9. INVESTING STRATEGIES FOR TRADING STOCKS AS OVERREACTION TRIGGERED BY TECHNICAL TRADING RULES WITH BIG DATA CONCERNS

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Abstract

The meaning of technical indicators is to transmit overshooting signals, which lead investors to believe that they may beat the market when the overshooting signals have been triggered. The study aims to examine whether investors could exploit profits when the overreaction signals were revealed by some technical indicators. Meanwhile, several findings are exposed. First, momentum (contrarian) strategies are suggested as overbought (oversold) signals emitted, which differ from our cognition. Second, higher cumulative abnormal returns (CARs) are demonstrated for buying instead of selling the constituent stocks of SSE 50 when overshooting signs occurred, after comparing with those of DJIA 30 and FTSE 100. Third, since superior performance is revealed, investors may apply the BB trading rule instead of others as overreaction trading signals are emitted.

Keywords: *Herding Behavior; Investing Strategies; Overreaction; Technical Indicators; Big Data*

JEL Classification: *G11*

1. Introduction

Forecasting stock prices can be a challenging task due to the efficient market hypothesis (Fama, 1991), which suggests that relevant information is quickly and accurately reflected in stock prices. However, this viewpoint faced challenges from the overreaction hypothesis (Debondt & Thaler, 1985) and herding behaviors (Chalmers *et al.*, 2013). The overreaction hypothesis posits that investors may excessively react to positive news due to their overconfidence (Chuang & Lee, 2006). Consequently, stocks may become overbought (oversold) until these stocks' intrinsic values have been restored (Benlemlih *et al.*, 2021). Herding behaviors, on the other hand, involve investors following the crowd and disregarding their private information, even when it contradicts

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fundamental data (Litimi *et al.*, 2016). As a result, investors tend to chase rising or falling stock prices influenced by the emotional sentiment associated with behavioral finance (Huang & Ni, 2017).

In contrast to prior studies, our research focuses on utilizing the constituent stocks of DJIA 30, FTSE 100, and SSE 50 (hereinafter referred to as US-30, UK-100 and China-50 by placing the country's name first). We contend that market participants have the opportunity to invest in constituent stocks, rather than solely relying on stock index spots. Consequently, our study aims to investigate whether the outcomes differ across these three representative stock markets when using their constituent stocks. Additionally, we examine if market participants would outperform the markets as overbought or oversold signals generated by stochastic oscillator indicators (SOI), relative strength indicators (RSI), and Bollinger Bands (BB). Furthermore, this study examines cumulative abnormal returns (CARs) over 1-, 2-, 3-, 4-, and 5-week periods for the constituent stocks of these indices, facilitating a comparative analysis.

The study reveals a variety of impressive findings. Firstly, our results suggest that momentum strategies are more suitable when overbought trading signals are detected, while contrarian strategies are recommended in the case of oversold trading regulations indicated by the SOI, RSI, and BB. This finding challenges the prevailing belief that contrarian strategies are commonly employed in response to overreaction trading signals. Secondly, we argue that the utilization of overshooting signals tends to yield superior performance in the stock markets of developing economies, such as China, as compared to developed economies like the US and the UK. Thirdly, we highlight that trading China-50's constituent stocks with overreaction signs leads to higher CARs when compared to those of US-30 and UK-100. Lastly, we demonstrate that employing BB trading rules may result in improved CARs, suggesting that investors might prefer to utilize the BB trading rule over other approaches when trading these particular constituent stocks.

Our study offers valuable contributions to the existing literature from multiple perspectives. Firstly, to the best of our knowledge, there is a scarcity of comprehensive exploration in the relevant studies regarding whether investors can beat the market as overreaction signs are generated by SOI, RSI, and BB. This study fills that gap by providing a thorough analysis of this aspect. Secondly, this study suggests employing appropriate trading strategies as the occurrence of overbought and oversold signals, which could be advantageous for investors trading US-30, UK-100, and China-50 component stocks. These strategies serve as practical guidelines for investors seeking to optimize their trading decisions based on these specific signals. Lastly, we add to the existing body of literature by utilizing the component stocks of three representative indices, thereby providing solid and reliable results that strengthen the overall body of research in this field.

