Examining the Profitability of Similarity-based Futures Trading Strategies

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Abstract: We propose a novel similarity-based trading analysis that is associated to the investment decision-making process of technical investors who predict future returns through charting. While the traditional technical trading analysis assumes that investors consistently follow one particular trading rule, we allow the investors refer to a set of trading rules while making their decisions. In our analysis, the trading indicator is formed based on a weighted average of all previously observed values of the subsequent returns and the weights measure how similar the current pattern and those past patterns are. We examine the profitability of these similarity-based trading rules in nine futures markets, and in six of the nine markets, we find significantly positive returns robust to data-snooping adjustments and transaction costs.

Keywords: technical trading rules, similarity-based trading rules, futures markets, profitability of trading rules

1. Introduction

This paper proposes a more realistic decision-making process for technical investors who make investment decisions through charting. We employ a similarity-based approach of Gilboa and Schmeidler (1995) and Gilboa, Lieberman and Schmeidler (2006, 2011)[1], and assume that the decision-making process of a technical investor can be organized as the following three steps. First, the investor predicts future n-day returns based on a vector of current characteristics that is sufficient for his assessment of the future returns, and to depict the present scenario of the stock market.

Second, the investor searches for the similar patterns in a specific time window prior to the current date and make an assessment of the future returns based on how similar these past patterns and the current pattern are ,and how rewarding the subsequent returns of the similar patterns are. Third, the investor is assumed to form a similarity-based indicator which is an assessment of the future n-day returns depending on the similarity-weighted average of all previously observed values of the subsequent returns. If the subsequent returns of the past patterns similar to the current pattern are mostly positive (negative), the investor has a positive (negative) assessment of the future n-day returns and chooses to enter a long (short) position.

The proposed decision-making process is different from the traditional technical strategies in several aspects. First, the SBTR allows technical investors to consider several technical trading rules simultaneously, when the vector of current characteristics includes multiple technical indicators. On the contrary, the literature mostly assumes that a technical investor consistently makes investment decisions according to one particular trading rule during the entire sample period.[2] Second, the process uses the values of the technical indicators as the measurement of similarity. Therefore, the magnitude of the indicators has a role in the decision-making process. Third, investors are assumed to enter a long position only when the

[1] The original idea of the similarity-based approach is designed to generate an assessment of a variable based on certain characteristics. Both the variable of interest and the vector of the characteristics are at time t. Unlike these papers, we apply the approach to predict the future returns based on a vector of the characteristics prior to the current trading date. Therefore, our empirical results are purely based on out-of-sample tests.

[2] Hsu and Kuan (2005) argue that technical investors do not stick to only one particular trading rule without incorporating other available information. Investors may rely on the information from several simple rules and make investment decisions in practice.

similarity-weighted subsequent returns of the similar past patterns are positive, whereas the traditional rules consistently follow the buy/sell signals and ignore the fact that the historical returns following a buy (sell) signal could be on average negative (positive) over a past period of time.

The proposed decision-making process is closely related to the analogical reasoning of Hume (1974) and Giloa and Schmeidler (1995) and the availability heuristic of Tversky and Kahneman (1973). To form an assessment of future returns under uncertainty, it is not a trivial task for evaluating all possible outcomes and their possibilities. This gives rise to the difficulties in fitting the problem to the framework of expected utility theory, where all possible outcomes and possibilities are required. Therefore, the representative investor in our framework employs analogical reasoning to predict future returns based on past experience, which is all technical investors attempt to achieve. The possibilities of the possible outcomes are judged by the similarity of the past and the current price patterns. Therefore, the subsequent returns of the more similar past patterns, which are considered as the possible outcomes with higher possibilities, have more weights when deriving the similarity-based prediction of future returns. The judgmental heuristic coincides with Tversky and Kahneman (1973) who document the availability heuristic where the investor evaluates the probability of events by the ease of relevant instances come to mind.

To construct the vector of characteristics to depict the market condition and to measure the similarity of current and past patterns, we consider four technical trading classes. Three of them are widely examined in the literature: the MA rules, the rules based on the relative strength index (RSI rules, hereafter), and the trading range breakthrough rules (TRB rules, hereafter). For the forth class, we test the profitability based on the similarity of the past 5-day Candlesticks patterns. We empirically test the profitability of the similarity-based trading rules (SBTRs, hereafter) based on these four trading classes with the historical prices in nine futures markets including futures on S&P 500 index (SP1), soybean, sugar, wheat, lumber cocoa silver, live cattle and corn[3]. The empirical tests include the t-tests for the null hypothesis that the mean

[3] Although testing the profitability of trading rules on index prices has the advantage on relative long period of time, examining the profitability on futures markets generates convincing results since the transactions costs are easy to control and the short-sale constraints are avoided. For example, Brock, Lakonishok and LeBaron (1992) suggest that although they find predictive power of technical rules, transactions costs should be carefully considered before implementing these strategies. They also

returns of the SBTRs equal zero, the t-tests for the null hypothesis that the mean buy and mean sell returns equal the unconditional buy-and-hold (B/H, hereafter) mean returns, the robustness check for the mean returns by reexamining the sub-period performance and the tests for the data-snooping biases. We also draw a comparison among these SBTRs and the traditional technical rules to investigate the trading behaviors of the SBTR investors.

The empirical findings are organized as follows. First, the daily and weekly SBTRs do generate positive and significant returns which are higher than the unconditional B/H mean returns. We find that the t-statistics of the strategy returns, which defined by Brock, Lakonishok and LeBaron (1992), reject the hypothesis that the strategy returns equal zero. With the full sample period, the strategy based on the MA rules with ten-year moving window for lumber futures generates the highest daily returns across these futures markets. The returns of daily SBTRs are robust to the data-snooping biases and transaction costs in six of the nine futures markets, and the strategy consistently outperforms the B/H mean returns using different sub-periods. However, although the returns of weekly SBTRs are .significantly different from zero, they are not robust after the data-snooping adjustments.

Second, the comparison between the SBTRs and the traditional technical rules suggests that only the former consistently produces positive returns higher than the B/H mean returns. The profitability of the SBTRs relies on the flexible signals triggered by the similarity-based predictors, that is, the SBTRs do not assume that the investor always follows the traditional technical signals. For example, the SBTR investor enters a short (long) position in some situation when the shorter-term MA is above (below) longer-term MA and the empirical results show that the mean return following these sell (buy) signals is actually negative (positive). This suggests that even the SBTR investor only considers the MAs, which are considered as trend-following indicators, as the characteristic to make an assessment of future returns, he may adopt the trend reversal strategy in some situation, especially when the MA difference highly deviates from zero. This provides evidence that the magnitude of the MA difference provides useful information for future price

suggest that opportunities might exist in the future markets where transactions costs are very small. Moreover, Sullivan, Timmermann and White (1999) conduct bootstrap simulation using index futures prices to determine whether transactions costs or short-sale constraints account for the success of trading rules examined by Brock, Lakonishok and LeBaron (1992).

movements.

Third, we find that the choice of the moving window where the SBTR investor searches for the similar past patterns is crucial for the strategy returns. The best choice of the moving window for the SBTRs is not always the maximum length of ten year, and the threshold rate is not always 100%. We attribute this to the limited attention of the investors. The most readily available information that is likely to attract the technical investors' immediate attention is the most recent and the most similar pattern on the price charts. Overall, this paper contributes the literature on the technical trading by proposing a realistic decision-making process for the technical investors and confirming the profitability of the SBTRs with rigorous tests and with transaction costs.

The remainder of this paper is organized as follow. Section 2 introduces the universe of technical indicators that are used by the SBTR. Section 3 introduces the similarity-based decision-making process for the technical investors and the approaches for adjusting the data-snooping biases. Section 4 presents the empirical results. Section 5 concludes the paper.

2. Universe of technical indicators

The investor following the SBTRs considers the traditional technical indicators as the characteristics to depict the current market scenario and forecast the future returns. Traditionally, a moving average rule generates buy and sell signals with simple averages of two different time periods. When the shorter-term MA rises above (falls below) the longer-term MA, a buy (sell) signal is triggered. The logic of the strategy is that a price trend is initiated when the shorter-term MA penetrates the longer-term MA. Brock, Lakonishok and LeBaron (1992) and Sullivan, Timmermann and White (1999) provide evidence on the profitability of MA rules even for large firms, while Hsu and Kuan (2005) find that MA rules generates the most profitable returns among other strategies. For the choice of the period of moving averages, we follow Brock, Lakonishok and LeBaron (1992). The combinations of the shorter- and longer-term MA is denoted as MA$s-l$, where s=1, 5, 10, 20, 50, 100, 150, l=5, 10, 20, 50, 100, 150, 200, and $s<l$. Thus, the MA rules include a total number of 28 $\big((1+7)*7/2=28\big)$ shorter- and longer-term combinations. Taking the time period of moving window into consideration, the total number of strategies we test is 112.

