

Investor Sentiment and the Index Futures Market's Reaction: Evidence from Internet Search

Xiaolin Wang^a, Feng Zhao^b, Qiang Ye^a, Yi Kou^a

a School of Management, Harbin Institute of Technology, China

b Naveen Jindal School of Management, University of Texas at Dallas, USA

Abstract

Using search frequency in Baidu (search volume index) as a direct measure of investor sentiment in the index futures market, we find that (1) the effect of investor sentiment on futures prices depends on market conditions (market run-ups versus run-downs); (2) the abnormal search volume index induces large overpricing (underpricing) when market run-ups (market run-downs) occur; (3) the abnormal search volume index predicts return reversal in the short term; (4) the effect is mainly caused by the searches of investors who use personal computer (PC) devices; and (5) the restrictions have a significant effect on investor sentiment. Overall, our results show a new empirical pattern of investor sentiment in Chinese index futures markets.

Keywords: Investor sentiment, search volume index, PC-based search volume, CSI 300 index futures market

1 Introduction

Baker and Wurgler (2006, 2007), Brown and Cliff (2005) and Kumar and Lee (2006), Drake and Roulstone et al. (2012) argue that investor sentiment predicts stock returns in the cross-section which indicates that investor sentiment induces stock prices movement and affects expected returns. Da and Engelberg et al. (2014) point that if uninformed noise traders base their trading decisions on sentiment, then extreme sentiment changes will temporarily lead to more noise trading, greater mispricing.

More and more research is measuring investor sentiment using Internet search activities. In a series of innovative studies, Da, Engelberg, and Gao (2011, 2013) use the Google search volume index (SVI) on ticker symbols as a proxy for firm-specific investor attention in addition to daily Internet search volume from millions of households to reveal market-level sentiment. Da and

Engelberg et al. (2014) use daily internet search volume from millions of households to measure market-level sentiment. Drake and Roulstone et al. (2012) use abnormal Google search volume to express investor information demand for specific information. These results suggest that Internet search activities can be useful proxies for attention, sentiment or information demand in addition to news, advertisement, extreme returns, trading volume, open interest and media attention. (Chan, 2003; Aboody and Lehavy et al., 2010; Chemmanur and Yan, 2010; Kurov, 2010; Barber and Odean, 2011; Yu and Yuan, 2011; Li and Yu, 2012)

Our study complements and extends these studies to the Chinese futures market. With the global trend in financialization, the participation of retail investors in Chinese futures markets has surged to unprecedented level. To our knowledge, no work has yet examined the effects of search volume on index futures markets, and relatively few studies use the SVI as a proxy variable for investor sentiment in futures and other derivatives markets. This may be because the SVI mainly reflects the behavior of individual investors. By using aggregate position as a proxy for investor sentiment, Wang (2001) shows that small trader sentiment hardly forecasts future market movements. Goddard et al. (2015) argue that significant differences exist between the futures and stock markets regarding the purpose of trade, the composition of investors and investor trading habits. Therefore, this study aims to determine whether the conclusion about SVI in the global futures markets is applicable to the Chinese futures market.

2 Background and Hypothesis Development

The China Financial Futures Exchange (CFFEX) set the base value for beginning trade in China's first financial futures, the CSI 300 index futures, at 3,399 points for official launch on April 16, 2010. Although the CFFEX subsequently issued a series of restrictions to keep out small retail investors,¹ the retail trading in the CSI 300 index futures market is still booming as a result of the contemporaneous stock market frenzy. After the stock market crash, CFFEX adjusted the trade parameters of index futures to weaken the effect of the futures market on the stock market.

Figure 1 shows that the price of CSI 300 stock index futures reached a peak of 5,274 points in 2015 and then fell sharply. The dramatic fall occurred due to the CFFEX issuing a swathe of

¹ Investors must make a minimum deposit of RMB500,000 to open a trading account, and must pay cash deposits equivalent to 15% of the contract value for nearby month contracts and 18% for longer-term contracts. Foreigners are not allowed to trade index futures.

measures designed to limit market speculation from July to September 2015.² The new rules are

