable proportion of the other positive components. Further, the liquidity component is larger than the asymmetric information component in all three phases (except for fundamentals in Phase II), indicating that variations in liquidity costs in the carbon

<sup>32</sup> The time subscript is suppressed. The first two moments of price change are derived in Appendix B. Note that since the MRR has constant parameters, its conditional volatility is constant. Madhavan et al. (1997), therefore, estimate this model for every interval into which they divided the trading day. In contrast, the DJM model has time-varying parameters and allows for intraday analysis with one estimation (done separately for each market phase here to illustrate differences between phases of the market).

<sup>33</sup> We emphasise that in the DJM model expected volume and duration affect conditional returns and return volatility. Hence, comparisons of estimates with those of more static models, such as the MRR, ought to bear in mind these variations in intensity across trades/agents.



market contribute to price change volatility more than private information. This is perhaps reasonable to expect in a compliance market, where regulatory news impacting on the perception of the size of net (excess) supply of allowances has a prominent effect on liquidity conditions (Ellerman et al., 2014).

In terms of the dissection by agent of the volatility components, the uninformed and fundamentals contribute roughly similarly to risk (C.VAR) (fundamentals slightly less, especially in Phase III) but the informed contribute the most. On average, in Phase I the informed contribute to risk slightly more than both the uninformed and the fundamentals combined, in Phase II one and half times more, and in Phase III three times more. Thus the contribution of private information to conditional volatility increases over the phases, even though overall volatility decreases considerably. Note that, in all phases, the contribution of asymmetric information to volatility increases monotonically with trading intensity (from the uninformed to the fundamentals to the informed), but the liquidity cost component is lowest for the fundamentals and highest for the informed (i.e., a U-shaped relationship between liquidity costs and trading intensity). Thus, not all volatility components have a linear relationship with trading intensity, and the DJM model is able to reveal non-linearity in volatility components due to variations in liquidity.

The conditional variance over all transactions is almost identical to the realised variance, as should be, but the AR( $m$ ) process seems to overestimate variations in intensity of the informed and underestimate those of the uninformed and fundamentals.<sup>34</sup> This is reflected in some disparity between the conditional and actual variance for each agent. The patterns described above on conditional variance and its components, however, are mirrored in the realised variance and, hence, the model is able to reveal, and performs reasonably well, in reflecting actual price variations.

In summary, conditional volatility and its components vary by trading intensity and the type of agent expected to carry out the next trade. If the next trade is expected to be informed, it will have, on average, the largest impact on the variance of price change, and this impact is mainly due to liquidity and information with a large counter interacting effect. The MRR ignores the information embedded in variations in volume and duration and, therefore, does not provide a breakdown of price change by agent type. It tends to underestimate fixed liquidity costs, and underestimates (overestimates) total liquidity costs for uninformed (informed) trades. It also overestimates (underestimates) asymmetric information costs for uninformed (informed) trades. This is because it provides constant average estimates.

In terms of hourly patterns, Fig. 2 plots the hourly percentage proportions of all the components of conditional volatility, including public information ( $\sigma_e^2$ ) and price discreteness ( $2\sigma_e^2$ ). The large negative interaction component that counterbalances a substantial part of the sum of the other positive components is a prominent feature. This component is almost perfectly negatively correlated with the liquidity component. In Phase I, this component has a small element of risk aversion, but in Phases II and III risk aversion disappears and the interaction component is made purely from the interplay between adverse selection and liquidity costs. Being

negative, and increasingly so from Phase I to Phase III, is a testament to the dual role of intensity in increasing the asymmetric information component but decreasing the liquidity cost component of conditional volatility. Thus, as trading intensity rises, the effect of information asymmetry on volatility increases and the effect of liquidity costs decreases, but at different rates. This varies by every transaction, hour and phase and, hence, the different patterns exhibited in Fig. 2.

