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# Cognitive biases, downside risk shocks, and stock expected returns

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A B S T R A C T

This paper finds that the pricing effect of past stock downside risks in stock markets is greatly influenced by two cognitive biases: the representativeness heuristic bias and the conservatism bias. The two cognitive biases can cause investors to misreact to past downside risks of stocks, resulting in abnormal returns. Using the pseudo-Bayesian model, we theoretically describe how investors' incorrect belief updates, influenced by two cognitive biases regarding downside risks of a stock, affect future stock returns under four scenarios. Our empirical analysis confirms that biased beliefs lead to a positive correlation between short-term downside risk shocks and future stock returns, while a negative correlation exists between long-term downside risk shocks and future stock returns. This phenomenon is prevalent in the Chinese A-share market, even after controlling for several commonly used firm characteristics. Similar results are also observed in the US stock market. Furthermore, more active retail investors and low investor sentiments can strengthen the anomalous relation.

## 1. Introduction

Investor cognitive bias is one of the main reasons for abnormal movements in stock prices (Ahmad, 2022; Ang et al., 2006a). According to behavioral finance theory, the decision-making process and judgment under uncertain conditions are greatly influenced by people's cognition, leading to mispricing and market inefficiency (Fischer & Lehner, 2021; Hirshleifer, 2015). This paper mainly considers two typical cognitive biases that commonly affect investor decision-making in the investment market: representativeness heuristic bias and conservatism bias. The two cognitive biases can cause investors to incorrectly collect and process past information in different periods resulting in mispricing (Barberis et al., 1998; Fisher & Statman, 2000; Lam et al., 2010). These influences are particularly pronounced in emerging stock markets whose major market participants are immature individual investors. Thus, investigating how the two cognitive biases affect stock prices is meaningful.

Representativeness heuristic bias was first proposed by Tversky and Kahneman (1974). The authors argue that human beings are accustomed to making judgments and decisions based on fresh information, which results in investors updating their beliefs too dramatically. Conservatism bias was first proposed by Edwards (1968). The author argues that human beings believe that recent information is only temporary. They are accustomed to clinging onto prior beliefs based on earlier information, resulting in their slow updating of beliefs. Barberis et al. (1998) first analyze the impact of the two biases in the stock market using a Markov process model. Guo et al. (2017) and Lam et al. (2010) also focus on this impact alternatively using a pseudo-Bayesian model. They all find that the two biases can make investors misreact to past stock earnings and then misprice in the stock market. Some later studies, such as Chen

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and Doukas (2022) and Otuteye and Siddiquee (2015), further investigate when the mispricing performs more significantly and how to avoid it. However, all these studies mainly focus on investors' misreactions to past stock earnings caused by the two biases and do not examine whether the two biases affect the pricing effects of other stock pricing factors.

This paper argues that representativeness heuristic bias and conservatism bias can also affect investors' attitudes toward past downside risks and further impact future stock returns. The downside risk is used to measure the possibility and magnitude of losses for an asset or a portfolio in the case of an adverse economic scenario. It is also referred to as left-tail risk in some literature (Atilgan et al., 2020). According to Ang et al. (2006a), investors' aversion to losses generally far exceeds the enjoyment of equivalent gains; thus, downside risk usually plays a very important role in the asset pricing process. From the perspective of behavioral finance, downside risks can easily lead to irrational behaviors because investors are highly averse to losses and tend to focus closely on them, particularly in emerging stock markets (Ang et al., 2006a; Bai et al., 2021; Benartzi & Thaler, 1995). Most other pricing factors do not exert such a strong influence on investors. According to some existing empirical studies, investors tend to pay significantly different levels of attention to losses in various time periods. For example, Piccoli et al. (2017) found that investors tend to overemphasize recent losses and neglect prior losses in a short-term horizon; whereas Atilgan et al. (2020) discovered that investors are insensitive to recent losses and cling to prior beliefs in a long-term horizon. These results are in accord with the psychological descriptions of representativeness heuristic bias and conservative bias, respectively.

To better understand how past downside risks impact future returns when investors exhibit representativeness heuristic bias and conservatism bias, this paper first constructs a simple theoretical model to describe the mechanism. Specifically, based on Ang et al. (2006a) and Atilgan et al. (2020), investors' loss aversion preferences are taken into account, resulting in a low (high) equilibrium price for stocks with high (low) expected downside risk. We assume that the true downside risk of a stock is unknown and that investors can only estimate it based on the past realized downside risk calculated with appropriate proxies. Following Lam et al. (2010), we apply a pseudo-Bayesian model to characterize investors' process of updating wrong beliefs with biased attention assignment schemes. The model demonstrates that the representativeness heuristic bias leads to a positive correlation between past downside risk shocks and future returns, while the conservatism bias results in a negative correlation between them. Given that conservatism bias and representativeness heuristic bias often coexist in stock markets, we investigate two potential combinations: conservatism bias is more salient in the short term while representativeness heuristic bias is more pronounced in the long term; conservatism bias is more prominent in the long term while representativeness heuristic bias is more evident in the short term (Barberis et al., 1998; Lam et al., 2010). According to our model, if investors follow the former scheme, the combined effects of the two biases should result in a negative correlation between short-term downside risk shocks and future stock returns, as well as a positive correlation between long-term downside risk shocks and future stock returns. If investors follow the latter scheme, then short-term downside risk shocks should be positively correlated with future stock returns while long-term downside risk shocks should exhibit a negative relationship.

To determine which scheme is most suitable for the actual stock markets, we conducted an empirical study using all non-financial listed companies in the Chinese A-share market from January 1997 to June 2022. Since 2015, the Chinese stock market has become the second-largest stock market in the world by market capitalization, according to data from the China Securities Regulatory Commission. Compared to developed markets, the Chinese market has some beneficial features for our additional tests. For example, stocks in the Chinese market are more sensitive to downside risk with a higher risk exposure (Zhen et al., 2020); relatively unsophisticated investors dominate the Chinese market and are more likely to make biased decisions (Barber & Odean, 2008; Chuang & Susmel, 2011; Jiang et al., 2020). Our findings indicate a positive correlation between the average downside risk shock in the most recent two months and the one-month-ahead excess return, while a negative correlation exists between the average downside risk shock over the previous twelve months excluding the most recent two months and the one-month-ahead excess return. Even after controlling for various commonly used firm-level characteristics, these anomalous relationships remain significant. The results are in line with our model inference and confirm the influence of both representativeness heuristic bias and conservatism bias on the pricing effects of downside risks in the Chinese stock market. Specifically, the former is more pronounced in a shorter time horizon while the latter predominates over a longer period.

Moreover, we observe that the aforementioned anomalous relationships are more pronounced among stocks with a higher proportion of active retail investors and during periods of low investor sentiment. This phenomenon aligns with the argument that irrational psychological tendencies are more likely to influence retail investors (Atilgan et al., 2020; Chuang & Susmel, 2011), and that loss aversion tends to be stronger when investor sentiment is negative (Bi & Zhu, 2020; Hao et al., 2018; Qadan, 2019; Wang & Song, 2021). To test the robustness of our empirical findings, we also explored alternative methods for constructing downside risk shocks, adjusted stock returns using different pricing factor models, and utilized alternative subsamples. Nevertheless, we still obtained consistent results. Finally, we conducted further tests on the relationships using data from the US stock market to expand our findings. Our results indicate that similar relationships exist in the US stock market, but they are shorter-lived compared to those observed in the Chinese stock market. We attribute this difference to the dominance of relatively sophisticated investors who are prone to making rational decisions in the US stock market, which leads to shorter periods of their misreactions to downside risks.

Overall, this paper examines the impact of investor representativeness heuristic bias and conservatism bias on the intertemporal relationship between past downside risk shocks and future returns from a behavioral finance perspective, using both modeling and empirical approaches. Our contribution to the literature lies in several ways. Firstly, we expand upon existing research on cognitive biases (e.g., Barberis et al. (1998), Lam et al. (2010), Fisher and Statman (2000), and Kariofyllas et al. (2017)), by arguing that both representativeness heuristic and conservatism biases not only result in investors' misreaction towards past earnings but also towards previous downside risks. Secondly, our findings also contribute to the literature on downside risk, such as Ang et al. (2006a), Bali et al. (2014a), Kelly and Jiang (2014), and Long et al. (2018). We argue that the pricing effects of past downside risk in different subintervals are distinct, resulting in anomalous relationships between past downside risk shocks and future returns. Thirdly, we have found that the relationships are significantly present in the Chinese stock market. Moreover, more active retail investors and low investor sentiment can strengthen these relationships. Finally, we have also observed the presence of such relationships in the US stock market; however, their duration is much shorter than that of the Chinese stock market.

The rest of the paper is organized as follows. Section 2 introduces the theoretical model. Section 3 describes the dataset and the variables. Section 4 shows the main empirical results. Section 5 provides a variety of robustness tests. Section 6 additionally provides evidence from the US stock market. Section 7 concludes.

## 2. Theoretical model

### 2.1. Model assumptions

#### 2.1.1. Stock price and downside risk

Following the basic setting of the model from Barberis et al. (1998) and Lam et al. (2010), we assume that there is one stock in the market and $N_t (N_t > 0)$ denotes the earning of the stock at time $t$; $N_t$ follows a martingale process, i.e., $E(N_{t+\tau}|N_t) = N_t (\tau = 0, 1, \cdots)$, and investors realize this. Using a discounting model, the asset is priced at time $t$ as $P_t$ given by

$$P_t = E_t\left(\frac{N_{t+1}}{(1+\delta)} + \frac{N_{t+2}}{(1+\delta)^2} + \cdots\right) = \sum_{\tau=1}^{\infty} E_t\left(\frac{N_{t+\tau}}{(1+\delta)^{\tau}}\right) \tag{1}$$

where $E_t(\cdot)$ represents investors' expectations at time $t$ based on past information and $\delta$ ($\delta > 0$) is the discount rate of the stock. The economic implication of $1/(1+\delta)^{\tau}$ is the present value at time $t$ of a unit payoff at time $t+\tau$. Different from Lam et al. (2010), this paper assumes that $\delta$ is a random variable exogenous to $N_{t+\tau}$ rather than a constant; investors keep updating their beliefs about $1/(1+\delta)^{\tau}$ based on new information, and the updating process is independent of investors' expectation of $N_{t+\tau}$. Then, we can simplify Eq. (1) as

$$P_t = \sum_{\tau=1}^{\infty} E_t\left(\frac{1}{(1+\delta)^{\tau}}\right) E_t(N_{t+\tau}) = N_t E_t\left(\sum_{\tau=1}^{\infty} \frac{1}{(1+\delta)^{\tau}}\right) = N_t E_t\left(\frac{1}{\delta}\right) \tag{2}$$

Downside risk is strongly correlated with $\delta$. This type of risk typically refers to the potential and magnitude of losses that an asset or portfolio may incur in the event of an unfavorable economic scenario. Most literature measures stock downside risk with a low partial moment (LPM), value at risk (VaR), conditional value at risk (CVaR), or maximum drawdown (MDD) (Atilgan et al., 2020). According to Ang et al. (2006a), investors exhibit loss aversion, resulting in a negative relationship between stock downside risk and the willingness to pay for stocks with equivalent future expected earnings. Therefore, there exists a positive correlation between stock discount rate and downside risk. Several empirical studies have tested this positive relationship and yielded favorable evidence, including but not limited to Ang et al. (2006a), Huang et al. (2012), Kelly and Jiang (2014), among others. There are also other studies that have found a negative relationship, such as Bali et al. (2014a), Atilgan et al. (2020), Zhen et al. (2020), and others. However, these studies argue that the abnormal relationship is caused by investors' irrational behavior, which leads to misestimations of downside risks and distorts the theoretical positive relationship. For instance, some of them explicate the anomaly by positing that investors tend to underestimate the persistence of downside risk while overvaluing stocks with substantial recent losses.

Overall, we can conclude that the "true" downside risk of stocks (without estimation errors) should theoretically be positively related to the stock discount rate. If we let the random variable $\lambda$ represent the "true" downside risk of stocks, then $\lambda$ should be positively related to $\delta$. For the sake of simplicity, we make the assumption that $\delta = \exp(\theta_0 + \theta_1\lambda)$, where $\theta_0$ and $\theta_1$ are constants with $\theta_1 > 0$. Although this form may not be entirely accurate, it is not crucial for producing the results. As λ cannot be directly observed by investors, we assume that they update their beliefs about λ based on the past signals $s_t, s_{t-1}, \cdots, s_{t-k+1}$, where $s_t = \lambda + u_t$ and $u_t$ i.i.d.$N(0, {\sigma_u}^2)$ represents the corresponding random shock (or noise), which is independent of stock earnings. In practical terms, $s_t$ can be considered as the actualized value of a downside risk proxy (such as LPM, VaR, CVaR, or MDD) that is calculated using daily returns from month $t$. Then, we have

$$P_t = N_t E_t\left(\frac{1}{\delta}\right) = N_t E(\exp(-\theta_0 - \theta_1\lambda)|s_t, s_{t-1}, \cdots, s_{t-k+1}) \tag{3}$$

Eq. (3) demonstrates that the equilibrium price $P_t$ is contingent upon investors' beliefs regarding $\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}$.

#### 2.1.2. Updating method with cognitive biases

The representativeness heuristic bias and conservatism bias can exert a significant impact on investors' inference process regarding λ, leading to erroneous belief updating. To quantify the impact of the two cognitive biases, we adopt the pseudo-Bayesian approach proposed by Lam et al. (2010). In contrast to the classical Bayesian approach (which employs accurate updating procedures), the pseudo-Bayesian method incorporates investors' behavioral biases by assigning varying degrees of attention or weight to past information. We adopt a non-informative prior distribution for λ, namely $P(\lambda) \propto 1$. According to the classical Bayesian method, if investors do not have cognitive biases, the posterior distribution of $\lambda$ is given as follows:

$$\begin{aligned} P(\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}) &= \frac{P(s_t, s_{t-1}, \cdots, s_{t-k+1}|\lambda)P(\lambda)}{P(s_t, s_{t-1}, \cdots, s_{t-k+1})} \\ &\propto P(s_t, s_{t-1}, \cdots, s_{t-k+1}|\lambda) \propto \prod_{l=1}^{k} L(s_{t+1-l}|\lambda) \end{aligned} \tag{4}$$

where $L(s_{t+1-l}|\lambda) = \frac{1}{\sigma_u\sqrt{2\pi}}\exp\left(-\frac{(s_{t+1-l}-\lambda)^2}{2\sigma_u{}^2}\right)$ and $\propto$ indicates that the left side and the right side of the symbol are directly proportional. Revising beliefs according to Eq. (4) can lead to the attainment of the equilibrium price under rational expectations, implying that any irrational financial anomaly would be eliminated. The statement is in line with Friedman (1979) perspective that rational investors can access the accurate specification of the "true" economic model and unbiased estimates of coefficients in an efficient market. In cases where cognitive biases are present, incorrect weights $w_1, w_2, \cdots, w_k$ may be assigned to signals $s_t, \cdots, s_{t-k+1}$ resulting in a biased posterior distribution as follows:

$$P(\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}) \propto \prod_{l=1}^{k} L(s_{t+1-l}|\lambda)^{w_l} \tag{5}$$

Since $s_{t+1-l}|\lambda$ follows the normal distribution, the posterior distribution in Eq. (5) also follows the normal distribution, that is, $\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}\ N\left(\frac{\sum_{l=1}^{k} w_l s_{t+1-l}}{\sum_{l=1}^{k} w_l}, \frac{\sigma_u{}^2}{\sum_{l=1}^{k} w_l}\right)$ (The proof is available in Appendix A1). By utilizing Eq. (3) in conjunction with the formula for computing the mean of a logarithmic normal distribution, we can obtain that

$$\begin{aligned} P_t &= N_t \exp\left(-\theta_0 - \frac{\theta_1 \sum_{l=1}^{k} w_l s_{t+1-l}}{\sum_{l=1}^{k} w_l} + \frac{\theta_1{}^2 \sigma_u{}^2}{2\sum_{l=1}^{k} w_l}\right) \\ &= N_t \exp\left(-\theta_0 - \theta_1\lambda - \frac{\theta_1 \sum_{l=1}^{k} w_l u_{t+1-l}}{\sum_{l=1}^{k} w_l} + \frac{\theta_1{}^2 \sigma_u{}^2}{2\sum_{l=1}^{k} w_l}\right) \end{aligned} \tag{6}$$

Eq. (6) shows that shocks $u_t, u_{t-1}, \cdots, u_{t-k+1}$ can result in mispricing when investors have cognitive biases.

