International Review of Economics and Finance 39 (2015) 253–265

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

MA trading rules, herding behaviors, and stock market overreaction

Yensen Ni[a], Yi-Ching Liao[a], Paoyu Huang[b,*]

[a] Department of Management Sciences, Tamkang University, Taiwan, ROC
[b] Department of International Business, Soochow University, Taiwan, ROC

ARTICLE INFO

Article history:
Received 6 March 2014
Received in revised form 12 April 2015
Accepted 20 April 2015
Available online 1 May 2015

JEL classification:
G02
G11
G14

Keywords:
Moving average
Herding behavior
Overreaction

ABSTRACT

We determine whether investors profit from employing moving average trading rules that consider either "wide" or "in-depth" concerns. Our remarkable findings are as follows: First, investors benefit from purchasing the constituent stocks of SSE50 as dead crosses emerge. These stocks may be the result of the herding behaviors of individual investors who account for over 80% of investors in China's stock markets. Second, negative weekly returns increase in trading the constituent stocks of DJ30 and FTSE100 because returns increase considerably on golden-cross days as a result of stock price overreaction. These results remain robust by concerning investors' risk aversion, and even high risk aversion as investors suffer losses. In addition, our findings imply that stock market overreaction and herding behaviors are incorporated into technical analysis.

1. Introduction

Share prices are difficult to predict because all available information fully reflects the efficient market hypothesis (Fama, 1965, 1970). This viewpoint is challenged by the disposition effects proposed by Kahneman and Tversky (1979), as well as by the overreaction hypothesis presented by De Bondt and Thaler (1985). Furthermore, investors may overreact to the information and even to private information because of their excessive self-confidence (Chuang & Lee, 2006; Daniel, Hirshleifer, & Subrahmanyam, 1998). Individual and institutional investors often predict future prices with reference to technical indicators because these indicators are related to contrarian strategies based on the overreaction hypothesis or on the momentum strategy induced by excessive self-confidence. The effectiveness of moving average (MA) and other technical indicators has been confirmed by relevant studies, along with the informational content of trading rules (Bessembinder & Chan, 1995; Brock, Lakonishok, & LeBaron, 1992; Gençay, 1999; Gençay, Ballocchi, Dacorogna, Olsen, & Pictet, 2002; Gençay, Dacorogna, Olsen, & Pictet, 2003; Gençay & Stengos, 1997, 1998; Lento & Gradojevic, 2007; Lo, Mamaysky, & Wang, 2000; Metghalchia, Marcucci, & Chang, 2012; Ni, Lee, & Liao, 2013; Yu, Nartea, Gan, & Yao, 2013).

MA trading rules are widely employed in practice and are examined extensively in academic researches. Therefore, we review relevant studies for further investigation. With regard to MA trading rules, the golden and dead crosses that are emitted in accordance with the interaction between short and long MA lines are often employed in stock trading in US markets (Bessembinder & Chan, 1995; Brock et al., 1992). In addition, Gençay (1998) confirmed that stock prices can be predicted on the basis of the signals triggered by the

* Corresponding author. Tel.: +886 23111531x3421.
E-mail address: hpy@scu.edu.tw (P. Huang).

http://dx.doi.org/10.1016/j.iref.2015.04.009

MA trading rules. Gençay (1996) also indicated that stock market returns can be predicted by the signals generated from MA trading rules. Shintani, Yabu, and Nagakura (2012) revealed that trading signals such as the golden or dead crosses triggered by MA trading rules can predict future stock prices. Metghalchia et al. (2012) disclosed that MA trading rules can estimate future prices according to previous price patterns. Hong and Satchell (in press) proposed that the MA rule is popular because it can identify price momentum; and it is a simple way of exploiting price autocorrelation structure without necessarily determining its precise structure.

Moreover, Fifield, Power, and Donald Sinclair (2005) indicated that institutional investors often demonstrate superior performance when MA trading rules are applied to trading in emerging stock markets, even after subtracting transaction costs. Yu et al. (2013) reported that the MA trading rules have stronger predictive power in the emerging stock markets of Malaysia, Thailand, Indonesia, and the Philippines than in the highly developed stock market of Singapore. Nonetheless, Day and Wang (2002) determined that the buy and hold returns based on MA trading rules may not display improved performance. Heng, Azizan, and Yeap (2012) revealed that market participants who impose technical trading rules gain positive returns when transaction costs are not subtracted. However, these positive returns are not observed once these costs are subtracted. Chiang, Ke, Liao, and Wang (2012) disclosed that stock trading by following the trading signals triggered by stochastic oscillator indicators (SOI) in addition to MA trading rules enhances performance. Wang, Chao, and Chang (2012) reported that many institutional investors profit by trading stocks according to the trading signals triggered by SOI indicators.

In addition, Neely, Weller, and Dittmar (1997) found strong evidence of significant out-of-sample excess returns in connection with the rules for six exchange rates by using genetic programming techniques to derive technical trading rules. Lento, Gradojevic, and Wright (2007) tested the profitability of Bollinger Bands (BB) technical indicators and revealed that the BB technical indicators are unable to generate profits in excess of the buy-and-hold trading strategy.

Furthermore, we document that the trading signals triggered by technical indicators are likely to be related to momentum or contrarian strategies. For instance, we argue that the use of MA trading rules is closely related to momentum strategies because investors may have the momentum to either purchase shares with the emergence of the golden cross or to short-sell shares as the dead cross is triggered in accordance with MA trading rules (Bessembinder & Chan, 1995; Brock et al., 1992; Loh, 2007). Hou and Li (2014) suggested that the CSI 300 stock index futures market intensifies positive feedback trading in the underlying spot market. This occurrence is detrimental to informational efficiency.

Certain investors may adopt contrarian strategies as technical indicators, such as the categorization of SOI into overbought or oversold zones[1]. For instance, certain investors short-sell stocks when the SOI falls into the overbought zones, whereas other investors buy stocks when the SOI falls into the oversold zones.

Nonetheless, technical indicators have been challenged in recent studies. For example, Shynkevich (2012) argued that while various technical trading rules exhibit superior predictability in the first half of the sample period, this superiority is not observed in the second half, thus indicating that stock markets are increasingly efficient over time. Gradojevic and Gençay (2013) indicated that technical indicators are essentially imperfect because investors face considerable trading uncertainty.

Recently, Caporin, Ranaldo, and Santucci de Magistris (2013) showed that the high and low prices of equity shares are largely predictable on the basis of their past realizations. Taylor (2014) used a set of models that permit time-variation in risk-adjusted returns to portfolios with the respective technical trading rules, and revealed that profits evolve slowly over time by relying on the ability of investors to short-sell stocks. Gradojevic and Lento (2015) suggested that financial customers employing technical trading activities cause frequent violations of exchange rate movements driven by order flow, and highlighted the profitability of technical indicators constructed from order flows.

Lento and Gradojevic (2007) explored the profitability of technical trading rules by evaluating their ability to outperform the naïve buy-and-hold trading strategy. The employment of the moving average cross-over rules, filter rules, Bollinger Bands, and trading range break-out rules for testing S&P/TSX 300 Index, the Dow Jones Industrial Average Index, NASDAQ Composite Index, and the Canada/U.S. spot exchange rate, revealed that the profitability of the technical trading rules is enhanced with a combined signal approach.

While investigating relevant studies, we note that either MA trading rules or technical indicators may assist investors in trading stocks. We then argue that the MA trading rule with “wide” concerns, such as the trading signals triggered by both MA and SOI[2] trading rules, may benefit investors in stock trading. Furthermore, the MA trading rule with “in-depth” concerns, such as the trading signals triggered by applying MA trading rules related to stock price performance on golden-cross (dead-cross) days[3], assist market participants in stock trading. In other words, investors may profit more from employing MA trading rules with either “wide” or “in-depth” concerns than from applying the MA trading rule alone, which is in accordance with the observation that profitability of the technical trading rules is enhanced with a combined signal approach (Lento & Gradojevic, 2007).

Combined technical trading signals often include two trading signals emitted according to two or more technical trading rules [e.g., MA, relative strength index (RSI), SOI, and moving average convergence/divergence (MACD)]. In the current study, we determine whether or not investors profit from employing MA trading rules with “wide” concerns (i.e., by combining MA and SOI trading signals). This concept has been widely explored in relevant studies. However, we also investigate the employment of MA trading rules with

[1] As indicated in the relevant studies, the SOI falls into the overbought zone when the SOI values are over 70, 75, and 80. Likewise, the SOI falls into the oversold zone when the SOI values are below 30, 25, and 20.

[2] SOI is introduced in Section 2.2.

