The Dynamic Relationship between Volatility, Volume and Open Interest in CSI 300 Futures Market

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Abstract: - This paper investigates the dynamic relationship between volatility, volume and open interest in CSI 300 futures market using asymmetric GARCH model, Granger causality test, variance decomposition and impulse response function based on 1-min data. ARMA-EGARCH model is employed and find that both contemporaneous and lagged volume is positively related to volatility, and current open interest has positive effect on volatility while lagged open interest has negative effect. Furthermore, volume is positively related to volatility and open interest is negatively linked to volatility when take (lagged) volume and (lagged) open interest into account simultaneously. The Granger causality test indicates that there is unidirectional Granger causality from return to open interest, whereas there is bidirectional Granger causality between open interest (return) and volume. Variance decomposition and impulse response function reveal that most variance of return, volume or open interest is triggered by itself. These results imply that volume and open interest are complementary in information dissemination, while volume measures the trade activity and open interest indicates market depth.

Key-Words: - Index futures, open interest, volatility, EGARCH, VAR, Granger causality test, high-frequency data, time series forecasting

1 Introduction

Time series forecasting is an important issue in financial market due to its fruitful implication for investment and risk management. Recently, trend classifiers and agent based modeling techniques are carried out in financial time series prediction to provide guidance for investment [1, 2], and scholars have paid much attention to forecasting the behavior of financial assets and developing sophisticated trading system based on price pattern [3, 4]. Furthermore, risk would amplify and complicate when algorithmic trading is becoming more and more popular [5]. Risk is linked to volatility, how to forecast time series (volatility) is essential for investment and risk management [6]. Also, the valuation of financial derivatives and hedging depends on the volatility dynamics [7, 8].

Index futures are cash-settled futures contracts on the value of a particular stock market index. Index futures are used for speculation, arbitraging and hedging due to the characteristics of margin trading and short selling. In index futures market, volatility is an appropriate variable for measuring the time for the market to fully incorporate new information because it reflects the magnitude of price movement within a period. Open interest measures the number of outstanding traded contracts at a time point, while volume represents the number of contracts traded in a period. Open interest is a crucial variable in index futures markets, which indicates trading activity. The information role of volume and open interest and their relationship with price changes (volatility) has get much attention of scholars.

There are two theoretical explanations for the relationship between volume and volatility, mixture of distributions hypothesis (MDH) and sequential information arrival models (SIA). Clark(1973) argues that the mixture of distributions hypothesis (MDH) can explain the distribution of futures prices. And volatility is positively related to information arrival, volume is a good proxy for the information arrival since information flow is unobservable[9]. Clark implies a positive relationship between volume and volatility. Tauchen and Pitts(1983) extend MDH, argue that traders revise their valuations due to information arrival, so the greater the disagreement between traders, the larger the volatility and volume[10]. Epps and Epps (1976) assume both volume and volatility are positively related to the amount of disagreement among traders initiated by information arrival, then there is a positive causal relation from volume to returns (volatility)[11]. Sequential information arrival models(SIA) proposed by Copeland (1976) and Jennings, Starks and Fellingham (1981) postulate a positive correlation between volatility and volume measured over the period of information arrival, lagged volume could forecast current returns[12, 13].

Various studies have examined the relationship between volume and volatility in index futures market. Gannon(1995) reports a strong positive correlation between futures volume and volatility [14]. Ragunathan and Peker (1997) conclude that unexpected volume has a greater impact on volatility than expected volume, and positive volume shocks have a greater impact on volatility than negative shocks in Sydney Futures Exchange[15]. Ap Gwilym, McMillan and Speight (1999) find that there is contemporaneous relationship between volume and volatility, and lagged volume can explain the current volatility[16]. Watanabe (2001) indicates that there is a significant positive relationship between volatility and unexpected volume, also the relationship vary with regulation[17]. McMillan and Speight (2002) reveal a positive contemporaneous relationship between volume and absolute returns with bidirectional causality in UK, which is consistent with sequential arrival of information hypothesis[18]. Pati and Rajib (2010) find evidence of contemporaneous and lagged trading volume is related to the current volatility significantly using ARMA-GARCH model[19]. Zwergel and Heiden(2012) get a positive and contemporaneous relation between volume and volatility in German, both MDH and SIA are verified[20].

There are several views about the economic role of open interest, a proxy for hedgers' opinion (Kamara, 1993) [21], hedging demand (Chen et al., 1995) [22], market depth (Bessembinder and Seguin, 1993) [23] and divergence of traders (Bessembinder et al., 1996) [24]. Brooks (1998) suggests that there is informational relationship between volatility and open interest [25].

