International Review of Economics and Finance 69 (2020) 48–62

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Intraday sentiment and market returns

Bin Gao [a,*], Xihua Liu [b,**]

[a] School of Business, Guangxi University for Nationalities, Nanning, China
[b] School of Economics, Qingdao University, Qingdao, China

ARTICLE INFO

JEL classification:
G1
G12

Keywords:
Intraday sentiment
Returns predictability
Spillover effect
Contagion effect
Out-of-sample forecasting

ABSTRACT

We investigate intraday sentiment factor and its relation to near-term returns in both the stock market and stock index futures market. For study near-term sentiment effect, we construct stock index futures sentiment and stock sentiment at 5-minutes frequency. In each market system, we show sentiment variables are a strong positive predictor of subsequent stock market returns and stock index futures returns in 5-minutes horizons. In the two market system, the evidence suggests that 1) sentiment variables have a spillover effect that they affect relevant other market's future returns significantly and 2) sentiment variables have contagion effect that they affect relevant other market's future sentiment significantly. Finally, we show an out-of-sample forecasting test and confirm the sentiment variables have powerful predictability to returns in short-term.

1. Introduction

For decades, there is a phenomenon that many finance practitioners search for investment opportunities and predict asset returns based on quantitative analysis and high-frequency data. It has clashed with the traditional efficient market hypothesis (EMH) in explaining the lack of predictability in liquid asset returns. This paper examines how intraday investor sentiment affects stock and futures market return basing on 5-minutes data. We find that intraday investor sentiment has better predict power on future returns. (see Fig. 3)

With the development of behavioral finance, a number of researchers, such as a) De Long, Shleifer, Summers, and Waldmann (1990, Campbell and Kyle (1993), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Mendel and Shleifer (2012), Li (2014), Baker, Hollifield, and Osambela (2016) build theoretic model and explore the role of sentiment to explain the excess returns. Moreover, other recent empirical work also documents that sentiment factor plays a systematic role in asset pricing in both the stock market and futures market.

The prior sentiment indexes usually are sampled at a monthly, weekly and daily frequency in empirical researches. Most stock sentiment indexes usually are sampled at monthly data in empirical researches [Brown and Cliff (2005), Baker and Wurgler (2006), Baker, Wurgler, and Yuan (2012), Kim and Ha (2010), Kurov (2010), Kumar and Lee (2006), Li (2015), Li and Yang (2017) Schmeling (2009), Stambaugh, Yu, and Yuan (2012, 2014), Verma and Soydemir (2009), Yu and Yuan (2011)]. Some stock sentiment indexes also usually are sampled at weekly data [Brown and Cliff (2005); Joseph, Babajide Wintoki, and Zhang (2011)] and daily data [Wang, Keswani, and Taylor (2006); Yang and Zhou (2015)]. In sentiment-futures returns relationship researches, futures sentiment are sampled at weekly [Wang (2001); Wang (2003); Kurov (2008); Yang and Gao (2014)] and daily data [Gao and Yang (2017; 2018); Safa

* Corresponding author.
** Corresponding author.
E-mail addresses: financestudy@foxmail.com (B. Gao), xihua-liu@163.com (X. Liu).

https://doi.org/10.1016/j.iref.2020.03.010
Received 5 January 2017; Received in revised form 23 July 2018; Accepted 25 March 2020
Available online 25 April 2020
1059-0560/

and Maroney (2012); Yang and Gao (2014)]. However, empirical researches pay little attention to intraday data which is more important and informational in practice.

Recent sentiment-return research ignored the intraday sentiment effect. There are several reasons for us to focus on intraday sentiment effect. Our idea is supported by both practice and theoretic conclusion. In actual investment practice, intraday high-frequency trading is more and more popular. Intraday high-frequency trading has short holding periods and trade frequently. At the beginning of the 2000s, intraday high-frequency trading represented less than 10% of all equity trades in the United States, whereas, by late 2012, intraday high-frequency trading accounted for approximately 50% of all U.S. equity-exchange trading volume, and between 40% and 60% of trading activity across all U.S. financial markets for stocks, options and currencies from the reports of Popper (2012), and Kirilenko and Lo (2013). In the Chinese financial market, Gao and Yang (2018) show the ratio of volume to open interest in the Chinese market is 8 times more than the ratio in the overseas mature market. They find that intraday trading is almost popular stock index futures market.

Short-term sentiment effect is validated by some pricing model and financial experiment. It has been testified irrational factor is systemic and important in the short-term investment. For example, Schwartz and Smith (2000) developed two-factor futures pricing model; Cortazar and Naranjo (2006) developed N-factor futures pricing model, they both show deviations cannot be ignored in short-term, however, the deviations are expected to revert toward zero in long-term. Investors could not realize their sentimental behavior and cancel its effect and return to ration in short-term. By using the functional magnetic resonance imaging, McClure, Laibson, Loewenstein, and Cohen (2004) examined the neural correlates of time discounting while subjects made a series of choices between monetary reward options that varied by the delay to delivery, and demonstrated that irrational factors have more effect in the short-term decision-making.

Short-term sentiment effect is also supported by other empirical articles. Brown and Cliff (2004) investigate investor sentiment and near-term stock market returns by weekly, monthly sentiment, and find sentiment variables are strongly correlated with contemporaneous market returns, but sentiment has little predictive power for near-term future returns. Yang and Gao (2014) find the term structure of stock sentiment and stock index futures are downward-sloping by comparing the annual contributions of the daily, weekly, monthly sentiment. Yang and Zhang (2014) also find the term structure of the stock sentiment and the individual stock sentiment are downward-sloping; they pay attention to heterogeneous influences of the sentiment index sampled at the weekly, monthly and quarterly frequencies. These empirical conclusions show short-term sentiment effect is important than long-term. However, these studies do not investigate the investor sentiment effect in intraday data.

In this paper, we investigate the relationship between sentiment and subsequent market returns base on 5-minutes frequency data in the Chinese stock index and stock index futures markets. It contributes to the literature in the following aspects. First, to the best of our knowledge, this is the first study to explore the intraday sentiment effect. We construct separately sentiment measures into two markets, stock index market and stock index futures market. The stock sentiment proxies are commonly cited sentiment measures such as the trading volume, adjusting turnover rate, ARMS index, buy-sell imbalance and psychological line index. The stock index futures sentiment proxies are the trading volume, open interest, RSI index, buy-sell imbalance and psychological line index. Many of these measures contain related information. Consequently, we employ principal component analysis as a means of extracting composite unobserved sentiment measures.

Second, we examine the statistical causality between intraday sentiment and the market returns, and we see the single market as a system. Specifically, we explore the bidirectional relation in a vector autoregression (VAR) model by 5-minutes data. We show that stock sentiment is a strong positive predictor of subsequent stock market returns at the 1% level. In contrast, stock index returns is a strong negative predictor of subsequent levels and changes of stock sentiment at the 1% level. Two independent market studies each came to the same conclusions. Stock index futures sentiment could positively predict future stock index returns at the 5% level. However, the impact of stock index returns on stock index futures sentiment is negative obviously at the 1% level.

Third, we identify how one market sentiment affects relevant other market sentiment and returns. We see both stock index market and stock index futures market as a system in a vector autoregression (VAR) model. The evidence confirms that sentiment variables have a spillover effect[1] that they affect relevant other market's future returns significantly. We find that stock sentiment (stock index futures sentiment) affects subsequent 5-minutes horizons stock index futures returns (stock index returns) positively at the 1% level. The evidence also confirms that sentiment variables have contagion effect[2] that they affect relevant other market's future sentiment significantly. We show that positive stock sentiment (stock index futures sentiment) cause subsequent 5-minutes horizons stock index futures sentiment (stock sentiment) positively at the 1% level.

In the last, we show an out-of-sample forecasting test and confirm the sentiment variables have powerful predictability to returns in short-term. Our results are helpful for understanding the irrational factors have more effect on high-frequency decision-making. This is good news for investors trying to use sentiment measures for short-term market timing. It appears that some strategies based on high-frequency sentiment are profitable during intraday trading.

The rest of the paper is organized as follows. Section 2 we construct intraday stock sentiment and intraday stock index futures sentiment and describe their summary statistics. Section 3 presents the methodology and the empirical results from the VAR model.

