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A new investor sentiment indicator (*ISI*) based on artificial intelligence: A powerful return predictor in China☆

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ABSTRACT

This paper utilizes deep learning approach widely documented in artificial intelligence, and proposes an investor-sentiment indicator (*ISI*) that is consistent with the purpose of forecasting stock market returns. We find that *ISI* is positively correlated with future stock market returns at a monthly frequency, but negatively associated with subsequent returns over a longer horizon. Moreover, *ISI* outperforms other well-recognized predictors both in and out of sample, and can predict cross-sectional stock returns sorted by industry. We also show a positive association between monthly *ISI* and dividend growth rate, which indicates that investors' expectations about future cash flows may contribute to the return predictability of *ISI*.

1. Introduction

As early as Keynes (1936), researches find that investor sentiment can impact asset pricing, as investors are not fully rational and are more likely to be affected by psychological factors when making decisions. Since then, investor sentiment has been considered as an important factor of asset pricing (Statman, 2000; Brown and Cliff, 2005; Baker and Wurgler, 2006; Stambaugh et al., 2012; Shen and Yu, 2013). For example, Baker and Wurgler (2006) show that investor sentiment plays a significant role in market predicting. Fisher and Statman (2000), and Lee et al. (2002) also confirm the importance of investor sentiment on stock price forecasting. Moreover, Huang et al. (2015) show that the sentiment factor far exceeds other well-known macro indicators in predicting returns.

However, it is still difficult and challenging to precisely measure investor sentiment, as investor sentiment is not directly observable. Existing literature has proposed various investor sentiment indicators, but there still exists some limitations when using these measures to predict stock returns. For instance, the close-end fund discount, or the number on IPOs, which is often used as proxy for investor sentiment (Lee and Shleifer, 1991; Pontiff, 1995; Brown and Cliff, 2005), may only reflect one aspect of investor sentiment. Even though Baker and Wurgler (2006) use the first principal component of six well-documented proxies as measure of investor sentiment, it may contain a substantial amount of common approximation errors that are not relevant to future stock returns (Huang et al., 2015). Some investor-sentiment indicators computed using big data method (Da et al., 2011; Tetlock, 2007; Schumaker et al., 2012) may also be biased, as they are constructed based on a subjectively pre-set emotional dictionary (Dalgleish et al., 2003; Cohen, 2011; Rao et al., 2014).

Artificial Intelligence (AI) provides us an ideal opportunity to precisely capture investor sentiment, as AI can directly estimate investor sentiment without a pre-set emotional dictionary or selecting principle component, and thus help reduce forecasting bias caused by subjective interference or common approximation errors. In addition, with its independent deep learning ability, AI can precisely tell the assignment of a word's sentiment value in a specific scenario, given that one word may reflect different degree of sentiment with respect to different scenarios (Deng and Yu, 2014; Chong et al., 2017; Ding et al., 2015).

Our main empirical approach is as follows. We begin by using Baidu AI open platform to compute investor sentiment indicator (*ISI*), based on articles and comments crawled from Stock Blog of Sina Finance, and

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examine the relationship between *ISI* and future stock returns.[1] We find that *ISI* is strongly positively correlated with future aggregate market returns at a monthly frequency, indicating a powerful return predictability of *ISI*. Moreover, the positive association between *ISI* and future stock returns remains statistically significant even after controlling the effect of other well-recognized macro indicators and traditional investor-sentiment measures, suggesting that *ISI* contains extra information about future returns. The forecast encompassing tests also support this finding. The stronger return predictability of *ISI* is also significant using a 3- or 6-month interval.

In addition, we use portfolio analysis to test the economic significance of *ISI*. Consistent with Huang et al. (2015), we show that when following the trading strategy based on the above association between *ISI* and future stock return, a mean-variance investor, who allocates between equities and risk-free asset, can earn higher Certainty Equivalent Return (CER) gain and Sharp Ratio than those using trading strategies based on other factors. Besides, we investigate the predictive power that *ISI* has on stock returns sorted by industry. We find that the return predictability of *ISI* is more significant in industries with high macroeconomic systematic risk, which is in line with Baker and Wurgler (2006, 2007), Stambaugh et al. (2012) and Shen and Yu (2013).

Furthermore, we investigate the economic driving force of the predictive power of *ISI*, i.e., whether the predictability comes from time variations in cash flows or discount rates. We show that *ISI* is significantly positively associated with future aggregate dividend growth, but is not related to future dividend-price ratio. Thus, investors' expectations about future cash flows may contribute to the return predictability of *ISI*.

This study contributes to the literature in the following ways. On one hand, we extend literature on investor sentiment by constructing a new investor sentiment indicator (*ISI*) that is aligned with the purpose of predicting subsequent returns. After controlling the effect of other well-documented macro indicators and measures of investor sentiment used in literature, *ISI* is still statistically significantly associated with future stock returns. In addition, investors can earn higher future returns with better asset allocation according to the stronger predictability of *ISI*. Thus, *ISI* is a statistically and economically significant predictor of subsequent returns.

On the other hand, we complement literature on behavioral finance by showing that AI independent deep learning method can be used to better capture investor sentiment. As psychological factors cannot be observed directly, existing studies use various indirect proxies that may have some limitations (e.g., forecasting bias, subjective interference, and et al.). Utilizing the deep learning ability of AI, we conduct a new measure of investor sentiment (i.e., *ISI*) and show that *ISI* outperforms other well-documented indicators in predicting future stock returns. Thus, AI can be used to capture psychological factors that may be related to investor decisions and stock price.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 discusses the construction of the *ISI* and the other variables. Section 4 reports the regression results both in and out of sample, examines the overlap of information content among indicators that may be associated with future stock returns, and investigates the return predictability of the *ISI* over longer horizons. Section 5 identifies the effect of *ISI* on subsequent returns using asset allocation approach. Section 6 tests the effect that *ISI* has on portfolio returns sorted by industry. Section 7 further explores the driving force of *ISI*, and Section 8 concludes the paper.

2. Literature review

Except for the traditional predicting factors in classical asset pricing model, investor sentiment has been considered as an important factor affecting stock market returns since the 19th century (Statman, 2000; Brown and Cliff, 2005; Baker and Wurgler, 2006; Stambaugh et al., 2012; Shen and Yu, 2013). Such work shows that investors are not fully rational, and are more likely to be affected by some psychological factors, such as sentiment, when making trading decisions.

However, there is still no consensus on the effect of investor sentiment on stock market returns. Keynes (1936) documents that investor sentiment can affect asset prices due to the well-known psychological fact, i.e., people with high sentiment tend to make overly optimistic judgments and choices. Since then, Lee et al. (2002) show that emotions are positively correlated with excess returns; that is, the higher the mood, the more the excess returns, and vice versa. Dergiades (2012), and Kim and Kim (2014) find supportive evidence using US and Korean data, respectively. However, some studies provide opposite conclusions. Fisher and Statman (2003) report that high sentiment is followed by low stock returns, and vice versa. Schmeling (2009) finds that sentiment negatively forecasts aggregate stock market returns, and this relationship also holds for returns of value stocks, growth stocks, small stocks, and for different forecasting horizons. Stambaugh et al. (2012), Brown and Cliff (2004) and Baker and Wurgler (2006) also find a negative association between investor sentiment and future stock market returns. Furthermore, Huang et al. (2015) compare the predictability of investor sentiment with those of other factors, and show that investor-sentiment indicator can predict the stock market better than almost all of the popular macroeconomic indicators.

Existing literature has proposed various investor-sentiment indicators. For instance, Statman (2000), and Brown and Cliff (2004) use direct indicators, such as *AAII* (American Association of Individual Investors), *CCI* (Consumer Confidence Indicator) and *II* (Investors Intelligence), as proxies for investor sentiment. While Du and Hu (2015), and Pontiff (1995) use indirect indicators, such as *Volume* (Trading Volume), *DCEF* (Discount of Closed-end Fund) and *NIA* (New Investor Accounts), to measure investor sentiment. In addition, many studies have developed various comprehensive methods. For example, Baker and Wurgler (2006) use principal component analysis and construct a novel investor-sentiment indicator (*BW*) that aggregates the information from six proxies, i.e., IPO quantity, IPO first-day returns, closed-end fund discount rate, turnover rate, new share issuance, and dividends. Yi and Mao (2009), and Huang et al. (2015) optimize the investor-sentiment indicator based on *BW*, and show that their optimized indicator has more powerful return predictability. In addition, the development of Internet provides scholars an opportunity to construct investor sentiment indicators by applying big data method (Da et al., 2011). However, almost all of the previous literature adopts the emotional dictionary methods. Specifically, Bollen et al. (2011), and Oh and Sheng (2011) use emotional dictionaries to analyze investor sentiment based on the information crawled from Twitter and Blog, respectively. Many others (Tetlock, 2007; Loughran and Mcdonald, 2011; Schumaker et al., 2012; Manela and Moreira, 2016; Oliveira et al., 2016) also contribute to this area utilizing emotional dictionary methods.

