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Can investors profit by utilizing technical trading strategies? Evidence from the Korean and Chinese stock markets

Yensen Ni[1], Min-Yuh Day[2], Yirung Cheng[1] and Paoyu Huang[3*]

*Correspondence: hpy315315@gmail.com
[3] Department of International Business, Soochow University, No. 56, Sec. 1, Kueiyang St, Taipei 100, Taiwan
Full list of author information is available at the end of the article

Abstract

The idea of this study is derived from observing the profitability of stock investments following the phenomena of continuously rising (or falling) prices of stocks and continuously overbought (or oversold) signals emitted by technical indicators. We employ the standard event study approach and technical trading strategies to explore whether investors would exploit profits in trading the constituent stocks of the Korea Composite Stock Price Index 50 and Shanghai Stock Exchange 50 when the aforementioned continuous phenomena occur. We find that both the Korean and Chinese stock markets are not fully efficient; this finding may enhance the robustness of the existing literature. In addition, we reveal that contrarian strategies are appropriate for the trading stocks listed on the Korean stock market for all the cases investigated in this study. However, momentum strategies are appropriate for the Chinese stock market when continuously rising stock prices and overbought signals are simultaneously observed. These findings imply that the difference in investor behaviors between the Korean and Chinese stock markets might result in dissimilar trading strategies being employed for these two markets.

Keywords: Technical analysis indicator, Continuously rising or falling prices, Overreaction, Herding behavior, Momentum strategies, Contrarian strategies

Introduction

Essentially, individuals attempt to earn higher yields by trading in stocks. Thus, forecasting stock prices is regarded as an important characteristic of market participants. However, stock prices are difficult to predict because they are affected by numerous factors, including investor behavior. As Wang and Guo (2020) mention, investors' behavior can cause severe fluctuations in a certain financial market. In the real world, investors tend to buy past winners and sell past losers, causing stock prices to rise or fall continuously (Lakonishok et al. 1992). They are frequently attracted toward chasing rising or falling stocks (Ni et al. 2020).

As per the efficient market hypothesis (EMH), all the available information is completely reflected in stock markets (Fama 1965, 1970). Therefore, investors might find it difficult to predict future stock prices to generate excess returns (Latif et al. 2011).

However, this viewpoint is challenged by weak-form market efficiency (Da Dalt et al. 2019; Masteika and Rutkauskas 2012) and technical analyses (Tian et al. 2002; Yu et al. 2013). In fact, studies have illustrated that investors can make more profits by applying technical indicators, such as the stochastic oscillator indicator (SOI) and relative strength index (RSI) for trading stocks (Chiang et al. 2012; Chong and Ng 2008; Shik and Chong 2007; Wang et al. 2012). In general, market participants are likely to trade stocks when prices rise or fall continuously (Fock et al. 2005). Tempted to buy or sell stocks, investors may induce the occurrences of overbought or oversold signals and intend to utilize contrarian or momentum strategies for trading stocks, following overreaction or trend-following concerns.

In comparison to the global economy, Asia markets have experienced a dramatic economic development in recent decades. In this context, China and Korea have received considerable attention from stock market participants following their significant economic growth. As the second largest economy worldwide (Park 2020), China's economic growth rate was 6.5% in 2018, and it used to surge to 11.4% in 2005 (Lu et al. 2020). China's stock markets have attracted investors' interest with its astounding economic expansion (Pan and Mishra 2018). Sim and Chang (2006) reveal that the growth of the Korean stock market has accelerated since the late 1980s in keeping with the boom of the Korean economy. In March 2017, the Korea Stock Exchange ranked as the 14th largest exchange worldwide with a market capitalization of $1.33 trillion adjusted US dollars. Korea's importance in the financial market is reflected through its market capitalization to gross domestic product ratio, which is at 110.64% (Hong et al. 2017). In summary, since both China and Korea have demonstrated their importance in the global economy, investors should seriously evaluate the stock markets of these two countries.

In addition, although studies report that market participants may predict future stock prices by applying technical trading rules (Wang et al. 2015; Zhu et al. 2015), we speculate that the continuous phenomena[1] may provide more valuable information for investors to exploit profits. To link investor trading behavior in the real world, we attempt to determine whether investors can make profits by applying trading strategies, which is the motivation behind this study. We argue that it is worth investigating whether contrarian strategies for overreaction or momentum strategies based on trends should be employed. The stock markets of Korea and China, regarded as the representatives of Asia, are analyzed in this study. By employing the constituent stocks of the Korea Stock Price 50 Composite Index (KOSPI 50) and Shanghai Stock Exchange 50 Index (SSE 50), we examine whether investors could apply proper strategies to make profits when continuously overbought (or oversold) signals are emitted by SOI or RSI, which seems seldom explored in the relevant literature.

In this study, we established several valuable findings. First, we provide evidence to enhance the robustness of the existing literature, exhibiting that both the Korean and Chinese stock markets are not fully efficient. Second, we reveal that contrarian strategies are appropriate for trading the constituent stocks of KOSPI 50, which might result from

[1] The continuous phenomena mean that "continuously rising (or falling) stock prices and overbought (or oversold) signals emitted together" or "continuously rising (or falling) stock prices and K80 or RSI70 (K20 or RSI30) emitted together" in the following context.

the overreaction of the stock market due to the continuous phenomena. Third, momentum strategies are suitable for trading the constituent stocks of SSE 50, as continuously rising prices and RSI ≥ 70 are observed. Although previous studies report that the contrarian effect exists in Chinese stock markets (Shi et al. 2015; Shi and Zhou 2017), the momentum and contrarian effects are often associated with the length of the estimation periods, holding periods, and sample periods under investigation (Shi et al. 2015). Therefore, we speculate that studies related to the momentum and contrarian effects of the Chinese stock market may report mixed results. More importantly, the majority of investors in the Chinese stock market are individual investors contributing to higher prices when continuously rising prices are observed (Shi and Zhou 2017). This circumstance indicates that momentum strategies are appropriate when continuously rising stock prices or overbought signals are observed (Ni et al. 2015).

This study contributes to the literature in several ways. To the best of our knowledge, this is the first study to explore whether investors would profit from trading stocks under the continuous phenomena. Most investors believe that applying technical analysis to trading stocks may result in better returns than those provided by the market. However, this study reports that investors adopting both continuous overbought (oversold) signals and continuous rising (or falling) stock prices occur together as trading signals would generate a much higher profit as compared with employing either of them solely. Moreover, this study illustrates that investment strategies are dissimilar for the Korean and Chinese stock markets, which might be due to different market situations (i.e., non-internationalized or internationalized) and compositions of investors (i.e., individuals or institutions) in these two stock markets.

The remainder of this paper is organized as follows. "Section Literature review" reviews the relevant literature. "Section Data and methodology" describes the data and the methodology used in this study. "Section Empirical analysis and results" presents the empirical analysis and its results. Finally, "Section Further investigation" presents the conclusions of the study.

Literature review

This study is guided by several theories, including the EMH, overreaction hypothesis, and herding behavior, to explore the market and investor behaviors with regard to technical analysis and trading strategies.

