The informational role of trade duration: The case of an index options market

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The informational role of trade duration: The case of an index options market

Abstract

Under a structural market microstructure model framework, this study examines whether there is a significant information role of inter-transaction time (referred to as trade duration) among options trades. To answer this research question, we extend the MRR model (Madhavan, Richardson, and Roomans, 1997) to incorporate trade duration into the structural model and analyze the high-quality transaction dataset of the KOSPI 200 options market, which is the most liquid and remarkable derivatives market in the world.

We find that the duration between two consecutive options trades conveys meaningful information, and that the implications of trade duration are significantly different across option moneyness. While fast trading indicates informed trading in an out-of-the-money (OTM) options market, also known as a speculative market, the opposite is true in the case of in-the-money (ITM) options trading. This study provides robust results because the same patterns for the information content of the trade duration are observed after we control trade sizes or intraday time periods. We also find that the informational role of trade duration becomes more significant when informed trading is more concentrated, liquidity is relatively lower, many days are left before maturity date, and the market is more volatile.

JEL Classifications: G10, G15

Keywords: Inter-transaction time (trade duration); KOSPI 200 options; Market microstructure; Price impact; Structural model

1. Introduction

In the field of market microstructure research, making inferences about the information content of trades based on their size, direction, and intensity is a steady research interest for both theoretical and empirical studies. While the first classical market microstructure studies suggest purely theoretical backgrounds (Admati and Pfleiderer, 1988; Copeland and Galai, 1983; Easley and O'Hara, 1987; Garman, 1976; Glosten and Milgrom, 1985; Parlour, 1998; Kyle, 1985), later empirical studies directly test the theories and hypotheses suggested in the previous studies. This testing is made possible by the advent of high performance data processing systems and increased accessibility of the intraday transaction-level datasets of major financial markets. However, the findings of empirical studies are inconsistent with one another, and their conclusions vary with regard to structure, maturity, and behavior of markets. Thus, these remain unresolved empirical topics.

The following are examples of such issues. Though the majority of studies claim that trade size matters and that the information content of trades differs significantly depending on size, there are two distinctly opposing views about investor-preferred size of trades and about the relationship between trade informativeness and size. Some studies claim that large trades carry greater information content than small trades (Ahn, Kang, and Ryu, 2010; Easley, Kiefer, and O'Hara, 1997a, 1997b; Easley and O'Hara, 1987; Holthausen, Leftwich, and Mayers, 1987, 1990; Kang and Ryu, 2010; Lin, Sanger, and Booth, 1995), whereas other studies report opposing evidence and claim that informed investors prefer using smaller trades and fragment their trades to camouflage their trading intentions (Alexander and Peterson, 2007; Barclay and Warner, 1993; Chakravarty, 2001; Chou and Wang, 2009; Chung, Chuwonganant, and Jiang, 2008, Huang and Masulis, 2003; Kim and Ryu, 2012; Kyle, 1985; Ryu, 2012*a*). Studies that examine the information content of trade direction (buy or sell) also exhibit two opposing opinions. Many previous studies find that purchase trades generally have greater permanent price impacts than sell trades and conclude that purchase trades are more informative (Ahn, Kang, and Ryu, 2010; Easley, Kiefer, O'Hara, and Paperman, 1996; Neal, 1992; Vijh, 1988, 1990). They attribute this result to market friction such as short-sale constraints, dealers' strategic behaviors, or asymmetric payoff structures of financial assets. In contrast, Ryu (2013) recently finds that sell trades can be more informative than purchase trades in the absence of friction and asymmetry.

While the issues related to the information content of trade size and direction have been continuously addressed since the onset of market microstructure studies, academics have only recently started to focus on the informational role of inter-transaction times between trades. In their seminal empirical paper, Dufour and Engle (2000) incorporate inter-transaction times (i.e., "trade duration") into their vector autoregressive (VAR) framework and find that the price impact of trades becomes greater as the duration between trades becomes shorter. Considering that the size of permanent price impact generally increases with the degree of informed trading, they interpret this result as follows: "Fast trading means informed trading." Many of the following empirical studies adopt the VAR framework of Dufour and Engle (2000) and examine the global stock markets (Chen, Li, and Cai, 2008; Furfine, 2007; Liu and Maheu, 2012; Spierdijk, 2004; Xu, Chen, and Wu, 2006). Their results also support the hypothesis that fast trading indicates informed trading. On the other hand, some recent empirical studies by Peng (2001), Grammig, Theissen, and Wünsche (2011), and Bentran-Lopez, Grammig, and Menkveld (2012) find that the price impact of trades increases with the trade duration. They argue that fast trading is mostly related to noisy trading, not to informed trading.

The inconsistent results of previous studies imply that, as in the case of studying trade size and direction, the trade duration is decided by strategic decisions of informed and liquidity traders and their interactions. In other words, the information content of trade duration can show greater variation depending on variables in the trading environments of financial markets, such as market structure, degree of informed trading, market maturation, and investor behavior. Since investors often make strategic decisions regarding their trades (Lee, Eom, and Park, 2013; Obizhaeva and Wang, 2013), the information content of inter-transaction time and the relationship between trade duration and informed trading are not easily predicted without serious and intensive data analysis. Much room for interpretation on the information content of trade duration is evident even in classical market microstructure studies. For example, the famous "sunshine trading hypothesis" of Admati and Pfleiderer (1988) can be interpreted either way regarding the information content of trade duration. The sunshine trading hypothesis assumes that informed traders prefer trading when markets become relatively liquid. Since a shorter duration between trades indicates greater liquidity, we can expect active participation of informed traders who want to enjoy the ample liquidity as follows: shorter duration (i.e., fast trading) means a higher concentration of informed trading. Meanwhile, the active participation of informed traders can also discourage the participation of liquidity traders and/or uninformed traders. As a result, the liquidity will decrease, and slow trading will prevail in the market. In this situation, we observe a positive relationship between trade duration and informed trading.

In addition to the inconsistency, previous studies that examine the information content of trade duration are not fully satisfactory, and we think that more in-depth research is needed to obtain the clear economic implications of trade duration. In particular, the following reasons motivate us to start this study.