3. Data and measurement of variables

3.1. Data

To construct investor sentiment indicator (*ISI*), we crawl the articles and comments in the Stock blog of Sina Finance monthly during the period from June 2000 to June 2018.[2] We eliminate articles whose

[1] Baidu AI platform is the largest artificial intelligent analysis open platform in China, and Sina Finance is the most closely watched financial website in China. We will introduce more about both in Section 3.

[2] In the process of crawling, we include comments and reprinted articles. The comments contain some experts' opinions, which will also be read by some traders, thus affecting their trading behaviors and the stock price. And it is reasonable to analyze the sentiment in reprinted articles. They express the reprinted author's recognition of the same article, which enhances the initial sentiment value, therefore we should count the emotional value twice if the same article appears twice.

Table 1
Average Click Rate of the Financial websites, 2000:06–2018:06. Table 1 shows the average hits per day of the four comparable websites, and PV is the number of click times during the sample period; while UV denotes the number of people who click.

	Sina Finance	Snowball	Netease Finance	Hexun Network
Average click rate per day (PV)	429,000	323,400	223,000	222,920
Average click rate per day (UV)	225,919	101,440	201,600	174,720

sentiment value is smaller (greater) than the mean value of investor sentiment minus (plus) three standard deviations. Finally we get a total of 1,286,000 articles during the sample period, with an average of 6,000 articles in each trading month, accounting for 80% of the total stock-related articles. In addition, the datas in subsection 3.2 are available from Wind, which is one of the most popular financial databases in China, covering the most comprehensive financial data in Chinese stock market. The sample period is over June 2000 to June 2018.[3]

3.2. Measurement of variables

3.2.1. Investor sentiment indicator (ISI)

We utilize deep learning method widely documented in artificial intelligence, and proposes an investor sentiment indicator (*ISI*). We first adopt a Python web crawler to crawl articles and comments in the Stock Blog of Sina Finance monthly during the sample period.

The Sina Finance blog is a well-known financial website in China. It includes various transaction data, and there are a number of stock analysts who publish their viewpoints on stock market. We compute investor-sentiment indicators using articles in this website for following reasons. Firstly, as shown in Table 1, Sina Finance has the highest average Click-Through Rate (CTR) per day within the sample period, compared with other popular financial websites in China (e.g., Snow Ball, Netease Finance and Hexun Network). Thus, Sina Finance is more representative than other websites.[4] Secondly, the investor sentiment impounded in the articles in different websites may be similar.[5] Thus, in order to avoid the repetition of information, we only choose Sina Finance as representative website.

The Stock blog contains the opinions of the stock analysts on the aggregate stock market, instead of individual stocks. Thus, we do not give different weights to different articles based on stock values. The Stock blog column is more ideal for our research in three ways. Firstly, this column contains the opinions of stock analysts, who may have more inside information and expertise above average, therefore giving rise to a greater contribution to the return predictions (Abarbanell, 1991; Krische and Lee, 2001; Scherbina, 2006; Moshirian et al., 2009). Secondly, retail traders, who dominate the Chinese securities market, are more likely to follow the opinions of stock analytical articles, such as articles in the Sina Stock Blog (Chemmanur and Yan, 2009; Yuan, 2012). Last and most importantly, this column focuses on the articles about stocks, thus there is no need to filter the articles.

Table 2
Examples of sentiment analysis. The table provides several examples of sentiment analysis results using the Baidu AI, which can automatically calculate the sentiment value thanks to the NLP (Natural Language Processing) that pre-developed and pre-adjusted by many specialized teams.

Examples	Emotional level (positive)	Emotional level (passive)
The Shanghai Stock Exchange Indicator fell slightly	0.34	0.66
The Shanghai Stock Exchange Indicator fell slightly in expectations.	0.60	0.40
The Shanghai Stock Exchange Indicator fell slightly in expectations, and is expected to rebound tomorrow.	0.72	0.28
The energy sector stock sustainability is very strong.	0.82	0.18
Stimulated by the policy, the energy sector stock sustainability is very strong.	0.88	0.12
Stimulated by policy, superimposed demand recovery, energy sector stocks continue to be very strong.	0.91	0.09

Next, we compute sentiment value by uploading the crawled text into the Application Programming Interface (API) of the Baidu AI open platform sentiment analysis tool.[6] Baidu AI platform is the largest open artificial intelligent analysis platform in China among four other alternatives (Baidu, Tencent, Ali and iFLYTEK), with a well-established service cooperation chain.[7] Moreover, with the Logistic Regression, it combines the most popular textural models (BERT, CNN, Att-BLSTM and so on), which makes it possible to provide a function of independent deep learning, giving rise to a greater possibility for the results to be more accurate (Deng and Yu, 2014; Schmidhuber, 2015; Litjens et al., 2017). In addition, the Baidu AI open platform has been widely used in finance, retail, manufacturing, government affairs and other fields, which makes Baidu AI the most authoritative platform in China.[8]

The Baidu AI can automatically calculate sentiment value of article using Natural Language Processing (NLP), which is pre-developed and pre-adjusted by many specialized data programmers (Stenetorp et al., 2012; Cambria and White, 2014).[9] To be specific, we briefly summarize the calculation steps as follows. Baidu AI measures investor sentiment by firstly segmenting the words into nouns, verbs and adjectives, and then computes the frequency (p_i) of all the words sorted; secondly, matching the words with the sentiment value in the database automatically, each word (after data clearing for useless words) will be assigned a sentiment value v_i;[10] thirdly, by multiplying the frequency of each word with the sentiment value and then summing them up ($\sum_{i=1}^{n} p_i \times v_i$), it obtains the

[3] In subsection 4.1, we calculate the forecasting results when the economic crisis period is deleted, finding the forecasting ability is not affected seriously by the economic crisis.

[4] From Table 1, we can see that the Sina Finance has the highest hits with a 429 thousand PV and 226 thousand UV per day. (Snow Ball at https://xueqiu.com/; Netease Finance at https://money.163.com/; Hexun Network at http://www.hexun.com/).

[5] On the one hand, the same article will be published on different platforms through different accounts. Therefore, the sentiment based on the articles in different websites are highly correlated. On the other hand, analysts may have herding effect, which leads to similarities in the attitudes of articles in different websites (Trueman, 1994; Bushee, 1998; Liao et al., 2011; Crawford et al., 2012).

[6] The Application Programming Interface code is posted at https://aip.baidubce.com/rpc/2.0/nlp/v1/sentiment_classify_custom, and the tutorials are published at http://ai.baidu.com/forum/topic/show/942825.

[7] There are 500 technical support enterprises, 300 customer enterprises, including more than 150 financial enterprises.

[8] There are 88% of the enterprises believe that artificial intelligence can effectively help the overall operation of the enterprise reduce costs, and 87% of the enterprises affirm the value of artificial intelligence in improving the precision of service, in particular, 59% percent of securities companies said artificial intelligence would play a big role in stock investment.

[9] A natural language processing (NLP) technology enables natural language communication between humans and computers. The NLP in this platform provides a full set of self-base rich Chinese language processing modules (including 6 Chinese processing core technologies such as morphology, syntax, semantics and the like), which makes it solve the problems of word boundary definition, syntactic fuzziness and defective or irregular input.

[10] The negative words are such as, blame, downgrade, shortfall, plunge, slowdown, tumble, hurt and so on; the positive words are such as, surge, upgrade, repurchase, declare, jump, undervalue, customary, unsolicited and so on. They are all included in the big database.

