National Accounting Review

NAR, 3(1): 115–136.
DOI: 10.3934/NAR.2021006
Received: 08 February 2021
Accepted: 10 March 2021
Published: 17 March 2021

http://www.aimspress.com/journal/NAR

Research article

Does investor sentiment affect stock pricing? Evidence from seasoned equity offerings in China

Changqing Luo*, Zijing Li and Lan Liu

Finance school, Hunan University of Technology and Business, Changsha, Hunan Province, China

* **Correspondence:** Email: Changqingluo@hnu.edu.cn; Tel: +8613787006581.

Abstract: Seasoned equity offerings attract a great deal of attention from investors in China's stock market, and they provide natural experimental environment for examining relationship between investor sentiment and asset pricing. We measure the investor sentiment on the individual stock level and examine its impact on stock pricing by using seasoned equity offerings (SEO) samples in the China's stock market from 2006 to 2019. The study shows that investor sentiment gradually rises during the Pre-SEO window and stays at a relatively high level after the new equity issuance. Meanwhile, investor sentiment is a significant pricing factor during the SEO window. However, the role of investor sentiment is different during different stages of SEO events, with a negative and positive impact on the Pre-SEO window and Post-SEO window respectively. Overall, this study identifies the pricing mechanism of investor sentiment in Chinese SEO market and provides some policy implications for portfolio management and market regulation.

Keywords: investor sentiment; asset pricing; seasoned equity offerings; event study

JEL Codes: G1, G10, G12

1. Introduction

Since the introduction of the private placement system in 2006, the seasoned equity offerings have become an important financing tool for listed companies in China's stock markets. According to Wind financial database, in 2019, the total amount of SEO financing exceeds 85 billion U.S dollars, which accounted for 44.2% of the equity financing in China's stock markets. SEO has played a significant role in the Chinese financial market. However, the persistent high discount of SEO pricing leads the investors to doubt the efficiency of the China's stock markets. Yang et al. (2019) report an average SEO discount of 13.01% from 2007 to 2016 in China, and the high SEO discount relates to information asymmetry (Hertzel and Smith, 1993; Chan and Chan, 2014; Yang et al., 2019), transaction cost measures of illiquidity (He et al., 2014) and price manipulation occurring prior to an SEO (Gerard and Nanda, 1993). Moreover, China's stock market is a typical emerging market in which the individual investors are major participants, and the market fluctuation is highly prone to be driven by investor sentiment, especially reflected in the suspension of the circuit breaker mechanism in China. It was officially implemented on January 1, 2016, but it was triggered four times only 4 trading days later. And the market value of China's stock market declined by 12.85%, evaporating 6.8 trillion yuan in just 4 trading days. Although the proportion of retail investors transactions in China's stock market decreased recently, it remained at 55% in 2019.[1] The high proportion of retail investors is an important incentive for the high volatility of the A-share market. By the end of 2019, the average annual turnover rate of A-share market was 330%, which was four times as high as the turnover rate of the American stock market. Besides, from 2009 to 2019, the 20-day historical volatility of the Shanghai and Shenzhen 300 Index remained at 28%, while the volatility of the S&P 500 was only 8.6%. Compared with the mature financial market, China's stock market is still an emerging market, and market fluctuation is significantly influenced by irrational sentiment. This characteristic of China's stock market provides a quasi-natural environment for investigating investor sentiment and asset pricing.

Theoretically, investor sentiment has an impact on stock pricing at least by four aspects. Firstly, optimism or pessimism will affect the subjective value function that is concave over gains and convex over losses， which will affect people evaluate risk (Li and Yang, 2013; Wang et al., 2020). Secondly, sentiment also affects the distribution function through subjective probability, finally affects the probability weight function, through the probability weighting function (Ebert and Strack, 2015; Barberis et al., 2016). Thirdly, according to the reference point effect, investor sentiment can affect relative asset value in the mind of investors (Wang et al., 2015; Werner and Zank, 2019). Lastly, sentiment can change the information processing efficiency, creativity, and other ability of the human brain. The response to information will affect the expected return on assets (Huang et al., 2019; Maqsood et al., 2020).

Empirically, the relationships between investor sentiment and the asset price are not quite consistent. Adam (2015) proves that investor sentiment plays a critical role in asset pricing. Others insist that investor sentiment affects the stock prices, but it is merely a mispricing factor rather than a pricing factor, such as Luo and Ouyang (2014). Moreover, the existing empirical studies mainly focus on the market level sentiment, and the individual stock sentiment and its impact on stock pricing are rarely investigated. Therefore, the information contained in individual firms may be neglected. Based on the previous studies, we attempt to provide micro-level evidence on the relationship between investor sentiment and stock pricing by using the investor sentiment of individual stock in China's stock market.

To study the impact of investor sentiment on stock return, we conduct an empirical study by using the seasoned equity offerings (SEO) data in China's stock market. SEO events in China's stock market provide an ideal experiment environment for our study. China's stock market is less efficient compared with the US stock market and other mature markets. It is featured as a high turnover rate, high volatility, and a high portion of individual investors who are sensitive to information and volatility (Ni et al.,

[1] Data comes from the Shanghai Stock Exchange (http://www.sse.com.cn/) and Shenzhen Stock Exchanges (http://www.szse.cn/).

2015). Meanwhile, SEO events are also important for listed companies and investors. SEO events are generally paid a lot of attention, and this hot event can easily drive investor sentiment. Additionally, SEO underpricing, abnormal return around SEO implementation day, long-term low return and other price anomalies are puzzling for practitioners and academicians (Chen et al., 2019). The traditional financial theory has limited ability to explain the abnormal price movement. Some researchers argue that the pricing anomalies could be caused by investor sentiment. Thus, using SEO companies on individual stock levels could be helpful for us to study the impact of the sentiment during particular hot event periods.

In this paper, we examine the influence of investor sentiment on stock prices during the SEO window in China's stock market. The main finding is as follows. Firstly, the investor sentiment toward SEO companies gradually increases during the Pre-SEO window, then after the implementation of the placement, there is a leaping growth of investor sentiment which keeps at a relatively high level during the Post-SEO period. Secondly, the empirical results also show that investor sentiment is a significant factor for asset pricing during the SEO period, and its overall influence on asset prices is lower than that of market factor and size factor, but higher than the value factor. Thirdly, the investor sentiment negatively affects asset pricing before the implementation of SEO, and this influence becomes positive during the Post-SEO window and dominates the whole SEO window.

The contribution of this paper mainly includes threefold. Firstly, instead of using the market-level sentiment, we measure the investor sentiment based on the aspect of individual stocks. By doing so, we can investigate the relationship between individual sentiment and stock return in a more precise way. Additionally, we examine the impact of investor sentiment on SEO pricing in a specific period which includes the Pre-SEO and Post-SEO periods, and this quasi-natural experiment helps us to understand how investor sentiment affects stock pricing. Moreover, we extend the Fama-French model by considering the role of investor sentiment. Based on the constructed model, we provide new evidence that investor sentiment significantly influences the stock return by using seasoned equity offerings samples in China's stock market.

The rest of the paper is organized as follows. Section 2 reviews the related literature and further clarifies the purpose and the basis of our work. Section 3 measures the investor sentiment on the individual stock level and analyzes the characteristics of investor sentiment during the SEO window. Section 4 extends the Fama-French model to examine the impact of investor sentiment on stock pricing in the SEO window. The final section is the conclusion and implication.

2. Literature review

Under the hypothesis of efficient market theory, asset pricing is decided by the fundamentals or systematic risk factors, while more and more researchers find the traditional asset pricing theory is hard to explain the stock market anomalies, such as small firm effect, P/E ratio effect, weekend effect, and so on (Lakonishok et al., 1994; Kothari and Shanken, 1997). Thus, some scholars develop behavioral finance theory to investigate the composition of asset prices (Kahneman and Tversky, 1979). Among different kinds of behavioral factors, some literature stresses that stock return could be affected by the investor sentiment in particular market situations, such as infectious diseases (Donadelli et al., 2017), soccer games (Kaplanski and Levy, 2010a; 2014) and aviation disasters (Kaplanski and Levy, 2010). Investor sentiment can be defined as the optimism/pessimism of an investor about the future stock market activity (Baker and Wurgler, 2006) or as the way investors form beliefs (Barberis et al., 1998). Investor sentiment has many expansion possibilities given its relation to other research areas such as physics, computer science, or mathematics (López-Cabarcos et al., 2020). Meanwhile, significant progress has been made in sentiment tracking techniques that extract indicators of mood directly from social media content such as microblogs content, and in particular large-scale Twitter feeds, which contributes to stock market prediction (Bollen et al., 2011; Sprenger et al., 2014).