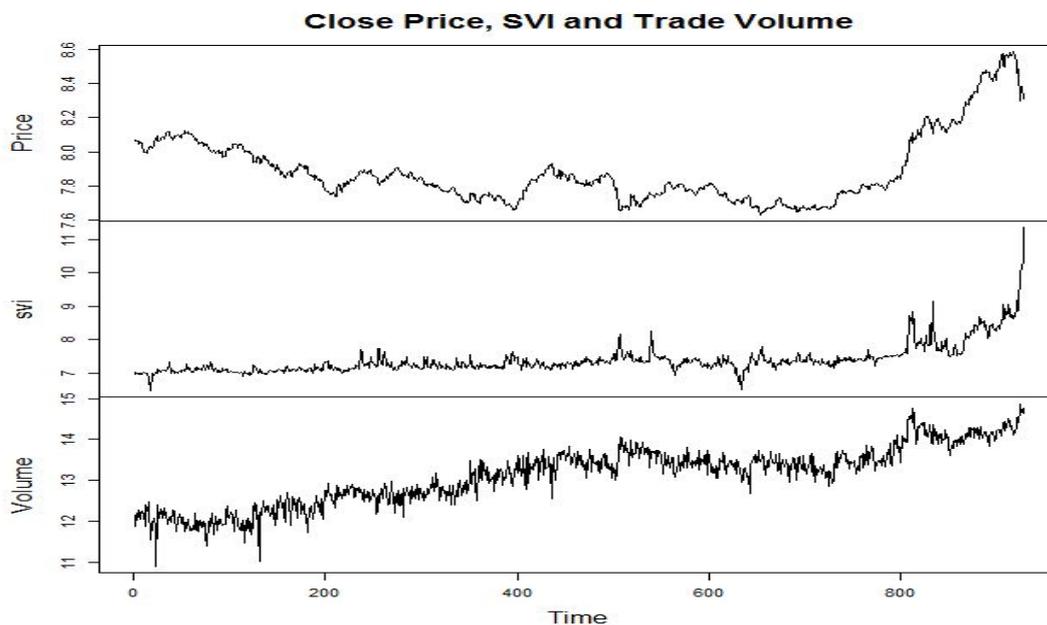


Figure 1 The logarithmic trends of index futures price, Baidu search volume index, and trading volume

as follows:

A. Increase the commission for trading. The commission is increased by about seven times, from 0.23% to 1.5%. Meanwhile, a new commission requires investors to pay RMB1 for each order (including open, closed and cancelled orders). In particular, the commission becomes 100 times greater, from 0.23% to 23%, if the investor closes a position opened on the same date.

B. Increase the cash deposit. The cash deposit is increased from 10% to 40%. The efficiency of capital changes to one quarter.

C. Limit trade volume. Before the stock market crash, the trade volume is not limited. The new rules forbid investors to trade more than 10 contracts in one account. This rule immediately prevents a majority of trade.

In a study of the investment behavior of individual investors, Barber and Odean (2011) point out that the purchase decisions of individual investors are greatly affected by limited investor

² The new rules of the CFFEX immediately came into effect in 2015, with margin requirements for futures trading raised, along with transaction fees and restricted trading positions in stock index futures: "A hedging account is a designation for investors who use futures to offset risks from their holdings in the stock market. Such accounts are exempt from limits on opening more than 10 contracts in a day, according to CFFEX rules announced in September." (www.bloomberg.com)

attention and past stock returns and that individual investors are the net buyers of attention-grabbing stocks. Their conclusion explains why investor attention has positive effects on short-term stock returns in many studies. However, investors in the futures markets can hold both long and short positions compared with the stock market. Thus, individual investors can be net buyers and net sellers of attention-grabbing futures. An important distinction between this study and previous studies is that the SVI, which cannot be used as a proxy for investor attention in the futures markets, is more likely to be used as a proxy for the magnitude of investor sentiment. We thus make the following hypothesis.

Hypothesis 1 (H1): *A search volume index that cannot be used as a proxy for investor attention in the futures market is more likely to be used as a proxy for the magnitude of investor sentiment.*

A large body of literature starting from Black (1986) suggests that investor sentiment and the resulting noise trading can affect asset prices. If uninformed noise traders base their trading decisions on sentiment, then extreme sentiment changes will temporarily lead to more noise trading and greater mispricing. As investors in the futures market can hold both long and short positions, the SVI cannot predict future returns like the equity market can. The effect of investor sentiment on futures prices depends on market conditions (bullish verses bearish markets). We thus make the following hypotheses.

Hypothesis 2A (H2A): *Abnormal search volume indexes induce overpricing when market run-ups occur.*

Hypothesis 2B (H2B): *Abnormal search volume indexes induce underpricing when market run-downs occur.*

Hypothesis 2C (H2C): *Abnormal search volume indexes predict return reversal in the short-term by arbitrageurs in the futures market.*

In early research, in which search volumes are based on Internet search engines used as proxies for investor attention, the search volumes are usually obtained from Google Trends data, and the index formed is based on the number of Internet searches using a particular keyword. However, this index does not reflect the demand from different search devices. Kamvar and Baluja (2006) argue that there are great differences between Google users who search on mobile devices

and those who search on PC devices. Compared with PC users, mobile users enter words with shorter lengths and are much less likely to click on links, and the links they click on tend to be top ranking, probably because searching is more difficult given that mobile screens display limited information. Kamvar et al. (2009) point out that the difference in search behavior on mobile devices is due to the absence of a uniform display port. Dyson et al. (2001) show that on a screen, a moderate line length (about 55 characters per line) at normal reading speed provides better comprehension. Obviously, a mobile device with a smaller screen must downsize the characters or shorten the line length, thereby reducing the readability of the text. Church, Smyth and Cotter (2007) note that mobile searching clearly indicates a higher alteration rate than personal computer (PC) searching, and mobile search users improve the previous content input to obtain better search results. All of these studies indicate that mobile searches cannot compete with PC searches in terms of the search process, the number of results obtained, and readability. Search engine usage in Chinese characters shows similar behavioral characteristics (Wang et al., 2013). Therefore, we submit that investors who search using mobile devices are less likely to correctly judge the information on the screen than investors who search using PC devices. Investment behavior based on incorrect information or the incorrect comprehension of information coincides with the characteristics of noise traders (Black, 1986). We find that investor attention from different devices features heterogeneity. PC-based investor attention has a more favorable effect on the market, reflected mostly in its unified effect on price with no clear increase in volume. In contrast, mobile-based investors tend to show the effects of noise trading in their market performance, reflected mostly in the obvious lack of effect on prices and a significant increase in volume. Therefore, we extend Da's (2011) theory by suggesting that among the SVI's effects, the PC-based SVI plays a decisive role in asset pricing, whereas the mobile-based SVI is primarily associated with noise trading with no obvious effect on asset prices. We propose our next hypothesis as follows.