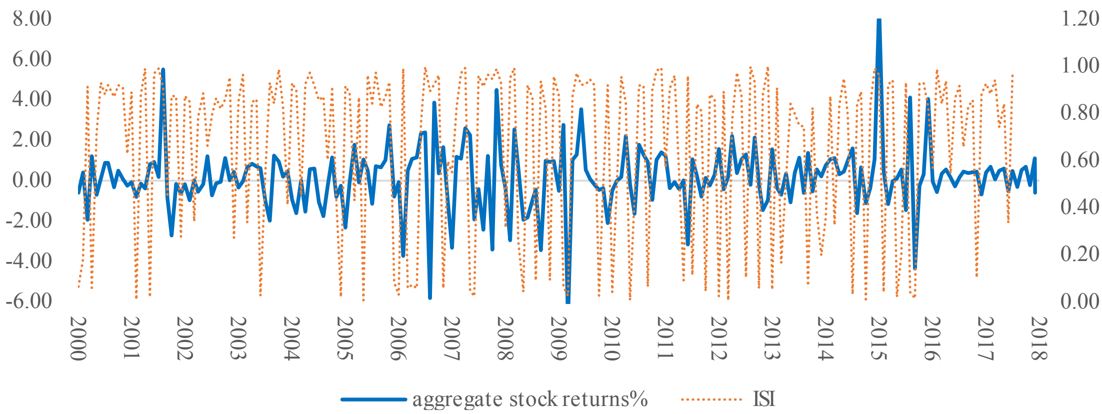

Fig. 1. Fluctuation of aggregate stock returns and the ISI, 2000:06–2018:06
The solid line depicts the aggregate stock returns in the June 2000 to June 2018 period. The dashed line depicts the investor sentiment indicator (*ISI*) over the same time period. In the analysis, each sentence has a positive and negative sentiment value, we use the positive value ranging from 0 to 1 to measure the emotional level of each sentence in the text. By averaging the emotional values of all of the texts mined from the Stock blog of Sina Finance in a month, we obtain the *ISI* indicator for the month.

initial sentiment for each article; in addition, for another forth unique step, based on independent deep learning technology, Baidu AI can precisely adjust the assignment of a word's sentiment value in a specific scenario, given that one word may reflect different degree of sentiment with respect to different scenarios (Deng and Yu, 2014; Chong et al., 2017; Ding et al., 2015).[11]

Most of previous literature analyzes sentiment by constructing emotional dictionaries (Tetlock, 2007; Loughran and Mcdonald, 2011; Bollen et al., 2011; Oh and Sheng, 2011; Schumaker et al., 2012; Manela and Moreira, 2016)[12]. But such textural method relays on the appropriateness of the pre-set emotional dictionary[13]. Besides, there exists the problem of assigning too high or too low an emotional value (Dalgleish et al., 2003; Cohen, 2011; Rao et al., 2014). Additionally, this method cannot adjust the sentiment value according to different situations, given that one word may reflect a different degree of sentiment in different scenarios. Artificial Intelligence (AI) provides us an opportunity to reduce the above concerns. On the one hand, with the ready-made and widely-used objective programming, AI can directly estimate investor sentiment without a pre-set emotional dictionary so as to reduce the problems of lacking appropriate Chinese emotional dictionary and assigning too high or too low an emotional value. On the other hand, with its independent deep learning ability, AI can precisely tell the assignment of a word's sentiment value in a specific scenario, which is more reasonable than the dictioanary method (Deng and Yu, 2014; Chong et al., 2017; Ding et al., 2015).

Specific examples are given in Table 2. It can be seen that very subtle changes from the sentence may result in different emotional values, indicating the high sensitivity of the AI analysis platform.

As shown in Table 2. Each sentence in the analyzed text can be assigned a positive and a negative sentiment value. We use the positive value, ranging from 0 to 1, to measure the emotional level of each sentence in the text. By averaging the emotional values of texts posted within a month, we get the mothly investor sentiment indicator (*ISI*).

According to the data, *ISI* has a mean value of 0.66, a median value of 0.68 and a maximum value of 0.99 in March of 2015. As shown in Fig. 1, the investor sentiment constructed by *ISI* moves synchronically with aggregate stock returns, indicating a positive correlation. This is consistent with previous studies, such as Lee et al. (2002) and Kim and Kim (2014).

3.2.2. Traditional investor sentiment indicators

Previous literature commonly use investor-sentiment indicator constructed by Baker and Wurgler (2006) to represent the investor sentiment. Similarly, we construct a new index *NCICSI* on the basis of *BW* as traditional measure of investor sentiment, as the price limit trading rules in China may lead to the incomplete transmission of information and an invalid first-day earning of IPOs (Wu et al., 2017; Thomadakis et al., 2016; Liao et al., 2011). In this case, we remove the first-day earning of IPOs proxy. Besides, some monthly data of the proxies used to estimate *BW* is not available in the Chinese financial market. Therefore, we replace three proxies that are not available for the monthly data on the basis of *BW*, then using the number of IPOs, the closed-end fund discount rate, trading volume, consumer confidence indicator, and new investor account opening numbers to obtain a new indicator (*NCICSI*) for our analysis. In addition to *NCICSI*, we also select two single investor-sentiment indicators for comparison, including the volume of transactions and the closed-end fund discount rate.

We compute the monthly turnover rate (VOL_t) as follows:

$$VOL_t = \frac{V_t - V_{t-1}}{V_{t-1}}, \tag{1}$$

where V_t is the trading volume of the whole stock market in month t; V_{t-1} is the trading volume of the whole stock market in the month t-1. If VOL_t is positive, the market trading is active and the investors are emotionally bullish; while if VOL_t is negative, the market trading is sluggish and the investors are emotionally bearish.

The closed-end fund discount rate (CF_t) is computed as follows:

$$\mathrm{CF}_t = \frac{cf_t - cf_{t-1}}{cf_{t-1}}, \tag{2}$$

where cf_t is the closed-end fund discount rate at month t; cf_{t-1} is the closed-end fund discount rate at month t-1.

[11] Cause Baidu AI have not yet published its code totally, you can refer to the similar website BERT, https://github.com/google-research/bert, which is also one of the source code of Baidu AI as introduced above, to better understand the deep learning.

[12] This approach first needs to pre-select a large number of words that express positive and negative emotions, and then assign each one a value according to the degree of sentiment it expresses. And the final emotional value of the text is obtained by adding up the emotional values of each word.

[13] The "Harvard-IV-4 dictionary" (Tetlock, 2007) and "Loughran-McDonald dictionary" (Loughran and Mcdonald, 2011) are typical examples for English vocabulary, and the "HowNet dictionary" is for Chinese vocabulary. Since the English dictionary cannot be used in Chinese, and meanwhile the Chinese dictionary vocabulary construction is not aimed at the financial field, which will bring some noise, it is difficult to operate a suitable emotional dictionary method in the Chinese stock market.

Table 3
Correlations between predictor variables, 2000:06–2018:06. Table 3 shows the correlations between 10 well recognized predictor variables in literatures and the *ISI*. For definitions of each indicator, see subsections 3.2.1, 3.2.2 and 3.2.3. The sample period is over June 2000 to June 2018.

Variable	*RVOL*	*BM*	*NTIS*	*SHIB*	*ER*	*R*	*GB*	*INFL*	*NCICSI*	*VOL*	*CF*
BM	0.01										
NTIS	−0.10	0.15									
SHIB	−0.08	−0.30	0.06								
ER	0.02	0.13	−0.19	−0.09							
R	−0.03	0.02	0.06	0.45	−0.02						
GB	−0.23	−0.16	0.16	0.54	−0.14	0.38					
INFL	0.03	0.51	−0.05	−0.36	0.41	−0.09	−0.34				
NCICSI	0.18	0.08	−0.19	−0.11	0.17	−0.21	−0.05	0.17			
VOL	0.13	0.25	−0.02	−0.14	0.21	−0.12	−0.01	0.21	0.51		
CF	0.22	0.06	−0.01	−0.32	0.15	−0.35	−0.05	0.11	0.46	0.58	
ISI	0.01	0.04	−0.03	−0.13	0.11	−0.01	0.08	0.03	0.23	0.21	0.28

3.2.3. *Other macroeconomic indicators*

Following Goyal and Welch (2008), we consider five macroeconomic indicators which have better predictive power in their results, including excess stock returns volatility (*RVOL*), Book-to-market ratio (*BM*), Net equity expansion (*NTIS*), Government bond rate (*GB*) and Inflation (*IFL*). However, Goyal and Welch (2008) does not contain monetary policy indicators, which can also affect the stock market through the flow of capital and announcement effect (Christiano et al., 2008; Sellin, 2010). In addition, government intervention in the Chinese financial market is common (Fleisher and Risk, 1998; Green, 2004; Chen et al., 2016). Thus, it is necessary to compare *ISI* with monetary policy indicators. Finally, we select the following eight macroeconomic indicators.

(1) Excess stock returns volatility (*RVOL*): computed using a 12-month moving standard deviation, as in Mele (2007).
(2) Book-to-market ratio (*BM*): value-weighted book-to-market value ratio for stocks incorporated in the Shanghai Composite Indicator.
(3) Net equity expansion (*NTIS*): ratio of a 12-month moving sum of net equity issued by SSE (Shanghai Stock Exchange)-listed stocks to the total end-of-year market capitalization of SSE stocks.
(4) Government bond rate (*GB*): 3-month government bond issuance rate.
(5) Inflation (*IFL*): the CPI for urban consumers.
(6) Shanghai Interbank Offered Rate (*SHIB*): Shanghai commercial banks' interest rate for financing.
(7) RMB exchange rate (*ER*): RMB against the US dollar.
(8) Central bank reserve ratio (*R*): deposit reserve ratio charged by the central bank to commercial banks that is used to adjust credit.

We compute excess stock return as the interpreted variable, which is computed as the log of return on the aggregate stock market (the weighted average return on market value) minus the risk-free rate (return on 10-year Treasury bonds).

