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The difference in the intraday return-volume relationships of spot and futures: a quantile regression approach

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Abstract
This study illuminates the difference in the intraday return-volume relationships of spot and index futures. The quantile regression analyses show that the widening effect of the spot trading volume on the distribution of spot returns disappears within a short period of time, whereas that of the futures trading volume on the distribution of spot returns remains over the relatively long term. The short-term effect of the spot volume and the long-term effect of the futures volume are consistent for trading volume shocks. The findings suggest that the spot volume is primarily induced by the demand for hedging or differences of opinion, whereas the futures volume contains information about price movements.

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Keywords Index futures; information channel; intraday information content; option-implied volatility; quantile regression; return-volume relationship

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1 Introduction

For decades, the relationship between asset prices and trading volumes has attracted the interest of academics and practitioners, who have developed many theoretical models and conducted various empirical analyses to understand this relationship. Building this understanding is important because trading activity patterns are useful for studying financial market efficiency and the public and private information revelation processes in securities markets. Theoretical models related to the price-volume relationship include the sequential information model (Copeland, 1976; Jennings and Barry, 1983), the mixture of distributions model (Clark, 1973; Tauchen and Pitts, 1983), the information asymmetry model (Kyle, 1985; He and Wang, 1995), and the heterogeneous opinion model (Harris and Raviv, 1993; Kandel and Pearson, 1995). Relevant empirical studies investigate such topics as the contemporaneous return-volume relationship (Karpoff, 1987) and the return variance-volume relationship (Epps and Epps, 1976; Lee and Rui, 2002; Gebka and Wohar, 2013). In addition, recent studies examine dynamic aspects of the return-volume relationship (Chen et al., 2001; Chuang et al., 2009; Gebka and Wohar, 2013) and its sequential and intraday relationships (Ryu, 2015; Webb et al., 2016).

The previous studies on this topic collectively conduct extensive theoretical and empirical analyses (Lin, 2013), but each of them has some individual limitations. First, although many studies examine Granger causality for the conditional mean and/or variance, this property need not hold for other aspects of the model, including the probability distribution. For instance, Diks and Panchenko (2005) point out that the test of Hiemstra and Jones (1994) may not accurately evaluate Granger non-causality. Thus, analyses must directly examine the relationship between the trading volume and the distribution of returns. Second, when a derivatives market exists, the market should be considered as alternative means for trading the underlying assets (Park et al., 2019). Specifically, because the market frictions related to shorting assets may cause a negative price-volume relationship, the opportunity to take short positions in the derivatives market can affect the price-volume relationship as well. As Kocagil and Shachmurove (1998) mention, if the price-volume relationship in the spot market is affected by market frictions regarding short sales, then studies must account for the derivatives market, in which taking short positions is less costly (Ryu, 2013; Sim et al., 2016), to more clearly and thoroughly analyze the effect of short sale restrictions on the price-volume relationship. In addition, the fraction of informed investors in the derivatives market may differ from that in the spot market, suggesting that the association between trading volumes and the distribution of returns should also differ across the two markets. Finally, although many related studies examine the relationship between the realized return variance and trading activity (Foucault et al., 2011; Valenzuela et al., 2015) the relationship between the option-implied volatility and trading volumes has drawn less attention. The option-implied volatility reflects ex-ante expectations of future price fluctuations and is reported to provide information for return forecasting (Giot, 2005; Jiang and Tian, 2005; Han et al., 2012; Song, Ryu, and Webb, 2016, 2018). Thus, if the trading volume affects the distribution of returns, it should consistently and significantly affect the option-implied volatility as well. Further, because investors in the options market can choose from various options with different strike prices suitable for their trading objectives and intentions, the implied volatilities of options at different moneyness levels also reflect different intentions (Kim and Ryu, 2015; Chun et al., 2019; Lee and Ryu, 2019). Thus, examining the relationships between trading volumes and various implied volatilities (i.e., the implied volatilities constructed from options with different strike prices and maturities) can aid in understanding the impact of trading volumes on the distribution of returns.

This study investigates the intraday relationship between asset returns and trading volumes in the KOSPI 200 spot and index futures markets, which are liquid and popular financial markets, to fill the gaps mentioned above.[1] First, following Chuang et al. (2009), we employ Koenker and Bassett's (1978) quantile regression method (QRM) to address the issue regarding the Granger non-causality test described above. Second, we compare the effects of spot and futures trading volumes on returns to account for the existence of the derivatives market. Third, we examine whether the intraday relationships between the spot and futures trading volumes and the option-implied volatility are consistent with the return-volume relationships revealed in the QRM analyses. Our empirical results suggest that the effects of spot and futures trading volumes on spot index returns differ in duration. We find that spot and futures trading volumes both widen the distribution of spot returns but that this effect reverses within a very short period of time in the case of spot trading volumes. When we consider innovations in trading volumes to control for autocorrelation, we again find that trading volume shocks have strong expansive effects on the distributions of returns in both the spot and futures markets. Similarly, we again observe a reversal in the relationship between spot returns and trading volume shocks in the spot market, whereas the effect persists over the long term in the futures market. In addition, only the futures trading volume is significantly and positively associated with the volume-weighted implied volatility in the options market, although we do find that an increase in the spot trading volume leads to an increase in the implied volatility of at-the-money (ATM) options, which have abundant liquidity and the highest spot volatility sensitivity and vega values among options of different moneyness levels (Ni et al., 2008; Rourke, 2014; Ryu and Yang, 2019). In contrast, the futures trading volume is strongly related to the implied volatility of out-of-the-money (OTM) options, which provide substantial leverage and speculative trading opportunities (Ryu and Yang, 2018; Yang, Kutan, and Ryu, 2018).

Our empirical results provide meaningful implications and are in line with those of previous studies on the return-volume relationship. First, we observe the well-known positive relationship between absolute returns and trading volumes in the context of intraday spot and futures trading. However, the relationships in the two markets differ, as we observe a short-term relationship for spots and a relatively long-term relationship for futures. This result implies that active trading in the stock market is more attributable to disagreements regarding asset prices than to information asymmetry among market participants. These disagreements extend the distribution of returns, but the distribution reverts when the disagreements are resolved. On the contrary, large futures trading volumes precede large spot-price fluctuations in the long run, which implies that investors with information advantage induce increases in futures volumes. This conclusion is supported by the relationships between trading volumes and option-implied volatilities for both futures and options. Investors trading ATM options, which can be traded

[1] We analyze the KOSPI 200 futures market, which is one of the most representative derivatives markets in the Asia-Pacific region. We also consider the implied volatility constructed from transactions in the KOSPI 200 options market, one of the most highly liquid and speculative options markets worldwide. Section 4 briefly explains our rationale for analyzing the futures and options markets and introduces the characteristics of KOSPI 200 futures and options trading.

quickly, are much more sensitive to spot trading volumes, whereas OTM options, which provide the advantages of speculative and leverage trading, are more closely related to futures trading volumes.

The remainder of this paper proceeds as follows. Section 2 reviews the literature related to the price-volume relationship. Section 3 summarizes the QRM used in this study. Section 4 briefly introduces the KOSPI 200 futures and options markets and explains our rationale for focusing on these derivatives markets. Section 5 describes the sample data, and Section 6 reports the empirical results. Finally, Section 7 concludes.

2 Literature review

Several classical analyses and theoretical models try to explain the relationship between asset prices (or returns) and trading volumes. First, according to the sequential information model, market participants receive information about the value of an asset sequentially and, thus, some investors receive an information advantage. These investors then trade the asset with less informed investors. Copeland (1976) shows that this information diffusion process generates several temporary equilibria. Jennings et al. (1981) extend this model by assuming that risk-averse investors try to maximize their expected utility of wealth. In addition, Jennings and Barry (1983) further extend it by incorporating speculation by traders in advantageous positions during the information diffusion process.

Second, the mixture of distributions model relates trading volumes to daily price fluctuations by assuming that price volatility is driven by the number of daily transactions. Clark (1973) argues that daily price variance is a random variable with a mean that is proportional to the mean daily number of transactions, which explains the positive relationship between trading volumes and price volatility. Tauchen and Pitts (1983) use a variance components framework to explain the multiple daily changes in traders' estimations of the fair price and, thus, derive the joint probability distribution of the price and trading volume. This approach has the advantage that the model only depends on a few parameters that can be easily interpreted.

Third, the information asymmetry model is a dynamic trading model in which some market participants are better informed than others (Huang and Stoll, 1997; Madhavan et al., 1997; Ryu, 2011, 2016, 2017; Chung et al., 2016). Kyle (1985) assumes that informed traders intentionally make gradual trades to avoid revealing private information too quickly and, thus, earn more profits. Furthermore, Glosten and Milgrom (1985) show that even risk-neutral market makers require positive rewards for liquidity provision in the presence of informed traders. He and Wang (1995) propose a multi-period model with information differences in which investors obtain both public and private information about the fair price of a stock and then trade based on their expected risk-adjusted gains. In this model, high trading volumes caused by exogenous information are accompanied by price volatility, whereas those caused by existing information are not.

Finally, the heterogeneous opinion model is unique as compared to other models because it assumes that a single piece of information can be interpreted differently by different investors

(Ahn et al., 2008; Ryu, 2015; Yang, Ahn, Kim, and Ryu, 2017; Seok et al., 2019). Harris and Raviv (1993) show that when investors interpret information differently, absolute returns are positively related to trading volumes, consecutive returns are negatively serially correlated, and trading volumes are positively autocorrelated. Kandel and Pearson (1995) propose a model in which agents interpret information using different likelihood functions and show that this model yields the return-volume relationship observed in the market.

A strand of the empirical literature investigates the patterns and possible underpinnings of the price-volume relationship. Gallant et al. (1992) show that trading volumes and conditional volatility are positively correlated and that high trading volumes tend to follow large price movements. In addition, they find that much of the leverage effect is explained by lagged trading volumes and that the risk-return relationship is positive when lagged volumes are incorporated in the analysis. Gervais et al. (2001) reveal that stocks with unusually high (low) daily or weekly trading volumes tend to increase (decrease) in price over the following month, and they argue that the return premium for stocks with high trading volumes is driven by enhanced visibility, which generates additional demand. Chae (2005) compares trading volumes before scheduled corporate announcements to those before unscheduled announcements to investigate investors' responses to the revelation of private information. His empirical analysis shows that trading volumes decrease before scheduled announcements but not before unscheduled announcements, implying that trading slows when traders believe that they are on the inferior side of information asymmetry. Yang, Kim, Kim, and Ryu (2018) use a structural vector autoregression model to show that demand shocks decrease stock returns, whereas supply shocks increase returns. Barber and Odean (2008) test the hypothesis that retail traders tend to, on net, buy stocks that draw news coverage, implying that attention-grabbing stocks simultaneously experience high returns and trading volumes. Their empirical analyses on news, trading volumes, and returns suggest that individual investors more aggressively buy stocks that receive more public attention. Banerjee and Kremer (2010) model the relationship between trading volumes and disagreements on the interpretation of public information and conclude that trading volumes and price volatility are positively correlated when market participants strongly but infrequently disagree on the interpretation of public information.