[1] Yang and Gao (2014) and also study the spillover effect in futures market, they investigate the contemporaneous relation between sentiment variables and relevant other market's returns in daily/weekly/monthly frequency. In this paper, they investigate the statistical causality between intraday sentiment variables and relevant other market's returns.

[2] Baker et al. (2012) show that sentiment is contagious across six major stock markets. In this paper, they investigate whether sentiment is contagious across underlying stock market and stock index futures market.

Table 1
Summary statistics of stock sentiment proxies at 5-minutes frequency

	TV	ARMS	PSY	ATR	BSI
Mean	16.459	2.200	51.581	0.006	0.008
Median	16.430	1.079	50	0.026	0.031
Maximum	19.329	35.646	100	1.16	0.333
Minimum	14.769	0.082	8.333	−0.652	−0.333
Std. Dev.	0.580	3.550	15.211	0.097	0.247
Skewness	0.356	4.579	0.031	0.431	−0.060
Kurtosis	3.056	28.940	2.665	8.198	1.339
Jarque-Bera	203.892	302709.00	46.52	11104.54	1109.86
Probability	0	0	0	0	0
Observations	24192	24192	24192	24192	24192

Table 1 presents the summary statistics of stock sentiment proxies. The variables incudes trading volume (TV), ARMS index (ARMS), adjusting turnover rate (ATR), buy–sell imbalance (BSI), psychological line index (PSY). We do logarithm of treatment on the trading volume data. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.

Section 4 describes the out-of-sample forecasting test. Section 5 concludes.

2. Data

The China Financial Futures Exchange launched the country's first stock index futures on April 16, 2010. Only after five years, the China Securities Regulatory Commission announced the volume of CSI 300 stock index futures reached 1.9 trillion on April 2015, and exceeded E-Mini S&P500 index future (average volume 47 billion), and became the world's largest stock index futures product. We choose trading data from the time 9:30–11:30 and 13:00–15:00 in each trading day.[3] The paper selected the dates from April 19, 2010, to September 30, 2014. The data includes a total of 1080 days. The in-sample period ranges from April 16, 2010, to May 16, 2012, covering 504 days and 24192 5-minutes data. The out-of-sample period ranges from May 17, 2012, to September 30, 2014, also covering 504 days and 24192 5-minutes data. The data is from the China Financial Futures Exchange (http://www.cffex.com.cn), the Wind database and the RESSET database.

2.1. 1. Stock sentiment

In this part, we set up (Shanghai Shenzhen 300 index) stock sentiment. We decided to form a composite sentiment index based on their first principal component. Based on the related existing literature, we consider five separate proxies: trading volume (TV), ARMS index (ARMS), adjusting turnover rate (ATR), buy-sell imbalance (BSI), psychological line index (PSY).

Trading volume (TV). Trading volume, or more generally liquidity, can be viewed as a stock sentiment index by Baker and Wurgler (2006). For instance, Baker and Stein (2004) note that if short-selling is more expensive than opening and closing long positions, irrational investors are more likely to trade, and thus add liquidity, when they are optimistic and betting on rising price rather than when they are pessimistic and betting on falling price.

ARMS index (ARMS). The ARMS index is a stock sentiment indicator by Brown and Cliff (2004) and Wang et al. (2006). The ARMS index is a modification of ADV/DEC, which incorporates volumes. ADV/DEC is the ratio of the number of advancing issues to declining issues. This measure is the ratio of the number of advances to declines standardized by their respective volumes.

Adjusting turnover rate (ATR). Baker and Stein (2004) suggest that the turnover rate can serve as a sentiment index. But the turnover rate can't show whether it is investors' optimistic or pessimistic. Yang and Zhang (2014) suggest that use adjust turnover rate. If the return is above zero, it means when the stock market is bullish, and high turnover rate means high sentiment. If the return is below zero, it means the when the stock market is bearish, and the high turnover rate means low sentiment.

Specifically, the adjusted turnover rate (*ATR*) is as follows:

$$ATR_{it} = \frac{R_{it}}{|R_{it}|} \times \frac{VOL_{it}}{\text{shares outstanding at time t}}.$$

Where, R_{it} is the return of stock i at time t, VOL_{it} is the trading volume of stock i at time t.

Buy–sell imbalance (BSI). The fourth proxy is based on Buy–sell imbalance (BSI). Kumar and Lee (2006) use the trading activities of retail investors to measure changes in their sentiments. Chordia, Roll, and Subrahmanyam (2002) and Han and Kumar (2013) use transaction data to classify trades as buyers or sellers according to the Lee and Ready (1991) algorithm: if a trade is executed at a price above (below) the quote midpoint, it is classified as a buy (sell).

We define the time t *BSI* for the stock i as:

[3] CSI 300 stock index futures' trading hours are from the time 09:15–11:30 and 13:00–15:15. CSI 300 stocks' trading hours are from the time 09:30–11:30 and 13:00–15:30. Thus we choose the common time period from 9:30–11:30 and 13:00–15:00.

$$BSI_{it} = \frac{BV_{it} - SV_{it}}{BV_{it} + SV_{it}}.$$

Here, BV_{it} is the buyer-initiated volume of stock i at time t, SV_{it} is the seller-initiated volume of stock i at time t. If $BSI > 0$, that is, the buyer-initiated volume is greater than the seller-initiated volume.

Psychological line index (PSY). The fifth proxy is based on Psychological line index (PSY). The Psychological Line is a sentiment indicator by Kim and Ha (2010) and Yang and Gao (2014). The indicators could detect undertones for a trend change of market. The psychological line index (PSY) is as follows:

$$PSY_t = T^u / T \times 100.$$

Where T^u is the numbers when the closing price of the stock i at time t is higher than the closing price of the stock i at time $t-1$, and T is the trading period.

The in-sample selected data from April 19, 2010, to May 16, 2012. The data is from the RESSET database. The stock index sentiment proxies are measured 5-minutes. Table 1 presents the summary statistics of Stock sentiment proxies in the CSI300 index market.

A composite index is based on their first principal component. This procedure leads to the stock index sentiment index SS:

$$SS_t = 0.256TV_t + 0.412ARMS_t + 0.613PSY_t + 0.484ATR_t + 0.391BSI_t.$$

Each of the four components was standardized. The first principal component explains 57% of the (standardized) sample variance, and only the first eigenvalue is far above 1.00, so we conclude that one factor captures the common variation.

2.2. Stock index futures sentiment

In this part, we set up the Shanghai Shenzhen 300 index futures sentiment. We decided to form a composite sentiment index based on their first principal component. Based on the related existing literature, we consider five separate proxies: trading volume (TV), RSI index (RSI), open interest (OI), buy-sell imbalance (BSI), psychological line index (PSY).

Trading volume (TV). Baker and Stein (2004) note that trading volume can stand for market liquidity; it could be as a sentiment indicator. Scheinkman and Xiong (2003) note that volume reveals the underlying difference of opinion, which are in turn related to valuation levels when short selling is difficult. Yang and Gao (2014) also use trading volume as stock index futures sentiment proxies.

Relative strength index (RSI). The relative strength index is a popular futures market indicator showing whether the futures market is oversold or overbought. Kim and Ha (2010) use the relative strength index as one of sentiment indicator to form a composite index of sentiment. Chen, Chong, and Duan (2010) also serve the relative strength index as sentiment proxy to construct the composite investor sentiment index. The relative strength index (RSI) is as follows:

$$RSI_t = 100 \cdot RS_t / (1 + RS_t) \quad ,$$

$$RS_t = \frac{\sum_{t=1}^{6} \max(P_t - P_{t-1}, 0)}{\sum_{t=1}^{6} \max(P_{t-1} - P_t, 0)} \quad .$$

Where P_t is the closing price of stock index futures i at time t, and P_{t-1} is the closing price of stock index futures i at time $t-1$.

Psychological line index (PSY). The third proxy is based on psychological line index (PSY). The psychological line is a sentiment indicator by Kim and Ha (2010). The psychological line is a good indicator for predicting short-term reversals of the futures market by Yang and Gao (2014).

Buy–sell imbalance index (BSI). The fourth proxy is based on buy-sell imbalance (BSI). Wang (2011) also use the buy-sell imbalance as a sentiment indicator from the Taiwan electronic stock index (TE) and the Taiwan financial stock index (TF). We define the time-t BSI for stock index futures i as:

$$BSI_{it} = \frac{BV_{it} - SV_{it}}{BV_{it} + SV_{it}}.$$

Here, BV_{it} is the buyer-initiated volume of stock index futures i at time t, SV_{it} is the seller-initiated volume of stock index futures i at time t.

