Pacific-Basin Finance Journal 68 (2021) 101616

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

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

Predictive ability of similarity-based futures trading strategies

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ARTICLE INFO

JEL classification:
G17
G40

Keywords:
Technical trading
Similarity-based analogical reasoning
Futures markets

ABSTRACT

A trading rule that draws on the similarity-based analogical reasoning is proposed in an attempt to simulate the technical trading mentality—one that selectively perceives structural resemblances between market scenarios of the present and the past. In more than half of the nineteen futures markets that we test against for profitability of this similarity-based trading rule, we find evidence of predictive ability that is robust to data-snooping and transaction-cost adjustments. When aided by an exit strategy that liquidates the trader's positions across some evenly-spaced time points, this rule generates the most robust returns and survives the in- and out-of-sample tests.

1. Introduction

As Sharpe (1975) points out, it is said that the military is usually well prepared to fight the previous war—an intriguing old saying that reminds us of how susceptible we are to past experiences of our own when projecting the future. In this paper, such experience driven projection of the future takes place in technical trading. We assume that technical traders are "similarity-based", meaning that their judgements of present market conditions and projections of probable future returns are derived from recognizing vivid, concrete patterns of similarities portrayed by a multitude of technical indicators between market scenarios of the present and the past. To the best of our knowledge, the assumption itself is the first attempt in the literature to render the behavioral motive behind technical trading with similarity-based analogical reasoning (Hume, 1748).

Specifically, we resort to the Case-based Decision Theory of Gilboa and Schmeidler (1995), Billot et al. (2005), and Gilboa et al. (2006, 2011) in conceptualizing the technical trading mentality where belief formation leading to the execution of eventual buy-sell decisions comes as a direct consequence of traders' selectively perceiving structural resemblances between scenario-analogies. Unlike Barber and Odean (2000) and Grinblatt and Keloharju (2009) who challenge the exact nature of trading (it can be hazardous to your health), this paper investigates how people trade and what lies behind their decision making process. Most important, using the futures markets as one particular application of economic interest, we add a novel perspective to the technical trading literature by depicting trading decision making as a psychological process that reasons by analogy.

The similarity-based trading rule (SBTR) is thus devised to manifest the case-based logic. To initiate the SBTR, traders must be capable of constructing a "mental reference" of information entities. This amounts to devising a vector of explanatory variables that represents the quantitative characteristics of financial information. Because the preferred way of processing information can be very

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https://doi.org/10.1016/j.pacfin.2021.101616
Received 15 April 2020; Received in revised form 30 June 2021; Accepted 8 July 2021
Available online 16 July 2021
0927-538X/

unique, the SBTR is naturally adoptable as a univariate or a multivariate strategy depending on the traders' preferred parameterization for the vector of quantitative characteristics. At the same time, we assume that traders are in possession of a knowledge-/data-base comprising historical cases of the vector of quantitative characteristics. The historical cases of the vector serve to depict the market scenarios of the past, while its present case portrays the market scenario today. To decide if any past market scenarios resemble the present, and assess the extent to which they resemble the present, a similarity-based trader is equipped with a similarity function that embodies a user-definable measure of distance so as to quantify the extent to which two objects are similar. Using this similarity function, traders then conduct similarity searches, within moving windows of specifically chosen time lengths prior to the present date, based on the degree of similarity between market scenarios of the past and the present. Probable future returns under the current market scenario are then predicted using the similarity-weighted average of all corresponding past returns. A positive (negative) similarity-weighted average of past returns would indicate a buy (sell) trading signal. This similarity-weighted average of past returns is hereafter referred to as the "stochastic averaging predictor" of the SBTR.

In terms of time frame, the SBTR is applicable daily or weekly.[2] In the former, the SBTR adopts the day-trade mechanism as depicted by Kuo and Lin (2013) and Barber et al. (2014), where a similarity-based trader enters (closes) his/her trading positions at the opening (closing) price on the same day. As for a weekly strategy, we assume that traders enter (close) their trading positions at the beginning (end) of each week.