Numerous studies have examined the information role of open interest in financial (especially futures) market. Figlewski (1981) suggests that the open interest can explain volatility in GNMA futures market [26]. Bessembinder and Seguin (1993) examine the relationship between volatility and market depth (measured as open interest) in eight futures markets, and report a negative influence of expected open interest on volatility [23]. Ragunathan and Peker(1997) demonstrate that market depth (open interest) affect volatility, and positive open interest shocks have stronger impacts than negative shocks [15]. Fung and Patterson (1999) use VAR to examine the relation among volatility and open interest in five currency futures markets, and find volatility is negative related to open interest, but volatility have no predictive power on open interest [27]. Chang et al.(2000) indicate that open interest which measures the demand for hedging increase while unexpected volatility increases [28]. Watanabe(2001) shows that there is a significant negative relationship between volatility and expected open interest in Nikkei 225 index futures market, furthermore, the relationship is regulation-varying [17]. Ferris et al.(2002) document that implied volatility links open interest through pricing error [29]. Girma and Moutgoue (2002) investigate the relationship between spread variability and open interest in petroleum futures market, and uncover that contemporaneous and lagged open interest can explain spreads volatility, so the sequential information arrival hypothesis is verified [30]. Motladiile and Smit (2003) get the evidence of positive shocks in open interest increases the volatility in South African stock index futures market [31]. Yang et al. (2004) investigate the information role of open interest in long-term, and find that open interest share same information as price for storable commodities futures, but price drive open interest, not verse vice [32]. Floros(2007) reports that current open interest can explain GARCH effect of returns, investors may utilize the information of open interest in forecasting futures price in the long term in Greek [33]. Yen & Chen(2010) examine the interrelationship between volatility and open interest in three Taiwan's stock index futures market, and find that both current and lagged open interest help to predict future volatility, both sequential information arrival hypothesis and traders with trade time discretion tend to trade when market is relatively liquid hypothesis are confirmed [34]. Kumar and Pandey(2010) find insignificant relationship between volatility and open interest for most commodity futures markets in India [35].

Investigating the relationship between volatility, volume and volatility is essential in market microstructure literature because it is heuristic for time series forecasting. However, due to the various market structures, the empirical relationship remains unresolved. Moreover, most studies are conducted in developed markets, few studies explore this issue in emerging markets like China. This paper fills the gap by examining the extent to which volume and open interest explain the return (volatility) in CSI 300 index futures market using elaborate methodology and high-frequency data set. This article contributes to literature in three ways. First, to the best of our knowledge, this is the first study to explore volume, open interest and return (volatility) dynamics in CSI 300 index futures market, a newly established financial derivative market in China. Second, it tests the mixture distribution hypothesis, sequential information arrival hypothesis and market efficiency in index futures market in China. Third, it goes beyond GARCH, VAR and Granger causality techniques. We examine how volume and open interest explain the GARCH effects of returns, and investigate the long-run relationship between return, and volume, open interest.

The remainder of the study is organized as follows. Section 2 outline the data and methodology we use in this study. Section 3 describes the empirical result of this study. The discussion is reported in section 4. Section 5 provides conclusions.

2 Data and Method

2.1 Data Sources

There are two stock exchanges in mainland China, Shanghai Securities Exchange established in 1990, and Shenzhen Securities Exchange established in 1991. Along with the economic growth of China, two stock markets have grown rapidly. Shanghai Stock Exchange is the world's 6th largest stock market by market capitalization at US$2.5 trillion as of Dec 2012, and Shenzhen is the world’s 16th by market capitalization at US$1.15 trillion. CSI 300 index was introduced by the China Securities Index Company, Ltd. on April 8, 2005. It consists of 300 largest and actively traded A-share companies listed on Shanghai and Shenzhen Stock exchange, and share about 70% of market capitalization in China. CSI 300 index comprehensively measures the movement of A-share markets in China.

On April 16, 2010, China Financial Futures Exchange launched CSI 300 futures contract, which is the first index futures in mainland China. The outline of CSI 300 index futures is presented in Table 1. The size of CSI futures contract is RMB 300 multiplied by the value of CSI 300. There are four contracts traded simultaneously, current, next month and next two quarter-month contracts. The contract will expire on the third Friday of the contract (delivery) month. The tick size is set 0.2 index point. After launched, CSI 300 futures market is active. In year 2012, the transaction volume is about 105 million units, and the transaction amount is approximately 43.8 trillion RMB.