The vector of the characteristic, x_t, for the SBTR based on MA$s-l$ contains only one element: the different between s-day MA and l-day MA.

The RSI is the most frequently used counter-trend indicator (Wong, Manzur and Chew, 2003). The calculation of the RSI starts with the relative strength which is measured by an average upward price change divided by an average downward price change over a predetermined time period. The RSI is expressed as an oscillator that has a range of 0 to 100. A value of the RSI close to 100 suggests an overbought market, and a sell signal triggered when the RSI rises above a predetermined entry threshold, for example, 70. On the contrary, a value close to 0 indicates an oversold market, and a buy signal is generated when it goes below 30. For the SBTRs, the time period of the RSI includes 5, 10, 20, 50, 100, 150 and 200 days prior to the trading date. The SBTRs based on these RSI are denoted as RSIp, where p =5, 10, 20, 50, 100, 150, 200. The SBTRs do not have the predetermined entry threshold since the RSI is only considered as the characteristic to determine the similarity of the past and current market state. The buy (sell) signal is generated when the similarity-based indicator, namely, the similarity-weighted averages of the subsequent returns, is above (below) 0. The vector of the characteristics, x_t, for the SBTR based on the RSIp contains only one element: the p-days RSI.

The TRB trading strategies generate buy signal when the price penetrates the resistance level which is defined as the local maximum and generate sell signal when the price penetrates the support level defined as the local minimum. The idea behind this strategy is that if the price exceeds the previous peak where the selling pressure induces resistance, the resistance area is broken through and a new price trend is initiated. The breakout then is considered as a buy signal. On the other hand, if the price moves below the previous low, the price is expected to drift downward since the support level that many investors are willing to buy is broken through. In this study, the TRB rules are defined in accordance with the MA rules, that is, the local maximum and minimum prices are based on the past 5, 10, 20, 50, 100, 150, and 200 days previous to the current prediction date. The SBTRs based on these TRB indicators are denoted as Maxmin p, where p =5, 10, 20, 50, 100, 150, 200. The vector of the characteristics, x_t, for each Maxmin p contains two elements: the difference between the current closing price and the maximum price during the past p days prior to the current date, and the difference between the current closing price and the minimum price during the past p days.

The three classes of the technical indicators above are the most popular trading rules and have been examined extensively in the technical trading literature. Since the SBTR do not assume trading strategies and only consider the technical indicators as the assessment of current market condition and of future returns, we include several indicators which may depict the current scenario of the futures markets. We include the historical volatility of past 30-day daily returns, the average trading volume over past 5-day, and the logarithm differences in volume of the current date and the average volume over past 5-day. Moreover, we propose a method to characterize the past 5-day Candlestick patterns and can be applied to the SBTR.

We assume that each Candlestick can be expressed as three elements: the difference in closing price and opening price, the difference in highest price and the maximum of closing price and opening price (the upper shadow), and the difference in lowest price and the minimum of the closing price and opening price (the lower shadow). Therefore if we consider the past 5-day Candlestick patterns to depict the current market condition, then we have 15 elements in the characteristic vector. In addition, we include the difference in the average price of the closing price and opening price of two consecutive Candlesticks. Finally, to determine how similar of the current market condition and past prices patterns, we calculate the similarity-weighted averages of subsequent returns based on these 19 elements in the characteristic vector.

As for the mixed strategies, since in the first step of the proposed decision-making process, investors determine a set of characteristics to make an assessment of future returns and depict the current market condition, we can choose any single indicator into the vector of characteristics. In this paper, we use the following mixed strategies where the vector contains: all MA$s-l$ indicators, all RSIp, all Maxmin p, all indicators of MA$s-l$, RSIp, and Maxmin p, 5-past Candlesticks with all MA$s-l$ indicators, 5-past Candlesticks with all RSIp, 5-past Candlesticks with all Maxmin p, and 5-past Candlesticks with all indicators, respectively.

3. Trading model

3.1 Decision-making process for similarity-based technical traders

Assume that a technical investor attempts to make an assessment of future returns over n days, that is $y_{[t+1,t+n]}$ at time t. The investor relies on a set of characteristics $x_t = \{x_t^1, \ldots, x_t^d\}$ to depict the current scenario of the stock market and predict the future returns. The investor is assumed to search for the similar patterns in a specific time window previous to the current date, that is, he evaluates the similarity between the current x_t and a database consisting of $\{x_i^1, \ldots, x_i^d, y_{[i+1,i+n]}\}$, for $i = 1, \ldots, m$, where m denotes the total number of the database. For example, if the investor searches for the similar pattern over the past 1 year prior to the current date, m is 250.

To form a prediction of future returns, the investor uses the similarity between the characteristics x_i on a particular trading date and the characteristics x_t on the current date as the weight on the subsequent n-day return after the particular trading date. Formally, the prediction of future return at date t can be written as:

$$y_{[t+1,t+n]}^s = \frac{\sum_{t-m \leq i < t} s(x_i, x_t) y_{[i+1,i+n]}}{\sum_{t-m \leq i < t} (x_i, x_t)}, t = 1, \ldots, N \tag{1}$$

where $y_{[t+1,t+n]}^s$ denotes the predicted value of future n-day return after the date t. $s(x_i, x_t)$ is a similarity function measuring how similar x_i and x_t are. The investor is assumed to search for similar trading date for a time period of m-day prior to the trading date t. In this study, m is assumed to be 250, 750, 1250 or 2500. N denotes the number of weeks over the total sample period.

The future or subsequent n-day returns from date t or date i is defined as:

$$y_{[t+1,t+n]} = ln\left(\frac{C_{t+n}}{O_{t+1}}\right) \tag{2}$$

where C_{t+n} is the closing price at date $t+n$ and O_{t+1} is the opening price at date $t+1$.

If the Euclidean distances are employed to measure the distance between the two vectors, x_i and x_t, the similarity function then can be defined as:

$$s(x_i, x_t) = exp\big(-d(x_i, x_t)\big) \tag{3}$$

where $d(x_i, x_t) = \sqrt{\sum_{j=1}^{d} \left(x_i^j - x_t^j\right)^2}$. Therefore, when $x_i = x_t$, we have $s = 1$. When the differences between each element in the vectors x_i and x_t increase, the value of the similarity function decreases, which decreases the weighting on the subsequent n-day return after date i, namely, $y_{[i+1,i+n]}$. To evaluate the distances of two characteristic vectors, we also use standardized Euclidean distances and Mahalanobis distances. Hereafter, for the method of measuring the distances, the Euclidean distance is denoted by E; the standardized Euclidean distance is denoted by StdE; and the Mahalanobis distance is denoted by Mah. On each forecast date, we first calculate the distances between any available trading dates prior to the current date within the moving window and then calculate the similarity-weighted averages of subsequent returns of each available trading date. We also set a threshold rate to control the number of trading dates used to form the predictors. For example, if the threshold rate is 10%, after calculating the distances, we sort the available trading dates according to the similarity and only use the subsequent returns of 10% the most similar trading dates to form the predictors.

At the end of each day, the similar-based predictor $y^s_{[t+1,t+n]}$ is evaluated and the technical investor is assumed to enter a long or short position according to the sign of $y^s_{[t+1,t+n]}$. A positive sign of the similar-based predictor generates a buy signal while a negative sign indicates a sell signal. The performance of this strategy is evaluated by its mean weekly return over the full sample period. Following Brock, Lakonishok and LeBaron (1992), the t-statistic of the "Buy-Sell" mean return is defined as:

$$\frac{\mu_b-\mu_s}{(\sigma^2/N_b+\sigma^2/N_s)^{1/2}} \tag{4}$$

where μ_b and N_b denote the mean return and number of signals (weeks) for the Buys and μ_s and N_s denote the mean return and number of signals (weeks) for the Sells. σ^2 is the estimated variance for the entire sample. The t-test tests the null hypothesis that the difference of the Buy-Sell return equals zero. The t-statistics for the Buys and Sells are:

$$\frac{\mu_b-\mu}{(\sigma^2/N+\sigma^2/N_b)^{1/2}} \tag{5}$$

and:

$$\frac{\mu_s-\mu}{(\sigma^2/N+\sigma^2/N_s)^{1/2}} \tag{6}$$

where μ and N denote the unconditional B/H mean return and number of observations. The tests test the null hypothesis that the mean returns of buys or sells equal the unconditional B/H mean return. Since the investor is assumed to buy or sell according to the sign of the similarity-based predictor, the mean return of the similarity-based technical trading strategy "Buy-Sell" can be written as:

$$\mu_b - \mu_s = \frac{\sum_{t=1}^{N} sign\left(y^s_{[t+1,t+n]}\right) y_{[t+1,t+n]}}{N_b + N_s} \tag{7}$$

where $N = N_b + N_s$ is the number of observations (number of weeks over all sample period). $sign\left(y^s_{[t+1,t+n]}\right)$ denotes the sign of the similarity-based predictor $y^s_{[t+1,t+n]}$, which indicates the buy/sell signals.