3 Quantile regressions of trading volumes

Investors may participate in the stock market for a wide variety of reasons. For example, if uncertainty in the price of a stock increases, and, as a result, more disagreements arise, transactions could become more frequent. Market liquidity may be another reason for active trading. Further, when transaction costs are low owing to the abundant liquidity, informed traders are more likely to exploit their information advantages. However, regardless of the scenario, both positive and negative information can increase trading volumes. Thus, the average effect of trading volumes on stock returns may be ambiguous. Instead, increasing trading volumes should tend to widen the distribution of stock returns. Previous studies have, therefore, consistently argued that trading volumes are closely associated with the volatility rather than with the level of returns, although some studies may disagree on the rationale.

Active trading may indicate a large negative return, but it can nevertheless be followed by a large positive return. Thus, if the overall market does not shift upward or downward on average, the effects of trading volumes on returns may offset, and pinpointing the precise relationship can be difficult. To thoroughly investigate the effect of trading volumes on returns, then, we should examine the relationship between trading volumes and the distribution (e.g., quantiles) of returns rather than that between trading volumes and the conditional mean of returns.

The conditional mean function of the ordinary least square (OLS) method defines the relationship between the means of the distributions of the dependent and independent variables. This method assumes that the distribution of the dependent variable is not affected by the values of the covariates, or, in other words, that the independent variables affect only the central tendency of the dependent variable's conditional distribution and not the scale or shape of the distribution. Thus, if the independent variables are expected to affect the shape of the distribution, the analysis requires a regression method that is robust to changes in the shape of probability distribution. Koenker and Bassett (1978) therefore devise the QRM as an extended version of OLS to address this issue. The QRM can be regarded as a generalization of the OLS method to a group of conditional quantile functions, and this setup eliminates estimation bias when estimating the response of a variable with a heterogeneous distribution.[2] This methodology, therefore, is effective when the relationship among variables is asymmetric or varies at the tails of the distribution and, thus, cannot be properly captured by the classical OLS method. Recent studies utilize this property of the QRM to analyze the asymmetric return-volatility relationship (Badshah, 2013; Badshah et al., 2016).

The standard OLS model can be defined as

$$\mathbf{y} = \mathbf{X}^{\mathrm{T}}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{1}$$

where $\mathbf{y}$, $\mathbf{X}$, $\boldsymbol{\beta}$, and $\boldsymbol{\varepsilon}$ are the dependent variable vector, the independent variable matrix, the coefficient matrix, and the vector of residuals, respectively. The coefficient vector $\boldsymbol{\beta}$ is normally estimated using a quadratic loss function. In other words, given observations $\{\mathbf{y}_i, \mathbf{X}_i\}_{i=1}^{n}$, the estimation is performed by minimizing the following quadratic loss function over $\boldsymbol{\beta}$:

$$\textstyle\sum_{i=1}^{n}\left(\mathbf{y}_i - \mathbf{X}_i^{\mathrm{T}}\boldsymbol{\beta}\right)^2. \tag{2}$$

The OLS method estimates the conditional expectation $\mathrm{E}[\mathbf{y}|\mathbf{X} = \boldsymbol{x}]$ by minimizing this quadratic loss function. In contrast, median regression, which is the simplest form of the QRM, estimates the conditional median of $\mathbf{y}$, given that $\mathbf{X} = \boldsymbol{x}$, by minimizing the following loss function:

$$\textstyle\sum_{i=1}^{n}\left|\mathbf{y}_i - \mathbf{X}_i^{\mathrm{T}}\boldsymbol{\beta}\right|. \tag{3}$$

[2] Koenker and Hallock (2001) show that this bias is a major drawback of the OLS method.

The QRM starts from Equation (3) by first defining the quantile loss function, ρ_q, as

$$\rho_q = \sum_{i=1}^{n}\left[q\mathrm{I}_{[0,\infty)}\left(\mathbf{y}_i - \mathbf{X}_i^{\mathrm{T}}\boldsymbol{\beta}\right)\left|\mathbf{y}_i - \mathbf{X}_i^{\mathrm{T}}\boldsymbol{\beta}\right| - (1-q)\mathrm{I}_{(-\infty,0]}\left(\mathbf{y}_i - \mathbf{X}_i^{\mathrm{T}}\boldsymbol{\beta}\right)\left|\mathbf{y}_i - \mathbf{X}_i^{\mathrm{T}}\boldsymbol{\beta}\right|\right], \tag{4}$$

where the identification function, $\mathrm{I}_A(x)$, is defined as

$$\mathrm{I}_A(x) = \begin{cases} 1, \text{if } x \in \mathrm{A}; \text{and} \\ 0, \quad \text{otherwise.} \end{cases}$$

Given the definition of ρ_q in Equation (4), we can minimize $\rho_{0.5}$ instead of minimizing Equation (3). Similarly, the QRM can be conducted for another quantile value by replacing q in ρ_q with the corresponding quantile value.

4 KOSPI 200 spot, futures, and options markets

The Korean economy has been growing consistently at a remarkable pace, and Korea's financial market is becoming a leading emerging market that influences securities markets worldwide (Ryu et al., 2017; Yang, Ryu, and Ryu, 2017). Weathering two major financial crises during the last few decades (Seo et al., 2019), the Korean economy has been growing and developing at a steady pace, ranking as the world's 12th largest economy. The representative market index of the Korea Exchange (KRX), the KOSPI 200, is a value-weighted index constructed based on the prices of the 200 listed firms with the largest market capitalizations. The KRX also has two representative index derivatives products, KOSPI 200 futures and options. The KOSPI 200 futures and options markets are highly liquid and renowned derivatives markets. The high liquidity and active investor participation in these markets are driven by low transaction costs as measured by bid-ask spreads, market depth, and taxes and other costs. Because of the low transaction costs in the KOSPI 200 futures and options markets (Lee et al., 2015; Kim et al., 2015; Song, Park, and Ryu, 2018), speculative and professional investors implement sophisticated trades and enjoy an information edge on the overall market index and economic forecasts by trading KOSPI 200 futures and options. Therefore, shocks and news in the spot index markets are instantly followed by changes in trading volumes and prices in the derivatives markets.

Compared to developed markets, the KOSPI 200 spot, futures, and options markets have interesting investor participation patterns. Whereas the dominant market players in developed financial markets are institutional investors, both individual investors, who are often driven by sentiment and biases, and domestic and foreign institutional investors, who are relatively sophisticated and often take positions based on economic circumstances, actively participate in the KOSPI 200 spot and derivatives markets. The balanced investor compositions of these markets and the resulting rapid information spillovers and linkages provide an ideal setting for addressing the research question in this study.

All of the KOSPI 200 spot, futures, and options markets open at 9:00 on each normal trading day. The spot market closes at 15:00, whereas the derivatives markets extend for 15 minutes and close at 15:15. Four contracts with different maturities are available for both futures and options on each trading day. For futures, the four maturities are the second Thursdays of the next upcoming March, June, September, and December. The four option maturities are the second Thursdays of the three consecutive near-term months and the next upcoming quarterly month (i.e., March, June, September, or December). Trading activities are concentrated on the futures and options contracts that are closest to maturity; contracts with longer maturities are rarely traded and exhibit little market liquidity.

5 Sample data

We consider one-minute observations of the KOSPI 200 spot index returns; the trading volume of the KOSPI 200 index, which reflects the aggregate trading values of individual stocks; trading volumes (in terms of value) of KOSPI 200 futures; and the implied volatilities constructed from KOSPI 200 options prices. Our dataset runs from January 3, 2005 to June 30, 2014.[3]

This study analyzes a one-minute intraday dataset to examine the intraday return-volume relationships of spot and index futures. Our motivation for analyzing high-frequency, one-minute intraday data is as follows. We consider the rapid information flow and trading in the KOSPI 200 futures and options markets in this era of high-frequency trading. Intraday trading overwhelms other lower-frequency trading conventions (Easley et al., 2012; Park and Ryu, 2019). Further, in the KOSPI 200 futures and options markets, professional investors are better informed through processing market-wide or public information faster compared to their index derivative competitors (Ahn et al., 2010; Ryu, 2016), but these investors must act on their information advantages quickly to make significant profits. Many trades and quotes occur within a minute in the index derivatives markets.

Futures volumes are measured based on the nearest-maturity contracts. Options-implied volatilities are calculated based on the volume-weighted averages of the implied volatilities of each option contract. Given previous findings that implied volatility dynamics and underlying asset returns are significantly related (Lee and Ryu, 2013) and that information contents and properties significantly vary across options of different moneyness levels (Ryu et al., 2015; Yang, Choi, and Ryu, 2017) in the Korean market, we calculate the options-implied volatilities separately for moneyness groups. The moneyness of a call (put) option is calculated as the ratio of the underlying asset price (strike price) to the strike price (underlying asset price). Options contracts are categorized as OTM if their moneyness values are less than 0.975 and as ATM if their values are between 0.975 and 1.025. For each intraday sampling interval, we calculate the

[3] We use the sum of the trading values of individual stocks to consider various stock sizes. We thank an anonymous reviewer for this suggestion.

implied volatilities separately for OTM and ATM options contacts. We only consider observations for the period between 09:00 and 14:50 each day to prevent any non-synchronous trading effects between the spot and futures markets.

This study utilizes four main variables. First, the percentage return to the KOSPI 200 spot index over each one-minute period, *r*, is employed as the spot return, the main dependent variable. Next, the natural logarithms of the KOSPI 200 spot and futures trading volumes, which are denoted as *lsv* and *lfv*, respectively, are used as the main independent variables. We also include the first difference of the implied volatility of KOSPI 200 index options, *div*, to consider the impact of trading volumes on the return volatility. We use the first difference rather than the level of the implied volatility because of its high persistence. Table 1 provides preliminary summary statistics for the main variables. The spot return is close to zero on average over the sample period, and, thus, we observe no linear time trend. Both the spot return and the change in the implied volatility (i.e., *div*), which can be interpreted as the change in the overall option price level, have extremely large kurtosis values. This result implies that intraday returns do not change substantially over such a short period of time. In addition, the trading volume of index futures is often extreme compared to that of stocks because the spot volume is composed of the trading volumes of various stocks, whereas an index futures contract is a single tradable asset.