3.3. *Relation to other predictors*

Table 3 reports the correlation coefficients among *ISI* and the other 11 indicators. We find that there are little correlations between investor-sentiment indicators (*NCICSI*, *CF*, *VOL* and *ISI*) and macroeconomic predictors (*RVOL*, *BM*, *NTIS*, *GB*, *IFL*, *SHIB*, *ER* and *R*), indicating that investor-sentiment indicators may contain different economic information, compared with other popular macroeconomic indicators. Besides, among the four investor sentiment indicators (*NCICSI*, *CF*, *VOL* and *ISI*), *ISI* has smallest correlation coefficients with macroeconomic indicators, indicating the information overlapping between *ISI* and macroeconomic indicators are small. In addition, the correlation coefficients between *ISI* and *NCICSI*, *VOL* and *CF* are 0.23, 0.21 and 0.28 respectively, which suggests that *ISI* contains substantially different information when compared to traditional investor sentiment indicators.

Table 4
In-sample predictive regression estimation, 2000:06–2018:06. The table reports the ordinary least squares estimate of b and the R^2
statistic for the predictive regression model,
$r_{t+1} = a + bX_t + c\sum_{i=0}^{n} MR_{t-i} + \varepsilon,$
where r_{t+1} represents the value-weighted excess stock returns at time t+1; X_t represents the predictor variable and MR_{t-i} represents the value-weighted average stock returns at time t-i. By incrementally adding n, when it equates to 0, the regression equation has the highest degree of significance. That means we include the MR_t in our regression as the control variable for forecasting r_{t+1}. The statistical significance of b is used to test the null hypothesis that the predictor variable in the first column is not a significant predictor for excess returns at a monthly frequency. The brackets below the b estimates report the Newey-West t-statistics, and *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, according to wild bootstrapped p-values. The sample period is over June 2000 to June 2018. The last three rows report the estimate of b and the R^2 statistic for the following predictive regression model,
where $f_{i,t}$ is the principal components of the 11 well recognized indicators (m = 1, 2, 3); *ISI* is the indicator of investor sentiment that we build.

Predictor	b	$R2$ (%)
RVOL	0.44 [0.27]	1.11
BM	0.31** [1.92]	1.85
NTIS (−)	0.09 [0.31]	0.03
SHIB (−)	0.31** [1.88]	1.96
ER	0.58* [1.48]	1.11
R (−)	0.27* [1.68]	1.12
GB (−)	0.13 [1.65]	0.24
INFL (−)	0.02 [-0.03]	0.01
NCICSI	0.58* [1.67]	2.16
VOL	0.45* [1.68]	1.06
CF	0.59 [1.11]	2.14
ISI	1.43*** [5.22]	12.9
ISI(1)	1.77*** [5.28]	13.2
ISI(f_1)	1.38*** [4.99]	11.3
ISI(f_2)	1.26*** [4.93]	8.35
ISI(f_3)	1.19*** [4.89]	8.11

4. Predictive regression analysis

4.1. *In-sample regression tests*

We use the AR model to analyze the predictive power of *ISI* and the other 11 indicators:

$$r_{t+1} = a + bX_t + c\sum_{i=0}^{n} MR_{t-i} + \varepsilon, \tag{3}$$

where r_{t+1} is the value-weighted excess stock returns at month t+1; X_t is the predictor variable; $MR_{t\text{-}i}$ represents the value-weighted average returns at time t-i. By incrementally adding *n*, when it equates to 0, the regression equation has the highest degree of significance, that means we include the one period lag MR_t in our regression as the control variable for forecasting r_{t+1}. We want to test the significance of *b* in equation (3) for every predictor. To make more reliable inferences, we use a heteroscedasticity- and autocorrelation-robust t-statistic and compute a wild bootstrapped p-value to test H_0: $b = 0$ against H_1: $b > 0$ in equation (3). To be comparable, we standardize all of the macroeconomic indicators. In addition, we take the negative of *NTIS*, *SHIB*, *R*, *GB* and *INFL* before estimating equation (3), so that H_1: $b > 0$ is applicable to each indicator.

Table 4 reports the OLS estimation of *b* and the corresponding t-statistic for each predictor in equation (3). As for the eight popular macroeconomic indicators, four of them display significant predictive ability at the 10% level in the second column of Table 4: *BM*, *SHIB*, *ER* and *R*. Amongst them, *SHIB* has the largest t-statistic (1.88) and *ER* has the largest *b* estimate (0.58). *NCICSI*, *VOL* and *CF* do not perform as well as the previous studies (Yi and Mao, 2009; Lee and Shleifer, 1991) with relatively small Newey-West t-statistic. However, *ISI* exhibits significant predictability at the 1% level, and its *b* estimate (1.43) well above that of any other predictor, including *NCICSI*. The *b* estimate for *ISI* has the expected economic meaning: a one-standard-deviation increase in *ISI* is associated with a 143 basis points increase in the next month's excess returns. We also show the results eliminating the economic crisis period (the year 2008) from the sample period in Table 4 column *ISI(1)*. It seems that the economic crisis has little effect on the predictability of *ISI*, so we include the economic crisis period for the following analysis.

These results imply that the return predictability of *ISI* is more powerful than that of traditional investor sentiment indicators. We try to explore it further by comparing their affecting mechanism for stock returns. The traditional investor sentiment indicators reflect the expectations of all the traders in the market as they are constructed by stock trading data. While *ISI* reflects the expectations of stock analysts, which leads to a more accurate prediction ability of *ISI* from two aspects. On the one hand, intuitively, analysts may have more inside information and expertise above average, and this will make their opinions themselves more accurate in predicting stock returns (Abarbanell, 1991; Krische and Lee, 2001; Scherbina, 2006). On the other hand, compared with institutional investors, retail investors are not good at making independent analytical judgments due to the lack of experience themselves, which leads them to follow others' opinions (especially the stock analysts), making the price finally meet the analysts' expectations, which seems to be caused by a powerful predictability of *ISI* (Banerjee, 1992; Chemmanur and Yan, 2009; Keynes, 1936; Kraus and Stoll, 1972; Yuan, 2012).[14]

As monthly forecasts contain many uncertain factors, the R^2 statistics in the third column of Table 4 are reasonably small. Campbell and Thompson (2008) argue that a monthly R^2 statistic of approximately 0.5% represents a statistically meaningful degree of predictability. Therefore, we think the monthly R^2 should exceed or approximate this standard. The monthly R^2 (12.9%) of *ISI* is well above 0.5%, which means the predictability of *ISI* is statistically meaningful. In addition, it is much larger than the second largest R^2 (2.16%) of *NCICSI*.

Overall, the second and third columns of Table 4 demonstrate that the predictability of *ISI* at a monthly frequency is obviously and significantly stronger than that of the other popular macroeconomic indicators or the commonly used traditional investor sentiment indicators.

However, the good performance may be due to the analytical articles in Stock blog of Sina Finance but not due to the construction of *ISI* itself. To alleviate potential concerns over the above issue, we compare our Baidu AI method with an emotional-dictionary based sentiment indicator

Table 5
The Granger Test, 2011:01–2012:02 (Daily). Table 5 shows the Granger Test for *ISI* and *OSMten*, proposed by Cheng and Lin (2013), which is basically consistent with our data source, using daily data from January 2011 to February 2012, and the time lag is from 1 to 5. MR represents the value-weighted market average returns; VLM represents the trading volume of the whole market. We report the slopes and P-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Hypothesis	F statistic				
	Lag (-1)	Lag (-2)	Lag (-3)	Lag (-4)	Lag (-5)
OSMten is not the Granger reason for the MR	1.001 (0.318)	0.553 (0.576)	0.518 (0.670)	0.781 (0.538)	0.553 (0.736)
OSMten is not the Granger reason for the VLM	6.197** (0.013)	4.287** (0.015)	3.306** (0.021)	1.987* (0.097)	1.925* (0.090)
ISI is not the Granger reason for the MR	2.125* (0.091)	2.129* (0.089)	3.012** (0.042)	1.128** (0.041)	1.901* (0.091)
ISI is not the Granger reason for the VLM	8.771** (0.011)	6.438** (0.016)	6.136** (0.008)	1.090* (0.082)	1.871* (0.088)

(*OSMten*) proposed by Cheng and Lin (2013), whose data source is basically consistent with ours.[15] Thus, we can compare their performance after controlling the effect of the articles. To be consistent, we use a Granger test method and the same sample period, as in Cheng and Lin (2013). As shown in Table 5, when the lag period is from 1 to 5, it accepts the null hypothesis that *OSMten* is not the reason for the market average returns (*MR*) at the 5% level; and reject the null hypothesis that *OSMten* is not the reason for the stock market volume (*VLM*), which is also significant at the 5% level. It means *OSMten* can only affect the trading volume effectively, but the ability for forecasting market average returns is limited. Meanwhile, as for our *ISI*, both the two null hypotheses are rejected significantly, which means that the *ISI* not only can predict the trading volume, but also the market average returns. In this way, we recognize that Baidu AI contributes more to the forecasting of market returns.