2. Literature Review

To gain a comprehensive understanding of the existing literature, we conducted a survey encompassing efficient and inefficient markets, overreaction, herding behavior, investing strategies, and technical analysis. The efficient market hypothesis (EMH) posits that market prices promptly incorporate all available information, precluding the possibility of earning excess profits according to previous information (Guan *et al.*, 2016). Based on the EMH, share prices are expected to reflect the collective beliefs of market participants concerning the anticipated risk and return of the stocks (Guidi *et al.*, 2011). However, contrasting viewpoints persist. While Rizvi *et al.* (2014) argue for increased market efficiency, several studies challenge this notion. For instance, Ţitan *et al.* (2015) find that a majority of investors do not perceive the market to be entirely efficient. Moreover, a variety of hedge funds consistently outperform the market (Metzger & Shenai, 2019), and Lim and Brooks (2011) present the adaptive market hypothesis as an explanation for the rationalization of stock price predictability.

In the context of overreaction, According to Mushinada (2020), market participants frequently exaggerate private news as a result of overconfidence. Stock price overreaction can be characterized as an emotional response driven by greed or fear in response to new information (Otchere & Chan, 2003). Ni *et al.* (2015) suggests that market participants may derive benefits from buying constituent stocks of the China-50 when dead crosses occur, as this is indicative of stock price overreaction. As a result of investors' overreaction to news, stocks can become overbought or oversold, finally reverting to their underlying values (Ni *et al.*, 2019). Concerning herding behavior, Spyrou (2013) describes it as individuals trading stocks contrary to their initial assessment, instead following the prevailing trend from prior trading. The erosion of investor sentiment is closely associated with the emergence of herding behavior, leading to irrational investor behavior in real-world settings (Philippas *et al.*, 2013; Yousaf *et al.*, 2018). Herding behavior, driven by collective behavior and disregard for private information, directly influences stock price volatility (Blasco *et al.*, 2012).

When it comes to investing strategies, momentum and contrarian strategies, are widely discussed among investment strategists (Balvers & Wu, 2006). Momentum trading involves buying stocks with positive returns and selling stocks with negative returns, with traders relying on past price changes (Duxbury & Yao, 2017; Hong & Stein, 1999). Hoitash and Krishnan (2008) suggest that momentum trading is particularly suitable for stocks of firms with high speculative intensity. On the other hand, contrarian strategies involve buying past losers and selling short past winners (Chen *et al.*, 2018; De Haan & Kakes, 2011). Empirical evidence demonstrates that portfolios based on contrarian strategies can yield significant positive returns (Day & Ni, 2023), as these strategies help mitigate stock volatility (Cho *et al.*, 2019). In terms of technical analysis, relevant research demonstrates that stock markets may not be totally efficient, as useful information can be obtained from technical trading (Chen *et al.*, 2010; Menkhoff & Taylor, 2007). Technical analysis uses past market prices, turnover volume and technical indicators to predict stock price changes (Zhang & Lou, 2021), which assumes that market behavior patterns may remain consistent (Sadique & Silvapulle, 2001).

Technical indicators (e.g., SOI, RSI and BB) have shown potential for generating profits for investors. Day *et al.* (2023) find that trading signs triggered by SOI can present a better performance in predicting stock prices, making it a favored choice among institutional investors (Saetia & Yokrattanasak, 2021). Additionally, Day and Ni. (2023) state that RSI may generate positive risk-adjusted returns. Chong and Ng (2008) discover that RSI yields higher returns compared to the buy-and-hold strategy in most cases, using long-term data of the FT30 Index. Furthermore, BB is widely regarded as a favored technical indicator for capturing rapid price fluctuations (Abbey & Doukas, 2012l; Ni *et al.*, 2020). BB trading strategy based on wavelet analysis has been reported to be highly profitable, demonstrating greater returns on CSI 300 stock index futures (Chen *et al.*, 2018). Moreover, we postulate that the effectiveness of SOI, RSI and BB may be in relation to stock market overreaction, as market participants are advised to trade when these technical indicators generate overshooting signs. Given the limited exploration of trading signs generated by SOI, RSI and BB, our study aims to examine if investors can outperform the market by using these technical indicators.

