Retail investors and overpricing of left-tail risk: evidence from the Korean stock market

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Abstract
The authors examined whether stocks with higher left-tail risk measures earn higher or lower futures returns. Specifically, the authors estimate the cross-sectional principal component of a battery of left-tail risk measures and analyze future returns on stocks with high principal component values. In contrast to finance theories on the risk–return trade-off relationship, the study results show that high left-tail risk stocks have lower future returns. This finding is robust to various left-tail risk measures and controls for other risk factors. Moreover, the negative relationship between the left-tail risk and returns is more pronounced for stocks that are actively traded by retail investors. This empirical result is consistent with behavioral theory that when investors make decisions based on experience, they tend to underweight the likelihood of rare events.

Keywords Left-tail risk, Behavioral finance, Retail investors, Principal component analysis

Paper type Research paper

1. Introduction
We examine whether the firm-specific left-tail risk is overestimated or underestimated in Korean stock markets. Although the effect of aggregate market tail risk on the cross-section of stock returns has been discussed both theoretically and empirically in the literature (Allen *et al.*, 2012; Kelly and Jiang, 2014; Stoja *et al.*, 2023), the effect of firm-specific tail risk has only recently gained attention in finance research. The study of the effect of firm-specific tail risk poses challenges from both theoretical and empirical standpoints because no single prediction can be derived from either.

From a theoretical standpoint, Lichtenstein *et al.* (1978) predict that rare extreme events are typically overestimated in terms of their likelihood, and Tversky and Kahneman (1992) suggest that people tend to be overweight with small probabilities of loss or gain in value

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functions. For example, people are more concerned about the risk of death than the actual probability and are willing to pay a high insurance premium to avoid it. In contrast, Hertwig *et al.* (2004) argue that when people make decisions based on experience rather than a description of a probability distribution, they tend to underestimate the likelihood of rare events. The recent global financial crisis is an example of this phenomenon in financial markets, in which investors underestimate the probability of a spiral of defaults because default events are rare. If this hypothesis is true, investors who make decisions based on experience will underestimate the likelihood of or underweight the value of the expected event in the pricing of stocks with high left-tail risk. Therefore, psychological theories cannot predict the effect of tail risk on the cross-section of stock returns.

Empirical studies provide mixed results on the relationship between left-tail risk and stock returns. While some studies, such as Huang *et al.* (2012), find a positive association between extreme downside risk and stock returns, others, such as Atilgan *et al.* (2020), find a negative relationship between left-tail risk and future stock returns as measured by value-at-risk. This inconsistency makes it difficult to support a single model or theory. However, a negative relationship between left-tail risk and returns has been observed in other countries. Long *et al.* (2019) use a comprehensive dataset of stocks from 39 countries and report a significantly negative relationship between left-tail risk and returns. Therefore, the puzzling finding is not specific to the US market, and there may be several reasons for this negative relationship.

To provide further evidence for the Korean stock market, we empirically test the cross-sectional relationship between left-tail risk and stock returns at the individual stock level rather than at the market level. As Long *et al.* (2019) show, the results can depend on the measure used as a proxy for left-tail risk. Therefore, we conduct a principal component analysis with various left-tail risk measures and use the first principal component (PC1) as a representative proxy. We sort stocks into quintile portfolios each month based on the magnitude of PC1 and then explore their returns in the following month. Our results suggest a significantly negative relationship between left-tail risk and stock returns in Korea as measured by the excess returns, CAPM alpha and FF3 alpha of the zero-cost long-short portfolio. Our double-sort portfolio analysis further confirms that this relationship is robust to controlling for various characteristics such as market beta, size, book-to-market ratio, momentum and liquidity.

While our findings are consistent with those of previous empirical studies conducted on international stock markets, they cannot be reconciled with the traditional risk-based theory of asset pricing. To address this issue, we examine the effect of unskilled traders on the negative relationship between left-tail risk and stock returns. Hertwig *et al.* (2004) propose that decision-makers may underestimate the likelihood of rare events or underweight the event in their valuation function when they receive information through the experience of repeated decisions compared to when they obtain information from prior descriptions. Based on this model, we hypothesize that investors who rely on their short-run experience rather than long-run historical data may underestimate the physical probability of left-tail events or their risk-neutral probability. Individual retail investors can be regarded as such type of investors because they typically have relatively less investment experience and are less skilled at inferring the physical probability of left-tail events from historical data.

Both underestimating the physical probability and underweighting the risk-neutral probability result in the overpricing of stocks with a higher left-tail risk; subsequently, these stocks will have lower future returns. If this decision-making process is the reason for the negative relationship, the overpricing of stocks with high left-tail risk would be more pronounced for stocks that are highly traded by individual retail investors. We confirm this conjecture through a double-sort portfolio analysis.

The Korean stock market provides a unique opportunity to test the Hertwig *et al.* (2004) model. Specifically, the Korean Exchange (KRX) offers daily trading volume information by investor type, which enables us to identify the proportion of retail trading for each stock. Sorting stocks into quintile portfolios according to the proportion of retail trading reveals that retail investors' trading volumes account for up to 75% of the total trading volume of stocks in the highest portfolio. This allows us to investigate whether the decision-making process of unskilled investors could be a reason for the overpricing of left-tail risk.

Although previous studies, such as Eom *et al.* (2023), have explored the impact of left-tail risk on the cross-sectional returns of stocks in the Korean market, our study makes several unique contributions. First, we employ principal component analysis to derive more refined left-tail risk measures. Compared with the results obtained using individual left-tail risk measures, the anomaly becomes more pronounced when considering the principal components derived from all measures. Second, we investigate the reasons behind the left-tail risk anomaly using both risk-based and behavioral theories. Notably, no existing studies have provided behavioral explanations that encompass the influence of retail traders. Furthermore, by providing evidence that refutes the explanatory power of the risk-based theory, we offer a stronger rationale for understanding anomalies within the behavioral finance framework. This study contributes to the existing literature by elucidating these issues.

The rest of this paper is organized as follows. Section 2 describes the data used and methodology of variable construction. The empirical results are presented in Section 3 and a behavioral explanation of the phenomenon is provided in Section 4. Finally, Section 5 concludes the paper.

2. Data and variables

2.1 Data

We conducted research on stocks in the KOSPI market from January 1998 to May 2020. All data were collected from DataGuide provided by FnGuide. Raw data were filtered under the following conditions to remove outliers from the sample: First, the sample includes only common stocks with closing prices higher than KRW 1000. Information collected within 15 days before the delisting date of each stock was eliminated. In addition, we exclude stocks with absolute returns greater than 30% and stocks with zero-money trading from the daily data. Finally, we exclude the observations of trading money in the lowest 1st percentile of daily trading money for the entire sample period. A total of 3,626,937 firm-day observations satisfied the sample conditions. We use the CD-91 rate as a risk-free rate to estimate excess returns.