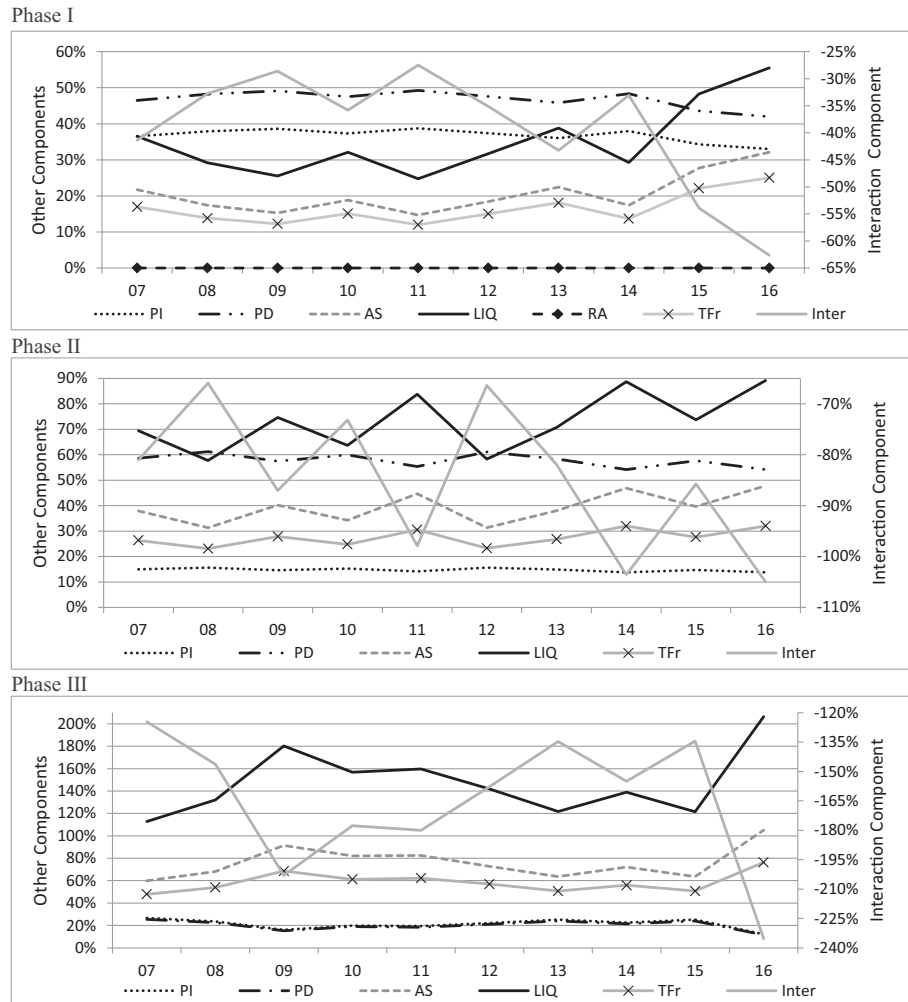
As far as the positive components are concerned, the order from the largest to the smallest in Phase I is price discreteness, public information, liquidity and asymmetric information. In Phase II the order is liquidity, price discreteness, asymmetric information and public information. In Phase III the order is liquidity, asymmetric information, and public information or price discreteness, with the latter two ranking similarly. Thus, the relative importance of components in terms of their contribution to volatility changes across phases, with liquidity being more prominent in the latter two phases and most prominent in Phase III. Asymmetric information and liquidity rise monotonically from Phase I to Phase III, public information decreases in Phase II and rises slightly in Phase III, and price discreteness increases slightly in Phase II and decreases substantially in Phase III. Risk aversion is present only in Phase I and is a very small proportion of volatility. Thus, even though the proportion of OTC trades in the fifteen minutes prior to a trade exhibited significant jumps in Phase I, these jumps did not affect the volatility of carbon prices by much on average.

Note that asymmetric information ranks lowest in Phase I, third in Phase II and second in Phase III, and this attests to the increasing role of private information in the carbon market. However, liquidity rises to prominence as its component increases from Phase I to Phase III. The importance of price discreteness in Phase I is perhaps linked to the behaviour of carbon traders in submitting round lots and prices as well as the change of the minimum tick size from €0.05 to €0.01 on 27 March 2007 (Palao and Pardo, 2014).<sup>35</sup> Note that even though the proportion of this component increased in Phase II and decreased substantially in Phase III, its importance relative to other components decreased from Phase I to Phase III in favour of liquidity and asymmetric information.

In terms of hourly variations, the proportions of almost all components exhibit a zig-zag pattern with slightly different trends over the trading hours and in each phase. In general, the proportions due to public information and price discreteness exhibit relatively less variations over the trading day than the proportions of the other positive components of volatility. This result supports the theoretical assumption of the random rate of public information arrival, and indicates a roughly constant effect over the trading day of the rounding of order sizes reported by Palao and Pardo (2014). The asymmetric information component exhibits a generally mild U-shaped hourly pattern in Phase I, a rising trend in Phase II, and a rise in the first three hours of trading followed by a decline to 15:00 h and a sudden increase in the last hour of trading in Phase III. This highlights differences across phases in the effect on volatility of private information possession.

<sup>34</sup> We conduct a side sensitivity analysis on the effect of extreme volume and extreme intensity trades (results available from the authors). Excluding the former has no material effect on model parameter estimates or the proportion of variance explained, because extreme volume trades are not extreme intensity trades. Excluding the latter has no material effect on the return distribution, but some effect on parameter estimates. The latter may slightly perturb the segregation of trades into three regimes and, hence, the proportions attributable to each type of agent. However, the proportion of total variance explained by trading frictions increases, indicating a slight improvement in model fit. We opt to conduct the main analysis while including these trades as they are legitimate.

<sup>35</sup> Palao and Pardo (2014) show that carbon traders tend to simultaneously round the sizes and prices of their orders in clusters of five contracts to simplify their trading process when uncertainty is high, market liquidity is poor and the desire to open new positions or cancel old ones is strong. Their analysis covers screen trades of Phase II futures maturing in December 2010, 2011 and 2012 which collectively traded from September 2006 to December 2012. The DJM results demonstrate that this rounding behaviour seems either to have been even stronger in Phase I contracts and much less so for Phase III contracts, or its effect on volatility decreased from Phase I to Phase III. See also Rotfuß (2009).



**Fig. 2.** Conditional variance components by hour of the day. This figure shows the percentage proportion of conditional variance in every hour of the trading day. *PI* is public information, *PD* is price discreteness, *AS* is asymmetric information (adverse selection), *LIQ* is liquidity, *RA* is risk aversion, *Inter* is the interaction of liquidity, information and risk aversion, and *TFr* is the proportion due to all trading frictions (i.e., the sum of *AS*, *LIQ*, *RA* and *Inter*). There is no risk aversion component in Phases II and III. The right vertical axis shows the interaction component only.