Open interest (OI). The fifth proxy is based on Open interest (OI). By Wang (2001), Open interest is the futures sentiment index, rather than net positions or excess long (or short) positions, is chosen to study returns predictability in futures markets. Simon and Wiggins III (2001) also consider open interest as a sentiment indicator which provides a more-intuitive reading of trade actions.

The in-sample period ranges from April 16, 2010, to May 16, 2012, covering a total of 24192 observations. The data is from the China Financial Futures Exchange and the Wind database. The stock index futures sentiment proxies are measured by 5-minutes data.

A composite index is based on their first principal component. Because the influence of macroeconomic variables is weak in the short term, we don't consider each proxy with respect to the macroeconomic variable.

This procedure leads to the stock index futures sentiment index (FS), for example (IFL0, 5-minutes):

Table 2
Summary statistics of stock index futures sentiment proxies at 5-minutes frequency

	TV	OI	RSI	PSY	BSI
Mean	9.212	11.432	50.566	47.618	0.003
Median	9.300	11.620	50.412	48.609	0.000
Maximum	10.904	12.212	99.877	87.500	0.334
Minimum	0.000	7.537	0.001	0.000	−0.333
Std. Dev.	0.699	0.651	17.247	14.015	0.201
Skewness	−1.660	−2.453	0.058	−0.604	−0.033
Kurtosis	9.478	9.767	2.690	4.266	1.569
Jarque-Bera	20565.15	27941.21	43.78	1225.39	796.52
Probability	0.000	0.000	0.000	0.000	0.000
Observations	24192	24192	24192	24192	24192

Table 2 presents the summary statistics of the stock index futures sentiment proxies. The variables incudes trading volume (TV), RSI index (RSI), open interest (OI), buy–sell imbalance (BSI), psychological line index (PSY). We do logarithm of treatment on the trading volume data and open interest data. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.

Table 3
Summary statistics of market sentiment and returns at 5-minutes frequency

	SS	FS	SR	FR
Mean	0.000	0.000	0.000	0.000
Median	−0.249	−0.053	0.000	0.000
Maximum	3.179	5.229	0.026	0.028
Minimum	−2.716	−3.840	−0.023	−0.037
Std. Dev.	1.446	1.076	0.003	0.003
Skewness	1.416	0.295	0.152	0.034
Kurtosis	7.433	3.476	9.111	11.852
Jarque-Bera	11447.180	237.156	15502.930	32436.860
ADF	−7.25***	−16.12***	−96.96***	−102.82***
DW	2.000	2.000	2.004	2.002
Observations	24192	24192	24192	24192

Table 3 presents the summary statistics of four variables in CSI300 index market and CSI300 index futures market. SR denotes stock market returns of CSI300 index. SS denotes stock market sentiment in CSI300 index market. FR denotes futures returns of CSI300 index futures. FS denotes futures sentiment in CSI300 index futures. Test critical values of ADF at the 1% are about −3.43 in our sample. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.

$$FS_t = 0.025\mathrm{TV}_t + 0.678RSI_t + 0.265PSY_t + 0.683BSI_t \; - 0.040OI_t$$

where each of the four components was standardized. The first principal component explains 53% of the (standardized) sample variance, and only the first eigenvalue is far above 1.00, so we conclude that one factor captures the common variation.

2.3. Summary statistics

Table 3 shows summary statistics of stock index futures sentiment at 5-minutes data. The average of the futures returns (FS), the average of the futures returns (FR), the average of the futures sentiment (FS) and the average of the stock sentiment (SS) are 0. Looking at standard deviation values, we can see that the standard deviations of sentiment variables are larger than returns variables. It shows the sentiment variables are more changeful. The DW values of all variables in Table 3 are around 2, so we can reject the autocorrelation hypothesis. And the levels of ADF is at 1% level, it shows that all variables are stable-series.

3. Methodology and results

3.1. Sentiment variables and returns in the single market as a system

Some of our earlier analysis suggests that market returns and sentiment index may act as a system. In the section, we estimate a set of VAR models in stock market and stock index futures market. The goal is to see how sentiment index and market returns interact in stock market and stock index futures market.

3.2. The model is

$$Y_t = \mu + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t$$

Table 4
5-minutes VAR-returns and sentiment levels

Plane A				Plane B			
Independent variable	Lag	Dependent variable		Independent variable	Lag	Dependent variable	
		SS	SR			FS	FR
SS	1	0.5848***	0.0104***	FS	1	0.0624***	0.0042**
	2	0.2863***	−0.0055***		2	−0.0026	−0.0019
p-value		0.0000***	0.0000***	p-value		0.0000***	0.0230**
SR	1	−0.4349***	0.0628***	FR	1	−1.1799***	−0.0564***
	2	−1.0923***	−0.0774***		2	−0.5529***	−0.0016
p-value		0.0000***	0.0000***	p-value		0.0000***	0.0000***
Constant		0.0043	0.0025*	Constant		0.0025	0.0024*
Block exogenity		0.0000***	0.0000***	Block exogenity		0.000***	0.0499**
R^2		0.6158	0.0187	R^2		0.199	0.015

In Plane A, variables are the stock market sentiment (SS), the stock market returns (SR). In Plane B, variables are the stock index futures sentiment (FS) and the stock index futures returns (FR). In each column, the p-values show the joint significance of the own-lags values of the independent variable. Block exogenity reports the joint significance of all lags of all independent variables. White (1980) standard errors correct for heteroskedasticity. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

Table 5
5-minutes VAR-returns and sentiment changes

Plane A				Plane B			
Independent variable	Lag	Dependent variable		Independent variable	Lag	Dependent variable	
		ΔSS	SR			ΔFS	FR
ΔSS	1	−0.4094***	0.0094***	ΔFS	1	−0.5453***	0.0027**
	2	−0.1863	0.0049***		2	−0.1520***	−0.0004
p-value		0.0000***	0.0000***	p-value		0.0000***	0.0754*
SR	1	−0.4167***	0.0658***	FR	1	−4.3840***	−0.0430***
	2	−0.9791***	−0.0763***		2	−3.6039***	0.007
p-value		0.0000***	0.0000***	p-value		0.0000***	0.0341**
Constant		0.0041	0.0025*	Constant		0.0173	0.0023
Block exogenity		0.0000***	0.0000***	Block exogenity		0.0000***	0.0944*
R^2		0.1974	0.0178	R^2		0.4653	0.0113

In Plane A, variables are the change of stock market sentiment (ΔSS), the stock market returns (SR). In Plane B, variables are the change of stock index futures sentiment (ΔFS) and the stock index futures returns (FR). In each column, the p-values show the joint significance of the own-lags values of the independent variable. Block exogenity reports the joint significance of all lags of all independent variables. White (1980) standard errors correct for heteroskedasticity. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

where $Y_t = [SS_t,\ SR_t]$ or $Y_t = [FS_t,\ FR_t]$ for the 5-minutes VAR model. Firstly, we choose the metrics in the models. By AIC and BIC test, it suggests lags = 2 in the stock market and stock index futures market dates.

Table 4 reports the results from estimating the 5-minutes sample VAR using sentiment levels. For test the identify the statistical causality in both stock market and stock index futures market, we use stock market data in Plane A and use stock index futures market data in Plane B. The estimating of each independent variable is shown in the blocks of rows at lags one and two. In each column, the p-values show the joint significance of the own-lags values of the independent variable. Block exogenity reports the joint significance of all lags of all independent variables. We primarily interest the results in the first block of rows and the first column.

In Plane A of Table 4, the first block of rows shows that the level of stock sentiment variable is a powerful predictor of itself at the 1% level in the joint test. Both the 5-minutes and 10-minutes lags are significantly positive (+0.584, +0.286) at the 1% level. The next column reveals that stock sentiment could predict future stock index returns at the 1% level in the joint test. The 5-minutes lags are significantly positive (+0.0104) on future stock index returns at the 1% level. Looking at the second column, the impact of stock index returns on stock sentiment is negative obviously at the 1% level in the joint test. Both the 5-minutes and 10-minutes lags are significantly negative (−0.434, −1.092) at the 1% level.