Hypothesis 3 (H3): *Investor sentiment that has an effect on index futures returns is mainly caused by the searches of investors who use PC devices.*

Compared with the stock market, investors in the futures market are more inclined to make long-term investments. Accordingly, they are not easily affected by investor attention when

making trade decisions. In particular, the types of investor differ greatly between the futures and stock markets. In the futures market, many investors routinely engage in high frequency trading aimed at arbitrage. However, the new rules of the CFFEX restrict trading positions in stock index futures, resulting in almost completely limited high frequency trading (HFT). This provides us with a natural experimental setting in which to test the different influences of investor attention on the financial market with and without HFT. We thus make the following hypothesis.

***Hypothesis 4(H4):** Investor sentiment has less of an effect on the futures returns when more high frequency trading is conducted in the futures market.*

The rest of the paper is organized as follows. In Section 2 we describe our data. In Section 3, we examine the models and explain the results. In Section 5 we present our summary and conclusion.

3 Data Collection and Descriptive Statistics

3.1 Data Collection

In other investor sentiment research based on search volume, Google Trends is used as the data source (see Bank et al., 2011; Da et al., 2011; Da et al., 2013; Da et al., 2014). This study, however, examines the effect of search volume on the financial market using different search devices. Google Trends cannot distinguish between search volume coming from different devices. Thus, the Baidu Index Service is used in this study to obtain data on search volume. Baidu is similar to Google Trends, but it is able to differentiate search volumes obtained from different devices.

As the largest search engine in China, Baidu also has a degree of global influence. In 2014, Google's global market share was about 68% and Baidu's was 18% for the same day (according to the Internet data statistics center www.cnzz.com). However, in the Chinese market, Baidu's market share is 56%, and as the leading Chinese search engine it has great domestic influence. Accordingly, we have reason to believe that its data are fully reliable in range, quality and reliability (CNNIC). Given that Baidu mainly serves Chinese users, this study uses the Chinese market as the target market.

Prior studies focus mainly on the relationship between search volume and the stock market. However, Baidu's control over search results means it is unlikely to release all search information

on the stock market. Therefore, as the stock market data is incomplete, we choose the futures market as our research object. The CSI 300 index futures market is the most important futures market in China.

As shown in Figure 2, the keywords related to searches for “Stock Index Futures” are directly related to stock index futures. The Baidu Index Service provides us with an index of search times for a given keyword. Similar to Google Trends, the service reflects the relative search times of a keyword as shown in Figure 3. The difference is that the Baidu Index Service also subdivides the keyword search index according to the type of device used, forming a PC search index and a mobile search index. Quantitatively, the Baidu SVI is the sum of the PC and mobile SVIs.

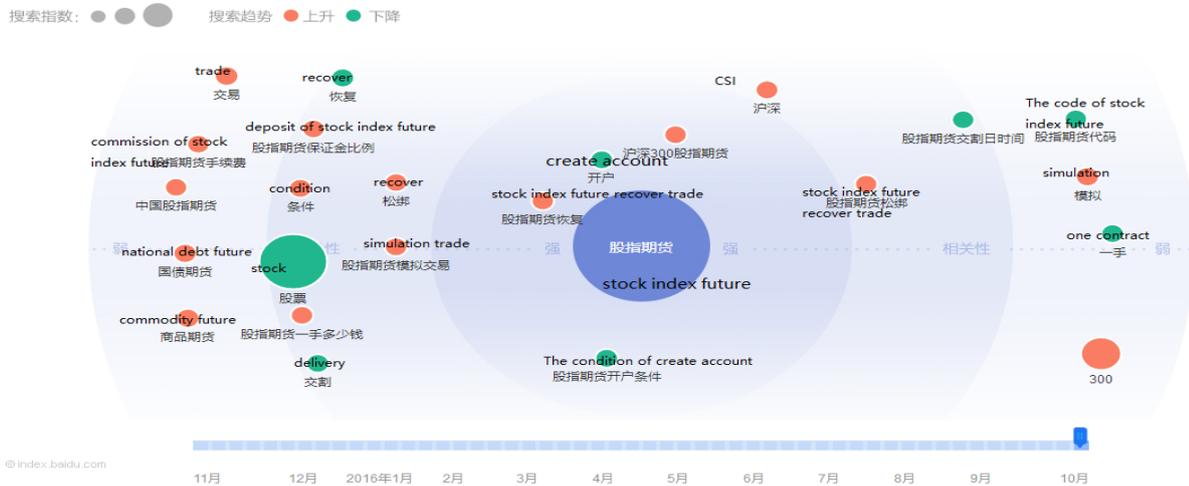


Figure 2 Baidu search trends for the keyword “Stock Index Futures”

*The figure shows the search results for the keyword “stock index futures” from the Baidu Index. In the diagram, circles denote keywords, circle size denotes search volume (a larger circle means a higher search volume), and the distance between circles denotes the degree of correlation between the two words (a shorter distance denotes a stronger correlation).