Theory

In the past, stock market efficiency has played an important role in financial literature (Fama 1970; Phan and Zhou 2014). An efficient market is assumed to incorporate all the available information immediately, and it is not possible to earn abnormal profits based on past information (Baciu 2014). In other words, the prices of assets in the efficient markets reflect the best estimates of agents in the market regarding the expected risks and returns of assets observed at that time (Guidi et al. 2011). As a result, the EMH offers a theoretical construct that accompanies the general belief in the value of accurate information (Hu 2012).

Although the EMH is widely researched in finance (Al Janabi et al. 2010), studies show that many stock exchanges worldwide may not follow this rule. For example, Latif et al.

(2011) point out that most investors in an actual stock market do not believe that the market is completely efficient. In fact, some market participants, such as high-frequency traders and hedge funds, can beat the market consistently (Masteika and Rutkauskas 2012), which encourages investors to screen stocks in an effort to secure more returns (Phan and Zhou 2014).

In the real world, technical analysis is widely found to challenge the well-known EMH (Bessembinder and Chan 1995). As a matter of fact, the reason behind employing technical trading rules might be explained by herding behavior due to investors' sentiments being aroused (Friesen et al. 2009; Menkhoff et al. 2012) or stock price overreaction resulting in stock prices to rebound later (Neely et al. 2014; Wang 2000). In other words, employing technical analysis would be in conjunction with academic aspects, including market efficiency, market inefficiency, overreaction, and herding behaviors.

As mentioned above, investors often overreact to private information because of excessive self-confidence (Chuang and Lee 2006), and the overreaction hypothesis is drawn out to challenge the EMH (De Bondt and Thaler 1985, 1987). Overreaction is an emotional response led by either greed or fear pertaining to receiving new information about a stock (Otchere and Chan 2003). Consequently, investors overreacting to news can cause stocks to be overbought or oversold until they return to their intrinsic value (Ni et al. 2019).

Furthermore, herding behavior has been seen with lots of interest in financial markets in recent years. Herding behavior is defined as people trading against their initial assessment but following the trend in the previous trade (Avery and Zemsky 1998). Although investors might not be able to predict stock prices based on the EMH (Malkiel and Fama 1970), they behave irrationally in the real world (Yousaf et al. 2018). As a result, investors follow collective behavior and ignore their private information due to herding behavior, even if this action is not supported by fundamental information (Litimi et al. 2016).

Technical analysis and trading strategies

As Gehrig and Menkhoff (2006) point out, technical analysis focuses on forecasting the movements of future prices according to past market prices, turnover volume, and technical indicators (Chen et al. 2016). Based on the assumption that the patterns of market behavior do not change over time, the past price series of stocks are assumed to recur in the future, which can be used to predict stock prices (Sadique and Silvapulle 2001). Proponents of the technical analysis believe that studying price movements in the form of price charts is required to forecast the possible future price movements of an asset (Murugaiah 2018).

Concerning trading strategies, momentum and contrarian strategies are the major investment strategies widely debated by investment strategists across the world (Aravind 2016); they are adopted for profit-making (Liao 2017). Duxbury and Yao (2017) claim that momentum can be defined as buying positive-return stocks and selling negative-return stocks. Essentially, momentum traders condition past price changes (Hong and Stein 1999) and may beat the market (Lee et al. 2012). Asness et al. (2013) reveal that the premia of momentum returns exist across diverse markets. In other words, momentum strategies are appropriately employed to trade international equity indices, commodities, and currencies (Novy-Marx 2012).

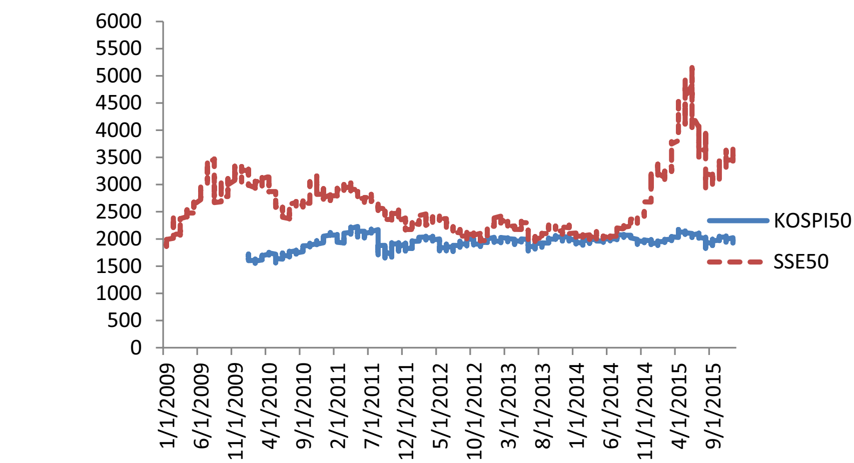


Fig. 1 Trends of the KOSPI 50 and SSE 50 indices from 2009 to 2015

Regarding contrarian strategies, Gopal (2016) argues that the contrarian strategies help in buying stocks that have been losers and selling short stocks that have been winners. In fact, contrarian strategies are formulated based on price reversals, which are the prices of stocks moving in the reverse direction from one period to the next (Jegadeesh and Titman 1993). As Da Dalt et al. (2019) point out, contrarian behavior could be led by overconfidence, which leads the prices of stocks to fluctuate more than their reasonable range and eventually causes the contrarian strategy to be profitable (Asif et al. 2018).

Data and methodology

Data

In this study, we use the daily data of the constituent stocks of KOSPI 50 and SSE 50 obtained from Datastream as our sample because of the following reasons. First, these constituent stocks are representative of the Korean and Chinese stock markets. Second, these constituent stocks may not have liquidity issues because they are regarded as large-cap stocks. Third, since small-cap stocks are likely to be local-oriented with limited international exposure (Eun et al. 2008), the price movements of these stocks might be manipulated. As Aggarwal and Wu (2006) reveal, over 50% of the stocks manipulated are “penny stocks” with very low average trading volume and market capitalization. Thus, we exclude small-cap stocks to prevent the average performance of stocks, such as abnormal returns (ARs) or cumulative abnormal returns (CARs)[2] from being manipulated.

The trends and descriptive statistics, including means, medians, standard deviations, minima, and maxima, of KOSPI 50 and SSE 50 for the period of 2009 to 2015[3] are presented in Fig. 1 and Table 1, respectively. As shown in Fig. 1, KOSPI 50 shows a fairly flat trend compared to SSE 50 during this period. Moreover, Table 1 shows that the range of SSE 50 is rather wide (1863 for the minimum and 5166 for the maximum), and

[2] The abnormal returns (ARs) are defined as the difference between the actual returns and expected returns generated by the market model. While the cumulative abnormal returns at t days (CAR(t)) are the cumulative abnormal returns from AR(1) to AR(t).