As for the relationship between investor sentiment and stock prices, some scholars argue that investor sentiment is a mispricing factor. Antoniou et al. (2013) note that a positive sentiment may cause the investor to make an optimistic judgment toward the expectation of asset prices. Thus, the asset prices could be affected by investor sentiment. Some alternative work points out that investor sentiment is one of the stock pricing factors rather than a mispricing factor, Frugier (2016) confirms that investor sentiment can be profitably used by practitioners. Zhou and Yang (2019) find the deviations of asset prices from fundamentals persist over time by the roles of stochastic investor sentiment and crowdedness. From the above literature, we can find that investor sentiment could affect the stock prices, while investor sentiment is a pricing factor or just a mispricing factor that has not been fully investigated. Inspired by the existing literature, we use China's stock market data to provide new evidence for the relationship between investor sentiment and asset pricing.

When investigating the relationship between investor sentiment and stock prices, scholars mainly employ two categories of methods. The first category includes linear and nonlinear regression, vector Auto-regression, Granger causality test, ARIMA model, GARCH model, and other econometric methods to directly investigate the relationship between investor sentiment and stock return (Zhu and Niu, 2016; Piñeiro-Chousa et al., 2018; Wang, 2020). The second category includes the CAPM and Fama-French models with investor sentiment. Antoniou et al. (2015) use the CAPM model as the benchmark model to examine the role of investor sentiment on asset pricing. Wu et al. (2016) and Yang and Zhou (2016) extend the Fama-French model by introducing the sentiment factors to examine the relationship between investor sentiment and stock return. Chen et al. (2019) investigate the applicability of the Fama-French five-factor model in China's stock market. For a particular period, the second type, especially the Fama-French model, is more convenient to explain how the abnormal return is formed after controlling the size, value effect, and other existing impacts. Thus, in line with most of the existing literature, we employ the Fama-French model as the benchmark model in our study to examine how investor sentiment affects stock prices.

Measuring investor sentiment is fundamental and important before investigating the impact of sentiment on stock prices. Most of the existing literature gathers proxies for investor sentiment on a market level (Han and Li, 2017; Hong and Li, 2020; Griffith et al., 2020). Although these methods can detect the influence of investor sentiment on asset price, it is not appropriate to apply them to examine its impact on individual stock levels. Since the market-level sentiment does not contain the investors' expectation towards individual stock, it could be more appropriate and precise to adopt the later method and measure the investor sentiment on the individual stock level.

Regarding the relationship between investor sentiment and stock prices, some scholars hold that investor sentiment has a positive effect on stock returns (McGurk et al., 2020; Li and Ran, 2020), but due to different research perspectives, many scholars empirically conclude that investor mood has an inverse effect on stock returns (Fisher and Statman, 2006; Bathia and Bredin, 2013; Baker et al., 2012). Furthermore, some scholars believe that the relationship between them is not stable. Baker et al. (2003) conclude that investor sentiment and stock market returns are conditional. Yang and Yan (2011) believe that investor sentiment has a critical point when it exerts influence on stock market return, and the effect will change at this point. Kim et al. (2015) studied that the relationship between investor sentiment and expected stock market returns is time-varying. Considering the different phases of seasoned equity offering, we form the hypotheses as follows based on the above analysis.

H_1: Investor sentiment is a pricing factor that significantly affects stock prices on the whole.

H_2: The relationship between investor sentiment and stock market returns are time-varying regarding the different phase of seasoned equity offering.

3. Investor sentiment evaluation on individual stock level

Previous works mostly apply surveys or indirect measures to evaluate the market-wide investor sentiment. Baker and Wurgler (2006) and Hung (2016) use consumer confidence indices, closed-end fund discounts, the equity share in new issues, and other market anomalies to construct a proxy of investor sentiment. Different from the above literature, we focus on the relationship between individual sentiment and asset pricing. To measure the investor sentiment, we incorporate the indicators provided by Yang and Zhou (2016), which include PE ratio, trading volume, relative strength index, turnover rate, bull and bear index, ADTM, and momentum index of each stock as follows.

(1) PE ratio (PE). PE ratio is the relative value of market price and earnings per share (EPS). The negative PE is an extreme case, which represents that the company has a negative economic profit. Generally, the higher the PE ratio of a stock, the higher expectations of investors for the stock, and the more optimistic investor sentiment.

(2) Trading volume (VOL). Trading volume is a signal of investor sentiment, Joseph et al. (2011) prove that investor sentiment is positively correlated with trading volume. Therefore, we use trading volume as a proxy variable of investor sentiment. The trading volume can reflect the participation of investors, and the investor sentiment is more optimistic with a higher value of trading volume.

(3) Relative strength index (RSI). RSI denotes the velocity of the stock price movement. For n days of RSI, the indicator of RSI is computed as:

$$RSI_t\text{=}100\text{-}[100/(1+\frac{MA_t^{(n)}(dc_t)}{MA_t^{(n)}(uc_t)})] \tag{1}$$

$MA_t^{(n)}$ defines the moving average of stock prices in n trading days. dc_t and uc_t are measured as:

$$uc_t\text{=}\begin{cases}\Delta P_t = P_t - P_{t-1} & if \;\; \Delta P_t > 0 \\ 0 & otherwise\end{cases} \quad \text{and} \quad dc_t\text{=}\begin{cases}-\Delta P_t = P_t - P_{t-1} & if \;\; \Delta P_t < 0 \\ 0 & otherwise\end{cases} \tag{2}$$

where $P_{i,t}$ is the closing price of stock i at day t. When RSI goes above 70, the stock is possibly overbought, and the investor sentiment is generally high. When this indicator falls below 30, the stock is oversold, and the investor is usually pessimistic.

(4) Adjusted turnover rate (ATR). Yang and Zhou (2016) point out that the ATR could be high both in the optimistic and pessimistic market. In our paper, we follow Yang and Zhou (2016)'s indicator:

$$ATR = \frac{R_{i,t}}{|R_{i,t}|} \times \frac{VOL_{i,t}}{SHARE_{i,t}} \tag{3}$$

where $R_{i,t}$ is the return of stock i at day t, $VOL_{i,t}$ is the trading volume and shares outstanding of stock i at day t. If ATR is larger than zero, which indicates that the stock market is bullish and the investor sentiment is optimistic. Otherwise, it is pessimistic. In summary, the investor sentiment is more optimistic with a higher value of adjusted turnover rate.

(5) Bull and Bear Index (BBI). BBI is the average price of moving average price. The higher the BBI indicator, the more optimistic the market is. The indicator BBI is as follow:

$$BBI = [(\sum_{t=-2}^{0} P_{i,t})/3 + (\sum_{t=-5}^{0} P_{i,t})/6 + (\sum_{t=-11}^{0} P_{i,t})/12 + (\sum_{t=-23}^{0} P_{i,t})/24]/4 \tag{4}$$

The bull and bear index can be used to capture investors' opinions on stock price movements by comparing the stock prices and the bull and bear index (Zhou and Yang, 2019). If the stock prices fall below the BBI index, it means the strength of sellers is stronger. Otherwise, the buyer power is stronger. In short, the investor sentiment is more optimistic with a higher value of the bull and bear index.

