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Research article

Volatility conditions and the weekend effect of long-short anomalies: Evidence from the US stock market

Wenhui Li[1,2,*], Normaziah Mohd Nor[1], Hisham M[1] and Feng Min[3]

[1] School of Economics and Management, University Putra Malaysia, Malaysia
[2] College of Mathematics and Finance, Hunan University of Humanities, Science, and Technology, Loudi 471000, China
[3] Zhejiang University of Finance & Economics, Hangzhou 310018, China

* **Correspondence:** Email: 271039891@qq.com; Tel: +8613469470551.

Abstract: This study examines the relationship between market volatility conditions and the weekend effect on size and profitability anomalies in the U.S. stock market. The study uses the ICSS model to divide the sample into high- and low-volatility periods. Empirical results indicate that the weekend effect of size and profitability anomalies is significant in low-volatility states and insignificant in high-volatility conditions, and it is consistent across different measures of stock market volatility and subsamples. Additionally, we identify the intra-week patterns of log returns on the VIX index as the driver of the weekend effect on profitability and size anomalies. Our study not only extends the understanding of the weekend effect of long-short anomalies but also provides new evidence on the effectiveness of volatility management in factor investing. It also has important implications for investors, who should consider improving their factor investment strategies based on our results.

Keywords: stock market volatility; weekend effect; factor investing; volatility management; ICSS model; VIX

JEL Codes: G11, G12, G14, G41

Abbreviations: OP: The profitability factor; ME: The size factor based on the Five-Factor Model

1. Introduction

The efficient market hypothesis assumes that returns cannot be predicted based on all available information and past returns. However, the presence of the weekend effect challenges this assumption. Ali and Ülkü (2020) and Singal and Tayal (2020) report that the weekend effect is observed in both equity and commodity markets, but it has been found that the weekend effect disappears after its initial identification (Olson et al., 2015; Steeley, 2001) or is reversed (Brusa et al., 2000; Gu, 2004). In contrast, Chiah and Zhong (2021) and Birru (2018) demonstrate that size and profitability anomaly return exhibit a significant weekend effect across all conditions.

Investors generally use the size and profitable factors proposed by Fama and French (2015) in the five-factor model to construct long-short investment portfolios. An investor would take long positions in stocks classified as small and highly profitable, anticipating their potential for superior out-performance. Moreover, the investor would take short positions in stocks classified as large size and low profitability, recognizing their potential for inferior underperformance. Additionally, empirical studies have shown a significant correlation between factor investing and stock market volatility (Xiong et al., 2022). Moreover, volatility management strategies have been identified as effective measures to mitigate the risks associated with factor investing (Moreira & Muir, 2017; Wang & Yan, 2021). Therefore, it is reasonable to suggest a potential relationship between equity volatility and the weekend effect observed in size and return anomalies.

While prior research has focused on the presence of size and profitability anomaly of the weekend effect, the issue of their potential disappearance remains unexplored. Furthermore, existing studies on the relationship between factor investing and stock market volatility have not examined the influence of volatility on the presence of the weekend effect on size and profitability anomalies. Consequently, this study aims to fill this gap in the literature by examining the impact of stock volatility on the weekend effect observed in size and profitability anomaly returns. By exploring stock volatility as a plausible driver, this study seeks to provide a comprehensive understanding of the dynamic interplay between market volatility, size and profitability factors and asset returns.

During periods of high volatility, investors tend to take more conservative positions in underlying factors, which reduces investments in risky assets and leads to the disappearance of the weekend effect of long-short anomalies. Conversely, during periods of low volatility, investors may take more aggressively leveraged positions in underlying factors, resulting in a significant long-short anomaly and the presence of the weekend effect. However, less research pays attention to investigating the correlation between the weekend effect of long-short anomalies and the state of volatility, and further research is needed.

The purpose of this study is to examine the relationship between market volatility conditions and the weekend effect on size and profitability anomalies. To achieve this objective, we developed several measures of U.S. stock market volatility and followed the research steps outlined below. First, we used the ICSS model to divide the sample into two subsamples representing high and low volatility periods. Next, we examined the weekend effects of long-short anomaly returns based on size and profitability in both high and low-volatility periods. In addition, we examine whether the VIX is the driver of the weekend effect of profitability and size anomalies.

Through our research, we make three important contributions to the existing literature. First, we provide further analysis of the weekend effect on long-short anomalies. Our findings suggest that market volatility conditions determined the weekend effect on profitability and size anomalies.

Specifically, we find that the weekend effect of size and profitability anomalies is significant during periods of low stock market volatility but insignificant during periods of high volatility. However, the findings of Chiah and Zhong (2021) and Birru (2018) suggest that the weekend effect on profitability and size anomalies is significant for all subsamples.

Second, our study not only provides new evidence on the effectiveness of volatility management in factor investing but also suggests a possible improvement in this area. We found that aggressively leveraged positions, specially long-legs, perform better than short-legs, leading to higher profits for investors. However, we did not find evidence supporting the effectiveness of conservative positions in reducing losses, as there was no significant difference between long-legs and short-legs in our empirical results. In addition, an investor interested in factor investment should also pay attention to the weekend effect under low-volatility conditions. Specifically, they could consider shifting their assets from long-leg stocks to short-leg stocks on Mondays and adopting the opposite strategy on Fridays.

Finally, we found that the VIX plays a critical role in driving the weekend effect of profitability and size anomalies in periods of low volatility. Our findings suggest that the VIX has an asymmetric impact on investment decisions, which becomes more significant under low volatility conditions.