[3] The period for the KOSPI 50 data is from 2010 to 2015 because its constituent stocks are available after 2010.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
KOSPI 50 index (2010–2015)	1488	1938.65	122.42	1552.79	2228.96
SSE 50 index (2009–2015)	1673	2659.27	586.53	1863.37	5166.35

This table reports the means, standard deviations, maxima, and minima of KOSPI 50 and SSE 50 indices over the data period 2009–2015

the standard deviation is also significantly large, which demonstrates that the SSE 50 is much more volatile than KOSPI 50.

In addition, we define continuous rising prices observed over two, three, and four days as the rising circumstances (i.e., the closing price of a stock at time t is higher than the closing price of the stock at time t-1) that would last for two, three, and four days. Similarly, continuously falling prices observed over two, three, and four days are denoted as falling situations (i.e., the closing price of a stock at time t is lower than the closing price of the stock at time t-1) that would last for two, three, and four days. We then explore whether investors could beat the markets while trading the constituent stocks of KOSPI 50 and SSE 50 when both continuous overbought (or oversold) signals emitted by SOI (or RSI) and continuous rising (or falling) prices occur simultaneously for two, three, or four days. We further investigate whether investment strategies differ by trading the constituent stocks of these two markets.

Table 2 shows the number of continuously rising (or falling) prices shown for two, three, and four days over the data period. As presented in the table, the samples of continuously rising prices are almost equal to those of continuously falling prices, indicating that the probability of the former is almost the same as that of the latter occurring over two, three, and four days.

Technical analysis indicators

Two technical analysis indicators, SOI and RSI, are applied in this study. Chiang et al. (2012) report that following the trading signals emitted by SOI would enhance trading performance. Furthermore, many institutional investors profit by trading stocks according to SOI (Wang et al. 2012). In addition, Shik and Chong (2007) claim that RSI trading rules can yield positive risk-adjusted returns for currency markets, indicating that investors can yield higher returns using the RSI trading rule (Chong and Ng 2008).

The SOI, called the K value, is sensitive to updates in stock prices. In fact, the K value may be modified because of changes in the highest and lowest prices during a certain period.[4] The SOI (or K-value) is measured as follows:

$$CL_t = P_t - \min(P_t, P_{t-1}, \ldots P_{t-8}) \tag{1}$$

$$HL_t = \max(P_t, P_{t-1}, \ldots P_{t-8}) - \min(P_t, P_{t-1}, \ldots P_{t-8}) \tag{2}$$

$$RSV = \frac{CL_t}{HL_t} \times 100 \tag{3}$$

[4] The 9-day K often applied in the real world is employed (i.e., N is set as 9 days in this study). We would treat RSV $_{t-1}$= K $_{t-1}$ for (4) when no prior K is available. Similarly, we use a 9-day for RSI for consistency.

Table 2 Samples of continuously rising (falling) prices

	KOSPI 50	SSE 50
	No	No
Panel A: Continuously rising prices		
Continuously rising price for 2 days	10,156	11,867
Continuously rising price for 3 days	3853	4546
Continuously rising price for 4 days	1569	1893
Panel B: Continuously falling prices		
Continuously falling price for 2 days	10,569	11,821
Continuously falling price for 3 days	4241	4673
Continuously falling price for 4 days	1803	1887

This table lists the numbers of continuously rising (falling) prices for 2, 3, and 4 days emitted for the constituent stocks of KOSPI 50 and SSE 50 over the data period 2009–2015

To prevent the samples from being over-counted without concerning overlapping issues, we consider another 2-day continuous rising (falling) price sample as 2 or more days after the previous sample as counted. We consider another 3-day continuous rising (falling) price sample as 3 or more days after the previous sample as counted. Lastly, we consider another 4-day continuous rising (falling) price sample as 4 or more days after the previous sample as counted

$$K_t = \frac{2}{3}K_{t-1} + \frac{1}{3}RSV_t, \tag{4}$$

where CL_t is the lowest closing price in N recent days subtracted from the latest closing price; HL_t refers to the difference between the highest and lowest closing prices in N days; RSV_t is set as the ratio of CL_t and HL_t; and K is the sum of 1/3 of the RSV value and 2/3 of the K value with lag 1. In general, K values range from 0 to 100, and the overbought signals are emitted when $K \geq 80$, and the oversold signals occur when $K \leq 20$. According to the overreaction hypothesis, investors might profit from short-selling stocks when the SOI falls into the overbought zones (i.e., $K \geq 80$) or by buying stocks when the SOI drops into oversold zones (i.e., $K \leq 20$).

Moreover, RSI is also sensitive to updated stock prices and ranges from 0 to 100. The calculation of this indicator begins with the definition of an index set as $I_{t,p} = \{i: t - p \leq i \leq t\}$, followed by the definition of the up-closes (U_i) and the down-closes (D_i), such that the following equations are satisfied:

$$\begin{aligned} &\mathrm{U}_i = \mathrm{C}_i - \mathrm{C}_{i-1} \quad \text{if} \quad \mathrm{C}_i > C_{i-1}; \text{otherwise}, \mathrm{U}_i = 0, \text{and} \\ &\mathrm{D}_i = \mathrm{C}_{i-1} - \mathrm{C}_i \text{ if } C_{i-1} > C_i;\ \text{otherwise}, D_i = 0, \end{aligned}$$

for any $I \in I_{t,p}$, where C_i is the closing price in period i. The next step is to define the other terms.

$$\begin{aligned} &\overline{U_{i,p}} = \text{average of } U_i \text{ over } I_{t,p}, \text{ and} \\ &\overline{D_{i,p}} = \text{average of } D_i \text{ over } I_{t,p}. \end{aligned}$$

Therefore, the relative strength is given by

$$RS_{t,p} = \frac{\overline{U_{t,p}}}{\overline{D_{t,p}}}.$$

The RSI at time t for period p is then defined as follows:

$$\mathrm{RSI}_{t,p} = 100 - \frac{100}{1 + RS_{t,p}}.$$

Essentially, stock price movements are upward only when the RSI is equal to 100. Conversely, the price movements are downward, merely when the RSI is 0. Therefore, the overbought trading signals are emitted when the RSI values are close to 100, and the oversold trading signals are emitted when the RSI values are close to 0. By employing a 9-day measurement, the overbought and oversold trading signals are shown when RSI values are above 70 and below 30 (i.e., RSI ≥ 70 or RSI ≤ 30), which would be deemed as the overbought zone or oversold zone, respectively.

Methodology

We use the standard event study method to explore the empirical results, and the linear specification of the model follows the assumed joint normality of asset returns. For any security i, the market model is

$$\begin{aligned} &R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \\ &E(\varepsilon_{it}) = 0 \mathrm{var}(\varepsilon_{it}) = \sigma^2_{\varepsilon_t}, \end{aligned} \quad (5)$$

where R_{it} and R_{mt} are the returns of security i and the market portfolio at time t, respectively, α_i and β_i are the parameters of the market model, and the expected value and variance of disturbance term ε_{it} are 0 and $\sigma^2_{\varepsilon_t}$.