### 2.1.3. *Weight assignment schemes to reflect cognitive biases*

The weights $w_1, w_2, \cdots, w_k$ reflect the attitude of investors towards information at different points in time. Previous research indicates that decision-makers who exhibit the representativeness heuristic bias tend to rely on recent small-scale samples as accurate representations of the entire population, leading them to disregard information from earlier periods (Tversky & Kahneman, 1974). In contrast, conservatism bias tends to cause investors to persist in their beliefs formed on earlier information (Edwards, 1968). Similar to Lam et al. (2010), we delineate the irrational behavior stemming from representativeness heuristic bias and conservatism bias through four abstract weight assignment schemes. If investors are solely influenced by the representativeness heuristic bias, we have.

(A):

$$1 = w_1 = w_2 = \cdots = w_{m_0} > w_{m_0+1} > \cdots > w_k = 0 \tag{7}$$

where $m_0$ $(1 \le m_0 < k)$ denotes recent $m_0$ observations. Scheme (A) argues that investors prefer recent information to past information. If investors are solely affected by conservatism bias, we have.

(B):

$$0 = w_1 < w_2 < \cdots < w_{n_0} = w_{n_0+1} = \cdots = w_k = 1 \tag{8}$$

where $n_0$ $(1 < n_0 < k)$ denotes recent $n_0$ observations. Scheme (B) argues that investors prefer past information to recent information. If investors exhibit both representativeness heuristic and conservatism biases, the weight assignment scheme can be considered a combination of Scheme (A) and Scheme (B), which we further distinguish into two sub-schemes. If $m_0 \ge n_0$, we have.

(C):

$$0 = w_1 < w_2 < \cdots < w_{n_0} = \cdots = w_{m_0} = 1 > w_{m_0+1} \cdots > w_k = 0 \tag{9}$$

Scheme (C) argues that investors pay more attention to the observation in the middle term and neglect the observation on both sides. If $m_0 < n_0$, we have.

(D):

$$1 = w_1 = w_2 = \cdots = w_{m_0} > \cdots > w_{q_0} < \cdots < w_{n_0} = w_{n_0+1} = \cdots = w_k = 1 \tag{10}$$

(10).where $w_{q_0} \ge 0$ denotes the minimum weight among $w_1, w_2, \cdots, w_k$. Scheme (D) argues that investors pay more attention to the observation on both sides and neglect the observation in the middle. Lam et al. (2010) only discuss the former three schemes, whereas we propose an additional Scheme (D) in this paper. Fig. 1 presents a graphical representation of the above four weight assignment schemes. The curves depicted in Schemes (C) and (D) are a composite of the curves illustrated in Schemes (A) and (B), contingent upon whether $m_0 \geq n_0$ or $m_0 < n_0$, respectively.

## 2.2. Theoretical results and conjecture

In this paper, we adopt $u_t, u_{t-1}, \cdots, u_{t-k+1}$ as downside risk shocks. Accordingly, we define $SU_t$ as the average value of the most recent $v$ downside risk shocks and denote $LU_t$ as the average value of past $k-1$ downside risk shocks excluding the most recent $v$ shocks, that is,

$$SU_t(v) = \frac{\sum_{l=1}^{v} u_{t+1-l}}{v},\ LU_t(v) = \frac{\sum_{l=v+1}^{k-1} u_{t+1-l}}{k-v-1}; 1 < v+1 < k \tag{11}$$

Intuitively, $SU_t$ and $LU_t$ represent the short-term and long-term downside risk shocks of the stock at time $t$, respectively. The log-return of the stock between time $t$ and time $t+1$ can be expressed as $R_{t+1} = lnP_{t+1} - lnP_t$. Then, the following proposition can be derived.

**Proposition 1**. *Suppose investors exhibit both representativeness heuristic and conservatism biases in their beliefs about downside risk, the resulting stock price $P_t$ follows Eq. (6) with weight assignment schemes (A) to (D) respectively, then $R_{t+1}$ can be expressed as.*

$$R_{t+1} = \alpha + \beta_1(v)SU_t(v) + \beta_2(v)LU_t(v) + \varepsilon_t(v); 1 < v+1 < k \tag{12}$$

where $\alpha$ is a constant; $\beta_1(v) = \theta_1(w_1 - w_{v+1})/\sum_{l=1}^{k} w_l$; $\beta_2(v) = \theta_1(w_{v+1} - w_k)/\sum_{l=1}^{k} w_l$; $\varepsilon_t(v)$ denotes a random variable satisfying $E(\varepsilon_t(v)|SU_t(v), LU_t(v)) = 0$; $k$ is the number of past signals taken into account; and $v$ denotes the number of most recent signals considered. Specifically, $\beta_1(v) \geq 0$ and $\beta_2(v)\rangle 0$ for Scheme (A); $\beta_1(v)\langle 0$ and $\beta_2(v) \leq 0$ for Scheme (B); $\beta_1(v)\langle 0$ and $\beta_2(v)\rangle 0$ for Scheme (C); $\beta_1(v) \geq 0$ and $\beta_2(v) \leq 0$ for Scheme (D).

**Proof:** See Appendix A2.

The intuitive economic implication of Proposition 1 is given as follows. The representativeness heuristic bias prompts investors to give significant attention to the new downside risk shock, but this enthusiasm dissipates rapidly. Consequently, the greater (lesser) the magnitude of the shock, the higher (lower) the downside risk attributed to the stock, resulting in a lower (higher) valuation. Subsequently, as investor attention wanes over time, there will be an accelerated increase (decrease) in future stock prices. In contrast, the conservatism bias prompts investors to initially overlook new downside risk shocks but gradually increase their attention towards them. Consequently, the higher (lower) the shock is, the greater (lesser) the estimated downside risk of a stock becomes. As investors focus intensifies on this shock over time, future stock prices will fall (rise) more rapidly. When both biases coexist, their effects manifest as a combination of the aforementioned mispricing processes.

Proposition 1 has demonstrated the varying impacts of short-term and long-term downside risk shocks on future stock returns, depending on the weight assignment schemes employed. However, it is difficult to determine which scheme is more likely to align with the stock market. Specifically, for example, Chen et al. (2007) find that representativeness heuristic bias causes most individual

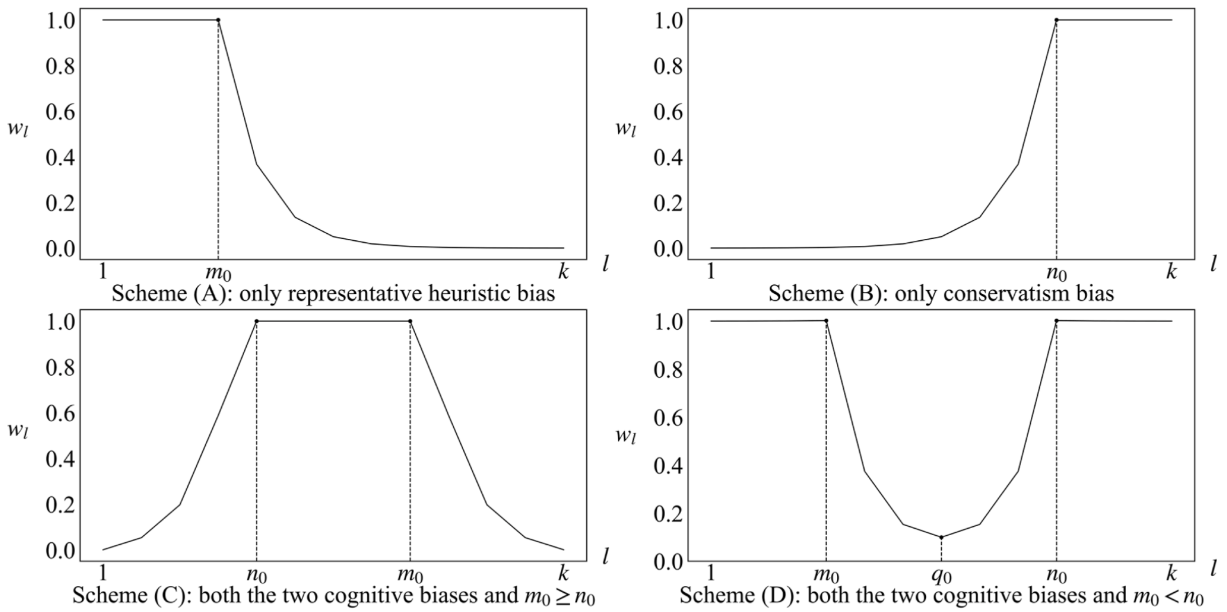


**Fig. 1.** The weight assignment scheme to reflect cognitive biases.

investors to make decisions based only on the performance of stocks in the most recent $1 \sim 4$ months and pay little attention to the performance in former months; Wu et al. (2009) find that conservatism bias can make investors underestimate the impact of earning announcements for at least one year, and there is little support for the over-use of the representativeness heuristic bias on the longer horizon; while Kariofyllas et al. (2017) find that representativeness heuristic bias significantly present within a more than one year's horizon. These results are inconsistent. What's more, these studies don't refer to downside risks, and thus their inference cannot be directly extrapolated to our application scenario. In the following sections, we will perform empirical analysis to determine the most suitable scheme for stock markets.

## 3. Data and variables

### 3.1. Data source and sample selection

Daily and monthly stock data for prices, returns, shares outstanding, market equity, volume of shares, and factors proposed by Fama and French (2015) in the Chinese stock market are retrieved from the CSMAR database. Additionally, fundamentals of financial statements are also obtained from the same source. The institutional ownership data is sourced from the RESSET database. We use the one-year treasury-bond yield as the risk-free rate. The sample comprises all non-financial listed companies and encompasses the period spanning from January 1997 to June 2022. Every month, we eliminate samples that have been listed for less than six months and those with more than 30% of missing data in the previous one month, one year, or two years.

### 3.2. Variable definitions

To avoid any potential biases caused by looking ahead, we calculate the excess cumulative rate of return for the following month at the end of each month. This allows us to accurately measure future stock returns and construct short-term downside risk shocks, long-term downside risk shocks, and other control variables based on 24 months' worth of historical data.

#### 3.2.1. Short-term and long-term downside risk shock

Rephrasing the mathematical notations introduced in Section 2, we consider $\lambda_i$ as the true measure of downside risk for stock $i$ in this section; $s_{i,t}$ denotes the downside risk signal (the actual value of a downside risk proxy) for stock $i$ at month $t$ and $u_{i,t}$ represents the corresponding downside risk shock. Since only $s_{i,t}, s_{i,t-1}, \cdots, s_{i,t-23}$ can be observable at the end of month $t$, $\lambda_i$ and $u_{i,t}, u_{i,t-1}, \cdots, u_{i,t-23}$ need to be estimated based on $s_{i,t}, s_{i,t-1}, \cdots, s_{i,t-23}$. In this study, we estimate $\lambda_i$ at the end of month $t$ by taking the mean of $s_{i,t}, s_{i,t-1}, \cdots, s_{i,t-23}$ as suggested by Fenner et al. (2020). Specifically, we calculate $\widehat{\lambda}_i^t = \frac{\sum_{l=1}^{24} s_{i,t+1-l}}{24}$, and then obtain an estimate of $u_{i,t+1-l}$ at the end of month $t$ using formula $\widehat{u}_{i,t+1-l}^t = s_{i,t+1-l} - \widehat{\lambda}_i^t, l = 1,2,\cdots,24$. Then, the short-term and long-term downside risk shocks of stock $i$ at month $t$ in our empirical analysis are computed as follows:

$$SU_{i,t} = \frac{\sum_{l=1}^{v} \widehat{u}_{i,t+1-l}^t}{v} \tag{13}$$

$$LU_{i,t} = \frac{\sum_{l=v+1}^{12} \widehat{u}_{i,t+1-l}^t}{12 - v} \tag{14}$$

where $SU_{i,t}$ is the average downside risk shock of the most recent $v$ months and $LU_{i,t}$ is the average downside risk shock over the past 12 months (1 year), excluding the most recent $v$ months. For the sake of simplicity, we shall also employ SU and LU as abbreviations for short-term downside risk shock and long-term downside risk shock, respectively. In this paper, we just set $v = 2$ by default unless otherwise stated. We also verify the validity of $SU_{i,t}$ and $LU_{i,t}$ computed with alternative values of $v$ in Section 5 to enhance the robustness of our analysis. Our findings indicate that these phenomena exhibit similar performance when $v \leq 5$, but demonstrate the most significant correlations when $v = 2$.

Based on Eqs. (13) and (14), it is crucial to select an appropriate proxy for measuring the historical downside risks of stocks (i.e., $s_{i,t}$, $s_{i,t-1}, \cdots, s_{i,t-23}$) when calculating $SU_{i,t}$ and $LU_{i,t}$. In the US stock market, previous research typically employs LPM, VaR, or CVaR to gauge downside risk of stocks. However, LPM, VaR, and CVaR are not applicable to Chinese A-share stocks due to specific trading regulations such as short-selling restrictions and price limits. According to Li et al. (2014) and Wang and Song (2021), the presence of short-selling barriers and price limits can lead to a gradual release of negative extreme movements over several trading days. LPM, VaR, and CVaR only focus on the tail distribution of daily returns (Atilgan et al., 2020) but ignore the situation where prices decline intermittently or continuously.