The remainder of this paper is organized as follows. Section 2 is the literature review. Section 3 introduces the data and methodology. Section 4 presents the empirical results for the weekend effect of cross-sectional return in different market volatility periods. Section 5 investigates the driver of the weekend effect on profitability and size anomalies based on the VIX. Finally, Section 6 concludes the study.

2. Literature review and hypothesis development

Our work is related to a large body of literature investigating the weekend effect. Cross (1973) first documents that stock price movements are not a random walk process, and the average returns on Mondays are lower than the average daily returns in the US stock markets. Additionally, the daily anomalies in the stock market are found with more convincing evidence (Keim & Stambaugh, 1984; Keloharju et al., 2016; Song & Balvers, 2022). Meanwhile, it has been found in the commodity futures market (Li et al., 2022; Qadan et al., 2022). Moreover, we found significant weekend effects in the VIX index (Idilbi-Bayaa & Qadan, 2022; Qadan, 2013). However, recent findings show that the day-of-the-week effect disappeared after it was first reported in 1973 (Olson et al., 2015). In addition, Banz (1981) also finds that small stocks outperform large stocks, which was considered a size anomaly. Ball et al. (2015) and Balakrishnan et al. (2010) found that profitable stocks outperform less profitable ones. It was called profitability anomaly. In addition, the weekend effect of the size and profitability anomalies are found. Birru (2018) shows that the size anomalies and profitability anomalies are higher on Mondays than on Fridays. Chiah and Zhong (2021) also present significant size anomalies in the Australian stock market.

Previous studies have identified the weekend effect in the stock and commodity markets, but it disappeared after its initial discovery. However, Birru (2018) and Chiah and Zhong (2021) suggest that the weekend effect of size and profitability anomalies is significant under all conditions, and there is no evidence of its disappearance. In this study, we test the following hypothesis to investigate the robustness of the weekend effect on size and profitability anomalies in the US stock market:

H1: The weekend effect of size and profitability anomalies disappeared in some periods.

Our work is also related to volatility management strategies and the risk of factor investing. Since Fama and French (2015) proposed a five-factor asset pricing model, factor investing has garnered global recognition and acceptance. Furthermore, volatility management strategies play a crucial role in factor investing because empirical evidence suggests that volatility management can effectively reduce the risk of factor investing (Moreira & Muir, 2017). However, the trading strategies implied by these studies are often not implementable in real-time (Cederburg et al., 2020).

Most volatility management strategies rely on the volatility-scaled approach, where portfolio returns are adjusted according to a constant or dynamically changing target volatility. Hocquard et al. (2013) developed the method of volatility scaling portfolios with constant target volatility, and subsequent studies have proposed different models of target volatility scaling. For example, Barroso and Santa-Clara (2015) constructed a constant target volatility management strategy by predicting the volatility of the momentum factor with the AR(1) model and using the predicted variance to scale the momentum returns, thereby avoiding a momentum crash. Daniel and Moskowitz (2016) constructed a dynamic volatility management strategy by predicting the volatility with the GARCH model. Moreira and Muir (2017) applied the adjusted target volatility strategy of Barroso & Santa-Clara (2015) to many more factor portfolios. Qiao et al. (2020) modified the volatility in the volatility management strategy to downside volatility based on Moreira & Muir (2017). Chen et al. (2019) further expanded the volatility management portfolio strategy and used the ARMA model to better predict portfolio volatility.

Volatility management strategies have become increasingly popular in recent years, particularly within factor investing. These strategies aim to manage a portfolio's exposure to volatility. Generally, portfolios are adjusted based on a target level of volatility. The effectiveness of such strategies in reducing risk and optimizing returns has been extensively documented. However, limited research has focused on the relationship between the weekend effect of size and profitability anomalies and volatility conditions, and how the weekend effect can be used to enhance the profitability of volatility management strategies. The following hypotheses are tested to investigate whether the weekend effect in the US stock market is dependent on the volatility states.

H2: The presence of the weekend effect on the size and profitability anomalies depends on the stock market volatility states.

3. Data and methodology

3.1. The definition of long-short anomaly return

Fama and French (1995) introduced a multifactor asset pricing model that includes five factors: market risk, size, value, profitability and investment. This model aims to explain the cross-sectional variation in stock returns and has been widely recognized as an important tool for empirical asset pricing research. As such, many investors rely on the factors of profitability (OP), investment, size (ME) and value to make investment decisions. This paper aims to investigate the weekend effect using profitability and size factors.

The size factor captures the difference in returns between small and large firms. Banz (1981) and Birru (2018) found that small stocks outperform large stocks. In a long-short portfolio, small firms contribute to the long-leg anomaly. In our study, the size anomaly return represents the average daily excess returns for portfolios based on firm size. We divided the investment portfolio into deciles according to firm size rankings. The size anomalies return is the difference between the average daily excess returns of the bottom 10% and the top 10% of firms ranked by size.

The profitability factor captures the difference in returns between high and low-profitability firms. High-profitability firms tend to outperform low-profitability firms. According to the studies conducted by Ball et al. (2015) and Birru (2018), high-operating profitability (OP) stocks have higher returns than low-operating profitability stocks. As a result, high operating profitability contributes to the long-leg anomaly in a long-short portfolio. In our study, the size anomaly return represents the average daily excess returns for portfolios constructed based on operating profitability. Moreover, the profitability anomalies return is the difference between the average daily excess returns of the bottom 10% and the top 10% of firms ranked by operating profitability.