Table 1: Summary statistics

		r	*lsv*	*lfv*	*div*
Mean		0.000	22.832	24.439	-0.007
Median		0.000	22.823	24.584	-0.008
Standard deviation		0.054	0.588	1.144	1.618
Skewness		-0.132	-0.022	-1.023	0.027
Kurtosis		25.087	0.088	2.102	15.937
Percentile	1st	-0.154	21.424	20.765	-4.682
	5th	-0.074	21.885	22.293	-2.372
	25th	-0.025	22.435	23.869	-0.653
	75th	0.025	23.230	25.197	0.639
	95th	0.075	23.805	26.012	2.358
	99th	0.150	24.180	26.549	4.671
Number of observations			818,915		

Note. This table reports summary statistics and percentiles for the spot index return, the spot trading volume (in value), the futures trading volume (in value), and the options-implied volatility. *r* is the percentage return on the KOSPI 200 index. *lsv* and *lfv* are the natural logarithms of the KOSPI 200 spot and futures volumes, respectively. *div* is the first difference of the volume-weighted implied volatility constructed from KOSPI 200 prices.

6 Empirical findings

6.1 Return-volume relationship

We conduct a set of quantile regressions to investigate the relationship between spot prices and lagged trading volumes. We first include the natural logarithms of spot and futures volumes, *lsv* and *lfv*, as separate independent variables:

$$r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lsv_{t-i} + \varepsilon_t, \quad (5)$$

$$r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lfv_{t-i} + \varepsilon_t. \quad (6)$$

Here, the dependent variable r_t is the spot index percentage return and T is the length of the entire sample period. We include $\frac{t}{T}$ and its square in the models to control for the time trend over the sample period. DOP_t is an opening session dummy variable that equals one when t is between 09:00 and 10:00 and zero otherwise. DCL_t is a closing session dummy variable that equals one when t is between 13:50 and 14:50 and zero otherwise. Although we do not specifically report them, noticeably many transactions take place one hour after opening and one hour before closing in both the spot and futures markets. Thus, the dummy variables for these sessions can control for this U-shaped intraday trading volume pattern. Following Chuang et al. (2009), who show that including the squares of lagged returns can weaken the effects of trading volumes on returns, we include the square of lagged index returns as a measure of historical volatility. Thus, we investigate the effect of trading volumes on the distribution of returns that cannot be explained by the returns themselves. r_{t-i} and r_{t-i}^2 denote the lagged spot index returns and their squared values, respectively. lsv_{t-i} and lfv_{t-i} denote the log values of lagged spot and futures trading volumes, respectively. Also, ε_t indicates the error term.

Both spot and futures trading volumes may affect the distribution of returns; therefore, we need to compare the relative sizes of their effects. To do so, we include the log ratio of the futures trading volume as an independent variable to the spot trading volume in the model. Thus, we replace the raw trading volume with the ratio, *fs*, to compare the significance of the spot and futures trading volumes:

$$r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i fs_{t-i} + \varepsilon_t, \quad (7)$$

where r_t is the spot index percentage return and fs_{t-i} is the difference between lfv_{t-i} and lsv_{t-i}.

Table 2 reports the quantile regression results for the relationship between returns and lagged trading volumes. Panels A, B, and C show the results for Equations (5), (6), and (7),

Table 2: Return-quantiles and trading-volumes relationship

Panel A. Spot trading volumes

Quantile	Lagged spot trading volumes at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0146***	0.0081***	-0.0057***
	(-7.87)	(4.37)	(-3.15)
0.05	-0.0097***	0.0034***	-0.0025***
	(-16.63)	(6.04)	(-4.67)
0.10	-0.0071***	0.0022***	-0.0019***
	(-16.74)	(5.27)	(-5.19)
0.25	-0.0037***	0.0007**	-0.0009***
	(-14.27)	(2.35)	(-3.64)
0.50	-0.0002	-0.0003	0.0001
	(-1.08)	(-1.34)	(0.52)
0.75	0.0026***	-0.0003	0.0007***
	(9.84)	(-1.14)	(2.92)
0.90	0.0056***	-0.0015***	0.0018***
	(14.12)	(-3.61)	(4.85)
0.95	0.0084***	-0.0020***	0.0018***
	(13.84)	(-3.23)	(3.04)
0.99	0.0138***	-0.0070***	0.0041**
	(9.66)	(-4.41)	(2.39)

Panel B. Futures trading volumes

Quantile	Lagged futures trading volumes at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0082***	0.0001	-0.0020***
	(-28.75)	(0.19)	(-5.45)
0.05	-0.0042***	0.0001	-0.0011***
	(-36.01)	(0.83)	(-8.79)
0.10	-0.0029***	-0.0001	-0.0006***
	(-33.31)	(-0.99)	(-7.38)
0.25	-0.0016***	-0.0001	-0.0003***
	(-26.15)	(-0.95)	(-5.64)
0.50	-0.0001***	0.0000	-0.0001
	(-3.14)	(-0.55)	(-1.26)
0.75	0.0011***	0.0000	0.0002***
	(16.39)	(0.18)	(3.53)
0.90	0.0024***	0.0000	0.0006***
	(23.67)	(0.04)	(6.03)
0.95	0.0038***	-0.0001	0.0006***
	(29.41)	(-0.75)	(4.90)
0.99	0.0074***	-0.0012***	0.0014***
	(27.26)	(-2.97)	(3.93)

Panel C. Futures/spot volume ratio

Quantile	Lagged futures/spot volume ratio at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0078***	-0.0002	-0.0012***
	(-33.79)	(-0.46)	(-3.47)
0.05	-0.0036***	0.0001	-0.0005***
	(-34.43)	(1.08)	(-3.69)
0.10	-0.0023***	0.0000	-0.0002**
	(-28.60)	(0.14)	(-2.45)
0.25	-0.0012***	0.0000	-0.0001
	(-20.18)	(0.42)	(-1.21)

Table continued

Table continued

0.50	-0.0001***	0.0000	0.0000
	(-2.46)	(0.09)	(-0.96)
0.75	0.0008***	-0.0001	0.0000
	(11.34)	(-1.36)	(0.33)
0.90	0.0018***	-0.0001	0.0001
	(20.92)	(-1.44)	(1.04)
0.95	0.0030***	-0.0003*	0.0001
	(23.95)	(-1.90)	(1.12)
0.99	0.0068***	-0.0011***	0.0009***
	(21.16)	(-2.95)	(2.64)

Note. This table shows the estimated coefficients, γ_i, on the spot trading value (Panel A), the futures trading value (Panel B), and the ratio of the futures trading value to the spot trading value (Panel C) for the following quantile regression models: Panel A: $r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lsv_{t-i} + \varepsilon_t$; Panel B: $r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lfv_{t-i} + \varepsilon_t$; Panel C: $r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i fs_{t-i} + \varepsilon_t$. *t*-values are reported in parentheses and are estimated using the Markov chain marginal bootstrap method (He and Hu, 2002). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

respectively. In Panel A, as expected, the spot trading volume has no significant effect on the median of index returns, whereas the coefficient on the spot trading volume over one-minute periods is consistently and significantly negative for return quantiles below the median. Conversely, this coefficient is estimated to be positive and significant for return quantiles above the median. This result shows that the distribution of returns widens following active trading in the spot market. In short, we confirm the positive effect of trading volumes on return volatility in intraday trading, as reported by previous studies using daily observations. Over two-minute periods, the return-volume relationship reverses. Once again, the sign of the coefficient changes after an additional minute passes. Thus, the positive effect of the spot volume on the return distribution may persist for only a short time.

As reported in Panel B of Table 2, the coefficients on futures trading volumes over a one-minute period are negative for quantiles below the median and positive for quantiles above the median, which is similar to the results for spot trading volumes. This finding indicates a positive relationship between the return volatility and futures transactions although these transactions are not directly linked to the spot index. Thus, the return-volume relationship may be at least partially due to informed trading in addition to demand pressure. However, the duration of the volume effect differs in the spot and futures markets. Increases in both spot and futures trading volumes increase the volatility of returns, but the effect of futures trading volumes does not significantly reverse in subsequent time periods, which differs from the results for spot trading volumes. In other words, the volatility of returns fluctuates in the short term after a change in the spot trading volume, whereas the distribution of returns can widen in the long term after a change in the futures trading volume. This result supports the hypothesis that investors with more private information about future market movements may try to exploit this knowledge using the leverage effect in the futures market. Several previous studies corroborate this finding that informed trading does play a significant role in futures markets (Chan, 1992; Tse, 1995; Min and Najand, 1999). Furthermore, in addition to widening the distribution, the futures trading volume significantly reduces the median of returns. If the return-volume relationship is induced by informed trading, this result indicates that, on average, informed trading based on bad news is more frequent in the futures market than that based on good news.

One possible explanation for this finding is the short sale constraint on stocks because informed traders are likely to take short futures positions as a substitute for selling stocks with large transaction costs (Figlewski and Webb, 1993). In contrast, buying stocks incurs lower transaction costs. The effect of futures volume on stock returns skewness is consistent with the study of Chang et al. (2007), which reports the greater volatility and lower skewness of stock returns when short sales are allowed.

The ratio of the futures trading volume to the spot trading volume, like the raw futures trading volume, consistently increases the return volatility after a minute has passed, as shown in Panel C of Table 2. The magnitude and significance of the estimated coefficients are almost the same as those of the futures trading volume. After three minutes, the volume ratio significantly widens the distribution of returns, especially for quantiles below the median. We find no significant effect of the volume ratio on the right side of the return distribution after three minutes, except in the case of extremely high returns (i.e., the 99th percentile), indicating that informed traders typically prefer futures trading to spot trading but that this preference is not as prominent in the case of good news about index returns. This finding again supports the notion that the short sale constraint can affect the return-volume relationship. However, the difference in the return-volume relationship for spot and futures volumes is consistent with the findings of Kocagil and Shachmurove (1998), who report bi-directional Granger causality between absolute returns and trading volumes in futures markets. The results indicate a positive relationship between the futures-spot trading volume ratio and the magnitude of the spot price movement, which means that futures volumes tend to be greater than spot volumes when prices fluctuate more heavily.

In fact, we find that both spot and futures trading volumes exhibit strong autocorrelation, as their one-lag autocorrelations are 0.8544 and 0.5979, respectively, which can cause estimation problems when we consider lagged trading volumes as independent variables. The reversal in the estimated coefficients for spot trading volumes in Table 2 may also result from the extreme autocorrelation of spot trading volumes. Given this clustering behavior, unexpected rather than expected trading volumes tend to affect the return distribution. To more clearly observe the effects of trading volumes and their progress, we must consider unexpected trading volumes, or trading volume shocks, rather than raw trading volumes. Thus, we estimate the autoregressive models given by Equations (8) and (9):

$$lsv_t = a_s + \sum_{i=1}^{3} b_{s,i} lsv_{t-i} + \varepsilon_{s,t}, \tag{8}$$

$$lfv_t = a_f + \sum_{i=1}^{3} b_{f,i} lfv_{t-i} + \varepsilon_{f,t}. \tag{9}$$

where $\varepsilon_{s,t}$ and $\varepsilon_{s,t}$ are the normally distributed error terms with mean 0.