4.2. Comparing the information content

To glean insight into the results in subsection 4.1 of the various predictabilities of different predictors, we then test the degree of overlapping information between *ISI* and the other 11 well recognized indicators by the following regression:

$$r_{t+1} = a + b_{ISI}ISI + \sum_{i=1}^{m} b_{f,i}f_{i,t} + c\sum_{i=0}^{n} MR_{t-i} + \varepsilon, \tag{4}$$

where r_{t+1} represents the value-weighted excess stock returns at time t+1; $f_{i,t}$ is the principal components from the eight macroeconomic indicators and the three traditional investor sentiment indicators ($m = 1, 2, 3$); MR_{t-i} represents the value-weighted average stock returns at time t-i, the same as equation (3). We gradually introduce one of the principal components into the original regression equation until m equates to three. This allows us to test the predictive power of *ISI* in a reasonably parsimonious manner after controlling for the information in other predictors. We also use a heteroscedasticity- and autocorrelation-robust t-statistic and compute a wild bootstrapped p-value to test H0: $b = 0$ against H1: $b > 0$ in equation (4).

The last three rows of Table 4 report the results of equation (4). The principal components $f_{i,t}$ of other 11 indicators do not change the coefficient b_{ISI} and its significance in equation (3), suggesting that *ISI* contains extra information about future returns.

Next, we use forecast encompassing tests to further examine the information content of *ISI*. We form a combined forecast of the predictive regression forecasts based on one of the 11 predictors and the *ISI* as

[14] Even though experts do not predict accurately, retail investors will play a sucker and a follower and make the price finally meet their expectations (Armstrong, 2004).

[15] Their data source is nearly almost the same with ours, with a certain degree of comparability, which is also from the Sina Finance. But unfortunately, we have not found an indicator based on exactly the same articles from Stock Blog of Sina Finance. And, due to some limits, we have not set up an emotional dictionary for comparing.

Table 6
Forecast encompassing tests, 2000:06–2018:06. The table reports the coefficient λ for the following model,

$r = (1-\lambda)\hat{r}^{i}_{t+1} + \lambda\hat{r}^{ISI}_{t+1} + \varepsilon$

where $\hat{r}^{i}_{t+1}$ is the estimated value from equation (3) using one of the 11 predictors and $\hat{r}^{ISI}_{t+1}$ is the estimated value from equation (3) using *ISI*; r_{t+1} is the real excess stock returns for the next period. λ is between 0 and 1, which represents the estimated weight on the predictive regression forecast based on *ISI* in a combination forecast that takes the form of a combination of predictive regression forecasts based on *ISI* and one of the non-*ISI* predictor variables. And the statistical significance is for testing the null hypothesis that the weight on the *ISI*-based forecast is equal to zero against the alternative hypothesis that the weight on the *ISI*-based forecast is greater than zero. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is over June 2000 to June 2018.

Predictor	λ
RVOL	1.00***
BM	1.00***
NTIS (−)	1.00***
SHIB (−)	1.00***
ER	1.00***
R (−)	1.00***
GB (−)	1.00***
INFL (−)	1.00***
NCICSI	0.79***
VOL	0.89***
CF	0.81***
ISI	–

follows:

$$r_{t+1} = (1-\lambda)\hat{r}^{i}_{t+1} + \lambda\hat{r}^{ISI}_{t+1} + \varepsilon, \tag{5}$$

where $\hat{r}^{i}_{t+1}$ is the estimated forecast value from equation (3) using one of the 11 predictors and $\hat{r}^{ISI}_{t+1}$ is the estimated forecast value from equation (3) using *ISI*; r_{t+1} is the real excess stock returns for the next period. λ is between 0 and 1, which represents the estimated weight on the predictive regression forecast based on *ISI* in a forecast that takes the form of a combination of predictive regression forecasts based on *ISI* and one of the non-*ISI* predictor variables. H_0:$\lambda = 0$ holds indicates the prediction of *ISI* makes no contribution to the optimal combination forecast given by equation (5). This means the predictive regression forecasts of the other 11 indicators encompass the predictive regression forecasts of *ISI*. In this case, the *ISI* does not contain extra information that is useful for forecasting the stock market returns beyond the information already found in the 11 existing predictors. Alternatively, H_1:$\lambda > 0$ holds indicates the *ISI* does not contain extra information that is useful for forecasting the stock market returns beyond the information already found in the 11 existing predictors.

The second column of Table 6 reports the estimates of λ in equation (5) for each popular predictor and indicates whether the estimates are significant, using the approach of Harvey et al. (1998). The λ estimates in Table 6 are all significant, so none of the predictive regression forecasts of the other 11 indicators encompass the *ISI*. To our surprise, the vast majority of the λ estimates are equal to one, and the remaining estimates are reasonably close to one, signifying the optimal combination forecast in equation (5) mostly benefits from the extra information contained in *ISI*, which is in line with our results in equation (4).

Table 7
Out-of-sample test results, 2010:06–2018:06. The second column reports the proportional reduction in mean squared forecast error (MSFE) for a predictive regression forecast of the excess returns based on the predictor variable in the first column relative to the prevailing mean benchmark forecast. The statistical significance is used to test the null hypothesis that the prevailing mean MSFE is less than the predictive regression MSFE based on the predictor variable in the first column. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The in- and out-of-sample periods are over June 2000 to June 2010 and June 2010 to June 2018, respectively.

Predictor	R^2 (%)
RVOL	−0.51
BM	−0.44
NTIS (−)	−2.11
SHIB (−)	0.78
ER	−0.06
R (−)	0.11
GB (−)	−0.81
INFL (−)	−1.88
NCICSI	1.27*
VOL	1.31*
CF	0.98*
ISI	4.21***

This subsection demonstrates that the *ISI* contains extra information when compared with the other 11 predictors. According to Byrne and Davis (2010), Jin et al. (2006) and Tourani et al. (2008), the transmission channel from the macroeconomic indicators to stock market is complicated and unsynchronized, so the predictability is limited. Whereas *ISI* derives its information from the judgements of analysts that is obtained by processing private and public information using their own abundant trading experience, whose forecast is more direct and synchronized (Abarbanell, 1991; Krische and Lee, 2001; Scherbina, 2006). Besides, since the analysts tend to obtain comprehensive information, including the macroeconomic ones, it is more reasonable to have a better predictability of *ISI* compared to the macroeconomic indicators. Interestingly, as the measure of investor sentiment, the information content of traditional investor sentiment indicators is different from that of *ISI*. It intuitively makes sense, given that the information contained in traditional investor sentiment indicators is derived from the aggregate transaction data, which contains the expectations of the whole investment participants with rational and irrational, mature and non-mature investors, so that the validity of the information is limited; while, the *ISI* derives its information from the expectations of analysts, which is more valid as explained in subsection 3.2.1 (Abarbanell, 1991;Krische and Lee, 2001; Scherbina, 2006). It's very reasonable to have a better predictability of *ISI*. In addition, the transmission of information in the Internet is much timely and extensive, which also gives rise to the possibility of *ISI* making more accurate forecasting.

4.3. Out-of-sample regression tests

Although the in-sample analysis provides more efficient parameter estimates and thus more precise return forecasting of *ISI*, Goyal and Welch (2008), among others, argue that out-of-sample tests seem more relevant for assessing genuine return predictability in real time and can avoid the in-sample over-fitting issue. In addition, out-of-sample tests are much less affected by the small-sample size distortions such as the Stambaugh bias (Busetti and Marcucci, 2012) and the look-ahead bias (Kelly and Pruitt, 2013, 2015). Hence, it is necessary to investigate the out-of-sample predictive performance of *ISI*.

Table 8
Long-term horizon predictive power, 2000:06–2018:06. The table reports the in-sample long-term horizon forecasting results for excess stock returns as follows: $r_{t+h} = a + bX_t + c\sum_{i=0}^{n} MR_{t-i} + \varepsilon$,
where r_{t+h} represents the value-weighted excess stock returns at time t + h; X_t represents the predictor variable; MR_{t-i} represents the value-weighted average stock returns at time t-i. By incrementally adding n, when it equates to 0, the regression equation has the highest degree of significance. That means we include the MR_t in our regression as the control variable for forecasting r_{t+1}. The statistical significance of b is used to test the null hypothesis that the predictor variable in the first column is not a significant predictor for excess returns over longer horizons. We report the slopes, Newey-West t-statistics, as well as the R^2s. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, according to wild bootstrapped p-values. The sample period is over June 2000 to June 2018, and h is assigned as 1-month, 3-month, 6-month, 9-month and 12-month periods, respectively.