In Plane B of Table 4, the first column shows that the level of stock index futures sentiment variable is a powerful predictor of itself the 1% level in the joint test. It also reveals that stock index futures sentiment could predict future stock index returns at the 5% level in the joint test. Looking at the second column, the impact of stock index returns on stock index futures sentiment is negative obviously at the 1% level in the joint test.

Table 6
5-minutes VAR-returns and sentiment levels in two markets

Independent variable	Lag	Dependent variable			
		SS	FS	SR	FR
SS	1	0.5967***	0.6318***	0.2614***	0.0440***
	2	0.6308***	0.1332	0.1574***	0.0155
	3	0.4120***	0.1897	0.1367***	0.0385
	4	0.2077***	0.0326	0.0561***	−0.0025
p-value		0.0000***	0.0000***	0.0000***	0.0000***
FS	1	0.1245***	0.0437***	0.0206***	0.0041***
	2	0.0144	0.0059	0.0043***	−0.0012
	3	0.0122	0.0539***	0.0009	0.0011
	4	−0.008	0.0387***	0.0003	0.0019
p-value		0.0014***	0.0000***	0.0000***	0.0000***
SR	1	−1.4219***	−0.5564***	−0.3203***	0.0450***
	2	−1.0479***	−0.3864**	−0.2373***	−0.0295
	3	−0.5611***	−0.2637	−0.1067***	−0.0331
	4	−0.2856***	−0.0756	−0.0443***	−0.0162
p-value		0.0000***	0.0000***	0.0000***	0.0000****
FR	1	0.4553***	−0.0351***	0.0011*	0.0023
	2	0.1749***	−0.0494***	0.0040***	−0.0004
	3	0.1583***	−0.0132	0.0006	−0.0027
	4	0.1171***	0.0089	0.0002	0.0035
p-value		0.0000***	0.0000***	0.0000***	0.2454
Constant		0.0036*	0.0039	0.0025**	0.0025
Block exogenity		0.000***	0.000***	0.000***	0.000***
R^2		0.6495	0.1156	0.1169	0.0227

Variables are the stock market sentiment (SS), the stock market returns (SR), and the stock index futures sentiment (FS) and the stock index futures returns (FR) as one system. White (1980) standard errors correct for heteroskedasticity. Block exogenity reports the p-value of an F-test that the coefficients on all lags of all independent variables (other than own-lags) are jointly zero. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

We find market returns are positively related to recent 5-minutes investors' sentiment. If speculators trade by their optimistic beliefs, it causes to increase future 5-minutes returns. Conversely, sentiment variables are negatively related to recent 5-minutes market performs. These results confirm that speculators would be inclined to sway and reverse their beliefs with recent high market performance.

The results from estimating the 5-minutes sample VAR with sentiment changes are presented in Table 5. In Plane A of Table 5, the first block of rows shows that the change of stock sentiment variable is a powerful predictor of itself at the 1% level in the joint test. It also reveals that the change of stock sentiment could predict future stock index returns at the 1% level in the joint test. Looking at the second column, the impact of stock index returns on the change of stock sentiment is negative obviously at the 1% level in the joint test. Both the 5-minutes and 10-minutes lags are significantly negative (−0.416, −0.979) at the 1% level.

In Plane B of Table 5, we show that the change of stock index futures sentiment variable is also a powerful predictor of itself the 1% level in the joint test. It also reveals that the change of stock index futures sentiment could predict future stock index returns at the 10% level in the joint test. Looking at the second column, the impact of stock index returns on the change of stock sentiment is negative obviously at the 1% level in the joint test.

In summary, this section reveals that sentiment variables are a strong positive predictor of subsequent stock market returns and stock index futures returns in 5-minutes horizons. In contrast, returns variables are a strong negative predictor of subsequent levels and changes of sentiment variables in 5-minutes horizons.

3.3. Sentiment variables and returns in two markets as a system

Some evidence suggests that the sentiment have spillover effect between the spot market and future market. Especially, Yang and Gao (2014) find stock sentiment affect stock index futures returns significantly. So sentiment variables and returns in both the stock market and stock index futures market may act as one system. For this reason, we estimate a set of VAR models with stock market returns (SR), stock sentiment (SS), stock index futures returns (FR) and stock index futures sentiment (FS). We want to identify the statistical causality in the system.

The model is

$$Y_t = \mu + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t$$

where $Y_t = [SS_t,\ SR_t, FS_t, FR_t]$ for the 5-minutes VAR model. Firstly, we choose the metrics in the models. By AIC and BIC test, it

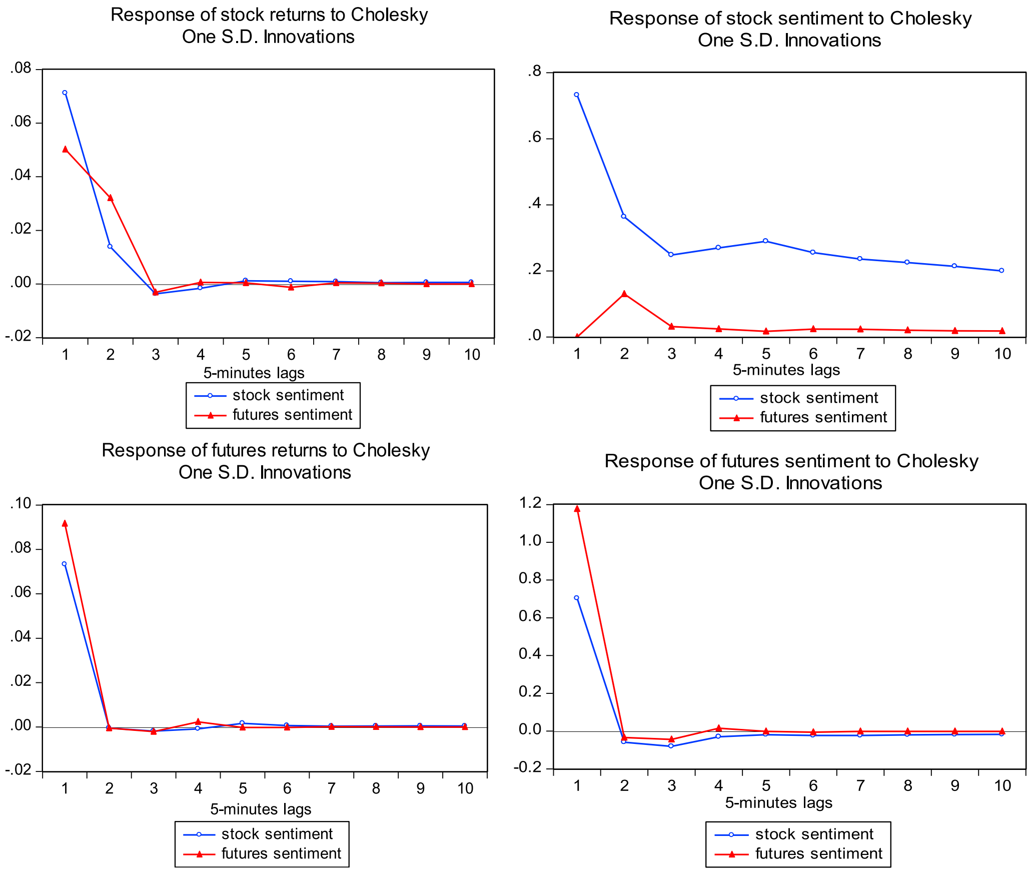

Fig. 1. Impulse response (IRs) functions to Cholesky one standard deviation shock.

suggests lags = 4 in the VAR model.

The results from estimating the 5-minutes sample VAR with sentiment levels are presented in Table 6. The results for the effect of sentiment variables on itself market returns resemble those reported in Table 4 for the 5-minutes sample. Our interest is to identify the statistical causality of the sentiment spillover effect between the spot market and future market in Table 6. Looking at the first rows, the block of the second column shows stock index futures sentiment (FS) is strongly positively related to its past stock sentiment (SS) at the 1% level in the joint test. The block of the fourth column shows stock index futures returns (FR) is strongly positively related to its past stock sentiment (SS). Looking down the second rows, the block of the first column shows stock sentiment (SS) is strongly positively related to its past stock index futures sentiment (FS) at the 1% level in the joint test. The block of the third column shows stock index returns (SR) is strongly positively related to its past stock index futures sentiment (FS).