We refer to the residuals of Equations (8) and (9), $\hat{\varepsilon}_{s,t}$ and $\hat{\varepsilon}_{f,t}$, as spot and futures trading volume shocks, $lsvs_t$ and $lfvs_t$. Similar to the log ratio of the futures volume to the spot volume, we can define the ratio of the futures volume shock to the spot volume shock (i.e., fss_t) as the difference between $lfvs_t$ and $lsvs_t$. In Appendix 4, we report the estimation results for Equations (8) and (9), which indicate the strong autocorrelations in spot and futures trading volumes as expected. We conduct quantile regressions using the trading volume shocks and their difference instead of raw trading volumes and the volume ratio defined in Equations (5), (6), and (7), as follows:

$$r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lsvs_{t-i} + \varepsilon_t, \quad (10)$$

$$r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lfvs_{t-i} + \varepsilon_t, \quad (11)$$

$$r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i fss_{t-i} + \varepsilon_t, \quad (12)$$

where the dependent variable r_t is the spot index percentage return. $lsvs_{t-i}$ and $lfvs_{t-i}$ are the lagged trading volume shocks which correspond to the estimated residuals in Equation (8) and (9). fss_{t-i} is the difference between $lfsvs_{t-i}$ and $lsvs_{t-i}$ and ε_t denotes the error term.

Table 3 shows the estimation results for the models that include trading volume shocks. Large price movements tend to appear immediately after large trading volume shocks in both the spot and futures markets. However, the effects of spot and futures volume shocks on lagged trading volume shocks differ significantly, as shown above. The estimated coefficients on lagged spot volume shocks are opposite of those on one-minute volume shocks. Thus, the positive effect of the spot volume on the return volatility may disappear within a minute, as the returns gradually return to their original distribution. Also, this pattern for spot trading volume shocks on the return distribution is confirmed in the result for five-minute intervals as shown in Appendix 3–2. According to the estimated coefficients on the spot volume shock in five minutes, they cannot significantly widen the return distribution. This finding implies that the return-volume relationship in the spot market may be attributable to disagreements rather than market information, in line with the finding of Goetzmann and Massa (2005), who show that dispersions of opinion are positively related to stock trading volumes at first but are negatively related to subsequent stock returns.

In contrast, the positive relationship between futures trading volume shocks and the magnitude of stock index movements persists over time, although the estimated coefficients at time *t*–2 for the 75th and 99th are not significant. Thus, the effect of futures volumes on the distribution of returns remains for a long period of time, and at least part of the effect is related

Table 3: Relationship between return quantiles and trading volume shocks

Panel A. Spot trading volume shocks			
Quantile	Lagged spot trading volume shocks		
	at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0071***	0.0128***	0.0160***
	(-4.17)	(7.72)	(9.28)
0.05	-0.0067***	0.0040***	0.0045***
	(-13.90)	(7.20)	(8.15)
0.10	-0.0049***	0.0021***	0.0026***
	(-12.45)	(5.42)	(6.87)
0.25	-0.0027***	0.0005*	0.0006**
	(-10.95)	(1.94)	(2.57)
0.50	-0.0002	-0.0005**	-0.0004**
	(-1.18)	(-2.53)	(-2.51)
0.75	0.0015***	-0.0008***	-0.0017***
	(5.60)	(-3.14)	(-6.82)
0.90	0.0033***	-0.0023***	-0.0034***
	(8.41)	(-6.09)	(-9.35)
0.95	0.0055***	-0.0032***	-0.0058***
	(8.47)	(-5.43)	(-9.83)
0.99	0.0080***	-0.0107***	-0.0126***
	(4.72)	(-7.14)	(-7.80)
Panel B. Futures trading volume shocks			
Quantile	Lagged futures trading volume shocks		
	at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0082***	-0.0009**	0.0002
	(-25.45)	(-2.04)	(0.32)
0.05	-0.0039***	-0.0006***	-0.0005***
	(-30.45)	(-4.14)	(-3.01)
0.10	-0.0026***	-0.0005***	-0.0003***
	(-29.99)	(-5.55)	(-3.53)
0.25	-0.0014***	-0.0004***	-0.0003***
	(-22.69)	(-5.82)	(-5.70)
0.50	-0.0002***	-0.0001**	-0.0002***
	(-3.76)	(-2.47)	(-4.42)
0.75	0.0009***	0.0001	-0.0001*
	(13.19)	(0.84)	(-1.87)
0.90	0.0021***	0.0002**	0.0000
	(20.36)	(2.05)	(0.18)
0.95	0.0035***	0.0004***	0.0000
	(25.66)	(2.93)	(0.16)
0.99	0.0070***	-0.0003	-0.0001
	(25.25)	(-0.73)	(-0.34)
Panel C. Futures/spot volume shock ratio			
Quantile	Lagged futures/spot volume shock ratio		
	at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0079***	-0.0026***	-0.0014***
	(-29.65)	(-5.99)	(-3.05)
0.05	-0.0036***	-0.0010***	-0.0010***
	(-31.01)	(-8.24)	(-6.72)
0.10	-0.0023***	-0.0008***	-0.0006***
	(-30.65)	(-8.14)	(-6.23)
0.25	-0.0012***	-0.0005***	-0.0004***
	(-19.85)	(-7.38)	(-6.70)
0.50	-0.0002***	-0.0001**	-0.0002***
	(-3.71)	(-2.12)	(-4.28)

0.75	0.0008***	0.0002***	0.0000
	(11.59)	(2.61)	(0.60)
0.90	0.0019***	0.0005***	0.0003***
	(19.30)	(4.80)	(3.47)
0.95	0.0031***	0.0008***	0.0005***
	(23.30)	(5.85)	(3.36)
0.99	0.0067***	0.0009**	0.0012***
	(21.79)	(2.07)	(2.80)

Note. This table shows the estimated coefficients, γ_i, on the spot trading volume shock (Panel A), the futures trading volume shock (Panel B), and the ratio of the futures trading volume shock to the spot trading volume shock (Panel C) for the following quantile regression models: Panel A: $r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lsvs_{t-i} + \varepsilon_t$; Panel B: $r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i lfvs_{t-i} + \varepsilon_t$; Panel C: $r_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}r_{t-i} + \sum_{i=1}^{3}\beta_{v,i}r_{t-i}^2 + \sum_{i=1}^{3}\gamma_i fss_{t-i} + \varepsilon_t$. *t*-values are reported in parentheses and are estimated using the Markov chain marginal bootstrap method (He and Hu, 2002). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

to informed trading rather than dispersions of opinion or temporary price impacts induced by demand pressure. The results for the futures/spot trading volume shock ratio in Panel C of Table 3 also support this trend. The ratio of one-minute futures trading volume shocks to spot trading volume shocks consistently widens the distribution of returns, and the corresponding ratios in the following time periods give the same result. In contrast with results in Table 2, the coefficients on the trading volume shock ratio are significant, which implies that the asymmetry owing to the short sale restriction is associated with predictable trading activity in the futures market. For the futures trading volume shock in five minutes in Appendix 3-2, it expands the left side of the return distribution, although there is no significant effect on the right side. To summarize, the spot volume only has a short-term effect on the distribution of returns, whereas the futures volume has a more long-term effect even when considering innovations in trading volumes.

6.2 Impact on implied volatility

The quantile regression estimation results consistently confirm that trading volumes extend the distribution of returns. This result can be interpreted as trading volumes increasing the volatility of returns. However, the volatility that determines the distribution of future returns is unobservable in practice, and the estimation results depend on the realized returns. Moreover, the absolute value of the realized returns may be affected not only by the volatility of returns but also by market microstructure factors, such as the market depth or spreads, and trading volumes are also related to these factors. Thus, it is necessary to confirm the return-volume relationship using a direct measure of the return volatility. We consider the option-implied volatility, which is the return volatility estimated by investors in the options market and which is free from market microstructure issues because it is not directly related to the spot or futures markets. If trading volumes are substantively associated with the return volatility rather than causing temporary effects, then we should observe a similar relationship with the implied volatility in the options market. To examine the relationship between trading volumes and the implied volatility, we conduct similar regressions with the change in the implied volatility as the dependent variable, as follows:

$$div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lsv_{t-i} + \varepsilon_t,$$

$$div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lsvs_{t-i} + \varepsilon_t, \quad (13)$$

$$div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lfv_{t-i} + \varepsilon_t,$$

$$div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lfvs_{t-i} + \varepsilon_t, \quad (14)$$

$$div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i fs_{t-i} + \varepsilon_t,$$

$$div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i fss_{t-i} + \varepsilon_t, \quad (15)$$

where div_t denotes the option-implied volatility that is calculated as the volume-weighted average of the Black-Scholes implied volatilities of all options, that of ATM options, or that of OTM options.

The estimation results using the volume-weighted implied volatility are reported in Panel A of Table 4. We find that the spot volume does not predict the return volatility over a one-minute period at the 5% significance level, whereas the coefficients on one-minute lagged futures trading volumes and the futures volume to spot volume ratio are both estimated to be significantly positive. This result implies that options investors assume a larger return volatility after an increase in futures trading volumes, which is consistent with the previous quantile regression results. We find no significant relationship between the spot trading volume and the option-implied volatility, which is consistent with the spot trading volume's short-term relationship with the distribution of returns.