Predictor	h = 1		h = 3		h = 6		h = 9		h = 12	
	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)
RVOL	0.44 [0.27]	1.11	0.35 [0.48]	1.27	0.22 [0.60]	1.26	0.21 [0.75]	1.38	0.21 [0.45]	1.35
BM	0.31** [1.92]	1.85	0.30** [1.93]	1.67	0.47** [-1.76]	1.50	0.49** [-1.98]	1.91	0.55** [-1.99]	1.99
NTIS (−)	0.09 [0.31]	0.03	0.04 [0.22]	0.05	0.02 [0.08]	0.00	0.01 [0.00]	0.00	0.00 [0.00]	0.00
SHIB (−)	0.31** [1.88]	1.96	0.23** [1.93]	2.22	0.36** [1.98]	2.26	0.44** [-2.21]	2.42	0.35* [1.68]	1.46
ER	0.58* [1.48]	1.11	0.51* [1.45]	1.15	0.66** [1.92]	1.22	0.43** [1.87]	1.41	0.45** [1.92]	1.41
R (−)	0.27* [1.68]	1.12	0.21* [1.56]	1.12	0.41** [1.88]	1.37	0.42* [1.74]	1.35	0.28* [1.81]	1.36
GB (−)	0.13 [1.65]	0.24	0.15 [1.31]	0.27	0.20 [1.22]	0.31	0.21* [1.66]	0.30	0.24* [1.58]	0.28
INFL (−)	0.02 [-0.03]	0.01	0.12 [-0.66]	0.06	0.24 [-0.83]	0.10	0.26 [-0.81]	0.08	0.24 [0.98]	0.10
NCICSI	0.58** [1.67]	2.16	−0.31** [-1.87]	2.15	−0.45** [-2.03]	2.39	−0.53 [-1.26]	0.48	−0.22 [1.45]	0.42
VOL	0.45* [1.68]	1.06	−0.23* [1.66]	1.07	−0.25** [1.91]	1.18	−0.28* [1.67]	0.95	−0.41 [1.00]	0.05
CF	0.59 [1.11]	2.14	−0.54 [1.04]	0.16	−0.35* [1.64]	0.17	−0.24 [1.01]	0.08	−0.37 [1.03]	0.05
ISI	1.43*** [5.22]	12.97	−1.51** [-1.95]	3.18	−2.31** [-1.86]	3.42	0.36 [1.11]	2.31	−0.20 [-0.62]	1.90

Following Goyal and Welch (2008), Kelly and Pruitt (2013), and many others, we use the coefficients obtained from the in-sample prediction regression to construct the following regression to predict the out-of-sample excess returns:

$$\widehat{r}_{t+1} = \widehat{a}_t + \widehat{b}_t \widehat{x}_t, \tag{6}$$

where $\widehat{a}_t$ and $\widehat{b}_t$ are the OLS estimates of a and b, respectively, in equation (3) based on data from the in-sample period and $\widehat{r}_{t+1}$ is the estimated excess stock returns for the next-period. We use June 2000 to June 2010 as the initial in-sample period and June 2010 to June 2018 as the forecasting out-of-sample period. Goyal and Welch (2008) show that the historical average is a very stringent out-of-sample benchmark, and individual economic variables typically fail to outperform the historical average. Thus, the historical average forecast serves as a natural benchmark. We compare it as follows:

$$\widehat{r}_{t+1} = (1/t)\sum_{i=1}^{t} r_i. \tag{7}$$

According to Campbell and Thompson (2008), we use the out-of-sample R^2 to measure the proportional reduction in MSFE for the predictive regression forecast based on *ISI* relative to it based on historical average. A positive value indicates that the predictive regression forecast outperforms the historical average; a negative value signals the opposite. Besides, according to Clark and West (2007), and West (1996), we use the MSFE-adjusted statistics to test the null hypothesis that the historical mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the historical mean MSFE is greater than the predictive regression MSFE (H_0: $R^2 \le 0$ against H_1: $R^2 > 0$).[16]

As shown in Table 7, nearly most of the eight well-recognized macroeconomic predictors fail to outperform the historical average benchmark in terms of MSFE at a monthly horizon, which is consistent with the findings of Goyal and Welch (2008). Although *SHIB* and *R* have positive R^2 statistics, the biggest (0.71%) is only one fifth of the value for the *ISI* (4.21%). It is interesting to note that *NCICSI*, *VOL*, *CF* and *ISI* outperform the historical mean benchmark with the positive R^2 statistics (1.27%, 1.31%, 0.98% and 4.21% respectively) and are significant according to the Clark and West (2007) statistic, which means they all outperform the mean benchmark and clears the out-of-sample hurdle. However, the impressive R^2 of *ISI* (4.21%) is almost three times larger than that of the second largest R^2 of *NCICSI* (1.27%), signifying that the out-of-sample test results for *ISI* are much better than those of the other indicators.

4.4. Predictability over longer horizons

The previous subsection is based on a monthly data, but one may argue whether *ISI* performs better compared to others in a longer period of time. In this subsection, we further discuss the predictability of *ISI* over longer horizons.

It is believed that investor sentiment may have long-term effects on stock market returns. Due to various limits of arbitrage, such as fundamental risk and noise trader risk, the price fluctuation caused by investor sentiment may not be completely eliminated by arbitrageurs over a short horizon, even when arbitragers recognize the opportunity (De Long et al., 1990; Shleifer and Vishny, 1997; Gromb and Vayanos, 2010). So, it is reasonable to have a lasting effect for investor sentiment on stock market returns. Furthermore, previous studies (e.g., Brown and Cliff, 2004, 2005; Baker et al., 2012) have shown that investor sentiment has a reversal long-term effects on stock returns; that is, investor sentiment can forecast the recent market positively but forecast the forward market in reverse. Meanwhile, Brown and Cliff (2004), Gertler and Gilchrist (1993), Husain and Mahmood (2001) and Tourani et al. (2008) suggest the macroeconomic indicators also have long-term effects on stock market returns. Therefore, it is necessary to compare the predictabilities for these indicators over longer horizons.

As shown in Table 8, nearly all of the predictabilities of the eight macroeconomic indicators for stock market returns increase with the prolongation of the period, which is consistent with Rozeff (1947), Palmer (1970), Gertler and Gilchrist (1993) and Tourani et al. (2008). These literature generally consider it may due to the hysteresis of the process for macroeconomic influencing, given that the long process from the economy to consumer confidence first, next conducts to investment and production, and then to the flowability of the capital market, finally to the market sentiment and trading behaviors. The *SHIB* still has the largest R^2 even up to 9-month interval (1.96%, 2.22%, 2.26% and 2.42% for 1-month, 3-month, 6-month and 9-month periods, respectively). What is totally different, the effects of the investor sentiment indicators on stock market returns are reversed as the horizon increases. More

[16] Clark and West (2007) develop the MSFE-adjusted statistic, which has an approximately standard normal asymptotic distribution when comparing forecasts from nested models. Comparing a predictive regression forecast to the historical average entails comparing nested models, as the predictive regression model reduces to the historical mean forecast model under the null hypothesis.

specifically, the corresponding regression coefficient is positive for the 1-month interval, whereas it is negative for the 3- and 6-month interval, which is basically in line with Benartzi (2001). Interestingly, when comparing all 12 indicators, the *ISI* performs better no matter how long the time window is. However, they are complementary and their performance difference diminishes as the horizon increases.

Next, we focus on the forecasting results of the *ISI* in equation (3) over longer horizons. Firstly, as shown by the *t* value in the last row, *ISI* can predict the stock market returns up to 6-month interval, but the predictive power over longer horizons is small and insignificant in general. Secondly, we find the regression coefficient of *ISI* is positive for 1-month interval (1.43), but is negative for 3-month and 6-month intervals (−1.51 and −2.31, respectively). A one-standard-deviation increase in *ISI* is associated with a 143 basis points increase in the next month stock returns, a 151 basis points decrease in the next three-month stock returns and a 231 basis points decrease in the next six-month stock returns. It indicates that the overpricing or underpricing caused by irrational investors can not be justified by subsequent economic fundamentals (Brown and Cliff, 2005). De Long et al. (1990), among others, provide theoretical explanations why sentiment can cause stock price over- or under-valued in the presence of limits of arbitrage, even though the arbitragers recognize the opportunity. This over-extrapolation phenomenon we find is consistent with the results in Benartzi (2001) and Baker and Wurgler (2006, 2007). Thirdly, the predictive power decreases as the horizon increases. In detail, the forecasting power peaks at 1-month interval, with the R^2 of 12.97%, comparing to the corresponding R^2 of 3.18% at 3-month interval and 3.42% at 6-month interval.

In conclusion, this subsection provides evidence that the *ISI* outperforms others not only at the usual monthly frequency, but also over longer horizons, affirming the conclusion in subsection 4.1. Furthermore, the predictability is gradually reversed over longer horizons, which is basically consistent with Benartzi (2001).