Table 1 Outline of CSI 300 index futures

Items	Specification
Underlying Index	CSI 300 Index
Contract Multiplier	RMB 300
Unit	Index point
Tick Size	0.2 point
Contract Months	Monthly: current month, next month, next two calendar quarters (four total)
Trading Hours	09:15 am - 11:30 am, 01:00 pm - 03:15 pm
Trading Hours on Last Trading Day	09:15 am - 11:30 am, 01:00 pm - 03:00 pm
Limit Up/Down	+/-10% of settlement price on the previous trading day
Margin Requirement	12% of the contract value
Last Trading Day	Third Friday of the contract month, postponed to the next business day if it falls on a public holiday
Delivery Day	Third Friday, same as "Last Trading Day"
Settlement Method	Cash Settlement
Transaction Code	IF
Exchange	China Financial Futures Exchange

Source: www.cffex.com.cn/en_new/sspz/hs300zs/

This study uses 1-min transaction data for CSI 300 futures from China Financial Futures Exchange (CFFEX). The sample period covers from July 1, 2012 to December 31, 2012. To get the continuous futures price series, we only use near-month futures prices data, and rollover to the next maturing contract on Monday of expire week. There are 2 trading sessions per day, 09:15-11:30(Beijing time) and 13:15-15:15 (15:00 on the last trading day) from Monday to Friday. Then we get 270 observations per day. The 1-min return is calculated as $R_t = \ln(P_t / P_{t-1})$.

Fig.1 provides the distribution of 1-min price series from July 1, 2012, to December 31, 2012. In the sample period, the Chinese stock market runs in a downtrend with a few transitory uptrends. The 1-min price series seem to be nonstationary.

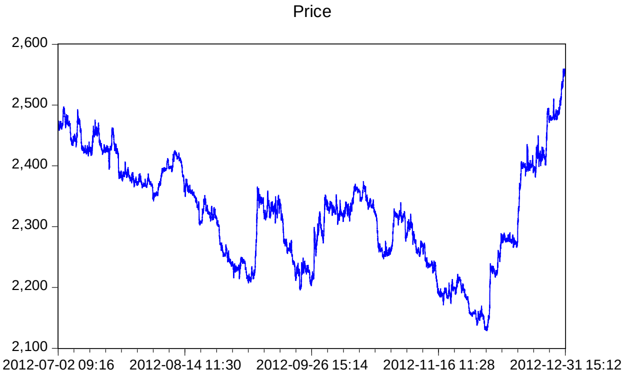

Fig.1 Movement of CSI 300 index futures price at each time from July 1, 2012, to December 31, 2012

Fig. 2 describes the distribution of 1-min return series from July 1, 2012, to December 31, 2012. It seems that return series are stationary and there is volatility clustering.

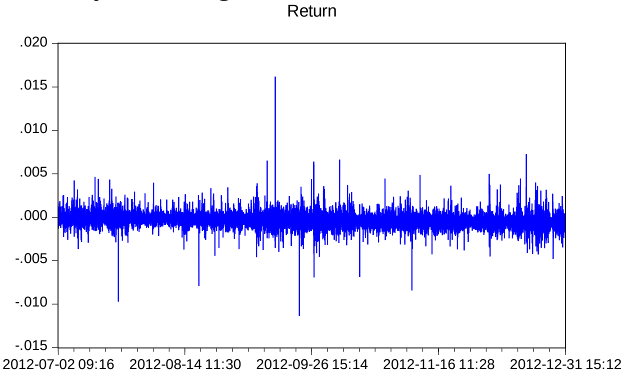

Fig.2 Movement of CSI 300 index futures return at each time from July 1, 2012, to December 31, 2012

Fig.3 demonstrates the distribution of 1-min volume series from July 1, 2012, to December 31, 2012. Volume fluctuates and it shrinks when contract expires

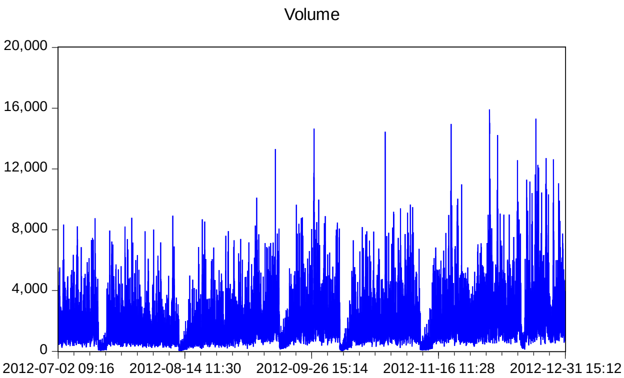

Fig.3 Movement of CSI 300 index futures volume at each time from July 1, 2012, to December 31, 2012

Fig.4 shows the distribution of 1-min open interest series from July 1, 2012, to December 31, 2012. The open interest fluctuates with circle, which is in accordance with the reality that the nearest contract is most active and the sample screening.