We address the issue of market timing by allowing traders to unload their trading positions under different exit strategies. We follow Lu et al. (2015) to consider the exit strategies of Marshall et al. (2006) (MYR) and Caginalp and Laurent (1998) (CL). While the MYR exit strategy is characterized by a predetermined date and condition to liquidate traders' trading positions once and for all, the CL exit strategy relies on an average exit price for the holding period so that traders can gradually unload their trading positions across some evenly-spaced time points.

We test the daily and weekly SBTRs for profitability against historical prices from nineteen futures markets. To ensure that the best-performing rules detected are indeed genuine, we apply the superior predictive ability test of Hansen (2005) to control for data-snooping bias. For robustness checks, we conduct out-of-sample experiments to see if the best-performing SBTRs selected from the first sub-period sample—based on their individual nominal *p*-values—would continue to perform well in the second sub-period sample. To address the effects of transactions costs on the profitability of the SBTRs, we follow Qi and Wu (2006) and Park and Irwin (2010) to consider the maximum one-way break-even transaction costs and the commissions per round-trip trade.

Our main findings can be summarized as follows. First, after data-snooping adjustment, we find that there exists a best daily SBTR that generates significantly positive profit in ten out of the nineteen futures markets at the 5 percent significance level. On the other hand, the best weekly SBTRs with the MYR exit strategy are profitable in six out of the nineteen futures markets at the 5 percent significance level while the best weekly SBTRs with the CL exit strategy are profitable in all futures markets at the 1 percent significance level. The sub-sample analyses confirm that the weekly SBTRs with the CL exit strategy generate the most robust excess returns. Second, we find that common to these best SBTRs is the application of a multivariate strategy that utilizes feasible combinations of the moving average, relative strength index, trading range breakthrough, and trading-volume moving average indicators in the construction of the vector of quantitative characteristics. Consistent with Park and Irwin (2010), we document favorable results for the technical trading rules that are applied to the commodity futures relative to the financial futures. Third, we find that, for an SBTR to outperform, the required moving time lengths for conducting similarity searches indeed matter, and they tend to vary across markets. Structural resemblances of the recent past—rather than those of the distant past—seem to induce greater impacts on a similarity-based trader's decision making. Lastly, to examine the after-cost performance of the SBTRs, we report the maximum one-way costs to break even for the best-performing SBTRs traded in each futures market. We show that the SBTRs still generate positive returns when a moderate transaction cost is assumed. Specifically, most of the best performing SBTRs robust to the data-snooping bias are profitable based on a one-way transaction cost of 0.025 percent or a one-way commission of $6.25. When the one-way commission is relatively high at $50, most of the SBTRs however are no longer profitable except for the weekly SBTRs with the MYR exit strategy.

The remainder of this paper is organized as follows. Section 2 introduces the similarity-based technical trading rules, and outlines the classes of technical indicators employed by the SBTR. Section 3 describes the empirical tests with data-snooping adjustments. Section 4 presents our empirical findings. In Section 5, we conclude this study.

[2] Although the similarity-based approach can be applied with fundamental analysis, we focus on technical indicators to form the similarity-based prediction. In particular, our paper tests the SBTR with high-frequency data (daily and weekly) in line with most of the studies on the technical trading rules, e.g., Brock et al. (1992), Hsu and Kuan (2005), Lu et al. (2015), Park and Irwin (2010), and Qi and Wu (2006). Furthermore, Lui and Mole (1998), Gehrig and Menkhoff (2006) and Menkhoff (2010) document that fund managers and dealers prefer using technical analysis for short-term forecasting. Lui and Mole (1998) also find that a skew towards reliance on technical analysis as opposed to fundamental analysis at shorter horizons reverses as the length of horizon considered is increased. Allen and Taylor (1989) and Tayler and Allen (1992) provide evidence that technical analysis is widely used especially at short horizons by the dealers in the London foreign exchange market. Baillie and Bollerslev (1994), Mark (1995), and Qi and Wu (2003) find that exchange rates are unforecastable at the 1- to 12-month horizons when lower frequency data (monthly or quarterly) are employed. Nevertheless, we also replicate the SBTR with monthly data, but do not report the empirical results due to limited space. The results show that although the mean return of the monthly SBTR is positive and significant, it is less robust than those for the daily and weekly SBTRs after the adjustment of data-snooping bias. These results are available from the authors upon request.