2.2 Proxies for left-tail risk

As explained in previous studies (Bali *et al.*, 2009; Atilgan *et al.*, 2020), value-at-risk (VaR), a proxy for left-tail risk, indicates the possible maximum loss of investment with a given probability in a specific period. According to these studies, we also measure the VaR at the end of month t using the 1st (i.e. VaR1) or 5th (i.e. VaR5) percentile of the daily returns for the prior year from month $t-11$ to month t, which must include at least 180 valid daily observations. The estimates from this method are negative because they are obtained from the left tail of the return distribution. Hence, they are multiplied by -1 before analysis to show that the higher the VaR value, the greater the left-tail risk. In addition to the VaR method for left-tail risk measurements, we use the expected shortfall (ES) method proposed by Artzner *et al.* (1999). ES quantifies losses expected to occur beyond the VaR threshold or losses investors do not expect but are likely to occur. ES was measured as the average of the values beyond the VaR threshold. Specifically, ES1 (ES5) at the end of month t is the average of the values equal to or less than the 1st (5th) percentile of the daily returns for the prior year from month $t-11$ to month t. At least, 180 valid daily observations were required for one year. Similar to the VaR measure, the ES estimates are multiplied by -1. Additionally, we use semi-variance (SEMI-V), which measures downside risk, as a left-tailed risk measure. The SEMI-V at the end of month t is estimated as the standard deviation of daily returns for the prior year from month $t-11$ to month t for days in which the return is less than the average daily return for that year. Finally, using all these variables, we conducted a principal component analysis and used the first principal component (PC1) as a representative proxy for the left-tail risk.

2.3 Control variables

In this study, we use several known cross-sectional factors as control variables to examine the relationship between left-tail risk and expected returns. We calculate all control variables at the end of month t as follows:

First, the book-to-market (BM) ratio is estimated for March of each year using the methodology of Fama and French (1992). The BM ratio is calculated by dividing the value of market equity at the end of December of the previous year by the annual book equity disclosed at the end of the previous year. The monthly BM observations were taken from the most recent March BM values, and the BM value in March was assigned to the BM observations from April to March of the following year.

Second, we defined the SIZE variable for each stock as the natural logarithm of the closing price multiplied by the number of outstanding shares.

Next, we calculate the momentum (MOM) variable by taking the cumulative return for the previous 11 months, from month $t-12$ to month $t-2$, following the methodology of Jegadeesh and Titman (1993).

To control for the short-term reversal effect, we define the return in month t as the short-term reversal (STR) variable as proposed by Jegadeesh (1990).

Furthermore, we control for the effect of extreme positive return on expected return using the MAX variable, which is estimated for each stock in each month as the average return of the five highest values in that month, with a requirement for a month to have at least 15 valid daily observations, following Bali *et al.* (2011).

To control for the effect of illiquidity, we follow the illiquidity measure of Amihud (2002), which is the average ratio of the absolute daily return to the daily trading money in each month.

We also control for the effect of idiosyncratic volatility (IVOL), calculated as the standard deviation of daily residuals obtained from regressions of excess returns on three factors (Fama and French, 1993) in a month, with a requirement for a month to have at least 15 valid daily observations, following Ang *et al.* (2006).

The market beta (BETA) of each stock in month t is obtained from the daily regressions of excess returns on excess market returns for a year from month $t-11$ to month t, with a requirement for a year to have at least 180 valid daily observations. The downside beta (Betadown) is estimated to be the same as the market beta but applies only to days when the market excess return is less than the average market excess return for one year.

To control for the coskewness variable, we run daily regressions of excess returns on market excess returns and squared market excess returns in one year from month $t-11$ to month $t-1$, and use the slope of the squared market excess returns as a proxy for the coskewness variable (Coskew) in month t, as proposed by Harvey and Siddique (2000).

Additionally, we control for trading volume and volume changes, following the methodology of Atilgan *et al.* (2020). We also construct two dummy variables: GKMHI (GKMLO), which is 1 if the trading money on the last trading day of the month is greater (less) than or equal to the highest (lowest) 10th percentile of the daily trading money for a month, and abnormal trading money (VOLDU), a proxy for volume changes created by subtracting the average daily trading money in month t from the average daily trading money in the previous 12 months from months $t-12$ to $t-1$. To ensure a reasonable sample size, we required at least 15 non-missing observations per month and 180 non-missing observations per year.

2.4 Summary statistics

Table 1 displays both the descriptive statistics (Panel A) and correlation matrix (Panel B) for the cross-sectional left-tail risk proxies and firm-specific characteristics. As Panel A shows, all left-tail risk variables have a positive skewness, with the 5% value-at-risk (VaR5) ranging from 1.12% to 13.56%. The median for VaR5 is 4.5% and its skewness is 1.5, suggesting that only a small number of stocks have a very high value-at-risk. This feature remained even after the principal component (PC1). In Panel B, we observe high cross-sectional correlations among the left-tail risk measures, such as VaR1, VaR5, ES1, ES5 and SEMI-V, indicating that these variables share common left-tail risk information. However, the correlations between the left-tail risk variables and control variables are low or mild. Size, IVOL and MAX have relatively high correlations with the left-tail risk variables, suggesting that lottery-like stocks also tend to have a high left-tail risk.

3. Empirical results

3.1 Portfolio analysis

This section examines the future performance of the portfolios sorted based on diverse measures of left-tailed risk. If investors overestimate the value of stocks with high left-tail risk, such stocks are likely to underperform, leading to negative returns and alphas in zero-cost long-short portfolios. This study further examines the potential influence of other characteristics on the negative association between left-tail risk and future returns by employing bivariate portfolio analysis. After controlling for these factors, a negative return is expected in the zero-cost long-short portfolio if the association is not influenced by other characteristics.

3.1.1 Single-sorted portfolios. At the end of month t, the stocks are grouped into quintile portfolios based on left-tailed risk measures. Portfolio 1 comprises the stocks with the lowest left-tail risk, whereas Portfolio 5 comprises those with the highest risk. Subsequently, value-weighted average excess returns are computed for each portfolio in the month $t+1$. Additionally, the abnormal returns in month $t+1$, as captured by the CAPM alpha and Fama-French-three-factor alpha, are reported for each portfolio. The CAPM alphas or Fama-French three-factor (FF3) alphas are intercepts estimated from the regressions of excess returns on the market excess returns or the three factors (Fama and French, 1993), respectively. The quintile portfolios are rebalanced monthly.

The results are presented in Table 2, where Panels A–E illustrate the outcomes obtained using VaR1, VaR5, ES1, ES5 and SEMI-V as measures of left-tailed risk, respectively. Regardless of the specific left-tail measure, stocks exhibiting high levels of left-tail risk possess significantly lower future returns than those exhibiting lower levels of left-tail risk, which generates negative returns for zero-cost long-short portfolios. Depending on the measures, the excess returns on the hedge portfolios range from −0.85% (VaR1) to 1.15% (SEMI-V) per month. While these returns are not statistically significant, they are economically significant when measured on a monthly basis. Interestingly, abnormal return performance is both statistically and economically significant in terms of the CAPM or the Fama-French three-factor alpha. For example, when SEMI-V is used, FF3 alpha is −1.71% with a t-statistic of −2.22.