## 6.5. Trading costs

### 6.5.1. Implied spread and agent type (trading intensity)

Traders' or dealers' bid-ask quotes (denoted by  $p_t^b$  and  $p_t^a$ , respectively) are ex-post rational as in [Glosten and Milgrom \(1985\)](#) and [Madhavan et al. \(1997\)](#). However, unlike the MRR where quotes are conditioned on the next trade being buyer or seller initiated only, the DJM model also conditions these quotes on the likely response of the agent who instigates the next trade and the degree of risk his trade is expected to represent. The ask price is  $p_t^a = \mu_{t-1} + \theta_t(1 - E[q_t|q_{t-1}]) + \varphi_t + \varepsilon_t$ , and the bid price is  $p_t^b = \mu_{t-1} - \theta_t(1 + E[q_t|q_{t-1}]) - \varphi_t + \varepsilon_t$ . Accordingly,  $\theta_t$  captures the permanent effect of the surprise in order flow, and  $\varphi_t$  the transitory effect, on bid and ask quotes. We also adopt [Madhavan et al.'s \(1997\)](#) interpretation of  $\varphi$  as the dealer's compensation for transaction costs, inventory costs and possibly the return to unique positions. The implied bid-ask spread, defined as  $p_t^a - p_t^b$ , is  $2(\theta_t + \varphi_t)$ . Its unconditional and conditional two moments are derived in [Appendix B](#). Note that the unconditional mean of the implied spread is constant, but both the conditional mean and variance change with every transaction, and this time variation is driven mainly by changes in expected trading intensity. Therefore, the implied spread and trading costs also vary by the type of agent expected to instigate the next trade and, hence, they incorporate

the opposing effects of expected trading intensity on information and liquidity. If the next transaction is expected to be informed then dealers respond to the expected high level of information asymmetry and trading intensity as a balancing act. If the expected increase in information asymmetry is greater than the expected reduction in liquidity costs then they increase the spread. Otherwise, they reduce the spread.

[Table 3](#) Panel A presents estimates of the implied spread (*IS*) and its information (*AS*), liquidity (*LIQ*) and risk aversion (*RA*) components by agent type. The average spread across all transactions decreases over the phases, indicating a monotonic reduction in trading costs from Phase I to Phase III, which is in line with the increasing market activity. The average implied spread is similar for uninformed and fundamental trades at around 22.0 cents, 8.6 cents, and 1.3 cents per tonne in Phase I, II and III, respectively. However, it is much lower for informed trades at around 3.2 cents, 1.1 cents and 0.9 cents in the three phases, respectively.<sup>36</sup> Thus, spreads are lowest if the next trade is expected to be informed. This is due mainly to the fact that most of these trades are high intensity block or OTC trades (*E.TI* is largest for these trades), and although

<sup>36</sup> Compared to our average phase values [Medina et al. \(2014\)](#) report smaller average estimates of the spread. The inclusion of OTC trades is the main reason for the difference since we are able to replicate their estimates when we exclude OTC trades and use the MRR model.

their information content is highest (AS is largest for these trades) their liquidity costs (LIQ) are negative (while their risk aversion component in Phase I is small). The DJM model shows that the reduction in liquidity costs these trades represent is larger than the increase in asymmetric information that accompanies them. Thus, the model, which adjusts spread components with the information embedded in trading intensity, attributes lower trading costs for high intensity trades, on average. It seems that in the carbon market traders reduce the spread with rising intensity, on average. Liquidity concerns seem to be overriding in this compliance market.<sup>37</sup>

The model provides richer insights through a decomposition that shows the magnitude of the opposing sources of the variation of the spread across agents. The asymmetric information (AS) cost component increases and the liquidity component decreases monotonically with trading intensity. Thus higher intensity trades are associated with lower liquidity costs but higher asymmetric information costs, which is in line with theory. The risk aversion cost component, which exists only in Phase I, is slightly lower for informed trades, which is consistent with expectations that the uninformed face riskier conditions when there is increased presence of informed agents. Finally, and as expected, the MRR's constant average estimates across all transactions of the information and liquidity components coincide with those of the DJM, but unlike the DJM the MRR is unable to provide a dissection by agent type. The MRR, therefore, implicitly overestimates the asymmetric information component and underestimates the liquidity component of the spread for uninformed and fundamental trades, and does the opposite for informed trades.

Note that the size of the combination of liquidity and risk aversion components relative to that of the information component, varies by market phase (trading environment) and agent type (trading intensity), and it is the relative magnitude between these forces that determines whether the implied spread has a decreasing relationship with trading intensity as in Phase I and Phase III, or a slightly inverted U-shaped relationship as in Phase II. This could indicate that traders in the carbon market manage their positions in a similar fashion to 'inventory' models (e.g., Stoll, 1978), and that they have optimal positions that they may want to revert to, either because these positions are less risky or less costly. Consequently, when trading intensity is expected to be low, they may charge more for providing liquidity, and when it is expected to be high, they would want to either increase the spread from fear of losing to the informed (an asymmetric information effect) or decrease it as they are able to adjust their inventories more readily towards target positions (an immediacy liquidity effect). Thus, higher expected trading intensity presents traders with a balancing act between increasing information costs and decreasing immediacy costs. Whichever effect dominates will determine whether the spread will be increased, decreased or unaltered for the next trade. This provides a reason why we observe a decreasing, increasing or a U-shaped relationship between volume and implied spread in some markets or periods. A generally decreasing relationship is observed in the continuous series used to represent the three phases of the carbon market. Thus, on average, immediacy concerns dominate adverse selection fears in setting spreads in the carbon market, even though adverse selection concerns increase with increasing intensity. The DJM, however, is flexible enough to reveal other patterns if they exist, or whichever effect domi-