Once the parameter estimates of the market model are given, the AR can be measured. The sample for evaluating AR is as follows:

$$AR_{i\tau} = R_{it} - \widehat{\alpha_i} - \widehat{\beta_i} R_{m\tau}, \quad (6)$$

where $R_{i\tau}$ and $R_{m\tau}$ are the returns of security i and the market in event period τ. Moreover, AR refers to the actual return minus the expected return during the event period, and $\widehat{\alpha_i}$ and $\widehat{\beta_i}$ are the parameters of the market model that are estimated by the data in the estimated period and are employed for measuring the expected return during the event period. By employing the data of KOSPI 50 and SSE 50 over a period of − 155 to − 6 days (i.e., a 150-day estimation period) before the event period from -5 to 5 days (i.e., an 11-day event period including the event day at day 0), we are able to estimate $\widehat{\alpha_i}$ and $\widehat{\beta_i}$, and then abnormal returns (ARs) would appear from day 1 to day 5 in the event period based on Eq. (6).

Generally, CAR is measured to evaluate whether investors can beat the market. Defined as the sample of CAR from $\tau1$ to $\tau2$, $CARi\tau$ ($\tau1$, $\tau2$) is the sum of the included ARs, that is, $CARi\tau\ (\tau1,\ \tau2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$, where $\tau1 = 1 < \tau2 = 5$. Investors would beat the markets by using momentum trading strategies when positive CARs are revealed. In contrast, investors are likely to make profits by using contrarian trading strategies when negative CARs are shown.

In addition, we argue that while trading signals are set as the simultaneous occurrence of both continuous rising (or falling) prices and continuous overbought (or oversold) signals, investors may generate more valuable information as compared with trading stocks as overbought (or oversold) signals are occurred in the relevant studies (Day et al. 2019; Rosillo et al. 2013).

As such, we categorize these continuous phenomena lasting for 2, 3, or 4 days as our events,[5] and calculate the 1-, 2-, 3-, 4-, and 5-day CARs when these diverse events occur. Given that investors may hold stocks for a short period, we then measure 1-, 2-, 3-, 4-, and 5-day CARs as a short window, as suggested by the relevant literature (Chopra et al. 1992; Marshall et al. 2006).

Based on the concern of event clustering, we have to prevent our samples from being over-counted because of overlapping. Thus, we count another two-day, three-day, or four-day sample of both continuous rising (or falling) price and continuous overbought (or oversold) occurred together by excluding the days employed for counting the previous two-day, three-day, or four-day sample.

Empirical analysis and results

We first measure the CARs for trading the constituent stocks of KOSPI 50 and SSE 50 when either continuous rising (or falling) prices are observed or continuous overbought (or oversold) trading signals are emitted by SOI or RSI.[6] However, we find that investors might not exploit profits because the low mean values are shown for trading these constituent stocks as the occurrence of either continuous rising (or falling) prices or continuous overbought (or oversold) trading signals.

Results of continuously rising prices and overbought signals[7]

The empirical results of the continuously rising prices and overbought signals are shown in Table 3 and plotted in Fig. 2. Table 3 shows that CARs are negative for trading the constituent stocks of KOSPI 50 as continuously rising prices and $K \geq 80$ (or $RSI \geq 70$) occur, especially for two days, because the CARs are statistically significant at the 1% level. Negative CARs imply that investors would not beat the market by employing momentum strategies. However, if contrarian strategies are applied, investors may profit from short-selling stocks as negative CARs appear. This finding shows that investors should not overreact to trade stocks as continuously rising stock prices and overbought signals occur. In other words, contrarian strategies would be appropriate for trading the constituent stocks of KOSPI 50, which might be caused by the overreaction to stock prices. We then infer that continuously rising prices may trigger the occurrence of $K \geq 80$ and $RSI \geq 70$, thereby resulting in both phenomena (continuous rising prices and continuous overbought signals) occurring together.

[5] We exclude the case of continuously rising (or falling) for 5 days in this study because of the concern of enough sample.

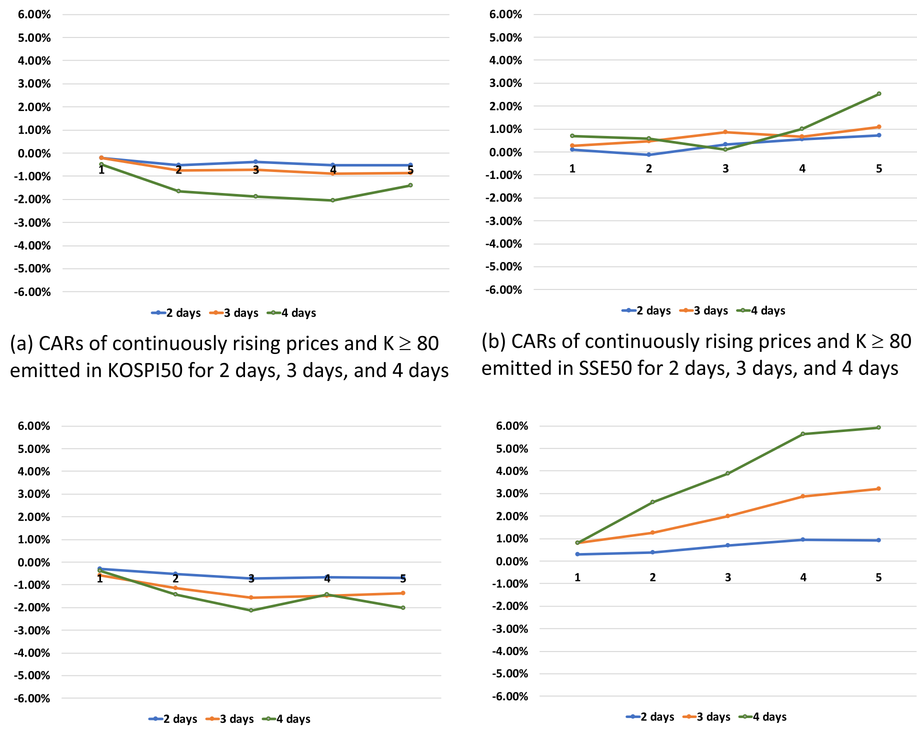
[6] The continuously technical trading signals employed in this study include continuous K80 and K20 shown for 2, 3, and 4 days as well as continuous RSI70 and RSI30 shown for 2, 3, and 4 days.

[7] Continuously rising (falling) prices and overbought (oversold) signals refer to the simultaneous occurrence of both continuous rising (falling) prices and continuous overbought (oversold) signals emitted by SOI (RSI).

