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# Considering all microstructure effects: The extension of a trade indicator model

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## HIGHLIGHTS

- We propose a microstructure model considering trade durations, sizes, spreads, and depth.
- Fast and large trades indicate informed trading in a highly liquid futures market.
- Higher liquidity decreases (increases) the permanent (temporary) spread component.

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ABSTRACT

By considering various market microstructure effects, this letter proposes a comprehensive trade indicator model incorporating trade duration, order sizes, bid–ask spreads, and market depth into a unified framework. Examining the intraday price behavior of the KOSPI200 futures market, we find that (i) fast trading indicates informed trading, (ii) stealth trading does not prevail, (iii) order-processing costs reach economies of scale, and (iv) liquidity significantly affects investors' order submission decisions in the highly liquid market.



## 1. Introduction

Kyle (1985) and Glosten and Milgrom (1985) suggest microeconomic and game-theoretic frameworks to describe the interactions among market participants and the resultant price behaviors (Cai et al., 2010; Luo, 2001; Morrison and Vulkan, 2005). Based on these economic frameworks, empirical market microstructure models have been developed to examine the intraday dynamics of asset prices, bid–ask spreads, and trading volume. These include trade indicator models that directly exploit the information conveyed by incoming trades, which have been widely used because of their theoretical elaborateness and empirical adaptability. Huang and Stoll (1997) and Madhavan et al. (1997), the two most representative trade indicator models (hereafter, the HS and MRR models, respectively), decompose price and spread changes induced by traded orders into the portion attributable to informed trading (i.e., the permanent portion) and that related to other trading motives, such as liquidity trading and/or compensation for inventory holding (i.e., the temporary portion).

Although these two trade indicator models are quite popular, they have critical shortcomings. The HS model is not appropriate for analyzing order-driven markets in which designated market makers do not exist and inventory holding costs cannot be defined. Furthermore, although order sizes and durations between trades are irregular and convey substantial information content, both the HS and MRR models assume that the sizes of incoming orders are the same and ignore variation in trade duration, which results in a loss of valuable information and causes biased estimation. Several studies extend existing trade indicator models by considering other information embedded in trades (Ahn et al., 2008, 2010; Angelidis and Benos, 2009; Chung et al., 2016; Grammig et al., 2011; Hagströmer et al., 2016; Ryu, 2011, 2013, 2015). However, only a few studies consider the various aspects and characteristics of incoming trades and the trading environment when analyzing the intraday price dynamics of financial markets.

This letter suggests a comprehensive trade indicator model incorporating various microstructure variables, such as trade

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duration, order sizes, and market liquidity (measured by market depth and quoted spreads). Our model assumes that investors can strategically adjust the speed of their trading by deciding the frequency and size of their orders. It also considers that the depth and spreads represent distinct dimensions of the liquidity property and are observable when investors decide to submit their orders. Market liquidity affects investors' strategic decision-making process, and it is a major consideration for derivatives traders in choosing their trading vehicle. If a market is deep, informed investors need not be concerned about adverse price movements, and the market can absorb price impacts generated by large orders. Meanwhile, smaller quoted spreads reduce the transaction cost of immediacy. Estimating the model using a highly liquid market dataset, we find that each variable conveys significant information on intraday transactions.

## 2. Theoretical framework

Eq. (1) demonstrates how an unobservable asset value ($\mu_t$) is formed when there is an unexpected incoming trade ($x_t - E[x_t|x_{t-1}]$) and an update to public information ($\varepsilon_t$).

$$\Delta\mu_t = \mu_t - \mu_{t-1} = (\theta_0 + \theta_1 \ln(T_t) + \theta_2\sqrt{V_t} + \theta_3 D_{t-} + \theta_4 S_{t-}) \times (x_t - E[x_t|x_{t-1}]) + \varepsilon_t, \quad (1)$$

where $x_t$ denotes a trade indicator variable that is 1 ($-1$) if the $t$th incoming trade is a buyer-initiated (seller-initiated) trade. $E[x_t|x_{t-1}]$ equals $\rho x_{t-1}$, and $\rho$ is the serial correlation of the indicator variable.[1] $\mu_t$ is the post-trade fundamental asset value; $T_t$ measures the inter-transaction time (i.e., trade duration) between the $t-1$th and $t$th trades; $V_t$ is the volume (i.e., order size) of the $t$th trade; $D_{t-}$ denotes the market depth measured as the sum of the sizes of outstanding orders immediately before the $t$th trade (therefore, its time subscript is denoted by $t-$); and $S_{t-}$ denotes the quoted bid–ask spread.

Existing trade indicator models under the MRR framework are nested in our model. While the original MRR model assumes that all orders have a unit size and the same inter-transaction time and therefore uses the single parameter $\theta_0$, our model describes various characteristics of incoming orders and trades in terms of trade duration (captured by $\theta_1$) and order size (captured by $\theta_2$). Furthermore, our model reflects the current market liquidity, which serves as the investors' decision variable, that is, whether they submit orders (captured by $\theta_3$ and $\theta_4$). ($\theta_0 + \theta_1 \ln(T_t) + \theta_2\sqrt{V_t} + \theta_3 D_{t-} + \theta_4 S_{t-}$) measures the permanent price impact of the $t$th trade and the information content embedded in the traded order.