nates. To represent phase prices, the above analysis is carried out using continuous series constructed from the December contracts that mature in each phase. We repeat the analysis on some individual December contracts and we report here the results for the December 2008 contract, as an example, but all results are available from the authors. This contract spanned all of Phase I and the first year of Phase II and was the most heavily traded on average during this period. The implied spread for this contract in Phase I is 0.2366, 0.2297 and 0.2504 for uninformed, fundamental and informed trades, respectively. For Phase II these values are 0.1323, 0.1436 and 0.2132. Thus, the DJM reveals that the spread for this contract exhibited a U-shaped relationship with trading intensity in Phase I, and a rising relationship in the first year of Phase II.<sup>38</sup> Accordingly, these results provide a possible explanation for the differences between Stoll (1978) who describes a U-shaped relation between spread and trade size, De Jong et al. (1996) who maintain that total spread is a decreasing function of volume, and Huang and Stoll (1997) and Ahn et al. (2002) who maintain that order processing costs are a decreasing function of volume. From the estimation results of our model trading intensity is negatively related to liquidity, but this relationship varies in magnitude across intensity regimes.<sup>39</sup> This would offer an explanation for the different-shaped relationships between volume and implied spread in different periods, markets or contracts.<sup>40</sup>

#### 6.5.2. Implied spread throughout the day

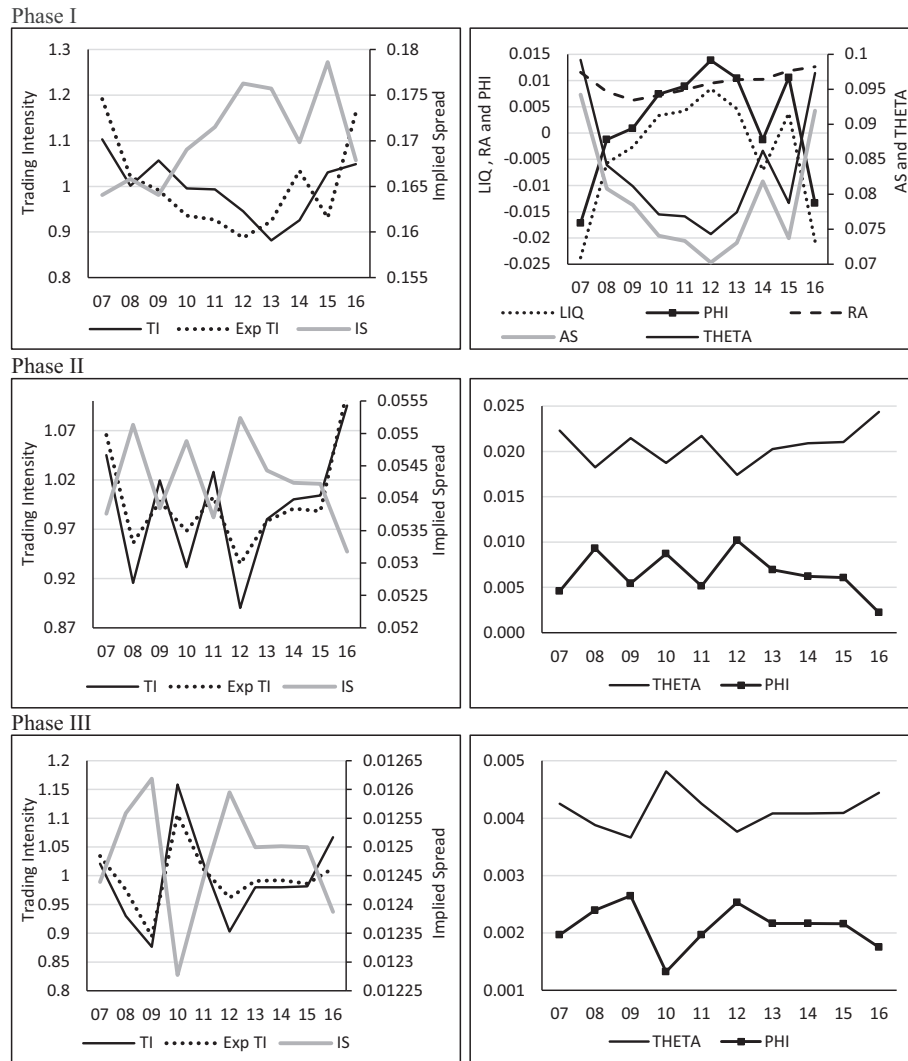
As the implied spread from the model is  $2(\theta_t + \varphi_t)$  it varies with expected trading intensity on a trade-by-trade basis. Fig. 3 shows the averages within each hour of the day of implied spread (IS), actual trading intensity (TI) and expected trading intensity (Exp TI). It is seen that the AR(m) process assumed for trading intensity captures much of the hourly variations in actual trading intensity. The implied spread follows different hourly patterns in each market phase. In Phase I it generally rises till midday, falls at 14:00 h, rises at 15:00 h and falls at 16:00 h. In Phase II it zigzags till 13:00 h and then decreases to an all-day low in the last hour. In Phase III a zigzag with higher amplitude and lower frequency (every two hours) is observed till 13:00 h followed by a decline. The correlation between hourly actual trading intensity and expected trading intensity is 0.62, 0.92, and 0.94 in Phase I, II and III, respectively. This, in turn, is reflected in the implied spread