First, the majority of studies that find a negative association between trade duration and informed trading depend on the VAR framework of Dufour and Engle (2000) or extended VAR models (e.g., Chen, Li, and Cai, 2008; Furfine, 2007; Xu, Chen, and Wu, 2006). Their results might be contaminated due to the arbitrary trade-event filtering process incurred in the VAR models. Furthermore, though some recent studies adopt the structural model approach to mitigate the problem of the VAR approach, their results are also inconsistent. For example, Grammig, Theissen, and Wünsche (2011) insist that the previous conclusion (i.e., fast trading means informed trading) is just an artifact of the VAR model and report the opposite result based on their structural model framework. In contrast, employing a structural market microstructure model, Ryu (forthcoming-d) finds that the price impact incurred by informed trading increases as the inter-transaction times become shorter. Considering these results, our suggestion sheds new light on duration-related issues by examining how the informational role of trade duration changes with the characteristics of assets that are traded under a same trading condition. An index options market is a strong candidate for our research topic because the options contracts exhibit different characteristics across option moneyness and maturity, whereas they are traded under the same trading condition and environment (e.g., options orders are transacted by a same trading mechanism in a same exchange and the options contracts of a same type have the same payoff structure). We also use an extended structural market microstructure model that can mitigate the possible shortcomings of the old VAR framework.

Second, while previous studies have focused on equity markets, little is known about emerging

derivatives markets. Though the KOSPI 200 options market plays a quite important role and captures the interest of global investors, there remains much to be analyzed about the informational role of options trades, and there is no research about the duration between options trades. Further, there is little market friction in the KOSPI 200 options market. The options market is highly liquid and characterized by extremely small bid-ask spreads and deep market depth. These traits of the KOSPI 200 options market make our results more interesting and reliable.¹

By employing the extended MRR model (Madhavan, Richardson, and Roomans, 1997) to incorporate the trade duration effect, we obtain the following implications about the informational role of trade duration in the KOSPI 200 options market, the most liquid and famous derivatives market in the world. First, the inter-transaction time between trades has significant information content in the KOSPI 200 options market. Second, the informational role of trade duration is clearly different according to option moneyness and leverage. We find a negative association between trade duration and informed trading for out-of-the-money (OTM) options, whereas a positive association is observed for in-the-money (ITM) options. Third, this pattern remains the same after we control for the effects of trade size and intraday time periods. Fourth, the informational role of trade duration is more important when informed trading is more concentrated, liquidity is relatively lower, maturity dates are many days away, and the market is more volatile.

The rest of this paper is organized as follows. Section 2 discusses the characteristics of the KOSPI 200 options market and explains why it provides the optimal experimental environment to examine the issues raised in this study. We also explain the sample data in this section. Section 3 introduces the extended MRR models and explains their structures. Section 4 presents our empirical findings and discusses their economic implications. The conclusion of this study is provided in Section 5.

2. KOSPI 200 Options Market and Sample Data

2.1 Characteristics of the KOSPI 200 options market

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The KOSPI 200 options product is the representative derivatives asset traded in the Korea Exchange (KRX). Currently, the KOSPI 200 options market is the most liquid and well-known index options market in the world. Despite its short history, it has maintained a position as a top-tier derivatives market. Until recently, its trading volume has been ranked first in the world. 2 The outstanding position of the KOSPI 200 options market has also been solidified due to the synergistic effect of combined trading with the KOSPI 200 futures product, one of the most liquid index futures in the

¹ More details about the KOSPI 200 options market are described in Section 2. Additional reasons why we focus on the KOSPI 200 options market are provided in that section.

 2 Refer to the website of the Futures Industry Association (www.futuresindustry.org). The top-tier position and importance of the KOSPI 200 options market are also well-documented in previous studies (Han, Guo, and Ryu, and Webb, 2012; Guo, Han, and Ryu, 2013; Lee and Ryu, 2013; Ryu, 2012*c*; Ryu, Kang, and Suh, forthcoming).

world 3

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Unlike derivatives markets of developed countries, the KOSPI 200 options market is dominated by individual investors. While domestic and foreign institutional investors are the major market players in established derivatives markets, individual investors' trades comprise a substantial portion of the total trading volume in the KOSPI 200 options market. Table 1 presents the trading activity from January 2003 to June 2005, classified according to investor types which are domestic individuals, domestic institutions, and foreigners. As shown in the table, the transactions of domestic individuals account for more than half of the total trading volume (51%) during the sample period (2003-2005). Though the active participation of the individual investors results in a speculative futures market, it also makes the market more liquid. These effects point to the pros and cons of the options market. On the one hand, most of the individual investors are extremely-short-term investors and day traders, and the trades made by these individuals can largely be characterized as noisy trading. Against the intentions of the government and the KRX, which have promoted index futures and options trading, individuals do not use index derivatives as hedging tools or trading vehicles for long-term portfolio management (Kim and Ryu, 2012; Ryu 2011, 2012*a*, 2012*b*, forthcoming-a, forthcoming-b, forthcoming-c). Their trading tends to make the market more volatile, unstable, and excessively speculative. On the other hand, market participants can enjoy the ample liquidity provided by numerous individual investors, which has enabled the KOSPI 200 options market to occupy the top position as a world-class index options market.

[Table 1 about here]

The KOSPI 200 options market is classified as a purely order-driven market in which there is no designated market maker. All trades are made by the central electronic limit order book (CLOB). The orders submitted by investors are fairly and transparently transacted according to the price and time priority rules. Meanwhile, this trading mechanism guarantees the anonymity of all market participants and market transparency. On a normal trading day, the KOSPI 200 options market opens at 09:00 and closes at $15:15⁴$ During the last 10 minutes (from 15:05 to 15:15) and during the hour long preopening session (from 08:00 to 09:00), standing orders are transacted under the uniform pricing rule.

³ Practically, KOSPI 200 futures serve as underlying assets of KOSPI 200 options. Since it is quite costly to construct a stock portfolio consisting of 200 underlying stocks, most professional investors use the futures as hedging and/or speculative tools related to options trading. In addition, academics and market experts believe that many derivatives traders in the Korean market participate simultaneously in both KOSPI 200 futures and options markets. This concurrent participation in both markets strengthens the association between the two markets (Ryu, 2011, 2013, forthcoming-a, forthcoming-b, forthcoming-c).

⁴ There are some exceptions. On the maturity dates, the trading session closes 25 minutes earlier than on normal trading days. The trading begins one hour later (at 10:00) on the first trading date of each calendar year and on Korea's scholastic aptitude test (SAT) date.

For other intraday periods (from 09:00 to 15:05), all submitted orders are immediately traded or consolidated into the limit order book.

Four different options contracts with varying maturities can be traded each day. The maturity dates are the second Thursdays of three consecutive near-term months and one month nearest to each quarterly cycle (March, June, September, or December). However, among the four contracts, only the nearest maturity futures contracts are actively traded. The other three longer-term contracts are rarely traded (Ahn, Kang, and Ryu, 2008, 2010; Ryu, 2011, forthcoming-b).⁵ The basic quoting unit of the KOSPI 200 options market is the "point." One point corresponds to 100,000 Korean Won (KRW). We present the sizes of estimated parameters in terms of both the points and the percentages of futures prices.