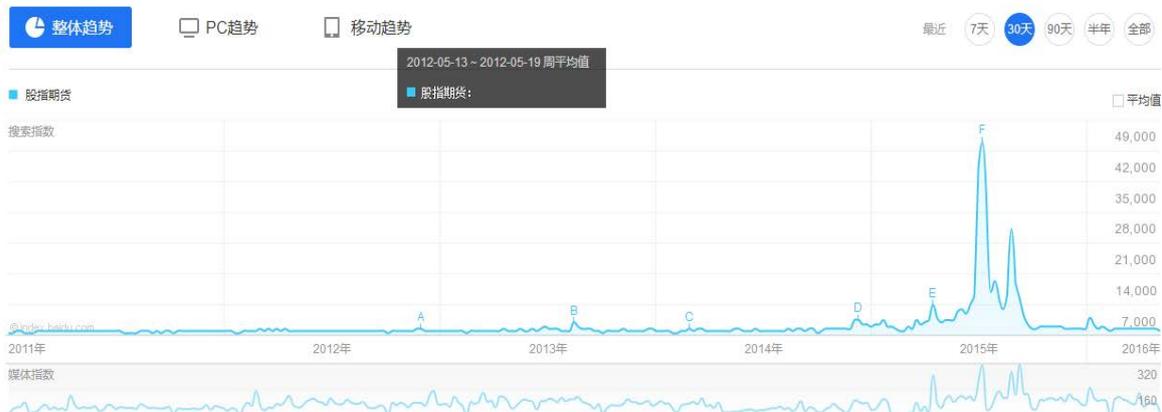


Figure 3 Baidu Index Search

*The search volume index shows periodicity. On this web page you can select “PC trend” and “mobile trend” to view the PC-based SVI and mobile-based SVI, respectively.

3.2 Descriptive Statistics

Our sample consists of CSI 300 stock index futures data and Baidu search data. We download the daily SVI for stock index futures from January 2011 to April 2016. The Baidu Index Service also subdivides the keyword search index according to the type of device, forming a PC search index (SVI_{pc}) and a mobile search index (SVI_{mobile}). As noted, the Baidu SVI consists of the PC and mobile SVIs combined.

An abnormal SVI (ASVI) is defined as the natural logarithm (ln) of SVI during the focal day minus the ln of the median SVI during the previous five days. According to Da, Engelberg and Gao (2011), this can capture abnormal changes in the individual investors' attention. We use both search volume and the returns of the CSI 300 spot market as control variables proved to be influential to futures prices. The variables used in our research are defined in Table 1.

Table 1 Variable Definition

Variable	Definition
<i>SVI</i>	Search Volume Index; aggregate search frequency from Baidu Trends based on the stock index futures.
<i>ASVI</i>	Abnormal SVI; the log of SVI during the day minus the log of median SVI during the previous five days according to Da, Engelberg & Gao (2011).
<i>ASVI_{mobile}/ASVI_{mob}</i>	Abnormal Search Volume Index of mobile phones; the log of SVI _{mob} during the day minus the ln of median SVI _{mob} during the previous five days according to Da, Engelberg & Gao (2011).
<i>ASVI_{pc}</i>	Abnormal Search Volume Index of personal computer (PC); the log of SVI _{mob} during the day minus the ln of median SVI _{mob} during the previous five days according to Da, Engelberg & Gao (2011).
<i>Mkt up dummy_t</i>	Measure of Market run-ups/downs in day t, which takes value of 1 when the return is positive and 0 when the return is negative
<i>Mkt up dummy × ASVI_t</i>	The intersect variables equal to Mkt up dummy variable multiply by the ASVI in day t.
<i>Ret_{f_t}</i>	The daily cumulative raw return of CSI300 index futures during day t.
<i>Ret_{f_{t+1}}</i>	The daily cumulative raw return of CSI300 index futures during day t+1.
<i>Ret_{f_{t+2}}</i>	The daily cumulative raw return of CSI300 index futures during day t+2.
<i>% chang in Vol</i>	The daily percentage change of volume on CSI300 index future during day t.
<i>% chang in Abs_{OI}</i>	the daily percentage change in the absolute open interest.

Table 1-Continued

<i>Volati</i>	Realized volatility of CSI 300 stock index futures during day t.
<i>Mkt up dummy</i> × <i>Abs_Ret</i>	The intersect variable equal to Mkt up dummy variable multiply by the absolute return.
<i>MVI</i>	Media Volume Index from Baidu Index.
<i>Ret_{f,t-i}</i>	The lagged asset-class returns of CSI300 index futures (up to five lags)

The new rules of the CFFEX restrict trading positions in stock index futures, resulting in almost completely limited HFT, which gives us a natural experimental setting in which to test the different influence of investor attention on the financial market with and without HFT.