3.2 Data-snooping adjustment

3.2.1 Reality check

A proper adjustment for data snooping bias is required when testing the predictive power of technical trading rules since the data-snooping occurs when a data set is repeatedly used to search for profitable strategies of trading systems. The bootstrap reality check (RC) of White (2000) provides a statistical procedure to quantify the effect of data-snooping by evaluating the performance of the best strategy in the context of the full universe of trading models. Formally, let φ_k denote the performance measure of the kth similarity-based trading strategy relative to the benchmark and $k = 1, \dots, K$. White's (2000) null hypothesis is that no superior strategy exists in the collection of K strategies. That is:

$$H_0 : max_{k=1,\dots,K}\, \varphi_k \leq 0 \tag{8}$$

Following the literature on the futures market (for example, Hsu and Kuan, 2005 and Park and Irwin, 2010), the benchmark can be set as the rule of no position (zero return) at all times.[4] Thus we have $\varphi_k = E(\mu_k)$ and μ_k is the return of the kth similarity-based trading strategy. To test the null hypothesis H_0, White (2000) derives the test statistic based on the maximum of the normalized sample average of $\mu_{k,t}$:

$$t^{RC} = max_{k=1,\dots,K} \sqrt{N}\, \overline{\mu_k} \tag{9}$$

where $\overline{\mu_k} = \sum_{t=1}^{N} \mu_{k,t} / N$, $\mu_{k,t}$ is the observation of μ_k at date t, and N is the number of observations (number of weeks over all sample period). t^{RC} denotes the

[4] Lukac and Brosen (1990) argue that technical trading returns on futures contracts are found (for example, Elton, Gruber and Rentzler, 1987 and Lukac, Brorsen and Irwin, 1988) to be uncorrelated or have a small negative correlation with traditional investment like stocks and bond. Therefore Park and Irwin (2010) suggest that the expected returns of technical trading rules are equal to the risk-free rate in the Capital Asset Pricing Model (CAPM). Zero profit is thus a reasonable benchmark, since the margin requirements are posted in treasury-bills.

test statistic of White's (2000) reality check. To find the asymptotic distribution of the test statistic, White (2000) suggests using Politis and Romano's (1994) stationary bootstrap to generate bootstrap resamples. The reality check p-value for testing H_0 is derived by comparing the test statistic t^{RC} to the quantiles of bootstrapped statistics:

$$t_b^{RC} = max_{k=1,\dots,K} \sqrt{N} \left(\overline{\mu_{k,b}} - \overline{\mu_k}\right), b = 1, \dots, B \tag{10}$$

where t_b^{RC} denotes the resampling test statistics in bth bootstrap resample; $\overline{\mu_{k,b}} = \sum_{t=1}^{N} \mu_{k,b,t} / N$ is the mean return of the kth similarity-based trading strategy in bth bootstrap resample; and B denotes the total number of bootstrap resamples. Finally, the p-value of White's (2000) reality check can be obtained by:

$$p_{RC} = \sum_{b=1}^{B} \frac{1_{\{t_b^{RC} > t^{RC}\}}}{B} \tag{11}$$

where $1_{\{t_b^{RC} > t^{RC}\}}$ takes the value one if the bth resampling statistic is larger than the test statistic, that is, $t_b^{RC} > t^{RC}$ and the value zero otherwise. The null hypothesis is rejected at the $\alpha\%$ significance level if $p_{RC} \leq \alpha\%$. Rejecting the null hypothesis suggests that the best technical trading strategy generates a mean net return greater than zero.

3.2.2 Superior predictive ability

Hansen (2005) argues that the reality check reduces the rejection probabilities since poor and irrelevant alternative strategies are inevitably included to test the null hypothesis. Hansen's (2005) superior predictive ability (SPA) test reduces the impact of the poor alternative strategies by adopting a studentized test statistic and a data-dependent null distribution. The test statistic of SPA is as follows:

$$t^{SPA} = max\left(max_{k=1,\dots,K} \frac{\sqrt{N}\overline{\mu_k}}{\hat{\sigma}_k}, 0\right) \tag{12}$$

where $\hat{\sigma}_k^2$ is a consistent estimator of $\sigma_k^2 = var\left(\sqrt{N}\overline{\mu_k}\right)$. Hansen (2005) introduces a different way to bootstrap the distribution of the test statistic to avoid the least favorable configuration and reduce the impact of the strategies with large negative returns. The centered returns of the bth bootstrap resample for kth trading strategy at date t is:

$$\mu_{k,b,t}^{c} = \mu_{k,b,t} - \overline{\mu_k} 1_{\{\overline{\mu_k} \geq -A_k\}} \tag{13}$$

The choice of the threshold rate A_k must ensure $\mu_{k,b,t}^{c}$ is a consistent estimator capturing all alternatives with $\mu_k = 0$. Following Hansen (2005) and Hsu and Kuan (2005), the threshold is set as $A_k = \hat{\sigma}_k \,/\left(4\mathrm{N}^{1/4}\right)$, where $\hat{\sigma}_k^2$ is computed based on the bootstrap resample:

$$\hat{\sigma}_k^2 = \frac{1}{B}\sum_{b=1}^{B}\left(\overline{\mu_{k,b}} - \overline{\mu_k}\right)^2 \tag{14}$$

The empirical distribution of t^{SPA} can be obtained by the bootstrap resample:

$$t_b^{SPA} = max\left(max_{k=1,\dots,K}\frac{\sqrt{N}\overline{\mu_{k,b}^c}}{\hat{\sigma}_k}, 0\right), b = 1, \dots, B \tag{15}$$

where $\overline{\mu_{k,b}^c} = \sum_{t=1}^{N}\mu_{k,b,t}^c\,/N$. Hansen's (2005) p-value of t^{SPA} is then determined by comparing the test statistic t^{SPA} to the quantiles of the bootstrapped statistics t_b^{SPA}:

$$p_{SPA} = \sum_{b=1}^{B}\frac{1_{\left\{t_b^{SPA} > t^{SPA}\right\}}}{B} \tag{16}$$

Since the choices of threshold rate A_k have impact on p_{SPA} in finite samples, Hansen (2005) introduces two additional estimators to provide the lower bound and upper bound for the distribution:

$$\mu_{k,b,t}^L = \mu_{k,b,t} - max(\overline{\mu_k}, 0) \tag{17}$$

$$\mu_{k,b,t}^U = \mu_{k,b,t} - \overline{\mu_k} \tag{18}$$

The bootstrapped distribution of $t_b^{SPA,L}$ and $t_b^{SPA,U}$ is realized as equation (15) by replacing $\overline{\mu_{k,b}^c}$ with $\overline{\mu_{k,b}^L}$ and $\overline{\mu_{k,b}^U}$, respectively. The p-values of lower and upper bounds, $p_{SPA,L}$ and $p_{SPA,U}$ are then determined by comparing the test statistic $t^{SPA,L}$ and $t^{SPA,L}$ to the quantiles of bootstrapped statistics $t_b^{SPA,L}$ and $t_b^{SPA,U}$, respectively.

The bootstrap method we applied to produce the distribution of the test statistics of White (2000) and Hansen (2005) closely follows the stationary bootstrap of Politis and Romano (1994). Assume that the original return matrix for all tested strategies is R, which is a $N \times K$ return matrix. N is the total number of observations in the full sample period, in our case, the total number is the number of weeks during the entire sample period, which is 1116. K is the total number of tested strategies, for example, for the MA trading class, total number of the combinations of shorter-, longer-term MA and the moving windows is 112. The algorithm of the stationary bootstrap is as follows:

First, a row of the original return matrix R is randomly selected as the first resampled row. Second, the second resampled row is randomly selected form R with a probability q, or it is set to the next row of the previously resample row with a probability $1 - q$. Repeat the second step until a $N \times K$ resampled return matrix is formed. For each bth resampled return matrix, t_b^{RC} and t_b^{SPA} can be obtained using equation (10) and (15).

We follow Hsu and Kuan (2005) to set the total number of the bootstrapped samples $B = 1000$, and the probability parameter $q = 0.1$. Several choices for B and q are also tested, however the results for the data-snooping tests are unchanged.

4. Empirical findings

For the empirical tests on the profitability of the SBTRs, we use the historical prices of nine futures markets with a whole sample period form 1982/04/21 to 2015/12/31. The nine futures markets include: S&P 500 futures (SP1), soybean futures, sugar futures, wheat futures, lumber futures, cocoa futures, silver futures, live cattle futures and corn futures. The longest time period of the technical indicators used is 200 days and the longest time period of the moving window tested is 2500 days, therefore we require the first prediction date to have at least 2700 observations previous to that date. This reduces our full sample period to 1993/01/04-2015/12/31. For the daily SBTRs, at the end of each day, the similarity-based prediction is formed and the SBTRs take a position starts at the opening price of the subsequent day and close the position at the closing price. The tests on the profitability of the SBTRs therefore are out-of-sample. As for the weekly SBTRs, the similarity-based predictors are formed at the end of each week, and the SBTRs take a position starts at the opening price of the subsequent start date of the week and then close position at the closing price of the end of that week. All SBTR strategy are examined and compared to the unconditional B/H mean returns on these futures.