(6) ADTM. ADTM is an indicator to describe the popularity of a stock. The calculation procedure of ADTM is as follow: ①if the open price at day t ($P_{open,t}$) is less than or equal to open price at day t–1($P_{open,t-1}$), define: DTM = 0, if $P_{open,t} > P_{open,t-1}$, DTM = max($P_{high,t}$–$P_{open,t}$, $P_{open,t}$–$P_{open,t-1}$), here, $P_{high,t}$ is the highest price in day t; ②if $P_{open,t} \geq P_{open,t-1}$, define: DBM = 0, if $P_{open,t} < P_{open,t-1}$, DBM = max ($P_{open,t}$–$P_{low,t}$, $P_{open,t}$–$P_{open,t-1}$), here, $P_{low,t}$ is the lowest price in day t; ③define STM and SBM is the sum of DTM and DBM in N days respectively; ④if STM > SBM, ADTM = (STM–SBM)/STM; if STM < SBM, ADTM = (SBM–STM)/SBM; if STM=SBM, ADTM = 0. ADTM is measured on a scale from −1 to 1. When ADTM is between 0.5 and 1, most of the investors have an optimistic sentiment on the stock. When ADTM is less than −0.5, investors generally have a pessimistic sentiment on the stock. Overall, the investor sentiment is more optimistic with a higher value of ADTM.

(7) Momentum index (MTM). Momentum Index is a short-term technical analysis tool that specializes in studying stock price fluctuations.

$$MTM = P_t - P_{t-6} \tag{5}$$

Kim and Sub (2018) believe that investor sentiment contains the momentum factor, and that sentiment is the cause of the momentum effect (Hao et al., 2018). When MTM is above 0, the stock prices is in an uptrend, otherwise in a downtrend. Generally, the investor sentiment is more optimistic with a higher value of MTM.

(8) Prospect value (PV). Besides these indicators, we construct a new variable for measuring the investor sentiment at the individual stock level according to the prospect theory proposed by Kahneman and Tversky (1979). The prospect theory argues that the value function reflects the investors' sensitivity to changes or relative value of wealth, rather than the absolute value of wealth. Thus, the prospect value of a particular stock implicitly represents the investor sentiment toward the stock price fluctuation. The prospect value consists of the value function and weighting function. The value function and weighting function are expressed as follow by referring to Barberis et al. (2016):

$$V(x) = \begin{cases} x^a, x \geq 0 \\ -\lambda(-x)^a, x < 0 \end{cases} \tag{6}$$

$$W^{+}(P)=\frac{P^{\gamma}}{(P^{\gamma}+(1\text{-}P)^{\gamma})^{1/\gamma}}, \text{ and } W^{-}(P)=\frac{P^{\delta}}{(P^{\delta}+(1\text{-}P)^{\delta})^{1/\delta}} \tag{7}$$

where V(x) is the value function with the x representing the relative wealth of the investors. Parameters α, γ, $\delta \in (0, 1)$, $\lambda > 1$, the greater the λ value, the higher the sensitivity of the representative investor to loss, γ and δ represent the sensitivity of investors to probability. $W^{+}()$ and $W^{-}()$ represents the probability weight function of the positive and negative returns respectively. Refering to the research of Barberis et al. (2016), we select the stock prices data of the 60 trading days before the issuance to calculate the logarithmic return rate of a specific stock. Then we arrange the 60 returns in ascending order, where the number of negative returns is m, and the number of positive returns is $n = 60-m$. Then, the return sequence can be obtained:

$$(r_{-m},\frac{1}{60};r_{-m+1},\frac{1}{60};...;r_{-1},\frac{1}{60};...;r_{n-1},\frac{1}{60};r_{n},\frac{1}{60}) \tag{8}$$

where r_{-m} and r_n is the minimum and maximum rate of return, respectively, and the same weight is assigned to the rate of return of each trading day, which is 1/60. The prospect value (PV) can be obtained as Equation (9):

$$PV=\sum_{j=-m}^{-1} v(r_j)\left[w^{-}(\frac{j+m+1}{60})-w^{-}(\frac{j+m}{60})\right]+\sum_{j=1}^{n} v(r_j)\left[w^{+}(\frac{n-j+1}{60})-w^{+}(\frac{n-j}{60})\right] \tag{9}$$

where PV represents the prospect value of a stock. This value comprehensively reflects the investor sentiment toward the fundamental and market information about the specific stocks. On the whole, the investor sentiment is more optimistic with a higher value of PV.

To obtain a comprehensive investor sentiment indicator, we use principal component analysis to aggregate the above sentiment information.

3.1. Summary of seasoned equity offerings in China's *stock market*

In China's stock market, regulations on issuing securities of listed companies were revised on May 6, 2006, and the requirement of profitability was lowered under this version of the regulation. Since the implementation of this law, seasoned equity offerings have become a major way of equity financing. Despite the decrease of both issuing numbers and amounts since 2017 (as shown in Figure 1), SEO is still one of the most vital sources of equity financing for listed companies. According to the statistics of RESSET financial database, in 2019, the total number of listed companies conducted SEO has reached 215, and these companies raised 603.8 billion Chinese Yuan. While in the same period, the number of IPOs is 201, and the total amount of raised capital is 244.1 billion Chinese Yuan in Shanghai Stock Exchanges and Shenzhen Stock Exchanges.

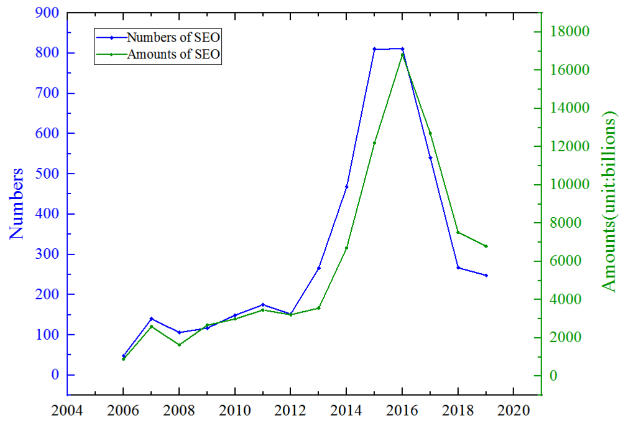

Figure 1. Summary of seasoned equity offerings in China's stock market (2006–2019). Note: the total number of listed companies conducted SEO and the amounts of SEO come from the statistics of RESSET financial research database[2].

In Figure 1, we can find the number of SEO dramatically increases from 2013 to 2015. This is because in 2015 the supervisory authorities issued multiple documents to streamline administration and delegate powers, thus simplify the approval process for private placement. However, since the deleveraging in the Chinese financial market in 2017, SEO is also affected by this stringent condition, thus, the number and amounts both decreases as shown in Figure 1.

Then, we limit our sample to non-financial listed companies. We also eliminate the specially treated companies (ST) to alleviate the impact of abnormal events. As for multiple seasoned equity offerings of the same company, we take the sample of the first SEO as the research object to prevent multiple SEO from affecting each other in a short period. Besides, we eliminate SEO events with missing transaction data or financial data of listed companies. Therefore the final valid sample is composed of 1774 listed companies in Shanghai stock exchanges and Shenzhen stock exchanges. The sample period is from 2006 to 2019. The industrial distribution of the samples is displayed in Table 1.

In Table 1, the materials industry raises the most amounts of capital among all industries, and the Capital Goods, Real Estate, Diversified Financials, Technology Hardware & Equipment and Banks consequently follows behind. The above industries are capital intensive and need more funds to support development. By judging the number of SEO and amounts, we can also find the Materials industry, Real Estate industry, and Diversified Financials industry are the cornerstone of China's stock market.

[2]RESSET Financial Research Database is mainly for colleges and universities, financial research institutions, research departments of financial enterprises in China, providing support for empirical research and model test.

Table 1. Industry distribution of seasoned equity offerings.

Industry	No.	Amounts (billion CNY)	Industry	No.	Amounts (billion CNY)
Automobiles& Components	156	355.268	Materials	690	1210.369
Banks	24	483.660	Media	159	271.275
Capital Goods	898	1139.744	Pharmaceuticals, Biotechnology& Life Sciences	234	350.049
Commercial &Professional Services	109	111.839	Real Estate	183	606.745
Consumer Durables& Apparel	161	183.457	Retailing	97	253.582
Consumer Services	66	90.076	Semiconductors& Semiconductor Equipment	105	149.677
Diversified Financials	86	597.794	Software & Services	348	424.466
Energy	84	234.726	Technology Hardware& Equipment	375	577.732
Food & Staples Retailing	23	48.391	Telecommunication Services	6	65.795
Food, Beverage & Tobacco	168	259.310	Transportation	120	448.756
Health Care Equipment& Services	84	108.958	Utilities	171	498.863
Household& Personal Products	9	4.294			

Note: The division of industries is based on the industry classification standards formulated by the China Securities Regulatory Commission (CSRC) in 2012, and the amounts of SEO come from the statistics of WIND financial database.