In this section, it reveals that stock sentiment (SS) is a strong positive predictor of subsequent stock index futures sentiment (FS) and stock index futures returns (FR) in 5-minutes horizons. At the same time, stock index futures sentiment (FS) is also a strong positive predictor of subsequent stock sentiment (SS) and stock index returns (SR) in 5-minutes horizons. The evidence suggests that 1) sentiment variables have a spillover effect that they affect relevant other market's future returns significantly and 2) sentiment variables have contagion effect that they affect relevant other market's future sentiment significantly.

3.3. Impulse responses

To determine the dynamic movement of sentiment spillover effect and sentiment contagion effect, we look at the IRs of each factor to driving sentiment shocks in this section.

We look at impulse response from an unrestricted VAR model. It shows the movements of the market returns in response to driving sentiment shocks at 5-minutes horizons in the first column. Turning first to the IRs of the unrestricted VAR in the first column of Fig. 1, a one-standard deviation shock to stock sentiment initially raises the 5-minutes stock returns about 8 basis points, and the response then quickly drop down to zero. A one-standard-deviation shock to futures sentiment initially raises the 5-minutes stock returns about 5 basis points, and the response then quickly drop down to zero. Similarly, the response of the stock index futures returns initially peaks at the 5-minutes lags (see Fig. 2).

The second column of Fig. 1 plots the IRs of sentiment variables. The IRs of sentiment variables is much larger than the IRs of returns. For example, the initial response of stock sentiment to a 1 standard deviation itself shock is at the peak around 75 basis points, the

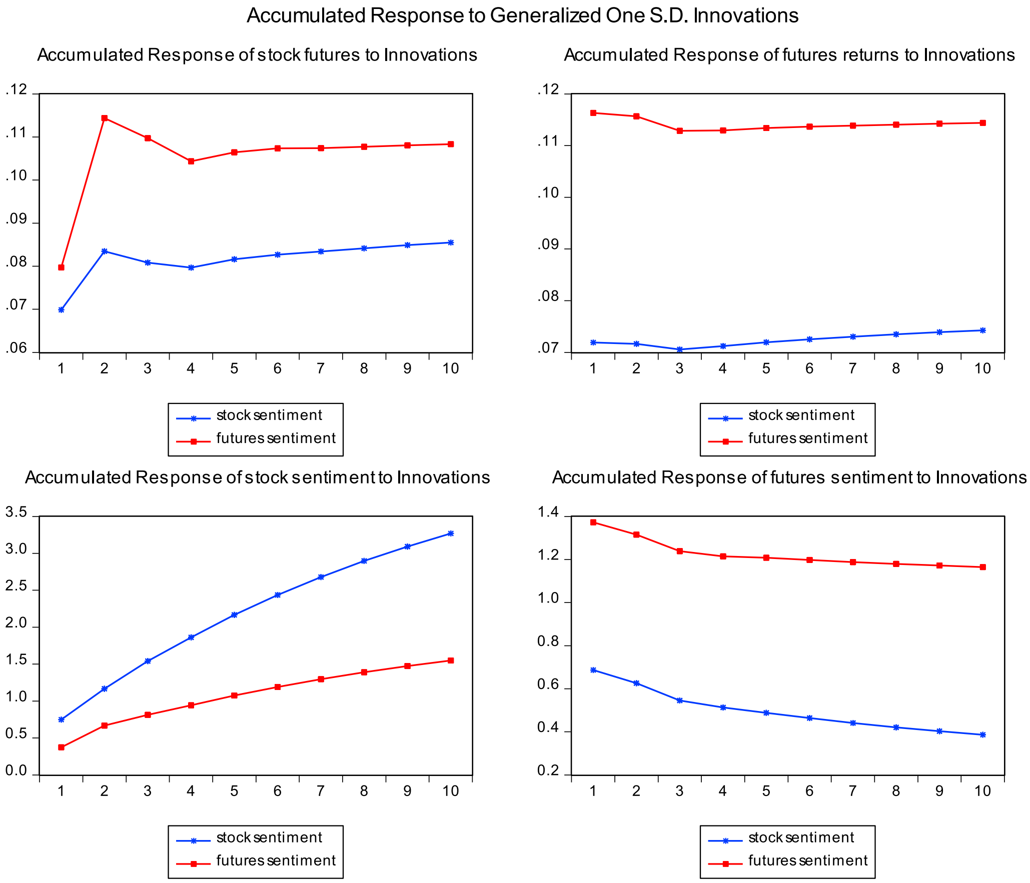

Fig. 2. Accumulated Response of Impulse Response (IRs) functions.

response then drops down to 20 basis points. The initial response of stock sentiment to a 1 standard deviation futures sentiment shock is around zero, peaking after 10 min, and then drop down to zero. The shape of the IRs of futures sentiment is similar to the shape of the IRs of futures, but the IRs of futures sentiment is much larger.

We add three Figures for robustness:(1) Accumulated response of Impulse Response (IRs) functions, (2) Impulse response (IRs) functions to generalized one standard deviation shock, (3) Monte Carlo methods along with Impulse response (IRs) functions. We find the IRs of sentiment shocks have short-term effect significantly.

3.4. Robustness

We check the robustness of our results of sentiment levels by the use 15-minutes data. The results from estimating the 15-minutes sample VAR with sentiment levels are presented in Table 7. In Plane A, we have included the stock sentiment (SS), the stock market returns (SR) in the system. In Plane B, we have included the s the stock index futures sentiment (FS) and the stock index futures returns (FR) in the system. The results of Table 7 resemble those reported in Table 4 for the 5-minutes data. The levels of sentiment variables are a strong positive predictor of subsequent stock market returns and stock index futures returns at the 1% level in 15-minutes horizons. In contrast, returns variables are a strong negative predictor of the subsequent sentiment variables levels in 15-minutes horizons.

We check the robustness of our results of sentiment changes by the use 15-minutes data. In Table 8, we show that the change of sentiment variable is also a powerful predictor of market returns the 1% level in the joint test. It reveals that the change of sentiment variable could predict market returns at the 10% level in the joint test. Similarly, with Table 5, the impact of returns on the change of sentiment variable is negative obviously at the 1% level.

Nextly, we check the robustness of our results of sentiment changes in two markets by the use of 15-minutes data. We use the changes of stock sentiment (ΔSS), the stock market returns (SR), and the stock index futures sentiment (ΔFS) and the stock index futures returns (FR) as one system. The evidence in Table 9 suggests that the changes of sentiment variables have a spillover effect that they affect relevant other market's future returns significantly. At the same time, the changes of sentiment variables have a contagion effect that they affect relevant other market's sentiment significantly.