To gauge the left-tail risk, we utilized the five measures recommended in the extant literature. Although the results are generally consistent across all the measures, the measure

Table 1.
Summary statistics

Panel A: Descriptive statistics

	Mean	STD	25th Pctl	Median	75th Pctl	Min	Max	Skew	Kurt
VaR1	8.27	2.75	6.20	7.74	9.78	2.10	15.42	0.70	−0.17
VaR5	5.03	2.03	3.70	4.51	5.73	1.12	13.56	1.51	2.45
ES1	9.49	2.68	7.50	9.14	11.24	2.41	17.21	0.37	−0.56
ES5	6.88	2.39	5.22	6.41	8.06	1.70	14.69	0.98	0.61
SEMI-V	2.34	0.77	1.82	2.18	2.69	0.72	5.28	1.03	0.84
PC1	0.31	1.62	−0.84	0.14	1.28	−4.54	6.21	0.46	0.15
SIZE	11.97	1.73	10.74	11.70	13.02	6.35	18.49	0.54	0.32
BM	1.70	1.27	0.94	1.41	2.14	0.03	11.76	2.95	14.78
MOM	22.52	35.80	8.09	18.48	29.17	−56.97	481.54	5.17	47.86
STR	1.90	5.73	0.70	1.43	2.11	−11.60	140.35	15.26	337.32
ILLIQ	0.12	0.61	0.00	0.01	0.05	0.00	14.02	15.33	297.44
Coskew	−0.05	0.05	−0.07	−0.04	−0.02	−0.26	0.11	−0.83	2.05
BETA	0.76	0.26	0.57	0.73	0.92	0.06	1.60	0.48	0.08
Betadown	0.90	0.28	0.71	0.90	1.08	0.03	2.03	0.33	0.93
IVOL	2.64	1.13	1.92	2.31	3.01	0.52	9.40	1.73	3.80
MAX	4.17	1.69	3.08	3.75	4.73	0.74	14.33	1.56	3.21
VOLDU	−0.08	2.51	−0.13	−0.01	0.04	−23.67	52.09	9.70	227.29
GKMHI	0.13	0.05	0.10	0.12	0.15	0.00	0.50	0.99	6.77
GKMLO	0.18	0.06	0.14	0.18	0.21	0.00	0.50	0.13	1.80

Panel B: Correlation

	VaR1	VaR5	ES1	ES5	SEMI-V	Coskew	Beta down	BETA	SIZE	BM	MOM	STR	ILLIQ	IVOL	MAX	VOLDU	GKMHI
VaR5	0.87																
ES1	0.95	0.81															
ES5	0.96	0.96	0.93														
SEMI-V	0.95	0.94	0.93	0.98													
Coskew	0.00	0.03	−0.02	0.01	0.03												
Betadown	0.25	0.21	0.28	0.25	0.21	−0.46											
BETA	0.23	0.21	0.25	0.24	0.20	0.00	0.78										

(*continued*)

Table 1.

Panel B: Correlation

	VaR1	VaR5	ES1	ES5	SEMI-V	Coskew	Beta down	BETA	SIZE	BM	MOM	STR	ILLIQ	IVOL	MAX	VOLDU	GKMHI
SIZE	−0.37	−0.34	−0.36	−0.37	−0.37	0.11	0.14	0.33									
BM	0.12	0.13	0.10	0.13	0.16	0.03	−0.11	−0.16	−0.35								
MOM	0.11	0.12	0.10	0.11	0.13	0.00	0.00	0.01	0.03	0.04							
STR	−0.01	−0.01	−0.01	−0.01	0.01	0.00	−0.02	−0.02	0.01	0.04	−0.01						
ILLIQ	0.03	0.03	0.02	0.03	0.06	0.02	−0.07	−0.08	−0.12	0.06	0.00	0.00					
IVOL	0.56	0.58	0.54	0.59	0.59	0.00	0.04	0.02	−0.28	0.09	0.15	0.26	0.08				
MAX	0.53	0.55	0.51	0.56	0.56	0.02	0.10	0.11	−0.20	0.08	0.14	0.47	0.05	0.90			
VOLDU	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01	−0.05	−0.01	−0.08	−0.12	0.00	−0.17	−0.18		
GKMHI	−0.04	−0.04	−0.04	−0.04	−0.04	0.01	−0.02	−0.01	0.05	−0.02	−0.01	0.11	0.00	0.00	0.03	0.00	
GKMLO	0.08	0.08	0.08	0.08	0.08	−0.02	0.03	0.02	−0.08	0.02	0.02	−0.13	−0.01	0.02	−0.02	0.00	−0.17

Note(s): This table shows the descriptive statistics (Panel A) and the correlation matrix (Panel B) for the cross-section of the left-tail risk proxies and firm-specific characteristics. The time-series average was computed for each stock to obtain one representative value, and then cross-sectional statistics were calculated. The sample period covers January 1998 to May 2020, and 3,626,937 firm-day observations were used in the analysis. The definitions of all variables are given in Section 2
Source(s): Created by authors

Portfolio	1 (Low)	2	3	4	5 (High)	High-Low
Panel A: VaR1						
Excess return	0.52	0.80*	1.03**	0.57	−0.33	−0.85
	(1.35)	(1.66)	(2.09)	(0.94)	(−0.54)	(−1.59)
CAPM-alpha	0.04	0.22	0.33*	−0.18	−1.04**	−1.08**
	(0.23)	(1.06)	(1.66)	(−0.56)	(−2.47)	(−2.19)
FF3-alpha	0.05	0.23	0.31	−0.31	−1.33**	−1.38**
	(0.27)	(1.10)	(1.48)	(−0.76)	(−2.46)	(−2.12)
Panel B: VaR5						
Excess return	0.61	0.77	1.05**	0.61	−0.47	−1.08*
	(1.54)	(1.62)	(2.04)	(1.04)	(−0.73)	(−1.83)
CAPM-alpha	0.15	0.17	0.39***	−0.13	−1.24***	−1.39***
	(0.74)	(0.87)	(2.81)	(−0.44)	(−2.88)	(−2.72)
FF3-alpha	0.17	0.25	0.27	−0.28	−1.45***	−1.62**
	(0.70)	(1.05)	(1.56)	(−0.73)	(−2.74)	(−2.41)
Panel C: ES1						
Excess return	0.52	0.85*	0.90*	0.51	−0.14	−0.66
	(1.30)	(1.68)	(1.74)	(0.88)	(−0.26)	(−1.35)
CAPM-alpha	0.03	0.22	0.23	−0.24	−0.83**	−0.86*
	(0.17)	(1.03)	(1.44)	(−0.82)	(−2.09)	(−1.88)
FF3-alpha	0.06	0.31	0.14	−0.37	−1.16**	−1.22*
	(0.30)	(1.29)	(0.82)	(−0.97)	(−2.26)	(−1.93)
Panel D: ES5						
Excess return	0.57	0.97*	0.79	0.69	−0.53	−1.09*
	(1.42)	(1.94)	(1.39)	(1.31)	(−0.80)	(−1.82)
CAPM-alpha	0.09	0.37	0.11	−0.07	−1.28***	−1.37**
	(0.49)	(1.48)	(0.47)	(−0.29)	(−2.63)	(−2.51)
FF3-alpha	0.12	0.45	−0.04	−0.19	−1.49**	−1.61**
	(0.59)	(1.52)	(−0.14)	(−0.62)	(−2.45)	(−2.25)
Panel E: SEMI-V						
Excess return	0.59	0.68	1.18**	0.48	−0.56	−1.15*
	(1.43)	(1.39)	(2.32)	(0.83)	(−0.84)	(−1.78)
CAPM-alpha	0.12	0.07	0.48**	−0.25	−1.30***	−1.42**
	(0.59)	(0.37)	(2.49)	(−0.83)	(−2.67)	(−2.42)
FF3-alpha	0.16	0.16	0.30	−0.37	−1.55**	−1.71**
	(0.65)	(0.68)	(1.39)	(−0.93)	(−2.54)	(−2.22)
Panel F: PC1						
Excess return	0.59	0.97**	0.83	0.65	−0.60	−1.19*
	(1.44)	(1.99)	(1.55)	(1.10)	(−0.91)	(−1.92)
CAPM-alpha	0.10	0.38	0.14	−0.11	−1.35***	−1.46**
	(0.59)	(1.37)	(0.66)	(−0.43)	(−2.61)	(−2.54)
FF3-alpha	0.15	0.45	0.01	−0.33	−1.53**	−1.67**
	(0.73)	(1.34)	(0.04)	(−0.92)	(−2.39)	(−2.25)