To more clearly examine the difference in the effects of spot and futures trading volumes on the return volatility, we divide the options into two subgroups (i.e., ATM and OTM options) according to their moneyness levels (i.e. the ratios of their strike prices to the stock index). We calculate the volume-weighted average of the implied volatilities of individual options at each option moneyness level. In general, option investors prefer ATM to OTM options for quick trades because ATM options are usually more liquid than OTM options are. In addition, traders in the spot market who want to hedge unfavorable volatility risk may prefer ATM options because the vega of these options is relatively greater than that of OTM options. However, OTM options are more advantageous for informed trading, which requires waiting for the

Table 4: Effects of trading volumes and volume shocks on option-implied volatility

	Spot		Futures		Futures/Spot	
Coefficient	Volume	Shock	Volume	Shock	Volume	Shock
Panel A. Volume-weighted implied volatility						
γ_1	0.0106*	0.0091	0.0102***	0.0088***	0.0104***	0.0087***
	(1.92)	(1.58)	(6.18)	(5.17)	(6.16)	(4.98)
γ_2	-0.0055	-0.0011	0.0025	0.0060***	0.0041**	0.0073***
	(-0.91)	(-0.19)	(1.39)	(3.55)	(2.31)	(4.17)
γ_3	-0.0048	-0.0040	0.0042**	0.0079***	0.0056***	0.0092***
	(-0.86)	(-0.70)	(2.57)	(4.66)	(3.30)	(5.25)
Panel B. ATM option-implied volatility						
γ_1	0.0083***	0.0087***	0.0000	-0.0001	-0.0013*	-0.0010
	(2.70)	(2.74)	(0.01)	(-0.10)	(-1.70)	(-1.25)
γ_2	0.0039	0.0099***	0.0016**	0.0016**	0.0009	0.0006
	(1.22)	(3.16)	(2.01)	(2.01)	(1.12)	(0.76)
γ_3	-0.0048	0.0052*	0.0003	0.0010	0.0003	0.0005
	(-1.61)	(1.68)	(0.33)	(1.30)	(0.39)	(0.70)
Panel C. OTM option-implied volatility						
γ_1	0.0154**	0.0144*	0.0259***	0.0237***	0.0272***	0.0248***
	(2.02)	(1.81)	(10.34)	(9.23)	(10.45)	(9.32)
γ_2	-0.0034	0.0071	0.0120***	0.0224***	0.0149***	0.0251***
	(-0.41)	(0.89)	(4.42)	(8.63)	(5.37)	(9.28)
γ_3	-0.0023	0.0099	0.0064**	0.0212***	0.0081***	0.0226***
	(-0.29)	(1.24)	(2.54)	(8.25)	(3.09)	(8.45)

Note. This table shows the estimated coefficients on the spot trading volume (volume shock), the futures trading volume (volume shock), and the ratio of the futures trading volume (volume shock) to the spot trading volume (volume shock) for the following predictive regression models for the option-implied volatility: Spot: $div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lsv_{t-i} + \varepsilon_t$ and $div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lsvs_{t-i} + \varepsilon_t$; Futures: $div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lfv_{t-i} + \varepsilon_t$ and $div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i lfvs_{t-i} + \varepsilon_t$; Futures/Spot: $div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i fs_{t-i} + \varepsilon_t$ and $div_t = \alpha + \beta_{tr}\frac{t}{T} + \beta_{trs}(\frac{t}{T})^2 + \beta_{op}DOP_t + \beta_{cl}DCL_t + \sum_{i=1}^{3}\beta_{r,i}div_{t-i} + \sum_{i=1}^{3}\gamma_i fss_{t-i} + \varepsilon_t$. The option-implied volatility is defined as the volume-weighted average of the Black-Scholes implied volatilities of all options (Panel A), ATM options (Panel B), and OTM options (Panel C). t-values are reported in parentheses and are estimated using the Newey-West approach with ten lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

market to change, than ATM options are because OTM options provide higher leverage than ATM options do. Thus, the implied volatilities of ATM and OTM options may reflect the views of short-term and informed traders, respectively, in the options market.

Panels B and C of Table 4 show that the implied volatilities of ATM and OTM options have opposite effects. Changes in the implied volatility of ATM options are significantly and positively associated with one-minute lagged spot trading volumes but not with lagged futures trading volumes. On the contrary, only futures trading volumes and the future/spot volume ratio are positively related to changes in the implied volatility of OTM options at the 1% significance level. This result implies that the return-volume relationship in the spot market over one-minute periods is closely related to ATM options, which are important to investors who want to make quick transactions or hedge volatility risk in the spot market. However, futures trading, which is related to the volatility of returns over the long term, affects OTM options, which are highly related to informed trading. Actually, these results for ATM and OTM options are the same in the estimation results for a five-minute interval in Appendix 3-3. Again, the relationship between trading volumes and the implied volatility supports the hypothesis that spot trading volumes have only a short-term effect, whereas futures trading volumes affect the distribution of returns over the long run.

7 Conclusions

This study investigates the intraday relationship between the returns and trading volumes of stocks and index futures. We perform quantile regressions of spot returns on spot and futures trading volumes to identify the effect of trading volumes on the return distribution. Our empirical results suggest that both spot and futures trading volumes extend the distribution of spot returns but that these effects persist for different durations. The effect of spot trading volumes on returns disappears within an extremely short period of time, whereas futures trading volumes have a significant influence on spot returns even after a few minutes have passed. When we consider innovations in trading volumes, the distribution of returns temporarily widens owing to large shocks to spot trading volumes, but this effect reverses quickly, whereas the effect of an increase in the futures trading volume persists over time. The finding of a short-term effect of spot trading volumes but a long-term effect of futures trading volumes is consistently supported by the results for trading volume innovations. In the predictive regressions for the option-implied volatility, only the futures trading volume is significantly and positively related to the volume-weighted implied volatility in the options market. However, increases in spot trading volumes precede increases in the implied volatility of ATM options, which can be traded quickly and serve as effective hedging tools. In contrast, futures trading volumes are closely associated with the implied volatility of OTM options, which offer high leverage and, thus, are, favorable for informed trading. Our findings suggest that the return-volume relationship differs significantly for spot and futures trading volumes. Specifically, the return-volume relationship for spot trading is mainly attributable to disagreements, whereas futures contracts may serve as tools for informed trading.

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Appendix 1: Quantile regression estimation results for all independent variables

1-1. Quantile regressions with spot trading volumes

	Quantile																	
	0.01		0.05		0.1		0.25		0.5		0.75		0.9		0.95		0.99	
Variables	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Const.	0.1795	7.07	0.1400	17.30	0.1107	20.92	0.0660	18.97	0.0079	3.58	-0.0460	-13.24	-0.0899	-14.74	-0.1272	-13.96	-0.1512	-6.81
$\frac{t}{T}$	-0.1233	-18.76	-0.0354	-19.52	-0.0197	-14.17	-0.0078	-8.26	0.0005	0.80	0.0113	11.72	0.0232	16.36	0.0395	18.85	0.1316	23.79
$(\frac{t}{T})^2$	0.1637	28.58	0.0545	32.39	0.0329	24.65	0.0139	15.92	-0.0005	-0.80	-0.0172	-19.30	-0.0369	-28.26	-0.0601	-31.31	-0.1733	-34.12
DOP_t	-0.0303	-21.77	-0.0155	-33.25	-0.0096	-28.51	-0.0038	-19.79	0.0005	2.88	0.0048	22.80	0.0092	27.63	0.0128	25.35	0.0260	19.59
DCL_t	0.0017	1.40	0.0004	1.09	0.0004	1.72	0.0010	5.92	0.0011	8.47	0.0016	9.23	0.0015	5.58	0.0007	1.89	-0.0025	-2.68
r_{t-1}	0.1665	16.60	0.0725	16.62	0.0428	15.63	0.0153	8.62	0.0091	6.57	0.0121	6.82	0.0360	11.79	0.0658	15.52	0.1499	14.44
r_{t-2}	0.0320	3.00	0.0541	14.63	0.0628	22.81	0.0629	37.83	0.0526	30.10	0.0537	34.08	0.0428	14.72	0.0301	7.50	-0.0135	-1.22
r_{t-3}	-0.0173	-1.57	0.0079	2.08	0.0162	6.20	0.0183	10.79	0.0151	11.95	0.0098	6.05	-0.0045	-1.72	-0.0275	-7.09	-0.0659	-6.21
r_{t-1}^2	-2.6234	-11.42	-1.7779	-20.93	-1.3033	-23.02	-0.6265	-21.37	-0.0110	-0.58	0.5560	22.20	1.2528	26.32	1.6314	20.10	2.6871	12.04
r_{t-2}^2	-2.2728	-11.65	-1.2397	-19.40	-0.8221	-18.43	-0.3157	-11.86	0.0132	0.66	0.3241	13.49	0.8236	19.04	1.1668	14.91	2.0880	11.37
r_{t-3}^2	-2.2148	-11.37	-1.1732	-14.81	-0.7444	-16.67	-0.2621	-11.55	0.0179	1.33	0.3074	12.01	0.7411	16.23	1.1252	12.62	2.1427	10.38
lsv_{t-1}	-0.0146	-7.87	-0.0097	-16.63	-0.0071	-16.74	-0.0037	-14.27	-0.0002	-1.08	0.0026	9.84	0.0056	14.12	0.0084	13.84	0.0138	9.66
lsv_{t-2}	0.0081	4.37	0.0034	6.04	0.0022	5.27	0.0007	2.35	-0.0003	-1.34	-0.0003	-1.14	-0.0015	-3.61	-0.0020	-3.23	-0.0070	-4.41
lsv_{t-3}	-0.0057	-3.15	-0.0025	-4.67	-0.0019	-5.19	-0.0009	-3.64	0.0001	0.52	0.0007	2.92	0.0018	4.85	0.0018	3.04	0.0041	2.39

1-2. Quantile regressions with futures trading volumes

	Quantile																	
		0.01		0.05		0.1		0.25		0.5		0.75		0.9		0.95		0.99
Variables	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Const.	0.1450	16.40	0.0675	20.48	0.0454	19.06	0.0261	16.33	0.0047	4.57	-0.0119	-6.94	-0.0278	-10.30	-0.0449	-12.23	-0.0850	-8.59
$\frac{t}{T}$	-0.0896	-15.62	-0.0317	-17.07	-0.0202	-15.81	-0.0091	-10.35	0.0004	0.75	0.0131	13.31	0.0256	19.93	0.0391	21.52	0.1165	21.09
$(\frac{t}{T})^2$	0.1268	24.97	0.0498	27.90	0.0327	26.73	0.0147	17.68	-0.0005	-0.80	-0.0187	-20.64	-0.0386	-31.58	-0.0587	-33.21	-0.1545	-29.66
DOP_t	-0.0275	-18.76	-0.0156	-31.32	-0.0100	-27.79	-0.0041	-18.14	0.0004	2.60	0.0051	22.16	0.0098	29.89	0.0133	25.19	0.0249	15.72
DCL_t	-0.0015	-1.63	-0.0024	-7.00	-0.0022	-8.60	-0.0005	-2.93	0.0009	6.86	0.0028	18.59	0.0038	15.07	0.0037	11.36	0.0011	1.37
r_{t-1}	0.1399	13.66	0.0664	16.21	0.0416	14.23	0.0148	7.62	0.0092	6.36	0.0118	6.16	0.0342	12.61	0.0605	15.53	0.1355	12.91
r_{t-2}	0.0189	1.67	0.0517	13.73	0.0633	24.96	0.0629	39.48	0.0527	29.54	0.0538	30.15	0.0408	15.70	0.0237	5.62	-0.0260	-2.19
r_{t-3}	-0.0315	-3.16	0.0070	1.83	0.0158	5.86	0.0181	11.46	0.0151	12.39	0.0091	4.91	-0.0056	-2.39	-0.0292	-7.38	-0.0684	-6.30
r_{t-1}^2	-2.7527	-13.23	-1.8155	-20.75	-1.3456	-24.76	-0.6366	-23.41	-0.0109	-0.51	0.5633	21.40	1.2789	26.55	1.6606	22.77	2.7502	13.70
r_{t-2}^2	-2.1832	-12.49	-1.2172	-17.89	-0.7909	-17.61	-0.3013	-11.14	0.0121	0.65	0.3208	13.23	0.8024	18.27	1.1306	14.36	2.0216	10.16
r_{t-3}^2	-2.2136	-12.04	-1.1708	-15.23	-0.7477	-17.13	-0.2658	-10.76	0.0198	1.35	0.3083	10.80	0.7486	19.03	1.1318	14.46	2.1479	11.25
lfv_{t-1}	-0.0082	-28.75	-0.0042	-36.01	-0.0029	-33.31	-0.0016	-26.15	-0.0001	-3.14	0.0011	16.39	0.0024	23.67	0.0038	29.41	0.0074	27.26
lfv_{t-2}	0.0001	0.19	0.0001	0.83	-0.0001	-0.99	-0.0001	-0.95	0.0000	-0.55	0.0000	0.18	0.0000	0.04	-0.0001	-0.75	-0.0012	-2.97
lfv_{t-3}	-0.0020	-5.45	-0.0011	-8.79	-0.0006	-7.38	-0.0003	-5.64	-0.0001	-1.26	0.0002	3.53	0.0006	6.03	0.0006	4.90	0.0014	3.93