[3] The golden-cross day is defined, and the golden cross is triggered by $SMA_t > LMA_t$ and $SMA_{t-1} < LMA_{t-1}$. The dead-cross day is defined as well, and the dead cross is triggered by $SMA_t < LMA_t$ and $SMA_{t-1} > LMA_{t-1}$.

"in-depth" concerns [i.e., by combining MA trading rules with the percentage of increasing (decreasing) prices on golden-cross (dead-cross) days]. This idea has seldom been examined.

In this study, we employ trading rules such as MA(5, 20), MA(5, 60), and MA(20, 60)[4] because 5-day, 20-day, and 60-day MAs are widely applied as weekly, monthly, and quarterly MAs in practice. This employment is different from the use of the 1-day MA as short-term MA and that of the 100-day MA as the long-term MA (Bessembinder & Chan, 1995; Brock et al., 1992). Furthermore, this study not only explores MA trading rules with the SOI indicator but also examines MA trading rules in relation to stock price performance during golden-cross (dead-cross) days. To the best of our knowledge, this study is the first to examine whether or not the employment of MA trading rules by incorporating both "wide" and "in-depth" concerns affects the trading of the constituent stocks of the Dow Jones 30 index (DJ30), the FTSE 100 index (FTSE100), and the Shanghai 50 index (SSE50).

In this paper, we report remarkable findings that can contribute to existing literature. For instance, market participants can profit more from buying than from short-selling the constituent stocks of SSE50 when the dead cross is emitted. We infer that the results are likely attributed to the herding behaviors of individual investors. These behaviors result in the overselling of shares and the undervaluing of share prices when the dead cross is emitted given that approximately 80% of the total trading volume in China is contributed by individual investors.

In addition, negative weekly mean returns increase when trading the constituent stocks of DJ30 and FTSE100 as stock returns increase during golden-cross days. The results may be interpreted according to stock price overreaction, which is likely induced by the herding behaviors displayed on golden-cross days. As a result, the overreaction phenomena during this period are adjusted in the short run, as highlighted in the negative weekly return after a superior stock price performance was observed on golden-cross days.

The results imply that the contrarian strategy is appropriate when MA trading rules with "in-depth" concerns are employed. This concept has rarely been explored in relevant studies although many practitioners trade stocks as the golden cross emerges. As a result, the exploration of these issues not only contributes to existing literature but also helps investors distinguish whether or not trading stocks according to various MA trading signals is worthwhile.

The remainder of this paper is organized as follows. Section 2 introduces the data and MA trading rules. Section 3 presents the empirical results and analyses. Section 4 provides our concluding remarks.

2. Introduction of data and MA trading signals

We collect the daily data for the constituent stocks of DJ30, FTSE100, and SSE50 over the period of 2005–2009 from Datastream and then plot these time series in Figs. 1–3. These stock indices declined after 2007, possibly as a result of the 2008 stock market crisis.

2.1. Moving average (MA)

The n-day simple MA is defined below:

$$MA_{t,n} = \frac{1}{n}\sum_{i=t-n+1}^{t} P_i, \tag{1}$$

where $MA_{t,n}$ is the n-day moving average at time t and P_i is the closing price at time t.

Under the MA trading rule, the golden cross emerges when the short-term MA increases beyond the long-term MA, thus indicating the end of the downward trend and the start of the new upward trend. By contrast, the dead cross emerges when the short-term MA drops below the long-term MA, thereby suggesting the end of the upward trend and the start of the new downward trend. Therefore, the golden and dead crosses are defined as follows:

$$\text{The golden cross is}: \mathrm{SMA}_t > \mathrm{LMA}_t \ \text{ and } \mathrm{SMA}_{t-1} < \mathrm{LMA}_{t-1}, \tag{2}$$

$$\text{The dead cross is}: \mathrm{SMA}_t < \mathrm{LMA}_t \ \text{ and } \mathrm{SMA}_{t-1} > \mathrm{LMA}_{t-1}. \tag{3}$$

Market participants who are familiar with technical analysis may trade stocks as the golden cross or dead cross emerges because these crosses are regarded as the signals for stock trading.

2.2. Stochastic oscillator indicator (SOI)

The SOI that is sensitive to the share price is updated over the price range between the highest and the lowest prices in a certain period, as provided below[5]:

$$\mathrm{K}_t = \frac{2}{3}\mathrm{K}_{t-1} + \frac{1}{3}\mathrm{RSV}_t, \tag{4}$$

[4] In this study, the first numbers in the brackets for these cases denote the trading days for short-term MA, whereas the second numbers in these brackets indicate the trading days for long-term MA.

[5] The 9-day and 14-day MAs are frequently employed to measure K values in practice.

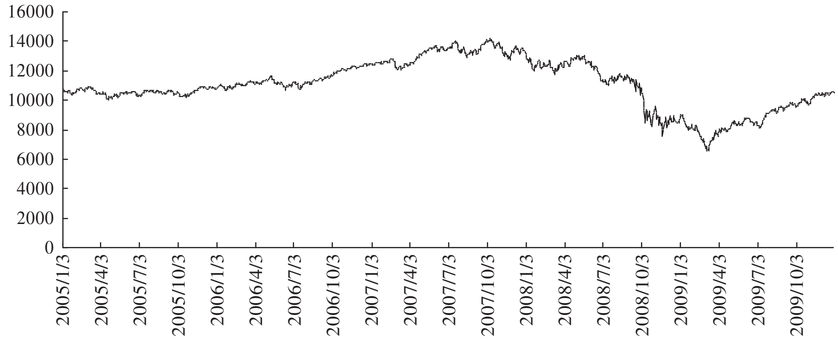

Fig. 1. Dow Jones 30 index (US).

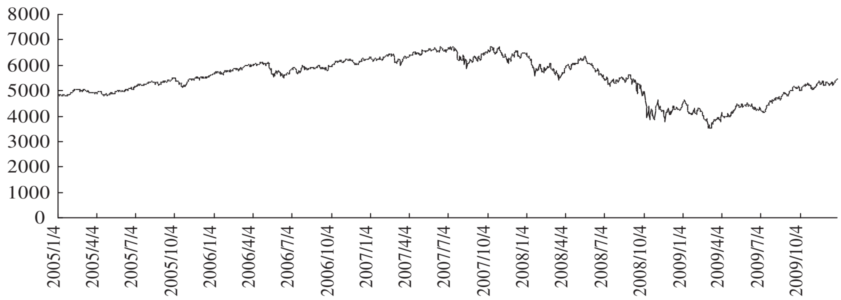

Fig. 2. FTSE 100 index (UK).

where:

$$\mathrm{CL}_t = \mathrm{P}_t - \min(\mathrm{P}_t, \mathrm{P}_{t-1}, \ldots, \mathrm{P}_{t-8}), \tag{5}$$

$$\mathrm{HL}_t - \max(\mathrm{P}_t, \mathrm{P}_{t-1}, \ldots, \mathrm{P}_{t-8}) - \min(\mathrm{P}_t, \mathrm{P}_{t-1}, \ldots, \mathrm{P}_{t-8}), \tag{6}$$

$$\mathrm{RSV}_t = \frac{\mathrm{CL}_t}{\mathrm{HL}_t} \times 100, \tag{7}$$

CL_t is measured as the lowest closing price in n recent days subtracted by the most recent closing price. HL_t is defined as the difference between the highest and the lowest closing prices within n days. RSV_t is determined by CL_t over HL_t. In addition, the K value is the sum of 1/3 of the RSV value and 2/3 of the K value at lag 1. According to the equations above, K values range from 0 to 100. Moreover, SOI is linked to the overreaction hypotheses. For instance, an SOI value of over 70 is set as the overbought zone and that below 30 is regarded as the oversold zone[6].

3. Empirical results and analyses

3.1. Descriptive statistics

The means and standard deviations (S.D.) of the constituent stocks of the FTSE100 are higher than those of the constituent stocks of DJ30 and SSE50 because the former includes various small-scale stocks and high stock price volatilities.

3.2. Weekly returns for trading based on diverse MA trading rules

We determined whether or not investors profit from employing MA trading rules with "wide" and "in-depth" concerns. We mainly focus on whether weekly returns deviate from zero if they replace daily and monthly returns as the trading signals emitted by these trading rules for the constituent stocks of DJ30, FTSE100, and SSE50 indices.

[6] We argue that the overbought and oversold zones set according to SOI are closely related to the overreaction hypothesis proposed in relevant studies.