The calculation of the different returns of long-short portfolios is as follows: $DIFR = R^{Top10} - R^{Bottom10}$, R^{Top10} is the average return of the long portfolios, and it ranks in the top 10%. $R^{Bottom10}$ is the average return of the short legs, and it is in the bottom 10%. If the difference in returns ($DIFR$) is significantly different from 0, we refer to it as the long-short anomaly return. Otherwise, referred to as the cross-sectional return. The data were obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The sample period is from January 1, 1990, to February 28, 2022, with 8030 observations, as the availability of the VIX started in 1990. It is the driver of the weekend effect on long-short anomaly returns. To examine the weekend effect of stock market anomalies, we define the weekend return as the Friday return minus the Monday return for the long-short anomaly (Birru, 2018). If it is significantly different from 0, the weekend effect of long-short anomaly returns is present. Otherwise, it disappears.

3.2. Descriptive statistics

Table 1 shows the cross-sectional returns over 32 years from January 1, 1990, to February 28, 2022. The results show that the cross-sectional returns sorted by OP and ME have the highest returns on Mondays and the lowest returns on Fridays. Specifically, the average cross-sectional returns sorted on OP and ME are 0.1748 and 0.1091 on Mondays, respectively, while they are −0.0635 and −0.1397 on Fridays. These results suggest that cross-sectional returns vary over the course of a week and that abnormal returns are likely to occur on Mondays and Fridays.

Table 1. Descriptive statistics of cross-sectional return day over a week.

	Mon.	Tue.	Wed.	Thu.	Fri.
Panel A: OP					
Mean	0.1748	0.0496	0.0020	−0.0459	−0.0635
S.D.	1.1072	1.0440	1.0571	1.0220	1.0036
Kur.	4.9044	6.6728	5.9594	4.0164	9.6196
Skew.	0.5582	−0.1953	0.0021	−0.1908	−0.6952
Min.	−6.4100	−8.0900	−8.8600	−5.4800	−7.4600
Max.	7.7200	6.7100	5.7600	4.7700	5.3500
Num.	1530	1661	1660	1632	1620
Panel B: ME					
Mean	−0.0428	0.0091	0.0182	−0.0124	0.0501
S.D.	1.2260	1.1365	1.1670	1.1455	1.0122
Kur.	8.7534	5.6480	5.2869	7.8147	5.5038
Skew.	−0.4660	0.4744	−0.1254	0.2928	0.8034
Min.	−8.4000	−6.3600	−7.4900	−6.3900	−3.8100
Max.	8.3500	7.5300	6.1100	9.8300	6.5100
Num.	1530	1661	1660	1632	1620

3.3. GARCH model with structural volatility breaks

We take the return of the S&P 500 Index to classify the high and low-volatility states, for the S&P 500 Index has much more companies than Dow Jones Industrial Index, and VIX is estimated from options written on that. We use the Iterative, cumulative sums of squares (ICSS) algorithm to estimate the structural breakpoint of volatility. The method was put forward by (Inclan & Tiao, 1994), who assumed that the time series has a constant variance in the initial interval. However, a great event will lead to significant fluctuations in financial markets, and the variance will change a lot and remain constant over a period; the volatility structure was abrupt. The time at which the big event occurs is the break structural breakpoint; the period between the two adjacent structural breakpoints keeps a constant variance. ICSS is an effective method for investigating the structural breaks of financial volatility sequence, which is supported by Zhao and Wen (2022), Gong and Lin (2018) and Wen et al. (2018). In this paper, we adopt the ICSS algorithm to evaluate the structural breaks of volatility in the stock market.

The ICSS algorithm is constructed as follows. First, we define the structure breaks of the volatility in the stock market. r_t is the return, which satisfies an independent normal distribution with an expected value of 0, the variance of δ_t^2. And there are t observations in the sample. Assuming N_T structural breaks of volatility in the sample period, they would divide the time series into N_{T+1} intervals. β_1, β_2, $\beta_3, \cdots$, β_{Nt}, which stands for structural breaks. Meanwhile, the $\beta_1 < \beta_2 < \beta_3 \cdots < \beta_{Nt} < T$. K_i^2 represents the volatility of each interval. $\delta_0^2 = K_0^2, 1 < k < \beta_1$; $\delta_{NT}^2 = K_{NT}^2, \beta_{Nt} < k < T$.

And then, we define the cumulative sum of squares. Let $C_k = \sum_{t-1}^{k} r_t^2$ and $k = 1,2,\dots,T$ indicates the cumulated sum squares of the residual series $\{r_t\}$, then$C_t = \sum_{t-1}^{T} r_t^2$. Third, use D_k statistics for iteration. Define $D_k = \frac{C_K}{C_T} = \frac{K}{T}$ and $D_0 = D_T = O$. If the time series is homologous with variance, the D_k statistics follow the Brownian Bridge process of up and down volatility around the zero axis. When the sample has one or more breaks in variances, the D_k statistics would depart from zero and with a particular probability value over a specific boundary. More specifically, as the$K^*$is the value of K at $max_k|D_k|, max_k\sqrt{\frac{T}{2}}|D_k|$ exceeds 1.628 upper and lower boundary. It could be concluded that there is a volatility break point in the interval, $K^*$is the estimated breakpoint and $\sqrt{\frac{T}{2}}$ is used to standardize the distribution.