<sup>38</sup> As the number of zero-duration trades that do not show a change in price is relatively high in each phase of the continuous series used in the main analysis, we also conduct a side analysis in which we exclude these trades. The average implied spread of the remaining trades exhibits a clear U-shaped relationship with trading intensity (0.1628, 0.1507 and 0.2349 for uninformed, fundamental, and informed agents in Phase I series). Thus, spread estimates are sensitive to the treatment of these trades. In our main analysis we have opted to include them as legitimately registered trades that seem to be strategically segmented (or iceberg orders, since the ICE Platform allows such 'hidden-size' order submission functionality).

<sup>39</sup> Mizrahi and Otsubo (2014) also report a positive (negative) relationship between the implied spread of EUA (CER) futures and volume for the December 2009 contract. They find that the increase in the spread for EUAs is due to information costs and the reduction in the spread for CERs is due to liquidity costs. The DJM presented here provides a clear rationale for these observations through a theoretical structure model of prices. It shows that the reciprocal play between information and liquidity operates on a trade-by-trade basis and occurs in EUA futures. It also shows that even if the presence of informed agents increases, and hence the AS component of costs, the spread may still decrease with intensity because of dominating negative liquidity costs.

<sup>40</sup> The MRR uses one parameter to summarise the order processing cost component and its adjustments to variations in liquidity and risk. Unlike Huang and Stoll (1997) who report a much higher proportion of order-processing costs, the MRR is rather restrictive and probably underestimates this component. This may also be the reason why Benz and Hengelbrock (2008) report a small and insignificant transaction cost component,  $\varphi$ . It is also a further qualification of Mizrahi and Otsubo's (2014) deduction that "the high AS implies presence of informed traders and, hence, higher implied spread by market maker" since it may not always be the case that implied spread increases if the asymmetric information increases.

<sup>37</sup> This offers an explanation for Ibikunle et al.'s (2016) observation that price impact of large block trades in Phase II is not as high as that of medium block trades. It is also consistent with the fact mentioned in Section 4 that a sizable proportion of trades are zero-duration trades, and of those that show a change in price do contribute to price volatility (and hence price impact), but least so in Phase II. This is consistent with the proposition of strategic trading by the informed documented in Kalaitzoglou and Ibrahim (2013a).



**Fig. 3.** Trading intensity and implied spread and its components by hour of the day. This figure shows trading intensity (TI), expected trading intensity (Exp. TI), implied spread (IS) and its components by hour of the day in the three market phases. The implied spread components are asymmetric information (AS), liquidity (LIQ) and risk aversion ( $RA = RA-I + RA-L$ , where  $RA-I$  and  $RA-L$  are the information and liquidity related components of risk aversion).  $THETA = AS + RA-I$  and  $PHI = LIQ + RA-L$  across transactions in a regime  $\pi$ .  $PHI = LIQ$  and  $THETA = AS$  in Phases II and III. This decomposition is described in the caption of Table 3 but presented here by hour of day.

being highly (negatively) correlated with expected trading intensity ( $-0.68$ ,  $-0.89$ , and  $-0.94$  in the three phases), even though the scale of the variations in implied spread is relatively small. The model, therefore, captures hourly patterns in actual returns (Fig. 1), volatility (Fig. 1) and trading intensity, and reflects these in implied spread. Trading costs, therefore, vary throughout the day due to variations in expected trading intensity.

The structural nature of the model can tell us more about the sources of these hourly patterns with a spread decomposition into information, liquidity and risk aversion effects. The right-hand-side column of Fig. 3 shows the hourly averages of these components. The largest spread component is asymmetric information in every hour, as expected and as is consistent with prior studies (e.g., Mizrahi and Otsubo, 2014; and Medina et al., 2014). The next largest is liquidity, followed by risk aversion (although this is small and exists only in Phase I). Importantly, the inverse relationship between asymmetric information and liquidity is clear throughout. This highlights the trade-off between information and liquidity effects on trading costs, and the changing nature of this trade-off with the trading intensity of every transaction and throughout the trading day. When asymmetric information increases, liquidity

concerns decrease, and vice versa. The average implied spread in the case of the continuous series analysed here follows the hourly variations in the liquidity component because liquidity costs change with trading intensity at a higher rate than information costs, and this highlights the importance of liquidity variations on changes in trading costs in the carbon market. Obviously, this does not have to always be the case for all markets, periods, contracts, or even trades, and varies depending on the relative rate of change in liquidity versus information costs as expected intensity varies. The DJM's flexibility incorporates this.