This paper contends that maximum drawdown (MDD) is a more appropriate measure for assessing downside risk in the Chinese A-share market. MDD represents the percentage decline in asset value from its peak to trough over a specified time period (Bacon, 2012; Grossman & Zhou, 1993). It is one of the most popularly used asset evaluation indicators. Compared with LPM, VaR, and CVaR, MDD places greater emphasis on intermittent or continuous declines, making it more suitable for the Chinese A-share market. The present study computes the MDD of stock $i$ at month $t$ by means of

$$MDD_{i,t} = \max_{0 \le \tau \le K_t} \left\{ \frac{\max\limits_{0 \le \nu \le \tau} \left\{ P^t_{i,\nu} \right\} - P^t_{i,\tau}}{\max\limits_{0 \le \nu \le \tau} \left\{ P^t_{i,\nu} \right\}} \right\} \triangleq s_{i,t} \tag{15}$$

where $P^t_{i,0}$ is the price of stock $i$ at the beginning of month $t$, $P^t_{i,k}$ is the price of stock $i$ on the $k$ th trading day of month $t$, and $K_t$ is the number of trading days for month $t$. Fig. 2 compares the empirical distribution of MDD with VaR in the Chinese A-share market as an example, where VaR is calculated as the 95% quantile of daily stock returns multiplied by $-1$ (Atilgan et al., 2020). According to Fig. 2, the empirical distribution of VaR exhibits anomalies at the 5% and 10% levels, whereas no such abnormalities are observed in the empirical distribution of MDD. Additionally, the majority of samples exhibit an MDD exceeding 10%, indicating that persistent or intermittent declines are pervasive throughout the Chinese A-share market.

### 3.2.2. Other control variables

The relationship between SU (or LU) and future stock returns may be explained by some other firm-level characteristics. A large number of studies have shown that some firm-level characteristics have obvious predictive abilities on future stock returns, which is inconsistent with the efficient market theory (these phenomena are also called market anomalies in some studies). Therefore, if these firm-level characteristics exhibit underlying associations with SU (or LU), they may further impact the relationship between SU (or LU) and future returns. To mitigate the impact of these firm-level characteristics, we have developed a set of control variables based on previous research and presented them in Table 1.

Specifically, the characteristics of Beta, Size, BM, Invest, and Profit in Table 1 are suggested by Fama and French (2015) as having a significant impact on future stock returns. The indicators of REV and MOM in Table 1 are commonly considered as proxies of investors' overreaction to past earnings. Previous studies find that they respectively have a similar influence on future stock returns as SU and LU (Jegadeesh, 1990; Jegadeesh & Titman, 1993). The indicators of MAX, MIN, (Co–)Skew, and (Co–)Kurt in Table 1 are commonly considered as proxies for investor lottery preference. Lottery preference is one of the main causes of the negative correlation between past risks and future returns (Bali et al., 2011). Abnormal Turn and Turn in Table 1 are commonly considered as indicators of investor attention (Barber & Odean, 2008). Related literature argues that investors tend to overreact to fresh or obvious news on stocks that receive more attention. The ILLIQ in Table 1 is commonly considered as an indicator of stock illiquidity. Amihud (2002) discovered that stocks with higher levels of illiquidity are associated with an expected return premium. Beta Down and TDR in Table 1 are generally regarded as systematic downside risk proxies, where stock systematic downside risk is just a small part of stock total downside risk and should have positive return premiums (Kelly & Jiang, 2014). The IVOL in Table 1 denotes the risk of stock-specific volatility. A lower IVOL is typically associated with higher future returns (Ang et al., 2006b). The CVRG in Table 1 denotes the extent of analyst coverage, and it has been found to have a positive correlation with fundamental performance (Lee & So, 2017). The DISP in Table 1 represents the dispersion of earnings forecasts made by analysts, which has been found to have a negative correlation with stock returns (Johnson, 2004). The SUE in Table 1 represents the standardized unexpected earnings of stocks. It has been observed that the cumulative abnormal returns of a stock tend to move towards an earnings surprise for several weeks after the announcement of its earnings (Livnat & Mendenhall, 2006). Furthermore, just as we employ downside risk shocks instead of simply considering downside risks in our paper, a similar approach can also be applied to some of the aforementioned controls. In addition, we incorporate four commonly utilized shocks in prior research, namely LIQU, VOLDU, IVOLSU, and IVOLLU. Specifically, the LIQU in Table 1 represents the impact of stock liquidity shock within the past month. Bali et al. (2014b) have demonstrated that the equity market exhibits an underreaction to shocks in individual stock liquidity. The VOLDU in Table 1 represents the recent monthly shock of stock dollar volumes. The study conducted by (Huang & Heian, 2010) found a positive correlation between VOLDU and future returns. Finally, we adopt the same methodology as SU and LU to construct short-term IVOL shocks (IVOLSU) and long-term IVOL shocks (IVOLLU) alternatively. Numerous studies have demonstrated a strong correlation between the recent month's IVOL shock and future stock returns (Fenner et al., 2020).

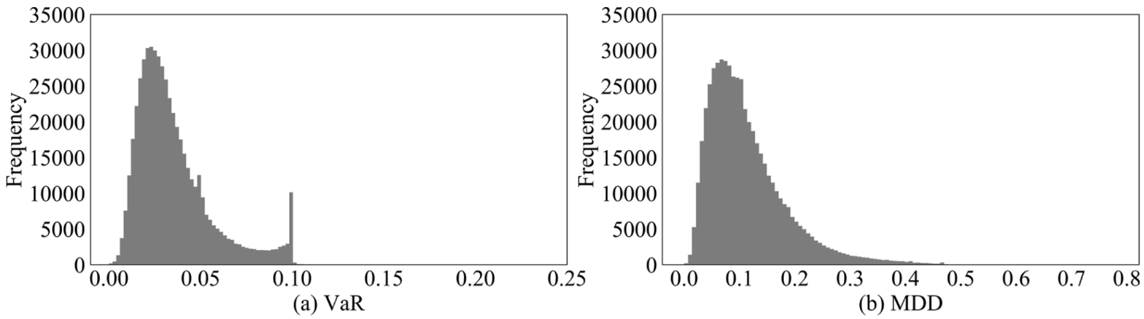


**Fig. 2.** The empirical distribution of VaR and MDD.

**Table 1**
Control Variables.

| Variable | Definition |
|---|---|
| Beta | The market beta of each stock with respect to the value-weighted market index, more details in Fama and French (2015). |
| Size | The logarithm of market equity, more details in Fama and French (2015). |
| BM | The logarithm ratio of book equity to market equity, more details in Fama and French (2015). |
| Invest | The growth rate of total assets, more details in Fama and French (2015). |
| Profit | The annual revenues minus cost of goods sold, interest expense, selling expense, general expense and administrative expense divided by book equity, more details in Fama and French (2015). |
| REV | The average excess return of each stock during the previous month, more details in Klein (1990). |
| MOM | The average excess return of each stock during the past 11 months after skipping one month, more details in Jegadeesh and Titman (1993). |
| MAX | The highest excess returns of each stock in the previous month, more details in Bali et al. (2011). |
| Skew | The skewness of stock excess returns in the previous month, more details in Ang et al. (2006a). |
| Kurt | The kurtosis of stock excess returns in the previous month, more details in Ang et al. (2006a). |
| Co-Skew | The coefficient of the squared excess market return term from a regression of the excess returns of each stock on the excess market returns and the squared excess market returns in the previous month, more details in Ang et al. (2006a) and Schneider et al. (2020). |
| Co-Kurt | The coefficient of the cubed excess market return term from a regression of the excess returns of each stock on the excess market returns and the cubed excess market returns in the previous month, more details in Ang et al. (2006a) and Schneider et al. (2020). |
| Abnormal Turn | The ratio of the total turnover in the previous month to the total turnover in the past year, more details in Statman et al. (2006). |
| Turn | The average turnover of each stock in the previous month, more details in Statman et al. (2006). |
| ILLIQ | The logarithmic form of the absolute excess return of each stock divided by its trading volume averaged over the past year, more details in Amihud (2002). |
| LIQU | The difference between the absolute excess return of each stock divided by its trading volume averaged over the recent month and its past 12-months average multiplying by −1, more details in Bali et al. (2014b). |
| VOLDU | The abnormal dollar volume calculated as the difference between the monthly dollar volume and its past 12-month average, more details in Atilgan et al. (2020). |
| Beta Down | The sensitivity of each stock toward the value-weighted market index during the days that the market return is lower than its mean value in the previous month, more details in Ang et al. (2006a). |
| TDR | The common volatility component of a stock relative to the market downside risk in the previous month, more details in Kelly and Jiang (2014). |
| IVOL | The standard deviation of the error terms calculated from a five-factor model proposed by Fama and French (2015) in the previous month, more details in Ang et al. (2006b). |
| IVOLSU | The short-term shock of IVOL constructed similarly to SU, more details see Eq. (13). |
| IVOLLU | The long-term shock of IVOL constructed similarly to LU, more details see Eq. (14). |
| CVRG | The number of analysts following a stock in the recent year, more details in Atilgan et al. (2020). |
| DISP | The standard deviation of earnings per share forecasts provided by analysts divided by the absolute value of the mean of them for the recent fiscal year, more details in Johnson (2004). |
| SUE | The difference between stock actual earnings per share and the expected analysts' forecast scaling by its price for the recent fiscal year, more details in Livnat and Mendenhall (2006). |

### *3.3. Descriptive statistics*

Table 2 reports the descriptive statistics metrics for SU, LU, and all the control variables listed in Table 1. There are 7 statistics metrics in total: average value (Mean), standard deviation (SD), 25% quantile value (Q25%), median value (Q50%), 75% quantile value (Q75%), the linear correlation coefficient between SU and another variable (Corr SU) and the linear correlation coefficient between LU and another variable (Corr LU). It is worth noting that the autocorrelation coefficient between SU and LU is just 0.01. This implies that there is no obvious intertemporal association with each other.

## 4. Empirical results

In this part, we first test the anomalous relation between SU (or LU) and future stock returns by univariate portfolio analysis, bivariate portfolio analysis, and firm-level cross-sectional regression analysis, which are widely used in previous empirical asset pricing literature. Then, we further investigate which stock is the main source of the anomaly and when the anomaly performs more obviously.

### *4.1. Univariate portfolio analysis*

In this section, we construct decile portfolios to test the anomalous relation between SU (or LU) and one-month-ahead returns of stocks. The decile portfolios are formed by sorting stocks based on SU (or LU) each month. Most of all, we construct the zero-cost portfolio which takes a long position in the highest SU (or LU) decile portfolio and a short position in the lowest SU (or LU) decile portfolio to test whether there are significant return differences between the highest and the lowest decile portfolio. The return of the zero-cost portfolio (the return difference between the extreme decile portfolios) formed based on SU represents the effect of representativeness heuristic bias, while the return of the zero-cost portfolio formed based on LU represents the effect of conservatism bias.

Table 3 presents the performance of the decile portfolios formed based on SU and LU. First, we only focus on SU. We can see that the average one-month ahead excess return of the lowest equal-weighted decile portfolio (Port 1) formed based on SU is 0.53% and the average one-month ahead excess return of the highest equal-weighted decile portfolio (Port 10) is 1.33%. The average excess return

**Table 2**
Descriptive statistics.

| | Mean | SD | Q25% | Q50% | Q75% | Corr SU | Corr LU |
|---|---|---|---|---|---|---|---|
| SU | −0.0010 | 0.0520 | −0.034 | −0.008 | 0.024 | 1.00 | −0.01 |
| LU | −0.0010 | 0.0220 | −0.013 | −0.002 | 0.010 | −0.01 | 1.00 |
| Beta | 1.0619 | 0.5707 | 0.753 | 1.067 | 1.363 | 0.13 | −0.02 |
| Size | 21.6078 | 1.2999 | 20.680 | 21.568 | 22.429 | 0.00 | 0.04 |
| BM | 0.5447 | 0.3548 | 0.302 | 0.487 | 0.726 | 0.02 | −0.05 |
| Invest | 0.1095 | 0.2211 | 0.000 | 0.071 | 0.186 | 0.01 | 0.02 |
| Profit | 0.0604 | 0.1635 | 0.028 | 0.071 | 0.115 | 0.01 | 0.01 |
| REV | 0.0005 | 0.0067 | −0.003 | 0.000 | 0.004 | −0.37 | 0.09 |
| MOM | 0.0005 | 0.0021 | −0.001 | 0.000 | 0.002 | 0.12 | −0.20 |
| MAX | 0.0548 | 0.0287 | 0.032 | 0.048 | 0.074 | 0.23 | 0.11 |
| Skew | 0.0478 | 0.7934 | −0.425 | 0.036 | 0.518 | −0.10 | 0.03 |
| Kurt | 0.8790 | 1.8637 | −0.355 | 0.382 | 1.534 | −0.10 | −0.04 |
| Coskew | −0.0756 | 0.4133 | −0.339 | −0.079 | 0.186 | −0.12 | 0.04 |
| Cokurt | −0.1479 | 7.5220 | −0.918 | −0.144 | 0.616 | −0.01 | 0.00 |
| Abnormal Turn | 0.0839 | 0.0608 | 0.044 | 0.068 | 0.106 | 0.10 | −0.05 |
| Turn | 0.0024 | 0.0025 | 0.001 | 0.002 | 0.003 | 0.09 | 0.03 |
| ILLIQ | 2.0841 | 1.1181 | 1.212 | 1.919 | 2.828 | 0.01 | 0.08 |
| LIQU | 3.4504 | 98.7791 | −0.793 | 0.361 | 2.633 | −0.03 | 0.03 |
| VOLDU | 0.0033 | 0.1844 | −0.028 | −0.004 | 0.015 | 0.07 | −0.11 |
| Beta Down | 1.1451 | 1.2175 | 0.561 | 1.155 | 1.734 | 0.07 | −0.01 |
| TDR | 0.0269 | 0.0251 | 0.015 | 0.022 | 0.032 | 0.17 | 0.03 |
| IVOL | 0.0164 | 0.0087 | 0.010 | 0.015 | 0.021 | 0.26 | 0.05 |
| IVOLSU | −0.0001 | 0.0064 | −0.004 | −0.001 | 0.003 | 0.41 | 0.01 |
| IVOLLU | 0.0000 | 0.0027 | −0.002 | 0.000 | 0.002 | 0.17 | 0.51 |
| CVRG | 6.8855 | 14.8345 | 0.000 | 0.000 | 7.000 | −0.01 | −0.01 |
| DISP | 0.3664 | 0.5314 | 0.163 | 0.286 | 0.457 | −0.01 | −0.02 |
| SUE | −0.0438 | 0.1391 | −0.047 | −0.017 | −0.004 | 0.02 | −0.01 |

Notes: This table presents the descriptive statistics metrics for SU, LU, and various monthly firm-specific variables from January 1997 to June 2022. Statistics metrics include: average value (Mean), standard deviation (SD), 25% quantile value (Q25%), median value (Q50%), 75% quantile value (Q75%), the linear correlation coefficients between SU and another variable (Corr SU) and the linear correlation coefficients between LU and another variable (Corr LU).