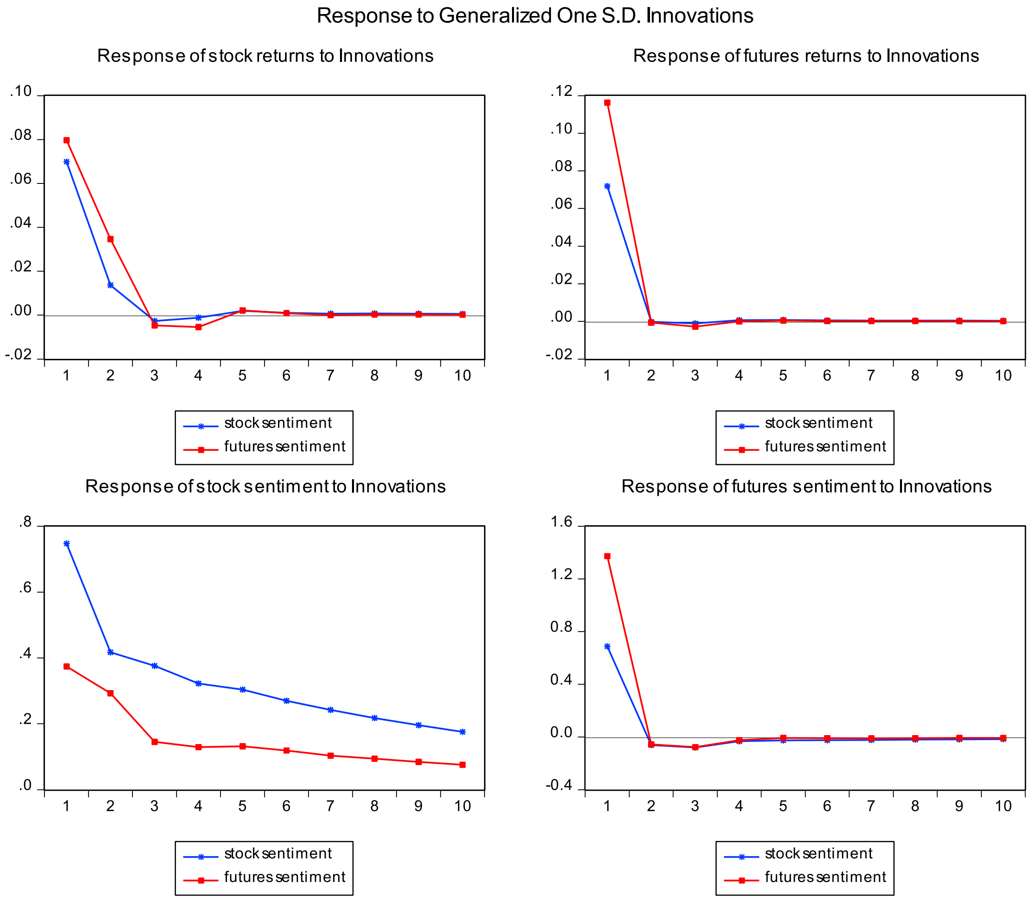

Fig. 3. Impulse response (IRs) functions to generalized one standard deviation shock.

Table 7
15-minutes VAR-returns and sentiment levels

Plane A				Plane B			
Independent variable	Lag	Dependent variable		Independent variable	Lag	Dependent variable	
		SS	SR			FS	FR
SS	1	0.6122***	0.0060**	FS	1	0.4585***	0.0173***
	2	−0.0636***	0.0050**		2	0.3902***	−0.003
p-value		0.0000***	0.0000***	p-value		0.0000***	0.0000***
SR	1	−0.1412***	0.0225**	FR	1	−0.9225***	−0.0682***
	2	0.2788***	0.0105		2	−0.6308***	−0.0006
p-value		0.0000***	0.0163**	p-value		0.0000***	0.0000***
Constant		−0.0002	0.000	Constant		0.0026	0.000
Block exogenity		0.000***	0.0235**	Block exogenity		0.000***	0.000***
R^2		0.335	0.016	R^2		0.408	0.030

In Plane A, variables are the stock market sentiment (SS), the stock market returns (SR). In Plane B, variables are the stock index futures sentiment (FS) and the stock index futures returns (FR). In each column, the p-values show the joint significance of the own-lags values of the independent variable. Block exogenity reports the joint significance of all lags of all independent variables. White (1980) standard errors correct for heteroskedasticity. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

3.5. Additional evidence

Moreover, we add new findings that there is intra-day sentiment descending effect. This paper assumes that the intra-day sentiment effect appears when investor's sentiment influences the stock index futures market: investor's sentimental impact on contract returns at

Table 8
15-minutes VAR-returns and sentiment changes

Plane A				Plane B			
Independent variable	Lag	Dependent variable		Independent variable	Lag	Dependent variable	
		ΔSS	SR			ΔFS	FR
ΔSS	1	−0.2385***	0.0054***	ΔFS	1	−0.5581***	0.0136***
	2	−0.4708***	−0.0021		2	−0.1656***	0.006
p-value		0.0000***	0.0000***	p-value		0.0000***	0.0000***b
SR	1	0.0054***	0.0232**	FR	1	−0.8982***	−0.0590***
	2	−0.0021	0.0131		2	−0.652***	0.0103
p-value		0.0000***	0.0215***	p-value		0.0000***	0.0000***
Constant		0.0001	0.0000	Constant		0.0028	0.0000
Block exogenity		0.0000***	0.0117**	Block exogenity		0.0000***	0.0110**
R^2		0.245	0.017	R^2		0.4192	0.018

In Plane A, variables are the change of stock market sentiment (ΔSS), the stock market returns (SR). In Plane B, variables are the change of stock index futures sentiment (ΔFS) and the stock index futures returns (FR). In each column, the p-values show the joint significance of the own-lags values of the independent variable. Block exogenity reports the joint significance of all lags of all independent variables. White (1980) standard errors correct for heteroskedasticity. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

Table 9
15-minutes VAR-returns and sentiment changes in two markets

Independent variable	Lag	Dependent variable			
		ΔSS	ΔFS	SR	FR
ΔSS	1	0.3359***	−0.0147**	0.0050**	0.0042**
	2	−0.6284***	0.003	−0.0014	0.0006
	3	−0.2196***	−0.0117*	−0.0009	−0.003
	4	−0.2556***	−0.0113*	−0.0033	−0.0024
p-value		0.0000***	0.0383**	0.0264**	0.0132**
ΔFS	1	−0.0372*	−0.6509***	0.0236***	0.0182***
	2	0.0143	−0.3683***	0.0247***	0.0144**
	3	−0.0064	−0.1758***	0.0160***	0.009
	4	0.0096	−0.0581***	0.0081**	0.0113**
p-value		0.0568*	0.0000***	0.0000***	0.0000***
SR	1	−1.2654***	−0.2614***	−0.2818***	0.0873***
	2	0.0062	−0.0568	−0.1352***	0.1036***
	3	−0.1534	0.1391**	−0.0242	0.0928***
	4	0.0809	0.1518**	−0.0028	0.0837***
p-value		0.0000***	0.0000***	0.0000***	0.0000***
FR	1	1.1833***	0.4947***	0.2550***	−0.1352***
	2	0.3730***	−0.3610***	0.1633***	−0.0889***
	3	0.1956**	−0.2838***	0.0574**	−0.0830***
	4	−0.0112	−0.1656**	0.0241	−0.0842***
p-value		0.0000***	0.0000***	0.0000***	0.0000***
Constant		−0.0004	0.0036	0.0000	0.0000
Block exogenity		0.0000***	0.0000***	0.0000***	0.0000***
R^2		0.3231	0.4345	0.0301	0.0190

Variables are the changes of stock market sentiment (ΔSS), the stock market returns (SR), and the stock index futures sentiment (ΔFS) and the stock index futures returns (FR) as one system. White (1980) standard errors correct for heteroskedasticity. Block exogenity reports the p-value of an F-test that the coefficients on all lags of all independent variables (other than own-lags) are jointly zero. The sample period ranges from April 16, 2010 to May 16, 2012, covering a total of 24192 observations.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

the opening and closing periods is inconsistent with the impact on different periods. To prove this assumption, taking CSI 300 stock starting time (9:30) as the beginning, and marking every an hour as K, we divide daily open time into 4 intervals: 9:30–10:29, K = 1; 10:30–11:30, K = 2; 13:00–13:59, K = 3; 14:00–15:00, K = 4. The model is as follows.

$$R_{futures,t} = a_0 + a_1 D_1 S_{spot,t} + a_2 D_2 S_{spot,t} + a_3 D_3 S_{spot,t} + a_4 D_4 S_{spot,t} + e_t; \tag{1}$$

$$R_{futures,t} = a_0 + a_1 D_1 S_{futures,t} + a_2 D_2 S_{futures,t} + a_3 D_3 S_{futures,t} + a_4 D_4 S_{futures,t} + e_t. \tag{2}$$

Table 10
Intra-day Effect of Investor's Sentiment

Coefficients	model 1	model 2	Wald test	model 1	model 2
α_0	0.002	0.002**	Coefficient restrictions	$(\alpha_1 = \alpha_2)$	$(\alpha_1 = \alpha_2)$
	[1.691]	[2.212]	F-statistic	0.025	**73.137*** **
α_1	0.044***	0.071***	Probability	0.875	0.000
	[21.669]	[52.576]	Coefficient restrictions	$(\alpha_2 = \alpha_3)$	$(\alpha_2 = \alpha_3)$
α_2	0.043***	0.054***	F-statistic	**17.026*** **	3.167*
	[16.813]	[35.347]	Probability	0.000	0.0752
α_3	0.029***	0.050***	Coefficient restrictions	$(\alpha_3 = \alpha_4)$	$(\alpha_3 = \alpha_4)$
	[12.547]	[31.986]	F-statistic	0.797	0.022
α_4	0.026***	0.049***	Probability	0.372	0.883
	[11.957]	[30.584]			
Adjusted R-squared	0.199	0.391			