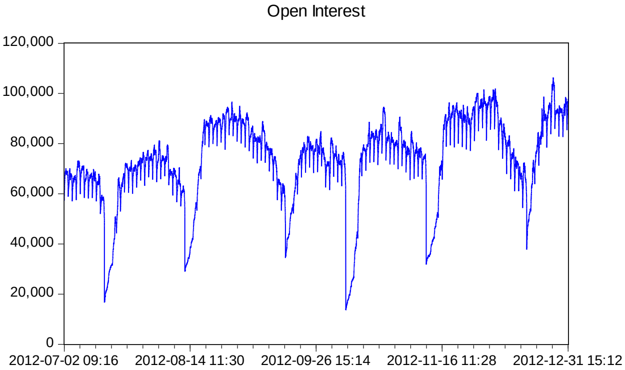

Fig.4 Movement of CSI 300 index futures open interest at each time from July 1, 2012, to December 31, 2012

Table 2 presents the summary statistics of the CSI 300 futures price, return, volume and open interest. The mean 1-min intraday return is 8.10E-07 with a standard deviation of 0.0006. The returns are volatile measured by standard deviation. The distributions of all series are highly leptokurtic and price, return and volume series are positively skewed while open interest series is negatively skewed. The null hypothesis of normally distributed is rejected while Jarque-Bera statistics are highly statistically significant. ADF statistics of return, volume and open interest are significant statistically, indicating these series are stationary, while price series is nonstationary.

Table 2 Summary statistics of the sample

	P_t	R_t	V_t	OI_t
Mean	2313.15	8.10E-07	1611.8	72337.9
Median	2315.6	0	1298.5	74455.5
Maximum	2542	0.02	15925	104201
Minimum	2113	-0.01	23	12416
Std. Dev.	91.17	0.0006	1267.8	16843.3
Skewness	0.02	0.66	2.54	-1.14
Kurtosis	2.25	32.93	14.515	4.34
Jarque-Bera	800 (0.000)	1272664 (0.000)	224452 (0.000)	9982 (0.000)
ADF	0.2125 (0.9982)	-181.4191 (0.0001)	-19.858 (0.0000)	-4.1795 (0.0047)
Obs.	34020	34020	34020	34020

Note: Figures in parentheses are the *p*-values

The Ljung BOX-Q (LB-Q) statistics of return, squared return are computed and displayed in table 3. All value of LB-Q statistics of returns and squared returns are significant statistically, indicating that there is volatility clustering in returns series. The null hypothesis of identical and independent observations and no serial dependence in returns and squared returns series are rejected.

Table 3 Autocorrelation of return, squared return series

LB-Q statistic	LB-Q(4)	LB-Q(8)	LB-Q(12)
Return	15.896	28.701	40.576
	(0.003)	(0.000)	(0.000)
Squared Return	254.19	400.52	485.43
	(0.000)	(0.000)	(0.000)

Note: Figures in parentheses are the *p*-values

2.2 Research Method

The CSI 300 futures returns exhibits time-varying volatility, excess kurtosis, volatility clustering. Most studies about volatility dynamics utilize GARCH class models, GARCH class models are also effective in forecasting price volatility due to accommodating volatility clustering (Bollerslev, 1986)[36]. To accommodate the observed time-varying and persistent patterns in returns volatility and asymmetry in return shocks, we utilize ARMA-EGARCH model bellow.

$$R_t = c + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

$$\varepsilon_t \mid \Omega_{t-1} \sim \mathrm{GED}(0, \sigma_t^2) \tag{2}$$

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{n} \beta_j \mathrm{Ln}(\sigma_{t-j}^2) \tag{3}$$

R_t is the return of CSI 300 futures at time t, ε_t is the error conditional on the information set Ω_{t-1}, and it follows Generalized Error Distribution (GED). α_i is coefficient of ARCH term, which measures the impact of current shocks on volatility. β_j is the coefficient of GARCH term, which measures the impact of previous shocks on volatility. γ measures the asymmetric effect of shocks on volatility, negative shocks have stronger influence than positive shocks when $\gamma<0$.