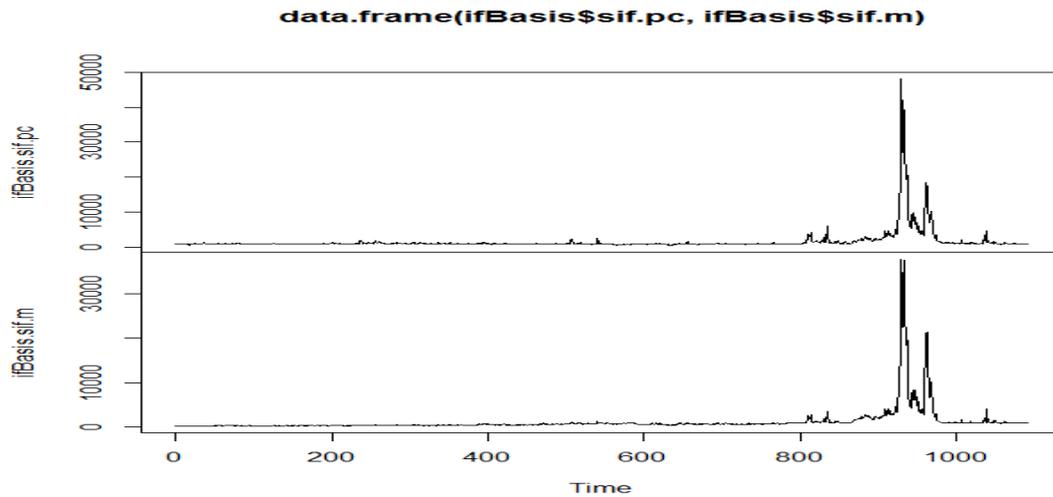


Figure 4 SVIpc vs SVImobile

Figures 4 show the high correlation between the SVIs (ASVIs) and the price and volume of the CSI 300 stock index futures. All of these variables reach a peak in 2015 and then fall sharply. Accordingly, in the following analysis, we divide our data sample into two periods (“before regulation sample and after regulation sample”) based on the announcement of the first restrictions on July 7, 2015.

Table 2 reports the statistics for the data sample from January 2011 to April 2016. According to our statistical results, the five-day ASVI ranges from -0.8 to 1.4, whereas the mean ASVI is approximately 0.08. The return on stock index futures ranges from -9.9 to 10.22. The volume of

stock index futures ranges from RMB4, 727 to RMB2, 882, 235.

Table 2 Sample Descriptive Statistics

<i>Before Restrictions</i>					
	<i>Num</i>	<i>Mean</i>	<i>Std. Dev</i>	<i>Min</i>	<i>Max</i>
<i>ASVI</i>	927	0.0879	0.2059	-0.7304	1.4138
<i>ASVI_pc</i>	927	0.0914	0.2324	-0.7670	1.4870
<i>ASVI_mobile</i>	927	0.0881	0.2005	-0.6760	1.4667
<i>Return</i>	927	0.0539	1.5535	-9.5713	9.1475
<i>% Chang in Vol</i>	927	0.8377	21.8731	-64.9672	80.8133
<i>Vol</i>	927	631320.60	434705.80	54138	2882235
<i>After Restrictions</i>					
	<i>Num</i>	<i>Mean</i>	<i>Std. Dev</i>	<i>Min</i>	<i>Max</i>
<i>ASVI</i>	159	0.0701	0.2991	-0.8714	1.3075
<i>ASVI_pc</i>	159	0.0822	0.3069	-0.844	1.4261
<i>ASVI_mobile</i>	159	0.0604	0.3096	-0.8934	1.4171
<i>Return</i>	159	0.0227	3.1285	-9.9164	10.2269
<i>% Chang in Vol</i>	159	1.5954	32.6049	-93.5993	307.4043
<i>Vol</i>	159	368438.70	705354.60	4727	2425793
<i>Full Sample</i>					
	<i>Num</i>	<i>Mean</i>	<i>Std. Dev</i>	<i>Min</i>	<i>Max</i>
<i>ASVI</i>	1089	0.0864	0.2233	-0.8714	1.4138
<i>ASVI_pc</i>	1089	0.0911	0.2458	-0.8440	1.4870
<i>ASVI_mobile</i>	1089	0.0850	0.2211	-0.8934	1.4667
<i>Return</i>	1089	0.0395	1.8892	-9.9164	10.2269
<i>% Chang in Vol</i>	1089	0.9018	23.7158	-93.5993	307.4043
<i>Vol</i>	1089	596726.90	497292.10	4727	2882235

4 Empirical Analysis

4.1 The Influence of Abnormal Search Volume

Previous studies indicate that the ASVI is positively related to extreme stock returns and abnormal turnover (e.g., Da Zhi et al., 2011). We doubt that the ASVI is influenced by the volatility of the market. The panel regression results are reported in Table 3, where the dependent variables are ASVI, ASVI_{pc} and ASVI_{mob}, respectively. The explanatory variables include the daily order imbalance as measured in the absolute return (Abs_Ret); the market volatility dummy variable (dummy=0 when the market is down and 1 when the market is up); the intersect variable dummy×Abs_Ret, which is equal to the market volatility dummy variable multiplied by the absolute return; the daily percentage of change in volume; the daily percentage of change in absolute open interest; and the media volume index.

Table 3
The Influence of ASVI

Our dependent variables are ASVI, ASVIpc and ASVImob respectively. Explanatory variables include the daily order imbalance as measured in the absolute return (Abs_Ret), Mkt up dummy variable (when the return is positive dummy=1, otherwise the return is negative dummy=0), the intersect variable Mkt up dummy \times Abs_Ret equal to Mkt up dummy variable multiply by the absolute return, the daily percentage change in the volume, the daily percentage change in the absolute open interest and Media Volume Index.