In addition, we divided the structural breaks into positive and negative ones to evaluate the changes in the volatility states. The favorable structural breaks mean the volatility increased compared to the upfront period. In contrast, the negative ones indicate that the volatility is decreased. Moreover, we also consider the magnitude of volatility. If it is higher than 1%, it is in high-volatility states. Otherwise, it is in low-volatility states.

We used the AR (1)- GARCH(1,1) model to investigate the daily anomalies for cross-sectional return because the GARCH model is good at capturing the volatility dynamics of time series data. In addition, the GARCH-type model is used to investigate the daily anomalies in kinds of the financial market, such as Qadan et al. (2019) and Auer (2014). In addition, we should pay attention to its time-delay terms (Wang, 2019). We also used the AR (1)- GARCH model to examine the weekend effect of cross-sectional return.

Furthermore, return in the stock market is highly correlated with volatility states. Dahmene et al. (2021) report that stock index returns fall as investors become more risk-averse following a positive shock to the volatility index. Therefore, we add the structural breaks of volatility into the AR (1)-GARCH model to investigate the weekend effects of cross-sectional return.

$$r_t = c_0 + \beta r_{t-1} + \theta\text{VOLA} + \sum_{i=1}^{4} c_i D_{it} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{h_t} z_t \; z_t \sim i.i.d.N(0,1) \tag{2}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma h_{t-1} + \mu D_k \tag{3}$$

where r_t is the cross-sectional return, $D_{it}$is the dummy variable, which is used to examine the weekend effect. If D_{1t} is the dummy variable on Mondays, D_{2t} is the dummy variable on Tuesdays, … and so on. Thursday is the basement. If it is on Monday, $D_{1t} = 1$, while $D_{2t} = D_{3t} = D_{5t} = 0$. c_i is the influence of the dummy variable for the day over a week. If it is significant, it means that this day in a week significantly impacts cross-sectional return. D_k describe the structural breaks of volatility. If the volatility is in high states $D_k = 1$, otherwise $D_k = 0$. the μ denotes structural beak effects on the risk compensation of the stock market.

4. The empirical results

4.1. Breakpoint test of the volatility

The ICSS model was used to test for structural breaks in volatility states, which were then used to classify the entire sample into high and low-volatility states. The results are shown in Table 2. Panel A of Table 2 shows six structural breaks, with volatility increasing in two periods (from July 24, 2007, to June 24, 2009 and from June 11, 2020, to June 11, 2020) and decreasing in the other four periods.

We also classified the volatility states based on the average volatility of the entire sample, which was 0.1080. If the volatility exceeded this average value, it was included in the sample of high-volatility states, while if it was below this value, it was included in the sample of low-volatility states. Two subsamples, from July 24, 2007, to December 21, 2011 and from February 21, 2020, to February 28, 2022, were found to have higher volatility than the average and were therefore placed in the high-volatility state samples. The remaining subsamples were placed in the low volatility condition samples.

The high-volatility subsamples were associated with significant events, such as the global financial crisis from 2007 to 2009 and the COVID-19 pandemic from 2020 to 2022. The empirical results suggest that volatility increased significantly during these events. For example, Hsu and Tang (2022) report that the COVID-19 pandemic caused unexpected conditional volatility in the stock market due to sentiment, while Choi (2022) showed that both the global financial crisis (2007–2010) and the COVID-19 pandemic (2020–2022) increased volatility. Thus, the empirical results of the ICSS model accurately captured the structural breaks in volatility.

Table 2. Detected volatility shifts in the US.

Period	Standard Deviation	Volatility states
Panel A: The breakpoints and volatility conditions		
January 3rd, 1990 ~ July 14, 2007	0.92%	Low
July 15, 2007, ~June 21, 2009	2.10%	High
June 22, 2009, ~ September 17, 2011	1.21%	High
September 18, 2011, ~February 14, 2020	0.78%	Low
February 15, 2020, ~ June 14, 2020	3.69%	High
June 15, 2020, ~February 28, 2022	1.08%	High
Panel B: The volatility conditions		
Period	Standard Deviation	Volatility states
January 3rd, 1990 ~ July 14, 2007	0.92%	Low
July 15, 2007, ~ September 17, 2011	2.10%	High
September 18, 2011, ~ February 14, 2020	0.78%	Low
February 15, 2020, ~ February 28, 2022	3.69%	High

4.2. The weekend effect of size anomaly under high and low volatility states

Next, we will further examine whether the weekend effect of the size anomaly is related to the stock market volatility states. We use the size anomaly return, which was first discovered by Banz (1981), to examine the weekend effect based on the minus return between Mondays and Fridays. Specifically, we use ME10 (ME20) to represent the size anomaly return. This refers to the difference in returns between the top 10% (20%) and the bottom 10% (20%) based on size. The data comes from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Additionally, we split the data into low-volatility and high-volatility subsamples based on the ICSS results, the empirical results are reported in Table 3.

Our results demonstrate that the weekend effect of size anomalies is significant under low-volatility market states and disappears under high-volatility market states. Across all subsamples and conditions of the low-volatility state, ME10(ME 20) is significantly positive on Mondays and negative on Fridays. Furthermore, the difference in return between Mondays and Fridays is significantly positive under low-volatility states. In contrast, there is no significant difference between Mondays and Fridays under high-volatility conditions. These findings suggest the weekend effect of size anomalies is highly correlated with the market volatility states.

Table 3. The weekend effect of size anomalies under high and low-volatility states.