2. Methodology

This section introduces the SBTRs. We first define the stochastic averaging predictor for an outcome variable of interest, and present the decision rule based on the predictor. Then, we prescribe the vector of quantitative characteristics with the classes of technical indicators that are most prevalent in real-life trading. Finally, we construct the set of SBTRs.

2.1. The similarity-based technical trading rule

We begin by assuming that a similarity-based trader is in possession of a set of information signals conveyed by a vector of quantitative characteristics of dimension k, i.e., $x_t = (x_{1,t}, \dots, x_{k,t})$, where $x_{j,t}$ can be a specific trading indicator, such as the difference between the shorter-term and the longer-term moving averages, the value of the relative strength index over the past 10 days, or the difference between the opening and closing prices on a trading day. Conditional on the available information signals at time t, traders will then attempt to forecast future returns, which we refer to as a (real-valued) outcome variable y_t. In this study, y_t indicates either the next 1-day (daily) or the next 5-day (weekly) future returns. Define $\widehat{y}_t^s$ as the stochastic averaging predictor of y_t such that

$$\widehat{y}_t^s = \frac{\sum_{i=1}^{m} s(x_t, x_{t-i}) \cdot y_{t-i}}{\sum_{i=1}^{m} s(x_t, x_{t-i})} \tag{1}$$

where $s: R^k \times R^k \to (0, \infty)$ is a similarity function. The value of $s(x_t, x_{t-i})$ measures the degree of similarity between x_t and x_{t-i}. The more similar that x_t and x_{t-i} are, the larger the value of $s(x_t, x_{t-i})$. The similarity function we use is $s(x_t, x_{t-i}) = \exp(-d(x_t, x_{t-i}))$, where $d(x_t, x_{t-i}) = \sqrt{\sum_{j=1}^{k} \left(\frac{x_{j,t} - x_{j,t-i}}{\sigma_j}\right)^2}$ defines a standardized Euclidean norm and σ_j is the sample standard deviation of the element j in the vector of quantitative characteristics. The standardized Euclidean norm scales each coordinate difference between x_t, and x_{t-i} by dividing it by the standard deviation of the values in the corresponding coordinate over the moving window.

The $\widehat{y}_t^s$ so defined in Eq. (1) is a stochastic weighted averaging of the past returns y_{t-i} over the last m periods, and hence known as a "stochastic averaging predictor" (Gilboa and Schmeidler, 1995). In this paper, the SBTR based on $\widehat{y}_t^s$ has the following trading rule:

$$\begin{cases} \text{If } \widehat{y}_t^s > 0, \text{enteralongposition;} \\ \text{If } \widehat{y}_t^s < 0, \text{enterashortposition.} \end{cases} \tag{2}$$

In other words, the SBTR would recommend that the investor buys when $\widehat{y}_t^s > 0$, because based on the past experience of the investor, the future return is more likely to be positive when the signal vector is x_t. A similar argument applies to the case where $\widehat{y}_t^s < 0$.

One can certainly opt for other measures of similarity—for example the Mahalanobis metric—to quantify the distance between any two vectors of quantitative characteristics. In our case, we use the standard Euclidean norm because it is simple to implement and more appropriate as a distance measure when different scales and sources of quantitative characteristics are involved.