1-3. Quantile regressions with the futures/spot volume ratio

	Quantile																	
	0.01		0.05		0.1		0.25		0.5		0.75		0.9		0.95		0.99	
Variables	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Const.	-0.0773	-58.50	-0.0477	-130.34	-0.0361	-135.95	-0.0183	-91.38	0.0000	0.41	0.0184	86.34	0.0371	134.15	0.0504	122.04	0.0821	69.90
$\frac{t}{T}$	-0.1274	-19.62	-0.0540	-27.53	-0.0362	-27.30	-0.0185	-21.50	-0.0006	-0.92	0.0195	20.42	0.0391	27.24	0.0580	25.64	0.1442	25.00
$(\frac{t}{T})^2$	0.1600	25.95	0.0700	35.79	0.0470	35.25	0.0231	27.70	0.0004	0.65	-0.0244	-26.90	-0.0506	-35.56	-0.0756	-33.51	-0.1800	-32.96
DOP_t	-0.0332	-21.05	-0.0187	-36.53	-0.0120	-33.52	-0.0052	-23.78	0.0003	2.07	0.0058	26.61	0.0116	33.57	0.0160	28.28	0.0288	19.26
DCL_t	-0.0073	-7.06	-0.0049	-15.40	-0.0037	-17.47	-0.0013	-7.88	0.0008	7.06	0.0033	21.03	0.0051	21.88	0.0058	17.45	0.0048	6.13
r_{t-1}	0.1564	15.63	0.0755	19.18	0.0471	18.00	0.0157	8.97	0.0092	6.21	0.0129	6.75	0.0383	13.84	0.0678	16.64	0.1452	12.94
r_{t-2}	0.0218	2.16	0.0550	15.18	0.0638	23.62	0.0635	37.10	0.0527	29.65	0.0541	32.44	0.0419	15.28	0.0269	5.95	-0.0282	-2.83
r_{t-3}	-0.0256	-2.34	0.0080	2.23	0.0165	6.43	0.0183	11.55	0.0151	11.91	0.0093	5.93	-0.0049	-1.77	-0.0277	-7.03	-0.0691	-6.87
r_{t-1}^2	-2.7977	-13.13	-1.8869	-20.07	-1.3880	-24.38	-0.6572	-24.04	-0.0138	-0.70	0.5780	21.78	1.3052	23.74	1.7197	19.84	2.8645	13.37
r_{t-2}^2	-2.2847	-11.20	-1.2555	-19.68	-0.8321	-17.09	-0.3255	-11.26	0.0096	0.47	0.3366	13.75	0.8380	18.93	1.1781	13.26	2.0189	11.24
r_{t-3}^2	-2.2438	-11.54	-1.2010	-14.36	-0.7799	-16.26	-0.2782	-13.51	0.0178	1.42	0.3233	12.45	0.7818	16.33	1.1744	13.01	2.1824	11.91
fs_{t-1}	-0.0078	-33.79	-0.0036	-34.43	-0.0023	-28.60	-0.0012	-20.18	-0.0001	-2.46	0.0008	11.34	0.0018	20.92	0.0030	23.95	0.0068	21.16
fs_{t-2}	-0.0002	-0.46	0.0001	1.08	0.0000	0.14	0.0000	0.42	0.0000	0.09	-0.0001	-1.36	-0.0001	-1.44	-0.0003	-1.90	-0.0011	-2.95
fs_{t-3}	-0.0012	-3.47	-0.0005	-3.69	-0.0002	-2.45	-0.0001	-1.21	0.0000	-0.96	0.0000	0.33	0.0001	1.04	0.0001	1.12	0.0009	2.64

1-4. Quantile regressions with spot trading volume shocks

	Quantile																	
	0.01		0.05		0.1		0.25		0.5		0.75		0.9		0.95		0.99	
Variables	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Const.	-0.0855	-70.80	-0.0513	-129.15	-0.0385	-137.10	-0.0196	-107.21	-0.0002	-1.79	0.0190	93.64	0.0386	139.77	0.0526	124.32	0.0878	74.28
$\frac{t}{T}$	-0.1622	-27.35	-0.0655	-40.35	-0.0431	-35.13	-0.0210	-24.43	-0.0005	-0.91	0.0214	23.36	0.0446	38.09	0.0673	34.93	0.1652	31.67
$(\frac{t}{T})^2$	0.1952	34.62	0.0806	50.94	0.0533	43.68	0.0254	29.88	0.0004	0.65	-0.0261	-29.74	-0.0556	-48.58	-0.0839	-44.29	-0.2004	-40.58
DOP_t	-0.0334	-21.13	-0.0183	-31.13	-0.0118	-34.17	-0.0049	-23.12	0.0004	2.73	0.0058	26.90	0.0112	34.64	0.0155	33.17	0.0272	18.32
DCL_t	-0.0060	-5.97	-0.0042	-11.91	-0.0032	-13.53	-0.0009	-5.99	0.0009	7.05	0.0032	19.45	0.0047	18.77	0.0052	15.81	0.0040	4.52
r_{t-1}	0.1784	16.67	0.0785	21.75	0.0442	16.46	0.0124	6.61	0.0057	4.13	0.0089	4.91	0.0362	13.71	0.0671	17.65	0.1558	15.04
r_{t-2}	0.0475	4.22	0.0578	15.93	0.0661	28.98	0.0641	39.64	0.0530	30.51	0.0547	31.84	0.0442	17.98	0.0338	7.94	-0.0099	-0.90
r_{t-3}	-0.0061	-0.53	0.0113	3.23	0.0186	8.03	0.0191	11.52	0.0159	12.46	0.0102	6.68	-0.0050	-2.02	-0.0249	-6.74	-0.0734	-6.94
r_{t-1}^2	-2.7381	-15.16	-1.8345	-24.55	-1.3560	-26.57	-0.6461	-23.79	-0.0112	-0.56	0.5739	20.71	1.2822	24.28	1.6843	19.96	2.8067	11.25
r_{t-2}^2	-2.5040	-11.35	-1.3181	-21.21	-0.8707	-19.91	-0.3489	-13.59	0.0161	0.89	0.3484	15.32	0.8751	24.67	1.2979	16.41	2.2810	13.39
r_{t-3}^2	-2.5006	-12.51	-1.3050	-19.99	-0.8528	-18.44	-0.3003	-13.06	0.0187	1.27	0.3620	14.24	0.8719	17.63	1.2992	17.61	2.3711	12.14
$lsvs_{t-1}$	-0.0071	-4.17	-0.0067	-13.90	-0.0049	-12.45	-0.0027	-10.95	-0.0002	-1.18	0.0015	5.60	0.0033	8.41	0.0055	8.47	0.0080	4.72
$lsvs_{t-2}$	0.0128	7.72	0.0040	7.20	0.0021	5.42	0.0005	1.94	-0.0005	-2.53	-0.0008	-3.14	-0.0023	-6.09	-0.0032	-5.43	-0.0107	-7.14
$lsvs_{t-3}$	0.0160	9.28	0.0045	8.15	0.0026	6.87	0.0006	2.57	-0.0004	-2.51	-0.0017	-6.82	-0.0034	-9.35	-0.0058	-9.83	-0.0126	-7.80

1-5. Quantile regressions with futures trading volume shocks

	Quantile																	
	0.01		0.05		0.1		0.25		0.5		0.75		0.9		0.95		0.99	
Variables	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Const.	-0.0900	-70.20	-0.0534	-128.22	-0.0398	-144.50	-0.0203	-101.67	-0.0003	-2.63	0.0194	98.02	0.0399	131.98	0.0547	121.40	0.0904	74.75
$\frac{t}{T}$	-0.1434	-24.38	-0.0570	-33.69	-0.0381	-30.34	-0.0182	-21.60	-0.0002	-0.30	0.0200	21.87	0.0397	29.81	0.0600	29.16	0.1559	30.73
$(\frac{t}{T})^2$	0.1766	32.36	0.0728	44.00	0.0488	38.69	0.0228	28.45	0.0001	0.09	-0.0249	-28.70	-0.0512	-39.22	-0.0776	-37.78	-0.1913	-39.74
DOP_t	-0.0316	-22.60	-0.0175	-28.78	-0.0112	-33.11	-0.0047	-22.21	0.0005	3.12	0.0057	25.58	0.0109	31.42	0.0150	28.02	0.0264	16.12
DCL_t	-0.0043	-4.94	-0.0037	-12.80	-0.0029	-14.48	-0.0009	-6.47	0.0009	7.54	0.0031	19.00	0.0045	19.76	0.0045	15.87	0.0030	3.79
r_{t-1}	0.1493	14.22	0.0703	17.66	0.0425	16.47	0.0116	5.93	0.0058	4.07	0.0087	4.69	0.0334	11.65	0.0607	15.17	0.1388	13.78
r_{t-2}	0.0273	2.47	0.0563	15.10	0.0658	29.06	0.0638	37.28	0.0533	28.97	0.0550	29.98	0.0430	16.68	0.0273	7.00	-0.0210	-1.85
r_{t-3}	-0.0227	-1.97	0.0090	2.21	0.0180	6.45	0.0195	11.72	0.0157	12.00	0.0100	5.98	-0.0048	-1.84	-0.0259	-6.88	-0.0716	-6.90
r_{t-1}^2	-2.7046	-14.56	-1.8455	-20.99	-1.3608	-25.11	-0.6491	-22.29	-0.0093	-0.45	0.5731	19.51	1.2840	24.32	1.6928	18.87	2.8088	13.50
r_{t-2}^2	-2.2498	-10.67	-1.2496	-20.33	-0.8268	-18.54	-0.3253	-12.13	0.0140	0.76	0.3383	13.80	0.8444	20.53	1.1954	14.83	2.1195	10.54
r_{t-3}^2	-2.3889	-12.43	-1.2683	-17.62	-0.8174	-19.74	-0.2910	-14.31	0.0190	1.39	0.3431	14.26	0.8233	16.44	1.2447	16.01	2.2588	11.95
$lfvs_{t-1}$	-0.0082	-25.45	-0.0039	-30.45	-0.0026	-29.99	-0.0014	-22.69	-0.0002	-3.76	0.0009	13.19	0.0021	20.36	0.0035	25.66	0.0070	25.25
$lfvs_{t-2}$	-0.0009	-2.04	-0.0006	-4.14	-0.0005	-5.55	-0.0004	-5.82	-0.0001	-2.47	0.0001	0.84	0.0002	2.05	0.0004	2.93	-0.0003	-0.73
$lfvs_{t-3}$	0.0002	0.32	-0.0005	-3.01	-0.0003	-3.53	-0.0003	-5.70	-0.0002	-4.42	-0.0001	-1.87	0.0000	0.18	0.0000	0.16	-0.0001	-0.34