2.2 Why the KOSPI 200 options market?

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The ample liquidity and the unique investor participation rate of the KOSPI 200 index options market present a valuable and interesting opportunity to study the characteristics of options markets. The KOSPI 200 options market provides an ideal setting to investigate the information value of trade duration for the following reasons.

First, as we briefly point out in our introduction, in the index options market, all options contracts classified by strike price are traded under the same market structure and similar trading environments. For example, all investors use the same information source (i.e., market-wide information and news about the Korean economy), and all submitted orders are transacted by the CLOB. In these situations, distinct patterns for the informational role of trade duration by options contracts indicate that the different characteristics are due to option moneyness (i.e., option leverage).

Second, the definition of information in the KOSPI 200 options market is somewhat different from that in equity markets. In the latter markets, informed investors make transaction decisions based on their private information, which they expect to place them in superior positions for relatively long periods. In contrast, in the index options market, investors achieve information advantages by processing public and market-wide information faster than other traders and by acquiring trading skills and knowledge. Such advantages can disappear quickly if the information is not immediately utilized. In these situations, we assume that timing is important for the informed investors, and, as a result, the trade duration carries more meaning than in the equity markets.

Third, we expect to obtain uncontaminated results by analyzing the intraday transaction data of the KOSPI 200 options market because the market has little friction and can absorb almost all demands of derivatives investors in the Korean market. Bid-ask spreads are quite narrow, market depths are great

⁵ This situation is the same in the KOSPI 200 futures market, which is closely related to the KOSPI 200 options market. Refer to Ryu (2011, 2012*a*, 2012*b*, 2013, forthcoming-a, forthcoming-d) for details on the KOSPI 200 futures market.

(Ahn, Kang, and Ryu; 2008, 2010), and no short-sale constraints exist. 6 Further, unlike the other developed markets such as the NYSE or NASDAQ, there are no designated market makers and no upstairs market for heavy traders in the KOSPI 200 options market, which creates anonymity for investors. These traits enable informed investors to freely submit their orders based only on their intraday trading strategies without caring about market friction, exposing trading intentions, transaction costs, or the adverse price movements of large trades and/or fast trading in a non-liquid market. Therefore, we can accurately measure the information content of trade duration in this options market.

Fourth, combined with the fluent liquidity, the guaranteed investor anonymity in the options market has two opposing implications on the trading intensity described by trade duration and trade size. In the KOSPI 200 options market, informed investors might have little incentive to fragment their trades.⁷ The informed investors are not concerned about the adverse price movements incurred by their large trades, and they can take part in the assured liquidity while maintaining anonymity. If they actually trade in this way, the size of each trade is greatly informative, while the trade duration gives little information. On the other hand, informed traders often prefer to hide their trading intentions by spreading their trades over multiple small transactions (Anand and Chakravarty, 2007). In this case, the trade duration becomes a much better indicator of informed trading. In sum, the question of the significance of trade duration remains to be empirically investigated.

Finally, a long-standing argument exists among market practitioners and academics about the role of KOSPI 200 options trading because many continue to believe that the market is dominated by noisy and uninformed trading. If this kind of noisy trading is prevalent, then fast trading might be merely the result of noisy and/or liquidity trading, leading to the conclusion that higher trading intensity is not informative. To investigate this debated issue, more in-depth study on the options market is required.

2.3 Sample data

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This study's sample data is real-time trade and quote (TAQ) data of KOSPI 200 options from January

⁶ If short-sale constraints exist, we may not obtain the correct implications of the information roles of trade duration. Under short-sale constraints, negative information is only partially reflected in asset prices and trades because informed investors cannot freely submit sell orders even if they are sure of the decreases in asset prices (Diamond and Verrecchia, 1987). In this situation, long trade durations can be a result of either no information or negative information, and we cannot differentiate between them. Another liquid derivatives market of Korea is the ELWs (Equity-Linked Warrants) market. Liquidity providers comprised of established financial institutions operate this market. Only these institutions can write the ELWs, whereas individual investors cannot. That is, individuals cannot submit sell orders if they do not own the ELWs. This structure (i.e., short-sale constraints only binding to individual investors) adds to the asymmetry among market participants, and, as a result, the ELW market is not as appropriate for our analysis as is the KOSPI 200 options market.

⁷ Informed traders often fragment their trades for many strategic reasons. This strategy is called "stealth-trading."

2003 to June 2005. Our dataset is filtered based on the following procedure. First, we only include the intraday transaction data of the nearest maturity contracts because the liquidity of longer-term maturity options is extremely low. Second, excluding the pre-opening and closing sessions, we include all trades and quotes recorded during the continuous session of each trading day in the final sample. Third, we define the option moneyness metric of call (put) options as *S*/*K* (*K*/*S*), where *S* is the current stock price and *K* is the strike price. We exclude options contracts for which moneyness is less than 0.88 or greater than 1.12. This strategy allows us to exclude extremely deep ITM and OTM options from the analysis because they are quite non-liquid. Fourth, if the daily number of options contract transactions is less than ten, that day is also excluded from the final sample.

Our dataset gives detailed and exact information on transaction prices, quantities, bid/ask spreads, market depth, transaction time, and trade directions. An important advantage of the dataset is that it includes an exact classification of the trade direction. The time stamp on each order and trade indicates whether the trade is initiated by a buyer or a seller, information that is essential for a reliable estimation using the structural MRR model (and its extensions), which critically depends on trade indicator variables.⁸

KOSPI 200 options have monthly maturity dates, but KOSPI 200 futures that are closely related to options trading have quarterly maturity dates. To eliminate the possible effect of maturity biases on the model estimation, we construct ten options series, each covering a three-month period. For example, the first options series covers January to March of 2003, and the second series spans from April to June of 2003. The last options series covers a longer four-month period from March to June of 2005. For each options series, we define six moneyness categories: 0.88~0.93, 0.93~0.96, 0.96~0.98, 0.98~1.0, 1.0~1.04, and 1.04~1.12. Table 2 presents summary statistics of the sample data with respect to the ten options series according to moneyness category. The table reports the number of trades, number of contracts, weighted average transaction price, average trade size, and average trade duration for call options and put options, respectively.⁹

[Table 2 around here]

Table 2 shows patterns of market liquidity measures and prices in call options and in put options. For both call and put trading, the inter-transaction time between trades is shortest and the number of transactions is highest in slightly OTM options for which moneyness lies between 0.98 and 1.0. The trading volume measured in the number of contracts is highest in OTM options for which moneyness

⁸ We explain the trade indicator variables and structures of the MRR model and its extensions in Section $\overline{3}$.