**Table 3**
Univariate portfolio analysis.

| | SU | | | | LU | | | |
|---|---|---|---|---|---|---|---|---|
| | EV | | VW | | EV | | VW | |
| | Alpha | Mean | Alpha | Mean | Alpha | Mean | Alpha | Mean |
| Port 1 | −0.88 | 0.53 | −0.71 | 0.23 | 0.26 | 1.49 | 0.48 | 1.33 |
| Port 2 | −0.43 | 0.90 | −0.17 | 0.68 | 0.06 | 1.36 | 0.23 | 1.00 |
| Port 3 | −0.37 | 0.98 | −0.29 | 0.59 | 0.06 | 1.32 | 0.36 | 1.08 |
| Port 4 | −0.24 | 1.15 | −0.06 | 0.77 | 0.10 | 1.36 | 0.21 | 1.02 |
| Port 5 | −0.17 | 1.21 | 0.01 | 0.84 | −0.04 | 1.24 | 0.06 | 0.81 |
| Port 6 | −0.09 | 1.27 | 0.15 | 0.97 | −0.23 | 1.07 | 0.00 | 0.73 |
| Port 7 | −0.03 | 1.31 | 0.27 | 1.10 | −0.23 | 1.05 | −0.11 | 0.64 |
| Port 8 | 0.08 | 1.44 | 0.37 | 1.18 | −0.41 | 0.88 | −0.47 | 0.27 |
| Port 9 | 0.16 | 1.52 | 0.33 | 1.18 | −0.45 | 0.85 | −0.10 | 0.65 |
| Port 10 | −0.01 | 1.33 | 0.33 | 1.10 | −0.99 | 0.41 | −0.73 | 0.09 |
| High - Low | 0.87*** | 0.79*** | 1.04*** | 0.87*** | −1.25*** | −1.08*** | −1.21*** | −1.24*** |
| | (3.26) | (3.06) | (3.28) | (2.77) | (-5.51) | (-5.37) | (-4.12) | (-4.49) |

Notes: This table presents average excess returns and alphas (%) of decile portfolios formed monthly based on SU (or LU) from January 1997 to June 2022. Port 1 is the decile portfolio of stocks with the lowest SU (or LU) and Port 10 is the decile portfolio of stocks with the highest SU (or LU). High - Low means the differences between Port 10 and Port 1. Mean represents the average one-month-ahead excess return of the portfolio. Alpha denotes the average one-month-ahead excess return adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015). EW represents the result for the equal-weighted portfolio. VW represents the result for the value-weighted portfolio. Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

difference between Port10 and Port1 (High-Low) is 0.79% with a Newey and West (1987) t-statistic of 3.06, which is significant at the 1% level. The value-weighted average excess return difference between Port 10 and Port 1 (High-Low) is 0.87% with a significantly positive Newey and West (1987) t-statistic of 2.77. These results indicate that the stock with a higher SU has a significantly higher expected excess return than the stock with a lower SU.

Next, we examine whether the average excess return of the zero-cost portfolio formed based on SU can be explained by asset pricing models. We use the five-factor model containing market, size, value, profit, and investment factors presented by Fama and French (2015) to adjust the excess return of the portfolio. The results show that the abnormal return (alpha) of the zero-cost portfolio remains positive. Specifically, the equal-weighted zero-cost portfolio exhibits an alpha of 0.87% with a t-statistic of 3.26, which is significant at the 1% level; the value-weighted zero-cost portfolio exhibits an alpha of 1.04% with a t-statistic of 3.28, which is significant at the 1% level. All the results above indicate that representativeness heuristic bias can make the stock with higher SU have higher future expected returns.

The results of the decile portfolios formed based on LU are opposite to those formed based on SU. The average excess return of the lowest equal-weighted decile portfolio (Port 1) formed based on LU is 1.49%, and the highest equal-weighted decile portfolio (Port 10) formed based on LU is 0.41%. The average excess return difference between Port 10 and Port 1 is −1.08% with a t-statistic of −5.37, which is significant at the 1% level. The average excess return difference remains negative even after adjusting for the five-factor model. Moreover, there exist similar results when we alternatively adopt value-weighted decile portfolios. These results indicate that conservatism bias can make the stock with higher LU have lower future expected returns.

Overall, Table 3 confirms that SU and LU are positively and negatively related to future stock returns, respectively. The results also confirm that Scheme (D) in Proposition 1 is in line with the Chinese stock market, meanwhile reject the other three schemes since they cannot generate such relationships.

### 4.2. Bivariate portfolio analysis

We have observed that SU is positively related to future stock returns and LU is negatively related to future stock returns. However, according to previous studies, the anomalous relation may be explained by some commonly used firm-specific characteristics, which have been found to significantly impact future stock returns. Therefore, in this section, we control for the influence of these characteristics one by one using the bivariate portfolio analysis method.

Above all, we investigate whether the firm-specific characteristics listed in Table 1 can potentially explain the anomalous relation between SU (or LU) and future returns. We first calculate the cross-sectional averages of each characteristic for the quintile portfolios formed based on SU (or LU) each month, and then report the average time-series differences between the highest quintile portfolio and

**Table 4**
Bivariate portfolio analysis based on 5*5 dependent double sorts.

| | SU (1) Difference | (2) Alpha | (3) t-statistic | LU (4) Difference | (5) Alpha | (6) t-statistic |
|---|---|---|---|---|---|---|
| SU | | | | −0.0090*** | −0.83*** | (-4.92) |
| LU | −0.0026*** | 0.60*** | (2.98) | | | |
| Beta | 0.3055*** | 0.63*** | (3.29) | 0.0225*** | −0.91*** | (-5.07) |
| Size | 0.1107*** | 0.75*** | (3.72) | 0.1585*** | −0.87*** | (-5.57) |
| BM | 0.0209*** | 0.74*** | (3.61) | −0.0330*** | −0.88*** | (-4.71) |
| Invest | 0.0252*** | 0.70*** | (3.40) | 0.0136*** | −0.84*** | (-4.58) |
| Profit | 0.0137*** | 0.66*** | (3.40) | 0.0001 | −0.85*** | (-5.55) |
| REV | −0.0044*** | 0.45** | (2.41) | 0.0012*** | −0.79*** | (-4.43) |
| MOM | 0.0005*** | 0.57*** | (3.16) | −0.0006*** | −0.70*** | (-4.22) |
| MAX | 0.0070*** | 0.79*** | (3.71) | 0.0024*** | −0.84*** | (-4.54) |
| Skew | −0.1543*** | 0.64*** | (3.15) | 0.0586*** | −0.86*** | (-4.77) |
| Kurt | 0.0411 | 0.69*** | (3.27) | −0.0924*** | −0.87*** | (-4.52) |
| Coskew | −0.2216*** | 0.59*** | (2.88) | 0.0498*** | −0.81*** | (-4.39) |
| Cokurt | −0.2663* | 0.65*** | (3.19) | −0.0117 | −0.86*** | (-4.67) |
| Abnormal Turn | 0.0174*** | 0.82*** | (3.99) | −0.0108*** | −0.93*** | (-5.11) |
| Turn | 0.0004*** | 0.87*** | (4.52) | 0.0001* | −0.76*** | (-4.59) |
| ILLIQ | −0.0595*** | 0.75*** | (3.65) | −0.0871*** | −0.84*** | (-4.61) |
| LIQU | −1.1834 | 0.70*** | (3.39) | 3.9834** | −0.82*** | (-4.40) |
| VOLDU | 0.0265*** | 0.74*** | (3.61) | −0.0250*** | −0.91*** | (-4.92) |
| Beta Down | 0.3636*** | 0.64*** | (3.19) | 0.0149 | −0.80*** | (-4.39) |
| TDR | 0.0067*** | 0.63*** | (3.10) | 0.0005** | −0.92*** | (-4.77) |
| IVOL | 0.0034*** | 0.89*** | (4.26) | 0.0001 | −0.79*** | (-4.24) |
| IVOLSU | 0.0050*** | 1.00*** | (4.76) | −0.0004*** | −0.87*** | (-4.61) |
| IVOLLU | 0.0008*** | 0.75*** | (3.62) | 0.0028*** | −1.06*** | (-6.32) |
| CVRG | 1.4695*** | 0.69*** | (3.59) | 1.0780*** | −0.91*** | (-5.78) |
| DISP | −0.0049 | 0.70*** | (3.52) | 0.0121 | −0.88*** | (-5.12) |
| SUE | 0.0094*** | 0.70*** | (3.36) | −0.0016 | −0.88*** | (-4.68) |

Notes: This table presents results from the equal-weighted bivariate portfolios based on 5*5 dependent double sorts of various firm-specific characteristics and SU (or LU) between January 1997 and June 2022. Column (1) (or (4)) represents the average difference in firm-specific characteristics between the highest and the lowest SU (or LU) quintile portfolio. The bivariate portfolios are formed as follows: first, quintile portfolios are formed monthly based on a firm-specific characteristic; then, additional quintile portfolios are formed based on SU (or LU) within each firm-specific characteristic quintile. Port 1 is the combined portfolio of stocks with the lowest SU (or LU) in each firm-specific characteristic quintile. Port 5 is the combined portfolio of stocks with the highest SU (or LU) in each firm-specific characteristic quintile. Alpha (%) denotes the average one-month-ahead excess return difference between Port 5 and Port 1 adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015), and the corresponding Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

the lowest quintile portfolio in Column (1) (or Column (4)) of Table 4. We can see that the average difference in each characteristic formed based on either SU or LU quintiles is significantly far from zero, besides DISP.

Then, we sort stocks based on SU (or LU) and each firm-specific characteristic following the bivariate portfolio analysis method to test whether the relation between SU (or LU) and future return can be explained by these firm-specific characteristics. It is worth noting that the number of companies in the Chinese A-share markets seems inadequate to conduct 10*10 bivariate sorted portfolios as Atilgan et al. (2020) in the early years of the sample, e.g., there are only approximately 750 firms at the end of 1997. To obtain enough firms per portfolio, we alternatively adopt the 5*5 dependent double sorts. Specifically, we first sort stocks into quintile portfolios based on a firm-specific characteristic each month; then, we sort stocks into quintile portfolios based on SU (or LU) for each firm-specific characteristic quintile portfolio. Port 1 represents the combined portfolio with the lowest SU (or LU) in each firm-specific characteristic quintile, and Port 10 represents the combined portfolio with the highest SU (or LU) in each firm-specific characteristic quintile. Columns (2) and (3) of Table 4 show that the abnormal return between Port 10 and Port 1 formed based on SU is significantly positive no matter which firm-specific characteristic is controlled. Columns (5) and (6) of Table 4 show that the abnormal return between Port 10 and Port 1 formed based on LU is significantly negative no matter which firm-specific characteristic is controlled. These results show that the abnormal return based on SU and LU cannot be explained by the firm-specific characteristics listed in Table 1.

### *4.3. Firm-level cross-sectional regression analysis*

The bivariate portfolio analysis method can only control for firm-specific characteristics one by one. To control for all the characteristics at the same time, we further run firm-level cross-sectional regressions for each month. The dependent variable is the one-month-ahead excess returns for each stock, the independent variables are lagged SU, LU, and control variables are listed in Table 1 (Fama & MacBeth, 1973). Columns (1) to (3) of Table 5 show the estimation from the ordinary least squares (OLS) method, and Columns (4) to (6) of Table 5 report the estimation from the weighted least squares (WLS) method presented by Asparouhova et al. (2013).

Column (1) shows that the slope coefficient of SU is 0.041, which is significant at the 5% level without considering LU. Column (2) shows that the slope coefficient of LU is −0.087, which is significant at the 1% level without considering SU. Column (3) shows that SU and LU still obtain a positive and a negative slope coefficient, respectively, when we consider both SU and LU at the same time. Similar

**Table 5**
Firm-level cross-sectional regressions.

| | OLS | | | WLS | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| SU | 0.041** | | 0.036** | 0.044** | | 0.038** |
| LU | | −0.087*** | −0.066** | | −0.096** | −0.076** |
| Beta | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| Size | −0.004*** | −0.004*** | −0.004*** | −0.004** | −0.004** | −0.004** |
| BM | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Invest | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Profit | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| REV | −0.001 | −0.002* | −0.001 | −0.001 | −0.002 | −0.001 |
| MOM | 0.001 | 0.000 | 0.001 | 0.001 | 0.000 | 0.001 |
| MAX | −0.002 | −0.001 | −0.002 | −0.002* | −0.001 | −0.002* |
| Skew | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Kurt | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Coskew | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| Cokurt | −0.004 | −0.003 | −0.004 | −0.005 | −0.004 | −0.005 |
| Abnormal Turn | −0.003** | −0.003** | −0.003** | −0.003** | −0.003** | −0.003*** |
| Turn | −0.005*** | −0.005*** | −0.005*** | −0.005*** | −0.005*** | −0.004*** |
| ILLIQ | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| LIQU | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 |
| VOLDU | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Beta Down | 0.003** | 0.003** | 0.003** | 0.003** | 0.003** | 0.003** |
| TDR | 0.006** | 0.006** | 0.006** | 0.006** | 0.006** | 0.006** |
| IVOL | −0.004*** | −0.004*** | −0.004*** | −0.004*** | −0.003*** | −0.003*** |
| IVOLSU | 0.000 | 0.001 | 0.000 | 0.000 | 0.001 | 0.000 |
| IVOLLU | −0.002*** | −0.001 | −0.001 | −0.002*** | −0.001 | −0.001 |
| CVRG | 0.002* | 0.002* | 0.002* | 0.002 | 0.002* | 0.002 |
| DISP | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 |
| SUE | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |

Notes: This table presents the result from the cross-sectional regressions of future stock returns on SU, LU and various control variables between January 1997 and June 2022. The first three columns present results estimated for one-month-ahead excess returns using the ordinary least squares (OLS) methodology. The last three columns present results estimated for one-month-ahead excess returns using the weighted least squares (WLS) methodology from Asparouhova et al. (2013), where each one-month-ahead excess return is weighted by one plus the prior month's excess return on each stock. Reported coefficients are time-series averages from monthly Fama and MacBeth (1973) regressions. To simplify the table, all the control variables are normalized. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels using the Newey and West (1987) procedure, respectively.

results are also observed in Columns (4) to (6) for the WLS regressions. Overall, these results show that SU and LU have an opposite impact on future returns in the cross-section and the anomalous relationships cannot be explained by the variables listed in Table 1.

### 4.4. Mean-variance spanning tests

Since SU and LU use the information on downside risks, which empirically have a significant influence on future stock returns, there is a logical question whether SU and LU provide extra information besides traditional downside risk proxies. To answer the question, we provide a mean–variance spanning test on the hypothesis of whether the zero-cost portfolio formed based on SU (or LU) can be spanned or replicated in the mean–variance space by a set of benchmark portfolios formed based on traditional downside risk proxies following Kan and Zhou (2012).

The mean–variance spanning test is a test on the hypothesis of whether $N$ target assets lie outside the mean–variance frontier of other $K$ benchmark assets, which was first proposed by Huberman and Kandel (1987). Bekaert and Urias (1996), De Roon et al. (2001), and Kan and Zhou (2012) provide additional tests of the same hypothesis. Statistically, we run a regression of the returns of the zero-cost portfolio formed based on SU (or LU) on the returns of the zero-cost portfolio formed based on several downside risk proxies, that is

$$r_t^{SU}\left(or r_t^{LU}\right) = a + \sum_{j=1}^{s} b_j r_t^j + \epsilon_t \tag{16}$$

where $r_t^{SU}$ (or $r_t^{LU}$) represents the returns of the zero-cost portfolio formed based on SU (or LU) at month $t$; $r_t^j$ represents the returns of the zero-cost portfolio formed based on proxy $j$ at month $t$; there are $s$ downside risk proxies in total. The spanning hypothesis is equivalent to the following parametric restrictions on the model

$$H_0 : a = 0 \; and \; \sum_{j=1}^{s} b_j = 1 \tag{17}$$

Our paper considers 5 downside risk proxies in total: Beta Down, TDR, VaR, LPM, and $\overline{\text{MDD}}$. Beta Down and TDR are two systemic downside risk proxies, which are parts of aggregate downside risk and have been introduced in Table 1. VaR and LPM are two widely used aggregate downside risk proxies, where VaR is calculated as the 95% quantile of daily stock returns multiplied by $-1$ (Atilgan et al., 2020) and LPM is calculated as the average square for the stock return lower than zero (Bali et al., 2014a; Liu et al., 2021). $\overline{\text{MDD}}$ represent the aggregate downside risk proxy used in this paper, that is the average monthly maximum drawdown of the stock within the past two years (that is $\widehat{\lambda}_i^t$ introduced in Section 3.2.1). It is worth noting that the “aggregate” is just used to be distinguished from “systemic” in this section and it is omitted by default in other sections.