4.1 Comparison of SBTRs and traditional technical rules

Table 1 presents the annualized returns of the B/H strategies that buy the future at the opening prices and sell it at the closing prices on a daily basis in nine futures markets, respectively. The total sample period is from 1993/01/04 to 2015/12/31, and the four sub-periods includes 1993/01/04-1998/12/31, 1999/01/01-2004/12/31, 2005/01/01-2010/12/31 and 2011/01/01-2015/12/31, respectively. The best annual return of whole sample period is 12.28% which is the B/H return on the soybean future. The worst annual return of whole sample period is the B/H return on the lumber future, which is -29.43%. The best annual return over four sub-periods is the B/H return on the sugar future for the first sub-period, while the worst is the return on lumber for the third sub-period. The descriptive statistics for these nine futures markets and all sub-periods show that our sample includes various market situations. The dispersion in the return standard deviations in different markets and different sub-periods also assure that the empirical tests of SBTR are conducted in the heterogeneous market conditions.

To investigate the buy/sell signals triggered by the SBTR and draw a comparison between the SBTR and traditional technical strategies, we first examine the best technical rules in these futures markets. Table 2 reports the annualized returns of the best strategy that follows the traditional technical rules for the whole sample period. For example, for the SP1 future, the best strategy that follows the traditional technical rules is MA10-20 and the strategy return is 1.27%. The return standard deviation of this strategy is 16.18% and the t-tests as defined in (4) do not reject the null hypothesis that the Buy-Sell return equals the unconditional B/H return.

Table 1: Descriptive statistics for the daily returns on futures

The table presents the summary statistics for the unconditional B/H returns on futures on a daily basis. The full sample period tested is from 1993/01/04 to 2015/12/31. To examining the robustness of the SBTR returns, the full sample period is divided into four sub-samples with roughly equal lengths. These four sub-samples include following data periods, respectively: 1993/01/04-1998/12/31, 1999/01/01-2004/12/31, 2005/01/01-2010/12/31, 2011/01/01-2015/12/31. The returns and the standard deviations are reported in percentage. The number of observation is denoted by No..

Sample period	19930104-20151231			19930104-19981231			19990101-20041231			20050101-20101231			20110101-20151231		
Market	Mean	Stdev	No.	Mean	Stdev	No.	Mean	Stdev	No.	Mean	Stdev	No.	Mean	Stdev	No.
SP1	4.07	16.18	5778	12.74	13.93	1516	0.06	18.45	1507	0.25	18.78	1512	3.01	11.75	1243
Soybean	12.28	21.98	5773	6.41	16.83	1513	11.86	22.15	1507	21.85	26.99	1512	8.27	20.51	1241
Sugar	2.19	30.76	5735	28.32	24.48	1499	24.09	35.22	1491	-15.22	33.95	1507	-34.63	27.40	1238
Wheat	-16.28	24.32	5644	-1.34	20.34	1511	-7.02	23.40	1507	-36.11	30.53	1511	-22.15	20.65	1115
Lumber	-29.43	25.36	5773	-13.21	25.62	1518	-12.06	24.34	1508	-51.95	27.00	1511	-43.03	24.10	1236
Cocoa	11.77	25.76	5733	23.69	22.38	1498	20.56	29.92	1491	1.23	26.81	1507	-0.42	22.68	1237
Silver	-2.61	21.33	5752	0.15	17.62	1506	4.06	13.92	1497	6.20	22.16	1508	-24.69	30.00	1241
Live_cattle	-6.73	12.90	5768	-6.64	12.80	1510	6.83	13.25	1508	-15.88	12.84	1510	-12.17	12.61	1240
Corn	6.07	24.50	5772	7.50	18.11	1513	0.06	20.80	1505	15.43	31.47	1512	0.24	25.70	1242

Table 2 shows that among all these futures markets, the best technical rules that generates the best return is MA10-50 for the sugar future. The strategy return is 22.77% with a standard deviation of 30.73%. The t-stats for Buy-Sell is 3.55 suggesting the return is significant from zero. Overall, Table 2 suggests that the traditional technical strategies do not consistently generate significant returns among these futures markets. Five of the nine futures markets have the strategy returns which are not significant different from zero.

Then, to draw a comparison between the SBTR and traditional technical strategies, we use the SBTR based on the same technical indicators that generates the best returns for these market respectively. For each futures market, we fix the technical indicators and let the threshold parameter, the method of measuring the similarity and the moving window chosen by the best SBTR returns. Table 3 reports the annualized SBTR return for the nine futures markets. For example, with the MA10-20, the best SBTR in the SP1 market is the strategy that uses a moving window of 10 years, a 50% threshold and the standardized Euclidean distance to measure the similarity. The strategy return is 5.22% which is larger than that of the traditional technical rule in Table 2, however the t-stats for Buy-Sell is still not significantly different from zero.

Table 3 suggests that the SBTR do provide better returns than those using the traditional technical rules. All SBTR returns improve except for that in the soybean future market. For example, for the lumber future market, the SBTR based on the same technical indicators which generates the best return with traditional rules produces an annualized return of 33.77%. The return is larger than 12.22% in Table 2. This suggests that the SBTR generates more accurate buy/sell signals than the traditional technical rules. However, the t-stats for Buy-Sell return in the SP1, soybean, cocoa future markets are still not significant.

Table 2: Best traditional technical strategies

The table presents the annualized return and the technical indicators of the best traditional technical strategies for each futures market. The returns and the standard deviations are reported in percentage. The full sample period tested is from 1993/01/04 to 2015/12/31. The t-stats is defined as (4)-(6). The number of the days that the technical indicators generate buy (sell) signals is denoted by No..

Market	Best strategy	Buy-Sell return			Buy return			Sell return			t-stats		
		Mean	Stdev	Hit-ratio	Mean	Stdev	No.	Mean	Stdev	No.	Buy-Sell	Buy-B/H	Sell-B/H
SP1	MA10-20	1.27	16.18	51.26	4.42	12.82	3493	3.54	20.26	2285	0.13	0.06	-0.08
Soybean	RSI10	12.67	21.98	51.12	23.76	21.82	3031	-0.41	22.15	2742	2.64	1.49	-1.56
Sugar	MA10-50	22.77	30.73	51.98	24.58	29.78	2912	-20.91	31.67	2823	3.55	2.03	-2.08
Wheat	MA10-20	6.16	24.33	50.53	-10.44	25.40	2737	-21.78	23.24	2907	1.10	0.47	-0.82
Lumber	MA10-150	12.22	25.42	51.36	-18.39	24.70	2702	-39.15	25.92	3071	1.96	1.19	-1.08
Cocoa	MA50-150	0.79	25.77	50.81	11.79	24.89	3055	11.75	26.73	2678	0.00	0.00	0.00
Silver	RSI10	6.05	21.32	52.16	3.27	20.49	3022	-9.12	22.21	2730	1.39	0.80	-0.81
Live_cattle	RSI20	5.15	12.90	50.45	-1.44	12.12	3170	-13.18	13.78	2598	2.17	1.20	-1.32
Corn	MA1-20	16.20	24.48	51.85	21.55	24.19	2983	-10.48	24.79	2789	3.14	1.77	-1.85

Table 3: Similarity-based strategies based on the best traditional technical indicators

The table presents the annualized return of the SBTRs based on the best traditional technical indicators that generate the best return during whole sample period for each futures market. The returns and the standard deviations are reported in percentage. The full sample period tested is from 1993/01/04 to 2015/12/31. The t-stats is defined as (4)-(6). For each SBTR, the length of time window, threshold rate and the method of calculating the distances of two characteristic vectors are chosen by the SBTR that generates the best returns while the technical indicators are fixed. The lengths of moving window, the threshold rates and the distance measures are reported in the parentheses after the technical indicators of the SBTRs. For the method of measuring the distances, the Euclidean distance is denoted by E; the standardized Euclidean distance is denoted by StdE; and the Mahalanobis distance is denoted by Mah. The number of the days that the technical indicators generate buy (sell) signals is denoted by No..