Table 3 CARs of continuously rising prices and K ≥ 80 (RSI ≥ 70) emitted (2009–2015)

Holding days	KOSPI 50			SSE 50		
	N	Mean	t-test	N	Mean	t-test
Panel A: Continuously rising prices and K ≥ 80 emitted						
Panel A1: Continuously rising prices and K ≥ 80 for 2 days						
1	473	− 0.0020	− 2.432**	324	0.0010	0.657
2	473	− 0.0052	− 4.028***	324	− 0.0012	− 0.483
3	473	− 0.0039	− 2.646***	324	0.0033	1.017
4	472	− 0.0051	− 3.061***	324	0.0055	1.495
5	472	− 0.0051	− 2.940***	324	0.0072	1.719*
Panel A2 Continuously rising prices and K ≥ 80 for 3 days						
1	116	− 0.0002	− 0.125	91	0.0017	0.375
2	116	− 0.0024	− 0.995	91	0.0059	0.938
3	116	− 0.0032	− 1.085	91	0.0052	0.711
4	116	− 0.0038	− 1.287	91	0.0011	0.120
5	116	− 0.0036	− 1.149	91	0.0038	0.400
Panel A3: Continuously rising prices and K ≥ 80 for 4 days						
1	35	− 0.0028	− 0.747	25	0.0043	0.752
2	35	− 0.0090	− 1.698*	25	0.0011	0.142
3	35	− 0.0118	− 2.447**	25	− 0.0074	− 0.779
4	35	− 0.0116	− 2.380**	25	0.0035	0.261
5	35	− 0.0054	− 0.821	25	0.0143	1.021
Holding days	**KOSPI 50**			**SSE 50**		
	N	**Mean**	**t-test**	**N**	**Mean**	**t-test**
Panel B CARs of continuously rising prices and RSI ≥ 70 emitted						
Panel B1: Continuously rising prices and RSI ≥ 70 for 2 days						
1	283	− 0.0029	− 2.800***	402	0.0030	1.656*
2	283	− 0.0053	− 3.562***	402	0.0037	1.347
3	283	− 0.0072	− 4.179***	401	0.0068	2.045**
4	282	− 0.0067	− 3.152***	401	0.0095	2.554**
5	282	− 0.0069	− 2.940***	401	0.0093	2.187**
Panel B2: Continuously rising prices and RSI ≥ 70 for 3 days						
1	53	− 0.0028	− 1.330	103	0.0050	1.194
2	53	− 0.0060	− 1.561	103	0.0089	1.412
3	53	− 0.0085	− 1.597	103	0.0132	1.736*
4	53	− 0.0080	− 1.331	103	0.0191	2.058**
5	53	− 0.0067	− 1.201	103	0.0228	2.390**
Panel B3: Continuously rising prices and RSI ≥ 70 for 4 days						
1	15	0.0018	0.394	27	0.0001	0.006
2	15	− 0.0029	− 0.594	27	0.0135	1.009
3	15	− 0.0056	− 0.964	27	0.0190	1.134
4	15	0.0003	0.051	27	0.0279	1.544
5	15	− 0.0065	− 1.023	27	0.0272	1.440

We investigate whether the CARs, including 1-, 2-, 3-, 4-, and 5-day CARs, would be different from 0 if investors take the long positions (We present the results of taking long positions only because the results of taking a short position are opposite to the results of taking a long position) on the constituent stocks of KOSPI 50 and SSE 50 as continuously rising prices for 2, 3, and 4 days occurred. We also present the statistics of t-tests for these CARs. In addition, *, **, and *** represent 10%, 5%, and 1% significance levels, respectively



(a) CARs of continuously rising prices and K ≥ 80 emitted in KOSPI50 for 2 days, 3 days, and 4 days

(b) CARs of continuously rising prices and K ≥ 80 emitted in SSE50 for 2 days, 3 days, and 4 days

(c) CARs of continuously rising prices and RSI ≥ 70 emitted in KOSPI50 for 2 days, 3 days, and 4 days

(d) CARs of continuously rising prices and K ≥ 70 emitted in SSE50 for 2 days, 3 days, and 4 days

Fig. 2 CARs of continuously rising K ≥ 80 or RSI ≥ 70 for KOSPI 50 and SSE 50

However, most of the CARs revealed in Table 3 are positive for the constituent stocks of the SSE 50. In fact, the positive CARs shown after continuously rising prices and overbought signals imply that investors would beat the market if they employ momentum strategies as in the observed phenomena, particularly for the continuously rising prices and RSI ≥ 70 emitted for two and three days, following the statistical significance at the 5% level. We speculate that this situation might stem from the herding behavior of individual investors, observed in trading for over 80% of the Chinese stock market. Thus, chasing high prices might be suitable for trading the constituent stocks of SSE 50. In addition, the mean value of CAR 5 is 2.28% for trading the constituent stocks of SSE 50 as continuously rising prices and RSI ≥ 70 for 3 days are emitted, indicating that investors might profit from trading these constituent stocks.

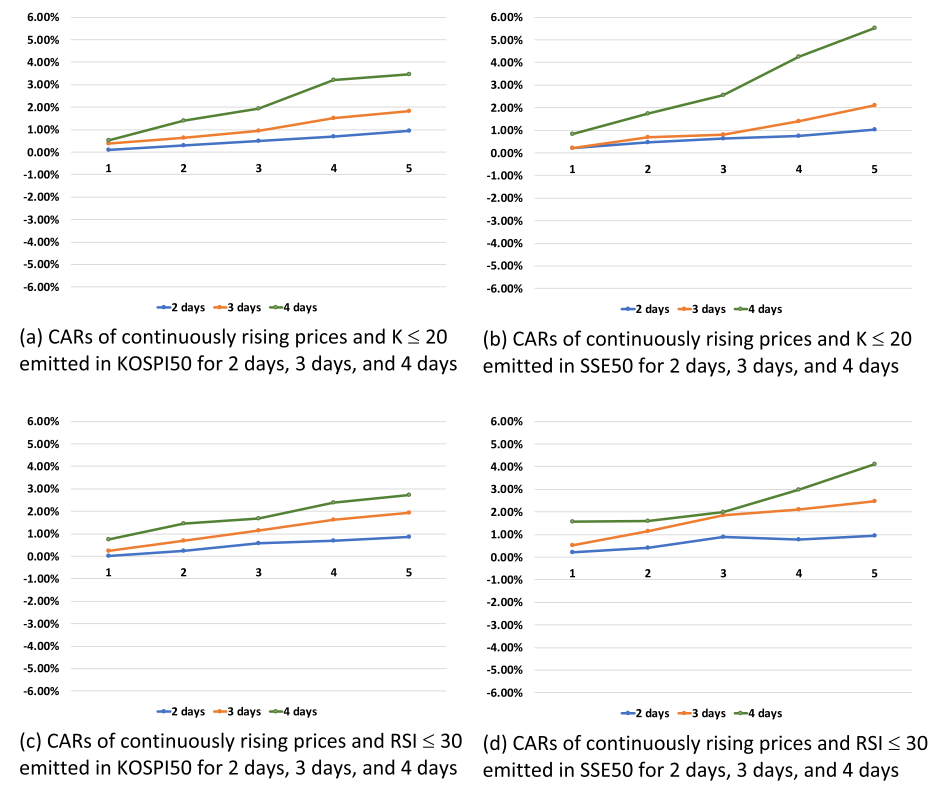
Results of continuously falling prices and oversold signals

The results of the continuously falling prices and overselling signals are shown in Table 4 and Fig. 3. Table 4 reports that CARs are positive for trading the constituent stocks of KOSPI 50 when continuously falling prices and oversold signals (i.e., K ≤ 20 and RSI ≤ 30) are emitted for two or three days, as most of the CARs are statistically significant at the 5% level. Positive CARs after continuously falling prices and oversold signals imply that investors would beat the market after the observed phenomena occurred if they use contrarian strategies. This finding indicates that contrarian strategies would be