To investigate the impact of volume and open interest on the persistence of volatility, we extend the EGARCH model with an exogenous explanatory variable of volume (or open interest) in the variance equation. If volume (open interest) has significant influence on volatility, the coefficient of $\delta(\delta_1)$ is significant statistically.

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{n} \beta_j \mathrm{Ln}(\sigma_{t-j}^2) + \delta V_t(OI_t) \tag{4}$$

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{n} \beta_j \mathrm{Ln}(\sigma_{t-j}^2) + \delta_1 V_{t-1}(OI_{t-1}) \tag{5}$$

To examine the extent to which volume and open interest explain the persistence of volatility, we add volume and open interest in EGARCH model simultaneously. If volume and open interest have joint effects on volatility, the coefficients of δ_2 (δ_4) and δ_3(δ_5) are significant statistically.

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{n} \beta_j \mathrm{Ln}(\sigma_{t-j}^2) + \delta_2 V_t + \delta_3 OI_t \tag{6}$$

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{n} \beta_j \mathrm{Ln}(\sigma_{t-j}^2) + \delta_4 V_{t-1} + \delta_5 OI_{t-1} \tag{7}$$

Because GARCH model does not accommodate the causality relationship between volume, open interest and volatility, we build VAR model between volume, open interest and volatility, and employ Grange causality test.

In addition, we build a three-variable VAR model and take variance decomposition and impulse response function to examine the dynamics between volume, open interest and volatility.

$$\begin{bmatrix} R_t \\ V_t \\ OI_t \end{bmatrix} = \Phi_1 \begin{bmatrix} R_{t-1} \\ V_{t-1} \\ OI_{t-1} \end{bmatrix} + \Phi_2 \begin{bmatrix} R_{t-2} \\ V_{t-2} \\ OI_{t-2} \end{bmatrix} + \cdots + \Phi_p \begin{bmatrix} R_{t-p} \\ V_{t-p} \\ OI_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \tag{8}$$

3 Empirical Result

3.1 Variance Equation with only Volume

Table 4 displays the estimates of ARMA-EGARCH model with only contemporaneous volume in variance equation. All coefficients are significant statistically at 1% level, suggesting that the model fits the sample. The coefficient of γ is negative and significant statistically, suggesting that negative shocks have a greater impact on volatility than positive shocks. Moreover, the coefficient of δ is positive significantly statistically, indicating that contemporaneous volume leads to increase in the volatility persistence.

Table 4 Results of ARMA-EGARCH model with only contemporaneous volume

Variable	Coefficient	*p*-value
c	-8.14E-06	0.0001
ϕ_1	-1.4423	0.0000
ϕ_2	-0.4424	0.0000
θ_1	1.3664	0.0000
θ_2	0.3665	0.0000
α_0	-20.1973	0.0000
α_1	0.1546	0.0000
γ	-0.0183	0.0029
β_1	-0.2327	0.0000
δ	0.0008	0.0000

Note: ARMA(2,2)-EGARCH(1,1) model fits the sample

The results of ARMA-EGRACH model with only lagged volume in variance equation are presented in table 5. All coefficients are significant statistically at 5% level, suggesting that the model fits the sample. The coefficient of γ is positive and significant statistically, suggesting that positive shocks have a greater impact on volatility than negative shocks after taking lagged volume into account. Moreover, the coefficient of δ is positive significantly statistically, indicating that lagged volume leads to increase in the volatility persistence.

Table 5 Results of ARMA-EGARCH model with only lagged volume

Variable	Coefficient	*p*-value
c	-4.73E-06	0.0188
ϕ_1	-0.6041	0.0000
ϕ_2	0.3953	0.0000
θ_1	0.5460	0.0000
θ_2	-0.4536	0.0000
α_0	-0.3876	0.0000
α_1	0.1125	0.0000
γ	0.0281	0.0000
β_1	0.9800	0.0000
δ_1	3.74E-06	0.0004

Note: ARMA(2,2)-EGARCH(1,1) model fits the sample

3.2 Variance Equation with only Open Interest

Table 6 demonstrates the estimates of ARMA-EGARCH model with only contemporaneous open interest in variance equation. All coefficients are significant statistically at 5% level, suggesting that the model fits the sample. The coefficient of γ is positive and significant statistically, suggesting that positive shocks have a greater impact on volatility than negative shocks. Moreover, the coefficient of δ is positive significantly statistically, indicating that contemporaneous open interest leads to increase in the volatility persistence.