Note that, in Phase I, the risk aversion component (which is not a function of intensity) has the same hourly pattern as the liquidity component and not the information component, and this highlights the link in the carbon market during its pilot phase between the risk aversion component and liquidity but not information (as is also reflected in the significance of  $\hat{\phi}_3$  but not of  $\hat{\theta}_3$ ). Accordingly, liquidity related costs in Phase I vary inversely with trading intensity in a smooth fashion, but positively with shocks in liquidity. As risk aversion is approximated by the proportion of OTC trades in the preceding 15 min of trading, this is evidence that OTC trades during Phase I experienced sudden increases that caused a



**Table 5**

Return components, spread and variance by agent and trade sign.

		Phase I			Phase II			Phase III		
		Uninf	Fund	Inf	Uninf	Fund	Inf	Uninf	Fund	Inf
Ad. Selection	<b>B</b>	<b>0.0025</b>	<b>0.0146</b>	<b>0.2828</b>	<b>0.0055</b>	<b>0.0347</b>	<b>0.1342</b>	<b>0.0002</b>	<b>0.0013</b>	<b>0.0170</b>
	$B_{t-1}$	0.0024	0.0143	0.2464	0.0055	0.0346	0.1095	0.0002	0.0013	0.0154
	$O_{t-1}$	0.0027	0.0147	0.3574	0.0055	0.0348	0.1359	0.0002	0.0013	0.0178
	<b>O</b>	<b>0.0024</b>	<b>0.0145</b>	<b>0.2721</b>	<b>0.0054</b>	<b>0.0346</b>	<b>0.1171</b>	<b>0.0002</b>	<b>0.0013</b>	<b>0.0162</b>
	$B_{t-1}$	0.0025	0.0145	0.2784	0.0056	0.0346	0.1407	0.0002	0.0013	0.0189
	$O_{t-1}$	0.0022	0.0143	0.2412	0.0051	0.0345	0.1093	0.0002	0.0013	0.0148
Liquidity	<b>B</b>	<b>0.0991</b>	<b>0.0842</b>	<b>-0.2773</b>	<b>0.0366</b>	<b>0.0096</b>	<b>-0.1206</b>	<b>0.0067</b>	<b>0.0053</b>	<b>-0.0126</b>
	$B_{t-1}$	0.0990	0.0840	-0.3773	0.0366	0.0096	-0.1275	0.0067	0.0053	-0.0135
	$O_{t-1}$	0.0993	0.0845	-0.2284	0.0368	0.0097	-0.0958	0.0067	0.0053	-0.0108
	<b>O</b>	<b>0.0993</b>	<b>0.0846</b>	<b>-0.2629</b>	<b>0.0367</b>	<b>0.0098</b>	<b>-0.1089</b>	<b>0.0067</b>	<b>0.0053</b>	<b>-0.0117</b>
	$B_{t-1}$	0.0995	0.0847	-0.2427	0.0370	0.0099	-0.0956	0.0067	0.0053	-0.0100
	$O_{t-1}$	0.0992	0.0845	-0.2721	0.0366	0.0097	-0.1332	0.0067	0.0052	-0.0148
Risk aversion	<b>B</b>	<b>0.0087</b>	<b>0.0085</b>	<b>0.0066</b>						
	$B_{t-1}$	0.0079	0.0068	0.0058						
	$O_{t-1}$	0.0098	0.0105	0.0083						
	<b>O</b>	<b>0.0102</b>	<b>0.0112</b>	<b>0.0090</b>						
	$B_{t-1}$	0.0107	0.0120	0.0094						
	$O_{t-1}$	0.0087	0.0075	0.0070						
Implied spread	<b>B</b>	<b>0.2238</b>	<b>0.2198</b>	<b>0.0364</b>	<b>0.0845</b>	<b>0.0899</b>	<b>0.0136</b>	<b>0.0138</b>	<b>0.0131</b>	<b>0.0090</b>
	$B_{t-1}$	0.2207	0.2125	0.0329	0.0843	0.0887	0.0049	0.0137	0.0131	0.0083
	$O_{t-1}$	0.2247	0.2213	0.0535	0.0847	0.0919	0.0174	0.0138	0.0131	0.0095
	<b>O</b>	<b>0.2207</b>	<b>0.2145</b>	<b>0.0244</b>	<b>0.0843</b>	<b>0.0887</b>	<b>0.0091</b>	<b>0.0138</b>	<b>0.0131</b>	<b>0.0088</b>
	$B_{t-1}$	0.2228	0.2185	0.0475	0.0843	0.0888	0.0174	0.0138	0.0131	0.0093
	$O_{t-1}$	0.2190	0.2111	-0.0231	0.0843	0.0886	0.0068	0.0137	0.0131	0.0086
C. Variance ( $\times 100$ for Phase III)	<b>B</b>	<b>0.4009</b>	<b>0.3998</b>	<b>1.1648</b>	<b>0.0198</b>	<b>0.0199</b>	<b>0.0632</b>	<b>0.0283</b>	<b>0.0272</b>	<b>0.1736</b>
	$B_{t-1}$	0.4006	0.3991	0.5363	0.0197	0.0195	0.0466	0.0282	0.0270	0.0916
	$O_{t-1}$	0.4010	0.4000	2.4518	0.0199	0.0201	0.0678	0.0283	0.0273	0.2143
	<b>O</b>	<b>0.4006</b>	<b>0.3993</b>	<b>0.6775</b>	<b>0.0191</b>	<b>0.0192</b>	<b>0.0568</b>	<b>0.0282</b>	<b>0.0271</b>	<b>0.1604</b>
	$B_{t-1}$	0.4008	0.3997	0.7074	0.0196	0.0195	0.0845	0.0283	0.0272	0.3238
	$O_{t-1}$	0.4004	0.3989	0.5319	0.0190	0.0194	0.0449	0.0282	0.0271	0.0718
A. Variance ( $\times 100$ for Phase III)	<b>B</b>	<b>0.4170</b>	<b>0.8009</b>	<b>1.0088</b>	<b>0.0377</b>	<b>0.0360</b>	<b>0.0515</b>	<b>0.0881</b>	<b>0.0781</b>	<b>0.1169</b>
	$B_{t-1}$	0.3116	0.7209	0.9511	0.0336	0.0294	0.0004	0.0861	0.0605	0.1058
	$O_{t-1}$	0.4480	0.8177	1.0209	0.0393	0.0381	0.0648	0.0877	0.0876	0.1220
	<b>O</b>	<b>0.1075</b>	<b>0.4101</b>	<b>0.3540</b>	<b>0.0095</b>	<b>0.0122</b>	<b>0.0337</b>	<b>0.0275</b>	<b>0.0342</b>	<b>0.0858</b>
	$B_{t-1}$	0.2397	0.8663	1.0635	0.0290	0.0396	0.0343	0.0605	0.0796	0.1358
	$O_{t-1}$	0.0053	0.0129	0.0076	0.0003	0.0003	0.0335	0.0110	0.0104	0.0581