Table 4 CARs of Continuously Falling Prices and K ≤ 20 emitted (2009–2015)

Holding days	KOSPI 50			SSE 50		
	N	Mean	t-test	N	Mean	t-test
Panel A: CARs of continuously falling prices and K ≤ 20 emitted						
Panel A1: Continuously falling prices and K ≤ 20 for 2 days						
1	513	0.0010	0.929	439	0.0021	1.907*
2	512	0.0031	2.137**	439	0.0046	2.514**
3	512	0.0050	2.904***	437	0.0065	3.087***
4	511	0.0069	3.647***	437	0.0075	2.977***
5	511	0.0096	4.595***	437	0.0103	3.830***
Panel A2: Continuously falling prices and K ≤ 20 for 3 days						
1	123	0.0027	1.342	108	0.0001	0.037
2	123	0.0034	1.185	108	0.0024	0.519
3	123	0.0046	1.406	108	0.0015	0.239
4	123	0.0082	2.301**	108	0.0066	1.007
5	122	0.0085	2.145**	108	0.0109	1.635
Panel A3: Continuously falling prices and K ≤ 20 for 4 days						
1	48	0.0014	0.415	32	0.0062	1.307
2	48	0.0075	1.638	32	0.0104	1.094
3	48	0.0097	2.019**	32	0.0177	2.026*
4	48	0.0171	3.557***	32	0.0283	2.845***
5	48	0.0166	2.931***	32	0.0341	2.925***
Holding days	**KOSPI 50**			**SSE 50**		
	N	**Mean**	**t-test**	**N**	**Mean**	**t-test**
Panel B CARs of continuously falling prices and RSI ≤ 30 emitted						
Panel B1: Continuously falling prices and RSI ≤ 30 for 2 days						
1	272	0.0002	0.121	269	0.0021	1.353
2	272	0.0024	1.262	269	0.0042	1.662*
3	272	0.0057	2.543**	269	0.0089	3.131***
4	272	0.0069	2.799***	269	0.0078	2.468**
5	272	0.0085	3.009***	269	0.0096	2.827***
Panel B2: Continuously falling prices and RSI ≤ 30 for 3 days						
1	58	0.0021	0.622	75	0.0032	1.166
2	58	0.0045	1.214	75	0.0073	1.683*
3	58	0.0058	1.374	75	0.0095	1.874*
4	58	0.0093	1.995*	75	0.0133	2.099**
5	58	0.0110	2.010**	75	0.0152	2.181**
Panel B3: Continuously falling prices and RSI ≤ 30 for 4 days						
1	15	0.0051	1.168	31	0.0105	2.409**
2	15	0.0077	1.330	31	0.0044	0.950
3	15	0.0052	0.648	31	0.0014	0.230
4	15	0.0077	0.838	31	0.0088	1.267
5	15	0.0079	0.685	31	0.0163	2.008*

We investigate whether the CARs, including 1-, 2-, 3-, 4-, and 5-days CARs, would be different from 0 if investors take the long positions on the constituent stocks of KOSPI 50 and SSE 50 as either continuously falling prices for 2, 3, and 4 days occurred. We also present the statistics of t-tests for these CARs. In addition, *, **, and *** represent 10%, 5%, and 1% significance levels, respectively



(a) CARs of continuously rising prices and K ≤ 20 emitted in KOSPI50 for 2 days, 3 days, and 4 days

(b) CARs of continuously rising prices and K ≤ 20 emitted in SSE50 for 2 days, 3 days, and 4 days

(c) CARs of continuously rising prices and RSI ≤ 30 emitted in KOSPI50 for 2 days, 3 days, and 4 days

(d) CARs of continuously rising prices and RSI ≤ 30 emitted in SSE50 for 2 days, 3 days, and 4 days

Fig. 3 CARs of continuously rising K ≤ 20 or RSI ≤ 30 for KOSPI 50 and SSE 50

appropriate for trading the constituent stocks of the KOSPI 50 in such situations. We argue that this result might be caused by an overreaction to stock prices, which might eventually rebound after continuously falling prices and oversold signals, such as K ≤ 20 or RSI ≤ 30, occur.

Similarly, Table 4 shows that CARs are positive for trading the constituent stocks of SSE 50 when continuously falling prices and oversold signals (i.e., K ≤ 20 or RSI ≤ 30) are emitted, which indicates that contrarian strategies would be appropriate for trading the constituent stocks of SSE 50 in this situation. Moreover, the mean value of CAR 5 is 3.41% for trading the constituent stocks of SSE 50 as continuously rising prices and K ≤ 20 for four days occur, implying that market participants might profit from trading these constituents' stocks based on contrarian strategies.

Further investigation

Due to this updated concern, we extend our data to that of 2019, and the summary statistics as well as samples of continuously rising (or falling) prices, are presented in Tables 5 and 6.

Table 5 shows that the data range, as well as the standard deviation of SSE 50, are broader and larger than those of KOPSI 50, indicating that SSE 50 is more volatile than KOPSI 50. However, the range (from 2464 to 3559) and the volatility (standard deviation: 228) of SSE 50 during the period of 2016 to 2019 are much smaller than those from 2009 to 2015 (the range: 1863–5166, the standard deviation: 586). These descriptive statistics

Table 5 Summary Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
KOSPI 50 index (2016–2019)	970	2180.27	185.55	1835.28	2598.19
SSE 50 index (2016–2019)	972	3029.03	228.61	2464.36	3559.47

This table reports the means, standard deviations, maxima, and minima of KOSPI 50 and SSE 50 indices over the data period 2016–2019

Table 6 Samples of continuously rising (falling) prices

	KOSPI 50	SSE 50
	No	No
Panel A: Continuously rising prices		
Continuously rising price for 2 days	6715	6378
Continuously rising price for 3 days	2622	2500
Continuously rising price for 4 days	1064	1118
Panel B: Continuously falling prices		
Continuously falling price for 2 days	6780	5988
Continuously falling price for 3 days	2641	2315
Continuously falling price for 4 days	1045	1034

Table 2 lists the numbers of continuously rising (falling) prices for 2, 3, and 4 days emitted for the constituent stocks of KOSPI 50 and SSE 50 over the data period 2016–2019

imply that the Chinese stock market has become mature because both high volatility and the broad range of stock indices are likely to occur in the emerging stock market, especially at an early stage.

Table 6 lists the numbers of continuously rising (or falling) prices for 2, 3, and 4 days observed over the data period. The observations for continuously rising prices are rather close to those of continuously falling prices for these indices. However, the observations for continuously rising prices examined over two, three, and four days are slightly higher than those of continuously falling prices observed for two, three, and four days.

Table 7 reports that contrarian strategies might be still appropriate for the Korean stock market. However, the application of momentum strategies might not be appropriate for the Chinese stock market during this period. In fact, the Chinese stock market had been raised the weight by MSCI after 2015, which resulted in the market being dominated by institutional investors and being more rational. Thus, apart from investors selling stocks and causing the falling of stock prices during 2016–2019, the change of major participants in the market might be another reason for the adjustment of the trading strategy.