3.2. Event window of the seasoned equity offerings

To examine the relationship between investor sentiment and SEO pricing, we first use the data of the whole issuing window. Then, we set the event windows of seasoned equity offerings based on the existing literature and the issuance procedures in China's stock markets since there could exist different relationships regarding the different event windows. Clinton et al. (2014) report the appropriate length is 30 days. Huang et al. (2016) use multiple sample windows, and the longest window is from the initial announcement day to issue execution day. Based on the above works, we extend the sample window to lock-up expiration day of seasoned equity offerings. As shown in Figure 2, the whole event window consists of Pre-SEO and Post-SEO window, and the Pre-SEO window covers three sub-windows.

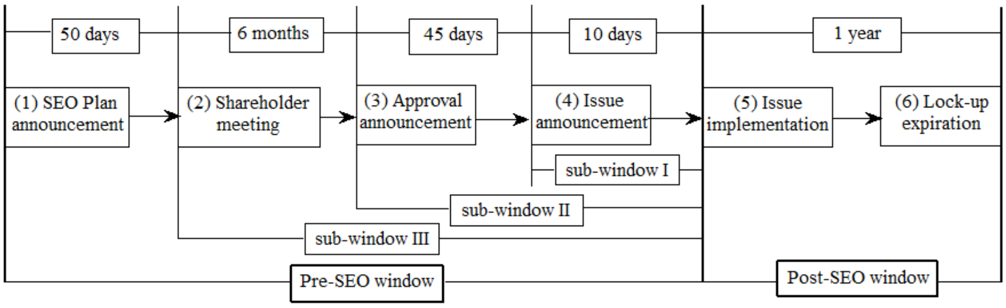

Figure 2. Seasoned equity offerings window in China's stock market. Note: Figure 2 illustrates the main procedures of a seasoned equity offering in China's stock market. After initial SEO plan announcement, the shareholder meeting vote on the insurance plan. Then, if the plan is approved, the listed company submits the issue application to CSRC. After the approval of the CSRC, the listed companies usually execute the issuance within about 55 days, and the newly issued shares are locked at least for 1 year.

There are some holidays and weekends during the SEO window, so the actual trading days are less than days shown in Figure 2. We eliminate the holidays and weekends, the trading days of Post-SEO window, Pre-SEO window, sub-window I, sub-window II, and sub-window III are respectively averaged at 251, 200, 9, 101, and 150 days. In our empirical study, we use data in each window to construct the asset pricing model and analyze the impact of investor sentiment on stock pricing.

3.3. Measurement of investor sentiment

In this section, we firstly display the descriptive statistics of the investor sentiment variables in Table 2. The original data is collected from the WIND database[3].

Table 2. Descriptive statistics of investor sentiment variables.

Variables	mean	median	min	max	variance	skewness	Kurtosis
PE	117.641	57.407	−25721.490	30811.490	2049.318	−5.701	1009.311
VOL	356.604	136.093	627.721	79653.414	270.648	9.220	116.636
RSI	57.608	56.104	14.306	98.853	10.025	−0.217	6.044
ATR	0.159	0.670	0.044	0.762	0.090	2.724	11.957
BBI	33.540	29.491	15.939	498.181	14.107	1.902	25.251
ADTM	0.353	0.605	−0.736	0.921	0.612	−0.329	6.554
MTM	0.045	0.223	−264.534	295.729	5.101	2.578	123.452
PV	−0.021	−0.018	−0.073	0.024	0.172	0.556	1.850

Note: VOL is measured at million Chinese Yuan. All variables are on a daily scale.

3Wind is the provider of financial data, information and services in mainland China. Wind has built up a financial database focusing on securities data, with a wide coverage of equities, funds, bonds, foreign exchanges, insurance, futures, derivatives, commodities, macro economy and financial news.

In Table 2, the mean and median value of PE is high and the median value of RSI and ADTM, which is respectively larger than 50 and 0.50, indicates that most of the companies are paid great attention during SEO window. The mean value of PV is negative, which suggests that the investors have a generally negative attitude toward the performance of SEO companies after equity financing. The investors are worried about the fact that some controlling majority shareholders can use the power to dilute the rights and interests of minority shareholders, and the companies may have a long-term undesired performance regarding the earning ability.

To avoid the impact of different measurement scales, we standardize the original variables of the investor sentiment. Then, in line with Baker and Wurgler (2006)[4] and Yang and Zhou (2016), we conduct the principal component analysis for each listed company in our sample. The results indicate that the KMO value equals 0.721, suggesting the original data is suitable for principal component analysis. We select the first component to measure investor sentiment on the individual stock level. As can be seen from Table 3, principal component analysis results show that the eigenvalue of the first principal component is 2.26, and the variance explanation rate is 58.651%, concluding that the first component can capture much of the common variation.

Table 3. Results of principal component analysis.

Variable	the first principal component	the second principal component	the third principal component
PE	0.186	0.063	−0.074
VOL	0.160	−0.088	0.124
RSI	0.120	0.151	−0.009
ATR	0.053	0.137	0.005
BBI	0.150	0.103	−0.054
ADTM	0.103	−0.147	0.135
MTM	0.075	0.020	0.123
PV	0.114	−0.065	0.004
eigenvalue	2.260	0.443	0.169
contribution rate	0.587	0.280	0.134
accumulated contribution rate	0.587	0.866	1.000

Note: Here, we mainly display the component score coefficient matrix and the variance explanation rate of factors.

$$\begin{aligned} INV_t = 0.1862PE_t + 0.1603VOL_t + 0.1204RSI_t + 0.0531ATR_t + 0.1503BBI_t \\ + 0.1027ADTM_t + 0.0746MTM_t + 0.1139PV_t \end{aligned} \tag{10}$$

where the investor sentiment of stock i at time t is $INV_{i,t}$, the aggregate investor sentiment at time t INV_t is the average of $INV_{i,t}$, and the measurement results are displayed in Figure 3.

4In line with Baker and Wurgler (2006), the first principal component explains 49% of the sample variance, concluding that one factor captures much of the common variation.

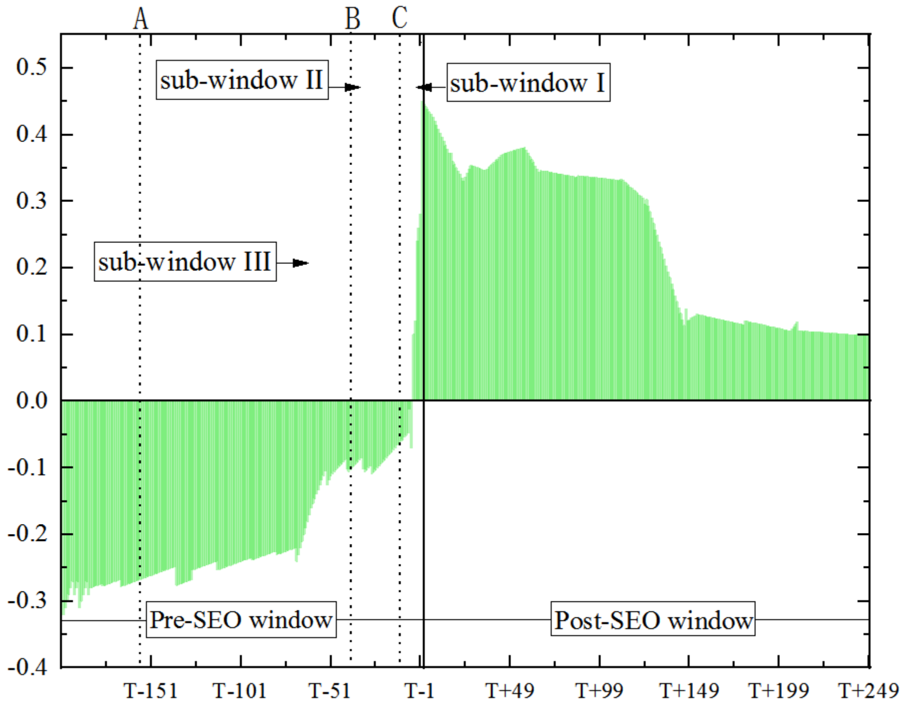

Figure 3. The investor sentiment during the seasoned equity offerings window. Note: in Figure 3, the x-axis denotes the time, and the y-axis is the investor sentiment. During the Pre-SEO window, the area CT, BC and AB are sub-window I, sub-window II, and sub-window III as the arrows point out.