Note(s): Stocks are sorted by the left-tail risk measure for each month, and the value-weighted portfolio returns for the following month are computed. High-Low in the last column represents the zero-cost long-short portfolio that buys Portfolio 5 and sells Portfolio 1. The Newey–West adjusted *t*-statistics with a lag of 12 are reported in parentheses. ***, ** and * indicate the 1%, 5% and 10% statistical significance, respectively
Source(s): Created by authors

Table 2.
Single-sorted portfolio return

that provides the most refined estimate of the left-tail risk remains ambiguous. Notably, the negative performance is more pronounced when we relax the condition to evaluate left-tail risk. For instance, VaR5 (ES5) showed more pronounced results than VaR1 (ES5). However, the appropriateness of the 5% criterion as a superior measure could not be definitively established. One approach to address this issue is to undertake a principal component analysis, as a common variation across all proxies is expected to yield a purer reflection of left-tail risk. Consequently, principal component analysis was carried out to derive the first principal component (PC1), which summarized all proxies.

Panel F of Table 2 presents the findings derived using PC1 as a refined gauge of the left-tail risk. Our analysis verifies the negative relationship between the left-tail risk and future returns. Notably, excess returns, CAPM alphas, and FF3 alphas are all statistically and economically significant. The use of PC1 generally improves the statistical and economic significance of portfolio performance.

Thus far, our findings demonstrate a negative association between left-tail risk and returns; however, this relationship exhibits a non-monotonic pattern. More specifically, we observe that returns increase with ascending levels of left-tail risk from Portfolio 1 to Portfolio 3 but subsequently decrease, culminating in negative returns for Portfolio 5. Further analysis reveals that only Portfolio 5 exhibits statistical significance with respect to returns. Moreover, the magnitude of the negative return for this portfolio is statistically significant, resulting in a significantly negative return for the high–low portfolio. This finding suggests that stocks with a high left-tail risk may be overvalued, leading to a subsequent decline in their prices in the future.

Overall, our study reveals a negative relationship between left-tail risk and future returns, which aligns with prior research, such as Atilgan *et al.* (2020) in the US stock market and Eom *et al.* (2023) in the Korean stock market. However, this finding is at odds with traditional risk-based asset pricing theories, which suggest that rational investors demand a higher premium for stocks with greater levels of risk than they seek to avoid. Left-tail risk is precisely what investors want to avoid because it represents the possibility of significant losses to their portfolios. As shown, the high–low portfolio returns are significantly negative, even after controlling for traditional risk factors.

3.1.2 Double-sorted portfolios. While our empirical finding appears to be robust, the negative relationship between left-tail risk and expected returns cannot be explained by traditional risk-based asset pricing theory. One possible explanation for this contradiction is the presence of certain characteristics that affect the cross-section of asset prices.

To examine this possibility, we employ double-sorted portfolio analysis. First, we sort the stocks into quintile portfolios based on the control variables, as explained in Section 2. We further categorize the stocks of each portfolio into quintile portfolios based on PC1. Thus, 25 portfolios are formed each month. After creating the portfolios, we calculate the value-weighted average excess returns of the five portfolios for the following month. Portfolio 1 (5) consists of all the stocks with the lowest (highest) values of PC1 in each portfolio, sorted by the control variable. We also report alphas for both the CAPM and the Fama-French three-factor model. To save space, we did not perform the same analysis as for the other left-tail proxies. As demonstrated earlier, PC1 exhibits the most significant negative relationship and can be considered the most appropriate measure compared to others. Table 3 presents the excess returns, CAPM alphas and FF3 alphas for Portfolios 1 and 5, and the zero-cost hedge portfolio, as we did earlier.

The first set of control variables includes traditional asset-pricing model factors that explain the cross-section of stock returns. These factors include the market beta (BETA), size (SIZE), book-to-market ratio (BM) and momentum (MOM, STR) (Jegadeesh, 1990; Fama and French, 1992, 1993, 1996; Jegadeesh and Titman, 1993; Carhart, 1997; Asness *et al.*, 2013). Excess returns on the long-short portfolio are still negative, regardless of the control factors. When controlling for SIZE and BM, the magnitude of the excess return on the hedge portfolio is reduced compared with the single-sort result. However, controlling for BETA and MOM increases excess returns. All excess returns are statistically significant except for BM. The