Market	SBTR with best traditional technical indicators	Buy-Sell return			Buy return			Sell return			t-stats		
		Mean	Stdev	Hit-ratio	Mean	Stdev	No.	Mean	Stdev	No.	Buy-Sell	Buy-B/H	Sell-B/H
SP1	MA10-20 (10Y, 50%, StdE)	5.22	16.17	52.63	6.01	15.45	4464	-2.54	18.43	1314	1.07	0.38	-0.85
Soybean	RSI10 (5Y, 60%, StdE)	12.35	21.98	52.24	16.67	22.58	4264	-0.14	20.19	1509	1.61	0.64	-1.23
Sugar	MA10-50 (1Y, 100%, Euclidean)	27.19	30.71	53.55	27.67	29.56	3044	-26.64	31.97	2691	4.23	2.34	-2.55
Wheat	MA10-20 (10Y, 60%, StdE)	17.06	24.31	50.66	1.27	22.47	1744	-24.13	25.08	3900	2.28	1.51	-1.19
Lumber	MA10-150 (3Y, 20%, StdE)	33.77	25.34	53.37	7.82	23.58	1600	-43.72	25.96	4173	4.37	3.29	-1.75
Cocoa	MA50-150 (5Y, 10%, StdE)	9.07	25.77	50.92	16.66	25.28	3587	3.61	26.54	2146	1.18	0.57	-0.79
Silver	RSI10 (5Y, 10%, StdE)	9.38	21.32	52.35	6.66	20.12	2923	-12.19	22.50	2829	2.12	1.23	-1.22
Live_cattle	RSI20 (1Y, 70%, StdE)	10.04	12.89	51.51	3.94	12.51	2427	-14.48	13.16	3341	3.38	2.18	-1.72
Corn	MA1-20 (10Y, 20%, StdE)	17.34	24.48	51.99	18.19	23.89	3715	-15.81	25.52	2057	3.19	1.49	-2.20

Next, to investigate the differences in the buy/sell signals generated by the SBTR and the traditional technical rules, Table 4 reports the mean returns, the average level of the technical indicators, and the number of days conditional on the following four scenarios: the SBTR generates a buy signal while the traditional rule also generates a buy signal; the SBTR generates a buy signal while the traditional rule rule generates a sell signal; the SBTR generates a sell signal while the traditional rule also generates a sell signal; the SBTR generates a sell signal while the traditional rule generates a buy signal.

For example, for the lumber future market, when the SBTR generates buy signals and the traditional rule generates the same ones, the mean return is 15.69%, and the mean level of MA10-150 is 12.34% (the percentage of the difference between shorter-term MA and longer-term MA with the longer-term MA as the denominator). When the SBTR generates buy signals and the traditional rule generates sell signals, the mean return is 13.48%, and the mean percentage of MA10-20 is -7.83%.

This suggests that the SBTR do not always follow the traditional signals. The SBTR still long the futures when the MA10 is below the MA20. Namely, although the traditional moving average strategies are considered as trend-following rules, the SBTR based on the MA indicators sometimes use the indicators as a counter-trend indicator, or it captures the trend earlier than the traditional rules. When the SBTR generates sell signals and the traditional rule generates buy signals, the annualized return of buying at opening price and selling at closing price is -44.34% and the mean percentage of the MA difference is 10.67%. This also suggests that the SBTR has a very different view on future returns from the traditional technical rules.

Overall, Table 4 shows the differences in the SBTR and the traditional rules. The SBTR uses the technical indicators as a measurement of the market situation and generate buy signals only when the similarity-weighted averages of the historical subsequent returns in the similar situation are above zero. Here the so-called similar situation is measured by the similarity function based on the technical indicators. Therefore, the SBTR do not stubbornly buy when the technical indicators generate buy signals. The magnitude of the technical indicators is only used to measure how similar between the historical price pattern and the current market situation are.

Table 4: Comparison of SBTR and traditional technical rules

This table presents the comparison between the SBTRs based on the technical indicators that generate the best return during the whole sample for each future market. The table shows the mean returns following buy/sell signals triggered by the SBTRs, the average levels of the technical indicators (denoted as ATI) when the signal is triggered (for the MA indicators, the level is calculated as the percentage of the differences in the longer-term MA and shorter-term MA divided by the longer-term MA) and the number of weeks (denoted as No.). The comparison is drawn conditional on the following scenarios: the SBTR and the traditional technical rule both generate a buy signal; the SBTR generates a buy signal while the technical rule suggests a sell; the SBTR and the technical rule both generate a sell signal; the SBTR generates a sell signal while the technical rule suggests a buy. The mean returns and the hit-ratios are in percentage. The number of the days that the technical indicators generate buy (sell) signals is denoted by No...The traditional technical rules in this table are denoted by TTR

Indicator		SBTR: buy; TTR: buy				SBTR: buy; TTR: sell				SBTR: sell; TTR: buy				SBTR: sell; TTR: sell				SBTR: buy	SBTR: sell
		Mean return	ATI	Hit-ratio	No.	Mean return	ATI	Hit-ratio	No.	Mean return	ATI	Hit-ratio	No.	Mean return	ATI	Hit-ratio	No.	ATI	ATI
SP1	MA10-20	4.85	0.89	54.64	3009	8.43	-0.92	53.26	1455	1.76	0.93	48.35	484	-5.0	-1.2	46.7	830	0.30	-0.43
Soybean	RSI10	26.83	67.65	54.41	2553	1.52	36.08	52.78	1711	7.38	64.42	46.86	478	-3.6	29.3	48.5	1031	54.98	40.41
Sugar	MA10-50	42.27	6.04	55.91	1905	3.25	-4.12	53.91	1139	-8.89	4.97	50.05	1007	-37.2	-6.0	52.7	1684	2.24	-1.91
Wheat	MA10-20	5.40	1.71	50.51	1368	13.75	-1.23	51.06	376	-26.26	2.20	49.96	1369	-23.0	-1.9	51.0	2531	1.07	-0.44
Lumber	MA10-150	15.69	12.34	53.85	1168	13.48	-7.83	48.61	432	-44.34	10.67	54.17	1534	-43.4	-9.5	53.5	2639	6.90	-2.06
Cocoa	MA50-150	7.93	5.47	52.14	2081	28.71	-4.29	53.32	1506	20.03	7.06	45.17	974	-10.0	-4.8	50.4	1172	1.37	0.58
Silver	RSI10	9.81	67.32	68.79	1605	2.83	33.93	74.05	1318	-4.14	66.70	28.02	1417	-20.3	34.1	37.8	1412	52.26	50.45
Live_cattle	RSI20	5.46	62.68	51.70	1472	1.61	38.92	52.57	955	-7.41	61.75	50.35	1698	-21.8	37.4	51.9	1643	53.33	49.76
Corn	MA1-20	22.88	3.44	53.94	2564	7.75	-1.59	52.22	1151	13.42	2.63	44.87	419	-23.3	-4.5	50.6	1638	1.88	-3.04

Although from Table 2 and 3, we find that the strategy returns do improve using the SBTR based on the same technical indicators that generates the best return under the traditional rules, Table 4 shows that the SBTR still make false prediction sometimes. For example, the SBTR based on MA10-20 in the SP1 market, the mean return is positive when SBTR generates sell signals and the traditional rule suggests sells. This suggests that the technical indicators that generate the best return with the traditional rules may not be the best measurement of similarity in the view of SBTR. So far the aim of Table 4 is to provide a comparison between the trading strategies of SBTR and traditional rules. Next, we reports the best SBTR in each future market when the technical indicators, the threshold parameter, the length of the moving window and the similarity function are chosen based on the best returns.

4.2 The best SBTR return

Table 5 presents the best annualized returns of the daily SBTR for each future market. These strategies assume that investors buy or sell at the opening prices according to the buy/sell signals generated by the SBTR and close the position at the closing prices on a daily basis. For example, for the SP1 market, the best SBTR measures the similarity using the 5-day Candlestick and all RSI indicators, with a moving window of 10 years, with a threshold level of 10% and with the Mahalanobis distance. The empirical findings from this table can be organized as follows. First, the best SBTRs for each future market do not use the same technical indicators that generate the best returns under the traditional rule. For example, the best technical indicator in Table 2 for the wheat future is MA10-20 while the best SBTR in Table 5 is based on MA50-100. This shows that even with the restriction using one single indicator, the best strategy under the traditional rule may not be the best in the view of the SBTR.

Second, the SBTR with multiple technical indicators may not be the best strategy. The SBTR with single technical indicators generates the best returns in the five of the nine futures markets. For example, the best SBTR for the sugar market use only the MA50-200 as the measurement of the similarity. The differences of the usage of technical indicators in different futures markets are widely accepted in the literature on the technical trading rules. For example, Hsu and Kuan (2005) document that the largest mean return for four stock index markets are generated by two different technical rules. Park and Irwin (2010) also document different best technical rules across 17 futures markets.

Third, the best lengths of moving window and the best threshold rates are not always the longest lengths or 100% threshold rate. We attribute this finding to that investors may be subjected to the limited attention and allocate the attention to the most salient and readily available information. The most salient information that is likely to attract the technical investors' immediate attention is the most recent and the most similar pattern on the price charts. Since the source of the technical trading profits may be the self-fulfilling of the subsequent prediction made by the technical indicator, if most traders rely on the most recent performance of the technical indicators or the most similar market condition to make investment decision, only recent and similar patterns can be referential for the future price patterns. This explains why the SBTRs based on the shorter time period of the moving window or the lower threshold rates have higher mean returns in some futures markets.