In this table the return components, the implied spread, the conditional variance and the actual (realised) variance of returns for the DJM model are presented by agent and trade sign indicator. *Uninf*, *Fund*, and *Inf* are uninformed, fundamental and informed transactions, respectively. **B** and **O** stand for buy and sell transactions at time  $t$ , respectively. These are further dissected into those that follow a buy at  $t-1$ ,  $B_{t-1}$ , and those that follow a sell at  $t-1$ ,  $O_{t-1}$ . *Ad. Selection* is  $\hat{\theta}_1 + \hat{\theta}_{2,\pi} E[s_t | H_{t-1}]$ . *Liquidity* is  $\hat{\phi}_1 + \hat{\phi}_{2,\pi} E[s_t | H_{t-1}]$ . *Risk Aversion* is  $(\hat{\theta}_3 + \hat{\phi}_3) E[p_t | H_{t-1}]$ , where  $E[p_t | H_{t-1}]$  is approximated by the proportion of OTC transactions in the 15-min interval that precedes and includes transaction  $t-1$ . *Implied Spread* is  $2(\text{Ad. Selection} + \text{Liquidity} + \text{Risk Aversion})$ . *C. Variance* is the conditional variance of returns given in Eq. (8). *A. Variance* is the actual (realised) variance of returns,  $(\Delta p)^2$ . The conditional and realised variance for Phase III are reported multiplied by 100.

depletion of liquidity. Dealer's compensated for the added exposure to the sudden illiquidity by increasing their spreads, albeit not by much judging by the size of the risk aversion component.

#### 6.6. Trade type: buys versus sells, and continuations versus reversals

The above analysis is symmetric in its treatment of buy and sell trades. The model does not explicitly formulate different effects of these transactions, apart from what is implicit in trading intensity and the autocorrelation of order flow. Do trading intensity and autocorrelation of order flow capture any differences between buys and sells? We use the trade sign variable to dissect transactions into buys and sells, and investigate the return components, the implied spread and the conditional variance given by the model for buys and sells separately. To also analyse the effects of trade continuations and reversals we further dissect buy and sell transactions into those that follow a buy and those that follow a sell. Table 5 presents this decomposition by agent type.

The results show that the adverse selection component of price change, which increases monotonically with trading intensity, is higher for buys than for sells in the three phases. Thus, there seems to be more information in buys than in sells in this compliance market. In contrast, the liquidity and the risk aversion components, which mainly decrease with increases in trading intensity, are

higher for sells than for buys in the three phases (risk aversion exists only in Phase I). Thus, the inverse relation between the asymmetric information and the liquidity components, and the link between the liquidity and risk aversion components, are largely preserved across trade sign (buys and sells). The risk aversion component is higher for sells than for buys and this points to the higher frequency of shocks in OTC sell trades in Phase I, which emphasises the price crashes in that phase. The implied spread and the conditional variance for buys and sells also exhibit the same patterns observed for all trades in Table 3, but shows that spread and volatility are mainly higher for buys than sells. Thus, the model differentiates by showing that buy trades are riskier and more costly than sell trades in all phases.

These characteristics are distinguished further by continuations or reversals. The results in Table 5 show that the adverse selection, liquidity and the risk aversion components of return, as well as the conditional variance and the implied spread, are all higher for reversing trades than for continuing trades. Thus, the model reveals that trade reversals carry more information, are riskier and, consequently, more costly than continuing trades.

These results over all transactions are consistent with evidence from other markets that buys are more informative and are associated with greater transaction costs (e.g., Hedvall et al., 1997) and that large trades have a greater price impact

(e.g., Easley and O'Hara, 1987). The results also support Ahn et al. (2002) and Huang and Stoll (1997) who show that the order processing cost is lower for larger trades, although in this analysis the latter is investigated on the total liquidity costs through the role of trading intensity.