	ME20-Mon	ME10-Mon	ME20-Fri	ME10-Fri	ME 20-Diff	ME 10-Diff
Panel A: All invents under low-volatility states						
Average return	0.0824***	0.1022***	−0.1000***	−0.1360***	−0.1824***	−0.2382***
t-value	3.7815	4.3646	−4.9390	−6.1886	−6.4634	−7.8978
Subsample1 January 1, 1990–July 23, 2007						
Average return	0.1409***	0.1658***	−0.1145***	−0.1654***	−0.2553***	−0.3312***
t-value	5.0946	5.3730	−4.5165	−5.8972	−7.1560	−8.4034
Subsample2 December 21, 2011–February 21, 2020						
Average return	−0.0327***	−0.0232	−0.0714***	−0.0782***	−0.0387**	−0.0550***
t-value	−2.6777	−1.9236	−6.0420	−6.3282	−2.4252	−3.4873
Panel B: All invents under high-volatility states						
Average return	0.0256	0.0250	−0.0195	−0.0477	−0.0451	−0.0727
t-value	0.3991	0.3844	−0.3111	−0.8275	−0.5056	−0.8215
Subsample3 July 24, 2007–December 21, 2011						
Average return	0.0902	0.0933	−0.0303	−0.0728	−0.1204	−0.1661
t-value	1.4073	1.5125	−0.4421	−1.1729	−1.2403	−1.7736
Subsample4 February 21, 2020–February 28, 2022						
Average return	−0.2298	−0.2455	0.0233	0.0516	0.2531	0.2971
t-value	−1.2200	−1.1932	0.1540	0.3550	1.1841	1.3072

Notes: ***and ** indicate statistical significance at 1%and 5%, respectively.

4.3. The weekend effect of profitability anomaly under high and low volatility states

We will investigate whether the weekend effect of the profitability anomaly also depended on the stock market volatility states. Since Ball et al. (2015) and Balakrishnan et al. (2010), found that profitable stocks outperform less profitable stocks, we examine the profitability anomaly by using OP10 (OP20) to represent the return of the top 10% (20%) operating profitability companies minus the bottom 10% (20%). The data for our analysis were obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. To ensure robustness, we also split the data into low-volatility and high-volatility subsamples based on the ICSS results. The empirical result is reported by Table 4.

Our results demonstrate that the weekend effect of the profitability anomaly depends on the stock market volatility conditions. Across all subsamples and conditions of the low-volatility state, OP10 (OP20) is significantly negative on Mondays and positive on Fridays. Similarly, the difference in returns between Mondays and Fridays is significantly negative under low-volatility conditions. However, these anomalies disappear under high-volatility states. Furthermore, the difference in returns between Mondays and Fridays is not significant. These findings suggest that stock market volatility conditions play a crucial role in determining the existence of the weekend effect of the profitability anomaly.

Table 4. The weekend effect of profitability anomaly under high and low-volatility states.

	OP20-Mon	OP 10-Mon	OP20-Fri	OP-Fri	OP -Diff	OP-Diff
Panel A: All invents under low-volatility states						
Average return	−0.1214***	−0.1804***	0.0379**	0.0611***	0.1592***	0.2413***
t-value	−6.0182	−5.9203	2.0482	2.3466	5.7931	5.9559
Subsample1 January 1, 1990–July 23, 2007						
Average return	−0.1319***	−0.2110***	0.0429	0.0820***	0.1747***	0.2930***
t-value	−5.0000	−5.4833	1.7658	2.4936	4.8390	5.6613
Subsample2 December 21, 2011–February 21, 2020						
Average return	−0.0992***	−0.1153**	0.0273	0.0172	0.1264***	0.1325***
t-value	−3.4211	−2.3666	1.0460	0.4121	3.2666	2.1195
Panel A: All invents under high-volatility states						
Average return	−0.1531	−0.1348	0.0182	0.0438	0.1716*	0.1806
t-value	−2.6173	−1.6594	0.3255	0.5512	2.1775	1.6246
Subsample3 July 24, 2007–December 21, 2011						
Average return	−0.2028	−0.1775	0.0134	0.0441	0.2162*	0.2216
t-value	−2.9028	−1.9848	0.2006	0.5015	2.2489	1.7868
Subsample4 February 21, 2020–February 28, 2022						
Average return	−0.0502	−0.0520	0.0283	0.0430	0.0786	0.0950
t-value	−0.4780	−0.3121	0.2765	0.2648	0.5728	0.4219

Notes: ***and ** indicate statistical significance at 1%and 5%, respectively.

4.4. The weekend effect of profitable and size anomalies based on regression results

Next, we will examine the weekend effect of profitable and size anomalies based on regression results. The empirical results are reported in Table 5.

It is easy to see that the weekend effect of profitable and size anomalies varies across volatility states. We find a significant positive coefficient for Monday on profitable anomalies (0.1859, $p < 0.01$), while the coefficient for Friday on size anomalies is smaller but still significant (0.0516, $p < 0.05$). Furthermore, volatility states, as represented by VOLA, have a significant coefficient of −0.0458 ($p < 0.05$) on size anomalies. However, in Panel B, which focuses on the high volatility state, both profitable and size anomalies disappear. The coefficients on Monday and Friday are no longer significant. On the other hand, in Panel C, which analyzes the low volatility state, the empirical results support the presence of significant weekend effects for both profitable and size anomalies. Specifically, profitable anomalies show a significantly positive coefficient for Monday (0.1967, $p < 0.01$), while size anomalies show a significant coefficient for Friday (0.0526, $p < 0.05$).