3. Study Design and Data

3.1. The Design of this Study

We adopt the event study approach to investigate trading performance in response to overreaction signals triggered by SOI, RSI and BB trading rules. The event study using the market model is widely employed in corporate finance and investments to examine expected returns, as it offers advantages over other models such as the constant expected return model and capital asset pricing model (Thompson, 1995; Carlson *et al.*, 2006; Ederington *et al.*, 2015). This approach was applied in various events, including capital deduction declarations (Chen, 2017), mergers (Pham & Ausloos, 2022), acquisitions (Jain *et al.*, 2019), and implementation of treasury stock (Urbscha & Watzka, 2020). Additionally, our study employs the component stocks of US-30, UK-100 and China-50 as samples, enabling the measurement of various values based on diverse technical trading rules and the derivation of different trading signals. It is worth noting that computing these measures (ARs and CARs) for various trading rules using big data analytics is challenging (He *et al.*, 2020).

Furthermore, we begin by categorizing the events based on overreaction signs triggered by SOI, RSI and BB. Subsequently, this study measures the CARs over 1, 2, 3, 4, and 5 weeks when these various events occur using the standard event-study approach. In order to account for transaction costs and their potential impact on abnormal returns, we chose to utilize weekly data instead of daily data in our empirical analyses. By extending the holding period to five weeks, we aim to avoid situations where transaction costs overshadow the observed abnormal returns. Our initial examination using daily data indicates that the CARs over a five-day holding period are significantly lower compared to those achieved over a five-week period. This finding suggests that investors may encounter challenges in generating profits that outweigh the associated transaction costs.

According to Ni *et al.* (2022), the identification of overbought and oversold trading signals is determined by the K values in relation to the SOI. The overbought zone is designated as K is higher than 80, while the oversold zone is defined as K is lower than 20. Correspondingly, as described by Basak *et al.* (2019), the RSI serves as a momentum oscillator utilized for assessing the recent gains and losses of the market, assigning a numerical value between 0 and 100. Specifically, the overbought zone is indicated by RSI>70, whereas the oversold zone is characterized by RSI<30, following the RSI methodology. Furthermore, Leung and Chong (2003) state that the area above the upper boundary of the BB is considered the overbought region, while the area below the lower boundary is regarded as the oversold zone. Generally, employing the BB with 2 standard deviations captures approximately 95% of price movements. Consequently, a buying (selling) sign is triggered as share prices cross the lower (upper) boundary from below (above).

Moreover, based on distinct events (e.g., K<20) defined in this study, there may be a sequence of two events. Consequently, two events occurring in succession may be unavoidable; however, we argue that two events occurring in succession may be permissible if there is no overlap that is likely to result in contaminated results. For instance, if our event is defined as K<20 occurring on two consecutive days, the overlapping issue may arise if K<20 occurs on three consecutive days, as the first and second events will overlap. However, our event would only be considered once for three consecutive days to prevent issues from duplicating. In addition, relevant studies (Day *et al.*, 2022; Ni *et al.*, 2019; Wu *et al.*, 2017) would concur with the aforementioned concern.

The event study approach lacks consensus regarding the appropriate number of observations for estimating the market model. Extensive analysis of relevant literature reveals a range of 100 to 300 observations utilized for market model estimation (Armitage, 1995; Bettis *et al.*, 1997; Thompson, 1995). Accordingly, we employ the DJIA 30, FTSE 100 and SSE 50 indices as market returns, given that using a uniform market return (Rm) would yield varying results for abnormal returns, we use the return series of the US-30, UK-100 and China-50 constituent stocks as Rm. To measure the parameters of the market model, we use the weeks -155 to -6 prior to the week in which the overbought or oversold trading signals were triggered. Subsequently, we compute the abnormal return (AR) as the difference between the actual return and the market model's expected return. Furthermore, the CAR at t weeks is derived by aggregating AR from week 1 to AR from week t. Recognizing that market participants often hold stocks for shorter durations, this study calculates CARs over 1-, 2-, 3-, 4-, and 5-week periods, employing a concise time window as recommended in relevant studies (Ahern, 2009). Following that, we then test if these CARs are significantly different from zero.