⁹ The number of trades reported in Table 2 is slightly smaller than the actual number of transactions because there is a slight loss when we construct the estimation sample. If there are defects in the raw data of a certain date, all transaction records for that day are excluded from the sample.

lies between 0.93 and 0.96. These facts indicate that OTM options are more liquid than ATM (at-themoney) and ITM options in the KOSPI 200 options market. The table also shows that option prices monotonically increase with option moneyness.

3. Models

The structural MRR model assumes that any incoming trade influences asset price in two ways: the permanent price impact due to informed trading and the temporary price effect due to uninformed and/or liquidity trading. Most structural models, such as that of Huang and Stoll (1997), assume the existence of market makers and design the spread component related to inventory holding cost, which makes them difficult to use in the analysis of purely order-driven markets where there is no market maker. However, the MRR framework is quite flexible and does not consider the inventory holding cost. Therefore, the MRR model and its extensions can be applied to any market, irrespective of structure. Another advantage of the MRR model is its robustness. Whenever the trade direction (i.e., buy or sell) is correctly specified, the MRR yields quite reliable estimation results. Its estimation procedure also uses the generalized method of moments (GMM) estimation technique, which is free from distributional assumptions and robust to heteroskedasticity and serial correlation of errors.

However, the original MRR version is incomplete in that the model assumes a uniform trade size and exogenously determined trade duration, whereas the majority of market microstructure research finds that the size and duration of a trade are closely related to its information content and market behavior. To overcome these shortcomings of the original version, we use an extended MRR model that implements the effects of trade duration and trade size. Because the MRR framework is highly flexible, it is easily modified. Also, because the model directly measures the change in asset prices and separately considers the effects of exogenous shocks, our extended models concentrate on the information content of trade duration without worrying about the confounding effects that might be caused by the model of Dufour and Engle (2000).

Under the advantageous MRR framework, we first propose a structural model that incorporates trade duration (the duration-dependent MRR (D-MRR) model). Equation (1) describes the changes in the fundamental value of an asset based on the unexpected portion of incoming trades and market innovation.

$$
\Delta \mu_t \equiv \mu_t - \mu_{t-1} = (\alpha_0 + \alpha_1 ln(T_t)) (x_t - E[x_t | x_{t-1}]) + \varepsilon_t
$$
\n(1)

In Equation (1) , x_t is the trade indicator variable, which takes a value of 1 (-1) if the initiating trade at time *t* is a buy (sell) trade. μ_t is the post-trade expected fundamental value of the asset. ε_t is a serially independent error term that describes the innovation in public beliefs. T_t is the duration between two consecutive trades at time *t*-1 and time *t*. $a_0 + a_1 ln(T_t)$ represents the permanent price impact of trade at

time *t* (i.e., the t^h trade). For this permanent price impact of the t^h trade, α_0 is the portion that is independent of the duration, and $\alpha_1 ln(T_t)$ is the portion that is directly dependent on the duration. α_1 captures the information content of the duration between the trades. The value of the conditional expectation $E[x_t|x_{t-1}]$ is equal to ρx_{t-1} , where ρ is the serial correlation of the trade indicator variable.

Equation (2) explains that the transaction price, P_t , is determined by the post-trade fundamental asset value, the temporary price effect component of the incoming trade, and the residual.

$$
P_t = \mu_t + (\beta_0 + \beta_1 ln(T_t))x_t + \xi_t \tag{2}
$$

In Equation (2), $\beta_0 + \beta_1 ln(T_t)$ represents the size of the temporary price effect component of the trade at time *t*, which is independent from the change in the fundamental value. If a trade is not made by an informed trader or if the information quality of the trade is low, the changed level of the asset price incurred by the trade will not be permanent. The price will soon return to the fundamental asset value. For this temporary price effect of the tth trade, β_0 is the portion that is independent of the duration, and $\beta_1 ln(T_t)$ is the portion that depends on the trade duration. β_1 captures the effect of the trade duration on the temporary portion. The residual *ξt* is the effect of rounding errors from price discreteness and discontinuity of the quoting unit.

Combining Equations (1) and (2) yields the following equation, which is used for the GMM estimation. Equation (3) shows how the intraday asset prices are formulated.

$$
\Delta P_t \equiv P_t - P_{t-1} = (\alpha_0 + \beta_0)x_t - (\rho \alpha_0 + \beta_0)x_{t-1} + (\alpha_1 + \beta_1)x_t \ln(T_t) - \beta_1 x_{t-1} \ln(T_{t-1}) - \rho \alpha_1 x_{t-1} \ln(T_t) + v_t
$$
, where $v_t = \varepsilon_t + \xi_t - \xi_{t-1}$ (3)

Combining Equation (3) and the information on the serial correlation of the trade-indicator variables, we set up the following moment equations for GMM estimation. Equation (4) shows the moment equations used to simultaneously estimate five model parameters: α_0 , β_0 , α_1 , β_1 , and ρ . In Equation (4), *υ0* is a constant drift term. The first equation shows the information on the serial correlation in the trade indicator variable. The second equation demonstrates that the constant drift term is set to the average pricing error. The last five normalizing equations are constructed from the OLS (ordinary least square) residuals implied by Equation (3).

$$
\begin{bmatrix}\nx_t(x_t - \rho x_{t-1}) \\
v_t - v_0 \\
x_t(v_t - v_0) \\
x_{t-1}(v_t - v_0) \\
x_t \ln T_t(v_t - v_0) \\
x_{t-1} \ln T_{t-1}(v_t - v_0) \\
x_{t-1} \ln T_t(v_t - v_0)\n\end{bmatrix} = 0
$$
\n(4)

Though the main concern of this study is trade duration, we know that market liquidity is generally described both as the trading frequency, which is the number of trades within a fixed time or the average inter-transaction time between consecutive trades, and as the trading volume, which is the size of each trade. An investor has two options when trading a large amount: make a single or a few large trades, or make a series of numerous small trades by fragmenting the trades. So, to examine the issues related to trade duration, we have to control the trade size, another dimension of the liquidity. The following equations explain how the effect of trade size is incorporated into the MRR framework.

$$
\mu_t = \mu_{t-1} + (\alpha_0 + \alpha_1 ln(T_t) + \alpha_2 \sqrt{V_t}) (x_t - E[x_t | x_{t-1}]) + \varepsilon_t
$$
\n(5)

In Equation (5), V_t is the size of an incoming trade at time *t* (i.e., the t^h trade). $\alpha_0 + \alpha_1 ln(T_t) + \alpha_2 \sqrt{V_t}$ represents the size of the permanent price impact of a trade at time *t*. For the permanent price impact of the t^h trade, α_0 is the portion that is independent of the trade duration and trade size, $\alpha_1 ln(T_t)$ is the portion that depends on the duration, and $\alpha_2 \sqrt{V_t}$ is the portion that depends on the size. That is, α_1 and a_2 capture the information contents of the duration between trades and trade size, respectively.