2.2. Prescribing the vector of quantitative characteristics

Because attention allocation is costly and requires effort (Kahneman, 1973; Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Barber and Odean, 2008), a similarity-based trader must be selective in his/her intended focus. We thus illustrate the SBTR using five prevalent classes of trading indicators to prescribe the vector of quantitative characteristics: the moving average (MA), relative strength index (RSI), trading range breakthrough (TRB), trading-volume moving average (VMA), and past 5-day Candlestick patterns. The information contents of these technical indicators are described as follows:

Moving Average (MA): MAs enable traders to identify current price trends, trend reversals, and the associated support and resistance levels. Traditionally, a technical trading rule based on the MA triggers buy (sell) signals through the upward (downward) crossovers of longer-term MAs by shorter-term MAs, where the MAs are calculated as the average closing prices over a specified period of time prior to the trading date, see, for example Brock et al. (1992), Sullivan et al. (1999), and Hsu and Kuan (2005).

Relative Strength Index (RSI): The RSI measures the changes in and speed of price movements and helps traders identify overbought or oversold conditions for an asset. The RSI is calculated as the ratio of average upward price changes to average downward price changes over a predetermined time period as in Wong et al. (2003) and Park and Irwin (2010). Conventionally, a technical trading rule based on the RSI generates sell (buy) signals when the RSI values are relatively high (low).

Trading Range Breakthrough (TRB): For TRB associated with the notion of support and resistance levels, we define the resistance level and the support level as the local maximum price and the local minimum closing price over a predetermined time period, respectively, following Brock et al. (1992), Sullivan et al. (1999), Hsu and Kuan (2005), and Park and Irwin (2010). A TRB trading rule generates buy signals when the price penetrates a resistance level and sell signals are generated by the crossing of the price over a support level.

Trading-volume Moving Average (VMA): VMAs are calculated as the average trading volume over a specified period of time that allow traders to identify trends in trading volume. A technical trading rule exploiting the VMA is typically constructed by entering a long position when the shorter-term VMA crosses upwards over the longer-term VMA, and by entering a short position when the opposite occurs. Alternatively, a high reading in the difference between the shorter- and longer-term VMAs can also be considered as an overbought signal (Pring, 1993). Karpoff (1987), Campbell et al. (1993), Blume et al. (1994), and Lee and Rui (2002) examine the informational content of trading volume on the contemporaneous and expected price changes.

5-day Candlestick patterns: Candlestick patterns, commonly characterized by a series of open-high-low-close prices, reflect the changing balance between supply and demand, investor sentiment and psychology.[3] To make feasible the adaptation of past 5-day Candlestick patterns to the SBTR, we construct each Candlestick pattern by three vital elements: the difference between the closing price and opening price, the difference between the highest price and the maximum of the closing price and opening price (the upper shadow), and the difference between the lowest price and the minimum of the closing price and opening price (the lower shadow). In addition, we include the differences between the average price of the closing price and opening price of two consecutive Candlesticks. Therefore, using the past 5-day Candlestick patterns to depict the current market condition will give rise to a vector of quantitative characteristics containing a total of 19 elements.

2.3. *Universe of SBTRs*

Based on the common observation that technical traders rarely rely on the sole use of one particular trading indicator while making investment decisions (Hsu and Kuan, 2005), we allow similarity-based traders to employ the SBTR as a univariate or multivariate strategy in which the vector of quantitative characteristics is prescribed with the values of a single type of trading indicator, or, that of a panel of mixture types.

In the following, we illustrate how to construct the vector of quantitative characteristics using the five types of technical indicators under a univariate SBTR and a multivariate SBTR.

2.3.1. *Univariate SBTRs*

Univariate SBTRs refer to the case where an SBTR prescribes the vector of quantitative characteristics by one and only one type of technical indicator at a time. For example, a similarity-based trader, who feels more comfortable with the MA rules, may judge how a past market scenario resembles the present based solely on how closely—as indicated by the similarity function—their MA quantitative characteristics match. As a consequence, the stochastic averaging predictor will be solely specified by the MA rules, with the vector of quantitative characteristics x_t comprising only the differences between the s-day and the l-day MAs. We follow Brock et al. (1992) for the choice of time periods to calculate the moving averages. The combinations of shorter- and longer-term MAs are denoted by MA$s-l$, where $s=1, 5, 10, 20, 50, 100$, $l=5, 10, 20, 50, 100, 150$, and $s<l$. Thus, the univariate SBTRs with the MA will include a total of 21 (6+5+4+3+2+1) shorter- and longer-term combinations.