1-6. Quantile regressions with the futures/spot volume shock ratio

	Quantile																	
	0.01		0.05		0.1		0.25		0.5		0.75		0.9		0.95		0.99	
Variables	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Const.	-0.0904	-72.19	-0.0532	-143.36	-0.0397	-141.30	-0.0201	-96.19	-0.0002	-1.88	0.0194	87.49	0.0398	131.99	0.0546	120.77	0.0911	74.88
$\frac{t}{T}$	-0.1408	-23.41	-0.0578	-28.95	-0.0384	-26.73	-0.0189	-20.44	-0.0004	-0.62	0.0200	20.42	0.0400	27.60	0.0604	27.58	0.1525	25.39
$(\frac{t}{T})^2$	0.1740	31.26	0.0735	36.27	0.0490	34.74	0.0233	26.75	0.0002	0.34	-0.0249	-27.15	-0.0514	-35.67	-0.0780	-35.29	-0.1882	-32.16
DOP_t	-0.0315	-22.73	-0.0175	-30.43	-0.0112	-34.80	-0.0047	-21.89	0.0005	3.03	0.0057	26.25	0.0110	32.49	0.0150	26.54	0.0263	15.36
DCL_t	-0.0049	-4.72	-0.0039	-12.26	-0.0031	-12.59	-0.0010	-6.23	0.0009	7.27	0.0031	20.38	0.0046	19.45	0.0049	14.90	0.0032	3.79
r_{t-1}	0.1544	14.94	0.0724	18.92	0.0439	16.39	0.0119	6.42	0.0058	4.28	0.0090	5.29	0.0347	12.56	0.0632	16.00	0.1449	14.21
r_{t-2}	0.0262	2.30	0.0568	14.75	0.0662	23.87	0.0641	37.11	0.0532	32.53	0.0548	28.82	0.0433	15.77	0.0285	6.55	-0.0203	-2.02
r_{t-3}	-0.0288	-2.55	0.0094	2.28	0.0183	5.89	0.0196	11.04	0.0158	12.84	0.0101	5.78	-0.0045	-1.80	-0.0263	-6.68	-0.0713	-6.23
r^2_{t-1}	-2.7848	-14.14	-1.9008	-21.19	-1.3916	-26.89	-0.6643	-25.44	-0.0104	-0.50	0.5868	20.22	1.3063	22.22	1.7362	19.70	2.8415	11.32
r^2_{t-2}	-2.2548	-11.08	-1.2403	-18.97	-0.8185	-16.67	-0.3260	-10.90	0.0115	0.55	0.3336	14.44	0.8394	19.07	1.1900	13.36	2.0795	9.27
r^2_{t-3}	-2.3243	-11.82	-1.2569	-16.59	-0.8088	-16.80	-0.2863	-13.27	0.0190	1.29	0.3363	13.97	0.8096	15.69	1.2259	14.72	2.2412	11.41
fss_{t-1}	-0.0079	-29.65	-0.0036	-31.01	-0.0023	-30.65	-0.0012	-19.85	-0.0002	-3.71	0.0008	11.59	0.0019	19.30	0.0031	23.30	0.0067	21.79
fss_{t-2}	-0.0026	-5.99	-0.0010	-8.24	-0.0008	-8.14	-0.0005	-7.38	-0.0001	-2.12	0.0002	2.61	0.0005	4.80	0.0008	5.85	0.0009	2.07
fss_{t-3}	-0.0014	-3.05	-0.0010	-6.72	-0.0006	-6.23	-0.0004	-6.70	-0.0002	-4.28	0.0000	0.60	0.0003	3.47	0.0005	3.36	0.0012	2.80

Appendix 2: Predictive regression results for the implied volatilities

	Spot		Futures		Futures/Spot	
Variable	Volume	Shock	Volume	Shock	Volume	Shock
Panel A. Volume-weighted implied volatility						
Const.	-0.0148	-0.0075***	-0.3959***	0.0005	-0.0302***	-0.0004
	(-0.24)	(-2.74)	(-11.37)	(0.17)	(-9.18)	(-0.15)
$\frac{t}{T}$	-0.0073	-0.0086	-0.1126***	-0.0444***	-0.0575***	-0.0411***
	(-0.46)	(-0.68)	(-7.32)	(-3.33)	(-4.40)	(-3.14)
$(\frac{t}{T})^2$	0.0119	0.0136	0.1068***	0.0459***	0.0574***	0.0431***
	(0.81)	(1.12)	(7.35)	(3.62)	(4.59)	(3.44)
DOP_t	-0.0144***	-0.0107***	-0.0279***	-0.0145***	-0.0202***	-0.0145***
	(-4.77)	(-3.92)	(-9.36)	(-5.22)	(-7.34)	(-5.25)
DCL_t	0.0007	0.0006	-0.0036	-0.0010	0.0058**	0.0003
	(0.22)	(0.23)	(-1.37)	(-0.38)	(2.19)	(0.11)
div_{t-1}	-0.6023***	-0.6025***	-0.6021***	-0.6023***	-0.6021***	-0.6023***
	(-266.29)	(-265.98)	(-265.88)	(-265.53)	(-265.88)	(-265.54)
div_{t-2}	-0.3902***	-0.3907***	-0.3901***	-0.3905***	-0.3901***	-0.3905***
	(-188.25)	(-188.18)	(-187.94)	(-187.82)	(-187.93)	(-187.79)
div_{t-3}	-0.2040***	-0.2050***	-0.2038***	-0.2047***	-0.2038***	-0.2047***
	(-116.99)	(-116.93)	(-116.88)	(-116.68)	(-116.86)	(-116.65)
Panel B. ATM option-implied volatility						
Const.	-0.1664***	-0.0051***	-0.0501**	-0.0059***	-0.0064***	-0.0068***
	(-3.64)	(-3.48)	(-2.56)	(-3.97)	(-3.87)	(-4.62)
$\frac{t}{T}$	-0.0329***	-0.0114	-0.0173**	-0.0085	-0.0051	-0.0046
	(-3.66)	(-1.61)	(-2.20)	(-1.18)	(-0.70)	(-0.64)
$(\frac{t}{T})^2$	0.0337***	0.0148**	0.0197***	0.0122*	0.0087	0.0087
	(4.09)	(2.26)	(2.70)	(1.84)	(1.29)	(1.31)
DOP_t	-0.0049**	-0.0032*	-0.0028	-0.0031*	-0.0013	-0.0027*
	(-2.52)	(-1.93)	(-1.56)	(-1.90)	(-0.76)	(-1.66)
DCL_t	-0.0109***	-0.0085***	-0.0076***	-0.0073***	-0.0071***	-0.0071***
	(-5.78)	(-4.85)	(-4.38)	(-4.24)	(-4.11)	(-4.11)
div_{t-1}	-0.5828***	-0.5850***	-0.5829***	-0.5850***	-0.5828***	-0.5850***
	(-88.99)	(-88.59)	(-89.02)	(-88.63)	(-89.01)	(-88.60)
div_{t-2}	-0.3416***	-0.3439***	-0.3416***	-0.3439***	-0.3416***	-0.3439***
	(-47.74)	(-47.54)	(-47.75)	(-47.55)	(-47.74)	(-47.54)
div_{t-3}	-0.1739***	-0.1753***	-0.1739***	-0.1753***	-0.1739***	-0.1753***
	(-32.70)	(-32.58)	(-32.71)	(-32.60)	(-32.70)	(-32.58)

Table continued

Table continued

Panel C. OTM option-implied volatility						
Const.	-0.2181***	-0.0021	-1.0224***	0.0204***	-0.0599***	0.0170***
	(-2.70)	(-0.49)	(-20.14)	(4.64)	(-11.96)	(3.95)
$\frac{t}{T}$	-0.0467**	-0.0211	-0.2892***	-0.1216***	-0.1373***	-0.1090***
	(-2.04)	(-1.11)	(-12.67)	(-6.12)	(-7.07)	(-5.56)
$(\frac{t}{T})^2$	0.0462**	0.0235	0.2649***	0.1143***	0.1286***	0.1030***
	(2.18)	(1.31)	(12.41)	(6.11)	(7.00)	(5.58)
DOP_t	-0.0228***	-0.0128***	-0.0533***	-0.0239***	-0.0324***	-0.0236***
	(-5.53)	(-3.42)	(-12.95)	(-6.25)	(-8.56)	(-6.16)
DCL_t	0.0033	0.0063	-0.0037	0.0026	0.0204***	0.0064*
	(0.79)	(1.64)	(-0.98)	(0.70)	(5.38)	(1.72)
div_{t-1}	-0.6079***	-0.6082***	-0.6075***	-0.6078***	-0.6076***	-0.6078***
	(-246.82)	(-246.03)	(-245.89)	(-245.06)	(-245.95)	(-245.10)
div_{t-2}	-0.3958***	-0.3963***	-0.3954***	-0.3957***	-0.3954***	-0.3957***
	(-177.10)	(-176.54)	(-176.54)	(-175.87)	(-176.59)	(-175.90)
div_{t-3}	-0.2097***	-0.2104***	-0.2094***	-0.2097***	-0.2094***	-0.2097***
	(-113.43)	(-113.21)	(-113.24)	(-112.70)	(-113.24)	(-112.67)

Note. This table shows the estimated coefficients on the control variables in Table 4. The estimated coefficients on the trading volumes and trading volume shocks are omitted because they are redundant. t-values are reported in parentheses and are estimated using the Newey-West approach with ten lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix 3: Estimation results for five-minute intervals