#### 6.7. Choice of order type (limit versus market orders)

A line of literature examines traders' order submission choice through basic statistics of data, probit models and game-theoretic equilibrium models. Keim and Madhavan (1995), for example, show that liquidity traders are likely to use market orders, while informed traders tend to use limit orders. Biais et al. (1995), and others, show that limit orders are preferred when the bid-ask spread is wide. Foucault (1999), and others, present evidence that the willingness to submit limit orders changes with price volatility, and submitting market orders when volatility is high is more costly since limit order traders require a higher compensation for the increased adverse selection. Handa et al. (2003) show that the choice between limit and market orders depends on the trader's belief about the probability of adverse selection. Bae et al. (2003) provide a brief summary of the literature and present evidence that traders at NYSE SuperDot place more limit orders than market orders when the bid-ask spread is wide, order size is large and high transitory volatility is expected.

In light of this literature, the model presented in this paper offers a natural tool for making order submission choices in the carbon market. It incorporates expected transaction size and duration, the dissection of which into regimes identifies the type of agent expected to submit the next trade. Moreover, Section 5 presents evidence that the model does reasonably well in predicting the direction of realised volatility and the intra-daily patterns in actual return, intensity, volatility and spread on a trade-by-trade basis. As these are the elements required, or used, by traders in choosing between market and limit orders, the model would be directly useful in this regard. Of the model's main features, three are of particular relevance. First, the model's dynamic nature allows for the decision on order choice to be made on a transaction-by-transaction basis, which is an obvious necessity in the trading environment. Second, the trichotomous dissection of intensity into three regimes and, hence, three types of agents, offers a refinement to the literature on order choice, which, on the main, assumes two types of agents only, informed and uninformed. More specifically, in some markets, such as Phase II, the model predicts an inverted J-shaped relationship between spread and trading intensity and a J-shaped relationship between volatility and trading intensity. The combined effect (ratio of implied spread to conditional variance) is an inverted U-shaped relationship in all three phases. Accordingly, market orders should be 'most' preferred if the agent expected to carry out the next trade is a fundamental trader in Phases I and III but an informed trader in Phase II. The order of decreasing preference for limit-order (rather than market order) submission across agents should be: informed, uninformed, and fundamental in Phases I and III, and fundamental, uninformed and informed in Phase II. This also relates to execution risk that increases with the inventory holding period (duration). This risk would, therefore, decrease with an increasing hazard rate (where the probability of a trade to occur increases with duration). Thus, in Phases I and III if the next trade is expected to be a fundamental trade, or in Phase II an informed trade, a market order would be preferred because execution risk is at its lowest. The third main relevant feature is the structural decomposition of volatility and spread into the adverse selection and liquidity components. Guided by the evidence from the literature reviewed above, traders may prefer to submit a limit order if the transitory volatility component (usually associated

with liquidity) for the next trade is expected to be higher. The model provides a direct estimate of this component, updated with every transaction.

## 7. Conclusion

This study proposes a new dynamic joint-expectations microstructural model of security prices and uses it to analyse price formation during the early development period of the European carbon market. This model updates the responsiveness of price change to surprises in order flow (information) and changes in signed liquidity costs by the expected type of agent that will instigate the next trade and the accompanying risk conditions. Thus, microstructure components of price change are made to vary with every transaction. The permanent (information) price component is found to be an increasing function solely of trading intensity, where different regimes of trading intensity change the sensitivity of price change to surprises in order flow. The transitory (liquidity) price component is decomposed into a constant order-processing part, a function of trading intensity that accounts for liquidity variations, and a risk-aversion part related to expected market risk conditions. This component is at its lowest (highest) when the next trade is expected to be a fundamental (informed) trade. Both components, which are updated after every transaction, determine the bid-ask quotes and the return variance, which are found to exhibit different patterns in different market phases. All these relations seem to strengthen when price volatility, the level of informed trading and the presence of OTC transactions are higher. It is found that trading intensity plays a dual role. It increases the information component and decreases the liquidity component, but at different rates. The net effect determines the result of the interplay between information and liquidity and their effect on prices. This resolves some conflicting results that appeared in the literature in analysing different markets, contracts or periods. The model also has a good predictive power on the hourly patterns in these measures, and differentiates the price impact of buy versus sell and continuing versus reversing trades.

Importantly, predictability in the autocorrelation of trading intensity informs quote setting and this induces the majority of autocorrelations observed in the level and conditional variance of price change. This important result reveals that such autocorrelations are generated by varying agent responses to surprises in order flow informed by the persistence of volume and duration over the recent trading history. As history constitutes observed public information, this indicates that autocorrelations in the level and volatility of price changes may very well be due to the speed and capacity by which traders learn to resolve information.

The model also provides direct trade-by-trade estimation of the components used by traders in choosing between limit and market orders. A market order in the carbon market is most preferred to a limit order if the next trade is expected to be a fundamental trade in Phases I and III but an informed trade in Phase II. Finally, buyer initiated trades are associated with a larger information component, lower liquidity component, wider spreads and higher volatility relative to seller initiated trades.

In conclusion, expected trading intensity is found to be an important determinant of intraday price formation, the direction of both the level and volatility of price change, and the hourly variations in spreads, volatility and their components.

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#### Appendix A–D. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.jbankfin.2015.11.004>.

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