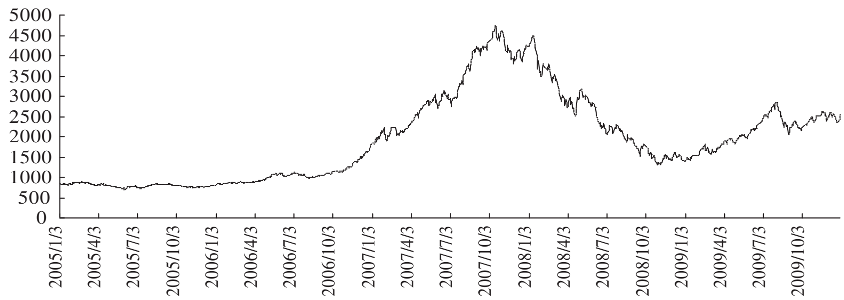

Fig. 3. Shanghai 50 index (China).

We investigate weekly returns[7] rather than daily and monthly returns for two main reasons. First, we argue that investors may not obtain increased returns in a day when transaction costs are factored in. Second, we argue that monthly returns are likely affected more by other irrelevant factors, as comparing with weekly returns.

In addition, we employ trading rules such as MA(5, 20), MA(5, 60), and MA(20, 60)[8], because 5-day, 20-day, and 60-day MAs are widely applied as weekly, monthly, and quarterly MAs in practice. This method differs from the use of 1-day MA as a short-term MA and of the 100-day MA as the long-term MA (Bessembinder & Chan, 1995; Brock et al., 1992).

We then gather the daily data on the constituent stocks of DJ30, FTSE100, and SSE50 over the data period of 2005–2009 from Datastream. The data trend is plotted as shown in Figs. 1–3. The upward stock market trend ended in 2008, possibly as a result of the stock market crisis in 2008[9].

We then determine whether or not investors profit from employing MA trading rules with either "wide" or "in-depth" concerns. Thus, we test whether or not the mean return deviates from zero when investors trade the constituent stocks of DJ30, FTSE100, and SSE50.

The study conducted by Dacorogna, Gençay, Müller, and Pictet (2001) proposes two performance measures that are related to the utility of a strategy for a risk-averse investor. In this approach, the maximization of performance measures implies the maximization of the expected utility for an investor. We therefore examine two risk-adjusted performance measures, namely, X_{eff} and R_{eff}. The former is defined as the return in relation to constant risk aversion and the latter is defined as the return under increased risk aversion as a result of losses incurred. Both performance measures are highly concerned with risk aversion. Furthermore, Neely (2003) suggests that risk-adjustment techniques should be seriously considered in the evaluation of trading strategies. Hence, we take these two risk-adjusted performances into account in this study.

We then measure X_{eff} and R_{eff} according to two steps because of the requirement to determine the S.D. using the equation shown below.

$$X_{eff} = \overline{X} - \frac{\gamma\delta^2}{2}, \tag{8}$$

where $\overline{X}$ is the mean return for each constituent stock; σ^2 is the S.D.; and γ is the reasonable value of the risk aversion.

In the first step, we determine the $\overline{X}$ for each constituent stock per year with Eq. (8). The second step is to obtain the mean $\overline{X}$. Subsequently, we determine whether or not mean $\overline{X}$ and the mean X_{eff} deviate from zero. In addition, we set 0.10 as the value of γ to measure X_{eff} as suggested by Dacorogna et al. (2001).[10]

Moreover, these researchers argue that risk aversion increases in the event of losses but declines because of gains. To measure X_{eff} defined as R_{eff}, we set 0.20 as the value of γ given that $\overline{X}$ is negative. Furthermore, we set 0.05 as the value of γ because $\overline{X}$ is positive, as per the suggestion of MÄuller, Dacorogna, and Pictet (1993).[11]

Subsequently, we investigate whether or not the mean return, mean X_{eff}, and mean R_{eff} deviate from zero. In Tables 2–4, we present the results for these mean returns when MA trading rules that consider "wide" concerns are employed. Similarly, in Tables 5–7, we indicate the results for the mean returns when MA trading rules that consider "in-depth" concerns are applied.

[7] In addition, we generate preliminary results that may not be consistent among daily, weekly, and monthly returns. Our results are consistent with those obtained by Gençay et al. (2002, 2003) and Dacorogna et al. (2001). Thus, we agree that a particular statistical model of asset returns that works with a given data horizon (e.g., daily) fails in another (e.g., weekly or monthly horizon).

[8] In this study, the first numbers in the brackets for these cases denote the trading days for short-term MA. The second numbers in these brackets indicate the trading days for long-term MA.

[9] We also employ the data obtained from the periods of 2005–2007 and 2008–2009. The results generated for these two sub-periods are similar to those obtained with data from the period of 2005–2009. This finding indicates that the results were not affected by the potential structural breaks caused by the 2008 stock market crisis.

[10] The recommended value of γ is between 0.08 and 0.15 (Dacorogna et al., 2001).

[11] High (low) risk aversion, such as γ, is reflected by market participants in the loss (gain) zone. The value of γ in the loss zone is suggested to be four times that in the gain zone.

Table 1
Descriptive statistics.
Table 1 reports the descriptive statistics for the constituent stocks of DJ30, FTSE100, and SSE50 including the means, standard deviations, maximums, and minimums.

	Number	Mean	S.D.	Min.	Max.
DJ30	37770	0.0003	0.0236	−0.3902	0.5798
FTSE100	84938	0.0009	0.0859	−0.9000	0.7324
SSE50	74791	0.0009	0.0318	−0.7600	0.5900

Table 2
Weekly mean returns as diverse MA trading rules with "wide" concerns emitted. Table 2 shows the weekly mean returns as each of three MA trading signals and each of three SOI trading signals are both triggered for the DJ30's, FTSE100's, and SSE50's constituent stocks. We explore whether these weekly mean returns are different from zero by taking the long positions for the constituent stocks of DJ 30, FTSE 100, and SSE 50, and then present the statistics of t tests[a] in Table 2. Panel A reveals the results of each of the golden crosses following MA(5, 20), MA(5, 60), and MA(20, 60) trading rules and each of the K ≥ 75, K ≥ 80, and K ≥ 85 are both triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively. Panel B reveals the results of each of the dead crosses following the MA(5, 20), MA(5, 60), MA(20, 60) and each of the K ≤ 25, K ≤ 20, and K ≤ 15 are both triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively.

		MA(5, 20)			MA(5, 60)			MA(20, 60)		
		N	Mean	t	N	Mean	T	N	Mean	t
Panel A: three matrices of 3 MA golden crosses by 3 SOI trading zones										
DJ 30	K ≥ 75	148	−0.0018	−0.877	126	0.0018	0.650	66	0.0048	1.433
	K ≥ 80	114	−0.0020	−0.700	104	0.0015	0.587	50	0.0045	1.087
	K ≥ 85	36	−0.0106	−2.238**	67	−0.0015	−0.481	32	0.0044	0.730
FTSE100	K ≥ 75	327	0.0001	0.044	248	−0.0019	−1.064	130	−0.0003	−0.131
	K ≥ 80	251	−0.0013	−0.553	204	−0.0025	−1.167	103	−0.0010	−0.335
	K ≥ 85	95	−0.0035	−0.608	132	−0.0006	−0.222	66	−0.0003	−0.103
SSE50	K ≥ 75	298	0.0036	1.309	193	0.0001	0.016	101	0.0038	0.858
	K ≥ 80	201	0.0030	0.802	162	−0.0017	−0.516	76	0.0025	0.469
	K ≥ 85	64	−0.0095	−1.230	115	−0.0051	−1.191	57	0.0037	0.575
Panel B: three matrices of 3 MA dead crosses by 3 SOI trading zones										
DJ 30	K ≤ 25	140	0.0034	1.795	121	0.0012	0.489	62	0.0034	0.822
	K ≤ 20	101	0.0088	3.360**	95	0.0019	0.689	40	0.0042	0.992
	K ≤ 15	32	0.0056	1.174	65	0.0054	1.889	31	0.0006	0.127
FTSE100	K ≤ 25	347	0.0019	1.168	275	0.0012	0.683	125	−0.0018	−0.576
	K ≤ 20	268	0.0011	0.547	234	0.0008	0.387	95	−0.0010	−0.281
	K ≤ 15	89	0.0080	2.266*	156	0.0005	0.211	60	0.0031	0.821
SSE50	K ≤ 25	291	0.0134	4.563**	205	0.0005	0.162	86	0.0031	0.416
	K ≤ 20	211	0.0151	4.168**	171	0.0017	0.476	74	0.0013	0.154
	K ≤ 15	68	0.0193	2.913**	108	0.0066	1.322	50	−0.0091	−1.155

[a] Most of our data samples pass either the normality or the skewed tests possibly because adequate samples were collected in this study.
* Significant at the 5% level.
** Significant at the 1% level.