5. Asset allocation

Following Huang et al. (2015), we further use portfolio analysis to test whether the predictability of *ISI* can be applied to actual asset allocation and yield some excess returns for portfolio investors. According to Kandel and Stambaugh (1996), Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), we compute the Certainty Equivalent Return (CER) gain and Sharp Ratio for a mean-variance investor who allocates between indicator equities and risk-free bills using a predictive regression forecast model. Specifically, at the end of month *t*, the investor optimally allocates w_{t+1} of the portfolio to equities and $1-w_{t+1}$ of the portfolio to risk-free bills during the subsequent month as follows:

$$w_{t+1} = \left(\frac{1}{\gamma}\right)\left(\frac{\widehat{r}_{t+1}}{\widehat{\sigma}_{t+1}}\right), \tag{8}$$

where γ is the investor's risk aversion coefficient, and we consider portfolio rules based on risk aversion coefficient of 3, $\widehat{r}_{t+1}$ is a forecast of excess stock returns and $\widehat{\sigma}^2 t+1$ is a forecast of its variance. We assume that the investor uses a 3-year moving window of past monthly returns to estimate the excess stock market returns and the variance of the next month.

Then, we calculate the certainty equivalent return (*CER*) for the investor who allocates the asset using equation (8) just like other literature:

$$CER_P = \overline{\mu}_P - \frac{1}{2}\gamma\widehat{\sigma}_P^2, \tag{9}$$

where $\overline{\mu}_p$ and σ_p^2 are the mean and variance of the asset portfolio return over the forecast period, respectively. We also compute the *CER* for the investor when he uses the historical mean benchmark to forecast the returns by equation (7). The *CER* gains can be recorded as the difference between the *CER* for the investor when he uses the predictive regression forecast generated by equation (3) to guide asset allocation and the *CER* when he uses the historical mean benchmark forecast generated by equation (7). We multiply this difference by 12 so that it can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the predictive regression forecast instead of the historical average forecast. In this method, we measure the economic value of return predictability.

To analyze the economic value of the return predictability of *ISI* over longer horizons, we extend our portfolio rebalancing frequency to 3-month and 6-month interval. For 3-month interval, at the end of the quarter, the investor uses a predictive regression and the asset allocation rule in equation (8) to determine the equity weight for the next three months; at the end of the next quarter, the investor updates the predictive regression and determines a new weight. For comparability, we calculate the *CER* gains here to the annual portfolio management fee as above. The investor follows analogous procedures in 6-month interval.

Table 9 shows the *CER* gains accruing to the predictive regression forecasts based on 12 indicators over June 2010 to June 2018 forecast evaluation period. At the monthly frequency, *ISI* results clearly stand out in terms of the economic value, providing a *CER* gain of 433 basis points during the sample period, which is the largest among all of the indicators, consistent with the significant results of *ISI* in Table 4. More specifically, an investor with a risk aversion of 3 would be willing to pay an annual portfolio management fee up to 4.33% to have access to the predictive regression forecast based on *ISI* instead of using the historical average forecast. Among the alternatives, only *SHIB*, *ER*, *NCICSI*, *VOL* and *CF* generate positive corresponding *CER* gains (23, 12, 171, 93 and 88 basis points during the period, respectively), but the corresponding gains are all less than half of *ISI*. In addition, *ISI* continues to generate considerable *CER* gains of 423 and 446 basis points at 3-month and 6-month interval, respectively, all of which are higher than those of the alternatives. The *CER* gains of *ISI* also extends beyond those of buy and hold strategy in the last row of Table 9.

The third column of Table 9 reports the annualized Sharpe ratio, which is the mean portfolio return in excess of the risk-free rate divided by the standard deviation. At various horizons, the other 11 comparative predictors rarely outperform the buy and hold strategy as measured by the Sharpe ratio. However, the Sharpe ratio of *ISI* is larger than the corresponding Sharp ratio of the buy and hold strategy, and as expected, the Sharpe ratio for the other 11 alternatives again well below that of *ISI*.

Table 9
CER gains, 2010:01–2018:01. The table reports the annualized certainty equivalent return gains and Sharpe ratios for a mean-variance investor with a relative risk coefficient of 3, who allocates between equities and risk-free bills using a predictive regression forecast based on the predictor variable in the first column over varies horizons. The equity weight is constrained to lie between −0.5 and 1.5, and the sample period is over June 2010 to June 2018.

predictor	One-month interval		Three-month interval		Six-month interval	
	CER gains	Sharpe Ratios	CER gains	Sharpe Ratios	CER gains	Sharpe Ratios
RVOL	−1.34	0.16	−1.24	0.18	−1.23	0.18
BM	−0.19	0.33	−0.22	0.32	−0.24	0.29
NTIS	−2.81	0.13	−2.11	0.16	−2.02	0.17
SHIB	0.23	0.32	0.25	0.34	0.45	0.38
ER	0.12	0.43	0.12	0.43	0.23	0.47
R	−0.33	0.26	−0.12	0.27	0.19	0.33
GB	−1.12	0.21	−1.23	0.18	−1.21	0.21
INFL	−0.19	0.32	−0.10	0.33	1.34	0.56
NCICSI	1.71	0.44	1.33	0.32	1.56	0.43
VOL	0.93	0.45	0.92	0.41	0.45	0.21
CF	0.88	0.36	0.89	0.37	0.67	0.29
ISI	4.33	0.66	4.23	0.59	4.46	0.77
Buy and hold	1.81	0.45	2.51	0.43	2.22	0.46

Overall, we show that the *ISI* can be applied to a real portfolio and can generate more economic value for strategic investors than the others. Further deepen the results in subsection 4.2, the information contained in *ISI* appears considerably more economical valuable than that contained in other popular predictors from the pioneering literature. These results are generally consistent with Huang et al. (2015), although we use different measures for investor sentiment.

6. Forecasting industry-sorted portfolios

From the above analysis, we know that *ISI* is a statistically and economically significant predictor of subsequent returns. However, investor sentiment may have totally different effects on stocks in different industries. Specifically, Stambaugh et al. (2012) suggest that stocks that are speculative, are difficult to value, hard to arbitrage and are likely to be more sensitive to investor sentiment. And Shen and Yu (2013) propose that industries with high macroeconomic risk are more subjective to the influence of market wide sentiment. Thus, in this subsection, we verify the above assumptions and investigate how well *ISI* can forecast in specific industries cross-sectionally. This not only gives us a deeper understanding on the predictive power of *ISI* but also helps to enhance the understanding of the economic nature of different industries.

Consider the following regression:

$$r^j_{t+1} = a + b_j ISI_t + \sum_{i=1}^{n} MR_{t-i} + \varepsilon_j, \tag{10}$$

where r^j_{t+1} is the monthly value-weighted excess stock returns for eight major industry portfolios, manufacturing, energy, technology, telecom, retail, health, environment and others, which is calculated according to the CSRC industry classification standard. We want to compare the coefficient *b* and R^2 of different industries to examine their sensitivities of *ISI*. To make more reliable inferences, we use a heteroscedasticity- and autocorrelation-robust t-statistic and compute a wild bootstrapped p-value to test H0: $b_j = 0$ against H1: $b_j > 0$ in equation (10).

Table 10 reports the estimation results for the predictive regressions of *ISI* in eight industries over the period June 2000 to June 2018. There is a fairly large dispersion of regression coefficient estimates in cross-section stocks sorted by industry in this paper. Specifically, technology, energy, telecom and manufacturing are the most predictable by *ISI* with the significant *b* values of 0.21, 0.35, 0.09 and 0.11, respectively, suggesting that they are significantly affected by *ISI*; whereas retail, health and environment present the lowest predictability with the relatively insignificant *b* values. This also indicates that when using the *ISI* for forecasting, an industry selection is necessary.

Table 10
Forecasting industry-sorted portfolios, 2000:06–2018:06. The table reports the b and R^2 statistic for different industry sorted portfolios:
$r^j_{t+1} = a + b_j ISI_t + \sum_{i=1}^{n} MR_{t-i} + \varepsilon_j$,
where r^j_{t+1} is the monthly value-weighted excess stock returns for eight major industry portfolios, manufacturing, energy, technology, telecom, retail, health, environment and others, which is calculated according to the CSRC industry classification standard. We report the slopes, Newey-West t-statistics, as well as the R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p-values. The sample period is over June 2000 to June 2018.