In Figure 3, we can find several characteristics of the investor sentiment during the SEO window. Firstly, the investor sentiment is gradually increasing after the initial plan announcement day to implementation day. With the diffusion of SEO information in the market, investors, analysts, and other participants pay more and more attention to the companies; as a result, the sentiment on the stocks will increase. Secondly, the investor sentiment rises sharply on the SEO implementation day. On this day, the investor generally overreacts to the issuance of the new shares, and the sentiment jumps to the highest level. After the SEO plan is executed, all information about the seasoned equity offerings is released to the public, and optimistic investors gradually revise their sentiment on the issued shares based on the released information, thus, the average investor sentiment is decreasing until lock-up expiration day. Thirdly, the investor sentiment during the Post-SEO window is higher compared to the Pre-SEO window. This phenomenon also reveals that SEO events are paid intensive attention after its implementation. This result could reveal that the prospect value could be a forward-looking indicator for asset price since the negative PV presented in the former section suggests a relatively pessimistic expectation toward the SEO events.

4. Empirical study

4.1. Model specification

We apply the Fama-French model in our empirical study. The Fama-French model explains the abnormal return by adding firm size and book-to-market factors.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_{SEN} SENT_t + \varepsilon_t \quad (11)$$

where $R_{i,t}$ is the equity return of seasoned equity offerings company, $R_{f,t}$ is the risk-free rate which is measured by the one-year time deposit. $R_{m,t}$ is the market return of the Shanghai Stock Exchange; $SENT_t$ is the investor sentiment factor; SMB_t and HML_t represent the size factor and book-to-market ratio weighted by the market capitalization, respectively; ε_t is the random error term. In line with Fama and French (1993), we obtain the factors SMB_t and HML_t according to the following procedures: (1) We first divide the whole sample into small market capitalization group (S) and big market capitalization group (B); We then divide each group into three sub-groups based on the book-to-market ratios of each listed companies, the top and bottom 30% of the sample are high (H) and low (L) groups, and the rest are the middle group (M); (2) We divide each group into three sub-groups based on the investor sentiment ($INV_{t,i}$) of each listed companies, the top and bottom 30% of the sample are optimistic (O) and pessimistic (P) groups and the rest is the neutral group (N); (3) We calculate these factors as follow according to Fama and French (2015).

To further distinguish the roles of investor sentiment and momentum factors in asset pricing, we construct the Carhart four-factor model to measure the momentum effect and reversal effect of asset prices. To be consistent with the three-factor construction method mentioned above, we follow Novy-Marx (2012) and employ the 2 × 3 grouping method of Fama and French (2012) to construct the momentum factor. Since the daily average yield weighted by the market capitalization is negative within 8 weeks and gradually tends to 0, but after 9 weeks of lag, it reverses to be positive, which indicates that the stock prices exhibits a reversal effect within 8 weeks, and the momentum effect appears after the ninth week, so this paper chooses the 9-week lagging momentum factor weighted by the market capitalization. Specifically: (1) On the last working day of each month, sort stocks according to their size, we divide the whole sample into small market capitalization group (S) and big market capitalization group (B); (2) Sort the cumulative returns lagging 9 weeks in order of magnitude. The top and bottom 30% of the sample are the losing portfolio (L) and the winning portfolio (W) respectively, and the rest are the middle group (M); (3) The two sorts cross each other to form six combinations: SL, SM, SW, BL, BM, BW, and we can calculate the Momentum factor: MOM = (SW + BW-SL-BL) /2. The Carhart four-factor asset pricing model in this paper is set as:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_t \quad (12)$$

where $R_{i,t}$ is the equity return of seasoned equity offerings company, $R_{f,t}$ is the risk-free rate which is measured by the one-year time deposit. $R_{m,t}$ is the market return of the Shanghai Stock Exchange; SMB_t and HML_t represent the size factor and book-to-market ratio weighted by the market capitalization, respectively; MOM_t is the 9-month lagging momentum factor weighted by the market capitalization; ε_t is the random error term.

4.2. Model estimation based on the whole SEO window

In this section, we investigate whether investor sentiment affects stock return during the whole SEO window. We construct Fama-French models with the sentiment factor. Table 4 provides descriptive statistics of asset price and its pricing factors. The average daily return is 0.7808%, indicating that the investor can get profits by holding stocks of listed companies that issue the new shares. The average daily market return is 0.6005%, which is larger than 0, the results suggest that the market timing of seasoned equity offerings could exist in China's stock market. CEOs or big shareholders may choose an advantageous time to issue new shares for financing more capital.

Table 4. Descriptive statistics of pricing factors.

Variables	Min	Max	Mean	Median	Variance	Skewness	Kurtosis
$R_{i,t}$	−5.383	9.819	0.781	1.309	6.331	−7.036	24.621
$R_{\mathrm{f,t}}$	0.002	2.413	0.034	0.025	0.653	7.140	8.841
$R_{\mathrm{m,t}}$	−7.738	9.759	0.601	1.007	6.184	−12.035	15.236
MRT	−0.143	1.644	0.709	0.925	5.090	−15.040	−9.362
SMB	−0.483	1.384	0.883	0.809	8.883	30.035	51.552
HML	−0.821	0.855	0.340	0.256	12.933	22.056	−15.661
MOM	−0.428	0.624	−0.118	−0.044	16.704	−5.904	14.905
SENT	−0.330	0.830	0.644	0.823	10.046	−5.719	20.523

Note: Here, $R_{i,t}$ is the return of stock i at day t, $R_{f,t}$ is the risk-free rate of return at day t, *MRT* is the market return in excess of risk-free rate at day t, *SMB* is the difference between the value-weighted return of a portfolio of small stocks and the value-weighted return of a portfolio of large stocks at day t, *HML* is the difference between the value-weighted return of a portfolio of high B/M stocks and the value-weighted return of a portfolio of low B/M stocks at day t, *MOM* is the difference between the value-weighted return of winning portfolio and the value-weighted return of losing portfolio at day t. *SENT* is the difference between the value-weighted return of a portfolio of optimistic mood stocks and the value-weighted return of a portfolio of pessimistic mood stocks at day t. All variables are daily data. The unit of daily return is %.

The regression results of the three-factor model and the extended model with investor sentiment are displayed in Table 5.

Table 5. Regression results of asset pricing model.

	Model I	Model II	Model III
Intercept	0.0066*	0.0047*	0.0032*
	(1.995)	(1.772)	(1.654)
MRT	0.4808***	0.5105***	0.6291***
	(23.925)	(26.331)	(30.702)
SMB	0.1069**	0.1788**	0.3842***
	(2.490)	(2.570)	(−15.824)
HML	0.000	−0.0092*	−0.0217*
	(1.027)	(1.652)	(1.659)
MOM		−0.0194*	
		(−1.883)	
SENT			0.0284***
			(9.606)
Adjusted-R^2	0.562	0.610	0.733

Note: ***, **, and * indicate significance at 1%, 5%, and 10% significance levels, respectively. The t-statistics of the coefficient estimates are reported in parentheses. Model I is the Fama-French three-factor model, Model II is the Carhart four-factor model, and Model III is the extended model with investor sentiment based on Model I. Here, *MRT* is a market value-weighted market premium factor, *SMB* is a market value-weighted size premium factor, *HML* is a market value-weighted book-to-market value premium factor, and *MOM* is the 9-month lagging momentum factor weighted by the market capitalization.