Eq. (2) demonstrates how the fundamental value ($\mu_t$), the temporary price effect of the $t$th trade ($\varphi_0 + \varphi_1 \ln(T_t) + \varphi_2\sqrt{V_t} + \varphi_3 D_{t-} + \varphi_4 S_{t-}$), which does not change the fundamental value (so, its effect is *temporary*), and the residual ($\xi_t$) (capturing price discreteness) determine the $t$th observable transaction price ($P_t$).

$$P_t = \mu_t + (\varphi_0 + \varphi_1 \ln(T_t) + \varphi_2\sqrt{V_t} + \varphi_3 D_{t-} + \varphi_4 S_{t-})x_t + \xi_t. \quad (2)$$

From Eqs. (1) and (2), the asset price change can be represented as follows.

$$\begin{aligned}\Delta P_t = {} & (\theta_0 + \varphi_0)x_t - (\rho\theta_0 + \varphi_0)x_{t-1} + (\theta_1 + \varphi_1)x_t \ln(T_t) \\ & - \varphi_1 x_{t-1}\ln(T_{t-1}) - \rho\theta_1 x_{t-1}\ln(T_t) + (\theta_2 \\ & + \varphi_2)x_t\sqrt{V_t} - \varphi_2 x_{t-1}\sqrt{V_{t-1}} - \rho\theta_2 x_{t-1}\sqrt{V_t} \\ & + (\theta_3 + \varphi_3)x_t D_{t-} - \varphi_3 x_{t-1} D_{t-1} - \rho\theta_3 x_{t-1} D_{t-} \\ & + (\theta_4 + \varphi_4)x_t S_{t-} - \varphi_4 x_{t-1} S_{t-1} - \rho\theta_4 x_{t-1} S_{t-} + e_t, \quad (3)\end{aligned}$$

where $e_t = \varepsilon_t + \xi_t - \xi_{t-1}$. Using Eq. (3) and the equation for describing the serial correlation of the trade indicator variable, we construct the GMM estimation equations for the parameter estimation.

$$\begin{aligned}& E[x_{t-1}(x_t - \rho x_{t-1}) \quad m_t \quad x_t m_t \quad x_{t-1}m_t \quad x_t \ln(T_t)m_t \\ & x_{t-1}\ln(T_{t-1})m_t \quad x_{t-1}\ln(T_t)m_t \quad x_t\sqrt{V_t}m_t \\ & x_{t-1}\sqrt{V_{t-1}}m_t \quad x_{t-1}\sqrt{V_t}m_t \quad x_t D_{t-}m_t \quad x_{t-1}D_{t-1-}m_t \\ & x_{t-1}D_{t-}m_t \quad x_t S_{t-}m_t \quad x_{t-1}S_{t-1-}m_t \quad x_{t-1}S_{t-}m_t] = 0, \quad (4)\end{aligned}$$

where $m_t = e_t - e_0$. $e_0$ denotes a constant drift term. The parameter estimates and GMM statistics are obtained via the two-step GMM method.[2]

## 3. Empirical findings

Our structural model is estimated using the real-time TAQ (Trade and Quote) dataset from the KOSPI200 futures market with little market friction. We choose the futures market because it is a highly liquid market without buy-sell asymmetry, dark pool issues, or designated market makers, resulting in an unbiased estimation. Further, it provides detailed, high-quality information that is frequently unavailable from other markets. Our unique dataset offers detailed and exact information on transaction prices, quantities, bid–ask prices, depth, transaction time, and trade directions.

Table 1 reports the estimation results for each futures series.[3] Panel A presents the estimation results for the permanent-impact-related parameters of our structural model. The significantly negative duration-related parameter ($\theta_1$) estimates reveal that the permanent price impacts of incoming trades decrease with trade duration after controlling for order characteristics and market liquidity. This suggests that fast trading is related to informed trading. The significantly positive size-related parameter ($\theta_2$) for all futures series means that large trades incur greater permanent price impacts and are more informed than smaller trades. This is clear evidence against stealth trading, in which informed traders generally split their orders to camouflage themselves or reduce adverse price impacts from illiquidity, making smaller traders potentially more informative.

The futures market is highly liquid and guarantees investor anonymity, which provides little incentive for informed investors to fragment their trades. Further, index futures traders achieve information advantages by processing public and market-wide information more rapidly than their competitors and by acquiring trading skills and knowledge. Such advantages disappear quickly if they do not utilize the information immediately. Thus, timing ability becomes more important in the index futures market, and, as a result, informed trading is implemented as a form of fast and large trading.

Most of the depth-related parameter ($\theta_3$) estimates are significantly negative, whereas most of the spread-related parameter

1 If hedging and inventory holding issues are considered, the expected value of the current trade indicator $x_t$ may be characterized by all past order flows such as $x_{t-1}, x_{t-2}, \ldots, x_0$. However, this is not the case in our framework, which assumes the absence of market makers and does not consider explicit inventory-holding costs.

2 We use an inverse spectral density matrix based on the Newey–West (Bartlett kernel) method. The use of other GMM methods (e.g., one-step GMM or CUGMM) or other kernels (e.g., truncated or Parzen kernels) does not alter our conclusions.

3 The online appendix explains how we construct our samples and provides summary statistics.