Table 10 presents the coefficients from the time-series regressions of intra-day spot market sentiment and futures market sentiment effect on the futures returns. In model 1, the independent variable is spot market sentiment. In model 2, the independent variable is futures market sentiment. The t-statistics are reported below the coefficients and corrected for heteroskedasticity using the White (1980) correction. We present the results of the Wald test F-statistic. The Wald test' F-statistic rejects the null of no different effect between α_i and α_j.
* Indicate significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

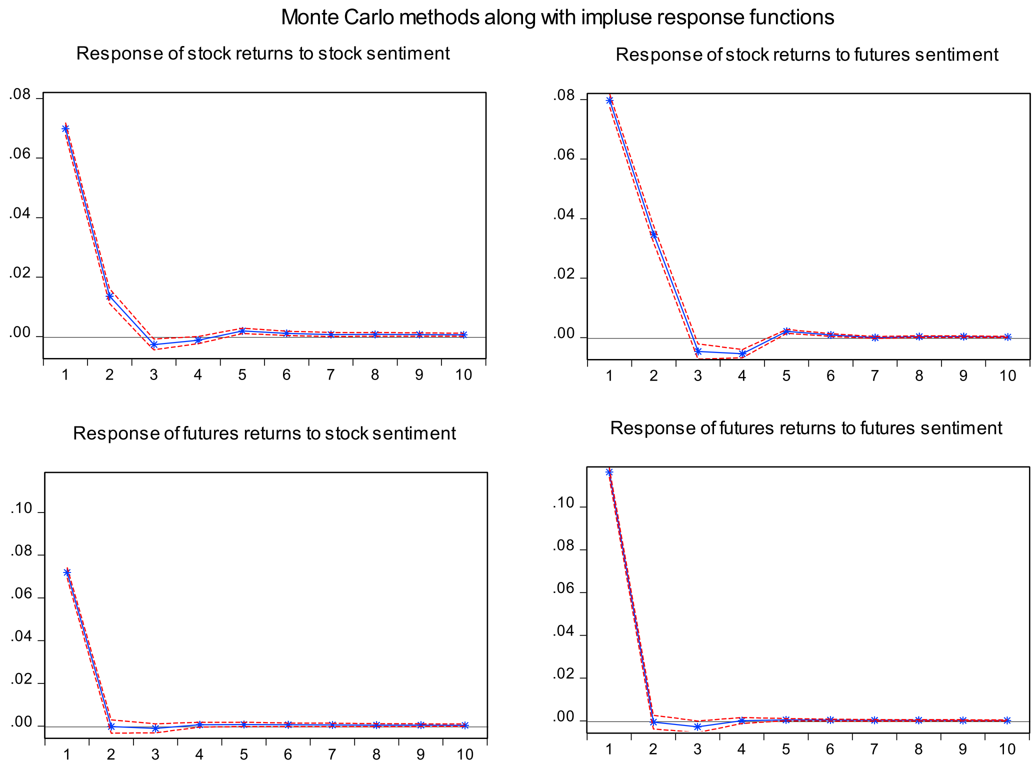

Fig. 4. Monte Carlo methods along with Impulse response (IRs) functions.

D_K is the dummy variable, representing the intra-day sentiment effect: when $t \in \{K = j\}$, $D_j = 1$. when $t \notin \{K = j\}$,$D_j = 0$. here, $j = 1, 2, 3, 4$. The model considers different levels of sentimental impact on futures contract returns at a different time. Coefficient α_j represents different levels of impact at every hour; α_j is significantly greater than 0, meaning in j period, the impact on CSI 300 futures contract is positive. Table 10 shows the result of "intra-day effect" test in the regression model.

Table 10 shows that it is a good fitting for considering investor's sentimental impact on contract returns. Particularly, the adjusted R^2 in each contract model nearly exceeds 20%. Compared with R^2 in Table 1, the adjustment R^2 of model 2 that considers intra-day model reaches a level of 39.1%, being twice many as R^2(19.9%) of model 1. Under a high-frequency environment, the intra-day effect of investor's sentimental impact on contract returns is extremely important.

Table 10 also indicates that coefficient α_j is significantly greater than 0 at 1% significance level, meaning that at four different times

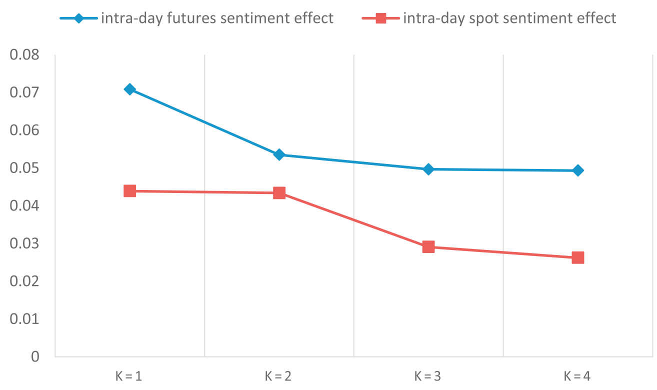

Fig. 5. Intra-day Effect of Investor's Sentiment on Stock Index Futures.

Table 11
The out-of-sample forecast

	RW	sentiment level			sentiment changes		
		stock market	futures market	two markets	stock market	futures market	two markets
RMSE criteria							
5-minutes	0.2502	0.0818	0.0794	**0.0760**	0.0817	0.0769	0.0766
15-minutes	0.2938	0.1007	0.0943	**0.0939**	0.0982	0.1017	0.098
1-hour	0.3995	0.1958	0.1976	**0.1951**	0.1998	0.2085	0.1993
MAD criteria							
5-minutes	0.1856	0.0545	0.0531	**0.0505**	0.0544	0.0511	0.0508
15-minutes	0.2255	0.0705	0.0666	**0.0663**	0.0744	0.0718	0.0694
1-hour	0.3036	0.1503	0.1518	**0.1487**	0.1518	0.1547	0.1490

We forecast over the last 5-minutes to 1-hours (the out-sample) of our sample and record the root mean square error (RMSE) and the mean absolute deviation (MAD) of the forecast versus the actual values. Lower RMSE and MAD values denote better forecasts, with the best statistics highlighted in bold. Forecasts are 1-step ahead. We first estimate models on the in-sample, and update the estimations at each observation in the out-sample. RW denotes a random walk forecast. VAR models include sentiment level and sentiment changes as variables. "Stock market" denotes a VAR model only with the stock market sentiment (SS) and the stock market returns (SR) as a system. "Futures market" denotes a VAR model only with the stock index futures sentiment (FS) and the stock index futures returns (FR) as a system. "Two markets" denotes a VAR model with the stock market sentiment (SS), the stock market returns (SR), the stock index futures sentiment (FS) and the stock index futures returns (FR) as a system. The out-of-sample period ranges from May 17, 2012 to September 30, 2014, covering 504 days and 24192 5-minutes data.

(9:30–11:30 and 13:00–15:00), investor's sentiment has a significantly positive impact on each contract. We present the results of the Wald test' F-statistic. The Wald test' F-statistic rejects the null of no different effect between α_i and α_j. In model 1, the Wald test' F-statistic is 17.026 at 1% significance level (at restrictions $a_2 = a_3$), meaning intra-day spot sentiment effect at morning is significantly greater than that at afternoon. In model 2, the Wald test' F-statistic is 73.137 at 1% significance level (at restrictions $a_1 = a_2$), within 1 h after the daily opening (9:30–9:59) intra-day futures sentiment effect is significantly greater than other time (see Fig. 4).

Fig. 5 describes the investor's sentimental impact futures returns in different time. Overall, it shows an obvious intra-day descending effect: 1 h after the opening, the impact is maximum; 1 h before the closing, the impact is minimal, and in other periods, the level of impact is medium.

4. Out-of-sample forecasting

In the in-sample test, we find the levels of sentiment variables and the changes of sentiment variables have predictability to returns in short-term. To determine if this is actually the case we show an out-of-sample forecasting test. We start our out-of-sample forecasts on May 17, 2012, so the evaluation period is 2012:06–2014:09.