It can be seen from the results in Table 6 that the explanatory power of the extended asset pricing model with investor sentiment has been significantly improved compared with Model I and Model II. The coefficient of the investor sentiment factor is 0.0284 with a t-statistic of 9.6061, which shows investor sentiment is an important factor affecting asset pricing during the private placement period. It is worth noting that compared with market factor (*MRT*) and size factor (*SMB*), the influence of investor sentiment (*SENT*) is relatively low. This indicates that in an emerging market such as the Chinese securities market, stock pricess during the private placement window are easily affected by the overall market conditions. Since the SMB factor is significant, the small companies have relatively high investment value. Besides the general explanation of the size effect in matured markets, the small listed firms usually are selected as shell target because the IPO is relatively constrained, this specialty also increases the value of small listed companies. Moreover, the momentum factor and sentiment factor affect prices in different directions. The momentum factor has a negative impact on the price. And its coefficient is −0.0194, which means that there is a reversal effect in the short-term and a momentum effect in the long-term. While the coefficient of the sentiment factor is 0.0284, signifying that the sentiment factor exerts a positive influence on the price.

4.3. Model estimation based on the whole SEO window

Due to different stages of the private placement window period, investor sentiment shows different evolutionary characteristics. Hence, this article takes this phenomenon into account and constructs an asset pricing model that introduces investor sentiment specifically for different window periods. The regression results are shown in Table 6.

Table 6. Regression results based on sub-SEO windows.

Sub-SEO windows	α	β_{SEN}	β_1	β_2	β_3	R^2
Pre-SEO window	0.014**	−0.032**	0.554***	0.409***	0.004	0.57
Post-SEO window	0.028***	0.066***	0.601***	0.367***	−0.062**	0.81
Sub window I	−0.077	0.034**	0.305**	−0.226	−0.009	0.53
Sub window II	−0.022***	−0.056**	0.437**	0.342***	0.026**	0.54
Sub window III	0.031***	−0.051**	0.422**	0.416***	−0.005	0.59

Note: β_1、β_2、β_3 and β_{SEN} represent the coefficient of market factor (*MRT*)、 size factor (*SMB*)、 value factor (*HML*) and sentiment factor (*SEN*T), respectively. The regressions take the form of Equation (11) ***, **, and * indicate significance at 1%, 5%, and 10% significance levels, respectively.

Judging from Table 6, the coefficients of investor sentiment are significant for all sub-windows, proving that investor sentiment is an important pricing factor, and this result is consistent with that of the whole sample. However, when comparing the results of different sub-windows, we can find the different roles of the investor sentiment. In the Pre-SEO window, investor sentiment has a significant negative impact on SEO excess returns. By contrast, investor sentiment has a significant positive impact on SEO excess returns in the Post-SEO window. In the Post-SEO window, the investor sentiment coefficient is 0.066, which is significant at the level of 1%, while in the Pre-SEO window, the investor sentiment coefficient is negative, which is significant at the 5% level. And on the whole, investor sentiment has a significant positive impact on SEO excess returns during the entire SEO window with a positive coefficient

(β_{SEN} = 0.0284), indicating that investor sentiment of Post-SEO window may play a more significant role in asset pricing during the whole issuing period of SEO.

The different roles played by investor sentiment during the Pre-SEO window and Post-SEO window could partly attribute to the special issuance system and pricing mechanism of private placement in the Chinese financial market. In the process of SEO, the issuing company issues new shares to no more than 10 investors, and the offering price refers to the stock prices in the secondary market. According to the guidance of *Measures for the Administration of Securities Issuance of Listed Companies,* the private placement price is not allowed to be less than 90% of its average price of 20 consecutive trading days prior to the pricing base date. Meanwhile, during the SEO period, major shareholders and institutional investors are both important participants. For our sample, there are 39.62% of the companies with the major shareholders who participate in the issuance as one of the 10 issuance objects, and 52.87% of the companies issue to institutional investors.

During the Pre-SEO window, there is a tendency that major shareholders and institutional investors have the motivation to depress the price of secondary stocks. The relatively low secondary market price is conducive to major shareholders to obtain more control and assets at a lower price. And it is helpful for institutional investors to reduce the costs and earn profits for portfolio management. Previous researches have provided empirical evidence of interest transfer in the process of SEO (Zhao et al., 2015; Shi et al., 2020). At this stage, although investor sentiment becomes gradually optimistic (as shown in Figure 3), the possible motivation of major shareholders and institutional investors may weaken the positive relationship between investor sentiment and asset price or even lead to a negative relationship. During the Post-SEO window, the interests of institutional investors, major shareholders, and other investors tend to be more consistent. This makes the relationship between sentiment factor and asset price return to a normal state, that is, optimism drives asset price to rise, and pessimism causes asset price to fall.

4.4. Regression in different market conditions

From a macro perspective, we selected two key events under the circumstance of systematic risk incidents of stock markets, namely, the global subprime mortgage crisis from October 2007 to November 2008, and the China stock market crash from June 2015 to February 2016 to verify whether the sentiment and asset prices maintain the overall positive relationship in crisis market situation.

Table 7. Regression results based on sub-SEO windows in crisis.

	Pre-SEO window		Post-SEO window		Whole crisis window	
	Crisis I	Crisis II	Crisis I	Crisis II	Crisis I	Crisis II
α	0.003	0.013*	−0.008	0.018*	0.005	0.016*
β_1	0.502**	0.835***	0.441**	0.730***	0.523**	0.849***
β_2	0.249**	0.238**	0.137*	0.220**	0.226**	0.239**
β_3	0.006	0.014*	−0.018*	−0.005	−0.008	0.006
β_{SEN}	0.012*	0.015*	0.027**	0.021**	0.016**	0.018**
Adjusted R^2	0.306	0.682	0.459	0.643	0.424	0.621

Note: β_1, β_2, β_3, and β_{SEN} represent the coefficient of market factor (*MRT*), size factor (*SMB*), value factor (*HML*), and sentiment factor (*SENT*), respectively. The crisis I denotes the period during the global subprime mortgage crisis, Crisis II denotes the period during China's stock market crash in 2015.

From Table 6 and Table 7, we conclude that investor sentiment negatively affects asset pricing before the implementation of SEO. But, this influence becomes positive during the Post-SEO window and dominates the whole SEO window. Judging from Table 7, the sentiment is still an important pricing factor and the positive relationship between sentiment and asset prices is still established in crisis. The small difference lies in that the sentiment and asset prices keep a positive relationship in Pre-SEO and Post-SEO periods.

To test whether the relationship between sentiment and stock prices is consistent under the idiosyncratic risk events from the micro perspective, we collect idiosyncratic risk events that occurred in China's stock market from 2006 to 2019 through the Sina Finance website and the Eastmoney Internet stock forum. We retain the listed companies that have private placements during this period, involving 764 listed companies. According to specific examples of micro risk incidents, we furtherly divide them into financial fraud type, corporate governance type and rumors type. Among them are 103 rumors type, 385 the financial fraud type, and 276 the corporate governance type.[5] We set the SEO implementation date as the event day, denoted as T = 0. The 10 days before and after the event day is taken as the event window, marked as [−10, 10], and 11 days to 110 days before the event date are selected as the estimated window of the event, recorded as [−11, −110]. First, we use the three-factor model to calculate the expected return ($E(R_{i,t})$), and the abnormal return ($AR_{i,t}$) is calculated by the difference between actual return and expected return during the event window. Next, the average abnormal return rate ($AAR_{i,t}$) is the average excess return rate on the t trading day of the private placement window period, and the average cumulative abnormal return (CAAR) is the cumulative average excess return rate of all samples during the window period. Mathematical expressions are displayed from the formula (13) to the formula (15).

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{13}$$

$$AAR_{i,t} = \frac{1}{N}\sum_{i=1}^{n} AR_{i,t} \tag{14}$$

$$CAAR(-t,t) = \sum_{-t}^{t} AAR_t \tag{15}$$

It can be concluded from Table 8 that when T = −4 and T = 7, the abnormal returns are not significant, indicating that idiosyncratic risk events have an impact interval of (−3, 6), with a total of 10 days. Besides, it can be seen from Table 8 that the relationship between sentiment and stock prices has undergone a process from negative correlation to positive correlation around SEO implementation day.