3-1. Relationship between returns and trading volumes

Panel A. Spot trading volumes			
Quantile	Lagged spot trading volumes at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0084	0.0217*	-0.0588***
	(-0.71)	(1.65)	(-5.27)
0.05	-0.0181***	0.0021	-0.0215***
	(-3.75)	(0.38)	(-5.04)
0.10	-0.0144***	0.0013	-0.0166***
	(-5.42)	(0.43)	(-6.68)
0.25	-0.0094***	-0.0013	-0.0051***
	(-5.50)	(-0.65)	(-2.93)
0.50	-0.0006	-0.0032**	0.0027**
	(-0.45)	(-2.26)	(2.30)
0.75	0.0081***	-0.0036*	0.0075***
	(4.82)	(-1.76)	(4.55)
0.90	0.0136***	-0.0052*	0.0163***
	(4.92)	(-1.77)	(5.60)
0.95	0.0116**	-0.0056	0.0236***
	(2.49)	(-1.09)	(5.47)
0.99	-0.0148	0.0059	0.0327***
	(-1.31)	(0.47)	(2.84)

Table continued

Table continued

Panel B. Futures trading volumes

Quantile	Lagged futures trading volumes at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0134***	-0.0045	-0.0210***
	(-3.46)	(-1.22)	(-7.01)
0.05	-0.0128***	-0.0032**	-0.0114***
	(-8.93)	(-2.26)	(-8.96)
0.10	-0.0091***	-0.0034***	-0.0077***
	(-10.64)	(-3.17)	(-9.86)
0.25	-0.0058***	-0.0011*	-0.0032***
	(-10.43)	(-1.88)	(-6.11)
0.50	-0.0015***	-0.0001	0.0009**
	(-3.69)	(-0.16)	(2.32)
0.75	0.0027***	0.0013**	0.0043***
	(4.96)	(2.15)	(8.06)
0.90	0.0058***	0.0027***	0.0081***
	(5.27)	(2.98)	(9.42)
0.95	0.0076***	0.0028*	0.0120***
	(4.98)	(1.82)	(9.63)
0.99	0.0047	0.0024	0.0197***
	(1.25)	(0.53)	(5.66)

Panel C. Futures/spot volume ratio

Quantile	Lagged futures/spot volume ratio at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0060	-0.0030	-0.0161***
	(-1.61)	(-0.63)	(-4.48)
0.05	-0.0084***	0.0005	-0.0075***
	(-5.86)	(0.32)	(-5.25)
0.10	-0.0056***	-0.0005	-0.0032***
	(-6.33)	(-0.53)	(-3.35)
0.25	-0.0038***	0.0003	-0.0009
	(-7.29)	(0.45)	(-1.32)
0.50	-0.0016***	0.0005	0.0008**
	(-4.00)	(1.23)	(1.99)
0.75	0.0006	0.0008	0.0023***
	(1.35)	(1.53)	(4.28)
0.90	0.0015	0.0019**	0.0048***
	(1.58)	(2.01)	(5.34)
0.95	0.0048***	0.0009	0.0069***
	(3.59)	(0.60)	(4.95)
0.99	0.0057	-0.0035	0.0171***
	(1.56)	(-0.88)	(4.67)

Note. This table shows the estimated coefficients, γ_i, on the spot trading volume (Panel A), the futures trading volume (Panel B), and the ratio of the futures trading volume to the spot trading volume (Panel C) for the same quantile regression models as used to create Table 2. *t*-values are reported in parentheses and are estimated using the Markov chain marginal bootstrap method (He and Hu, 2002). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3-2. Relationship between return quantiles and trading volume shocks

Panel A. Spot trading volume shocks

Quantile	Lagged spot trading volume shocks at time *t*-1	at time *t*-2	at time *t*-3
0.01	0.0114	0.0600***	0.0568***
	(1.03)	(5.94)	(5.90)
0.05	-0.0012	0.0202***	0.0251***
	(-0.23)	(4.12)	(5.65)
0.10	-0.0065**	0.0107***	0.0146***
	(-2.00)	(3.36)	(5.32)
0.25	-0.0051**	0.0001	0.0043**
	(-2.36)	(0.08)	(2.38)
0.50	-0.0002	-0.0038***	0.0005
	(-0.14)	(-3.14)	(0.38)
0.75	0.0050***	-0.0067***	-0.0053***
	(2.71)	(-3.60)	(-3.57)
0.90	0.0045	-0.0134***	-0.0122***
	(1.36)	(-4.79)	(-4.47)
0.95	0.0025	-0.0200***	-0.0198***
	(0.50)	(-4.39)	(-4.86)
0.99	-0.0337***	-0.0375***	-0.0488***
	(-3.29)	(-3.78)	(-5.71)

Panel B. Futures trading volume shocks

Quantile	Lagged futures trading volume shocks at time *t*-1	at time *t*-2	at time *t*-3
0.01	0.0029	0.0180***	0.0085*
	(0.62)	(3.44)	(1.79)
0.05	-0.0060***	0.0032	0.0017
	(-3.23)	(1.57)	(1.07)
0.10	-0.0051***	0.0005	0.0012
	(-5.15)	(0.45)	(1.11)
0.25	-0.0040***	-0.0008	-0.0003
	(-7.12)	(-1.26)	(-0.46)
0.50	-0.0015***	-0.0009**	-0.0001
	(-3.69)	(-2.56)	(-0.30)
0.75	0.0006	-0.0014**	-0.0011**
	(1.06)	(-2.29)	(-1.97)
0.90	0.0012	-0.0021**	-0.0022**
	(1.23)	(-2.21)	(-2.05)
0.95	0.0031*	-0.0041***	-0.0034*
	(1.86)	(-2.68)	(-1.71)
0.99	-0.0038	-0.0153***	-0.0116***
	(-0.82)	(-4.61)	(-2.95)

Panel C. Futures/spot volume shock ratio

Quantile	Lagged futures/spot volume shock ratio at time *t*-1	at time *t*-2	at time *t*-3
0.01	-0.0014	0.0035	-0.0055
	(-0.35)	(0.58)	(-1.11)
0.05	-0.0069***	-0.0004	-0.0024
	(-4.97)	(-0.28)	(-1.54)
0.10	-0.0052***	-0.0014	-0.0015
	(-5.69)	(-1.35)	(-1.32)
0.25	-0.0039***	-0.0011*	-0.0010
	(-7.85)	(-1.84)	(-1.63)

Table continued

Table continued

0.50	-0.0018***	-0.0006	-0.0003
	(-5.00)	(-1.41)	(-0.64)
0.75	0.0002	-0.0007	-0.0006
	(0.31)	(-1.26)	(-1.16)
0.90	0.0006	-0.0002	-0.0005
	(0.65)	(-0.15)	(-0.52)
0.95	0.0034**	-0.0012	0.0015
	(2.04)	(-0.75)	(0.89)
0.99	0.0013	-0.0102***	-0.0031
	(0.33)	(-2.84)	(-0.67)

Note. This table shows the estimated coefficients, γ_i, on spot trading volume shocks (Panel A), futures trading volume shocks (Panel B), and the ratio of the futures trading volume shock to the spot trading volume shock (Panel C) for the same quantile regression models as used to create Table 3. *t*-values are reported in parentheses and are estimated using the Markov chain marginal bootstrap method (He and Hu, 2002). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3-3. Effects of trading volumes and volume shocks on the option-implied volatility

	Spot		Futures		Futures/Spot	
Coefficient	Volume	Shock	Volume	Shock	Volume	Shock
Panel A. Volume-weighted implied volatility						
γ_1	0.0155	0.0259	0.0111	0.0142**	0.0110	0.0127
	(0.82)	(1.31)	(1.64)	(2.02)	(1.48)	(1.63)
γ_2	0.0079	0.0454**	0.0001	0.0161**	-0.0017	0.0111
	(0.38)	(2.38)	(0.01)	(2.37)	(-0.22)	(1.46)
γ_3	-0.0212	0.0298	-0.0145**	0.0073	-0.0146*	0.0029
	(-1.19)	(1.55)	(-2.19)	(1.07)	(-1.95)	(0.38)
Panel B. ATM option-implied volatility						
γ_1	0.0410***	0.0425***	0.0066*	0.0099***	-0.0001	0.0035
	(3.64)	(3.58)	(1.90)	(2.78)	(-0.03)	(0.91)
γ_2	-0.0107	0.0237**	-0.0059	0.0035	-0.0062	-0.0006
	(-0.88)	(2.06)	(-1.61)	(1.04)	(-1.55)	(-0.15)
γ_3	-0.0242**	0.0091	-0.0126***	-0.0009	-0.0112***	-0.0033
	(-2.25)	(0.79)	(-3.67)	(-0.26)	(-3.02)	(-0.86)
Panel C. OTM option-implied volatility						
γ_1	0.0342	0.0423	0.0291***	0.0284***	0.0280**	0.0273**
	(1.38)	(1.63)	(2.92)	(2.76)	(2.50)	(2.34)
γ_2	0.0028	0.0527**	0.0001	0.0216**	-0.0018	0.0171
	(0.10)	(2.06)	(0.01)	(2.11)	(-0.15)	(1.46)
γ_3	-0.0251	0.0306	-0.0080	0.0172*	-0.0075	0.0151
	(-1.05)	(1.20)	(-0.81)	(1.68)	(-0.66)	(1.30)

Note. This table shows the estimated coefficients on the spot trading volume (volume shock), the futures trading volume (volume shock), and the ratio of the futures trading volume (volume shock) to the spot trading volume (volume shock) for the same predictive regression models for the option-implied volatility as used to create Table 4. *t*-values are reported in parentheses and are estimated using the Newey-West approach with ten lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix 4: Estimation results for autoregressive models for spot and futures trading volume

	Constant	Lagged spot trading volume		
		at time *t*-1	at time *t*-2	at time *t*-3
Spot trading volume	1.8042***	0.5118***	0.2109***	0.1983***
	(152.75)	(396.82)	(139.59)	(173.57)
Adjusted R^2		77.51%		
	Constant	Lagged futures trading volume		
		at time *t*-1	at time *t*-2	at time *t*-3
Futures trading volume	6.2852***	0.4026***	0.1645***	0.1754***
	(221.64)	(310.87)	(106.68)	(138.44)
Adjusted R^2		40.83%		

Note. This table shows the estimation result for the autoregressive models for spot and futures trading volume: Spot trading volume: $lsv_t = a_s + \sum_{i=1}^{3} b_{s,i} lsv_{t-i} + \varepsilon_{s,t}$; Futures trading volume: $lfv_t = a_f + \sum_{i=1}^{3} b_{f,i} lfv_{t-i} + \varepsilon_{f,t}$. *t*-values are reported in parentheses and are estimated using the Newey-West approach with ten lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.