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The role of trading intensity estimating the implicit bid–ask spread and determining transitory effects[☆]

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ABSTRACT

In this paper, we investigate the information content of trading intensity applying the Madhavan, Richardson and Roomans (1997) structural model to express trading intensity as trading momentum in duration and volume. Using both transactions and intraday data from the Helsinki Stock Exchange Limit Order Bookmarket, we find that momentum in duration and volume enhances the information effect. We reach this conclusion based on the parametric effect determined by the sign and the magnitude of the coefficients associated with the trading intensity variables, the trading effect determined by the ratio of transitory effects to permanent effects, and the economic effect determined by the size of the implicit bid–ask spread. While we find that the implicit bid–ask spread and transitory effects are decreasing toward the end of the trading day in consistency with information models in the literature, there is a surge of trades at the market close, most probably due to information uncertainty at market opening in New York.

1. Introduction

The purpose of this paper is to investigate the information content of momentum[1] in trading in a limit order book market. A large body of market microstructure literature has examined price impact of trade using either the vector autoregressive (VAR) model (e.g. Hasbrouck (1991), and Dufour and Engle (2000)) or the generalized method of moments (GMM) estimator (e.g. Ahn, Cai, Hamao, and Ho (2002), and Grammig, Theissen, and Wuensche (2006)). These studies are based on the theory that a sequence of buy or sell trades reveals the content of private information. Easley and O'Hara (1992) show how markets learn from a sequence of trades that originate from strategically acting informed traders. Assuming that an informed trader would split up a large trade in smaller consecutive trades, they show how the rate at which information arrives to the market depends on the time and the size of a trade.

Empirically, the role of transaction time and volume has been examined with respect to the information hypothesis of Diamond and Verrecchia (1987), Admati and Pfleiderer (1988), and Easley and O'Hara (1992), among others. Mixed findings have been reported on the pattern of liquidity at higher trading intensity. Using the VAR approach, Dufour and Engle (2000) find, in line with the prediction of Easley and O'Hara (1992), that prices tend to be higher when traders observe short durations. Similarly, Easley, Engle, O'Hara, and Wu (2008) find that momentum in trading explains why the bid–ask spread tends to be higher when informed traders are expected to be present in the market. In contrast, using the GMM estimator, Grammig et al. (2006) find, in line with the prediction of Admati and Pfleiderer (1988), that momentum in trading reduces the impact of a trade.

The association between volatility persistence and trading intensity is well understood in the financial literature, with findings ranging from information effects (e.g., Lamoureux & Lastrapes, 1990) to trading effects (e.g., Gouriéroux, Jasiak, and Le Fol (1999)) and the clustering of trades (Engle (2000), and Narayan, Narayan, Popp, and D'Rosario (2011)).

Engle and Russell (1998) introduce an autoregressive model that features momentum in trading. This model is useful when characterizing the dynamic of trades at ultra-high financial data frequency,

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[1] In this context, momentum in trading as trading intensity refers to persistence in volatility, which measures a number of volatility determinants such as duration in Engle (2000), trading volume in Lamoureux and Lastrapes (1990), and share prices in Narayan et al. (2011).

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where price changes have more noise than information, short durations tend to follow short durations, and large trades tend to follow large trades. Extending on Engle (2000), Renault and Werker (2004) split the dynamic of trading intensity into a deterministic component corresponding to expected trading intensity and a stochastic component corresponding to innovation in trading intensity. In this paper we use their specification of the trading process to extend the Madhavan, Richardson, and Roomans (MRR) (1997) structural model.

The MRR (1997) model derives parameters of the implicit bid–ask spread based on changes in the order flow due to informed and uninformed trading. This structural model has been used to investigate the pattern of the implicit bid–ask spread in the Tokyo Stock Exchange (see Ahn et al. (2002)), and the duration effect of the adverse selection cost (see Grammig et al. (2006)). Our difference from Ahn et al. (2002) is that we incorporate trading measures in the MRR model they used. Moreover, our study differs from Grammig et al. (2006) in that our trading intensity measures in the MRR model express persistence in volatility, hence capturing momentum in trading as in Engle (2000) and Narayan et al. (2011). This extension is supported by Renault and Werker (2004) who infer that return volatility and variation in trading intensity are potentially linked to the same news events.

We estimate our model on transactions and intraday data for Nokia. The Nokia stock is the most traded stock at the Helsinki Stock Exchange (HEX), and one of the most active American Depository Receipts (ADR) at the New York stock Exchange (NYSE) at the time of this study, (1999 to 2004). We focus on the trading on the main market (HEX) including the trading period that overlaps with NYSE resulting in a data sample that spans six years of transactions with a total of 6,753,243 observations.

Using transactions data, we find that the parametric and the economic effect of trade duration disappear over time, whereas its trading effect does not. However, using intraday data, we find that the parametric, the economic and the trading effect of both trade duration and trading volume persist over the trading day. Specifically, we find that the trading intensity parameters are both negative and positive. This is an indication that informed and uninformed traders exhibit a complex trading behavior as in Easley et al. (2008). Therefore, unlike the findings of Grammig et al. (2006), the bid–ask spread might increase or decrease in a limit order book market without authoritative market makers.

Finally, we find that the adverse selection cost exhibits a U-shaped pattern. A plausible explanation for this pattern is that information spills over when NYSE is opening at the time when HEX is closing. With several markets opening at different times, the U-shaped pattern expresses the information flow across exchanges.

The rest of the paper proceeds as follows. In Section 2, we present a simple structural model to examine the price effect of momentum in trading. In Section 3, we present the empirical results on tick-by-tick data. In Section 4, we report the empirical results on intraday data. The last section concludes the paper.