3.2. Data

The weekly data for the indices is sourced from Datastream. Figure 1 depicts the post-2008 crisis upward trend observed in the DJIA 30, a quite stable movement observed in the FTSE 100, and two distinct peaks occurring in 2007 and 2015 for the SSE 50. Additionally, this study provides descriptive statistics for US-30, UK-100 and China-50, including weekly indices and weekly returns spanning the period from 2007 to 2016 in Table 1. The table encompasses measures such as means, medians, standard deviations, minimum values and maximum values. Notably, the indices and returns exhibit substantial disparities in their minimum and maximum values, leading to wide ranges as depicted in Table 1. Moreover, the China-50 can be characterized as a relatively volatile stock market, indicated by its higher standard deviation of 3.77% for weekly return data compared to 2.42% for US-30 and 2.66% for UK-100.

Figure 1. Trends of US-30, UK-100, and China-50 indices over 2007-2016

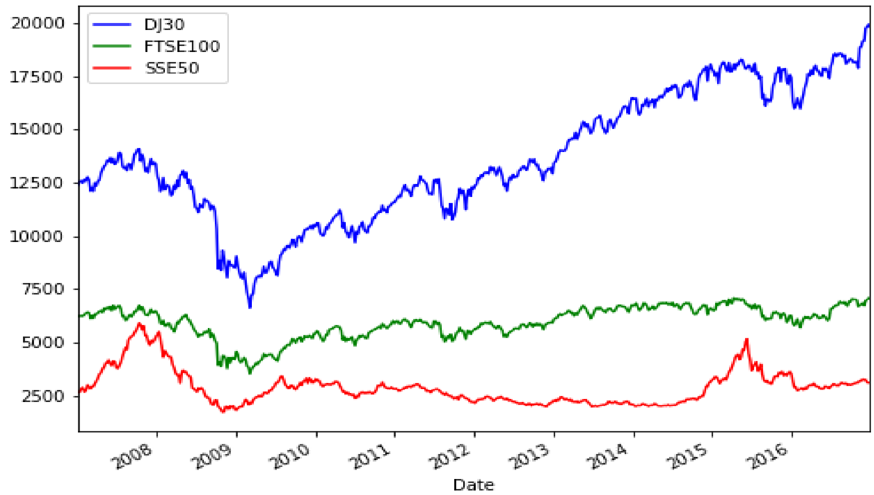

Table 1. Descriptive statistics of US-30, UK-100, and China-50 over 2007-2016

	Observations	Means	Standard Deviations	Minima	Maxima
Panel A: Weekly Index					
US-30	522	13622.59	3048.09	6626.94	19933.81
UK-100	522	5946.69	754.69	3530.70	7142.80
China-50	513	2884.01	811.02	1728.79	5903.26
Panel B: Weekly return					
US-30	522	0.12%	2.42%	-18.15%	11.29%
UK-100	522	0.06%	2.66%	-21.05%	13.41%
China-50	513	0.10%	3.77%	-13.84%	14.96%

Table 2 displays the frequencies of overbought (oversold) trading signals generated by these contrarian trading rules for the constituent stocks of US-30, UK-100, and China-50 throughout the data period. It is observed that the number of overbought trading signals exceeds that of oversold trading signals, a trend possibly influenced by the overall upward trends witnessed in these indices, particularly in the case of the US-30. Analyzing the trading signals, we observe that the quantity of overbought or oversold trading signals identified based on SOI values surpasses those identified through either RSI or BB indicators. This disparity in signal samples may stem from the differing criteria used to determine overbought or oversold trading signals within the frameworks of SOI, RSI, and BB.

Table 2. The samples of overbought and oversold generated by SOI, RSI, and BB

Technical indicators	US-30	UK-100	China-50
Panel A: SOI			
K is higher than 80	2838	6304	1192
K is lower than 20	690	2699	1939
Panel B: RSI			
RSI is higher than 70	1997	5380	2319
RSI is lower than 30	355	1277	1018
Panel C: BB			
Cross over BB Upper Band	510	1653	679
Cross over BB Upper Band	318	1017	315

Note: Panel A provides a comprehensive enumeration of the occurrences of K values exceeding 80 (K > 80) and falling below 20 (K < 20) for these constituent stocks. Similarly, Panel B presents the frequency of RSI values surpassing 70 (RSI > 70) and dipping below 30 (RSI < 30) for these constituent stocks. Lastly, Panel C outlines the number of instances in which the upper Bollinger Band (BB) was crossed (the lower BB was crossed) for the constituent stocks.