Table 6 shows that the hypothesis, that is the portfolio formed based on SU or LU is inside the mean–variance frontier of portfolios formed based on other downside risk proxies, is strongly rejected. In other words, SU and LU are clearly unique factors that provide extra information besides traditional well-known downside risk proxies.

### 4.5. Institutional ownership

The previous sections have confirmed that SU is positively related to future stock returns and LU is negatively related to future stock returns in the Chinese A-share market. In this section, we will investigate which stocks are the main source of the anomalous relation. According to Atilgan et al. (2020) and Chuang and Susmel (2011), institutional investors are more likely to make rational decisions with professional tools and teams. Therefore, we conjecture that the anomalies caused by representativeness heuristic bias and conservatism bias should be more pronounced for stocks in which retail investors are more active than stocks in which institutional investors are more active.

In Table 7, we uniformly divide stocks into three parts based on the ratio of institutional ownership (Ins) monthly. High Ins denotes the group with the highest institutional ownership ratio each month and Low Ins denotes the group with the lowest institutional ownership ratio each month. We report the performance of the decile portfolios formed based on SU and LU in the two extreme groups. We can see that the alpha formed based on SU with low ratios of institutional ownership is higher than that with high ratios of

**Table 6**
Mean-variance spanning tests.

| | LR | W | LM | F |
|---|---|---|---|---|
| SU | 79.5505 | 91.3970 | 69.6658 | 42.8911 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| LU | 20.0364 | 20.7375 | 19.3667 | 9.7318 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0001) |

Notes: This table reports the results of testing whether the abnormal returns caused by SU and LU can be spanned by several widely used downside risk proxies. The sample period is from January 1997 to June 2022. Column LR reports the result of likelihood ratio test; Column W reports the result of Wald test; Column LM reports the result of Lagrange multiplier test; Column F reports the result of F-test. More details see Kan and Zhou (2012). The corresponding p-values are in parentheses.

**Table 7**
Institutional ownership.

| | SU | | | | LU | | | |
|---|---|---|---|---|---|---|---|---|
| | EW | | VW | | EW | | VW | |
| | High Ins | Low Ins | High Ins | Low Ins | High Ins | Low Ins | High Ins | Low Ins |
| Port 1 | 0.57 | −0.09 | 0.41 | −0.45 | 1.36 | 1.40 | 1.14 | 1.25 |
| Port 2 | 0.72 | 0.52 | 0.56 | 0.12 | 1.27 | 1.13 | 1.04 | 0.88 |
| Port 3 | 0.81 | 0.78 | 0.49 | 0.53 | 1.21 | 1.12 | 1.04 | 0.80 |
| Port 4 | 0.92 | 0.85 | 0.76 | 0.53 | 1.42 | 1.06 | 1.08 | 0.66 |
| Port 5 | 0.96 | 1.04 | 0.69 | 0.81 | 1.04 | 0.88 | 0.76 | 0.52 |
| Port 6 | 1.23 | 0.94 | 0.98 | 0.65 | 1.01 | 0.86 | 0.85 | 0.53 |
| Port 7 | 1.16 | 1.01 | 1.02 | 0.75 | 0.80 | 0.82 | 0.47 | 0.47 |
| Port 8 | 1.42 | 1.10 | 1.33 | 0.89 | 0.89 | 0.69 | 0.76 | 0.45 |
| Port 9 | 1.41 | 1.13 | 1.23 | 0.74 | 0.71 | 0.60 | 0.53 | 0.37 |
| Port10 | 1.04 | 1.14 | 0.82 | 0.81 | 0.54 | −0.07 | 0.29 | −0.41 |
| High- | 0.47 | 1.22*** | 0.41 | 1.26*** | −0.81*** | −1.47*** | −0.84*** | −1.66*** |
| Low | (1.22) | (4.02) | (0.97) | (3.88) | (-3.00) | (-6.00) | (-2.60) | (-5.80) |
| Alpha | 0.37 | 1.10*** | 0.40 | 1.09*** | −0.62** | −1.21*** | −0.60* | −1.50*** |
| | (1.01) | (3.62) | (0.98) | (3.58) | (-2.31) | (-5.16) | (-1.78) | (-4.80) |
| Diff | | −0.73** | | −0.69** | | 0.59** | | 0.90*** |
| | | (-2.45) | | (-2.07) | | (2.33) | | (2.92) |

Notes: This table presents average excess returns and alphas (%) of decile portfolios formed monthly based on SU (or LU) with different levels of institutional ownership ratio from January 2001 to June 2022. High Ins means the subsample only containing the stock whose ratio of institutional ownership is higher than the 0.67 quantile each month, and Low Ins means the subsample only containing the stock whose ratio of institutional ownership is lower than the 0.33 quantile each month. Port 1 denotes the average one-month-ahead excess return for the decile portfolio with the lowest SU (or LU) in each subsample. Port 10 denotes the average one-month-ahead excess return of the decile portfolio with the highest SU (or LU) in each subsample. High - Low means the average one-month-ahead excess return difference between Port 10 and Port 1. Alpha denotes the average one-month-ahead excess return difference between Port 10 and Port 1 adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015). Diff denotes the differences in alphas between High Ins and Low Ins. EW represents the results for the equal-weighted portfolio. VW represents the results for the value-weighted portfolio. Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

**Table 8**
Investor sentiment.

| | SU | | | | LU | | | |
|---|---|---|---|---|---|---|---|---|
| | EW | | VW | | EW | | VW | |
| | High $ISI^{adj}$ | Low $ISI^{adj}$ | High $ISI^{adj}$ | Low $ISI^{adj}$ | High $ISI^{adj}$ | Low $ISI^{adj}$ | High $ISI^{adj}$ | Low $ISI^{adj}$ |
| Port 1 | 1.62 | −1.26 | 1.48 | −1.32 | 1.93 | 0.35 | 1.67 | 0.34 |
| Port 2 | 1.96 | −0.69 | 2.02 | −0.79 | 2.08 | 0.14 | 1.85 | 0.14 |
| Port 3 | 2.07 | −0.66 | 2.06 | −0.97 | 2.13 | 0.04 | 1.84 | −0.02 |
| Port 4 | 2.35 | −0.52 | 2.24 | −0.68 | 2.26 | 0.07 | 2.19 | 0.03 |
| Port 5 | 2.11 | −0.24 | 2.02 | −0.42 | 2.10 | −0.12 | 2.00 | −0.36 |
| Port 6 | 2.08 | −0.13 | 1.95 | −0.06 | 2.04 | −0.36 | 1.98 | −0.51 |
| Port 7 | 2.15 | −0.21 | 2.26 | −0.13 | 1.91 | −0.49 | 1.77 | −0.69 |
| Port 8 | 2.07 | 0.24 | 1.88 | 0.09 | 1.79 | −0.56 | 1.66 | −0.79 |
| Port 9 | 1.85 | 0.33 | 1.64 | 0.17 | 1.96 | −0.77 | 1.97 | −0.82 |
| Port10 | 1.32 | 0.20 | 1.29 | 0.07 | 1.39 | −1.28 | 1.06 | −1.39 |
| High- | −0.30 | 1.46*** | −0.19 | 1.39** | −0.54 | −1.63*** | −0.61 | −1.73*** |
| Low | (-0.30) | (2.97) | (-0.20) | (2.44) | (-1.40) | (-4.30) | (-1.10) | (-3.50) |
| Alpha | −0.14 | 1.69*** | −0.06 | 1.61*** | −0.46 | −1.61*** | −0.52 | −1.74*** |
| | (-0.18) | (3.61) | (-0.07) | (2.78) | (-1.22) | (-3.84) | (-1.10) | (-3.36) |
| Diff | | −1.83** | | −1.67* | | 1.15** | | 1.22* |
| | | (-2.11) | | (-1.68) | | (2.21) | | (1.82) |

Notes: This table presents average returns and alphas (%) of decile portfolios formed monthly based on SU (or LU) with different levels of $ISI^{adj}$ from January 2003 to June 2022. High $ISI^{adj}$ represents the subsample only containing the month when $ISI^{adj}$ is higher than the 0.67 quantile. Low $ISI^{adj}$ represents the subsample only containing the month when $ISI^{adj}$ is lower than the 0.33 quantile. Port 1 denotes the average one-month-ahead excess return for the decile portfolio with the lowest SU (or LU) in each subsample. Port 10 denotes the average one-month-ahead excess return of the decile portfolio with the highest SU (or LU) in each subsample. High - Low means the average one-month-ahead excess return difference between Port 10 and Port 1. Alpha denotes the average one-month-ahead excess return difference between Port 10 and Port 1 adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015). EW represents the result for the equal-weighted portfolio. VW represents the result for the value-weighted portfolio. The corresponding Newey and West (1987) adjusted t-statistics are presented in parentheses following the method in Hao et al. (2018). Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

institutional ownership. Similarly, the alpha formed based on LU with low ratios of institutional ownership is lower than that with high ratios of institutional ownership. What's more, the differences in alphas between High Ins and Low Ins are also significant. These results show that the two cognitive biases are more pronounced for stocks with less institutional participation and retail investors play the leading role in the SU and LU anomalies.

### 4.6. *Investor sentiment*

In this section, we will further investigate when investors appear to have more pronounced mis-reactions to SU and LU caused by representativeness heuristic bias and conservatism bias. Prior literature has argued that investor sentiment is the main source of several market anomalies since investors often have a higher level of loss aversion when investor sentiment is low (Bi & Zhu, 2020; Hao et al., 2018; He, 2022; Qadan, 2019; Wang & Song, 2021). A higher level of loss reversion should correspond to a lower price if all the other conditions remain unchanged (Ang et al., 2006a). Therefore, in our theoretical model, the level of loss aversion preference is positively correlated with parameter $\theta_1$ in Eq. (3). According to Eq. (12), a higher $\theta_1$ can cause a higher $\beta_1$ and a lower $\beta_2$, which means a more pronounced impact of SU and LU on future returns. Thus, we can conjecture that the abnormal return formed based on SU and LU should perform more obviously when investor sentiment is low.

To test this conjecture, we measure investor sentiment in the Chinese A-share market by the macro-adjusted investor sentiment index ($ISI^{adj}$), which was first proposed by Baker and Wurgler (2006) and was further improved by Ma and Sun (2012) to combine with China's national conditions. The index is formed based on the closed-end fund discount ratio, IPO volume, IPO return, market turnover, market volume, and consumer confidence index, which are beforehand adjusted by the Macro-economic Prosperity Index released from National Bureau of Statistics of China (more details in Ma and Sun (2012)). We uniformly divide stocks into three parts based on $ISI^{adj}$. High $ISI^{adj}$ denotes the subsample only containing months with the top 33.3% $ISI^{adj}$ and Low $ISI^{adj}$ represents the subsample only containing months with the bottom 33.3% $ISI^{adj}$. Table 8 reports the performance of decile portfolios formed based on SU and LU in the two groups. We can see that the alpha formed based on SU with low investor sentiments is higher than that with high investor sentiments. Similarly, the alpha formed based on LU with low investor sentiments is lower than that with high investor sentiments. What's more, the differences in alphas between High $ISI^{adj}$ and Low $ISI^{adj}$ are also significant. The finding is consistent with our conjecture mentioned above.

Overall, we find that investor sentiment has a great influence on the abnormal return formed based on SU and LU. Investors are more sensitive to past downside risks during the low investor sentiment period and thus the impact of the two cognitive biases appears to be more pronounced.

## 5. Robustness test

In this section, we provide several robust tests to confirm that SU is positively related to future stock returns and LU is negatively related to future stock returns.

**Table 9**
Alternative parameter $v$.

| $v$ | SU EW Alpha | p-value | VW Alpha | p-value | LU EW Alpha | p-value | VW Alpha | p-value |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.71** | 0.034 | 0.82 | 0.159 | −1.00*** | 0.000 | −0.85* | 0.060 |
| 2 | 0.87*** | 0.000 | 1.04** | 0.047 | −1.25*** | 0.000 | −1.21*** | 0.003 |
| 3 | 0.32 | 0.558 | 0.39 | 0.911 | −1.02*** | 0.000 | −0.91* | 0.056 |
| 4 | 0.24 | 1.000 | 0.32 | 1.000 | −0.97*** | 0.000 | −0.89* | 0.080 |
| 5 | 0.17 | 1.000 | 0.08 | 1.000 | −1.04*** | 0.000 | −0.98* | 0.053 |
| 6 | −0.05 | 1.000 | −0.09 | 1.000 | −0.83*** | 0.001 | −0.74 | 0.115 |
| 7 | −0.34 | 0.747 | −0.30 | 1.000 | −0.55** | 0.032 | −0.47 | 0.569 |
| 8 | −0.44 | 0.314 | −0.30 | 1.000 | −0.34 | 0.332 | −0.36 | 0.911 |
| 9 | −0.57 | 0.112 | −0.41 | 0.952 | −0.18 | 1.000 | −0.36 | 1.000 |
| 10 | −0.48 | 0.326 | −0.34 | 1.000 | −0.38 | 0.319 | −0.46 | 0.911 |
| 11 | −0.55 | 0.172 | −0.42 | 0.911 | −0.57** | 0.013 | −0.60 | 0.203 |

Notes: This table presents the difference in alphas (%) between the highest decile portfolio and the lowest decile portfolio formed monthly based on the SU (or LU) calculated with different values of $v$ from January 1997 to June 2022. EW represents the result for the equal-weighted portfolio. VW represents the result for the value-weighted portfolio. Port 1 is the decile portfolio of stocks with the lowest SU (or LU) and Port 10 is the decile portfolio of stocks with the highest SU (or LU). Alpha denotes the average one-month-ahead excess return difference between Port 10 and Port 1 adjusted by the market, size, value, profitability and investment factors from Fama and French (2015). We adopt the multiple testing adjustment approach proposed by Benjamini and Yekutieli (2001) to test the significant of all these zero-cost portfolios' returns and the corresponding adjusted p-values are reported in Columns p-value. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

### 5.1. Alternative windows

In the above empirical tests, we calculate SU and LU with window parameter $v = 2$ by default. In this section, we will calculate SU and LU with alternative values of $v$. The corresponding performances of decile portfolios are reported in Table 9.

Since we use the same data while evaluating a battery of portfolios formed based on SU or LU with different hyper-parameters, the concern of p-hacking or multiple testing may arise in this scenario (Harvey & Liu, 2021; Harvey et al., 2016; Hou et al., 2020). In other words, when there are many portfolios or factors that are tested, some will look significant purely by luck. Thus, the traditional single significance test (Newey and West (1987) adjusted $t$-test method) may be too conservative for Table 9. To avoid the lucky false discovery, we need to make the significance test more stringent. Specifically, we adopt the multiple testing adjustment method proposed by Benjamini and Yekutieli (2001) to test the significance of abnormal returns in Table 9. Although there are also some other multiple testing adjustment methods, e.g., Harvey et al. (2016), most of them are less stringent. The corresponding adjusted p-values are reported in Table 9.