Table 8 reveals that contrarian strategies would still be suitable for continuously falling prices and oversold trading signals ($K \leq 20$ or $RSI \leq 30$). We argue that if the observed phenomena occurred, authorities, even institutional investors, might start to buy stocks out of political and economic concerns and, consequently, the stock prices are likely to rebound.

Discussion

As mentioned in the introduction, investors tend to trade stocks when prices continuously rise or fall. Therefore, we attempt to identify the appropriate investment strategies for trading stocks when these phenomena occur. Based on our results, we suggest that

Table 7 CARs of continuously rising prices and K ≥ 80 (RSI ≥ 70) emitted (2016–2019)

Holding days	KOSPI 50			SSE 50		
	N	Mean	t-test	N	Mean	t-test
Panel A: Continuously rising prices and K ≥ 80 emitted						
Panel A1: Continuously rising prices and K ≥ 80 for 2 days						
1	389	− 0.09%	− 0.876	271	− 0.11%	− 0.79100
2	389	− 0.09%	− 0.596	271	− 0.12%	− 0.57000
3	389	− 0.19%	− 1.149	271	− 0.22%	− 0.86100
4	389	− 0.22%	− 1.194	271	− 0.27%	− 1.00400
5	389	− 0.15%	− 0.746	271	− 0.31%	− 1.09300
Panel A2 Continuously rising prices and K ≥ 80 for 3 days						
1	99	− 0.21%	− 1.186	69	− 0.05%	− 0.14700
2	99	− 0.70%	− 3.674***	69	− 0.49%	− 1.13800
3	99	− 0.54%	− 2.381**	69	− 0.81%	− 1.54300
4	99	− 0.21%	− 0.733	69	− 0.84%	− 1.41100
5	99	− 0.16%	− 0.556	69	− 0.67%	− 1.07900
Panel A3: Continuously rising prices and K ≥ 80 for 4 days						
1	38	− 0.37%	− 1.66	25	0.08%	0.14500
2	38	− 0.25%	− 0.635	25	− 1.10%	− 1.51200
3	38	− 0.40%	− 0.835	25	− 1.37%	− 1.55400
4	38	− 0.32%	− 0.795	25	− 0.72%	− 0.81600
5	38	− 0.37%	− 0.729	25	− 0.74%	− 0.82900
Holding days	**KOSPI50**			**SSE50**		
	N	**Mean**	**t-test**	**N**	**Mean**	**t-test**
Panel B CARs of continuously rising prices and RSI ≥ 70 emitted						
Panel B1: Continuously rising prices and RSI ≥ 70 for 2 days						
1	241	− 1.36%	− 1.008	295	− 0.21%	− 1.66700*
2	241	− 1.27%	− 0.933	295	− 0.20%	− 1.04600
3	241	− 0.98%	− 0.717	295	− 0.40%	− 1.75900*
4	241	− 0.99%	− 0.724	295	− 0.44%	− 1.79300*
5	241	− 0.96%	− 0.698	295	− 0.60%	− 2.25000**
Panel B2: Continuously rising prices and RSI ≥ 70 for 3 days						
1	51	− 0.08%	− 0.304	87	− 0.25%	− 0.86500
2	51	− 0.28%	− 0.849	87	− 0.39%	− 0.99300
3	51	− 0.35%	− 0.843	87	− 0.62%	− 1.35800
4	51	− 0.84%	− 1.775*	87	− 0.98%	− 1.67400*
5	51	− 0.80%	− 1.585	87	− 0.70%	− 1.06700
Panel B3: Continuously rising prices and RSI ≥ 70 for 4 days						
1	14	− 0.19%	− 0.304	17	− 0.75%	− 0.80600
2	14	− 0.31%	− 0.241	17	− 1.85%	− 2.22000**
3	14	− 0.05%	− 0.037	17	− 2.87%	− 3.32400***
4	14	− 0.74%	− 0.843	17	− 2.63%	− 3.06500***
5	14	− 0.35%	− 0.312	17	− 2.24%	− 2.39400**

We investigate whether the CARs, including 1-, 2-, 3-, 4-, and 5-day CARs, would be different from 0 if investors take the long positions (We present the results of taking long positions only because the results of taking a short position are opposite to the results of taking a long position) on the constituent stocks of KOSPI 50 and SSE 50 as continuously rising prices for 2, 3, and 4 days occurred. We also present the statistics of t-tests for these CARs. In addition, *, **, and *** represent 10%, 5%, and 1% significance levels, respectively

Table 8 CARs of Continuously Falling Prices and K ≤ 20 emitted (2016–2019)

Holding days	KOSPI 50			SSE 50		
	N	Mean	t-test	N	Mean	t-test
Panel A: CARs of continuously falling prices and K ≤ 20 emitted						
Panel A1: Continuously falling prices and K ≤ 20 for 2 days						
1	429	0.17%	1.806*	295	0.26%	2.243**
2	429	0.27%	1.796*	295	0.33%	2.213**
3	429	0.31%	1.979*	295	0.46%	2.705***
4	429	0.15%	0.893	295	0.48%	2.547**
5	429	0.17%	0.928	295	0.72%	3.714***
Panel A2: Continuously falling prices and K ≤ 20 for 3 days						
1	117	0.08%	0.524	81	0.29%	1.675*
2	117	0.16%	0.682	81	0.38%	1.575
3	117	0.07%	0.224	81	0.42%	1.493
4	117	0.19%	0.586	81	0.55%	1.966*
5	117	0.19%	0.547	81	0.66%	2.038**
Panel A3: Continuously falling prices and K ≤ 20 for 4 days						
1	39	0.03%	0.101	19	− 0.38%	− 1.290
2	39	− 0.11%	− 0.252	19	− 0.13%	− 0.340
3	39	0.05%	0.116	19	0.33%	0.745
4	39	0.42%	0.944	19	0.40%	0.717
5	39	0.56%	0.838	19	0.73%	0.832
Holding days	**KOSPI 50**			**SSE 50**		
	N	**Mean**	**t-test**	**N**	**Mean**	**t-test**
Panel B CARs of continuously falling prices and RSI ≤ 30 emitted						
Panel B1: Continuously falling prices and RSI ≤ 30 for 2 days						
1	203	0.14%	0.903	210	0.07%	0.560
2	203	0.16%	0.758	210	0.20%	1.259
3	203	0.51%	1.973**	210	0.25%	1.169
4	203	0.58%	1.912*	210	0.41%	1.680*
5	203	0.65%	1.993**	210	0.52%	1.881*
Panel B2: Continuously falling prices and RSI ≤ 30 for 3 days						
1	59	0.38%	1.501	51	− 0.10%	− 0.483
2	59	0.54%	1.377	51	0.18%	0.500
3	59	0.25%	0.577	51	0.41%	0.996
4	59	0.52%	1.010	51	0.48%	1.141
5	59	0.26%	0.480	51	0.62%	1.337
Panel B3: Continuously falling prices and RSI ≤ 30 for 4 days						
1	16	0.37%	0.471	19	− 0.71%	− 1.342
2	16	0.86%	0.644	19	− 0.07%	− 0.135
3	16	0.72%	0.553	19	0.37%	0.398
4	16	1.12%	0.794	19	0.91%	0.841
5	16	0.47%	0.353	19	1.60%	1.486