Table 6 reports the best weekly SBTRs that generate the best returns for each futures market. The strategies assume that investors buy or sell at the opening price on the first day of each week according to buy/sell signals generated by the SBTRs and close the position at the closing price on the last day of each week. The best technical indicators used by the SBTR in this table are different from those used in Table 5 where the daily SBTRs are reported. For example, the best SBTR for SP1 market use RSI100 as the measurement of how similar the current market condition and historical price patterns are, while the daily SBTR in Table 5 is based on Candlestick and all RSI indicators. The annualized returns produced by the best weekly SBTRs are smaller than those in Table 5. For example, in Table 5, the best daily SBTR for the soybean future generates a positive annualized return of 22.92% while the best return of the weekly SBTR in Table 6 is 13.54%. Also, almost all strategies on a weekly basis have smaller t-stats than those on daily basis except for the silver future. This suggests that the SBTRs produce better predictions when daily strategies are applied.

Table 5: Best similarity-based technical strategies on a daily basis

This table presents the mean annualized returns of the best SBTRs during the whole sample period for each future market. The SBTRs in this table assume that investors enter a position at the opening price according to the signal generated by the SBTR and close the position at the closing price on a daily basis. The technical indicators, the lengths of moving window, the threshold rates and the method of calculating the distances of two characteristic vectors used by the SBTRs are chosen by the SBTRs that generate the best returns. The lengths of moving window, the threshold rates and the distance measures are reported in the parentheses after the technical indicators of the SBTRs. The mean returns and the standard deviations are in percentage. For the method of measuring the distances, the Euclidean distance is denoted by E; the standardized Euclidean distance is denoted by StdE; and the Mahalanobis distance is denoted by Mah. The t-stats is defined as (4)-(6). The number of the days that the technical indicators generate buy (sell) signals is denoted by No.

Market	Best strategy	Buy-Sell return			Buy return			Sell return			t-stats		
		Mean	Stdev	Hit-ratio	Mean	Stdev	No.	Mean	Stdev	No.	Buy-Sell	Buy-B/H	Sell-B/H
SP1	Candlestick+RSI (10Y, 10%, Mah)	12.78	16.16	54.16	12.64	15.64	3851	-13.05	17.15	1927	3.60	1.61	-2.55
Soybean	Candlestick+RSI (10Y, 30%, StdE)	22.92	21.95	52.80	22.61	21.94	4494	-24.03	22.01	1279	4.23	1.51	-3.37
Sugar	MA50-200 (3Y, 90%, E)	31.88	30.69	54.52	28.07	29.33	3480	-37.75	32.69	2255	5.02	2.48	-3.32
Wheat	MA50-100 (1Y, 80%, StdE)	22.78	24.29	52.39	10.48	25.51	1752	-28.32	23.72	3892	3.49	2.38	-1.71
Lumber	MA1-5 (10Y, 90%, StdE)	35.59	25.33	52.85	20.56	24.73	864	-38.23	25.44	4909	3.97	3.42	-1.12
Cocoa	Candlestick (10Y, 20%, Mah)	23.01	25.73	52.90	22.34	25.66	4463	-25.36	25.98	1270	3.69	1.31	-2.94
Silver	MA10-20 (5Y, 10%, StdE)	11.32	21.32	51.72	8.83	19.55	2837	-13.74	22.90	2915	2.54	1.50	-1.44
Live_cattle	TRB50 (1Y, 30%, StdE)	11.51	12.89	51.84	5.40	12.64	2554	-16.36	13.07	3214	4.02	2.52	-2.12
Corn	Candlestick+alltech (5Y, 70%, StdE)	20.94	24.47	52.36	23.71	25.15	3288	-17.27	23.54	2484	3.98	2.09	-2.51

Table 6: Best similarity-based technical strategies on a weekly basis

This table presents the mean annualized returns of the best SBTRs during the whole sample period for each future market. The SBTRs assume that investors enter a position at the opening price of the subsequent start date of the week according to the signal generated by the SBTR and close the position at the closing price of the end date of that week. The technical indicators, the lengths of moving window, the threshold rates and the method of calculating the distances of two characteristic vectors used by the SBTRs are chosen by the SBTRs that generate the best returns. The mean returns and the standard deviations are in percentage. The lengths of moving window, the threshold rates and the distance measures are reported in the parentheses after the technical indicators of the SBTRs. For the method of measuring the distances, the Euclidean distance is denoted by E; the standardized Euclidean distance is denoted by StdE; and the Mahalanobis distance is denoted by Mah. The t-stats is defined as (4)-(6). The number of the weeks that the technical indicators generate buy (sell) signals is denoted by No.

Market	Best strategy	Buy-Sell return			Buy return			Sell return			t-stats		
		Mean	Stdev	Hit-ratio	Mean	Stdev	No.	Mean	Stdev	No.	Buy-Sell	Buy-B/H	Sell-B/H
SP1	RSI100 (1Y, 50%, E)	9.70	16.49	53.35	12.19	14.58	776	-5.07	19.55	418	2.44	1.12	-1.69
Soybean	TRB50 (3Y, 10%, E)	13.54	23.56	52.05	16.28	22.95	686	-9.86	24.36	509	2.67	1.39	-1.70
Sugar	30-day volatility (1Y, 20%, E)	18.39	32.12	54.19	20.14	32.05	580	-16.74	32.21	614	2.80	1.63	-1.60
Wheat	MA20-200 (10Y, 20%, E)	14.35	27.29	51.50	9.55	27.30	597	-19.36	27.28	572	2.54	1.29	-1.66
Lumber	MA10-50 (1Y, 20%, StdE)	20.36	30.55	54.81	14.51	31.72	529	-25.01	29.59	666	3.13	1.94	-1.67
Cocoa	MA10-20 (10Y, 30%, StdE)	22.97	28.28	54.69	26.12	28.13	804	-16.48	28.59	390	3.44	1.51	-2.45
Silver	MA5-20 (10Y, 30%, StdE)	15.75	28.00	53.72	17.17	25.62	631	-14.16	30.47	564	2.72	1.51	-1.63
Live_cattle	TRB50 (1Y, 10%, E)	12.02	15.34	52.38	12.03	15.53	641	-12.01	15.13	554	3.80	2.09	-2.30
Corn	Candlestick+MA (10Y, 10%, E)	18.36	26.54	53.56	20.86	27.76	635	-15.52	25.09	560	3.33	1.84	-2.00

4.3 Data-Snooping adjusted statistical tests and sub-sample analysis

The above results show the profitability of the SBTRs based on different technical indicators for generating positive returns. To check the robustness of the results, a sub-sample analysis is conducted. The full sample period is divided into four sub-samples with roughly equal lengths. These four sub-samples include the following data periods, respectively: 1993/01/04-1998/12/31, 1999/01/01-2004/12/31, 2005/01/01-2010/12/31 and 2011/01/01-2015/12/31.

Table 7 presents the sub-period performance of the best daily SBTRs that generates the best returns over the whole sample. The strategy returns of the best SBTRs for each future market generate positive return in the sub-periods except for the silver market. The best SBTR of the whole sample period for the silver future market generate a negative return of -0.13% during the third sub-period. Although most of the SBTRs have positive return in the sub-periods, the returns are not always significantly different from zero. For example, the best SBTR for the wheat future market generate a significant return of 22.78% in the whole sample period, however the strategy produce an annualized return of 7.54% in the second sub-period and it is not significant. To gain more robust conclusions on the consistency of the profitability of the SBTRs, a formal test to determine whether the best SBTR exists for the whole sample period is required. We then run the data-snooping tests on the returns of the SBTRs for these future markets respectively.

Table 8 presents the statistics of White's (2000) reality check and Hansen's (2005) superior predictive ability for the best SBTRs. The White's and Hansen's nominal p-value are testing for the null hypothesis that the best strategy does not provide a mean return greater than zero. The p-value of the White's (2000) reality check is defined as equation (11) and the p-values of the Hansen's (2005) superior predictive ability are defined as equation (16). The reality check and the superior predictive ability test the null hypothesis that no superior strategy exists in the collection of all SBTRs in the trading rule class. For the choice of the total number of bootstrap resamples, B and the probability parameter q, we follow Brock, Laconishok and LeBaron (1992) and Hsu and Kuan (2005) and assume $B = 1000$ and $q = 0.1$. Changing these parameters yields similar results. The table also reports the annualized returns of the best SBTRs for each future market.