Table 3 further provides insights into the average number of events per stock in these respective markets. Notably, Table 3 reveals that the average number of events (i.e., 94.6 events for K > 80, 66.57 events for RSI > 70, and 17 events for cross over BB upper band) among the 30 stocks in the US market (US-30) is higher compared to both the UK market (UK-100) with 63.04 events for K > 80, 53.8 events for RSI > 70, and 46.38 events for cross over BB upper band) among the 100 stocks, as well as the Chinese market (China-50) with 23.84 events for K > 80, 46.38 events for RSI > 70, and 13.58 events for cross over BB upper band) among the 50 stocks. These findings could be attributed to the superior performance of the US-30 index relative to the UK-100 index and the China-50 index over the examined data period.

Table 3. The average number of events per stock of US-30, UK-100, and China-50

Technical indicators	US-30 (30 Stocks)	UK-100 (100 Stocks)	China-50 (50 Stocks)
Panel A: SOI			
K is higher than 80	94.60	63.04	23.84
K is lower than 20	23.00	26.99	38.78
Panel B: RSI			
RSI is higher than 70	66.57	53.80	46.38
RSI is lower than 30	11.83	12.77	20.36
Panel C: BBs			
Cross over BB Upper Band	17.00	16.53	13.58
Cross over BB Upper Band	10.60	10.17	6.30

4. Empirical Results

Table 4 presents the 1-, 2-, 3-, 4-, and 5-week CARs associated with overreaction signs triggered by SOI, RSI, and BB. Panels A1-C1 provide the CARs results as the occurrence of overbought signs. Conversely, Panels A2-C2 depict the CARs and t-statistics when trading as the occurrence of oversold signals.

This study shows that all CARs are positive when long positions are taken on US-30, UK-100, and China-50 constituent equities when either overbought or oversold trading signals are emitted, which appears quite impressive to market participants. These findings suggest that investors may find momentum strategies advantageous when overbought signals are emitted, and contrarian strategies suitable when oversold signals are present. Furthermore, the trading performance for China-50 surpasses that of US-30 and UK-100, indicating greater potential for abnormal returns in developing economies compared to developed stock markets. Specifically, investors achieve a higher CAR (5), exceeding 4%, when trading China-50 constituent stocks in the presence of overbought signals compared to trading US-30 and UK-100 stocks. This shows that China's stock markets are not as developed as those in the United States and the United Kingdom. Moreover, the CARs derived from implementing BB trading rules are significantly higher than those obtained from SOI and RSI. Consequently, investors may find it beneficial to employ BB trading rules when trading these constituent stocks. In addition, this study extended our data set from 2007-2016 to 2007-2021 and found that the results were comparable to those from 2007-2016. We elucidate here instead of presenting similar findings using data from 2007 to 2021 to save space.

Table 4. CARs following trade signs generated by the SOI, RSI, and BB

Holding weeks	US-30			UK-100			China-50		
	CARs	t statistics		CARs	t statistics		CARs	t statistics	
Panel A1: K is higher than 80									
Week 1	0.04%	0.98		0.11%	2.67	***	0.96%	3.76	***
Week 2	0.17%	2.76	***	0.32%	5.55	***	2.28%	5.66	***
Week 3	0.27%	3.60	***	0.54%	7.98	***	3.13%	6.30	***
Week 4	0.42%	4.91	***	0.82%	10.84	***	3.58%	6.13	***
Week 5	0.54%	5.59	***	1.08%	12.89	***	4.15%	6.49	***
Holding weeks	US-30			UK-100			China-50		
	CARs	t statistics		CARs	t statistics		CARs	t statistics	
Panel A2: K is lower than 20									
Week 1	0.48%	2.69	***	0.78%	4.91	***	0.43%	3.46	***
Week 2	0.92%	4.18	***	1.33%	6.49	***	0.81%	4.71	***
Week 3	1.34%	5.10	***	1.69%	7.30	***	1.25%	5.99	***
Week 4	1.71%	5.72	***	1.83%	6.85	***	1.75%	7.22	***
Week 5	1.97%	5.74	***	2.08%	6.85	***	2.17%	8.01	***
Panel B1: RSI is higher than 70									
Week 1	0.09%	1.70	*	0.25%	5.58	***	1.16%	6.43	***
Week 2	0.19%	2.50	**	0.57%	9.09	***	2.22%	8.38	***
Week 3	0.29%	3.06	***	0.92%	11.94	***	3.27%	10.03	***
Week 4	0.43%	3.99	***	1.27%	14.43	***	4.28%	11.24	***
Week 5	0.55%	4.55	***	1.60%	16.33	***	5.34%	12.42	***
Panel B2: RSI is lower than 30									
Week 1	0.14%	0.44		0.40%	1.35		0.45%	2.45	**