Table 3.
Double-sort portfolio return

	Excess return			CAPM-alpha			FF3-alpha		
	1 (Low)	5 (High)	High-Low	1 (Low)	5 (High)	High-Low	1 (Low)	5 (High)	High-Low
BM	0.78*	0.10	−0.68	0.31*	−0.64*	−0.95**	0.00	−1.04***	−1.04**
	(1.83)	(0.18)	(−1.64)	(1.72)	(−1.87)	(−2.47)	(0.03)	(−2.64)	(−2.39)
BETA	0.64*	−0.64	−1.29***	0.20	−1.22***	−1.42***	−0.02	−1.60***	−1.58***
	(1.71)	(−1.24)	(−3.41)	(1.15)	(−3.17)	(−3.62)	(−0.14)	(−3.38)	(−3.75)
Betadown	0.83*	−0.32	−1.15**	0.32**	−0.93**	−1.24**	0.16	−1.28**	−1.43**
	(1.96)	(−0.54)	(−2.34)	(2.54)	(−2.09)	(−2.57)	(1.60)	(−2.41)	(−2.55)
Coskew	0.70*	−0.16	−0.86*	0.26	−0.85**	−1.11**	−0.04	−1.19**	−1.15**
	(1.74)	(−0.26)	(−1.91)	(1.38)	(−2.00)	(−2.47)	(−0.29)	(−2.26)	(−2.27)
GKMHI	0.60	−0.94	−1.54***	0.12	−1.63***	−1.75***	0.07	−1.86***	−1.94***
	(1.27)	(−1.47)	(−2.73)	(0.57)	(−3.45)	(−3.35)	(0.29)	(−3.29)	(−2.76)
GKMLO	0.56*	−0.46	−1.02*	0.09	−1.19***	−1.28***	0.01	−1.52**	−1.53**
	(1.68)	(−0.72)	(−1.88)	(0.45)	(−2.60)	(−2.66)	(0.03)	(−2.51)	(−2.43)
ILLIQ	0.85**	−0.06	−0.91**	0.46*	−0.65	−1.10**	0.02	−1.14**	−1.16**
	(2.09)	(−0.11)	(−1.97)	(1.95)	(−1.59)	(−2.39)	(0.12)	(−2.44)	(−2.43)
IVOL	0.63	0.02	−0.61	0.17	−0.70*	−0.87**	−0.06	−0.97**	−0.91**
	(1.52)	(0.03)	(−1.56)	(0.96)	(−1.92)	(−2.30)	(−0.36)	(−2.08)	(−2.00)
MAX	0.72*	−0.13	−0.86*	0.23*	−0.81**	−1.03**	0.10	−1.15**	−1.25**
	(1.82)	(−0.24)	(−1.92)	(1.88)	(−2.08)	(−2.55)	(0.78)	(−2.23)	(−2.12)
MOM	0.75*	−0.53	−1.29***	0.28*	−1.22***	−1.50***	0.01	−1.54***	−1.55***
	(1.88)	(−0.95)	(−3.10)	(1.71)	(−3.15)	(−3.55)	(0.11)	(−3.26)	(−3.23)
SIZE	1.11***	0.23	−0.87***	0.70***	−0.38	−1.08***	0.17	−0.86**	−1.03***
	(2.92)	(0.46)	(−2.67)	(3.07)	(−1.26)	(−3.58)	(1.34)	(−2.38)	(−2.85)
STR	0.72**	−0.28	−1.00**	0.25*	−0.98**	−1.23***	0.13	−1.32***	−1.45**
	(1.97)	(−0.48)	(−2.05)	(1.72)	(−2.40)	(−2.69)	(0.87)	(−2.75)	(−2.53)
VOLDU	0.65*	0.12	−0.52	0.22	−0.52	−0.74*	−0.08	−0.95**	−0.88**
	(1.70)	(0.22)	(−1.29)	(1.16)	(−1.33)	(−1.90)	(−0.61)	(−2.19)	(−2.01)

Note(s): The stocks were first sorted by control variable and subsequently sorted by PC1 within each control group. For each quintile by PC1, value-weighted returns are averaged across the control groups. To save space, excess returns, CAPM alphas and FF3 alphas are computed only for low-, high-, and high-minus-low portfolios. The Newey–West adjusted *t*-statistics with a lag of 12 are reported in parentheses. ***, ** and * indicate the 1%, 5% and 10% statistical significance, respectively
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FF3 alphas were slightly reduced for all controls but were still statistically significant without any exceptions. Thus, the underperformance of left-tail risk stocks cannot be attributed to a correlation with traditional asset pricing model factors. Moreover, the negative return on stocks with a high left-tail risk is not attributable to the momentum effect.

Second, we have incorporated controls for downside market risk measures, such as loading to downside market risk (Betadown) and coskewness with the market (Coskew), as a proxy for exposure to aggregate tail risk. While controlling for the aggregate tail risk slightly reduces the magnitude of all performance measures, the FF3 alpha of the hedge portfolio remains statistically significant at the 5% level. Thus, idiosyncratic tail risk is a distinct dimension of risk and aggregate tail risk cannot account for this anomaly.

Third, we introduce controls for preferences toward individual stock skewness such as idiosyncratic volatility (IVOL) and previous maximum return (MAX), which are negatively associated with stock returns (Ang *et al.*, 2006, 2009; Bali *et al.*, 2011; Hung and Yang, 2018). Therefore, the negative effect of the left-tailed risk could be correlated with these effects. Although controlling for these variables reduces the magnitude of the relationship, the anomaly remains statistically significant.

Finally, we control for liquidity measures related to trading activities such as ILLIQ, GKMHI, GKMLO and VOLDU (Amihud, 2002; Atilgan *et al.*, 2020). As with the results of the other controls, the anomaly remains significant even after controlling for liquidity measures.

In summary, the negative relationship between the left-tail risk and future returns is robust when controlling for traditional risk factors such as momentum, skewness and liquidity, suggesting that it is not a result of a correlation between the left-tail risk and these factors. Our findings are consistent with those of recent empirical studies, such as Atilgan *et al.* (2020), and we provide a possible explanation for this anomaly in the next section.

4. Discussion

In this section, we discuss the potential reasons for the left-tail risk anomaly by examining it through the lenses of both risk-based and behavioral theories.

4.1 Risk-based explanation

If the market price of the left-tail risk is negative, a negative relationship can be observed between the left-tail risk and future returns. To examine this possibility, we construct a portfolio that mimics the left-tail risk and test whether loadings on this factor can explain the left-tail portfolio return spread.

To mimic the common risk factors associated with the left-tail risk, we construct a top-minus-bottom (TMBO) portfolio using the methodology proposed by Fama and French (1993). Initially, at the end of each month, all stocks in the sample are categorized into two groups based on their market equity: small (S) and large (B), with the median market equity value serving as the dividing point. Additionally, the stocks were classified into three groups based on their PC1 values. Stocks with PC1 values equal to or below the 30th percentile of the PC1 values for that month were classified as bottom (BO), whereas stocks with PC1 values exceeding the 70th percentile were classified as top (T). The remaining stocks fall in category M. Next, we formed six portfolios (S/BO, S/M, S/T, B/BO, B/M and B/T) by combining the categorized groups and calculating the monthly value-weighted average returns for each portfolio. Finally, to create the monthly TMBO portfolio that mimics the left-tail factor of returns, we compute the difference between the average returns of the top two PC1 portfolios (S/T and B/T) and the average returns of the bottom two PC1 portfolios (S/BO and B/BO).

Following Ang *et al.* (2006), we estimate loadings on the left-tail factor by obtaining loadings on TMBO in the following regression model:

$$R_{i,t} = \beta_0 + \beta_{i,MKT} MKT_t + \beta_{i,TMBO} TMBO_t + \varepsilon_{i,t} \quad (1)$$

where $R_{i,t}$ is the excess return of stock i in month t. MKT_t is the market excess return in month t. $\beta_{i,MKT}$ is the loading on the market factor. $TMBO_t$ is the common risk factor related to the left-tail risk in month t. $\beta_{i,TMBO}$ is the loading on the left-tail factor.