	Before Restrictions Period 2011.1-2015.7.7			After R Restrictions Period 2015.7.8-2016.4.12			Full Sample Years 2011-2016		
	ASVI	ASVIpc	ASVImob	ASVI	ASVIpc	ASVImob	ASVI	ASVIpc	ASVImob
<i>Abs_Ret</i>	0.0704***	0.0779***	0.0602***	0.0926***	0.0839***	0.1018***	0.0740***	0.0747***	0.0717***
<i>Mkt up dummy_t</i>	-0.0075	-0.0101	-0.0035	0.0555	0.0229	0.0961	0.0170	0.0071	0.0279
<i>Mkt up dummy_t \times Abs_Ret</i>	-0.0328**	-0.0339**	-0.0341**	-0.1132***	-0.0962***	-0.1286***	-0.066***	-0.0594***	-0.0737***
<i>% chang in Vol</i>	0.0008**	0.0007*	0.0011***	0.000618	0.000185	0.0010	0.0009***	0.0007**	0.0012***
<i>% chang in Abs_OI</i>	0.00081	0.0005	0.0015	0.004236	0.005983	0.0031	0.0017	0.0016	0.0022*
<i>MVI</i>	0.06589***	0.0759***	0.0484***	0.0312**	0.0411***	0.0213*	0.0529***	0.0632***	0.0377***
<i>(Intercept)</i>	-0.0018	-0.0078	0.0119	-0.08049	-0.06691	-0.1015*	-0.0085	-0.0093	-0.0029
<i>Adj. R-squared</i>	0.2715	0.2698	0.1886	0.3699	0.3312	0.3747	0.2533	0.2481	0.2047

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4

Effect of Investor sentiment on Futures Return

The dependent variables are contemporaneous returns (column (1) and (2)), future CSI 300 index daily returns in the next day (columns (2) and (3)), future CSI 300 index daily returns in the next two days (columns (4) and (5), respectively). Explanatory variables include ASVI, dummy variable measure of market run ups and downs (*Market up/down dummy*), which takes value of 1 when the return is greater than zero and 0 when the return is less than zero in day t, the intersect variables *Market up/down dummy* * $ASVI_t$ equal to *Market ups_t dummy* variable multiply by the ASVI, the lagged asset-class returns (up to five lags), the realized volatility, and Baidu media search volume index. Data are from January 2011 to July 2015, before restrictions period.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Ret_{f(t)}$	$Ret_{f(t)}$	$Ret_{f(t+1)}$	$Ret_{f(t+1)}$	$Ret_{f(t+2)}$	$Ret_{f(t+2)}$
$ASVI_t$	-0.1639*** (-4.287)	-0.2977*** (-7.8108)	0.0799 (1.6314)	0.1987** (3.2286)	0.0767 (1.5621)	0.0596 (0.9605)
$Mkt\ up\ dummy_t$	-	1.1908*** (23.3733)	-	-0.0909 (-0.9949)	-	0.0593 (0.6432)
$Mkt\ up\ dummy_t \times ASVI_t$	-	0.4177*** (8.0909)	-	-0.2213** (-3.1396)	-	0.0307 (0.4323)
$Ret_{f(t)}$	-	-	-0.0329 (-0.895)	0.0181 (0.3696)	-0.0299 (-0.8104)	-0.053 (-1.0722)
$Ret_{f(t-1)}$	-0.0609 (-1.6817)	-0.0129 (-0.4801)	-0.0555 (-1.5344)	-0.0533 (-1.4791)	-0.0986** (-2.7208)	-0.0979** (-2.6919)
$Ret_{f(t-2)}$	-0.067 (-1.8954)	-0.0645* (-2.4765)	-0.1002** (-2.7999)	-0.0944** (-2.6472)	0.0639 (1.7832)	0.0624 (1.7352)
$Ret_{f(t-3)}$	-0.1047** (-2.9611)	-0.0682** (-2.6156)	0.0919* (2.5564)	0.1035** (2.8821)	0.0085 (0.2367)	0.0063 (0.1733)
$Ret_{f(t-4)}$	0.0792* (2.2275)	0.0752** (2.8721)	0.02 (0.569)	0.0223 (0.639)	-0.021 (-0.5963)	-0.0204 (-0.5802)
$Ret_{f(t-5)}$	0.0272 (0.7841)	-0.0023 (-0.0904)	-	-	-	-
$Volati$	-0.0396 (-1.1253)	0.0036 (0.1382)	-0.0323 (-0.9119)	-0.0323 (-0.9163)	-0.0371 (-1.0482)	-0.036 (-1.013)
$AMVI_t$	0.0693 (1.905)	0.0283 (1.057)	-0.0494 (-1.0396)	-0.0486 (-1.0271)	-0.0092 (-0.1938)	-0.0082 (-0.1707)
(Intercept)	0.027 (0.7903)	-0.5247*** (-14.9418)	0.0131 (0.3798)	0.0454 (0.8186)	0.0072 (0.2097)	-0.0196 (-0.3509)
Observations	931	931	932	932	932	932
Adj. R^2	0.0409	0.4802	0.0211	0.0317	0.0147	0.0129

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our results support H2B, which states that the market volatility dummy \times Abs_Ret is negatively related to the ASVI during each sample period. This indicates that investors pay more attention when the market is down and that the negative effect is more significant during and after the regulation period. However, the market volatility dummy is not related to the abnormal search volume.