Holding weeks	US-30			UK-100			China-50		
	CARs	t statistics		CARs	t statistics		CARs	t statistics	
Week 2	0.12%	0.27		0.68%	1.81	*	0.82%	3.08	***
Week 3	0.24%	0.45		0.68%	1.55		1.13%	3.59	***
Week 4	0.47%	0.75		0.52%	1.07		1.44%	3.95	***
Week 5	0.78%	1.12		0.54%	0.99		1.80%	4.42	***
Panel C1: Upper BB Cross									
Week 1	0.10%	1.04		-0.10%	-0.95		0.54%	1.79	*
Week 2	0.30%	2.09	**	0.20%	1.52		2.07%	3.99	***
Week 3	0.42%	2.48	**	0.47%	3.17	***	3.20%	5.19	***
Week 4	0.60%	2.92	***	0.81%	4.97	***	4.18%	5.47	***
Week 5	0.77%	3.53	***	0.97%	5.27	***	4.92%	6.04	***
Panel C2: Lower BB Cross									
Week 1	1.01%	3.51	***	0.60%	3.26	***	4.91%	2.56	**
Week 2	0.83%	2.41	**	0.47%	1.93	*	5.09%	2.67	***
Week 3	1.53%	3.67	***	1.16%	4.06	***	4.96%	2.49	**
Week 4	1.94%	4.71	***	1.64%	5.06	***	5.18%	2.60	***
Week 5	1.95%	4.26	***	1.60%	4.23	***	5.09%	2.49	**

*We investigate whether diverse CARs are significantly different from zero, as the occurrence of overbought and oversold is defined in this study. The significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.*

5. Further Investigation

The utilization of moving average (MA) trading rules was extensively studied in the literature (Bessembinder & Chan, 1995). These rules, involving the identification of golden crosses and dead crosses, rely on past price patterns (Metghalchia *et al.*, 2012) and are regarded as potential predictors of future stock prices (Shintani *et al.*, 2012). In this study, we investigate the potential for improved performance among market participants by employing MA trading rules. Specifically, we use a 5-week moving average (SMA) and a 20-week moving average (LMA) as indicators, following the widely used MA (5, 20) strategy in practice, because MA (5, 20) is a widely used technique among market practitioners (Mills, 2019). Additionally, the golden cross is identified when the current SMA value (SMA(t)) surpasses the current LMA value (LMA(t)), while the preceding SMA value (SMA(t-1)) is lower than the preceding LMA value (LMA(t-1)). Conversely, the dead cross is recognized as the current SMA value is lower than the current LMA value, while the previous SMA value is greater than the previous LMA value. To gauge the effectiveness of MA trading rules, we analyze the numbers of trading signals, including golden crosses and dead crosses, observed for the constituent stocks of US-30, UK-100, and China-50, employing the MA (5, 20) approach, as presented in Table 5.

Table 5. The samples of the Moving Average (MA) trading rule

MA Trading rules	US-30	UK-100	China-50
Golden Cross generated by MA (5, 20)	502	1493	509
Death Cross generated by MA (5, 20)	512	1531	499

The findings presented in Table 6 indicate that investors may achieve positive CARs when either golden cross or dead cross trading signals are observed, suggesting that market participants could outperform the market by taking long positions based on these signals. However, it is worth noting that the CARs associated with MA trading signals might not surpass those obtained from other trading signals. For instance, the CARs generated by BB trading signals demonstrate superior performance compared to the CARs derived from MA trading signals. This observation suggests that the application of MA trading rules may not result in superior performance due to concerns regarding market efficiency. Consequently, we posit that the trading performance attributed to a specific trading rule, such as MA, is likely to diminish as more market participants become acquainted with and adopt the same rule.