For univariate SBTRs with the RSI, the vector of quantitative characteristics is then prescribed by the past p-day RSI values, where p corresponds to 5, 10, 20, 50, 100, and 150, respectively. This amounts to a total of 6 univariate SBTRs with the RSI. For univariate SBTRs with the TRB, we use the difference between the current closing price and the local maximum price over a specific period of time prior to the current date and the difference between the closing price and the local minimum price as two elements in the vector of quantitative characteristics. In this study, we calculate the local maximum and minimum prices based on the past 5, 10, 20, 50, 100, and 150 days prior to the current date, and the univariate SBTR with the TRB is thus denoted as TRBp, where $p=5, 10, 20, 50, 100, 150$. The total is then 6 for the univariate SBTRs with the TRB. As for the univariate SBTRs with the combinations of shorter- and longer-term VMAs, they are denoted by VMA$s-l$, where $s=1, 5, 10, 20, 50, 100$, $l=5, 10, 20, 50, 100, 150$, and $s<l$. The value for VMA$s-l$ is the log difference between the shorter- and longer-term VMAs. Similar to the univariate SBTRs with the MA, the total number of univariate SBTRs with the VMA is 21. Lastly, when applying the 5-day Candlestick patterns, the vector of quantitative characteristics contains 19 elements discussed above. Overall, the total number of univariate SBTRs is 55 (21 for the MA, 6 for the RSI, 6 for the TRB, 21 for the VMA, and 1 for the 5-day Candlestick pattern).

2.3.2. *Multivariate SBTRs*

Multivariate SBTRs refer to the case where a similarity-based trading mentality is capable of processing a heterogeneous pool of information entities. In making conditional forecasts based on stochastic averaging of future returns, traders choose to prescribe the vector of quantitative characteristics with a multitude of different technical indicators. The set of the SBTRs is expandable upon any feasible combination of technical indicators; it is constrained only by the limit of one's computational power.

We demonstrate multivariate SBTRs by two sets of experiments. First, from any two of the MA, RSI, TRB, and VMA types of technical indicators, traders choose one indicator from each of them (981 rules), e.g., MA5-10 and 50-day RSI, or 10-day RSI and TRB50; traders choose one indicator from each of the MA, RSI and TRB types (756 rules), e.g., MA10-100, 100-day RSI, and TRB150; and traders choose one indicator from each of the MA, RSI, TRB, and VMA types (15,876 rules), e.g., MA20-50, 20-day RSI, TRB50, and VMA1-50. This yields a total of 17,613 multivariate SBTRs. In addition, these rules can be mixed with the 5-day Candlestick patterns by expanding the vector of quantitative characteristics with the 19 elements characterizing the 5-day Candlestick pattern. This yields another 17,613 SBTRs.

Second, we also use the following mixed strategies where the vector contains one of the following: the 5-day Candlestick pattern coupled with an indicator chosen from the MA, RSI, TRB, and VMA; all MA indicators; all RSI; all TRB; all VMA; all indicators of the

[3] See, for example, Caginalp and Laurent (1998), Marshall et al. (2006), Lu (2014), Lu et al. (2012), and Lu et al. (2015).

MA, RSI, TRB, and VMA; the past 5-day Candlestick pattern with all MA indicators; the past 5-day Candlestick pattern with all RSI; the past 5-day Candlestick pattern with all TRB; the past 5-day Candlestick pattern with all VMA indicators; and the past 5-day Candlestick pattern with all indicators. This yields a total of 64 SBTRs. Overall, the total number of the SBTRs with multiple types of technical rules is 35,290 (17,613 + 17,613 + 64).