We adopted an overlapping method with a 12-month estimation period and a rolling frequency of 1 month to obtain monthly loadings. Specifically, during the initial 12-month period of the sample (from month t to month $t+1$), we perform time-series monthly regressions following the model outlined in Equation (1) to derive the cross-section of β_{TMBO}. This process is repeated for the subsequent 12-month period (from month $t+12$ to month $t+13$) until the end of the sample period. Consequently, we obtained monthly β_{TMBO} values for each stock. These estimated β_{TMBO} values are then employed to classify stocks into quintile portfolios, and the value-weighted averages of these β_{TMBO} values are presented in the column labeled "pre-ranking β_{TMBO}" in Table 4.

The portfolios are reclassified monthly. Once the portfolios are formed, we calculate the value-weighted average excess and abnormal returns for each quintile portfolio one month after the formation date. We computed the time-series averages for each portfolio. Additionally, we estimate the loadings on the left-tail factor during the same period to calculate the average excess returns, aiming to explore any contemporaneous patterns between them. The post-ranking β_{TMBO} over the entire sample is estimated by conducting time-series monthly regressions of post-ranking portfolio returns on the left-tail factor while controlling for market, size and value factors. This control was necessary because FF3-alpha accounts for these factors.

Table 4. Single-sorted portfolios on left-tail risk factor loadings

Portfolio	Pre-ranking β_{TMBO}	Excess return	CAPM-alpha	FF3-alpha	Post-ranking β_{TMBO}
1 (Low)	−1.70***	0.28	−0.48	−0.59	−0.83***
	(−49.15)	(0.47)	(−1.37)	(−1.45)	(−9.28)
2	−0.74***	0.94*	0.24	−0.11	−0.42***
	(−33.05)	(1.77)	(0.94)	(−0.39)	(−6.02)
3	−0.31***	0.83	0.20	−0.03	−0.25***
	(−15.72)	(1.61)	(0.91)	(−0.12)	(−5.09)
4	0.07***	0.24	−0.37*	−0.56***	−0.12
	(3.43)	(0.51)	(−1.93)	(−2.78)	(−1.58)
5 (High)	0.80***	0.78*	0.21	0.36**	0.34***
	(24.51)	(1.70)	(1.24)	(1.98)	(7.91)
High-Low	2.49***	0.50	0.69	0.96*	1.17***
	(49.49)	(0.99)	(1.52)	(1.73)	(9.45)

Note(s): We adopted an overlapping method with a 12-month estimation period and a rolling frequency of 1 month to obtain monthly loadings. Specifically, during the initial 12-month sample period, we perform time-series monthly regressions following the model outlined in equation (1) to derive the cross-section of β_{TMBO}. This process was repeated for the subsequent 12-month period until the end of the sample period. Consequently, we obtained monthly β_{TMBO} values for each stock. These estimated β_{TMBO} values are then employed to classify stocks into quintile portfolios, and the value-weighted averages of these β_{TMBO} values are presented in the column labeled pre-ranking β_{TMBO}. The portfolios are reclassified on a monthly basis. Once the portfolios are formed, we calculate the value-weighted average excess and abnormal returns for each quintile portfolio one month after the formation date. We computed the time-series averages for each portfolio. Additionally, we estimate the loadings on the left-tail factor during the same period to calculate the average excess returns, aiming to explore any contemporaneous patterns between them. The post-ranking β_{TMBO} for the entire sample was estimated by conducting time-series monthly regressions of the post-ranking portfolio returns on the left-tail factor. The t-statistics are shown in parentheses. ***, ** and * indicate the 1%, 5% and 10% statistical significance, respectively
Source(s): Created by authors

$$R_{p,t} = \beta_0 + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \beta_{p,TMBO}TMBO_t + \varepsilon_{p,t} \quad (2)$$

where $R_{p,t}$ is the average excess return of portfolio p formed in the past β_{TMBO} in Equation (1).

As shown in Table 4, the results indicated a positive association between the pre- and post-ranking loadings on the left-tail risk factor. However, neither loading demonstrates a significant relationship with future stock returns. These findings suggest that risk-based theory alone fails to adequately explain the left-tail risk anomaly.

Next, we investigated the left-tail anomaly while controlling for β_{TMBO}. If abnormal returns can be attributed to risk, we would expect no distinction among the PC1-sorted portfolios once risk is considered. To this end, we initially sorted stocks based on their β_{TMBO} values and subsequently sorted them based on PC1. We then calculated the average across the β_{TMBO} dimension to effectively control for risk. Table 5 lists the value-weighted average excess returns, CAPM alphas, and FF3 alphas. Despite controlling for β_{TMBO}, we continue to observe a statistically significant return spread between the High and Low PC1 portfolios. This finding indicates that the left-tail anomaly persists even when accounting for risk using β_{TMBO}, thereby suggesting that risk-based theory cannot explain this phenomenon. Hence, in the next section, we explore a potential explanation for the left-tail anomaly from a behavioral theory perspective.

4.2 Behavioral explanation

The negative relationship between left-tail risk and stock returns poses a challenge to traditional risk-based theories of finance. To address this issue, we provide a behavioral explanation of the empirical results.

Hertwig *et al.* (2004) proposed that decision-makers exhibit different behaviors when they receive information through experience compared to when they obtain information from descriptions. Specifically, people tend to underestimate or underweight the likelihood of rare events when they make decisions based on their experiences with the occurrence of events. Based on this hypothesis, we suggest that investors who rely on their short-run experience rather than long-run historical data can underestimate the physical probability of left-tail events or their risk-neutral probability. Both underestimating the physical probability and underweighting the risk-neutral probability result in the overpricing of stocks with higher left-tail risk; subsequently, these stocks will have lower future returns. Thus, decisions based on experience can lead to a negative relationship between the left-tail risk and stock returns.

Panel A: Excess return, CAPM-Alpha and FF3-Alpha

	Ranking on PC1					
Controlling for $Pre\beta_{TMBO}$	1 (Low)	2	3	4	5 (High)	High-Low
Excess return	0.99**	0.71	0.87*	0.46	−0.19	−1.17***
	(2.20)	(1.38)	(1.67)	(0.80)	(−0.30)	(−2.64)
CAPM-alpha	0.47**	0.08	0.16	−0.33	−0.92**	−1.39***
	(2.44)	(0.44)	(1.01)	(−1.12)	(−2.39)	(−3.18)
FF3-alpha	0.19	−0.16	0.02	−0.52	−1.29***	−1.48***
	(1.31)	(−1.06)	(0.17)	(−1.39)	(−2.71)	(−3.10)

Note(s): This table presents the value-weighted average excess returns, CAPM alpha and FF3 alpha of PC1-sorted portfolios, controlling for loading to the left-tail risk factor. We initially sorted the stocks based on their β_{TMBO} values and subsequently sorted them based on PC1. We then calculated the average across the β_{TMBO} dimension to effectively control for risk
Source(s): Created by authors

Table 5. PC1 effect controlling for factor loading

Individual retail investors, who are categorized as “individuals” in KRX, typically have less investment experience compared to institutional investors, who are categorized as “institutions” in KRX. Owing to limitations in skills and data accessibility, retail investors may tend to make trading decisions based on their limited experience rather than conducting a thorough data analysis. Therefore, we anticipate that the overpricing of high left-tail risk stocks will be more pronounced for stocks that are actively traded by retail investors.