Table 6 Results of ARMA-EGARCH model with only contemporaneous open interest

Variable	Coefficient	*p*-value
c	-5.78E-06	0.0308
ϕ_1	0.8183	0.0000
ϕ_2	0.1690	0.0000
θ_1	-0.9154	0.0000
θ_2	-0.0720	0.0000
α_0	-1.1834	0.0000
α_1	0.2306	0.0000
γ	0.0294	0.0000
β_1	0.9340	0.0000
δ	2.92E-07	0.0000

Note: ARMA(2,2)-EGARCH(1,1) model fits the sample

The results of ARMA-EGRACH model with only lagged open interest in variance equation are presented in table 7. All coefficients are significant statistically at 5% level, suggesting that the model fits the sample. The coefficient of γ is positive and significant statistically, suggesting that positive shocks have a greater impact on volatility than negative shocks after taking lagged open interest into account. Moreover, the coefficient of δ_1 is negative significantly statistically, indicating that lagged open interest leads to reduction in the volatility persistence.

Table 7 Results of ARMA-EGARCH model with only lagged open interest

Variable	Coefficient	*p*-value
c	-5.26E-06	0.0215
ϕ_1	1.3967	0.0000

ϕ_2	-0.4600	0.0000
θ_1	-1.4300	0.0000
θ_2	0.4848	0.0000
α_0	-0.3628	0.0000
α_1	0.1076	0.0000
γ	0.0313	0.0000
β_1	0.9807	0.0000
δ_1	-1.03E-07	0.0000

Note: ARMA(2,2)-EGARCH(1,1) model fits the sample

3.3 Variance Equation with Volume and Open Interest

The empirical results above suggest that either contemporaneous or lagged volume (open interest) affects the volatility. What is the joint effect of volume and open interest is unsolved.

The estimation results of ARMA-EGRACH model with both contemporaneous volume and open interest in variance equation are presented in table 8. All coefficients are significant statistically at 1% level, suggesting that the model fits the sample. The coefficient of γ is negative and significant statistically, suggesting that negative shocks have a greater impact on volatility than positive shocks after taking both contemporaneous volume and open interest into account. Moreover, the coefficient of δ_2 is positive significantly while δ_3 is negative significantly, indicating that contemporaneous volume (open interest) leads to increase (reduction) in the volatility persistence if both contemporaneous volume and open interest are included.

Table 8 Results of ARMA-EGARCH model with both contemporaneous volume and open interest

Variable	Coefficient	*p*-value
c	-1.14E-05	0.0003
ϕ_1	1.5006	0.0000
ϕ_2	-0.5008	0.0000
θ_1	-1.6423	0.0000
θ_2	0.6426	0.0000
α_0	-18.3156	0.0000
α_1	0.0439	0.0000
γ	-0.0243	0.0028
β_1	-0.2275	0.0000
δ_2	0.0010	0.0000
δ_3	-3.05E-05	0.0000

Note: ARMA(2,2)-EGARCH(1,1) model fits the sample

Table 9 lists the empirical results of ARMA-EGRACH model with both lagged volume and open interest in variance equation. All coefficients are significant statistically at 5% level, suggesting that the model fits the sample. The coefficient of γ is positive and significant statistically, suggesting that positive shocks have a greater impact on volatility than negative shocks after taking both lagged volume and open interest into account. Moreover, the coefficient of δ_4 is positive significantly while δ_5 is negative significantly, indicating that lagged volume (open interest) leads to increase (reduction) in the volatility persistence when both lagged volume and open interest are included.

Table 9 Results of ARMA-EGARCH model with both lagged volume and open interest

Variable	Coefficient	*p*-value
c	-5.55E-06	0.0207
ϕ_1	1.3975	0.0000
ϕ_2	-0.4647	0.0000
θ_1	-1.4283	0.0000
θ_2	0.4876	0.0000
α_0	-2.5959	0.0000
α_1	0.1499	0.0000
γ	0.0349	0.0000
β_1	0.8318	0.0000
δ_4	8.28E-05	0.0000
δ_5	-2.47E-06	0.0000

Note: ARMA(2,2)-EGARCH(1,1) model fits the sample

3.4 Granger Causality Test

We build VAR model between volume, open interest and volatility and then take Granger causality test. Because Grange causality test is sensitive to lagged differences, we utilize LR(sequential modified LR test statistic, each test at 5% level), FPE(Final prediction error), AIC(Akaike information criterion), SC(Schwarz information criterion), HQ(Hannan-Quinn information criterion) statistics to determine the best lagged differences. The results of Granger causality test are presented in table 10. There is unidirectional Granger causality from return to open interest, while there is bidirectional Granger causality between return (volume) and volume (open interest). It means that return can be forecasted through volume, nor open interest. Volume measures the trade activity, and triggers the price volatility.