Industry	b	R^2 (%)
Manufacture	0.11** [2.01]	1.78
Energy	0.35*** [3.88]	1.72
Technology	0.21*** [-4.12]	2.21
Telecom	0.09** [2.11]	1.44
Shop	0.01 [1.09]	0.44
Health	0.13 [0.56]	0.65
Environment	0.08 [-0.23]	0.29
Others	0.19* [1.88]	1.68

We believe that the retail, health and environment industries are part of the hedging sectors with less non-systematic risks, so the market participants and the investment in these industries are non-speculative, focused on long-term investment. Therefore, they are less likely to be influenced by economic cycle, investor confidence and investor sentiment. In this case, we believe the recession and the low mood that followed will not affect the production or investment in these industries seriously, so will not the stock market (Stambaugh et al., 2012). However, the technology, energy, telecom and manufacture industries are cyclical industry with more non-systematic risks, so the market participants and the investment in these industries are radical and speculative, which are more likely to be influenced by economic cycle and investor sentiment. In this case, we believe that the economic or finance prosperity and the high mood that followed will affect the infrastructure projects and investment opportunities to a large extent, so will the stock market (Stambaugh et al., 2012; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Antoniou et al., 2013).

7. Cash flow and discount rate predictability

To glean insight into *ISI*'s predictive ability, it is necessary to investigate the driving force of it. Since existing pricing models suggest that stock prices are determined by both future expected cash flows and discount rates, we analyze whether *ISI* is able to forecast aggregate stock market returns by anticipating either cash flow or discount rate or both (Baker and Wurgler, 2006).

On the one hand, Fama and French (1989) and Cochrane (2008, 2011), among others, argue that aggregate stock market predictability comes from the time variation in discount rates. Under the discount rate channel, high *ISI* predicts high future returns at the monthly frequency because it predicts high discount rates. On the other hand, *ISI* may represent investors' biased belief about future cash flows (Baker and Wurgler, 2006). Under the cash flow channel, high *ISI* predicts high future returns at the monthly frequency because it predicts high cash flow.

To test whether the predictability of *ISI* is from either or both of the two channels, proxies of the channels are needed. We use the aggregate dividend price ratio as our discount rate proxy, since the fluctuation in aggregate dividend price ratio is primarily driven by discount rates (Cochrane, 2008, 2011). Then, we use the aggregate dividend growth as our primary cash flow proxy, which is widely used in similar studies (Binsbergen and Koijen, 2010; Campbell and Shiller, 1988; Cochrane, 2008, 2011; Fama and French, 1989; Garrett and Priestley, 2012; Kelly and Pruitt, 2013; Koijen and Van Nieuwerburgh, 2011; Lettau and Ludvigson, 2005; Menzly et al., 2004).

Thus, our study focuses on the following regressions,

$$\mathrm{Y}_{t+1} = a + bISI + cD/P_t + \varepsilon, \quad Y = D/P, DG \tag{11}$$

where D/P_{t+1} is the log of a twelve-month moving sum of dividend price ratio on the whole stock market of month t+1, DG_{t+1} is the log of a twelve-month moving sum of aggregate dividend growth rate on the whole market of month t +1. The forecasting power of *ISI* for DG_{t+1} and D/P_{t+1} in equation (11) represent the cash flow predictability channel and discount rate predictability channel, respectively.

Table 11 reports the results. *ISI* displays distinct effect between cash flow and discount rate. The slope of *ISI* for D/P_{t+1} is virtually equal to zero and statistically insignificant. However, the coefficient of *ISI* for DG_{t+1} is 3.77 at 10% significant level based on the one-sided wild bootstrapped p-value. The significant positive predictability of *ISI* for DG_{t+1} and no predictability for D/P_{t+1} indicate that *ISI* present significantly positive predictability for market returns by cash flow channel at the monthly frequency, which also means the investors may focus more on the dividend growth rate.

For comparison, Table 11 also reports the corresponding results of using other 11 indicators in place of *ISI*. All the regression coefficients of

Table 11
Forecasting cash flows and discount rates with investor sentiment, 2000:06–2018:06. This Table reports the estimation results for the regressions
$Y_{t+n} = a + bISI + cD/P_t + \varepsilon$, $(n = 1,3,6)$, $Y = D/P, DG$,
where D/P_{t+n} is the log of a twelve-month moving sum of dividend price ratio on the whole stock market of month t + n; DG_{t+n} is the log of a twelve-month moving sum of aggregate dividend growth rate on the whole market of month t + n. We report the regression slopes, as well as R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p-values. The sample period is over June 2000 to June 2018.

Predictor	DG_{t+1}		D/P_{t+1}		DG_{t+3}		D/P_{t+3}		DG_{t+6}		D/P_{t+6}	
	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)
RVOL	0.12	0.11	0.00	10.12	0.21	0.31	0.00	5.17	0.08	0.59	0.00	4.88
BM	2.34	3.23	0.31*	6.32	1.21	4.11	0.11*	7.90	1.56	4.18	0.13*	8.01
NTIS (−)	0.19*	1.23	0.00	5.90	0.88*	1.89	0.00	1.40	0.78*	1.01	0.00	1.35
SHIB (−)	4.12	6.21	0.33*	10.07	3.32	5.24	0.99*	10.17	2.45	6.01	0.97*	6.13
ER	1.34	5.99	0.09	18.01	1.44	7.99	0.01	1.01	1.56	6.04	0.01	1.22
R (−)	3.91*	2.17	0.02	6.90	2.31*	3.21	0.04	0.55	1.31	3.23	0.01	0.56
GB (−)	0.78	0.34	0.00	7.09	0.32	0.66	0.00	9.03	0.23	1.06	0.00	3.03
INFL (−)	0.12	1.56	0.00	10.78	0.82	2.53	0.00	7.91	1.22	3.53	0.00	9.19
NCICSI	1.11*	6.79	0.11	31.11	−1.02*	5.63	−0.88	18.14	−0.91	5.03	−0.12	8.23
VOL	3.10	3.60	0.00	30.17	−3.20	2.63	0.00	20.11	−3.56	2.88	0.00	12.12
CF	3.12	5.60	0.01	10.99	−4.16	1.60	0.21	4.93	−1.12	4.60	−2.21	9.00
ISI	3.77*	10.30	0.23	27.10	−2.13*	12.11	0.12	15.61	−1.22*	9.32	0.44	18.10

the other 11 indicators on D/P_{t+1} and DG_{t+1} are not as significant as *ISI*. It is generally consistent with the earlier evidence of relatively insignificant predictability and fewer effective economic information content of these indicators.

In order to further elucidate the economic driving source of the predictability of *ISI*, we extend our analysis to a longer horizon. For convenience, we rewrite the extended equation here as

$$Y_{t+n} = a + bISI + cD/P_t + \varepsilon, \quad (n = 3,6), \quad Y = D/P, DG \tag{13}$$

where D/P_{t+n} is the log of a twelve-month moving sum of dividend price ratio on the whole stock market of month t + n, DG_{t+n} is the log of a twelve-month moving sum of aggregate dividend growth rate on the whole market of month t + n.

If the predictability of *ISI* comes from the cash flow channel, it should have a strong negative predictability of *ISI* for DG_{t+3} (DG_{t+6}) and a weak predictability for D/P_{t+3} (D/P_{t+6}), given that *ISI* is a negative predictor for stock returns over longer horizons in subsection 4.4. And as expected, the significant negative predictability of *ISI* for DG_{t+n} and no predictability for D/P_{t+n} (n = 3,6) in Table 11 further confirm our conclusion.

In summary, the return predictability of *ISI* for aggregate stock market is coming from the cash flow channel, different from the popular time varying discount rate interpretation of market return predictability in other literature.[17] Our findings hence suggest that high sentiment causes the high expectations of stock returns because of investors' optimistic belief about future aggregate cash flows at the monthly frequency. While, when comes to 3- and 6-month interval, the high sentiment will cause a gradually decreasing expectations of stock returns for the overly optimistic belief about cash flow in the last month.

8. Conclusion

This study proposes a new investor-sentiment indictor (i.e., *ISI*) using AI independent deep learning process. We find that *ISI* outperforms other well-recognized indicators in predicting stock market returns at month frequency or over longer interval, both in and out of sample. Based on the this association between *ISI* and future stock return, a mean-variance investor can earn higher certainty equivalent return gain and Sharp Ratio, suggesting an economic significance of *ISI*. Furthermore, we show a positive association between *ISI* and dividend growth rate, which indicates that investors' expectations about future cash flows may contribute to the return predictability of *ISI*.

This paper extends literature on investor sentiment by constructing a new investor-sentiment indicator that is aligned with the purpose of predicting subsequent returns. In addition, we complement literature on behavioral finance by showing that AI independent deep learning process can be used to better capture investor sentiment. Moreover, according to our findings that *ISI* can better predict subsequent stock returns, our study also has important practical implications for investors to earn higher return following trading strategy based on *ISI*.

[17] Campbell and Ammer (1993), Chen and Zhao (2009), and Campbell et al. (2010) argue that since the nominal cash flows of Government bonds are fixed, any Government bond return predictability should be driven by time-varying discount rates alone. Thus, Government bond provides a clean discount rate proxy without any modeling assumption and variable choice.

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