3. Test with data-snooping adjustments

Data-snooping bias arises when the same data set is repetitively used to test for the statistical significance of the technical trading rules individually. In order to control for such bias, we employ Hansen's (2005) superior predictive ability (SPA) test. In the following, we first discuss how to calculate the strategic returns of the SBTRs and then how to adjust for data-snooping bias when examining the predictive ability of the SBTRs.

3.1. Strategic returns of SBTRs

Let *sign*(.) be an indicator function such that $\mathrm{sign}(\widehat{y}_t^s)$ indicates whether a similarity-based trader should enter a long or short position according to the stochastic averaging predictor $\widehat{y}_t^s$. Specifically, $\mathrm{sign}(\widehat{y}_t^s) = 1$ or -1 indicates a buy or sell signal when the stochastic averaging predictor $\widehat{y}_t^s$ predicts a positive or negative next 1-day (daily) or 5-day (weekly) future returns y_t. The strategic returns of the SBTRs, denoted by μ_t, can thus be defined by $\mu_t = \mathrm{sign}(\widehat{y}_t^s)y_t$.

For the three types of strategies considered in this paper—daily SBTRs, weekly SBTRs with the MYR exit strategy, and weekly SBTRs with the CL exit strategy—the strategic returns, realized at observation time t are computed as follows:

$$y_t^d = ln(\frac{C_t}{O_t}) \tag{3}$$

$$y_{n,t}^{\mathrm{MYR}} = ln(\frac{C_{t+n-1}}{O_t}) \tag{4}$$

$$y_{n,t}^{\mathrm{CL}} = \frac{\sum_{i=0}^{n-1} ln(\frac{C_{t+i}}{O_t})}{n} \tag{5}$$

where y_t^d denotes the realized return of a daily SBTR and is computed as the log difference between the closing price and the opening price on the same trading day t. For a weekly SBTR with the MYR exit strategy, the realized weekly return, $y_{n,t}^{\mathrm{MYR}}$, is the log difference between the closing price C_{t+n-1} on the last trading day of the week and the opening price O_t on the first trading day of the week, where n denotes the number of trading days within a week. For a weekly SBTR with the CL exit strategy, the similarity-based trader is assumed to enter a long or short position with n futures contracts and close them out one by one across some evenly spaced, predetermined time points $t, \ldots, t+n-1$, and the realized weekly return, $y_{n,t}^{\mathrm{CL}}$, is calculated as the average daily realized returns within a week.

Finally, once the strategy returns are calculated, the performance measure for an SBTR will be its mean return $\overline{\mu}$ calculated as follows,

$$\overline{\mu} = \sum_{t=1}^{N} \mu_t \Big/ N \tag{6}$$

where $\mu_t = \mathrm{sign}(\widehat{y}_t^s)y_t$ with $y_t \in \{y_t^d, y_{n,t}^{\mathrm{MYR}}, y_{n,t}^{\mathrm{CL}}\}$ as defined by (4), (5), and (6); N is the actual number of trading days or weeks involved.

3.2. Data-snooping adjustments

To test the null hypothesis that, among the set of SBTRs, none of them can generate significantly positive returns, one can employ White's (2000) reality check (RC) test to control for data-snooping bias. However, the RC test may be conservative because its null distribution is obtained under a least favorable configuration of parameter values. Moreover, the RC test may lose power when too many poor and irrelevant technical trading rules are included (Hansen, 2005; Hsu et al., 2010, 2014). To avoid the least favorable configuration and to improve the power property of the RC test, Hansen (2005) proposes the SPA test based on a recentering method.