Table 10 Results of Granger causality test

Relationship	Best Lag	F Statistics	Existing of Granger Causality
$R_t \xrightarrow{\times} V_t$	22	18.8899	Yes

		(0.0000)	
$V_t \xrightarrow{\times} R_t$	22	3.4585 (0.0000)	Yes
$R_t \xrightarrow{\times} OI_t$	16	4.1183 (0.0000)	Yes
$OI_t \xrightarrow{\times} R_t$	16	1.0553 (0.3931)	No
$V_t \xrightarrow{\times} OI_t$	15	9.0347 (0.0000)	Yes
$OI_t \xrightarrow{\times} V_t$	15	15.3451 (0.0000)	Yes

Note: Figures in parentheses are the *p*-values, $\xrightarrow{\times}$ means there is not Granger causality from left to right

3.5 Variance Decomposition

We build a three-variable VAR model of volume, open interest and return, the estimation of VAR is left out due to limited space. The variance decomposition of VAR model is presented in table 11. Most variance of return (volume or open interest) comes from itself. The impact of return on volume is stronger than on open interest, and the impact of volume on open interest is stronger than on return, while the impact of open interest on volume is stronger than on return.

Table 11 Results of variance decomposition

	lag	Return	Volume	Open Interest
Return	1	98.8495	0.9051	0.2455
	6	98.7645	0.9850	0.2505
	12	98.7637	0.9857	0.2505
	18	98.7637	0.9857	0.2506
	24	98.7636	0.9857	0.2507
Volume	1	0.0000	99.5391	0.4609
	6	0.9364	98.7013	0.3623
	12	0.9565	98.6427	0.4008
	18	0.9567	98.5715	0.4719
	24	0.9562	98.4973	0.5466
Open Interest	1	0.0000	0.0000	100
	6	0.1550	0.3716	99.4734
	12	0.2141	0.8174	98.9685
	18	0.2377	1.0252	98.7371
	24	0.2497	1.1338	98.6165

3.6 Impulse Response Function

The impulse response function is demonstrated in Fig.5, Fig.6, Fig.7. The impulse originated from either variable has tiny impact on the other. Similar to variance decomposition, the impact of impulse originated from return on volume (open interest) is stronger than volume (open interest) on return.