According to Table 9, regardless of using the equal-weighted or the value-weighted method, when $v \leq 5$, the alpha of the zero-cost portfolio formed based on SU is positive and the alpha of the zero-cost portfolio formed based on LU is negative. In addition, Table 9 shows that as the value of $v$ increases, the alpha of the zero-cost portfolio formed based on SU generally increases first and then decreases, while the alpha of the zero-cost portfolio formed based on LU generally decreases first and then increases. This is in line with the expressions in Scheme (D) and Eq. (12). Specifically, according to Scheme (D), weight $w_l$ will decrease first and then increase as $v$ increases; thus, the coefficient $\beta_1(v) \propto w_1 - w_{v+1}$ in Eq. (12), which represents the anomalous relation between SU and future returns, is supposed to increase first and then decrease as $v$ increases. Similarly, the coefficient $\beta_2(v) \propto w_{v+1} - w_k$ in Eq. (12), which represents the anomalous relation between LU and future returns, is supposed to decrease first and then increase as $v$ increases. Last but not the least, Table 9 shows that, when $v = 2$, the alphas of the zero-cost portfolios formed based on SU reach the maximum value and the alphas of the zero-cost portfolios formed based on LU reach the minimum value. Furthermore, they are statistically significant at least 5% level even after using the multiple testing adjustment.

### 5.2. Orthogonalization with respect to other characteristics

To ensure that the abnormal returns formed based on SU and LU are not driven by some market anomalies or firm-level characteristics, we use bivariate portfolios and firm-level cross-sectional regressions to control their influences in Table 4 and Table 5. In this section, we conduct another robustness check by orthogonalizing SU and LU via monthly cross-sectional regressions of control variables listed in Table 1, that is,

$$SU_{i,t}(LU_{i,t}) = \gamma_t + \sum_{j=1}^{J} \zeta_{j,t} Control^j_{i,t} + \epsilon_{i,t} \tag{18}$$

where $Control^j_{i,t}$ denotes the value of the $j$ th control variable for stock $i$ at time $t$; $\epsilon_{i,t}$ is the error term for stock $i$ at time $t$; and $\gamma_t$ and $\zeta_{j,t}$ are slope coefficients. We denote the error term from regression (18) as SU_Orth and LU_Orth. Table 10 reports the performance of the decile portfolio formed based on SU_Orth and LU_Orth. Table 10 shows that the magnitude of the difference in average excess

**Table 10**
Orthogonalization with respect to other firm-level characteristics.

| | SU_Orth | | | | LU_Orth | | | |
|---|---|---|---|---|---|---|---|---|
| | EW | | VW | | EW | | VW | |
| | Alpha | Mean | Alpha | Mean | Alpha | Mean | Alpha | Mean |
| Port1 | −0.72 | 0.60 | −0.40 | 0.40 | −0.14 | 1.16 | 0.21 | 0.87 |
| Port2 | −0.38 | 0.85 | −0.21 | 0.48 | 0.05 | 1.28 | 0.23 | 0.88 |
| Port3 | −0.35 | 0.98 | −0.09 | 0.62 | −0.01 | 1.22 | 0.19 | 0.86 |
| Port4 | −0.26 | 1.05 | −0.09 | 0.66 | 0.00 | 1.22 | 0.19 | 0.87 |
| Port5 | −0.02 | 1.23 | 0.09 | 0.77 | −0.18 | 1.08 | 0.11 | 0.80 |
| Port6 | −0.07 | 1.17 | 0.12 | 0.81 | −0.04 | 1.21 | 0.09 | 0.82 |
| Port7 | −0.06 | 1.22 | 0.23 | 0.91 | −0.21 | 1.09 | 0.06 | 0.81 |
| Port8 | 0.04 | 1.28 | 0.25 | 0.94 | −0.33 | 0.91 | −0.23 | 0.50 |
| Port9 | 0.05 | 1.28 | 0.28 | 0.98 | −0.30 | 1.03 | −0.23 | 0.54 |
| Port10 | −0.07 | 1.18 | 0.16 | 0.83 | −0.70 | 0.62 | −0.57 | 0.23 |
| High-Low | 0.66*** | 0.58*** | 0.56*** | 0.43** | −0.57*** | −0.53*** | −0.78*** | −0.64*** |
| | (5.14) | (4.57) | (2.64) | (2.13) | (-4.93) | (-4.46) | (-3.60) | (-2.83) |

Notes: This table presents average returns and alphas (%) of decile portfolios formed monthly based on the orthogonalized SU and LU from January 1997 to June 2022. SU_Orth is the orthogonalized SU done by running a contemporaneous regression of SU on all control variables. Similarly, LU_Orth is the orthogonalized LU done by running a contemporaneous regression of LU on all control variables. Port 1 is the decile portfolio of stocks with the lowest SU_Orth (or LU_Orth). Port 10 is the decile portfolio of stocks with the highest SU_Orth (or LU_Orth). High - Low represents the differences between Port 10 and Port 1. Mean denotes the average one-month-ahead excess return. Alpha denotes the average one-month-ahead excess return adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015). EW represents the result for the equal-weighted portfolio. VW represents the result for the value-weighted portfolio. Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

return between Port 10 and Port 1 decreases when replacing SU (or LU) with SU_Orth (or LU_Orth). However, the difference based on SU_Orth is still significantly positive, and the difference based on LU_Orth is still significantly negative. Moreover, the results remain similar even after adjusting for the five-factor model from Fama and French (2015).

### 5.3. Alternative factor models

According to arbitrage pricing theory, some common risk factors can explain several empirical abnormal returns. Since Fama and French (1993) proposed the classical three-factor model, a series of improved factor models have been proposed, including the four-factor model proposed by Carhart (1997), the five-factor model proposed by Fama and French (2015), the Q-factor model proposed by Hou et al. (2015), the Chinese four-factor model proposed by Liu et al. (2019), the behavioral three-factor model from Daniel et al. (2020), and the mispricing four-factor model from Stambaugh and Yuan (2017). In addition, recent empirical studies have found that characteristics such as idiosyncratic volatility (Ang et al., 2006b), lottery demand (Bali et al., 2011), and betting against beta factor (Frazzini & Pedersen, 2014) have strong explanatory power for the anomalous relation between past risks and future returns. Since the previous sections only consider the five-factor model, we will further test other factor models and related factors for robustness in this section. All the factors are constructed based on the data in the Chinese stock market from the CSMAR database.

Table 11 reports the coefficients of time-series regressions, where the dependent variable is the one-month-ahead excess returns of the zero-cost portfolio formed based on SU and LU, and the independent variables are the factors introduced above. The slope coefficient of the constant term represents the abnormal return (alpha) of the zero-cost portfolio. Table 11 shows that the abnormal return formed based on SU is significantly positive, and the abnormal return formed based on LU is significantly negative for each regression. It indicates that these factors cannot explain the influence of SU and LU on future stock returns.

### 5.4. Subsample analysis

In this section, we will examine whether the anomalous relation between SU (or LU) and future returns is robust across different subsamples. A total of 8 subsamples are considered, and the corresponding univariate analysis results are presented in Columns (1) to (8) of Table 12, respectively.

Subsample (1) is restricted to after 2006 because the Chinese A-share market carried out the non-tradable shares reform in approximately 2005, and it was almost finished at the end of 2006. Thus, the samples after 2006 are more representative. Subsample (2) excludes special treatment stocks each month. Special treatment is a unique regulation in the Chinese stock market that marks the listed company with negative profits for several successive years. The trading rules and pricing mechanism of special treatment stocks are different from those of normal stocks (Liu et al., 2019). Subsample (3) removes the sample with the lowest 30% market equity each month. Subsample (4) removes the sample with the lowest 30% liquidity each month. Subsample (5) removes the sample with the lowest 30% liquidity or the lowest 30% market equity each month. Subsample (6) is truncated at the highest and lowest 1% SU and LU each month to exclude outliers. Subsample (7) only contains the companies traded on the Shenzhen Stock Exchange. Subsample (8) only contains the companies traded on the Shanghai Stock Exchange. We find that no matter which subsample we adopt, the result is always in line with Table 3.

**Table 11**
Alternative factor models.

| | EW | | VW | |
|---|---|---|---|---|
| | SU | LU | SU | LU |
| C4 | 0.89*** | −1.12*** | 1.04*** | −1.21*** |
| Q4 | 0.70*** | −1.05*** | 0.78** | −1.16*** |
| CH4 | 0.61** | −1.16*** | 0.86** | −1.25*** |
| DHS3 | 0.73*** | −1.14*** | 0.86*** | −1.29*** |
| SY4 | 0.56** | −1.03*** | 0.50** | −1.14*** |
| C4 + FBAB + FMAX + FIVOL | 0.98*** | −0.87*** | 0.98*** | −0.98** |
| Q4 + FBAB + FMAX + FIVOL | 0.65** | −1.01*** | 0.66** | −1.18*** |
| CH4 + FBAB + FMAX + FIVOL | 0.49** | −1.09*** | 0.64** | −1.19*** |
| DHS3 + FBAB + FMAX + FIVOL | 0.65*** | −1.08*** | 0.73** | −1.24*** |
| SY4 + FBAB + FMAX + FIVOL | 0.49** | −0.94*** | 0.45* | −1.08*** |

Notes: This table presents results from the time-series regressions of the one-month-ahead excess return differences between extreme decile portfolios formed based on SU (or LU) on various asset pricing factors from January 1997 to June 2022. EW presents the result of equal-weighted decile portfolios and VW presents the result of value-weighted decile portfolios. There are five basic factor models: the four-factor model from Carhart (1997) (C4) including factors MKT, SML, HML, and CMA; the Q-factor model from Hou et al. (2015) (Q4) including factors MKT, ME, IA and ROE; the Chinese four-factor model from Liu et al. (2019) (CH4) including factors MKT, SMB_CH, VMG, and PMO; the behavioral three-factor model from Daniel et al. (2020) (DHS3) including factors MKT, FIN, and PEAD; the mispricing four-factor model from Stambaugh and Yuan (2017) (SY4) including factors MKT, SMA_SY, PERF, and MGMT. Moreover, we augment the baseline models by betting against beta factor (BAB), lottery demand factor (FMAX) and idiosyncratic volatility factor (FIVOL). FMAX and FIVOL factors are calculated based on 2x3 independent sorts on firm size according to the method in Fama and French (2015). FBAB factor is calculated following the method in Frazzini and Pedersen (2014). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels using the Newey and West (1987) procedure, respectively.

**Table 12**
Subsample analysis.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Panel A: Equal-weighted portfolio | | | | | | | | |
| SU | 0.91** | 0.88*** | 0.89*** | 0.97*** | 0.96*** | 0.84*** | 0.82*** | 0.79*** |
| | (2.51) | (3.32) | (3.22) | (3.31) | (3.24) | (3.21) | (2.79) | (2.71) |
| LU | −0.91*** | −1.25*** | −1.35*** | −1.29*** | −1.39*** | −1.26*** | −1.33*** | −1.03*** |
| | (-3.31) | (-5.36) | (-5.59) | (-5.67) | (-5.69) | (-5.52) | (-4.80) | (-4.32) |
| Panel B: Value-weighted portfolio | | | | | | | | |
| SU | 1.13*** | 1.10*** | 1.01*** | 1.11*** | 1.06*** | 0.97*** | 0.91** | 1.01*** |
| | (2.72) | (3.38) | (3.18) | (3.30) | (3.19) | (3.09) | (2.28) | (3.20) |
| LU | −0.93*** | −1.19*** | −1.25*** | −1.25*** | −1.29*** | −1.19*** | −1.30*** | −1.04*** |
| | (-2.71) | (-4.13) | (-4.05) | (-4.14) | (-4.14) | (-4.13) | (-3.57) | (-3.25) |

Notes: This table presents the difference in alphas (%) between the highest decile portfolios and the lowest decile portfolio formed monthly based on SU (or LU) using different subsamples. Panel A presents the result of equal-weighted portfolios and Panel B presents the result of value-weighted portfolios. Alpha denotes the average one-month-ahead excess return adjusted by the market, size, value, profitability and investment factors from Fama and French (2015). Subsample (1) is restricted to after 2006. Subsample (2) excludes special treatment stocks each month. Subsample (3) removes the sample with the lowest 30% market equity each month. Subsample (4) removes the sample with the lowest 30% liquidity each month. Subsample (5) removes the sample with the lowest 30% liquidity or the lowest 30% market equity each month. Subsample (6) is truncated at the highest and lowest 1% SU and LU each month to exclude outliers. Subsample (7) only contains the companies traded on the Shenzhen Stock Exchange. Subsample (8) only contains the companies traded on the Shanghai Stock Exchange. Columns (1) to (8) report the results of these subsamples, respectively. Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

### *5.5. Alternative risk measures*

In the above empirical tests, we always measure downside risk with MDD and then use it to calculate SU and LU. In this section, we construct SU and LU based on other downside risk measures and test whether the phenomenon remains unchanged. We consider three widely used downside risk measures: CDaR, CVaR and LPM. CDaR is the general form of MDD; and CVaR and LPM are often used in the European or US stock market (Atilgan et al., 2020; Chekhlov et al., 2005). CVaR and CDaR are both one-parameter families of risk measures, and CDaR is developed based on CVaR. CVaR represents the average value of the highest $(100-\alpha)$% daily stock returns multiplied by $-1$. CDaR represents the average value of the highest $(100-\alpha)$% drawdowns calculated from the beginning of the month to the end of each trading day, where drawdown denotes the declining rate of stock prices from the peak to the end within a time interval. When $\alpha=100$, CDaR is equivalent to MDD. LPM indicates the average square for stock returns, which is lower than a target value $\tau$ (Bali et al., 2014a; Liu et al., 2021).