4.2 Effects of Investor Sentiment on Futures Returns

Table 4 reports the results from the time series regressions, where the dependent variables are contemporaneous returns (column (1) and (2)), the future CSI 300 index daily returns for the next day (columns (2) and (3)) and the future CSI 300 index daily returns for the next two days (columns (4) and (5), respectively). The explanatory variables include ASVI, the dummy variable measure of investor sentiment (sentiment dummy) based on the positive and negative parts of the futures returns, which takes a value of 1 when the market is up and 0 when the market is down; the intersection variable sentiment \times ASVI, which is equal to the sentiment dummy variable multiplied by the ASVI and captures the pattern of investor attention in the periods of high investor sentiment and bearish sentiment; the lagged asset-class returns (up to five lags); the realized volatility; and the Baidu media SVI.

Columns (1) and (3) show that the influence of ASVI on the contemporaneous returns and returns for the next day is not significant. This supports H1, which states that the SVI cannot be used as a proxy for investor attention in the futures market. However, when we introduce the sentiment dummy variable, the intersection variable sentiment \times ASVI is negatively (positively) associated with the contemporaneous returns when market run-ups (market run-downs) occurs, thereby supporting H2A and H2B. Columns (2) and (4) show that the intersection variable sentiment \times ASVI is positively (negatively) associated with the returns for the next day when market run-ups (market run-downs) occur, whereas the effect is not significant with the returns for the next two days as shown in columns (5) and (6). This supports H2C, which states that investor sentiment predicts return reversals in the short term.

4.3 The influence of restrictions on investor sentiment

The relationship between the ASVI (ASVipc, ASVImob) and futures returns is not significant before the regulation period, indicating that investor attention has less of an effect

Table 5
The influence of Restrictions on Investor Sentiment

The dependent variables are contemporaneous returns, future CSI 300 index daily returns in the next day, and future CSI 300 index daily returns in the next two days, respectively. Explanatory variables include ASVI, the lagged asset-class returns (up to five lags), the realized volatility, and Baidu media search volume index.

	Before Restrictions			After Restrictions		
	$Ret_{f(t)}$	$Ret_{f(t+1)}$	$Ret_{f(t+2)}$	$Ret_{f(t)}$	$Ret_{f(t+1)}$	$Ret_{f(t+2)}$
$ASVI_t$	-0.0082 (-0.1948)	0.0148 (0.2694)	0.0955 (1.7201)	-0.5323*** (-6.3533)	0.3469** (2.8587)	0.0249 (0.2095)
$Ret_{f(t)}$	-0.0934* (-2.3531)	-0.0928* (-2.3456)	0.066 (1.6546)	-0.0876 (-1.0186)	0.127 (1.1942)	-0.0325 (-0.3116)
$Ret_{f(t-1)}$	0.0039 (0.0985)	0.0042 (0.1059)	-0.0406 (-1.0243)	-0.106 (-1.2439)	-0.0125 (-0.1273)	-0.1375 (-1.4302)
$Ret_{f(t-2)}$	-0.0458 (-1.1616)	-0.0464 (-1.1769)	0.0772 (1.9417)	-0.1454 (-1.8282)	-0.0622 (-0.6699)	0.0185 (0.2029)
$Ret_{f(t-3)}$	0.0719 (1.8156)	0.0716 (1.8121)	0.0133 (0.3342)	-0.0384 (-0.5009)	0.0802 (0.8969)	0.0092 (0.1047)
$Ret_{f(t-4)}$	0.0129 (0.3421)	0.0128 (0.3375)	0.0075 (0.1972)	0.1141 (1.4987)	0.0381 (0.4366)	-0.0692 (-0.8097)
$Volati$	-0.0475 (-1.2223)	-0.0475 (-1.2266)	-0.0274 (-0.7014)	0.2378 (1.4474)	0.1159 (0.6304)	0.5088** (2.8255)
$AMVI_t$	0.0051 (0.1266)	-0.0294 (-0.5377)	-0.0255 (-0.4625)	0.2833*** (3.558)	-0.1144 (-1.1258)	-0.0018 (-0.018)
(Intercept)	0.0132 (0.3496)	0.0123 (0.3279)	-0.0221 (-0.5831)	0.0585 (0.8276)	-0.0086 (-0.1065)	0.0968 (1.2228)
Observations	931	932	932	159	159	159
Adj. R^2	0.0055	0.006	0.0075	0.2781	0.0423	0.0295

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

on futures returns when there is more HFT in the futures market. As HFT traders are relatively professional compared with retail investors, prices that are too high due to investor attention will decrease because of HFT. The futures returns must eventually decline when HFT is present in the futures market, which supports H4. The positive coefficients of $ASVI_{pc}$ after regulation and the whole sample period supports H3, which states that the effect of investor attention on futures returns is mainly caused by the searches of investors who use PC devices.