Table 7: Sub-period analysis for the best daily SBTRs

This table presents the mean annualized returns of the best SBTRs during the whole sample period and during each sub-period for each future market. The SBTRs in this table assume that investors enter a position at the opening price according to the signal generated by the SBTR and close the position at the closing price on a daily basis. The technical indicators, the lengths of moving window, the threshold rates and the method of calculating the distances of two characteristic vectors used by the SBTRs are chosen by the SBTRs that generate the best returns. The mean returns and the standard deviations are in percentage. The lengths of moving window, the threshold rates and the distance measures are reported in the parentheses after the technical indicators of the SBTRs. For the method of measuring the distances, the Euclidean distance is denoted by E; the standardized Euclidean distance is denoted by StdE; and the Mahalanobis distance is denoted by Mah. The t-stats is defined as (4)

Market	Best strategy	Whole sample			Period 1			Period2			Period3			Period4		
		Mean	Stdev	t-stat	Mean	Stdev	t-stat	Mean	Stdev	t-stat	Mean	Stdev	t-stat	Mean	Stdev	t-stat
SP1	Candlestick+RSI (10Y, 10%, Mah)	12.78	16.16	3.80	5.09	13.95	0.90	9.88	18.44	1.32	24.15	18.71	3.17	11.83	11.73	2.25
Soybean	Candlestick+RSI (10Y, 30%, StdE)	22.92	21.95	5.02	17.75	16.79	2.60	33.46	22.06	3.72	28.20	26.96	2.57	10.01	20.51	1.09
Sugar	MA50-200 (3Y, 90%, E)	31.88	30.69	4.97	34.79	24.45	3.48	37.06	35.17	2.57	19.22	33.94	1.39	37.52	27.38	3.05
Wheat	MA50-100 (1Y, 80%, StdE)	22.78	24.29	4.46	19.13	20.30	2.32	7.54	23.40	0.79	35.74	30.53	2.88	30.78	20.61	3.15
Lumber	MA1-5 (10Y, 90%, StdE)	35.59	25.33	6.75	13.53	25.62	1.30	33.63	24.25	3.40	53.62	26.98	4.89	43.03	24.10	3.97
Cocoa	Candlestick (10Y, 20%, Mah)	23.01	25.73	4.28	35.36	22.32	3.88	28.19	29.90	2.30	20.11	26.78	1.84	5.33	22.68	0.52
Silver	MA10-20 (5Y, 10%, StdE)	11.32	21.32	2.55	13.10	17.60	1.83	1.14	13.92	0.20	-0.13	22.16	-0.01	35.35	29.96	2.63
Live_cattle	TRB50 (1Y, 30%, StdE)	11.51	12.88	4.77	6.07	12.80	1.17	17.27	13.21	3.21	19.45	12.82	3.73	7.38	12.63	1.30
Corn	Candlestick+alltech (5Y, 70%, StdE)	20.94	24.47	4.11	19.20	18.07	2.61	18.53	20.77	2.19	32.03	31.42	2.51	12.47	25.69	1.08

Table 8: Data-snooping adjustment for the best daily SBTRs

This table presents the data-snooping statistics for the best daily SBTRs in each future market. White and Hansens's nominal p-values are obtained from applying their procedures only to the best rule. The value of reality check is defined as (11). The lower, consistent and upper p-values of superior predictive ability is defined as (16)-(18). The mean annualized return is in percentage while all other statistics are actual values.

Market	Best strategy	Mean annual return	White's nominal p-value	Hansen's nominal p-value	Reality check	Superior predictive ability		
						Lower p-value	Consistent p-value	Upper p-value
SP1	Candlestick+RSI (10Y, 10%, Mah)	12.78	0.002	0	0.098	0.12	0.138	0.166
Soybean	Candlestick+RSI (10Y, 30%, StdE)	22.92	0	0	0.002	0.002	0.002	0.002
Sugar	MA50-200 (3Y, 90%, E)	31.88	0	0	0	0	0	0
Wheat	MA50-100 (1Y, 80%, StdE)	22.78	0	0	0.004	0.008	0.008	0.01
Lumber	MA1-5 (10Y, 90%, StdE)	35.59	0	0	0	0	0	0
Cocoa	Candlestick (10Y, 20%, Mah)	23.01	0	0	0.012	0.008	0.008	0.008
Silver	MA10-20 (5Y, 10%, StdE)	11.32	0.008	0.012	0.918	0.85	0.892	0.946
Live_cattle	TRB50 (1Y, 30%, StdE)	11.51	0	0	0.004	0	0	0
Corn	Candlestick+alltech (5Y, 70%, StdE)	20.94	0	0	0.028	0.038	0.04	0.044

Table 8 shows that all the best daily SBTRs generate significant positive returns consistently according to the White's and Hansen's nominal p-values. All the nominal p-values are less than 2% and most of them are zero, suggesting that for each bootstrapped sample, the best SBTRs always have positive returns. When compared the returns of the best SBTR to those of all possible SBTRs, the best SBTRs for the SP1 and silver futures are rejected at a 5% significant level. This suggests that the best SBTRs of the whole sample period do not always generate better returns than other possible SBTRs in each bootstrapped sample. Except for SP1 and silver futures, for all other future markets, there do exists a best SBTR consistently provide significant positive returns which are larger than all other possible SBTRs. Overall, Table 8 provides a rigid result that supports the robust profitability of the daily SBTRs.

Table 9 presents the sub-period performance of the best weekly SBTRs for each future market. These SBTRs mostly still generate positive returns during sub-periods, however the significance are lower than those when the daily basis is used. Table 10 presents the data-snooping statistical values for the best weekly SBTRs. Almost all SBTRs cannot generate robust returns after data-snooping adjustments. That is, the significant returns of the best weekly SBTRs that we find in Table 6 may not be the best in each bootstrapped resample and no superior strategy exists in the collection of these SBTRs.

Table 9: Sub-period analysis for the best weekly SBTRs

This table presents the mean annualized returns of the best SBTRs during the whole sample period and during each sub-period for each future market. The SBTRs assume that investors enter a position at the opening price of the subsequent start date of the week according to the signal generated by the SBTR and close the position at the closing price of the end date of that week. The technical indicators, the lengths of moving window, the threshold rates and the method of calculating the distances of two characteristic vectors used by the SBTRs are chosen by the SBTRs that generate the best returns. The mean returns and the standard deviations are in percentage. The lengths of moving window, the threshold rates and the distance measures are reported in the parentheses after the technical indicators of the SBTRs. For the method of measuring the distances, the Euclidean distance is denoted by E; the standardized Euclidean distance is denoted by StdE; and the Mahalanobis distance is denoted by Mah. The t-stats is defined as (4).

Market	Best strategy	Whole sample			Period 1			Period2			Period3			Period4		
		Mean	Stdev	t-stat	Mean	Stdev	t-stat	Mean	Stdev	t-stat	Mean	Stdev	t-stat	Mean	Stdev	t-stat
SP1	Candlestick+RSI (10Y, 10%, Mah)	9.70	16.49	2.87	1.32	12.80	0.26	16.37	17.62	2.32	12.29	20.19	1.52	8.65	13.83	1.41
Soybean	Candlestick+RSI (10Y, 30%, StdE)	13.54	23.56	2.81	6.45	18.32	0.88	16.45	23.29	1.77	27.51	28.81	2.39	1.58	22.34	0.16
Sugar	MA50-200 (3Y, 90%, E)	18.39	32.12	2.80	3.31	26.38	0.31	24.49	36.38	1.68	27.09	36.31	1.87	18.78	27.19	1.56
Wheat	MA50-100 (1Y, 80%, StdE)	14.35	27.29	2.54	-1.84	23.15	-0.20	13.95	24.78	1.41	22.28	33.36	1.67	26.14	26.49	2.12
Lumber	MA1-5 (10Y, 90%, StdE)	20.36	30.55	3.26	31.43	32.00	2.46	16.25	31.35	1.30	8.44	30.48	0.69	26.43	27.74	2.16
Cocoa	Candlestick (10Y, 20%, Mah)	22.97	28.28	3.97	11.97	21.02	1.42	22.31	33.95	1.64	42.64	30.79	3.47	13.17	24.93	1.20
Silver	MA10-20 (5Y, 10%, StdE)	15.75	28.00	2.75	4.41	24.78	0.45	14.50	20.72	1.75	26.41	33.27	1.99	18.10	32.16	1.27
Live_cattle	TRB50 (1Y, 30%, StdE)	12.02	15.34	3.83	9.85	15.93	1.55	14.75	15.69	2.35	10.70	14.93	1.79	12.94	14.71	1.99
Corn	Candlestick+alltech (5Y, 70%, StdE)	18.36	26.54	3.38	14.64	20.49	1.79	15.02	23.10	1.63	34.06	34.37	2.48	7.80	26.03	0.68

Table 10: Data-snooping adjustment for the best weekly SBTRs

This table presents the data-snooping statistics for the best weekly SBTRs in each future market. White and Hansens's nominal p-values are obtained from applying their procedures only to the best rule. The value of reality check is defined as (11). The lower, consistent and upper p-values of superior predictive ability is defined as (16)-(18). The mean annualized return is in percentage while all other statistics are actual values.