3.2.1. Returns for the MA with "wide" concerns

We argue that market participants may trade stocks given many trading signals, such as when the MA trading rule with the "wide" concern is emitted instead of only one trading signal. Panel A of Table 2 indicates the results of the matrices that consist of the golden crosses triggered by the MA(5, 20), MA(5, 60), and MA(20, 60) trading rules, as well as the SOI trading signals triggered by K ≥ 75, K ≥ 80, and K ≥ 85[12], for the constituent stocks of DJ30, FTSE100, and SSE50, respectively. Panel B of Table 2 presents the results of the matrices that consist of the dead crosses triggered by the MA(5, 20), MA(5, 60), and MA(20, 60) trading rules, as well as the SOI trading signals triggered by K ≤ 25, K ≤ 20, and K ≤ 15, for these constituent stocks.

Table 2 shows that investors suffer losses by short-selling the constituent stocks of SSE50 when the dead cross is triggered by the MA(5, 20) trading rules and an oversold zone, including K ≤ 25, K ≤ 20, and K ≤ 15. We argue that the results may be caused by overreaction as negative dead crosses are emitted, and this overreaction may undervalue the share price as the dead cross emerges. As a result, investors benefit more from purchasing the constituent stocks of SSE50 than from selling them in this instance. In addition, we employ the mean X_{eff} and the mean R_{eff} as suggested by Dacorogna et al. (2001). The results presented in Tables 3–4 are similar to those in Table 2, thus indicating that our findings remain robust.

[12] As indicated by relevant studies (Alsulaiman, 2013; Chen & Metghalchi, 2012; Cheung, 2007; Esichaikul & Srithongnopawong, 2010; Metghalchi, Chang, & Garza-Gomez, 2012; Mizrach & Weerts, 2009), the SOI falls into the oversold zone because the SOI values are below 30, 25, and 20. Similarly, the SOI falls into the overbought zone because the SOI values are above 70, 75, and 80. Instead of merely employing SOI/RSI values below 30, 25, and 20 (above 70, 75, and 80) that are regarded as oversold (overbought) signals, we also apply the low oversold (high bought) signals, such as SOI values below 15 (over 85), for further investigation. This consideration may provide valuable references to investors.

Table 3
Weekly mean X_{eff} as diverse MA trading rules with "wide" concerns emitted. Table 3 shows the weekly mean X_{eff} as each of three MA trading signals and each of three SOI trading signals are both triggered for the DJ30's, FTSE100's, and SSE50's constituent stocks. We explore whether these weekly mean X_{eff} are different from zero, and then present the statistics of t tests in Table 3. Panel A reveals the results of each of the golden crosses following MA(5, 20), MA(5, 60), and MA(20, 60) trading rules and each of the K ≥ 75, K ≥ 80, and K ≥ 85 are both triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively. Panel B reveals the results of each of the dead crosses following the MA(5, 20), MA(5, 60), and MA(20, 60) and each of the K ≤ 25, K ≤ 20, and K ≤ 15 are both triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively.

		MA(5, 20)			MA(5, 60)			MA(20, 60)		
		N	Mean	t	N	Mean	T	N	Mean	T
Panel A: three matrices of 3 MA golden crosses by 3 SOI trading zones										
DJ 30	K ≥ 75	148	−0.0019	−0.922	126	0.0017	0.623	66	0.0047	1.402
	K ≥ 80	114	−0.0020	−0.727	104	0.0014	0.562	50	0.0044	1.059
	K ≥ 85	36	−0.0108	−2.249*	67	−0.0016	−0.500	32	0.0043	0.707
FTSE100	K ≥ 75	327	−0.0001	−0.038	248	−0.0021	−1.134	130	−0.0004	−0.154
	K ≥ 80	251	−0.0015	−0.617	204	−0.0027	−1.227	103	−0.0011	−0.352
	K ≥ 85	95	−0.0037	−0.647	132	−0.0008	−0.286	66	−0.0004	−0.118
SSE50	K ≥ 75	298	0.0032	1.184	193	−0.0002	−0.069	101	0.0036	0.804
	K ≥ 80	201	0.0027	0.716	162	−0.0019	−0.592	76	0.0023	0.426
	K ≥ 85	64	−0.0099	−1.278	115	−0.0054	−1.256	57	0.0035	0.542
Panel B: three matrices of 3 MA dead crosses by 3 SOI trading zones										
DJ 30	K ≤ 25	140	0.0033	1.748	121	0.0011	0.448	62	0.0033	0.795
	K ≤ 20	101	0.0087	3.336**	95	0.0018	0.655	40	0.0041	0.972
	K ≤ 15	32	0.0055	1.160	65	0.0053	1.859	31	0.0005	0.108
FTSE100	K ≤ 25	347	0.0017	1.075	275	0.0011	0.612	125	−0.0020	−0.620
	K ≤ 20	268	0.0010	0.492	234	0.0007	0.329	95	−0.0011	−0.315
	K ≤ 15	89	0.0079	2.235*	156	0.0004	0.176	60	0.0030	0.794
SSE50	K ≤ 25	291	0.0131	4.471**	205	0.0002	0.066	86	0.0027	0.367
	K ≤ 20	211	0.0148	4.097**	171	0.0014	0.388	74	0.0009	0.104
	K ≤ 15	68	0.0189	2.851**	108	0.0063	1.272	50	−0.0093	−1.180

* Significant at the 5% level.
** Significant at the 1% level.

Table 4
Weekly mean R_{eff} as diverse MA trading rules with "wide" concerns emitted. Table 4 shows the weekly R_{eff} as each of three MA trading signals and each of three SOI trading signals are both triggered for the DJ30's, FTSE100's, and SSE50's constituent stocks. We explore whether these weekly R_{eff} are different from zero, and then present the statistics of t tests in Table 4. Panel A reveals the results of each of the golden crosses following MA(5, 20), MA(5, 60), and MA(20, 60) trading rules and each of the K ≥ 75, K ≥ 80, and K ≥ 85 are both triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively. Panel B reveals the results of each of the dead crosses following the MA(5, 20), MA(5, 60), and MA(20, 60) and each of the K ≤ 25, K ≤ 20, and K ≤ 15 are both triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively.

		MA(5, 20)			MA(5, 60)			MA(20, 60)		
		N	Mean	t	N	Mean	T	N	Mean	t
Panel A: three matrices of 3 MA golden crosses by 3 SOI trading zones										
DJ 30	K ≥ 75	148	−0.0019	−0.935	126	0.0017	0.616	66	0.0047	1.383
	K ≥ 80	114	−0.0021	−0.732	104	0.0014	0.556	50	0.0043	1.041
	K ≥ 85	36	−0.0108	−2.247*	67	−0.0016	−0.504	32	0.0042	0.690
FTSE100	K ≥ 75	327	−0.0001	−0.068	248	−0.0022	−1.174	130	−0.0004	−0.160
	K ≥ 80	251	−0.0015	−0.642	234	0.0006	0.317	103	−0.0011	−0.356
	K ≥ 85	95	−0.0039	−0.663	132	−0.0009	−0.329	66	−0.0004	−0.127
SSE50	K ≥ 75	298	0.0031	1.139	193	−0.0003	−0.096	101	0.0035	0.789
	K ≥ 80	201	0.0026	0.688	162	−0.0020	−0.618	76	0.0022	0.407
	K ≥ 85	64	−0.0100	−1.280	115	−0.0055	−1.275	57	0.0034	0.526
Panel B: three matrices of 3 MA dead crosses by 3 SOI trading zones										
DJ 30	K ≤ 25	140	0.0033	1.736	121	0.0010	0.430	62	0.0032	0.780
	K ≤ 20	101	0.0087	3.327**	95	0.0018	0.642	40	0.0041	0.965
	K ≤ 15	32	0.0055	1.161	65	0.0053	1.842	31	0.0005	0.102
FTSE100	K ≤ 25	347	0.0017	1.031	275	0.0011	0.596	125	−0.0020	−0.625
	K ≤ 20	268	0.0009	0.472	234	0.0006	0.317	95	−0.0011	−0.319
	K ≤ 15	89	0.0079	2.224*	156	0.0004	0.164	60	0.0030	0.786
SSE50	K ≤ 25	291	0.0131	4.448**	205	0.0001	0.037	86	0.0027	0.358
	K ≤ 20	211	0.0148	4.070**	171	0.0013	0.361	74	0.0008	0.095
	K ≤ 15	68	0.0188	2.818**	108	0.0063	1.257	50	−0.0095	−1.191

* Significant at the 5% level.
** Significant at the 1% level.