We further estimate the asset pricing models by considering the different types of idiosyncratic risk events. We use the Fama-French three-factor model introducing the sentiment factor to regress different types of micro risk incidents, and the regression results are shown in Table 9.

[5]Financial fraud type of incidents are mainly manifested as inventory fraud, inflated profits; corporate governance type of incidents are reflected as imperfect internal control of the company and transfer of interests, rumors type of incidents usually refer to rumors that are falsified afterwards or one-sided remarks triggering panic.

Table 8. The relationship between idiosyncratic risk incidents and stock price.

Event date	T_{AAR}	T_{CAAR}	Date	T_{AAR}	T_{CAAR}
T = −10	0.032	0.592	T = 1	−10.036***	−8.743***
T = −9	0.487	1.334	T = 2	−3.153***	−5.968***
T = −8	−1.650*	−1.071	T = 3	−2.402**	−2.078**
T = −7	−0.991	−0.041	T = 4	−2.579**	−1.784*
T = −6	−1.087	−0.533	T = 5	−1.977*	−1.901*
T = −5	0.373	0.680	T = 6	−1.795*	−1.684*
T = −4	−0.443	−0.305	T = 7	0.425	0.851
T = −3	2.060**	1.786*	T = 8	1.893*	0.910
T = −2	2.631***	3.023***	T = 9	−0.380	0.227
T = −1	3.804***	5.448***	T = 10	−0.063	−0.141
T = 0	−8.957***	−12.039***			

Note: AAR denotes the average abnormal return rate, CAAR denotes the average cumulative abnormal return during the window period. T_{AAR} and T_{CAAR} represent the t-value of AAR and CAAR. ***, **, and * indicate significance at 1%, 5%, and 10% significance levels, respectively.

Table 9. Regression results by considering idiosyncratic risk events.

Sub-SEO windows	Pre-SEO window			Post-SEO window		
	Type I	Type II	Type III	Type I	Type II	Type III
α	−0.001	0.011*	0.004	0.006	0.015*	0.009*
β_1	0.143*	0.759***	0.428**	0.207*	0.840***	0.066***
β_2	0.206*	0.254*	0.179*	0.189*	0.258**	0.232*
β_3	−0.009	0.006	−0.022*	0.021*	−0.005	0.029*
β_{SEN}	−0.011**	−0.025**	−0.059***	0.045**	0.028**	0.086***
Adjusted R^2	0.453	0.511	0.559	0.524	0.630	0.784

Note: Type I denotes the rumors type of micro risk incidents, Type II denotes the financial fraud type of micro risk incidents, Type III denotes the corporate governance type of micro risk incidents. There is 103 rumors type of micro risk incidents, 385 the financial fraud type of micro risk incidents and 276 the corporate governance type of micro risk incidents and the regressions take the form of Equation (11).

It can be seen from Table 9 that the relationship between the investor sentiment and stock prices still undergoes a process of reverse during the Pre-SEO window and the Post-SEO window, especially reflected in the corporate governance type. The results show that the main conclusion is robust after considering the different market conditions and idiosyncratic risk events.

5. Conclusions and Implications

In this study, we empirically answer whether investor sentiment affects stock pricing during the SEO window in China's stock market. By measuring the investor sentiment on the individual stock level and constructing the Fama-French asset pricing model incorporating investor sentiment, our study provides new evidence on the relationship between investor sentiment and stock pricing. Firstly, with the advancing of the private placement event, investor sentiment becomes gradually optimistic. Investors have a high degree of enthusiasm for the seasoned equity offerings, and after the implementation of the placement, there has been a leaping growth of investor sentiment, and it has remained at a high level for a relatively long period. Secondly, Investor sentiment is an important factor in asset pricing during the SEO period. Its overall contribution to asset prices is 0.0284, which is lower than the market factor and size factor, and higher than the value factor. Finally, in the Pre-SEO window and Post-SEO window, the influence of investor sentiment has a substantial change. During the Pre-SEO window, there is a negative relationship between investor sentiment and asset return, however, after the issuance, the investor sentiment has a positive influence on asset return.

The practical and policy implications of the above conclusions are as follows. Firstly, investor sentiment should be considered for portfolio management, and the investment strategies could be designed according to the heterogeneous relationships between investor sentiment and asset return during different periods of the SEO window. Secondly, for market regulators, since investor sentiment is a significant pricing factor, it should be regulated and guided to prevent the emergence of extreme market sentiment. Regulators can establish a monitoring mechanism for sentiment fluctuations in the capital market and take appropriate measures in due course to reduce market risks to prevent huge fluctuations in the capital market from impacting the financial market and the real economy. Thirdly, it is reasonable to strengthen investment education and adopt appropriate incentive measures to guide investors to establish a long-term value investment philosophy, reduce irrational "chasing up and killing down" behavior, and ultimately achieve the goal of reducing investor risks and stabilizing the stock market fluctuation.

The relationship between investor sentiment and asset pricing during the SEO period is investigated in this paper. However, the influence mechanism or the influence channel of investor sentiment are not fully explored in detail. Thus, the future research could focus on this issue and provide more concrete evidence on the influence mechanism of investor sentiment by using the behavioral finance theory.

Acknowledgments

We appreciate the funding support from the Natural Science Foundation of Hunan Province (No. 2020JJ4255) and the Innovative Research Program of Graduate Student in Hunan Province (CX20201077).

Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Adam S (2015) Forecasting returns with fundamentals-removed investor sentiment. *Int J Financ Stud* 3: 319–341.

Antoniou C, Doukas JA, Subrahmanyam A (2013) Cognitive dissonance, sentiment and momentum. *J Financ Quant Anal* 48: 245–275.

Antoniou C, Doukas J, Subrahmanyam A (2015) Investor sentiment, beta and the cost of equity capital. *Manage Sci* 62: 347–367.

Baker M, Stein JC, Wurgler J (2003) When Does the Market Matter? stock pricess and the Investment of Equity-Dependent Firms. *Q J Econ* 118: 969–1005.

Baker M, Stein JC (2004) Market liquidity as a sentiment indicator. *J Financ Mark* 7: 271–299.

Baker M, Wurgler J (2006) Investor sentiment and the cross-section of stock returns. *J Financ* 61: 1645–1680.

Baker M, Wurgler J (2007) Investor sentiment in the stock market. *J Econ Perspect* 21: 129–151.

Baker M, Wurgler J, Yuan Y (2012) Global, local, and contagious investor sentiment. *J Financ Econ* 104: 272–287.

Barberis N, Shleifer A, Vishny R (1998) A Model of Investor Sentiment. *J Financ Econ* 49: 307–343.

Barberis N, Huang M (2008) Stocks as lotteries: The implications of probability weighting for security prices. *Am Econ Rev* 98: 2066–2100.

Barberis N, Mukherjee A, Wang B (2016) Prospect theory and stock returns: An empirical test. *Rev Financ Stud* 29: 3068–3107.

Bathia D, Bredin D (2013) An examination of investor sentiment effect on G7 stock market returns. *Eur J Financ* 19: 909–937.

Bollen J, Mao H, Zeng X (2011) Twitter mood predicts the stock market. *J Comput Sci* 2: 1–8.

Chan K, Chan YC (2014) Price informativeness and stock return synchronicity: Evidence from the pricing of seasoned equity offerings. *J Financ Econ* 114: 36–53.

Chen YW, Chou RK, Lin CB (2019) Investor sentiment, SEO market timing, and stock prices performance. *Int J Financ Stud* 51: 28–43.

Chen R, Yu J, Jin C (2019) Internet finance investor sentiment and return comovement. *Pac-Basin Financ J* 56: 151–161.

Choi KH, Yoon SM (2020) Investor Sentiment and Herding Behavior in the Korean Stock Market. *Int J Financ Stud* 8: 34.

Chung SL, Hung CH, Yeh CY (2012) When does investor sentiment predict stock returns? *J Empir Financ* 19: 217–240.