Market	Best strategy	Mean annual return (%)	White's nominal p-value	Hansen's nominal p-value	Reality check	Superior predictive ability		
						Lower p-value	Consistent p-value	Upper p-value
SP1	RSI100 (1Y, 50%, E)	9.70	0.002	0	0.558	0.53	0.564	0.572
Soybean	TRB50 (3Y, 10%, E)	13.54	0.004	0.004	0.668	0.556	0.636	0.668
Sugar	30-day volatility (1Y, 20%, E)	18.39	0.004	0.002	0.694	0.598	0.648	0.666
Wheat	MA20-200 (10Y, 20%, E)	14.35	0.01	0.014	0.89	0.774	0.898	0.93
Lumber	MA10-50 (1Y, 20%, StdE)	20.36	0.002	0.002	0.382	0.256	0.292	0.312
Cocoa	MA10-20 (10Y, 30%, StdE)	22.97	0	0	0.058	0.034	0.05	0.058
Silver	MA5-20 (10Y, 30%, StdE)	15.75	0.004	0.002	0.672	0.628	0.726	0.788
Live_cattle	TRB50 (1Y, 10%, E)	12.02	0	0	0.096	0.082	0.092	0.106
Corn	Candlestick+MA (10Y, 10%, E)	18.36	0	0	0.254	0.314	0.37	0.404

4.4 Transaction cost

In this paper, the returns generated by the daily SBTRs are calculated based on the opening price in the subsequent day and the closing price at the end of that day following the buy/sell signals are triggered. Therefore the technical investor clears out his position each day and suffers from a two-way transaction cost daily.

To consider the impact of the transaction costs, we first follow Qi and Wu (2006) and report the maximum one-way transaction cost for the best daily SBTRs to be breaking even over the 23 trading years. Table 11 shows the mean returns of these best daily SBTRs for each future market and the number of round-trips of these strategies. Our total sample period includes 23 trading years. For example, the best SBTR for SP1 future generates a mean annualized return of 12.78%. The maximum one-way cost to be breaking even is 23*12.78%/(5778*2)=0.025% (the number of trades is the number of round-trips, 5778, multiplied by 2). Then for each SBTR, we present the mean annualized return when the one-way cost equals 0.025%-0.04% which is used by Qi and Wu (2006). When one-way cost is 0.04%, we find that the best SBTRs still generate positive returns in six of the nine futures markets.

Alternatively, Park and Irwin (2010) consider a range of transaction costs of $12.5-$100 per contract per round-trip trade. The transaction cost of $12.5 per round-trip is documented by Lukac and Brorsen (1990) who suggest that such low transaction is possible because commissions through discount brokers are around $12.5 and even lower for high volume trades or electronic trades. To convert the dollar transaction costs to percentage, we first estimate the average prices of these futures markets during whole sample period and calculate the average contract sizes as the average prices multiplied by the point value of the contract. Finally we divide the one-way transaction cost (which is the round-trip cost divided by 2) by the average contract size. For example, the average price of the SP1 future during the whole sample is 877.40 and the point value is $250, therefore the average contract size is $219,350. If the dollar transaction cost of one-way is $6.25, the percentage transaction cost is $6.25/$219,350=0.003%, which is lower than the maximum one-way cost for the best SBTR to be breaking even over the 23 trading years.

Table 11: Transaction cost

This table presents the mean return, the maximum one-way cost for the best SBTRs to be breaking even, a range of transaction cost and the after-cost returns. The number of round-trips is the number of the actual trading days that the SBTR generates a signal. The maximum one-way cost is the cost that makes the after-cost returns of the SBTRs be zero. The mean annualized return after-cost is the after cost returns of the SBTRs when the one-way cost is assumed to be 0.025% and 0.04%. The point value is the changes in values of the future contracts when the underlying increases one point. The average price if the averages of the futures prices during the whole sample period. The average contract size is the average future price multiplied by the point value, which is the average contract value during the whole sample for each future market. The rightmost column shows the transaction costs in percentage when the commission per round-trip is assumed to be $100 and $12.5.

Markets	Mean return	No. of round-trips	Trading years	Maximum one-way cost	Mean annualized return after-cost		Point value	Average price	Average contract size	Commission per round-trip	
					One-way cost=0.025%	One-way cost=0.04%				$100	$12.5
SP1	12.78%	5778	23	0.025%	0.22%	-7.32%	250	877.40	219,350	0.023%	0.003%
Soybean	22.92%	5773	23	0.046%	10.37%	2.84%	50	761.62	38,081	0.131%	0.016%
Sugar	31.88%	5735	23	0.064%	19.41%	11.93%	1120	12.03	13,474	0.371%	0.046%
Wheat	22.78%	5644	23	0.046%	10.51%	3.15%	50	417.76	20,888	0.239%	0.030%
Lumber	35.59%	5773	23	0.071%	23.04%	15.51%	110	253.44	27,878	0.179%	0.022%
Cocoa	23.01%	5733	23	0.046%	10.55%	3.07%	10	1847.73	18,477	0.271%	0.034%
Silver	11.32%	5752	23	0.023%	-1.18%	-8.69%	5000	10.16	50,800	0.098%	0.012%
Live_cattle	11.51%	5768	23	0.023%	-1.03%	-8.55%	400	81.81	32,724	0.153%	0.019%
Corn	20.94%	5772	23	0.042%	8.39%	0.86%	50	313.97	15,699	0.319%	0.040%

Table 11 shows that for a dollar one-way cost of \$12.5, the percentage transaction costs are all lower than the maximum one-way costs of these daily SBTRs, which suggesting that all SBTRs still generate positive returns. However using a higher dollar transaction cost of \$50, all the percentage costs are higher than the maximum one-way costs except for the SP1 future. Overall, using the transaction cost assumed by Qi and Wu (2006), we find the daily SBTRs generate positive after-cost returns in at least six of the nine futures markets. We report a range of dollar transaction costs and the maximum one-way costs to be breakeven to provide insights of the impact of transaction costs.

5. Conclusion

Although the profitability of the technical trading rules has been extensively examined in the existing literature, there are some major shortcomings in the traditional methodology. Most of these studies assume that technical investors follow a single technical rule during the full sample period and always enter a long (short) position following the buy (sell) signal. However, in practice, technical investors consider several technical indicators simultaneously to make an assessment for the future price movements and more importantly, the magnitude of the technical indicators provide useful information to help distinguish the trend following or the trend reversal of the future price movements.

This paper employs a similarity-based approach and attempts to propose a more realistic decision-making process for technical investors. The process considers the magnitude of the technical indicators as the characteristics to depict the current market condition and to predict the future returns. The process can take several technical rules into consideration simultaneously and the technical investors can make investment decisions even when these technical rules generate opposing buy/sell signals. The proposed similarity-based predictor for the future returns is based on the similarity-weighted averages of the subsequent returns of the past price patterns. A buy signal is triggered when the similarity-based predictor is above zero, and otherwise, a sell signal is triggered. The proposed decision-making process is designed to account for the charting procedure of technical investors in practice.

We test the profitability of the SBTRs in nine futures markets including SP1, soybean, sugar, wheat, lumber, cocoa, silver, live cattle and corn. We find that after considering data-snooping adjustments and transaction costs, the daily SBTRs generate positive and robust returns in six of the nine futures markets. However, although the returns of the weekly SBTRs are positive and significant, they are not robust after considering data-snooping adjustments. The comparison of SBTRs and traditional technical rules shows that the SBTRs do not always follow the signal of traditional technical signals. For example, while the traditional rules suggest a buy signal when shorter-term MAs exceed longer-term MAs, the SBTRs sometimes generate a buy signal when shorter-term MAs are below longer-term ones. This implies that the SBTRs only consider these indicators as a measure for how similarity of the current market condition and the historical patterns are. They generate a buy signal only when the similarity-weighted averages of the subsequent returns of these similar patterns are positive.

We also find that the choice of the moving window where the investors search for the similar pattern with the current pattern is crucial for the mean returns. The best time period of the moving window is not always the maximum length of ten years and the best threshold ratio is not always 100%. We attribute this to the limited attention of investors. Namely, since attention is a limited resource, the most recent and the most similar past price patterns are likely to attract the investors' immediate attention. Because the self-fulfilling nature of the subsequent prediction of the technical investors, the past price patterns during a shorter time period previous to the prediction date may be more referential than those in a longer time period.

The connection between limited attention and the profitability of SBTR requires more detailed examination. For example, Chen and Yu (2014) argue that the visual pattern of historical prices is a salient signal that attracts attention, which then inducing overreaction. Time-series tests on examining the relationship between trading signals generated by the SBTR and the measure of investor attention or overreaction might help understanding this connection. Moreover, cross-sectional tests on examine the trading signals and cross-sectional stock returns is also interesting for future studies.

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