Table 5
Weekly mean returns as diverse MA trading rules with 'in-depth' concerns emitted. Table 5 shows the weekly mean returns as each of three MA trading signals and each of four "in-depth" trading signals are both triggered for the DJ30's, FTSE100's, and SSE50's constituent stocks. We explore whether these weekly mean returns are different from zero by taking the long positions for the constituent stocks of DJ 30, FTSE 100, and SSE 50, and then present the statistics of t tests in Table 5. Panel A of Table 5 presents the weakly mean returns for buying stocks with stock returns over 1%, 2%, 3%, and 4% denoted as R ≥ 1%, R% ≥ 2%, R% ≥ 3%, and R% ≥ 4%, respectively, at the golden-cross days decided by MA(5, 20), MA(5, 60), MA(20, 60). Similarly, Panel B of Table 5 shows the weakly mean returns for short selling stocks with stock returns below 1%, 2%, 3%, and 4% denoted as R% ≤ −1%, R% ≤ −2%, R% ≤ −3%, and R% ≤ −4%, respectively, at the dead-cross day decided by MA(5, 20), MA(5, 60), and MA(20, 60).

		MA(5, 20)			MA(5, 60)			MA(20, 60)		
		N	Mean	T	N	Mean	t	N	Mean	T
Panel A: three matrices of 3 golden crosses by 4 different performances at golden-cross days										
DJ30	R% ≥ 1%	124	−0.0033	−1.381	57	−0.0037	−0.848	23	−0.0018	−0.295
	R% ≥ 2%	72	−0.0109	−2.555*	25	−0.0078	−0.863	12	−0.0150	−1.429
	R% ≥ 3%	25	−0.0359	−3.755**	7	−0.0105	−0.352	3	−0.0111	−0.397
	R% ≥ 4%	16	−0.0312	−1.739	5	0.0187	0.539	2	−0.0316	−0.970
FTSE100	R% ≥ 1%	304	−0.0041	−1.661	167	−0.0035	−1.517	43	−0.0058	−1.280
	R% ≥ 2%	190	−0.0085	−2.472*	81	−0.0079	−1.819	19	−0.0085	−1.182
	R% ≥ 3%	117	−0.0174	−2.856**	38	−0.0166	−2.796**	7	−0.0347	−2.694*
	R% ≥ 4%	59	−0.0253	−2.327*	25	−0.0187	−2.438*	3	−0.0472	−3.867
SSE50	R% ≥ 1%	296	0.0050	2.012*	157	0.0023	0.480	72	0.0054	1.008
	R% ≥ 2%	241	0.0047	1.434	112	0.0042	0.679	41	0.0077	0.825
	R% ≥ 3%	157	0.0027	0.600	57	0.0008	0.083	16	−0.0018	−0.185
	R% ≥ 4%	97	0.0044	0.702	30	0.0128	0.796	3	−0.0344	−8.554
Panel B: three matrices of 3 dead crosses by 4 different performances at dead-cross days										
DJ30	R% ≤ −1%	113	0.0020	0.763	73	−0.0024	−0.626	27	−0.0024	−0.413
	R% ≤ −2%	67	−0.0031	−0.623	37	−0.0007	−0.101	10	−0.0028	−0.278
	R% ≤ −3%	31	0.0065	0.752	14	−0.0021	−0.132	5	0.0031	0.258
	R% ≤ −4%	8	0.0242	0.621	8	0.0242	0.621	–	–	–
FTSE100	R% ≤ −1%	295	−0.0032	−1.378	176	0.0002	0.088	61	−0.0036	−0.720
	R% ≤ −2%	184	0.0007	0.177	82	0.0049	0.978	28	−0.0017	−0.202
	R% ≤ −3%	109	−0.0045	−0.599	44	0.0015	0.167	14	0.0038	0.391
	R% ≤ −4%	22	−0.0034	−0.224	22	−0.0034	−0.224	7	0.0092	0.533
SSE50	R% ≤ −1%	272	0.0034	1.090	136	−0.0030	−0.683	35	0.0000	0.003
	R% ≤ −2%	217	0.0014	0.387	84	−0.0090	−1.850	18	0.0034	0.284
	R% ≤ −3%	152	−0.0010	−0.207	43	−0.0226	−2.887**	9	−0.0282	−2.011
	R% ≤ −4%	26	−0.0213	−2.208*	26	−0.0213	−2.208*	3	−0.0413	−18.973**

* Significant at the 5% level.
** Significant at the 1% level.

3.2.2. Returns for the MA with "in-depth" concerns

We investigate MA trading rules in consideration of the stock return on the golden-cross (dead-cross) day. We argue that information may be generated on the golden-cross (dead-cross) days because the golden-cross (dead-cross) may not emerge if the share price of a stock did not rise (fall) to a certain level.

Furthermore, the percentages of increase (decrease) at which prices are regarded as either high or low on the golden-cross (dead-cross) days may not be unanimous. Thus, we determine whether or not weekly mean returns vary when investors trade stocks at share price that increase (decrease) by 1%, 2%, 3%, and 4% on the golden-cross (dead-cross) days. We exclude the case of share price increase (decrease) by 5% on the golden-cross (dead-cross) days because few samples can be obtained for this case. Moreover, the samples decline significantly when the set R% is over 5% (below −5%) because the price limits are set to 7% in the Taiwan Stock Exchange.

Panel A of Table 5 reveals that negative mean returns increase if investors buy the constituent stocks of DJ30 and FTSE100 while the stock returns increase by 2%, 3%, and 4% at the golden-cross day triggered by the MA(5, 20) trading rule. Negative weekly returns also increase when trading the constituent stocks of DJ30 and FTSE100 as returns increase considerably at the golden-cross day. This occurrence may be the result of the stock price overreaction on the golden-cross day. In addition, we adopt the X_{eff} and R_{eff} suggested by Dacorogna et al. (2001) for this investigation. The results shown in Tables 6–7 are similar to those in Table 5, thus indicating that our findings remain robust when the returns that concern risk aversion and even high risk aversion as investors suffer losses.

4. Further investigation

4.1. Comparison with simple MA trading rules

After employing the simple MA trading rule alone, the results show that investors would profit by employing the MA trading rules for the constituent stocks of SSE50 as the golden cross appears. However, investors are likely to suffer losses by short selling the constituent stocks of DJ30 and SSE50 indices as the dead cross appears. In line with this, we revealed that investors would profit more by buying SSE50's constituent stocks as the dead cross rather than the golden cross appears. These results are possibly caused by the herding behaviors of individual investors after receiving negative inputs. In the Chinese stock markets, more than 80% of market participants are individual investors.

Table 6
Weekly mean X_{eff} as diverse MA trading rules with 'in-depth' concerns emitted. Panel A of Table 6 presents the weakly mean X_{eff} for buying stocks with stock returns over 1%, 2%, 3%, and 4% denoted as R ≥ 1%, R% ≥ 2%, R% ≥ 3%, and R% ≥ 4%, respectively, at the golden-cross days decided by MA(5, 20), MA(5, 60), MA(20, 60). Similarly, Panel B of Table 5 shows the weakly X_{eff} for short selling stocks with stock returns below 1%, 2%, 3%, and 4% denoted as R% ≤ −1%, R% ≤ −2%, R% ≤ −3%, and R% ≤ −4%, respectively, at the dead-cross day decided by MA(5, 20), MA(5, 60), and MA(20, 60).