At each date t; we estimate the VAR models using data up to and including time t; and then forecast the next 5 min' returns at time t+1. First, we use a simple random walk. Second, we investigate out-of-sample forecasts for the six VAR models. We consider sentiment level and sentiment changes as variables. We separately see stock market, futures market and both two market as a system. We use two criteria to compare our forecasts across the models. The first is the Root Mean Squared Error, RMSE, of actual and forecasted returns, and the second is the Mean Absolute Deviation, MAD.

Table 11 lists the results of the out-of-sample comparisons. Lower RMSE and MAD values denote better forecasts. The best model RMSE or MAD is listed in bold. We note the following points regarding the forecasting performance of the models. First, the unconstrained VAR beats a random walk easily. Second, we find the VAR model with sentiment level in both two market system is the best performance. Third, the forecasts of the 5-minutes lags model are far better than those of the 15-minutes and 1-hour lags models. It suggests that the sentiment variables have powerful predictability to returns in short-term.

5. Conclusions

In summary, we investigate the intraday sentiment factor and its relation to near-term returns in both the stock market and stock index futures market. We find the sentiment variables have strong predictive power for near-term returns at 5 min frequencies and 15-minutes frequencies. Our tests do not support the conventional wisdom from Brown and Cliff (2004) that past sentiment does not affect market returns.

Frist, we investigate the causality between sentiment factor and its relation to near-term returns in the stock market and stock index futures market separately. In each market system, we show sentiment variables are a strong positive predictor of subsequent stock market returns and stock index futures returns in 5-minutes horizons. Second, we investigate the causality between two markets variables in one system, the evidence suggests that sentiment variables have a spillover effect that they affect relevant other market's future returns significantly and sentiment variables have contagion effect that they affect relevant other market's future sentiment significantly. Finally, we show an out-of-sample forecasting test and confirm the sentiment variables have powerful predictability to returns in short-term. It appears that some sentiment strategies are profitable during intraday trading.

Our findings could raise some interesting issues for future research. Future research may find it fruitful to examine whether our investor sentiment can help explain intraday pricing anomalies such as the intraday price discovery and volatility transmission. It is also interesting to study the predictive power of heterogeneous intraday sentiment from individual and institutional investors.

Acknowledgments

This work was supported by Social Sciences and Humanities Youth Foundation of Chinese Ministry of Education(18XJC790003), National Social Science Fund of China (No. 18BGL200), the Major theoretical and practical research projects in Shandong Province □18BSJJ03) ,the Key Research Projects on the Application Finance of Social Science Federation in Shandong province (2017-JRZZ-04) , (the Natural Science Foundation of Shandong Province of China (ZR2017BG012), the Natural Science Foundation of Guangxi Province of China(2018GXNSFBA281134), the Foundation for University Key Teacher by Guangxi Province of China (2018) and the Xiangsi Lake Youth Innovation Team Funds for Guangxi University for Nationalities (2018RSCXSHQN05).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2020.03.010.

References

Baker, S. D., Hollifield, B., & Osambela, E. (2016). Disagreement, speculation, and aggregate investment. *Journal of Financial Economics, 119*(1), 210–225.
Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets, 7*, 271–299.
Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645–1680.
Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local and contagious investor sentiment. *Journal of Financial Economics, 104*, 272–287.
Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics, 49*(3), 307–343.
Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance, 11*(1), 1–27.
Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. *Journal of Business, 78*(2), 405–440.
Campbell, J. Y., & Kyle, A. S. (1993). Smart money, noise trading and stock price behaviour. *The Review of Economic Studies, 60*(1), 1–34.
Chen, H., Chong, T. T. L., & Duan, X. (2010). A principal-component approach to measuring investor sentiment. *Quantitative Finance, 10*(4), 339–347.
Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics, 65*(1), 111–130.
Cortazar, G., & Naranjo, L. (2006). An N-factor Gaussian model of oil futures prices. *Journal of Futures Markets, 26*(3), 243–268.
Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance, 53*(6), 1839–1885.
De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *The Journal of Finance, 45*(2), 379–395.
Gao, B., & Yang, C. (2017). Forecasting stock index futures returns with mixed-frequency sentiment. *International Review of Economics & Finance, 49*, 69–83.
Gao, B., & Yang, C. (2018). Investor Trading Behavior and Sentiment in Futures Markets. *Emerging Markets Finance and Trade, 54*(3), 707–720.
Han, B., & Kumar, A. (2013). Speculative retail trading and asset prices. *Journal of Financial and Quantitative Analysis, 48*(2), 377–404.
Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54*(6), 2143–2184.
Joseph, K., Babajide Wintoki, M., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting, 27*(4), 1116–1127.
Kim, T., & Ha, N. (2010). *Investor sentiment and market anomalies, SSRN, Working Paper*.
Kirilenko, A. A., & Lo, A. W. (2013). Moore's Law Versus Murphy's Law: Algorithmic trading and its discontents. *The Journal of Economic Perspectives, 27*(2), 51–72.
Kumar, A., & Lee, C. (2006). Retail investor sentiment and return comovements. *The Journal of Finance, 61*, 2451–2486.
Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review, 43*, 107–127.
Kurov, A. (2010). Investor sentiment, the stock market's reaction to monetary policy. *Journal of Banking Finance, 34*(1), 139–149.
Lee, C., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance, 46*(2), 733–746.
Li, J. (2014). Multi-period sentiment asset pricing model with information. *International Review of Economics & Finance, 34*, 118–130.
Li, J. (2015). The asymmetric effects of investor sentiment and monetary policy on stock prices. *Applied Economics, 47*(24), 2514–2522.
Li, J., & Yang, C. (2017). The cross-section and time-series effects of individual stock sentiment on stock prices. *Applied Economics*. https://doi.org/10.1080/00036846.2017.1293795.

McClure, S. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2004). Separate neural systems value immediate and delayed monetary rewards. *Science, 306*(5695), 503–507.
Mendel, B., & Shleifer, A. (2012). Chasing noise. *Journal of Financial Economics, 104*(2), 303–320.
Popper, N. (2012). *High-speed trading no longer hurtling forward*. The New York Times. October 14.
Safa, M. F., & Maroney, N. C. (2012). Bid-Ask Spread, Futures Market Sentiment and Exchange Rate Returns. *Journal of Economic Cooperation and Development, 33*, 63–85.
Scheinkman, J., & Wei, X. (2003). Overconfidence and speculative bubbles. *Journal of Political Economy, 111*, 1183–1219.
Schmeling, M. (2009). Investor sentiment and stock returns: some international evidence. *Journal of Empirical Finance, 16*(3), 394–408.
Schwartz, E., & Smith, J. E. (2000). Short-term variations and long-term dynamics in commodity prices. *Management Science, 46*(7), 893–911.
Simons, D. P., & Wiggins, R. A., III (2001). SP futures returns and contrary sentiment indicators. *Journal of Futures Markets, 21*, 447–462.
Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics, 104*(2), 288–302.
Stambaugh, R. F., Yu, J., & Yuan, Y. (2014). The long of it: Odds that investor sentiment spuriously predicts anomaly returns. *Journal of Financial Economics, 114*(3), 613–619.
Verma, R., & Soydemir, G. (2009). The impact of individual and institutional investor sentiment on the market price of risk. *The Quarterly Review of Economics and Finance, 49*(3), 1129–1145.
Wang, C. (2001). Investor sentiment and return predictability in agricultural futures markets. *Journal of Futures Markets, 21*, 929–952.
Wang, C. (2003). Investor sentiment, market timing, and futures returns. *Applied Financial Economics, 13*, 891–898.
Wang, Y. H., Keswani, A., & Taylor, S. J. (2006). The relationships between sentiment, returns and volatility. *International Journal of Forecasting, 22*(1), 109–123.
Wang, Y. M., Li, C. A., & Lin, C. F. (2011). Investor sentiment spillover effects between the futures and spot markets. *Investment Management and Financial Innovations, 8*, 63–71.
Yang, C., & Gao, B. (2014). The term structure of sentiment effect in stock index futures market. *The North American Journal of Economics and Finance, 30*, 171–182.
Yang, C., & Zhang, R. (2014). Does mixed-frequency investor sentiment impact stock returns? Based on the empirical study of MIDAS regression model. *Applied Economics, 46*, 966–972.
Yang, C., & Zhou, L. (2015). Investor trading behavior, investor sentiment and asset prices. *The North American Journal of Economics and Finance, 34*, 42–62.
Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean-variance relation. *Journal of Financial Economics, 100*(2), 367–381.