To test our hypothesis, we define the retail trading proportion (RTP) as the ratio of individuals’ trading dollar volume to the total trading dollar volume, following Han and Kumar (2013). The Korean Exchange identifies the daily trading volume for each investor type in the Korean stock market. We compute the RTP for each stock on a monthly basis by calculating the daily volume. Accordingly, a high RTP for a particular stock indicates that it is more actively traded by individual investors who may be relatively unskilled and rely more on their limited experience.

As in the previous section, we analyze portfolios by sorting stocks based on the RTP and the PC1 of left-tail risk measures, resulting in 25 portfolios. For each RTP level, we investigate the return spread between high PC1 stocks and low PC1 stocks. Panel A of Table 6 shows the average RTP of the quintile portfolios sorted by RTP. The lowest RTP portfolio has individual investors’ trading volume accounting for 30% of the total trading volume, whereas the highest RTP portfolio has individual investors’ trading volume accounting for as much as 75%, indicating that high-RTP stocks may be highly influenced by the underestimation or

Table 6.
Effect of the trading of retail investors

Panel A: Level of RTP

	1 (Low)	2	3	4	5 (High)	High-Low
RTP	0.30***	0.39***	0.48***	0.58***	0.75***	0.45***
	(21.05)	(19.25)	(20.36)	(23.90)	(34.41)	(23.52)

Panel B: Double-sorted portfolios

	RTP1	RTP2	RTP3	RTP4	RTP5
1 (Low)	0.59	0.81*	0.94	1.16**	1.36**
	(1.41)	(1.66)	(1.46)	(2.41)	(2.57)
2	1.05*	0.80	0.91	1.82**	1.34***
	(1.93)	(1.58)	(1.54)	(2.13)	(2.61)
3	0.79	0.96	0.41	0.65	0.95
	(1.45)	(1.58)	(0.66)	(0.89)	(1.62)
4	0.80	0.63	0.38	0.17	1.55**
	(1.33)	(0.98)	(0.60)	(0.28)	(2.23)
5 (High)	−0.58	−0.38	0.26	−1.02	−0.95*
	(−0.52)	(−0.51)	(0.41)	(−1.58)	(−1.74)
High-Low	−1.06	−1.19**	−0.68	−2.18***	−2.32***
	(−0.94)	(−2.17)	(−0.94)	(−3.82)	(−4.32)
CAPM-alpha	−1.08	−1.41***	−1.05	−2.38***	−2.50***
	(−1.00)	(−2.61)	(−1.35)	(−4.12)	(−4.50)
FF3-alpha	−1.16	−1.19**	−0.35	−2.37***	−2.24***
	(−0.96)	(−2.01)	(−0.52)	(−3.63)	(−4.10)

Note(s): We define retail trading proportion (RTP) as the ratio of individuals’ trading dollar volume to the total trading dollar volume, following the approach of Han and Kumar (2013). The RTP was computed for each stock on a monthly basis by accumulating the daily volumes. Panel A shows the RTP levels for the quintile portfolios sorted by RTP. In Panel B, the value-weighted returns for the 25 portfolios are computed by sorting stocks based on the RTP and the PC1 of left-tail risk measures. The *t*-statistics are shown in parentheses. ***, ** and * indicate the 1%, 5% and 10% statistical significance, respectively
Source(s): Created by authors

underweighting of the left-tail risk by unskilled investors. The results presented in Panel B of Table 6 are consistent with the hypothesis that overpricing of high left-tail risk stocks is more pronounced for stocks that are more actively traded by retail investors. The excess returns, CAPM alpha and FF3 alpha for the hedge portfolio of the left-tail risk are not statistically significant for the RTP1 (lowest RTP) group, while they are statistically significant for RTP5 (highest RTP). Furthermore, the absolute value of the hedge portfolio return increases with the level of RTP, except for RTP3, confirming that the negative relationship between the left-tail risk and future returns is more pronounced for high-RTP stocks, which is consistent with Hertwig *et al.*'s (2004) hypothesis that people underestimate the likelihood of rare events when they make decisions based on experience.

To conduct a robustness check, we replicate the aforementioned analysis using alternative left-tail risk measures employed in constructing PC1, namely, VAR1, VAR5, ES1, ES5 and SEMI-V. The corresponding findings, which exhibit qualitatively consistent outcomes, are presented in Appendix Table A1.

5. Conclusion

While rational investors prefer to avoid the left-tail risk of individual stocks, and the risk-return trade-off predicts a positive premium for left-tail risk, recent empirical studies have reported mixed results in many international stock markets. Therefore, we conducted the principal component analysis using various left-tail measures to construct a single representative proxy. Interestingly, we find that in the Korean stock market, stocks with high left-tail risk earned lower returns in the following month. This negative relationship is statistically significant and robust when controlling for other factors known to explain the cross-sectional variation of stock returns, such as market beta, size, book-to-market ratio, momentum, skewness and liquidity.

To provide a behavioral explanation of our results, we investigate the effects of retail investors' decision-making processes. According to Hertwig *et al.* (2004), people tend to underestimate or underweight the likelihood of rare events when making decisions based on experience rather than description. As retail investors are likely to make decisions based on their investment experience, we expect the left-tail risk anomaly to be pronounced for stocks actively traded by individual retail investors. Our portfolio analysis reveals that the negative relationship is statistically significant only for stocks with the highest retail trading proportion (on average, 75%). Thus, we conclude that the negative relationship is due to the mispricing of the left-tail risk by retail investors, which may be due to the underestimation of the physical probability of the left-tail risk or the underweighting of such events in the pricing kernel.

This study contributes to the literature by providing a behavioral explanation for the negative relationship between left-tail risk and stock returns in the Korean stock market, which has not been previously discussed. Our results have implications for unskilled retail investors and the authorities responsible for protecting individual retail investors.

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Appendix

To conduct a robustness check, we replicate the aforementioned analysis (given in Table 6) using alternative left-tail risk measures employed in constructing PC1, namely, VAR1, VAR5, ES1, ES5 and SEMI-V. The corresponding findings are presented in Table A1, which shows qualitatively consistent outcomes.