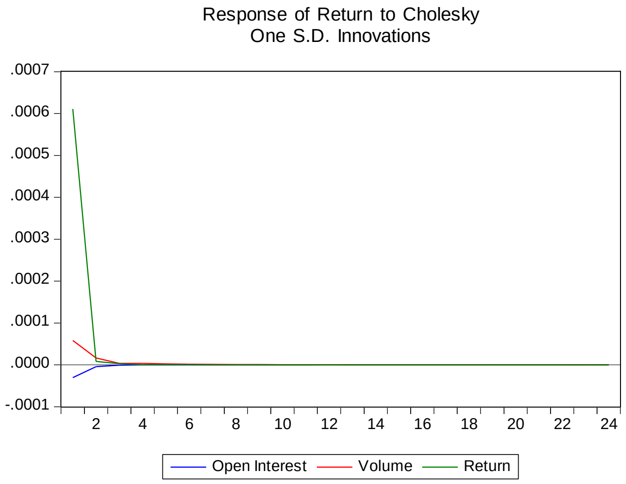

Fig.5 Response of return to innovation

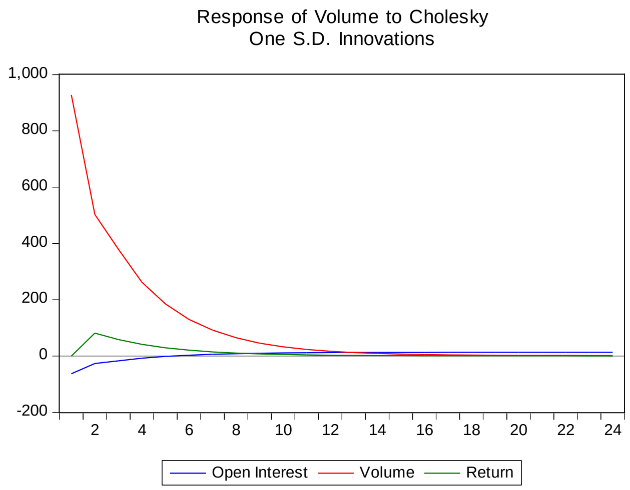

Fig.6 Response of volume to innovation

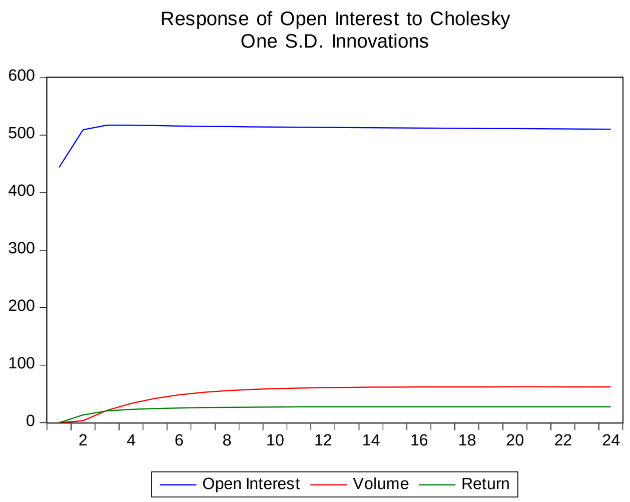

Fig.7 Response of open interest to innovation

4 Discussion

Investors pay much attention to the information role of volume (open interest) for several reasons. It is said that an upward trend is confirmed when volume (open interest) increase along with price increase, volume (open interest) reflects the trading activity. Also, volume (open interest) is a vital indicator in technical analysis. Volume measures the trade activity, while open interest measures the demand of hedging and market depth. Open interest and volume are complementary in information dissemination. The empirical results of ARMA-EGARCH model show that both contemporaneous and lagged volume lead to increase in the volatility persistence, which is similar to Yen and Chen (2010)[34], volatility increases when market is active. Furthermore, lagged open interest has significant negative impact on volatility persistence, whereas contemporaneous open interest has positive influence. This result seems to break the notion that open interest measures the demand of hedging and market depth. Two seasons may explain the contradiction. First, we using 1-min high frequency data, most investors don't trade frequently, the volume and open interest fluctuate synchronously in very short time. Second, investors tend to trade when market is active (Admati and Pfleiderer, 1988) [37], which means that open interest increases when volume increases. Also, both contemporaneous and lagged volume (open interest) leads to increase (reduction) in the volatility persistence when both volume and open interest are included in variance equation simultaneously, indicating that volatility increases when there is divergence.

The Granger causality test results show that return cause volume and open interest, which is similar to Yang et al. (2004) [32], investors tend to make decision according to price fluctuation. It is confused that open interest does not cause return, while volume cause return, indicating that one can predict the return through volume and make profit. The following reasons can explain the anomaly. First, the CSI 300 index futures market is active and plays a dominant role in price discovery process, strengthening the relationship of volume and return. Second, the investing decision according to the lagged volume may be unfeasible if transaction cost is included. Furthermore, there is bidirectional Granger causality between volume and open interest, confirming the notion that volume and open interest are complementary in information dissemination.

The empirical results of variance decomposition and impulse response function indicate that most variance of return (volume or open interest) comes from itself, confirming that CSI 300 index futures market is efficient.

5 Conclusions

Using 1-min high-frequency data, this article examine the dynamic relationship between volatility, volume and open interest in CSI 300 futures market. Unit root test indicates that return, volume and open interest series are stationary. LB-Q statistics of return series confirm volatility clustering and time-vary volatility. To accommodate the observed time-varying and persistent patterns in returns volatility, we utilize ARMA-EGARCH model to examine the asymmetric GARCH effect and the impact of volume or/and open interest on volatility. The empirical results show that both contemporaneous and lagged volume is positively related to volatility, and current open interest has positive effect on volatility while lagged open interest has negative effect. Furthermore, volume is positively related to volatility and open interest is negatively linked to volatility when take (lagged) volume and (lagged) open interest into account simultaneously. Both mixture of distribution hypothesis (MDH) and sequential information arrival hypothesis (SIA) are verified in CSI 300 index futures market. The Granger test indicates that there is unidirectional Granger causality from return to open interest, whereas there is bidirectional Granger causality between open interest (return) and volume. Variance decomposition and impulse response function reveal that most variance of return, volume or open interest is triggered by itself. These results imply that volume and open interest are complementary in information dissemination, while volume measures the trade activity and open interest indicates market depth.

The results have significant implications for the investors and policymakers. The results suggest that one can utilize the information of volume (open interest) to predict volatility in CSI 300 index futures market. Regulators should pay more attention when volume (open interest) is abnormal.

In the future, exploring the role of volume and open interest using ultra-high frequency data would be fruitful. Also, studying the investors' behaviours based on trading records is helpful for explaining the information role of volume and open interest.

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