Table 6. CARs following trade signs generated by MA

Holding Weeks	US-30			UK-100			China-50		
	CARs	t statistics		CARs	t statistics		CARs	t statistics	
Panel A: Moving Average Golden Cross (5, 20)									
Week 1	0.16%	1.21		-0.04%	-0.36		-0.34%	-1.34	
Week 2	0.38%	2.23	**	-0.02%	-0.12		0.02%	0.04	
Week 3	0.26%	1.28		0.03%	0.16		-0.03%	-0.05	
Week 4	0.35%	1.41		0.21%	1.03		0.41%	0.68	
Week 5	0.40%	1.45		0.45%	2.01	**	0.72%	1.11	
Panel B: Moving Average Death Cross (5, 20)									
Week 1	0.40%	2.89	***	0.27%	2.48	**	1.51%	1.79	*
Week 2	0.74%	3.63	***	0.60%	4.07	***	1.45%	1.70	*
Week 3	1.10%	4.67	***	0.77%	4.62	***	1.89%	2.08	**
Week 4	1.38%	5.55	***	1.10%	5.49	***	1.95%	2.12	**
Week 5	1.54%	5.68	***	1.30%	5.95	***	2.44%	2.53	**

*We investigate whether diverse CARs are statistically different from zero as the occurrence of the golden cross and dead crosse specified in this study. The significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.*

6. Conclusion

Market participants commonly utilize trading signals generated by various technical indicators. Technical indicators like SOI, RSI, and BB are often associated with overreaction signals. When these indicators indicate overbought or oversold conditions, investors may employ contrarian strategies. As such, this study aims to examine if investors can outperform the market by adopting these strategies and to compare the profitability across different indicators. Our findings aim to provide valuable insights and guidance for market participants in their trading activities involving the constituent stocks of US-30, UK-100, and China-50.

As such, this study may add to the body of existing literature by examining the potential of overshooting signals revealed by SOI, RSI, and BB to generate profitable opportunities. Firstly, the investigation of if investors are able to outperform the market by utilizing these overreaction signals, an aspect that has been seldom comprehensively explored in previous studies, adds to the existing literature. Secondly, we propose appropriate strategies for trading diverse overbought and oversold signals, offering potential advantages to market participants in trading these stocks. Lastly, using the constituent stocks of US-30, UK-100, and China-50 in this study reflects the practical limitations faced by investors who are unable to trade index spots directly, making our findings more relevant and applicable to real-world trading scenarios.

In addition, this study has several significant implications. Firstly, it suggests that investors have the potential to outperform the market by recognizing and utilizing various overshooting signals, specifically overreaction signals triggered by SOI, RSI, and BB. Secondly, our findings provide valuable and previously undisclosed information to enhance trading profitability in the presence of different overshooting signals. This highlights the importance of considering and incorporating the insights derived from these technical indicators in investors' trading strategies. Overall, the results indicate that the overshooting signals revealed by SOI, RSI, and BB offer valuable information for capitalizing on profit opportunities in the stock market.

While our study presents compelling results regarding the trading of these constituent stocks based on overreaction signs generated by the SOI, RSI, and BB, it would be important to address certain concerns that warrant further research. Firstly, future investigations could employ big data analytics to assess whether these findings persist when extending the analysis to include future data. Considering the potential existence of market efficiency, it is crucial to determine if the observed patterns hold over time. Secondly, beyond comparing the performance of constituent stocks from representative stock indices, such as US-30, UK-100, and CHINA-50, future studies could explore the performance of other investment commodities (e.g., bonds, ETFs, and cryptocurrencies) and commodity instruments (gold, crude oil, and natural gas) to ascertain the generalizability of our findings. Lastly, it would be valuable to evaluate long-term holding period returns (HPRs) rather than the short-term cumulative abnormal returns (CARs) utilized in our study, allowing for a more comprehensive assessment of the profitability and sustainability of the identified trading strategies.

Regarding the limitations of our study, it is important to note that our findings are specific to the overreaction signs generated by the SOI, RSI, and BB, and it remains uncertain whether similar results would be observed for other trading rules. Additionally, we addressed several issues by utilizing the event study approach, such as avoiding short event estimation periods with limited observations and insufficient events, excluding periods with potential information leakage, and preventing overlapping samples. However, it is worth noting that there is no agreement in the literature on the most appropriate window period for event estimation, which introduces a limitation to our study. Therefore, further research on determining the optimal window period is necessary as it remains an understudied topic in economics and finance, despite the widespread use of the event study approach.

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