		MA(5, 20)			MA(5, 60)			MA(20, 60)		
		N	Mean	T	N	Mean	t	N	Mean	T
Panel A: three matrices of 3 golden crosses by 4 different performances at golden-cross days										
DJ30	R% ≥ 1%	124	−0.0035	−1.432	57	−0.0038	−0.867	23	−0.0020	−0.321
	R% ≥ 2%	72	−0.0111	−2.593*	25	−0.0079	−0.873	12	−0.0154	−1.444
	R% ≥ 3%	25	−0.0363	−3.797**	7	−0.0107	−0.359	3	−0.0115	−0.407
	R% ≥ 4%	16	−0.0318	−1.769	5	0.0186	0.535	2	−0.0322	−0.971
FTSE100	R% ≥ 1%	304	−0.0043	−1.743	167	−0.0036	−1.567	43	−0.0060	−1.313
	R% ≥ 2%	190	−0.0088	−2.545*	81	−0.0080	−1.847	19	−0.0088	−1.215
	R% ≥ 3%	117	−0.0179	−2.882**	38	−0.0168	−2.817**	7	−0.0351	−2.729*
	R% ≥ 4%	59	−0.0261	−2.346*	25	−0.0190	−2.460*	3	−0.0480	−3.947
SSE50	R% ≥ 1%	296	0.0047	1.881	157	0.0020	0.405	72	0.0051	0.963
	R% ≥ 2%	241	0.0043	1.303	112	0.0038	0.616	41	0.0073	0.798
	R% ≥ 3%	157	0.0022	0.493	57	0.0004	0.042	16	−0.0020	−0.207
	R% ≥ 4%	97	0.0038	0.590	30	0.0121	0.760	3	−0.0352	−8.038 *
Panel B: three matrices of 3 dead crosses by 4 different performances at dead-cross days										
DJ30	R% ≤ −1%	113	0.0018	0.702	73	−0.0026	−0.656	27	−0.0025	−0.438
	R% ≤ −2%	67	−0.0034	−0.680	37	−0.0009	−0.128	10	−0.0029	−0.285
	R% ≤ −3%	31	0.0061	0.711	14	−0.0024	−0.148	5	0.0030	0.251
	R% ≤−4%	8	0.0238	0.613	8	0.0238	0.613	–	–	–
FTSE100	R% ≤ −1%	295	−0.0034	−1.463	176	0.0000	0.016	61	−0.0038	−0.765
	R% ≤−2%	184	0.0004	0.096	82	0.0045	0.916	28	−0.0020	−0.229
	R% ≤ −3%	109	−0.0049	−0.658	44	0.0009	0.104	14	0.0035	0.357
	R% ≤ −4%	22	−0.0040	−0.265	22	−0.0040	−0.265	7	0.0089	0.508
SSE50	R% ≤ −1%	272	0.0031	0.996	136	−0.0033	−0.755	35	−0.0003	−0.027
	R% ≤ −2%	217	0.0011	0.303	84	−0.0094	−1.918	18	0.0032	0.264
	R% ≤ −3%	152	−0.0013	−0.280	43	−0.0231	−2.949**	9	−0.0285	−2.035
	R% ≤ −4%	26	−0.0217	−2.244*	26	−0.0217	−2.244*	3	−0.0422	−25.016**

* Significant at the 5% level.
** Significant at the 1% level.

We argue that the results revealed for Table 8 should be regarded as "general" results[13] from trading these constituents' stocks when either the golden cross or dead cross appears. However, as we trade the constituent stocks of DJ30, FTSE100, and SSE50 as the MA trading rule with "wide" concerns instead of the simple MA trading rules emitted, we could obtain more evidence shown in Table 2, which could enhance the trading performance of these constituents' stocks. For example, we would be able to achieve better performance using the dead cross with K ≤ 25, K ≤ 20, and K ≤ 15 instead of the dead cross emitted only for trading the constituent stocks of SSE50. In addition, the performance would be enhanced when trading the constituent stocks of DJ30 as either gold cross or dead cross with "wide" concerns, compared with the results when employing the MA trading rule only. Furthermore, the statistically significant dominance in terms of profitability is shown for the trading of the constituent stocks of FTSE 100 as dead cross with K ≤ 15 instead of dead cross emitted only.

As for trading the constituent stocks of DJ30, FTSE100, and SSE50 using the MA trading rule with "in-depth" concerns instead of the simple MA trading rules emitted, Table 5 reveals that the statistically significant dominance in terms of profitability is achieved for the trading of the constituents stocks of FTSE100 as the golden cross with R% ≥ 2%, R% ≥ 3%, or R% ≥ 4% appeared, which is not demonstrated in the trading of the FTSE constituent stocks when only the golden cross appeared.

4.2. Comparing with MA trading rules employed in the literature

Aside from the MA(5, 20), MA(5, 60), and MA(20, 60) trading rules, we also applied MA(1, 100), MA(1, 150), and MA(1, 200) for comparison, and the results in terms of employing MA trading rule with either "wide" or "in-depth" concerns are presented in Tables 9–10. We revealed that the major finding is consistent with that for the MA trading rule with "in-depth" concerns. Negative weekly returns increased during the trading of the constituent stocks of DJ30 given the considerably increased returns in golden-cross days as a result of stock price overreaction.

In addition, the SMA and LMAs selected in this study might denote different MA(1, 100), MA(1, 150), and MA(1, 200) strategies. Therefore, the results may somewhat differ. Nonetheless, the contrarian strategy is appropriate for the constituent stocks of DJ30 and FTSE100 as shown in Table 10, especially when the golden cross trading signals with "in-depth" concerns appeared.

[13] In this study, we might regard that employing the MA trading rule with either "wide" or "in-depth" concerns as several "special" cases, which not only provide more evidences as the reference for trading the constituent stocks of DJ30, FTSE100, and SSE50, but also would enhance the performance of investing these constituents' stocks.

Table 7
Weekly mean R_{eff} as diverse MA trading rules with 'in-depth' concerns emitted. Panel A of Table 7 presents the weakly mean R_{eff} for buying stocks with stock returns over 1%, 2%, 3%, and 4% denoted as R ≥ 1%, R% ≥ 2%, R% ≥ 3%, and R% ≥ 4% at the golden-cross days decided by MA(5, 20), MA(5, 60), MA(20, 60). Similarly, Panel B of Table 5 shows the weakly mean R_{eff} for short selling stocks with stock returns below 1%, 2%, 3%, and 4% denoted as R% ≤ −1%, R% ≤ −2%, R% ≤ −3%, and R% ≤ −4%, respectively, at the dead-cross day decided by MA(5, 20), MA(5, 60), and MA(20, 60).

		MA(5, 20)			MA(5, 60)			MA(20, 60)		
		N	Mean	t	N	Mean	t	N	Mean	T
Panel A: three matrices of 3 golden crosses by 4 different performances at golden-cross days										
DJ30	R% ≥ 1%	124	−0.0035	−1.455	57	−0.0038	−0.875	23	−0.0022	−0.343
	R% ≥ 2%	72	−0.0112	−2.613*	25	−0.0080	−0.878	12	−0.0157	−1.455
	R% ≥ 3%	25	−0.0367	−3.815**	7	−0.0109	−0.364	3	−0.0119	−0.415
	R% ≥ 4%	16	−0.0323	−1.791	5	0.0185	0.532	2	−0.0328	−0.971
FTSE100	R% ≥ 1%	304	−0.0045	−1.772	167	−0.0036	−1.574	43	−0.0061	−1.327
	R% ≥ 2%	190	−0.0090	−2.571*	81	−0.0080	−1.852	19	−0.0089	−1.227
	R% ≥ 3%	117	−0.0182	−2.877**	38	−0.0169	−2.816**	7	−0.0354	−2.733**
	R% ≥ 4%	59	−0.0266	−2.341*	25	−0.0190	−2.456*	3	−0.0488	−4.014
SSE50	R% ≥ 1%	296	0.0046	1.833	157	0.0019	0.385	72	0.0050	0.946
	R% ≥ 2%	241	0.0042	1.253	112	0.0038	0.606	41	0.0073	0.792
	R% ≥ 3%	157	0.0021	0.468	57	0.0004	0.045	16	−0.0022	−0.223
	R% ≥ 4%	97	0.0036	0.552	30	0.0122	0.761	3	−0.0360	−7.499*
Panel B: three matrices of 3 dead crosses by 4 different performances at dead-cross days										
DJ30	R% ≤ −1%	113	0.0018	0.694	73	−0.0026	−0.661	27	−0.0025	−0.439
	R% ≤ −2%	67	−0.0034	−0.673	37	−0.0009	−0.127	10	−0.0029	−0.285
	R% ≤ −3%	31	0.0062	0.715	14	−0.0023	−0.145	5	0.0030	0.252
	R% ≤ −4%	8	0.0239	0.613	8	0.0239	0.613	–	–	–
FTSE100	R% ≤ −1%	295	−0.0035	−1.484	176	0.0000	−0.007	61	−0.0039	−0.781
	R% ≤ −2%	184	0.0003	0.061	82	0.0045	0.895	28	−0.0021	−0.247
	R% ≤ −3%	109	−0.0052	−0.679	44	0.0007	0.077	14	0.0033	0.338
	R% ≤ −4%	22	−0.0044	−0.290	22	−0.0044	−0.290	7	0.0087	0.496
SSE50	R% ≤ −1%	272	0.0030	0.957	136	−0.0034	−0.781	35	−0.0005	−0.047
	R% ≤ −2%	217	0.0010	0.273	84	−0.0095	−1.939	18	0.0030	0.252
	R% ≤ −3%	152	−0.0014	−0.303	43	−0.0233	−2.967**	9	−0.0288	−2.050
	R% ≤ −4%	26	−0.0220	−2.271*	26	−0.0220	−2.271*	3	−0.0431	−30.502**

* Significant at the 5% level.
** Significant at the 1% level.

5. Concluding remarks

We determine whether or not investors profit from trading the constituent stocks of DJ30, FTSE100, and SSE50 following the trading signals triggered by MA(5, 20), MA(5, 60), and MA(20, 60) trading rules. We then examine whether or not investors can increase their profit by applying MA trading rules with either "wide" or "in-depth" concerns.