In conclusion, based on the results, we can infer that the weekend effect of profitable and size anomalies disappears in high-volatility states, while it becomes significant in low-volatility states. These provide new evidence of the dependence on the weekend effect of size and profitable anomalies depending on volatility conditions.

Table 5. The results of the weekend effect of profitable and size anomalies based on regression results.

The weekend effect of OP			The weekend effect of ME		
Variable	Coefficient	z-Statistic	Variable	Coefficient	z-Statistic
Panel A: All invents					
C	−0.0528***	−3.0728	C	−0.0164	−0.9444
OP(-1)	0.0719***	6.4210	ME (−1)	0.0581***	5.3685
Mon.	0.1859***	7.8264	Mon.	0.0202	0.8009
Tue.	0.0926***	3.9305	Tue.	0.0128	0.5166
Wed.	0.0381	1.6804	Wed.	0.0251	1.0536
Fri.	0.0089	0.3547	Fri.	0.0516**	2.0605
VOLA	0.0189	0.9145	VOLA	−0.0458**	−2.0098
Panel B: High volatility					
C	−0.0004	−0.0088	C	−0.0699	−1.1597
OP(-1)	0.0292	1.1170	ME (−1)	0.0434*	1.7022
Mon.	0.1166	1.6423	Mon.	0.0196	0.2207
Tue.	0.0531	0.7250	Tue.	−0.0963	−1.0696
Wed.	0.0246	0.3592	Wed.	0.0085	0.0989
Fri.	−0.0614	−0.8026	Fri.	−0.0035	−0.0390
Panel B: Low-volatility					
C	−0.0539***	−3.0067	C	−0.0167	−0.9251
OP(-1)	0.0837***	6.6073	ME (−1)	0.0628***	5.1769
Mon.	0.1967***	7.7488	Mon.	0.0154	0.5952
Tue.	0.0915***	3.6787	Tue.	0.0204	0.7901
Wed.	0.0348	1.4519	Wed.	0.0240	0.9618
Fri.	0.0107	0.4070	Fri.	0.0526**	2.0007

Notes: ***and ** indicate statistical significance at 1%and 5%, respectively.

4.5. Robust test

In this section, we reexamine whether the weekend effect of the profitable and size anomalies depends on the stock market volatility states based on monthly realized volatility conditions. We follow the approach of Moreira and Muir (2017) and use realized volatility as a popular measure of volatility, which is highly correlated with stock market returns (Bollerslev et al., 2020; Chun et al., 2023; Patton & Sheppard, 2015).

We define the realized volatility over month t as the sum of the squared log-returns of the Standard &Poor's 500-stock index on each trading day during the month t. Its calculations are as follows: $RV_t = \sum_{i=1}^{n} r_{ti}^2$, r_{ti} is the log return of the Standard&Poor's500-stock index on the day i of the t month. Moreover, if this sum is greater than twice the average realized volatility (0.0040), we classify the month as having high volatility conditions; otherwise, we classify it as having low volatility states. To ensure robustness, we split the full sample into two subsamples, each with a similar number of observations. The empirical results are presented in Table 6.

Our analysis reveals that the weekend effect of the profitable and size anomalies is dependent on the stock market volatility states based on the realized volatility. When the realized volatility is in a high condition, the weekend effect of profitable and size anomalies is not significant. In contrast, when the realized volatility is in a low condition, the weekend effect of profitable and size anomalies is significant.

Panel A of Table 6 demonstrates the significant weekend effect of profitable and size anomalies under low volatility conditions. It shows that the difference in return between Mondays and Fridays is positive, with a significance level of 1%. This finding holds across the full sample and subsamples. In contrast, Panel B of Table 6 reports the weekend effect of profitable and size anomalies under high volatility conditions, indicating that the difference in return between Mondays and Fridays is not significantly different from zero.

Overall, our study provides new evidence about the weekend effect of the profitable and size anomalies and its dependence on the stock market volatility states based on monthly realized volatility. The results suggest that the weekend effect of profitable and size anomalies is more pronounced under low-volatility conditions and disappears under high-volatility conditions.

Table 6. Volatility states and the weekend effect of profitable and size anomalies based on the realized volatility.

Average return					t-value			
Sample	OP10	OP20	ME10	ME20	OP10	OP20	ME10	ME20
Panel A: Low volatility								
All invents	0.1823***	0.2526***	0.2013***	0.2593***	6.2037	6.1555	6.6614	8.1366
Subsample1	0.1448***	0.1655***	0.0987**	0.1460***	3.7012	3.1233	2.3134	3.5390
Subsample2	0.2180***	0.3369***	0.3080***	0.3748***	4.9246	5.3394	7.2064	7.7168
Panel B: high volatility								
All invents	0.0685	0.1181	−0.0630	−0.0381	0.8332	0.8886	−0.8240	−0.4891
Subsample1	0.0750	0.0999	−0.1722	−0.1597	0.5068	0.4284	−1.2037	−1.1326
Subsample2	0.0500	0.0774	0.0259	0.0733	0.7460	0.5938	0.3394	0.9045
Total	0.1635***	0.2303***	0.1576***	0.2101***	5.8264	5.6596	5.5632	7.0760

Notes: ***and ** indicate statistical significance at 1%and 5%, respectively.