Equation (6) also indicates that the temporary price effect components are comprised of three parts: the duration- and size-independent portion (β_0) , the duration-dependent portion $(\beta_1 ln(T_i))$, and the size-dependent portion $(\beta_2 \sqrt{V_t})$.

$$
P_t = \mu_t + (\beta_0 + \beta_1 ln(T_t) + \beta_2 \sqrt{V_t})x_t + \xi_t
$$
\n
$$
\tag{6}
$$

By combining Equations (5) and (6), a more complicated estimation equation is derived in Equation (7), as follows.

$$
\Delta P_t = (\alpha_0 + \beta_0)x_t - (\rho \alpha_0 + \beta_0)x_{t-1} + (\alpha_1 + \beta_1)x_t \ln(T_t) - \beta_1 x_{t-1} \ln(T_{t-1}) - \rho \alpha_1 x_{t-1} \ln(T_t) + (\alpha_2 + \beta_2)x_t \sqrt{V_t - \beta_2 x_{t-1}} \sqrt{V_{t-1} - \rho \alpha_2 x_{t-1}}
$$

(7)

We call this further extended MRR model a duration- and size-dependent MRR (DS-MRR) model. The GMM estimation equations of the DS-MRR model are given in Equation (8).

$$
\begin{bmatrix}\n x_t(x_t - \rho x_{t-1}) \\
 v_t - v_0 \\
 x_t(v_t - v_0) \\
 x_{t-1}(v_t - v_0) \\
 x_t \ln T_t(v_t - v_0) \\
 x_{t-1} \ln T_{t-1}(v_t - v_0) \\
 x_{t-1} \ln T_t(v_t - v_0) \\
 x_t \sqrt{V_t}(v_t - v_0) \\
 x_{t-1} \sqrt{V_{t-1}}(v_t - v_0) \\
 x_{t-1} \sqrt{V_{t-1}}(v_t - v_0) \\
 x_{t-1} \sqrt{V_t}(v_t - v_0)\n\end{bmatrix} (8)
$$

4. Empirical Findings

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4.1 The information effects of trade duration

This section presents our empirical findings, which support the significant information content of trade duration and its distinct role according to option moneyness. Table 3 shows the estimation results for the D-MRR model by option type (call or put). The table reports the estimated model parameters $(\alpha_0, \alpha_1, \beta_0, \beta_1)$ and their significance (using *t*-statistics) and presents the spread component measures $(PI = \alpha_0 + \alpha_1 \overline{lnT}$, $TE = \beta_0 + \beta_1 \overline{lnT}$, $IS = 2(PI + TE)$, $\gamma = PI/(PI + TE)$) and their relative values to transaction prices.10 Except in the case of deep ITM options, all model parameter estimates are statistically significant. For example, in the case of call options for which moneyness ranges from 0.96 to 0.98 (see column "*M3*" in Table 3), the average estimates of α_0 , α_1 , β_0 , and β_1 are 0.00055, -0.00011, 0.00334, and 0.00014 points, respectively. On average, the permanent price impact component (*PI*) equals 0.072% of the options price, and the temporary price effect component (*TE*) is equal to 0.658% of the options price. The model implied spread (*IS*) is 1.460% of the options price on average, and *γ* values indicate that about 10.0% of the implied spread is explained by informed trading.

[Table 3 around here]

In Table 3, our main interest is parameter α_1 , which captures the information content of trade duration. While other parameters, α_0 , β_0 , and β_1 , are often insignificant especially in ITM options, α_1 estimates are highly significant in every option moneyness category. This information indicates that incorporating the trade duration into the model is quite important and is an effective way to estimate the permanent price impacts and capture the information content of trades. The a_1 estimates imply that the informational role of trade duration varies with option moneyness, which characterizes options trading. The size of α_1 estimates monotonically increases with option moneyness. While α_1 estimates

¹⁰ The ρ estimates are not reported because they do not have important economic implications. \overline{lnT} denotes the average value of the trade duration in each futures series.

are always negative in OTM options, which are quite liquid and speculative (see columns "*M1*," "*M2*," and "*M3*" in Table 3), they are significantly positive in ITM options, which are less liquid (see columns " $M5$ " and " $M6$ " in Table 3). The signs of α_1 estimates indicate that the hypothesis "fast" trading means informed trading" is supported only in the case of OTM options trading, whereas the opposite is true in the case of ITM options trading. Considering the liquidity patterns across option moneyness, which are detected in Table 2 (i.e., OTMs are more liquid than ITMs), we can attribute the information content of trade duration to options market liquidity. This result is also noteworthy because the OTM options market has been known to be dominated by noisy traders though it is quite liquid and speculative. For example, Ahn, Kang, and Ryu (2008, 2010) claim that the OTM options market is dominated by individual investors who are regarded as uninformed and noisy, whereas the relative participation rate of institutional investors who are sophisticated and more informed monotonically increases with ITM options. However, our results reveal that higher trading intensity in the OTM options market is not necessarily noisy, and that the short trade duration reveals more concentrated informed trading. Since the OTM options market is highly competitive, informed investors might be required to trade fast to fully exploit their information superiority. This explanation is quite plausible considering that the information superiority is caused by fast information processing skills and fast trading ability based on market-wide and public information in the KOSPI 200 options market. In this situation, it is natural that fast trading indicates informed trading.

The positive signs of α_1 estimates in ITM options indicate that slower trading represents informed trading. One possible interpretation is that prudent trading is more informed, while hasty trading is less informed in the ITM options market where nominal prices are quite high, sophisticated and prudent investors dominate, and speculative investors are less prevalent. In addition, the ITM options market is less liquid compared to the OTM options market. Fast trading in the non-liquid market incurs higher transaction costs and is likely to be noisy, hasty, and aggressive, uninformed trading.