In addition, we employ the MA(5, 20), MA(5, 60), and MA(20, 60) trading rules instead of the MA trading rules utilized in relevant literature (Bessembinder & Chan, 1995; Brock et al., 1992) because MA5, MA20, and MA60 are regarded as the weekly, monthly, quarterly MAs, respectively, in practice.

Furthermore, the current study contributes to existing literature by enhancing MA trading rules through the incorporation of either "wide" or "in-depth" concerns. These concerns are rarely considered and studied both in relevant literature. In this study, we

Table 8
Weekly mean returns as the MA trading signals appear. Panel A of Table 8 reveals the results of each golden cross after MA(5, 20), MA(5, 60), and MA(20, 60) trading rules are triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively. Panel B of Table 8 reveals the results of each dead cross after the MA(5, 20), MA(5, 60), and MA(20, 60) are triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively.

	MA(5, 20)			MA(5, 60)			MA(20, 60)		
	N	Mean	t	N	Mean	t	N	Mean	t
Panel A: golden cross MA									
DJ30	150	−0.0018	−1.160*	150	0.0016	0.721	149	0.0063	1.746
FTSE100	368	−0.0005	−0.326	363	0.0004	0.141	359	0.0003	0.081
SSE50	337	0.0072	3.574**	315	0.0022	1.069	289	0.0033	0..065
Panel B: dead cross									
DJ30	150	0.0024	1.861	149	−0.0018	−0.809	148	0.0022	0.777
FTSE100	369	−0.0007	−0.516	362	−0.0035	−1.585	355	−0.0010	−0.399
SSE50	337	0.0082	3.852**	299	0.0004	0.157	296	−0.0002	−0.054

* Significant at the 5% level.
** Significant at the 1% level.

Table 9
Standard long MA trading rule with "wide" concerns. Panel A reveals the results of each golden cross after MA(1, 100), MA(1, 150), and MA(1, 200) trading rules and each of the K ≥ 75, K ≥ 80, and K ≥ 85 are triggered for the constituent stocks of DJ30, FTSE100, and SSE50, respectively. Panel B reveals the results of each dead cross after the MA(1, 100), MA(1, 150), and MA(1, 200) and each of the K ≤ 25, K ≤ 20, and K ≤ 15 are triggered for the constituent stocks of the DJ30, FTSE100, and SSE50, respectively.

		MA(1, 100)			MA(1, 150)			MA(1, 200)		
		N	Mean	t	N	Mean	T	N	Mean	T
Panel A: three matrices of 3 MA golden crosses by 3 SOI trading zones										
DJ 30	K ≥ 75	332	−0.0065	−2.546*	263	−0.0073	−2.767**	227	−0.0100	−2.977**
	K ≥ 80	256	−0.0061	−2.127*	207	−0.0077	−2.607*	175	−0.0085	−2.148*
	K ≥ 85	168	−0.0027	−0.849	147	−0.0084	−2.468*	114	−0.0152	−2.768**
FTSE100	K ≥ 75	699	−0.0077	−3.181**	578	−0.0109	−4.141**	495	−0.0143	−4.947**
	K ≥ 80	516	−0.0078	−2.604**	432	−0.0130	−4.046**	386	−0.0154	−4.372**
	K ≥ 85	381	−0.0089	−2.357*	303	−0.0147	−3.473*	267	−0.0180	−3.813**
SSE50	K ≥ 75	555	0.0031	0.990	438	0.0087	2.087*	393	0.0027	0.669
	K ≥ 80	449	0.0046	1.319	356	0.0115	2.457*	332	0.0032	0.726
	K ≥ 85	341	0.0053	1.301	272	0.0172	3.118**	264	0.0076	1.598
Panel B: three matrices of 3 MA dead crosses by 3 SOI trading zones										
DJ 30	K ≤ 25	341	−0.0006	−0.311	238	0.0018	0.788	230	0.0041	2.198*
	K ≤ 20	270	0.0009	0.414	193	0.0025	1.084	190	0.0044	2.178*
	K ≤ 15	199	0.0020	0.798	138	0.0011	0.435	149	0.0039	1.691
FTSE100	K ≤ 25	696	0.0010	0.480	576	0.0066	3.092**	512	0.0040	2.018*
	K ≤ 20	544	0.0003	0.120	477	0.0060	2.617**	424	0.0033	1.576
	K ≤ 15	381	0.0017	0.641	326	0.0084	3.057**	302	0.0036	1.481
SSE50	K ≤ 25	507	0.0013	0.441	382	0.0042	1.235	319	0.0043	1.168
	K ≤ 20	385	0.0009	0.260	323	0.0039	1.053	266	0.0026	0.661
	K ≤ 15	267	0.0013	0.325	240	0.0021	0.464	197	0.0026	0.578

* Significant at the 5% level.
** Significant at the 1% level.

Table 10
Standard long MA trading rule with "in-depth" concern. Panel A of Table 10 presents the weakly mean returns of buying stocks with stock returns over 1%, 2%, 3%, and 4% denoted as R ≥ 1%, R% ≥ 2%, R% ≥ 3%, and R% ≥ 4%, respectively, at the golden-cross days decided by MA(1, 100), MA(1, 150), MA(1, 200). Similarly, Panel B of Table 10 shows the weakly mean returns for short selling stocks with stock returns below 1%, 2%, 3%, and 4% denoted as R% ≤ −1%, R% ≤ −2%, R% ≤ −3%, and R% ≤ −4%, respectively, at the dead-cross day decided by MA(1, 100), MA(1, 150), and MA(1, 200).

		MA(1, 100)			MA(1, 150)			MA(1, 200)		
		N	Mean	t	N	Mean	T	N	Mean	T
Panel A: three matrices of 3 golden crosses by 4 different performances at golden-cross days										
DJ30	R ≥ 1%	762	−0.0051	−2.900**	591	−0.0043	−2.369*	501	−0.0066	−3.212**
	R ≥ 2%	428	−0.0082	−3.007**	323	−0.0093	−3.286**	267	−0.0133	−3.906**
	R ≥ 3%	226	−0.0125	−2.743**	158	−0.0156	−3.178**	140	−0.0212	−3.653**
	R ≥ 4%	135	−0.0110	−1.595	99	−0.0159	−2.210*	82	−0.0268	−3.115**
FTSE100	R ≥ 1%	1754	−0.0055	−4.037**	1435	−0.0059	−4.037**	1202	−0.0088	−5.222**
	R ≥ 2%	1096	−0.0082	−4.083**	884	−0.0078	−3.626**	749	−0.0122	−4.986**
	R ≥ 3%	666	−0.0108	−3.636**	558	−0.0102	−3.306**	458	−0.0157	−4.362**
	R ≥ 4%	431	−0.0133	−3.196**	354	−0.0161	−3.707**	269	−0.0176	−3.071**
SSE50	R ≥ 1%	1289	0.0031	1.592	1030	0.0088	3.616**	882	0.0024	0.925
	R ≥ 2%	969	0.0042	1.804	804	0.0101	3.650**	682	0.0032	1.057
	R ≥ 3%	688	0.0032	1.102	558	0.0095	2.657**	495	0.0031	0.806
	R ≥ 4%	465	0.0026	0.701	383	0.0124	2.699**	345	0.0039	0.816
Panel B three matrices of 3 dead crosses by 4 different performances at dead-cross days										
DJ30	R ≤ −1%	735	0.0022	1.242	585	0.0012	0.646	498	−0.0002	−0.090
	R ≤ −2%	407	0.0008	0.285	314	0.0021	0.735	264	-0.0011	−0.370
	R ≤ −3%	215	0.0008	0.173	154	0.0020	0.405	143	−0.0069	−1.480
	R ≤ −4%	134	−0.0013	−0.190	97	0.0028	0.392	84	−0.0091	−1.253
FTSE100	R ≤ −1%	1735	−0.0028	−2.106*	1434	0.0016	1.101	1191	−0.0025	−1.645
	R ≤ −2%	1084	−0.0049	−2.583*	895	0.0023	1.127	734	−0.0022	−1.056
	R ≤ −3%	652	−0.0089	−3.190**	530	0.0016	0.531	433	−0.0044	−1.411
	R ≤ −4%	392	−0.0101	−2.479*	342	0.0029	0.718	264	−0.0033	−0.747
SSE50	R ≤ −1%	1239	0.0020	0.963	952	0.0036	1.513	830	0.0027	1.045
	R ≤ −2%	935	0.0010	0.403	740	0.0039	1.431	671	0.0021	0.753
	R ≤ −3%	664	0.0002	0.063	542	0.0031	0.938	501	0.0021	0.598
	R ≤ −4%	479	−0.0018	−0.473	401	0.0022	0.541	355	0.0028	0.639

* Significant at the 5% level.
** Significant at the 1% level.

reveal that investors profit more from buying than from short-selling the constituent stocks of SSE50 when the dead cross is emitted. We infer that this result may be caused by the herding behaviors of individual investors who contribute over 80% of the total trading amount in China's stock markets. Moreover, negative returns increase if investors buy the constituent stocks of DJ30 and FTSE100 at the golden-cross day triggered by MA(5, 20), when stock returns increase by over 2%, 3%, and even 4%. This increase may be induced by the overreaction on the golden-cross days. In addition, the results remain robust when the risk aversion and even the enhanced risk-averse concerns of investors as induced by losses are taken into account.