We investigate whether the CARs, including 1-, 2-, 3-, 4-, and 5-days CARs, would be different from 0 if investors take the long positions on the constituent stocks of KOSPI 50 and SSE 50 as either continuously falling prices for 2, 3, and 4 days occurred. We also present the statistics of t-tests for these CARs. In addition, *, **, and *** represent 10%, 5%, and 1% significance levels, respectively employing a momentum strategy would have been appropriate for trading the constituent stocks of SSE 50 as continuously rising stock prices and RSI $\geq$ 70 (i.e., the overbought signals shown) over a period of two and three days were observed during 2009–2015. This might be because approximately 80% of the participants in the Chinese stock market are individual investors (Girardin and Joyeux 2013; Ni et al. 2015), who tend to be irrational and may not collect sufficient information to make investment decisions. However, contrarian strategies might be suitable for trading the constituent stock of SSE 50 over the data period 2016 to 2019, which is similar to the strategies employed by the Korean stock market. Since numerous stocks have been included as constituents of the MSCI for decades, the Korean stock market should have a high percentage of institutional investors (Bonizzi 2015). Similarly, based on the weight raised by the MSCI, the Chinese stock market may have been dominated by more institutional investors after 2015.

Additionally, investors might apply contrarian strategies for trading the constituent stocks of KOSPI 50 and SSE 50 as continuously falling stock prices and oversold trading signals, such as K $\leq$ 20 or RSI $\leq$ 30, are observed. Since contrarian strategies are formulated on the premise that the stock market overreacts to news (Gopal 2016) and could be led by overconfidence (Da Dalt et al. 2019), we argue that the findings might result from overreactions to continuously falling stock prices and oversold trading signals. In addition, we argue that political economics may interpret our findings. Ultimately, a sluggish economy negatively affects stock markets. Authorities, even institutional investors, would pull up stock markets if the falling stock prices result in the occurrence of the continuous phenomena. Eventually, the indices will increase and stock prices will rebound.

Conclusions

In general, investors might trade stocks when technical trading signals are emitted or chase rising (or falling) stock prices, which could result in continuously rising (or falling) prices for a few days. We conduct this study to determine whether investors can make excess profits, and find that investors might beat markets by applying suitable techniques and trading strategies when the phenomena occur. These findings demonstrate that markets might not be fully efficient and may not provide valuable information to investors.

This study also provides policy implications in two aspects. The government might try to internationalize its stock markets to avoid the markets being dominated by individuals who tend to make investment decisions irrationally. Investors should be patient while trading stocks because they may be able to exploit profits by employing proper technical indicators and strategies.

However, this study has some limitations. First, since Korea and China are the deemed representatives of Asian markets, we are not sure if the trading strategies suggested in this study are also appropriate for other markets, such as the US and the UK. Second, other methodologies, such as Spearman's rank correlation, multiple criteria decision-making methods, analytic hierarchy process, and consensus models, could have also been considered for conducting the research. Third, some informal issues, such as Confucianism in the Chinese stock market (Bashir and Yu 2020), seem to have significant effects on stock market performance evaluation. In future research, we will attempt to mitigate the aforementioned restrictions and find more diversified outcomes to enrich the literature.

Table 9 CARs of continuously rising prices and K ≥ 80 (RSI ≥ 70) emitted (2009–2015) with power disclosed

Holding days	KOSPI 50					SSE 50					
	N	Mean	t-test	ES	Power	N	Mean	t-test	SD	ES	Power
Panel A: Continuously rising prices and K ≥ 80 emitted											
Panel A1: Continuously rising prices and K ≥ 80 for 2 days											
1	473	−0.002	−2.432**	−0.112	**0.78**	324	0.001	0.657	0.027	0.037	0.01
2	473	−0.0052	−4.028***	−0.185	**0.99**	324	−0.0012	−0.483	0.045	−0.027	0.12
3	473	−0.0039	−2.646***	−0.122	**0.84**	324	0.0033	1.017	0.058	0.057	0.00
4	472	−0.0051	−3.061***	−0.141	**0.92**	324	0.0055	1.495	0.066	0.083	0.00
5	472	−0.0051	−2.94***	−0.135	**0.90**	324	0.0072	1.719	0.075	0.096	0.00
Panel A2 Continuously rising prices and K ≥ 80 for 3 days											
1	116	−0.0002	−0.125	−0.012	0.06	91	0.0017	0.375	0.043	0.039	0.02
2	116	−0.0024	−0.995	−0.092	0.26	91	0.0059	0.938	0.060	0.098	0.00
3	116	−0.0032	−1.085	−0.101	0.29	91	0.0052	0.711	0.070	0.075	0.01
4	116	−0.0038	−1.287	−0.119	0.36	91	0.0011	0.12	0.087	0.013	0.04
5	116	−0.0036	−1.149	−0.107	0.31	91	0.0038	0.4	0.091	0.042	0.02
Panel A3: Continuously rising prices and K ≥ 80 for 4 days											
1	35	−0.0028	−0.747	−0.126	0.18	25	0.0043	0.752	0.029	0.150	0.01
2	35	−0.009	−1.698*	−0.287	**0.52**	25	0.0011	0.142	0.039	0.028	0.04
3	35	−0.0118	−2.447**	−0.414	**0.79**	25	−0.0074	−0.779	0.047	−0.156	0.19
4	35	−0.0116	−2.38**	−0.402	**0.77**	25	0.0035	0.261	0.067	0.052	0.03
5	35	−0.0054	−0.821	−0.139	0.21	25	0.0143	1.021	0.070	0.204	0.00

Appendix A

We also use the software G* Power 3.1 (Faul et al. 2009) to derive power value. Furthermore, based on that when the power value is around 0.8 (Cohen 1992), the value may meet the power requirements. We then revealed that significant T values in Panels A1- A3 of Table 3 (i.e., Table 9 with incorporating power in this table in Appendix A) may meet the power requirement as revealed that most of them are around 0.8 except t value = − 1.698, 10% statistically significance. Note that *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Author contributions
Prof. Huang and Prof. Day collected and went through the initial screening of the data employed in this study. Prof. Ni and Prof. Day conducted the empirical results for this paper. Prof. Huang and Prof. Ni surveyed the relevant literature and interpreted empirical results. Prof. Ni and Prof. Cheng revised this paper. All of us read, finalized and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request at hpy315315@gmail.com.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Department of Management Sciences, Tamkang University, New Taipei, Taiwan. [2]Graduate Institute of Information Management, National Taipei University, New Taipei, Taiwan. [3]Department of International Business, Soochow University, No. 56, Sec. 1, Kueiyang St, Taipei 100, Taiwan.

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