4.4 The influence of investor sentiment from different search devices

Panel A of Table 6 reports the result from the time series regressions where the dependent variable is always the next day return. Explanatory variables include $ASVI_{pc}$, $ASVI_{mob}$, Mkt up dummy variable measure of the market run-ups and market run-downs which takes value of 1 when the returns are positive and 0 when the returns are negative, the intersection variables $Mkt\ up\ dummy \times ASVI$ equal to Mkt up dummy variable multiply by the ASVI to capture the pattern of investor sentiment in different across up or down markets, the lagged asset-class

Table 6
The Influence of ASVI_pc VS ASVI_mobile

<i>Panel A: The dependent variable is always $Ret_{f(t+1)}$.</i>				
	Before Restrictions		After Restrictions	
	(1)	(2)	(3)	(4)
$ASVI_{pc_t}$	0.0595 (0.8305)	0.2274* (2.4696)	0.6262* (2.4571)	0.5631 (1.6245)
$ASVI_{mobile_t}$	-0.0467 (-0.7177)	-0.0934 (-1.0754)	-0.3051 (-1.1347)	-0.2535 (-0.7439)
$Mkt\ up\ dummy_t$	-	0.0422 (0.4067)	-	-0.1468 (-0.6185)
$Mkt\ up\ dummy_t \times ASVI_{pc_t}$	-	-0.3579** (-2.784)	-	0.0512 (0.1121)
$Mkt\ up\ dummy_t \times ASVI_{mob_t}$	-	0.1313 (1.0278)	-	-0.0127 (-0.0241)
$Ret_{f(t)}$	-0.0956* (-2.4062)	-0.0871 (-1.5662)	0.0686 (0.6285)	0.1331 (0.8541)
$Ret_{f(t-1)}$	0.0047 (0.1187)	0.0163 (0.4142)	-0.0399 (-0.4055)	-0.051 (-0.4975)
$Ret_{f(t-2)}$	-0.0476 (-1.2051)	-0.051 (-1.3021)	-0.1012 (-1.0644)	-0.0989 (-1.0161)
$Ret_{f(t-3)}$	0.0711 (1.7977)	0.0758 (1.9272)	0.0715 (0.8067)	0.0727 (0.7887)
$Ret_{f(t-4)}$	0.0122 (0.3212)	0.0152 (0.4046)	0.0213 (0.2448)	0.0145 (0.1554)
Volati	-0.0477 (-1.2325)	-0.045 (-1.1684)	-0.0114 (-0.0584)	0.0011 (0.0052)
$AMVI_t$	-0.0312 (-0.565)	-0.0357 (-0.6521)	-0.178 (-1.6668)	-0.1821 (-1.6317)
(Intercept)	0.0136 (0.362)	-0.0133 (-0.2161)	-0.0342 (-0.4208)	0.0483 (0.3187)
$Adj. R^2$	0.0055	0.0201	0.0624	0.0374

<i>Panel B: The dependent variable is always Vol_{t+1}.</i>				
	Before Restrictions		After Restrictions	
	(1)	(2)	(3)	(4)
$ASVI_{pc_t}$	0.1099* (2.456)	-	0.3562*** (3.5227)	-
$ASVI_{moblie_t}$	-	0.1029* (2.5749)	-	0.4472*** (5.2287)
Vol_t	-0.431*** (-14.1172)	-0.4313*** (-14.1349)	-0.1465 (-1.808)	-0.1565* (-2.0352)
$AMVI_t$	0.1013* (2.2408)	0.1163** (2.8777)	-0.2299* (-2.401)	-0.2068* (-2.4572)
Volati	0.1032*** (3.3695)	0.1018*** (3.3258)	-0.2743 (-1.3782)	-0.239 (-1.2692)
(Intercept)	-9e-04 (-0.0311)	-0.0023 (-0.0763)	-0.0133 (-0.165)	-0.009 (-0.1167)
$Adj. R^2$	0.2109	0.2115	0.0894	0.1687
Observations	932	932	159	159

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

returns (up to five lags), the realized volatility, and Baidu media search volume index. The positively coefficients of $ASVI_{pc_t}$ in columns (2) and (3) support our Hypothesis (H3) that investor sentiment has effect on future returns is mainly caused by the search of investors who

use personal computer devices. The negatively coefficient of $\text{Mkt up dummy} \times \text{ASVI_pc}_t$ in columns (2) suggests that the ASVI-return relation on futures markets is market run ups/downs-depended due to both long and short positions exist in futures market. While, the positively coefficient between ASVI_pc_t and future return in columns (2) suggests that the ASVI-return relationship in equity market also exist in Chinese futures market due to the short sell restrictions after restrictions period.

Panel B of Table 6 reports the result from the time series regressions where the dependent variable is always the next day's trading volume. The explanatory variables include ASVI_pc , ASVI_mob , the one lagged volume, the realized volatility, and Baidu media search volume index. The positive coefficients of ASVI_mob in Columns (2) and (4) further demonstrate that the investor attention influences asset price through trading volume. When investors pay more attention to an asset, the trading volume increases and further affects the futures returns.

5 Conclusions

This study provides the first empirical investigation into the influence of investor sentiment on the stock index futures market. We find that search volume cannot be used as a proxy for investor attention as it is in equity markets because in the futures market the proxy is more likely to be investor sentiment. The effect of investor sentiment on futures prices depends on market conditions (bull versus bear markets, or market run-ups versus run-downs). We also find that the ASVI induces large overpricing (underpricing) when market run-ups (market run-downs) occur and predicts return reversals in the short term. Furthermore, our evidence demonstrates that the effect of investor sentiment on futures returns is mainly caused by the searches of investors who use PC devices. Mobile searches have no effect on price, only on trading volume. Investor attention influences asset prices through trading volume.

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