2. Information intensity parameters

Information intensity reflects the rate at which information arrives. We develop in this section a simple structural model incorporating information intensity parameters associated with momentum in trading intensity.

2.1. Characterizing the order flow when the trading intensity is not constant

In the market microstructure literature uncertainty has a price, a quantity and a time dimension. Specifically, sequential models explain uncertainty through a dynamic order flow reflecting variation in price movements (signed trades) and information arrivals (trading intensity) (e.g. Easley and O'Hara (1992)). For models assuming that trading intensity is constant (e.g. MRR (1997)), the order flow is solely defined in terms of price movements (signed trades) as,

$$\lambda_i = \phi_1(q_i - q_{i-1}) + \theta(q_i - \rho q_{i-1}), \tag{1}$$

where λ_i is the order flow variable at i, q_i is the signed trade, $\phi_1 \geq 0$ and increases when q_i is reversal due to momentum in trading, $\theta_1 \geq 0$ and increases when q_i is reversal due to informed trading and $\rho \geq 0$ and increases when q_i is persistent due to private information. Assuming that informed traders are present with $\rho = 1$ and q_i is reversal, the implicit bid–ask spread of (1) is given by $S_T = 2(\phi_1 + \theta_1)$. However, both informed and uninformed traders exhibit a complex behavior (see Easley et al. (2008)). Momentum in trading can be informative as in Easley and O'Hara (1992) or liquidity profiling as in Admati and Pfleiderer (1988). Different approaches can be used to model such a complex behavior (e.g. Easley et al. (2008)). The following model is a representation of a dynamic trading schedule:

$$\lambda_i = [(\phi_1 + \phi_2\psi_i)q_i - \phi_1 q_{i-1}] + [(\theta_1 + \theta_2 C_i)q_i - \rho\theta_1 q_{i-1}] \tag{2}$$

where $\phi_2 \geq 0$ and increases with trading intensity ψ_i, and $\theta_2 \geq 0$ and increases with innovation in trading intensity C_i, $E\psi_i = EC_i = 1$, $\psi_i > 0$ and $C_i > 0$. Accordingly, the implicit bid–ask spread is $S_D = [(2\phi_1 + \phi_2) + (2\theta_1 + \theta_2)]$. Hence, *if trading intensity tends to enhance information signals*, $\vartheta_D = (2\theta_1 + \theta_2)/S_D$ *would be greater than* $\vartheta_T = 2\theta_1/S_T$. Similarly, *if the cost of liquidity tends to increase with trading intensity*, S_D *would be greater than* S_T. Since both ψ_i and C_i are positive variables and capture momentum in trading, their properties echo those of the autoregressive conditional duration (ACD) model of Engle and Russell (1998).

Let v_i be the trading volume and $x_i = t_i - t_{i-1}$ be the trade duration between trades associated with irregularly spaced log prices, p_{it}, where i denotes the order in which prices are recorded and t the time at which prices occur and z_i be either x_i or v_i. Engle and Russell (1998) show that z_i can be rewritten as $z_i = \psi_i \varepsilon_i$, where ε_i is a positive error term and ψ_i is the expected trading intensity, and $\varepsilon_i = z_i/\psi_i$ is the standardized trade intensity residual with $E(\varepsilon_i) = E(\varepsilon_i)^2 = 1$ and $E(\varepsilon_i \varepsilon_{i-1}) = 0$. The ACD (1,1) is $\psi_i = \omega + \alpha z_{i-1} + \beta\psi_{i-1}$ with $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$ and $(\alpha + \beta) < 1$. We associate ψ_i with liquidity profiling, and $C_i = \varepsilon_i \varepsilon_{i-1}$ with informed trading.

2.2. Characterizing the dynamics of price changes

Let the return be $r_{it} = (p_{it}/p_{it-1})$ and its dynamic be $r_i = e_{1i} + e_{2i}$, where e_{1i} is related to shocks in fundamentals and $e_{2i} = n_i - n_{i-1}$ is related to pricing errors. With trading frictions and pricing errors, the dynamic of returns is $r_i = \lambda_i + e_{1i} + e_{2i}$. Writing the dynamic of returns in terms of (2) gives,

$$r_i = [(\phi_1 + \phi_2\psi_i)q_i - \phi_1 q_{i-1}] + [(\theta_1 + \theta_2 C_i)q_i - \rho\theta_1 q_{i-1}] + (e_{1i} + e_{2i}). \tag{3}$$

Eq. (3) blends transitory and permanent effects. The ratio of transitory effects to permanent effects is a measure of stock (market) quality. These effects determine both the level of the implicit bid–ask spread and variance. As shown above, the implicit bid–ask spread is the expectation of (3). Although, the variance is given by the second moment of (3):

$$\sigma_r^2 = 2\phi_1^2(1-\rho) + 2\theta_1^2\left(1-\rho^2\right) + \left(\phi_2^2 + \theta_2^2\right) + \left(2\sigma_2^2 + \sigma_1^2\right), \tag{4}$$

where (4) is computed given that, $Ee_{1i}e_{1i-1} = Ee_{2i}e_{2i-1} = 0$, and $E\psi_i = EC_i = E\psi_i^2 = EC_i^2 = 1$. The second moment of the MRR model is (4) minus $(\phi_2^2 + \theta_2^2)$. The ratio of transitory effects to permanent effects is,

$$\pi_{D,V} = \frac{\left[2\phi_1^2(1-\rho) + \phi_2^2\right] + 2\sigma_2^2}{\left[2\theta_1^2(1-\rho^2) + \theta_2^2\right] + \sigma_1^2}, \tag{5}$$