In contrast with α_1 estimates, β_1 estimates, which capture the duration dependency in the temporary price effect component, are significantly positive for all option moneyness categories. This finding is related to the fact that the increased inter-transaction time between trades implies a decrease in liquidity. In a relatively non-liquid market situation, the transaction costs increase, and thus the temporary price effect component and the options spread should increase. The overall patterns of *PI*, *TE*, *IS*, and *γ* across option moneyness are similar to those found in previous studies (Ahn, Kang, and Ryu, 2008, 2010). The *PI* and *γ* values show that the relative portion of informed trading increases with option moneyness, and a higher portion of the option spread is explained by informed trading as options move deeper into the money.

Although the results reported in Table 3 and the related discussions are clear, significant, and interesting, the effect of trade size should be considered when examining the role of trade duration because informed investors can coordinate large trades by adjusting trade frequency and size, two

elements of liquidity. The DV-MRR model can accommodate this need. Table 4 presents the estimation results of the DV-MRR model by option moneyness for call and put options, respectively. All parameter estimates $(a_0, a_1, a_2, \beta_0, \beta_1, \beta_2)$ shown in Table 4 are statistically significant. The table also reports the spread component measures of the DV-MRR model $(PI = \alpha_0 + \alpha_1 \overline{lnT} + \alpha_2 \sqrt{\overline{V}})$, $TE = \beta_0 + \beta_1 \overline{lnT} + \beta_2 \sqrt{V}$, $IS = 2(PI + TE)$, $\gamma = PI/(PI + TE)$) in terms of their relative values to options prices.¹¹

[Table 4 around here]

Table 4 shows that α_1 estimates, which capture the information effects of trade duration, show the same patterns across option moneyness as those found in Table 3. This finding indicates that the informational roles of trade duration remain the same after controlling for size. a_2 estimates, which capture the information effects of trade size, are also significant and have positive values in all option moneyness categories. This finding indicates that large trades are more informed than smaller trades, and that large trades have greater permanent impacts on options prices and spreads. The negative values of β_2 estimates support the economy of scale. As the trade size increases, the order processing cost per trade decreases and the temporary price effect component per trade also decreases.¹²

The high *t*-values of the α_2 and β_2 estimates also justify incorporating trade size into the structural model. However, the results in Table 4 are not qualitatively different from those in Table 3, as supported by the D-MRR model. Therefore, for the analyses in the next section, we continue to employ the D-MRR model for simplicity.¹³

4.2 Intraday analysis

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In previous sections, we analyze the information content of trade duration by measuring the effects of time between trades on intraday asset price formation. In this section, we consider that many microstructure studies have reported specific intraday patterns in microstructure variables. For example, the size and components of bid-ask spreads, the degree of informed trading, the proxies for liquidity, and the price impacts usually show *L*-shaped or *U*-shaped patterns, depending on the behavior of the market. Consistent with other financial markets, previous studies of the KOSPI 200 options market also report that microstructure variables exhibit systematic intraday patterns.

¹¹ \overline{V} denotes the average trade size in each futures series.

 12 Market microstructure theories explain that the permanent price impact component arises from information asymmetry among investors or the information embedded in the incoming trades. The temporary price effect component consists of the inventory holding costs and other trading costs such as the order-processing cost. In an order-driven market, the order processing cost is the most important part of the temporary price effect component.

 13 The results of the DV-MRR and D-MRR models provide the same indications; these will be provided upon request to the authors.

Considering this previous finding, we re-examine the information role of the trade duration based on the detailed intraday intervals to check for robustness.

Table 5 presents the estimation results of the D-MRR model with respect to the 17 intraday intervals of all continuous trading sessions (from 9:00 to 15:05).¹⁴ We divide the trading sessions into 30-minute intervals, except that the beginning and ending intervals are set shorter because previous microstructure studies report that informed trading and/or liquidity are concentrated in these intervals (Admati and Pfleiderer, 1988; Ahn, Cai, Hamao, and Ho, 2002; Angelidis and Benos, 2009; Huang, 2004; Huang and Stoll, 1997; Madhavan, Richardson, and Roomans, 1997; Ryu 2011).

[Table 5 around here]

As Table 5 shows, most of the α_1 and β_1 estimates are highly significant and show the consistent patterns that are found in Tables 3 and 4. These confirming results indicate that our findings about the informational role of trade duration hold when considering the intraday intervals. Table 5 shows additional interesting findings. First, the liquidity, indicated by the number of trades per minute, the number of contracts per minute, and the reciprocal of the trade duration, shows clear U-shaped intraday patterns in all moneyness categories.¹⁵ This finding indicates that the liquidity is more abundant at the beginning and end periods of each trading day than at mid-day, which is consistent with the findings of Admati and Pfleiderer (1988). Second, the permanent price impact component and the *γ*, which are important estimates related to the degree of informed trading, tend to increase around the end periods of each day and sharply increase after 14:50, which is the time when the continuous trading session of the KOSP 200 stock market closes. This result is in slight contrast with Ryu (2011), who reports that informed trading in the KOSPI 200 futures market is less concentrated after 14:50. We attribute this result to the traits of KOSPI 200 options trading. In the case of index options trading, the index futures are regarded as a liquid underlying asset. In other words, in the options market, simultaneous intraday trading, program trading, and arbitrage trading can be active as long as the intraday futures transactions are possible. Unlike the stock market, the end of the continuous trading session of the KOSPI 200 futures market is the same as that of the KOSPI 200 options market, 15:05. This end time encourages informed traders who want to implement strategic intraday trading to actively participate until 15:05. Another possibility is that informed investors are reluctant to hold overnight positions in the KOSPI 200 options market. If they are reluctant, the informed investors try to close their positions when the market closes. As a result, the concentration of informed trading at the end intervals becomes relatively high. Third, though we cannot find systematic

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 14 For the intraday analysis, we exclude the trading dates on which the transaction begins at 10:00 or when the options contracts mature.

¹⁵ To fairly measure the liquidity in each interval, we calculate the per-minute values by dividing the number of trades (contracts) by the length of each interval.

intraday patterns for the α_1 estimates in DOTM options, the α_1 estimates tend to increase with time in other options (see columns "*M3*," "*M4*," "*M5*," and "*M6*"). Considering that this kind of intraday pattern is also observed for options market liquidity, this result supports the possible association between the information content of trade duration and liquidity, which was explained in a previous section.