Given that history may repeat itself, we then determine whether investors can profit when diverse trading signals are emitted according to MA trading rules with “wide” and “in-depth” concerns while the constituent stocks of these three stock indices are being traded. The investigation of these concerns may enhance investment performance, which may be close to that of the optimal technical trading combination.

The paper contributes to literature by reporting remarkable findings that have rarely been disclosed in relevant studies. This study also provides additional incentives for investors to trade the constituent stocks of DJ30, FTSE100, and SSE30. Furthermore, these findings imply that stock market overreaction and herding behaviors are incorporated into technical analyses, which is a concept that is seldom observed in relevant literature.

Acknowledgment

The authors wish to thank the editor, Professor Carl R. Chen, and three referees for their constructive and helpful comments that contributed in improving the quality of this paper. Any remaining errors are our own responsibility.

References

Alsulaiman, E. T. (2013). Classifying technical indicators using K-medoid clustering. *Journal of Trading*, *8*(2), 29–39.
Bessembinder, H., & Chan, K. (1995). The profitability of technical trading rules in the Asian stock markets. *Pacific-Basin Finance Journal*, *3*, 257–284.
Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, *47*, 1731–1764.
Caporin, M., Ranaldo, A., & Santucci de Magistris, P. (2013). On the predictability of stock prices: A case for high and low prices. *Journal of Banking and Finance*, *37*(12), 5132–5146.
Chen, C. P., & Metghalchi, M. (2012). Weak-form market efficiency: Evidence from the Brazilian stock market. *International Journal of Economics and Finance*, *4*(7), 22–32.
Cheung, Y. W. (2007). An empirical model of daily highs and lows. *International Journal of Finance & Economics*, *12*(1), 1–20.
Chiang, Y. C., Ke, M. C., Liao, T. L., & Wang, C. D. (2012). Are technical trading strategies still profitable? Evidence from the Taiwan Stock Index Futures Market. *Applied Financial Economics*, *22*(12), 955–965.
Chuang, W. I., & Lee, B. S. (2006). An empirical evaluation of the overconfidence hypothesis. *Journal of Banking and Finance*, *30*, 2489–2515.
Dacorogna, M. M., Gençay, R., Müller, U. A., & Pictet, O. V. (2001). Effective return, risk aversion and drawdowns. *Physica A: Statistical Mechanics and its Applications*, *289*(1), 229–248.
Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and over-reaction. *Journal of Finance*, *53*(6), 1839–1885.
Day, T. E., & Wang, P. (2002). Dividends, nonsynchronous prices, and the returns from trading the Dow Jones Industrial Average. *Journal of Empirical Finance*, *9*(4), 431–454.
De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact. *Journal of Finance*, *40*, 793–805.
Esichaikul, V., & Srithongnopawong, P. (2010). Using relative movement to support ANN-based stock forecasting in Thai stock market. *International Journal of Electronic Finance*, *4*(1), 84–98.
Fama, E. F. (1965). The behavior of stock market prices. *Journal of Business*, *38*, 34–105.
Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance*, *25*, 383–417.
Fifield, S. G. M., Power, D. M., & Donald Sinclair, C. (2005). An analysis of trading strategies in eleven European stock markets. *European Journal of Finance*, *11*(6), 531–548.
Gençay, R. (1996). Non-linear prediction of security returns with moving average rules. *Journal of Forecasting*, *15*(3), 165–174.
Gençay, R. (1998). The predictability of security returns with simple technical trading rules. *Journal of Empirical Finance*, *5*(4), 347–359.
Gençay, R. (1999). Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *Journal of International Economics*, *47*(1), 91–107.
Gençay, R., Ballocchi, G., Dacorogna, M., Olsen, R., & Pictet, O. (2002). Real-time trading models and the statistical properties of foreign exchange rates. *International Economic Review*, 463–491.
Gençay, R., Dacorogna, M., Olsen, R., & Pictet, O. (2003). Foreign exchange trading models and market behavior. *Journal of Economic Dynamics and Control*, *27*(6), 909–935.
Gençay, R., & Stengos, T. (1997). Technical trading rules and the size of the risk premium in security returns. *Studies in Nonlinear Dynamics & Econometrics*, *2*(2), 23–34.
Gençay, R., & Stengos, T. (1998). Moving average rules, volume and the predictability of security returns with feedforward networks. *Journal of Forecasting*, *17*, 401–414.
Gradojevic, N., & Gençay, R. (2013). Fuzzy logic, trading uncertainty and technical trading. *Journal of Banking and Finance*, *37*(2), 578–586.
Gradojevic, N., & Lento, C. (2015). Multiscale analysis of foreign exchange order flows and technical trading profitability. *Economic Modelling*, *47*, 156–165.
Heng, F. T. K., Azizan, N. A., & Yeap, L. W. (2012). Technical trading systems as crystal balls in reducing risk: the Malaysian stock market. *International Business Management*, *6*(2), 140–146.
Hong, K. J., & Satchell, S. (2015). Time series momentum trading strategy and autocorrelation amplification. *Quantitative Finance* (Article in press).
Hou, Y., & Li, S. (2014). The impact of the CSI 300 stock index futures: Positive feedback trading and autocorrelation of stock returns. *International Review of Economics & Finance*, *33*, 319–337.
Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–292.
Lento, C., & Gradojevic, N. (2007). The profitability of technical trading rules: A combined signal approach. *Journal of Applied Business Research*, *23*(1), 13–27.
Lento, C., Gradojevic, N., & Wright, C. S. (2007). Investment information content in Bollinger bands? *Applied Financial Economics Letters*, *3*(4), 263–267.
Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance*, *55*(4), 1705–1770.
Loh, E. Y. L. (2007). An alternative test for weak form efficiency based on technical analysis. *Applied Financial Economics*, *17*, 1003–1012.
MÄuller, U. A., Dacorogna, M. M., & Pictet, O. V. (1993). A trading model performance measure with strong risk aversion against drawdowns. *Olsen Research Institute Discussion Paper, Zurich, Switzerland*.
Metghalchi, M., Chang, Y., & Garza-Gomez, X. (2012). Technical analysis of the Taiwanese stock market. *International Journal of Economics and Finance*, *4*(1), 90–102.

Metghalchia, M., Marcucci, J., & Chang, Y. -H. (2012). Are moving average trading rules profitable? Evidence from the European stock markets. *Applied Economics*, *44*(12), 1539–1559.

Mizrach, B., & Weerts, S. (2009). Highs and lows: A behavioral and technical analysis. *Applied Financial Economics*, *19*(10), 767–777.

Neely, C. J. (2003). Risk-adjusted, ex ante, optimal technical trading rules in equity markets. *International Review of Economics & Finance*, *12*(1), 69–87.

Neely, C. J., Weller, P., & Dittmar, R. (1997). Is technical analysis in the foreign exchange market profitable? A genetic programming approach. *Journal of Financial and Quantitative Analysis*, *32*(4), 405–426.

Ni, Y. S., Lee, J. T., & Liao, Y. C. (2013). Do variable length moving average trading rules matter during a financial crisis period? *Applied Economics Letters*, *20*(2), 135–141.

Shintani, M., Yabu, T., & Nagakura, D. (2012). Spurious regressions in technical trading. *Journal of Econometrics*, *169*(2), 301–309.

Shynkevich, A. (2012). Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking and Finance*, *36*(1), 193–208.

Taylor, N. (2014). The rise and fall of technical trading rule success. *Journal of Banking and Finance*, *40*(1), 286–302.

Wang, Z. M., Chao, S. C., & Chang, Y. T. (2012). Technical analyses and order submission behaviors: Evidence from an emerging market. *International Review of Economics and Finance*, *24*, 109–128.

Yu, H., Nartea, G. V., Gan, C., & Yao, L. J. (2013). Predictive ability and profitability of simple technical trading rules: Recent evidence from Southeast Asian stock markets. *International Review of Economics and Finance*, *25*, 356–371.