Table 13 reports the average excess returns and alphas of portfolios formed based on the SU and LU constructed based on $\text{CDaR}_{\alpha=90}$, $\text{CVaR}_{\alpha=90}$, and $\text{LPM}_{\tau=0}$, respectively. According to Table 13, we first find that the average excess return of deciles with higher SU is usually higher than that with lower SU (especially for portfolios from Port 1 to Port 9), and the average excess return of deciles with the highest LU is always lower than that with the lowest LU no matter which downside risk measure we adopt. These results are in keeping

**Table 13**
Alternative risk measures.

| | CDaR | | CVaR | | LPM | |
|---|---|---|---|---|---|---|
| | SU | LU | SU | LU | SU | LU |
| Port 1 | 0.54 | 1.50 | 0.85 | 1.40 | 0.70 | 1.37 |
| Port 2 | 0.86 | 1.32 | 1.11 | 1.37 | 0.92 | 1.42 |
| Port 3 | 1.01 | 1.39 | 1.20 | 1.31 | 1.13 | 1.25 |
| Port 4 | 1.16 | 1.31 | 1.18 | 1.21 | 1.23 | 1.20 |
| Port 5 | 1.23 | 1.29 | 1.32 | 1.15 | 1.30 | 1.15 |
| Port 6 | 1.21 | 1.05 | 1.33 | 1.18 | 1.31 | 1.10 |
| Port 7 | 1.36 | 1.01 | 1.27 | 1.07 | 1.31 | 1.17 |
| Port 8 | 1.41 | 0.89 | 1.21 | 0.91 | 1.34 | 0.96 |
| Port 9 | 1.52 | 0.81 | 1.26 | 0.87 | 1.34 | 0.87 |
| Port 10 | 1.34 | 0.45 | 1.09 | 0.56 | 1.08 | 0.56 |
| High - Low | 0.79*** | −1.05*** | 0.24 | −0.84*** | 0.37* | −0.81*** |
| | (3.04) | (-5.16) | (1.45) | (-4.43) | (1.69) | (-4.20) |
| Alpha | 0.88*** | −1.22*** | 0.26 | −0.95*** | 0.39* | −0.91*** |
| | (3.44) | (-5.32) | (1.53) | (-4.38) | (1.65) | (-4.19) |

Notes: This table presents average excess returns and alphas (%) of equal-weighted decile portfolios formed monthly based on the SU (or LU) constructed based on CDaR, CVaR, and LPM from January 1997 to June 2022. Port 1 is the decile portfolio of stocks with the lowest SU (or LU). Port 10 is the decile portfolio of stocks with the highest SU (or LU). High - Low means the differences between Port 10 and Port 1. The first eleven rows report the average one-month-ahead excess returns of each portfolio. Alpha denotes the average one-month-ahead excess return difference between Port 10 and Port 1 adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015). Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

with Table 3. Second, the abnormal return formed based on CDaR is more pronounced than the abnormal return formed based on CVaR and LPM. These phenomena are in accord with the viewpoint in Section 3 that the downside proxy paying more attention to intermittent or continuous declines is more suitable for stocks in the Chinese A-share market.

## 6. Evidence from the US stock market

To investigate whether the impact of representativeness heuristic bias and conservatism bias on downside risks are present in other stock markets, we further test the anomalous relation between SU (or LU) and future returns using the data from the US stock market. We obtain close prices, returns and market equities of stocks from the Center for Research in Security Prices (CSRP). The risk-free rate and monthly returns on the market (MKT), size (SMB), value (HML), profit (RMW), and investment (CMA) factors proposed by Fama and French (2015) are downloaded from Kenneth French's online data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The sample covers all the common stocks trading on the American Stock Exchange (Amex), New York Stock Exchange (NYSE) and Nasdaq from 1964 to 2020. We further remove the sample with a price less than \$5 and the sample that has more than 30% of trading days suspended in the previous week, month, or year at the end of each month.

Unlike the Chinese A-share market, we calculate the SU and LU of stocks in the US stock market based on weekly downside risks but not monthly downside risks. Specifically, similar to the method introduced in Section 3.2.1, past downside risks are proxied by weekly maximum drawdowns; the true value of the downside risk is estimated as the mean of the past 104 weeks' (approximately two years) downside risks; downside risk shocks are estimated as the differences between past downside risks and the estimated true downside risk. Then, SU is calculated as the average downside risk shock of the most recent $v$ weeks, and LU is calculated as the average downside risk shock over the past $52 - v$ weeks (approximately one year) after skipping the most recent $v$ weeks. The main reason for adopting weekly risks is that some studies, e.g., Lehmann (1990), find that the overreactions mainly happen at the weekly level in the US stock market, which makes the monthly window is too long to catch the overreaction. Our following empirical results also confirm that investors only overreact to the recent one- or two-weeks' downside risk shocks in the US.

Specifically, Table 14 shows the average excess returns and alphas of decile portfolios formed based on the SU (or LU) calculated with different values of $v$. According to Table 14, as parameter $v$ increases, the positive relation between SU and future returns and the negative relation between LU and future returns both become gradually inconspicuous. Especially when $v = 1$, the average excess returns and alphas based on SU are the most significantly positive, and the average excess returns and alphas based on LU are the most significantly negative. The results indicate that the investor with representativeness heuristic bias mainly overreacts to the recent one or two weeks' downside risk shocks, and the investor with conservatism bias mainly underreacts to the downside risk shocks excluding the recent one or two weeks. The relation is in keeping with the relation we find in the Chinese stock market, which also support Scheme (D). Moreover, compared with Table 9 which adopts the data in China, Table 14 shows that the misreactions caused by the two biases appear or disappear more quickly in the US stock market. It is in keeping with the view that investors in the US stock market may have a higher level of sophistication than those in the Chinese stock market, which could lead to a more efficient resolution of misreactions (Schwartz, 1991).

Overall, Table 14 confirms that the influence of representativeness heuristic and conservatism bias on the pricing effect of past downside risks is present not only in the Chinese A-share market but also in the US stock market. Moreover, the abnormal relation in the Chinese A-share market exists much longer than that in the US stock market.

## 7. Conclusions

The intertemporal relation between past downside risks and future returns is one of the key problems in the field of asset pricing. This paper discusses the influence of investor representativeness heuristic bias and conservatism bias on this intertemporal relation from the perspective of behavioral finance. This paper argues that the two cognitive biases widely exist in investors' decision-making process and, thus, significantly affect investors' attitudes toward past downside risks in different periods. Representativeness heuristic bias makes investors pay great attention to the new downside risk, but this enthusiasm fades quickly in the short term. In contrast, conservatism bias makes investors initially ignore the new downside risk, but they gradually start to pay more attention to it after a short period. Our theoretical model and empirical results show that the effects of the two cognitive biases are combined, that is representativeness heuristic bias mainly applies to short-term risks while conservatism bias mainly applies to long-term risks. It makes short-term downside risk shocks positively related to future stock returns and makes long-term downside risk shocks negatively related to future stock returns.

The above anomalous relation is widely present in the Chinese A-share market. These findings are stable across several robustness tests. This finding supplements the existing research on downside risk since these studies do not concern whether the pricing effects of past downside risks in different sub-periods differ. In addition, we further investigate which stocks are the main source of the phenomena and when these phenomena perform more explicitly. We find that stocks with more active retail investors and periods of low investor sentiments tend to have more pronounced anomalies. Last, we re-test the relationships using the data in the US; we find that the abnormal relationships are also present in the US but exist much shorter compared with China.

Overall, our paper shows that representativeness heuristic bias and conservatism bias play an important role in the pricing effect of past downside risks. They enable us to better understand the influence of past downside risk shocks on the equilibrium price. Our findings have the following two main practical implications: first, investors can obtain excess returns according to the anomaly proposed in our paper; second, regulators can reduce the mispricing caused by investors' cognitive bias and then improve market pricing efficiency by conducting financial knowledge popularization and guidance education for investors.

**Table 14**
Evidence from the US stock market.

| | | SU $v=1$ | $v=2$ | $v=4$ | LU $v=1$ | $v=2$ | $v=4$ |
|---|---|---|---|---|---|---|---|
| EW | Return | 1.21*** | 0.59*** | −0.01 | −1.20*** | −1.20*** | −1.09*** |
| | | (9.15) | (4.55) | (-0.05) | (-7.76) | (-7.96) | (-7.35) |
| | Alpha | 1.22*** | 0.60*** | −0.05 | −1.19*** | −1.17*** | −1.05*** |
| | | (9.36) | (4.34) | (-0.38) | (-7.88) | (-8.13) | (-7.42) |
| VW | Return | 0.94*** | 0.49*** | 0.05 | −0.85*** | −0.94*** | −0.88*** |
| | | (5.73) | (3.17) | (0.29) | (-4.26) | (-4.71) | (-4.60) |
| | Alpha | 1.02*** | 0.52*** | −0.01 | −0.84*** | −0.91*** | −0.82*** |
| | | (6.31) | (3.14) | (-0.03) | (-4.34) | (-4.69) | (-4.40) |

Note: This table presents average returns and alphas (%) of equal-weighted decile portfolios formed monthly based on the SU (or LU) calculated with different values of $v$ from 1964 to 2020 in the US stock market. Port 1 is the decile portfolio of stocks with the lowest SU (or LU) and Port 10 is the equal-weighted decile portfolio of stocks with the highest SU (or LU). Return means the differences between Port 10 and Port 1. Returns report the average one-month-ahead excess return difference between Port 10 and Port 1. Alpha denotes the average one-month-ahead excess return difference between Port 10 and Port 1 adjusted by the market, size, value, profitability, and investment factors from Fama and French (2015). Newey and West (1987) adjusted t-statistics are presented in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

### A1. Proof of Eq. (5)

According to Eq. (5), we have

$$\begin{aligned} P(\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}) &\propto \prod_{l=1}^{k} L(s_{t+1-l}|\lambda)^{w_l} \\ &\propto \prod_{l=1}^{k}\left(\frac{1}{\sigma_u\sqrt{2\pi}}\exp\left(-\frac{(s_{t+1-l}-\lambda)^2}{2\sigma_u^{\,2}}\right)\right)^{w_l} \propto \exp\left(-\frac{\sum_{l=1}^{k} w_l(s_{t+1-l}-\lambda)^2}{2\sigma_u^{\,2}}\right) \end{aligned} \tag{A.1}$$

Let $\mu = \frac{\sum_{l=1}^{k} w_l s_{t+1-l}}{\sum_{l=1}^{k} w_l}$, then we have

$$\begin{aligned} \sum_{l=1}^{k} w_l(s_{t+1-l}-\lambda)^2 &= \sum_{l=1}^{k} w_l\left((\mu-\lambda)^2 + 2\lambda\mu - 2\lambda s_{t+1-l} - \mu^2 + s_{t+1-l}{}^2\right) \\ &= \sum_{l=1}^{k} w_l(\mu-\lambda)^2 - \sum_{l=1}^{k} w_l\left(\mu^2 - s_{t+1-l}{}^2\right) \end{aligned} \tag{A.2}$$

where $\sum_{l=1}^{k} w_l(\lambda s_{t+1-l}) = \left(\sum_{l=1}^{k} w_l\right)*\lambda*\left(\frac{\sum_{l=1}^{k} w_l s_{t+1-l}}{\sum_{l=1}^{k} w_l}\right) = \sum_{l=1}^{k} w_l(\lambda\mu)$. Take Eq. (A.2) into Eq. (A.1), we have

$$\begin{aligned} P(\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}) &\propto \exp\left(-\frac{\sum_{l=1}^{k} w_l(\mu-\lambda)^2}{2\sigma_u^{\,2}} + \frac{\sum_{l=1}^{k} w_l\left(\mu^2 - s_{t+1-l}{}^2\right)}{2\sigma_u^{\,2}}\right) \\ &\propto \exp\left(-\frac{(\mu-\lambda)^2}{2\sigma_u^{\,2}\Big/\sum_{l=1}^{k} w_l}\right) \end{aligned} \tag{A.3}$$

Eq. (A.3) shows that the posterior distribution of $\lambda$, that is $\lambda|s_t, s_{t-1}, \cdots, s_{t-k+1}$, follows the normal distribution $N\left(\frac{\sum_{l=1}^{k} w_l s_{t+1-l}}{\sum_{l=1}^{k} w_l}, \frac{\sigma_u{}^2}{\sum_{l=1}^{k} w_l}\right)$.

### A2. Proof of Proposition 1

According to Eq. (6), we have

$$R_{t+1} = ln\frac{P_{t+1}}{P_t} = ln\frac{N_{t+1}\exp\left(-\theta_0-\theta_1\lambda-\frac{\theta_1\sum_{l=1}^{k}w_lu_{t+2-l}}{\sum_{l=1}^{k}w_l}+\frac{\theta_1{}^2\sigma_u{}^2}{2\sum_{l=1}^{k}w_l}\right)}{N_t\exp\left(-\theta_0-\theta_1\lambda-\frac{\theta_1\sum_{l=1}^{k}w_lu_{t+1-l}}{\sum_{l=1}^{k}w_l}+\frac{\theta_1{}^2\sigma_u{}^2}{2\sum_{l=1}^{k}w_l}\right)}$$
$$= ln\frac{N_{t+1}}{N_t}+\left(\frac{\theta_1\sum_{l=1}^{k}w_lu_{t+1-l}}{\sum_{l=1}^{k}w_l}-\frac{\theta_1\sum_{l=1}^{k}w_lu_{t+2-l}}{\sum_{l=1}^{k}w_l}\right) \tag{A.4}$$

Then, the conditional expectation of $R_{t+1}$ is given by

$$E(R_{t+1}|SU_t(v),LU_t(v)) = \alpha+\theta_1E\left(\frac{\sum_{l=1}^{k}w_lu_{t+1-l}}{\sum_{l=1}^{k}w_l}-\frac{\sum_{l=1}^{k}w_lu_{t+2-l}}{\sum_{l=1}^{k}w_l}|SU_t(v),LU_t(v)\right) \tag{A.5}$$

where $\alpha = E\left(ln\frac{N_{t+1}}{N_t}|SU_t(v),LU_t(v)\right) = E(lnN_{t+1}-lnN_t)$. Since $u_t,u_{t-1},\cdots,u_{t+1-k}$ are independent of each other, we have

$$E(u_{t+1-l}|SU_t(v),LU_t(v)) = \begin{cases} E(u_{t+1-l}|SU_t(v)); l\in[1,v+1) \\ E(u_{t+1-l}|LU_t(v)); l\in[v+1,k) \\ 0; else \end{cases} \tag{A.6}$$

Take Eq. (A.6) into (A.5), we have

$$E(R_{t+1}|SU_t(v),LU_t(v)) = \alpha+\theta_1E\left(\frac{\sum_{l=1}^{v}w_lu_{t+1-l}}{\sum_{l=1}^{k}w_l}-\frac{\sum_{l=1}^{v+1}w_lu_{t+2-l}}{\sum_{l=1}^{k}w_l}|SU_t(v),LU_t(v)\right)$$
$$+\theta_1E\left(\frac{\sum_{l=v+1}^{k}w_lu_{t+1-l}}{\sum_{l=1}^{k}w_l}-\frac{\sum_{l=v+2}^{k}w_lu_{t+2-l}}{\sum_{l=1}^{k}w_l}|SU_t(v),LU_t(v)\right)$$
$$= a+\theta_1E\left(\frac{\sum_{l=1}^{v}(w_l-w_{l+1})u_{t+1-l}}{\sum_{l=1}^{k}w_l}|SU_t(v)\right)$$
$$+\theta_1E\left(\frac{\sum_{l=v+1}^{k-1}(w_l-w_{l+1})u_{t+1-l}}{\sum_{l=1}^{k}w_l}|LU_t(v)\right) \tag{A.7}$$

Since $u_t,u_{t-1},\cdots,u_{t+1-k}$ i.i.d.$N(0,\sigma_u{}^2)$, we have

$$E(u_{t+1-l}|SU_t(v)\,) = \begin{cases} vE(x_1|x_1+x_2); l\in[1,v+1) \\ 0; l\notin[1,v+1) \end{cases} \tag{A.8}$$

where $x_1 = \frac{u_t}{v}\ N\left(0,\frac{\sigma_u{}^2}{v^2}\right)$, $x_2 = \frac{\sum_{l=2}^{v}u_{t+1-l}}{v}\ N\left(0,\frac{(v-1)\sigma_u{}^2}{v^2}\right)$; $x_1$ and $x_2$ are independent; $x_1+x_2\equiv SU_t(v)$. Consider the following equation

$$cov\left(x_1+x_2,\frac{var(x_2)}{var(x_1)}x_1-x_2\right) = var(x_2)-var(x_2) = 0 \tag{A.9}$$