4.3 Informativeness of trade duration and options market variables

The previous section reports that the magnitudes of α_1 and β_1 estimates exhibit some intraday patterns, which might indicate that the information content of trade duration is related to other microstructure variables that show systematic intraday patterns. To investigate this possible association, we carry out the following regression analysis.

$$
I_i = Const+Money_i+ln(\overline{T})_i+PI_i+\sqrt{\overline{V}}_i+TTM_i+Volatility_i+Intra-Dum_i+\varepsilon_i
$$
\n(9)

In Equation (9), *i* denotes the *i*-th one-hour-long trading interval of each trading day in the pooling sample. There are 4,708 intervals in the call options sample and 6,209 intervals in the put options sample. In each interval, the D-MRR model is estimated, and options market variables such as moneyness, trade duration, price impact, trade size, time to maturity, and volatility are calculated. In the above regression equation, the dependent variable *I* is defined as an information measure, which represents the size of the information content of trade duration and is expressed as $a_0+a_1lnT\big|_{T=90t\hbar}^{T=10t\hbar}$ percentile. The information measure is calculated based on the difference between the 10th and 90th percentiles of trade duration in each interval. *ε* denotes an error term, *Const* is a constant, \overline{T} is the average trade duration, \overline{V} is the average trade volume, *TTM* denotes the time to maturity, and *Intra-Dum* denotes a dummy variable that indicates the intraday interval of each trading day. *PI* is the average permanent price impact component, which equals $\alpha_0 + \alpha_1 ln(\overline{T})$. *Volatility* represents the realized volatility that is calculated using five-minute log returns.

Table 6 shows the regression results for call options and put options, respectively. The table reports that all coefficients of explanatory variables are significantly estimated. We can interpret the implication of the variables on the information content of trade duration based on their signs. The negative signs of *Money* mean that the information content of trade duration is greater in OTM options than in ITM options. The positive signs of $ln(T)$ indicate that, if other options market trading activities are controlled, the informational role of trade duration becomes more significant and important as trading becomes slower. The negative sign of $\sqrt{\bar{V}}$ is also consistent with the implication of the signs of $ln(\overline{T})$. These results imply that there remains little room for trade duration to provide additional explanation when higher trading activities (i.e., fast trading and large trades) dominate the market.

[Table 6 around here]

Table 6 reports that the coefficients of the *PI* variable are positive and highly significant. This result indicates that the informational role of trade duration becomes more significant when informed trading is more concentrated. The positive signs of *Volatility* indicate that the information content of trade duration is greater when the market is more volatile. The signs of *TTM* are also positive, which indicates that the additional information role of trade duration is diminished as the maturity date approaches. This finding is plausible in that, as opposed to information-based trading, other trading motives such as unwinding and closing positions govern options trading near the maturity dates.

5. Conclusions

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We examine the informational role of trade duration using the high-quality intraday dataset of KOSPI 200 options, which are the most actively traded and leading index derivatives in the world. Developing a structural market microstructure model which analyzes the real-time transaction data and incorporates the inter-transaction time between options trades, we find the following empirical results in the KOSPI 200 options market. Our empirical results indicate that the informational role of trade duration depends on option moneyness. We find that fast trading represents informed trading in the OTM options market, whereas slower trading is related to informed trading in the relatively less speculative and less liquid ITM options market. This informational role of trade duration becomes more important when informed trading is more concentrated, liquidity is relatively lower, there remain many days to maturity date, and the market is more volatile.

Our results provide trading implications for market practitioners and regulators. Considering that the trade duration conveys different information content across option moneyness, options investors have to make a judgment about the inter-transaction time. If fast (slower) trading governs in the OTM (ITM) options market, they may postpone submitting orders to avoid transacting with better informed traders and suffering losses. Our findings may guide regulators who often interrupt the market due to concerns about excessive trading and the severe money losses of uninformed domestic individual investors.¹⁶ Recently, the Korean government and the KRX have attempted to regulate Korea's index derivatives market due to concerns about the irrational exuberance of individual investors. The current regulation system totally relies on the price movement of the derivatives asset, on which the

¹⁶ It is known that the majority of individual investors are net losers in Korea's derivatives market (Ahn, Kang, and Ryu, 2008, 2010; Kang and Ryu, 2010; Kim and Ryu, 2012; Ryu, 2012*a*, 2012*b*, forthcoming-b, forthcoming-c,). To protect them from predatory informed investors (mainly consisting of foreign professional investors), the government and the KRX are working to design regulations and guidelines.

regulation authorities base their determinations of whether the market is overheated. However, this study demonstrates that trade duration should be considered as a useful trading indicator.

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Table 1. Trading volume by investor type

Note: This table shows the trading volume of KOSPI 200 options by investor type (domestic individuals, domestic institutions, and foreigners) for the sample period from January 2003 to June 2005. "Total" indicates the total trading volume of the index options. "Call options" and "Put options" indicate the trading volumes of call and put options, respectively. "*In contracts*" presents the number of contracts, and "*%*" indicates the percentage values. The source is the website of the Korea Exchange (www.krx.or.kr).

Table 2: Summary statistics of the options data

Note: This table presents the number of trades ("*No. of trades*"), the number of contracts ("*No. of contracts*"), the contract-weighted average transaction price ("*Price*"), and the average duration between two consecutive trades ("*Duration*") for each moneyness category of each options series. The prices are measured in points, and the durations are measured in seconds. "*M1,*" "*M2,*" "*M3,*" "*M4,*" "*M5,*" and "*M6*" denote options for which moneyness values are 0.88~0.93, 0.93~0.96, 0.96~0.98, 0.98~1.0, 1.0~1.04, and 1.04~1.12, respectively. We define the moneyness metric of call (put) options as *S/K* (*K/S*), where *S* is the stock price and *K* is the strike price. The last rows ("*Avg.*") provide the average values. Panel A shows the results for call options, and Panel B shows the results for put options.

Panel A. Call options

Panel B. Put options

Table 3. Estimation results of the duration-dependent (D-MRR) model

Note: Estimating the D-MRR model for each moneyness category of each options series, this table presents the permanent-impact-related estimates (the duration-independent parameter α_0 , the duration-related parameter α_1 , and the permanent price impact component $PI=\alpha_0+\alpha_1\overline{lnT}$), the temporary-effectrelated estimates (the duration-independent parameter *β*₀, the duration-related parameter *β*₁, and the temporary price effect component $TE=β_0+β_1\overline{nT}$), the model-implied spread ($IS=2(PI+TE)$), and the proportion of the permanent impact component in *IS* ($\gamma=PI(PI+TE)$). \overline{lnT} denotes the average log time between two consecutive trades. "*M1,*" "*M2,*" "*M3,*" "*M4,*" "*M5,*" and "*M6*" denote options for which moneyness values are 0.88~0.93, 0.93~0.96, 0.96~0.98, 0.98~1.0, 1.0~1.04, and 1.04~1.12, respectively. We define the moneyness metric of call (put) options as *S*/*K* (*K*/*S*), where *S* is the stock price and *K* is the strike price. All estimated coefficients are measured in points, and *PI*, *TE*, and *IS* are measured in percentage of options prices. *γ* values are presented in percentage. *t*-statistics are in parentheses. The last row ("*Avg.*") provides the average values. Panel A shows the results for call options, and Panel B shows the results for put options.