	RTP1	RTP2	RTP3	RTP4	RTP5
Panel A: VAR1					
1 (Low)	0.53	0.74	0.84*	1.14**	1.27***
	(1.30)	(1.49)	(1.71)	(2.47)	(2.61)
2	0.82*	0.82	1.04	1.39	1.43**
	(1.68)	(1.49)	(1.55)	(1.64)	(2.40)
3	1.28**	0.80	0.62	0.61	0.86
	(2.09)	(1.42)	(0.93)	(0.96)	(1.58)
4	0.69	0.50	0.40	0.42	1.50**
	(1.12)	(0.71)	(0.69)	(0.73)	(2.00)
5 (High)	−0.39	0.46	0.11	−1.17	−0.98*
	(−0.51)	(0.54)	(0.17)	(−1.56)	(−1.78)
High-Low	−0.76	−0.26	−0.73	−2.31***	−2.22***
	(−1.11)	(−0.44)	(−1.19)	(−3.51)	(−4.55)
CAPM-alpha	−0.85	−0.59	−1.03*	−2.57***	−2.47***
	(−1.35)	(−1.14)	(−1.65)	(−3.92)	(−4.79)
FF3-alpha	−1.05	−0.75	−0.53	−2.50***	−2.04***
	(−1.31)	(−1.22)	(−0.89)	(−3.54)	(−3.67)
Panel B: VAR5					
1 (Low)	0.59	0.83	1.06**	1.23**	1.37***
	(1.46)	(1.61)	(2.11)	(2.50)	(2.83)
2	0.80	0.77	0.76	1.65**	0.95
	(1.64)	(1.39)	(1.28)	(2.07)	(1.50)
3	1.07**	1.13*	0.70	0.64	1.80***
	(2.08)	(1.84)	(1.12)	(1.02)	(2.63)
4	0.63	0.43	0.46	0.33	0.76
	(0.95)	(0.69)	(0.73)	(0.48)	(1.30)
5 (High)	−0.61	0.53	0.23	−1.24**	−1.00*
	(−0.64)	(0.72)	(0.36)	(−2.13)	(−1.75)
High-Low	−1.13	−0.30	−0.83	−2.47***	−2.37***
	(−1.21)	(−0.60)	(−1.63)	(−5.20)	(−5.07)
CAPM-alpha	−1.16	−0.65	−1.27**	−2.70***	−2.58***
	(−1.29)	(−1.31)	(−2.42)	(−5.52)	(−5.13)
FF3-alpha	−1.23	−0.37	−0.82	−2.67***	−2.51***
	(−1.13)	(−0.82)	(−1.64)	(−5.19)	(−4.81)
Panel C: ES1					
1 (Low)	0.51	0.88*	0.85	1.21**	1.17**
	(1.24)	(1.76)	(1.53)	(2.42)	(2.01)
2	0.94*	0.57	1.10*	1.25	1.38***
	(1.75)	(1.11)	(1.67)	(1.29)	(2.87)
3	1.05*	0.92	0.55	0.48	0.84
	(1.79)	(1.53)	(0.83)	(0.78)	(1.45)
4	0.61	0.51	0.16	0.32	1.33*
	(0.87)	(0.79)	(0.26)	(0.53)	(1.95)
5 (High)	0.02	0.05	0.41	−1.10	−0.84
	(0.03)	(0.06)	(0.64)	(−1.46)	(−1.47)
High-Low	−0.52	−0.83	−0.43	−2.30***	−2.02***
	(−0.77)	(−1.51)	(−0.72)	(−3.42)	(−3.68)

(continued)

Table A1.
Effect of the trading of retail investors (robustness check)

	RTP1	RTP2	RTP3	RTP4	RTP5
CAPM-alpha	−0.59	−1.13**	−0.74	−2.55***	−2.23***
	(−0.92)	(−2.29)	(−1.18)	(−3.69)	(−3.94)
FF3-alpha	−0.99	−1.35**	−0.32	−2.47***	−1.85***
	(−1.29)	(−2.14)	(−0.54)	(−3.37)	(−3.40)
Panel D: ES5					
1 (Low)	0.57	0.75	0.66	1.31***	1.39***
	(1.38)	(1.50)	(1.33)	(2.83)	(2.75)
2	0.95*	1.04*	1.00	1.78**	1.37***
	(1.83)	(1.85)	(1.58)	(2.13)	(2.78)
3	0.83	0.85	0.53	0.40	1.09*
	(1.43)	(1.34)	(0.87)	(0.56)	(1.81)
4	0.97*	0.62	0.31	0.31	1.13
	(1.69)	(1.07)	(0.51)	(0.50)	(1.63)
5 (High)	−0.66	−0.02	0.51	−1.08*	−0.84
	(−0.59)	(−0.03)	(0.73)	(−1.73)	(−1.50)
High-Low	−1.07	−0.80*	−0.16	−2.40***	−2.29***
	(−0.99)	(−1.74)	(−0.27)	(−4.13)	(−4.61)
CAPM-alpha	−1.12	−1.05**	−0.54	−2.62***	−2.47***
	(−1.07)	(−2.31)	(−0.89)	(−4.39)	(−4.63)
FF3-alpha	−1.27	−0.82*	−0.03	−2.52***	−2.19***
	(−1.10)	(−1.66)	(−0.05)	(−3.84)	(−3.75)
Panel E: SEMI-V					
1 (Low)	0.58	0.81*	0.86	1.06**	1.48**
	(1.37)	(1.68)	(1.51)	(2.08)	(2.37)
2	0.72	0.83	0.91	1.29	1.53***
	(1.40)	(1.61)	(1.47)	(1.46)	(2.75)
3	1.22**	1.09*	0.60	0.62	0.98
	(2.49)	(1.66)	(0.95)	(1.04)	(1.53)
4	0.55	0.72	0.32	0.19	1.32*
	(1.00)	(1.10)	(0.54)	(0.32)	(1.92)
5 (High)	0.33	−0.67	0.47	−1.18*	−0.84
	(0.33)	(−0.83)	(0.78)	(−1.82)	(−1.47)
High-Low	−0.19	−1.46**	−0.39	−2.24***	−2.32***
	(−0.20)	(−2.29)	(−0.68)	(−3.85)	(−3.97)
CAPM-alpha	−0.28	−1.71***	−0.75	−2.43***	−2.47***
	(−0.30)	(−2.81)	(−1.13)	(−4.09)	(−4.28)
FF3-alpha	−0.67	−1.50**	−0.30	−2.37***	−2.18***
	(−0.62)	(−2.17)	(−0.47)	(−3.78)	(−3.88)

Note(s): We define retail trading proportion (RTP) as the ratio of individuals' trading dollar volume to the total trading dollar volume, following the approach of Han and Kumar (2013). The RTP was computed for each stock on a monthly basis by accumulating the daily volumes. Panels A–E present the value-weighted returns for 25 portfolios computed by sorting stocks based on the RTP and left-tail risk measures (VAR1, VAR5, ES1, ES5 and SEMI-V). The *t*-statistics are shown in parentheses. ***, ** and * indicate the 1%, 5% and 10% statistical significance, respectively

Source(s): Created by authors

Table A1.