5. The driver of the weekend effect of profitable and size anomalies

Sentiment has been identified as an important driver of daily anomalies in the stock market. Recent studies by Hirshleifer et al. (2020) and Singal and Tayal (2020) suggest that seasonal anomalies in sentiment follow the variation of returns over a week in the stock market. The VIX, a widely-used measure of market sentiment, is an important sentiment indicator according to Bandopadhyaya and Jones (2008) and Smales (2017). Birru (2018) has reported that the VIX is a driver of the day-of-the-week effect of profitable and size anomalies. In addition, Barinov (2022) has found that the High-minus-low profitability strategy has a negative loading on the VIX factor, which causes it to lose when the VIX rises. These findings suggest that the VIX could potentially be a driver of the weekend effect of profitability and size anomalies under different volatility conditions.

5.1. The weekend effect of the VIX under high and low conditions

In the following analysis, we examine the weekend effect of the VIX across different volatility conditions and present empirical results in Table 7. Our findings reveal that the weekend effect of VIX is significant, but the significance varies under high and low-volatility states. Specifically, we observe that the VIX tends to be higher on Mondays than on Fridays under low-volatility conditions, but this pattern is not significant across all the high-volatility subsamples.

Under low-volatility states, the minus returns of VIX are 0.0290, 0.0323 and 0.0318 for all invents, subsamples 1 and 2, respectively, and the difference from zero is significant at the 1% level. However, under high-volatility states, the minus returns of VIX are 0.0169, 0.0325 and 0.0098 for all invents, subsample1, and 2, respectively, and they are not significantly different from zero at the 5% level for subsample 3.

Table 7. The weekend effect of VIX under high and low volatility states.

	Mon.	Fri.	Minus
Panel A: All events (low-volatility states)			
Average return	0.0191***	−0.0099***	0.0290***
t-value	9.6202	−5.3955	10.3965
Subsample2 December 21, 2011–February 21, 2020			
Average return	0.0195 ***	−0.0129 ***	0.0323***
t-value	3.9496	−3.2542	4.9629
Subsample1 January 1, 1990–July 23, 2007			
Average return	0.0223***	−0.0095 ***	0.0318 ***
t-value	10.8486	−4.3582	10.7456
Panel B: All events (high-volatility states)			
Average return	0.0097	−0.0071	0.0169**
t-value	1.8541	−1.474	2.1713
Subsample4 February 21, 2020–February 28, 2022			
Average return	0.0104	−0.0222**	0.0325**
t-value	0.9875	−2.2448	2.0571
Subsample3 July 24, 2007–December 21, 2011			
Average return	0.0095	−0.0004	0.0098
t-value	1.582	−0.0668	1.1327

Notes: ***and ** indicate statistical significance at 1% and 5%, respectively.

Our results suggest that the significance of the weekend effect of the VIX also depends on the volatility conditions, and it is significant under low-volatility conditions, while it disappears in some cases under high-volatility conditions. It is different from Qadan (2013) and Qadan and Idilbi-Bayaa (2021), who report that Mondays (Fridays) are associated with positive (negative) changes in volatility. In addition, this finding is similar to the weekend effect of the size and profitability anomalies.

5.2. The high and low VIX and the weekend effect of profitability and size anomalies

We investigate whether the weekend effect of profitable and size anomalies is dependent on the level of VIX, which reflects investors' sentiment toward the stock market. We divide the sample into two groups based on the level of VIX. If the VIX is above 25 (the average), we categorize it as a high VIX, otherwise, we assign it to a low VIX. Additionally, Table 8 reports the relationship between high and low VIX and the weekend effect of profitability and size anomalies.

The findings show that the weekend effect of profitable and size anomalies is significantly influenced by the level of VIX. Specifically, when the VIX is low, the weekend effect of profitable and size anomalies is significant, but these anomalies disappear when the VIX is high. This result holds for all invents and subsamples. Panel A of Table 8 shows that the average minus return of profitable and size anomalies between Mondays and Fridays is positive and significant under low VIX conditions. Moreover, this result is consistent across subsamples. Panel B of Table 8 reports that the average minus returns of profitable and size anomalies between Mondays and Fridays are positive but insignificant under high VIX conditions. Our analysis suggests that the weekend effect of profitable and size anomalies is driven by the conditions of VIX, highlighting the importance of considering VIX in factor investing.

Table 8. Volatility states and the weekend effect of profitable and size anomalies based on VIX conditions.

Average minus return					t-value			
Sample	OP10	OP20	ME10	ME20	OP10	OP20	ME10	ME20
Panel A: Low volatility								
All invents	0.1749***	0.2480 ***	0.1785 ***	0.2396 ***	5.8722	5.9608	5.7611	7.3619
Subsample1	0.14785***	0.16385***	0.09005**	0.13225***	3.5271	2.8741	1.9979	3.0602
Subsample2	0.21865***	0.34415***	0.29685***	0.37505***	4.9437	5.5448	6.6547	7.4262
Panel B: High volatility								
All invents	0.1185	0.1603	0.0749	0.0937	1.6032	1.3759	1.0967	1.3199
Subsample1	0.1580	0.2134	0.0232	0.0257	1.3792	1.1820	0.1947	0.2154
Subsample2	0.0662	0.0485	0.1457	0.1766	0.6784	0.3073	1.6981	1.8988
Total	0.1635***	0.2303***	0.1576***	0.2101***	5.8264	5.6596	5.5632	7.0760

Notes: ***and ** indicate statistical significance at 1%and 5%, respectively.