Panel A. Call options

Panel B. Put options

Table 4. Estimation results of the duration- and volume-dependent (DV-MRR) model

Note: Estimating the DV-MRR model for each moneyness category of each options series, this table presents the permanent-impact-related estimates (the duration- and volume-independent parameter α_0 , the duration-related parameter α_1 , the volume-related parameter α_2 , and the permanent price impact component $PI = \alpha_0 + \alpha_1 \overline{lnT} + \alpha_2 \sqrt{V}$), the temporary-effect-related estimates (the duration- and volumeindependent parameter β_0 , the duration-related parameter β_1 , and the volume-related parameter β_2 , and the temporary price effect component $TE = \beta_0 + \beta_1 \overline{lnT} + \beta_2 \sqrt{V}$, the model-implied spread (*IS*=2(*PI*+*TE*)), and the proportion of the permanent impact components in *IS* ($\gamma = PI(PI+TE)$). \overline{lnT} denotes the average log time between two consecutive trades. "*M1,*" "*M2,*" "*M3,*" "*M4,*" "*M5,*" and "*M6*" denote options for which moneyness values are 0.88~0.93, 0.93~0.96, 0.96~0.98, 0.98~1.0, 1.0~1.04, and 1.04~1.12, respectively. We define the moneyness metric of call (put) options as *S*/*K* (*K*/*S*), where *S* is the stock price and *K* is the strike price. All estimated coefficients are measured in points, and *PI*, *TE*, and *IS* are measured in percentage of options prices. *γ* values are presented in percentage. *t*-statistics are in parentheses. The last row ("*Avg.*") provides the average values. Panel A shows the results for call options, and Panel B shows the results for put options.

| | α ⁰ (Coefficient.x100) | | | | | | | | | | | |
|----------------|---|--------|----------------|--------|----------|--------|-------|--------|----------|--------|----------|-------|
| Series | M1 | | M ₂ | | M3 | | M4 | | M5 | | M6 | |
| | 0.003 | (3.2) | 0.014 | (14.1) | 0.008 | (7.0) | 0.003 | (1.8) | -0.029 | (6.7) | -0.518 | (7.6) |
| 2 | -0.002 | (2.2) | 0.001 | (1.0) | 0.002 | (2.5) | 0.014 | (9.3) | -0.016 | (5.2) | -0.437 | (9.5) |
| 3 | -0.003 | (2.7) | -0.009 | (11.8) | -0.009 | (14.0) | 0.018 | (18.3) | -0.024 | (11.8) | -0.532 | (7.1) |
| $\overline{4}$ | -0.006 | (6.4) | -0.004 | (6.4) | 0.000 | (0.6) | 0.010 | (12.1) | -0.009 | (3.2) | -0.462 | (6.0) |
| 5 | -0.005 | (4.2) | -0.006 | (8.3) | 0.003 | (3.8) | 0.008 | (11.8) | -0.011 | (4.5) | -0.810 | (8.0) |
| 6 | 0.014 | (18.2) | 0.020 | (26.1) | 0.013 | (16.5) | 0.038 | (27.7) | 0.042 | (8.7) | -0.635 | (5.1) |
| 7 | -0.008 | (7.9) | -0.003 | (4.7) | 0.014 | (19.1) | 0.019 | (18.7) | 0.007 | (2.8) | -0.668 | (5.9) |
| 8 | -0.013 | (9.8) | -0.010 | (15.2) | -0.001 | (1.4) | 0.016 | (20.2) | 0.010 | (3.6) | -0.627 | (6.8) |
| 9 | -0.010 | (6.9) | -0.007 | (10.6) | 0.006 | (8.5) | 0.009 | (13.1) | 0.001 | (0.5) | -0.542 | (4.2) |
| 10 | -0.008 | (5.6) | -0.015 | (20.0) | -0.002 | (3.7) | 0.016 | (23.0) | 0.007 | (3.5) | -0.030 | (0.3) |
| Avg. | -0.004 | (2.4) | -0.002 | (3.6) | 0.003 | (3.8) | 0.015 | (15.6) | -0.002 | (1.2) | -0.526 | (6.1) |

Panel A. Call options

Panel B. Put options

Table 5. Intraday analysis

Note: This table shows the number of trades ("*No. of trades*") and the number of contracts ("*No. of contracts*") for 17 intraday intervals. Estimating the D-MRR model for each intraday interval, this table also reports the permanent-impact-related estimates (the duration-independent parameter α_0 , the durationrelated parameter α_1 , and the permanent price impact component $PI = \alpha_0 + \alpha_1 \overline{lnT}$, the temporary-effect-related estimates (the duration-independent parameter $β_0$, the duration-related parameter $β_1$, and the temporary price effect component $TE=β_0+β_1\overline{lnT}$, and the proportion of the permanent impact component in *IS* (γ =*PI*/(*PI*+*TE*)). $\overline{l}n\overline{T}$ denotes the average log time between two consecutive trades in a futures series. The two trading volume measures are presented both in raw values ("*raw*") and in per-minute values ("*per min.*"). All estimates are presented in points, and *PI*, *TE*, and *IS* are measured in percentage of options prices. *t*-statistics are shown in parentheses. Panel A shows the results for call options, and Panel B shows the results for put options.

Panel A. Call options

Panel B. Put options

Table 6. Regression analysis

Note: This table shows the estimation results of regression analysis, which demonstrate the relationship between the information content of trade duration and other trading- and options-related variables. The estimated coefficients of the regression and their corresponding *t*-statistics are reported. To construct the sample data for the regression analysis, the D-MRR model is estimated, and the trading- and options-related variables are measured per each one-hour-long trading interval of each trading day.

The dependent variable is the information measure of trade duration $(|I_T = \alpha_0 + \alpha_1 lnT|_{T=90t}^{T=10t}$ pct. Explanatory variables are average option moneyness ("*Moneyness*"), average trade duration $(ln(\overline{T}))$, average permanent price impact component (" $PI = \alpha_0 + \alpha_1 ln(T)$ "), square root of the average trade volume (" \sqrt{V} "), time to maturity ("*TTM*"), high-low volatility of each interval ("*Volatility*"), and the intraday dummy variable that indicates the intraday interval of each trading day ("*Intra-Dum*"). "*Obs.*" denotes the number of sample observations, and " Adj . R^{2} " denotes the adjusted R -squared value.