It shows that $x_1+x_2$ and $\frac{var(x_2)}{var(x_1)}x_1-x_2$ are independent of each other, and thus

$$E(x_1|x_1+x_2) = \frac{var(x_1)}{var(x_1)+var(x_2)}E\left((x_1+x_2)+\left(\frac{var(x_2)}{var(x_1)}x_1-x_2\right)|x_1+x_2\right)$$
$$= \frac{E(x_1+x_2|x_1+x_2)}{v} = \frac{SU_t(v)}{v} \tag{A.10}$$

According to Eq. (A.10), we have

$$E\left(\frac{\sum_{l=1}^{v}(w_l-w_{l+1})u_{t+1-l}}{\sum_{l=1}^{k}w_l}|SU_t(v)\right) = \frac{w_1-w_{v+1}}{\sum_{l=1}^{k}w_l}SU_t(v) \tag{A.11}$$

We can also get Eq. (A.12) in a similar way as Eq. (A.11), that is

$$E\left(\frac{\sum_{l=v+1}^{k-1}(w_l - w_{l+1})u_{t+1-l}}{\sum_{l=1}^{k}w_l}|LU_t(v)\right) = \frac{w_{v+1} - w_k}{\sum_{l=1}^{k}w_l}LU_t(v) \tag{A.12}$$

Take Eqs. (A.11) and (A.12) into Eq. (A.7), we have

$$E(R_{t+1}|SU_t(v), LU_t(v)) = \alpha + \theta_1\frac{w_1 - w_{v+1}}{\sum_{l=1}^{k}w_l}SU_t(v) + \theta_1\frac{w_{v+1} - w_k}{\sum_{l=1}^{k}w_l}LU_t(v) \tag{A.13}$$

Finally, rewrite Eq. (A.13) into the following form

$$R_{t+1} = \alpha + \beta_1(v)SU_t(v) + \beta_2(v)LU_t(v) + \varepsilon_t(v) \tag{A.14}$$

where $\alpha = E(lnN_{t+1} - lnN_t)$ is a constant; $\beta_1(v)=\theta_1(w_1 - w_{v+1})/\sum_{l=1}^{k}w_l$ and $\beta_2(v) = \theta_1(w_{v+1} - w_k)/\sum_{l=1}^{k}w_l$; $\varepsilon_t(v)$ denotes a random variable which satisfies the condition $E(\varepsilon_t(v)|SU_t(v), LU_t(v)) = 0$.

The remaining proofs are similar for the four schemes. Just take Scheme (D) as an example: following Scheme (D), for $\forall v+1 \in (1, k)$ there must have $w_1 \geq w_{v+1}$ and $w_{v+1} \leq w_k$, and thus we have $\beta_1(v) \geq 0$ and $\beta_2(v) \leq 0$.

## References


Ahmad, M. (2022). The role of cognitive heuristic-driven biases in investment management activities and market efficiency: A research synthesis. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-07-2020-0749

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of financial markets, 5*, 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *The review of financial studies, 19*, 1191–1239. https://doi.org/10.1093/rfs/hhj035

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*, 259–299. https://doi.org/10.1111/j.1540-6261.2006.00836.x

Asparouhova, E., Bessembinder, H., & Kalcheva, I. (2013). Noisy prices and inference regarding returns. *The Journal of Finance, 68*, 665–714. https://doi.org/10.1111/jofi.12010

Atilgan, Y., Bali, T. G., Demirtas, K. O., & Gunaydin, A. D. (2020). Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics, 135*, 725–753. https://doi.org/10.1016/j.jfineco.2019.07.006

Bacon, C. R. (2012). Practical risk-adjusted performance measurement. *John Wiley & Sons*. https://doi.org/10.1002/9781118673621

Bai, M., Qin, Y., & Zhang, H. (2021). Stock price crashes in emerging markets. *International Review of Economics & Finance, 72*, 466–482. https://doi.org/10.1016/j.iref.2020.12.007

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance, 61*, 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*, 427–446. https://doi.org/10.1016/j.jfineco.2010.08.014

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2014). Hybrid tail risk and expected stock returns: When does the tail wag the dog? *The Review of Asset Pricing Studies, 4*, 206–246. https://doi.org/10.1093/rapstu/rau006

Bali, T. G., Peng, L., Shen, Y., & Tang, Y. (2014). Liquidity shocks and stock market reactions. *The Review of Financial Studies, 27*, 1434–1485. https://doi.org/10.1093/rfs/hht074

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies, 21*, 785–818. https://doi.org/10.1093/rfs/hhm079

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics, 49*, 307–343. https://doi.org/10.1016/S0304-405X(98)00027-0

Bekaert, G., & Urias, M. S. (1996). Diversification, integration and emerging market closed-end funds. *the. Journal of Finance, 51*, 835–869. https://doi.org/10.1111/j.1540-6261.1996.tb02709.x

Benartzi, S., & Thaler, R. H. (1995). Myopic Loss Aversion and the Equity Premium Puzzle. *The quarterly journal of Economics, 110*, 73–92. https://doi.org/10.2307/2118511

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of statistics, 1165–1188*. https://doi.org/10.1214/aos/1013699998

Bi, J., & Zhu, Y. (2020). Value at risk, cross-sectional returns and the role of investor sentiment. *Journal of Empirical Finance, 56*, 1–18. https://doi.org/10.1016/j.jempfin.2019.12.004

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance, 52*, 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chekhlov, A., Uryasev, S., & Zabarankin, M. (2005). Drawdown measure in portfolio optimization. *International Journal of Theoretical and Applied Finance, 8*, 13–58. https://doi.org/10.1142/S0219024905002767

Chen, C., & Doukas, J. A. (2022). Stock price synchronicity, cognitive biases, and momentum. *European Financial Management, 28*, 59–112. https://doi.org/10.1111/eufm.12294

Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of behavioral decision making, 20*, 425–451. https://doi.org/10.1002/bdm.561

Chuang, W.-I., & Susmel, R. (2011). Who is the more overconfident trader? Individual vs. institutional investors. *Journal of Banking & Finance, 35*, 1626–1644. https://doi.org/10.1016/j.jbankfin.2010.11.013

Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short-and long-horizon behavioral factors. *The review of financial studies, 33*, 1673–1736. https://doi.org/10.1093/rfs/hhz069

De Roon, F. A., Nijman, T. E., & Werker, B. J. (2001). Testing for mean-variance spanning with short sales constraints and transaction costs: The case of emerging markets. *The Journal of Finance, 56*, 721–742. https://doi.org/10.1111/0022-1082.00343

Edwards, W. (1968). Conservatism in human information processing. *Formal representation of human judgment*. https://doi.org/10.1017/CBO9780511809477.026

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics, 116*, 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy, 81*, 607–636. https://doi.org/10.1086/260061

Fenner, R. G., Han, Y., & Huang, Z. (2020). Idiosyncratic volatility shocks, behavior bias, and cross-sectional stock returns. *The Quarterly Review of Economics and Finance, 75*, 276–293. https://doi.org/10.1016/j.qref.2019.05.004

Fischer, K., & Lehner, O. M. (2021). Behavioral Finance Research in 2020: Cui Bono et Quo Vadis? *ACRN Journal of Finance and Risk Perspectives*, *10*, 54-76. 10.35944/JOFRP.2021.10.1.004.

Fisher, K. L., & Statman, M. (2000). Cognitive biases in market forecasts. *The Journal of Portfolio Management, 27*, 72–81. https://doi.org/10.3905/jpm.2000.319785

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics, 111*, 1–25. https://doi.org/10.1016/j.jfineco.2013.10.005

Friedman, B. M. (1979). Optimal expectations and the extreme information assumptions of 'rational expectations' macromodels. *Journal of monetary Economics, 5*, 23–41. https://doi.org/10.1016/0304-3932(79)90022-9

Grossman, S. J., & Zhou, Z. (1993). Optimal investment strategies for controlling drawdowns. *Mathematical finance, 3*, 241–276. https://doi.org/10.1111/j.1467-9965.1993.tb00044.x

Guo, X., McAleer, M., Wong, W.-K., & Zhu, L. (2017). A Bayesian approach to excess volatility, short-term underreaction and long-term overreaction during financial crises. *The North American journal of economics and finance, 42*, 346–358. https://doi.org/10.1016/j.najef.2017.08.001

Hao, Y., Chou, R. K., Ko, K.-C., & Yang, N.-T. (2018). The 52-week high, momentum, and investor sentiment. *International Review of Financial Analysis, 57*, 167–183. https://doi.org/10.1016/j.irfa.2018.01.014

Harvey, C. R., & Liu, Y. (2021). Lucky factors. *Journal of Financial Economics, 141*, 413–435. https://doi.org/10.1016/j.jfineco.2021.04.014

Harvey, C. R., Liu, Y., & Zhu, H. (2016). and the cross-section of expected returns. *The Review of Financial Studies, 29*, 5–68. https://doi.org/10.1093/rfs/hhv059

He, Z. (2022). Asymmetric impacts of individual investor sentiment on the time-varying risk-return relation in stock market. *International Review of Economics & Finance, 78*, 177–194. https://doi.org/10.1016/j.iref.2021.11.018

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics, 7*, 133–159. https://doi.org/10.1146/annurev-financial-092214-043752

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies, 28*, 650–705. https://doi.org/10.1093/rfs/hhu068

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *The Review of Financial Studies, 33*, 2019–2133. https://doi.org/10.1093/rfs/hhy131

Huang, W., Liu, Q., Rhee, S. G., & Wu, F. (2012). Extreme downside risk and expected stock returns. *Journal of Banking & Finance, 36*, 1492–1502. https://doi.org/10.1016/j.jbankfin.2011.12.014

Huang, Z., & Heian, J. B. (2010). Trading-volume shocks and stock returns: An empirical analysis. *Journal of Financial Research, 33*, 153–177. https://doi.org/10.1111/j.1475-6803.2010.01266.x

Huberman, G., & Kandel, S. (1987). Mean-variance spanning. *The. Journal of Finance, 42*, 873–888. https://doi.org/10.1111/j.1540-6261.1987.tb03917.x

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance, 45*, 881–898. https://doi.org/10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance, 48*, 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jiang, J., Liao, L., Wang, Z., & Xiang, H. (2020). Financial literacy and retail investors' financial welfare: Evidence from mutual fund investment outcomes in China. *Pacific-Basin Finance Journal, 59*, Article 101242. https://doi.org/10.1016/j.pacfin.2019.101242

Johnson, T. C. (2004). Forecast dispersion and the cross section of expected returns. *The Journal of Finance, 59*, 1957–1978. https://doi.org/10.1111/j.1540-6261.2004.00688.x

Kan, R., & Zhou, G. (2012). Tests of Mean-Variance Spanning. *ANNALS OF ECONOMICS AND FINANCE, 13*, 139–187. https://doi.org/10.1111/j.1540-6261.1987.tb03917.x

Kariofyllas, S., Philippas, D., & Siriopoulos, C. (2017). Cognitive biases in investors' behaviour under stress: Evidence from the London Stock Exchange. *International Review of Financial Analysis, 54*, 54–62. https://doi.org/10.1016/j.irfa.2017.09.003

Kelly, B., & Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies, 27*, 2841–2871. https://doi.org/10.1093/rfs/hhu039

Klein, A. (1990). A direct test of the cognitive bias theory of share price reversals. *Journal of Accounting and Economics, 13*, 155–166. https://doi.org/10.1016/0165-4101(90)90028-3

Lam, K., Liu, T., & Wong, W.-K. (2010). A pseudo-Bayesian model in financial decision making with implications to market volatility, under-and overreaction. *European Journal of Operational Research, 203*, 166–175. https://doi.org/10.1016/j.ejor.2009.07.005

Lee, C. M., & So, E. C. (2017). Uncovering expected returns: Information in analyst coverage proxies. *Journal of Financial Economics, 124*, 331–348. https://doi.org/10.1016/j.jfineco.2017.01.007

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics, 105*, 1–28. https://doi.org/10.2307/2937816

Li, H., Zheng, D., & Chen, J. (2014). Effectiveness, cause and impact of price limit—Evidence from China's cross-listed stocks. *Journal of International Financial Markets, Institutions and Money, 29*, 217–241. https://doi.org/10.1016/j.intfin.2013.12.007

Liu, J., Stambaugh, R. F., & Yuan, Y. (2019). Size and value in China. *Journal of Financial Economics, 134*, 48–69. https://doi.org/10.1016/j.jfineco.2019.03.008

Liu, Z., Lu, S., & Wang, S. (2021). Asymmetry, tail risk and time series momentum. *International Review of Financial Analysis, 78*, Article 101938. https://doi.org/10.1016/j.irfa.2021.101938

Livnat, J., & Mendenhall, R. R. (2006). Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of accounting research, 44*, 177–205. https://doi.org/10.1111/j.1475-679X.2006.00196.x

Long, H., Jiang, Y., & Zhu, Y. (2018). Idiosyncratic tail risk and expected stock returns: Evidence from the Chinese stock markets. *Finance Research Letters, 24*, 129–136. https://doi.org/10.1016/j.frl.2017.07.009

Ma, X., & Sun, J. (2012). A Study on Investor Sentiment Index Building in China Stock Market. *Journal of Beijing Technology and Business University (Social Sciences), 27*, 89–95. https://doi.org/10.16299/j.1009-6116.2012.06.016

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*, 703–708. https://doi.org/10.2307/1913610

Otuteye, E., & Siddiquee, M. (2015). Overcoming cognitive biases: A heuristic for making value investing decisions. *Journal of Behavioral Finance, 16*, 140–149. https://doi.org/10.1080/15427560.2015.1034859

Piccoli, P., Chaudhury, M., Souza, A., & da Silva, W. V. (2017). Stock overreaction to extreme market events. *The North American Journal of Economics and Finance, 41*, 97–111. https://doi.org/10.1016/j.najef.2017.04.002

Qadan, M. (2019). Risk appetite, idiosyncratic volatility and expected returns. *International Review of Financial Analysis, 65*, Article 101372. https://doi.org/10.1016/j.irfa.2019.101372

Schneider, P., Wagner, C., & Zechner, J. (2020). Low-Risk Anomalies? *The Journal of Finance, 75*, 2673–2718. https://doi.org/10.1111/jofi.12910

Schwartz, R. A. (1991). Institutionalization of the equity markets. *Journal of portfolio Management, 17*, 44. https://doi.org/10.3905/jpm.1991.409310

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The review of financial studies, 30*, 1270–1315. https://doi.org/10.1093/rfs/hhw107

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *The Review of Financial Studies, 19*, 1531–1565. https://doi.org/10.1093/rfs/hhj032

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*, 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Wang, J., & Song, X. (2021). The Effect of Limited Attention and Risk Attitude on Left-tail Reversal: Empirical Results from A-Share Data in China. *Finance Research Letters, 102089*. https://doi.org/10.1016/j.frl.2021.102089

Wu, C.-H., Wu, C.-S., & Liu, V. W. (2009). The conservatism bias in an emerging stock market: Evidence from Taiwan. *Pacific-Basin Finance Journal, 17*, 494–505. https://doi.org/10.1016/j.pacfin.2008.12.002

Zhen, F., Ruan, X., & Zhang, J. E. (2020). Left-tail risk in China. *Pacific-Basin Finance Journal, 63*, Article 101391. https://doi.org/10.1016/j.pacfin.2020.101391