Clinton S, White JT, Woidtke T (2014) Differences in the information environment prior to seasoned equity offerings under relaxed disclosure regulation. *J Account Econ* 58: 59–78.

Donadelli M, Kizys R, Riedel M (2017) Dangerous infectious diseases: Bad news for main street, good news for wall street? *J Financ Mark* 35: 84–103.

Ebert S, Strack P (2015) Until the Bitter End: On Prospect Theory in a Dynamic Context. *Am Econ Rev* 105: 1618–1633.

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J Financ Econ* 33: 3–56.

Fama E, French K (1992) The Cross-section of Expected Stock Returns. *J Financ* 47: 427–466.

Fama EF, French KR (2015) A five-factor asset pricing model. *J Financ Econ* 116: 1–22.

Fisher KL, Statman M (2006) Market timing in regressions and reality. *J Financ Res* 29: 293–304.

Frazzini A, Lamont OA (2008) Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns. *J Financ Econ* 88: 299–322.

Frugier A (2016) Returns, volatility and investor sentiment: Evidence from European stock markets. *Res Int Bus Financ* 38: 45–55.

Gerard B, Nanda V (1993) Trading and manipulation around seasoned equity offerings. *J Financ* 48: 213–245.

Griffith J, Najand M, Shen J (2020) Emotions in the stock market. *J Behav Financ* 21: 42–56.

Han X, Li Y (2017) Can investor sentiment be a momentum time-series predictor? Evidence from China. *J Empir Financ* 42: 212–239.

Hao Y, Chou RK, Ko KC, et al. (2018) The 52-week high, momentum, and investor sentiment. *Int Rev Financ Anal* 57: 167–183.

He Y, Wang J, Wei KJ (2014) A comprehensive study of liquidity before and after SEOs and SEO underpricing. *J Financ Mark* 20: 61–78.

Hertzel MG, Smith RL (1993) Market discounts and shareholder gains for placing equity privately. *J Financ* 48: 459–485.

Hirshleifer D, Shumway T (2003) Good day sunshine: Stock returns and the weather. *J Financ* 58: 1009–1032.

Hong Y, Li Y (2020) Housing Prices and Investor Sentiment Dynamics: Evidence from China using a wavelet approach. *Financ Res Lett* 35: 101300.

Huang H, Jin G, Chen J (2016) Investor sentiment, property nature and corporate investment efficiency. *China Financ Rev Int* 6: 56–76.

Huang H, Li R, Bai Y (2019) Investor sentiment, market competition and trade credit supply. *China Financ Rev Int* 9: 284–306.

Huang Y, Uchida K, Zha DL (2016) Market timing of seasoned equity offerings with long regulative process. *J Corp Financ* 39: 278–294.

Hung PH (2016) Investor sentiment, order submission, and investment performance on the Taiwan Stock Exchange. *Pac-Basin Financ J* 39: 124–140.

Joseph K, Wintoki MB, Zhang ZL (2011) Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *Int J Forecasting* 27: 1116–1127.

Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision making under risk. *Econometrica* 47: 263–291.

Kaplanski G, Levy H (2010a) Exploitable predictable irrationality: The FIFA world cup effect on the U.S. stock market. *J Financ Quant Anal* 45: 535–553.

Kaplanski G, Levy H (2010b) Sentiment and stock pricess: The case of aviation distasters. *J Financ Econ* 95: 174–201.

Kaplanski G, Levy H (2014) Sentiment, irrationality and market efficiency: The case of the 2010 FIFA World Cup. *J Behav Exp Econ* 49: 35–43.

Kim JS, Ryu D, Seo SW (2015) Investor Sentiment and Return Predictability of Disagreement. *J Bank Financ* 42: 166–178.

Kima B, Suhb S (2018) Sentiment-based Momentum Strategy. *Int Rev Financ Anal* 58: 52–68.

Kothari SP, Shanken J (1997) Book-to-market, Dividend Yield, and Expected Market Returns: A Time Series Analysis. *J Financ Econ* 44: 169–203.

Lakonishok J, Shleifer A, Vishny RW (1994) Contrarian Investment, Extrapolation and Risk. *J Financ* 49: 1541–1578.

Li Y, Ran J (2020) Investor Sentiment and stock prices Premium Validation with Siamese Twins from China. *J Multinatl Financ Manage,* 100655.

Li Y, Yang L (2013) Prospect Theory, the Disposition Effect, and Asset Prices. *J Financ Econ* 107: 715–739.

López-Cabarcos MÁ, Pérez-Pico AM, Vázquez-Rodríguez P, et al. (2020) Investor sentiment in the theoretical field of behavioural finance. *Econ Res-Ekonomska Istraživanja* 33: 2101–2119.

Luo CQ, Ouyang ZS (2014) Estimating IPO Pricing Efficiency by Bayesian Stochastic Frontier Analysis: the ChiNext Market Case. *Econ Model* 40:152–157.

Maqsood H, Mehmood I, Maqsood M, et al. (2020) A local and global event sentiment based efficient stock exchange forecasting using deep learning. *Int J Inf Manage* 50: 432–451.

McGurk Z, Nowak A, Hall JC (2020) Stock returns and investor sentiment: textual analysis and social media. *J Econ Financ* 44: 458–485.

Ni ZX, Wang DZ, Xue WJ (2015) Investor sentiment and its nonlinear effect on stock returns-New evidence from the Chinese stock market based on panel quantile regression model. *Econ Model* 50: 266–274.

Novy-Marx R (2012) Is momentum really momentum? *J Financ Econ* 103: 429–453.

Piñeiro-Chousa J, López-Cabarcos MA, Pérez-Pico AM, et al. (2018) Does social network sentiment influence the relationship between the S&P 500 and gold returns? *Int Rev Financ Anal* 57: 57–64.

Renault T (2017) Intraday online investor sentiment and return patterns in the US stock market. *J Bank Financ* 84: 25–40.

Shi J, Yu C, Guo S, et al. (2020) Market effects of private equity placement: Evidence from Chinese equity and bond markets. *North Am J Econ Financ* 53: 101214.

Smales LA (2014) News sentiment and the investor fear gauge. *Financ Res Lett* 11: 122–130.

Sprenger TO, Tumasjan A, Sandner PG, et al. (2014) Tweets and trades: The information content of stock microblogs. *Eur Financ Manage* 20: 926–957.

Wu PC, Liu SY, Chen CY (2016) Re-examining risk premiums in the Fama–French model: The role of investor sentiment. *North Am J Econ Financ* 36: 154–171.

Yang C, Wu H (2019) Chasing investor sentiment in stock market. *North Am J Econ Financ* 50: 100975.

Yang C, Yan W (2011) Dose high sentiment cause negative excess return? *Int J Digital Content Technol Appl* 5: 211–217.

Yang CP, Zhou LY (2016) Individual stock crowded trades, individual stock investor sentiment and excess returns. *North Am J Econ Financ* 38: 39–53.

Zeng H (2020) Volatility Modelling of Chinese Stock Market Monthly Return and Investor Sentiment Using Multivariate GARCH Models. *Int J Account Financ Rev* 5: 123–133.

Zhao YF, Xia XP, Tang XX, et al. (2015) Private placements, cash dividends and interests transfer: Empirical evidence from Chinese listed firms. *Int Rev Econ Financ* 36: 107–118.

Zhou L, Yang C (2019) Stochastic investor sentiment, crowdedness and deviation of asset prices from fundamentals. *Econ Model* 79: 130–140.

Zhu B, Niu F (2016) Investor sentiment, accounting information and stock prices: Evidence from China. *Pac-Basin Financ J* 38: 125–134.

Wang L, Zhang Z, Wang Y (2015) A prospect theory-based interval dynamic reference point method for emergency decision making. *Expert Syst Appl* 42: 9379–9388.

Wang W (2020) Institutional investor sentiment, beta, and stock returns. *Financ Res Lett* 37: 101374.

Werner K, Zank H (2019) A revealed reference point for prospect theory. *Econ Theory* 67: 731–773.

Wang T, Li H, Zhang L, et al. (2020) A three-way decision model based on cumulative prospect theory. *Inf Sci* 519: 74–92.