5.3. The weekend effect of profitable and size anomalies and the VIX

To re-examine the VIX as the driver of the weekend effect of profitable and size anomalies, we add the OVX return to the mean equation. The equation is as follows: $r_t = c_0 + \beta r_{t-1} + \sum_{i=1}^{4} c_i D_{it} + \gamma_1\, vix + \gamma_2\, vix * Mon(Fri) + \varepsilon_t$. Given that the profitable and size anomalies return on Monday or Friday are significant for the full sample and low volatility states, we re-examine the relationship for those two samples to obtain a robust result. Table 9 presents the results.

It is easy to find that the VIX is the driver of the weekend effect of profitable and size anomalies. Panel A of Table 9 reports that VIX and the $vix * Mon$ significantly impact the profitable anomaly returns, and the coefficient of Mon. is no longer significant for all invents. Meanwhile, it also shows that the effect of VIX is significantly negative, and the coefficient of Fri. is insignificant for the size anomalies. This indicates that the VIX significantly impacts the weekend effect on profitability and size anomalies for all invents.

Panel B of Table 9 demonstrates similar results. It also shows that the VIX is the cause of the weekend effect on profitability and size anomalies under low-volatility conditions. If we add the VIX to the regression model, the dummy variable of Mondays and Fridays is no longer significant and the effect of the VIX is significant. There for, it provides direct evidence that the VIX is the driver of the weekend effect of profitable and size anomalies.

Table 9. The weekend effect of profitable and size anomalies and the VIX based on regression results.

Variable	Coefficient	z-Statistic	Variable	Coefficient	z-Statistic
Panel A: The weekend effect and the VIX based on regression results (all invents)					
C	−0.1149 ***	−4.1002	C	0.0710 **	2.3077
OP(-1)	0.0695 ***	6.1655	ME(−1)	0.0608 ***	5.6085
Mon	−0.0140	−0.2556	Mon	0.0197	0.7919
Tue	0.0905 ***	3.8503	Tue.	0.0127	0.5317
Wed	0.0373	1.6441	Wed	0.0301	1.2797
Fri	0.0076	0.3036	Fri	0.0780	1.2235
VIX	0.0042 ***	3.0767	VIX	−0.0056 ***	−3.5525
VIX*Mon	0.0121 ***	4.4624	VIX*Fri	−0.0017	−0.4683
VOLA	−0.0318	−1.3524	VOLA	−0.0561 **	−1.9870
Panel B: The weekend effect and the VIX based on regression results(low-volatilities)					
C	−0.1032 **	−2.8397	C	0.0616	1.7583
OP(-1)	0.1195 ***	7.9058	ME(−1)	0.0790 ***	5.3714
Mon	−0.0562	−0.7294	Mon	0.0037	0.1231
Tue	0.1172 ***	4.2715	Tue	0.0082	0.2843
Wed	0.0376	1.3988	Wed	0.0141	0.5005
Fri	0.0201	0.6901	Fri	0.1214	1.5583
VIX	0.0026	1.3580	VIX	−0.0044 **	−2.5120
VIX*Mon	0.0180	4.3660	VIX*Fri	−0.0037	−0.8152

Notes: ***and ** indicate statistical significance at 1%and 5%, respectively.

6. Conclusions

The results of this study reveal a significant relationship between stock market volatility conditions and the weekend effect on profitability and size anomalies. Specifically, our results show that the weekend effect is significant during periods of low stock market volatility, but becomes insignificant during periods of high volatility. Thus, our analysis identifies the VIX as a crucial factor in driving the weekend effect of profitability and size anomalies.

However, it is important to recognize the limitations of this study. First, our study focuses only on the weekend effect of size and profitability anomalies in the stock market without considering other potential factors such as lottery, distress and age. Future research could expand to include other factors to gain a more comprehensive understanding of the weekend effect of short and long anomalies. Second, the sample used in this study is based on data from the U.S. market, which may introduce regional and market-specific influences into the results. Further research could extend to other markets to confirm the generalizability of our findings.

Despite these limitations, the results of the study are not consistent with the empirical results of previous research on the significance of the weekend effect on profitability and size anomalies. While Chiah and Zhong (2021) and Birru (2018) suggested that the effect is significant for all subsamples, our study found that the weekend effect on profitability and size anomalies disappears under the condition of high stock market volatility. This indicates that the stock market volatility condition is an important factor to consider when analyzing the weekend effect on long-short anomalies. In contrast, both of them did not take into account the condition of stock market volatility and reported that the weekend effect was significant for all subsamples. However, our research suggests that the weekend effect remains significant for all subsamples when stock market volatility is not considered.

The results of this study have important implications for investors and practitioners involved in factor investing. The results highlight the importance of taking market volatility conditions into account when developing volatility management strategies. Specifically, during periods of low stock market volatility, investors may benefit from increased exposure to long-legged stocks on Mondays and reversing this approach on Fridays. By taking advantage of the significant weekend effect of short-long anomalies, investors have the potential to improve their performance from factor investing. However, it is notable that there was no significant difference between short and long positions during periods of high stock market volatility. This suggests that conservative positions may not offer significant advantages during periods of high volatility. Therefore, investors should carefully evaluate the prevailing market conditions and adjust their factor investing strategies accordingly.

Use of AI tools declaration

The authors declare that the substantive content, analysis, interpretation, and conclusions presented in this article are the result of human intellect, critical thinking, and extensive research efforts. The utilization of AI tools was restricted to the scope of language refinement, with no influence on the generation or development of the article's original ideas.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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