To conduct the SPA test in our case, we formally let the performance measure of the k-th SBTR be the mean return of it, $\overline{\mu}_k = \sum_{t=1}^{N} \mu_{k,t}/N$ for $k = 1, \ldots, K$ following the literature on the profitability of technical trading rules (Sullivan et al., 1999; Hsu and Kuan, 2005; Park and Irwin, 2010). The test statistic of Hansen's (2005) SPA test is defined as:

$$t^{SPA} = max(max_{k=1,\dots,K}\frac{\sqrt{N}\overline{\mu}_k}{\widehat{\sigma}_k}, 0) \tag{7}$$

where $\widehat{\sigma}_k^2$ is a consistent estimator of $\sigma_k^2 = \text{var}\left(\sqrt{N}\,\overline{\mu}_k\right)$.[4] Following Hansen (2005), we apply the stationary bootstrap of Politis and Romano (1994) to approximate the null distributions. To be specific, for $b = 1, \dots, B$, let $\overline{\mu}_k^b$ denote the sample mean of the b-th bootstrap sample. Define the recentering mean as $\widehat{\mu}_k = \overline{\mu}_k 1(\sqrt{N}\overline{\mu}_k \le -\widehat{\sigma}_k\sqrt{2loglog(N)})$, where $1(E)$ denotes the indicator function of the event E. The bootstrapped null distribution is given by:

$$t_b^{SPA} = max(max_{k=1,\dots,K}\frac{\sqrt{N}(\overline{\mu}_k^b - \overline{\mu}_k + \widehat{\mu}_k)}{\widehat{\sigma}_k}, 0). \tag{8}$$

The p-value of the SPA test is then approximated by $p^{SPA} = \sum_{b=1}^{B}\frac{1(t_b^{SPA} > t^{SPA})}{B}$, the proportion of times when the resampling statistics are larger than the test statistic. For a given significance level α, we will reject the null when $p^{SPA} < \alpha$ and conclude that there exists at least one SBTR that can generate a positive mean return.

Regarding the choice of the total number of bootstrap resamples B, and the probability parameter q for the stationary bootstrap, we follow Sullivan et al. (1999), and Park and Irwin (2010) to set $B = 500$ and $q = 0.1$.[5] Note that changing these parameters yields similar empirical results.

4. Empirical results

4.1. Data

Because the sample periods of the available data do not match, we test the profitability of the SBTRs against the historical prices of nineteen futures markets over two different sample periods. The first sample period ranges from 1995/01/01 to 2015/12/31, and forms our study sample "Group 1" (G1). G1 sample comprises futures markets of the corn, soybean, wheat, live cattle, lumber, cocoa, sugar, silver, oil, S&P 500, T-Bills, Eurodollar, YEN and GBP. On the other hand, the study sample "Group 2" (G2) represents the second sample period ranging from 2005/01/01 to 2015/12/31, and consists of the E-mini S&P, E-mini NASDAQ, EUR and AUD futures.[6]

G1 sample includes historical price data available for at least ten years before 1995/01/01, and G2 sample contains historical prices available for at least five years before 2005/01/01. The data availability allows for a maximum 10-year moving time window of G1 sample and a maximum 5-year moving time window of G2 sample for similarity search. Thus, for G1 sample, the choice of time length, m, as in Eq. (1), will take on a value of 250, 750, 1250 or 2500, so as to represent the 1-, 3-, 5- and 10-year moving windows, respectively. Similarly, for G2 sample the choice of time length for a moving window is set to 250, 750, or 1250, which correspond to 1, 3, and 5 years. With all feasible combinations of moving-window time lengths accounted for, the numbers of SBTRs total 141,380 ($(55 + 35, 290) \times 4$) and 106,035 ($(55 + 35, 290) \times 3$) for G1 and G2 samples, respectively.

The historical price data for the nineteen futures markets is obtained from the Quandl database which includes 78 futures contracts that account for 90% of US trading volume and provides several algorithmic approaches to create continuous contracts subject to several roll-over methods. For the empirical tests of daily SBTRs, we use the data based on the method that rolls over to the new contract on the last trading day of the expiring contract. Since the daily SBTRs assume that investors enter a long or short position at the opening price on the next day according to the signal generated by the similarity-based predictors and close the position at the closing price on the same day, the roll-over method asserts that investors open and close the positions of the same futures contracts.

For the empirical tests of weekly strategies, we construct a new futures prices series by applying two continuous futures prices obtained from the Quandl database. The Quandl database provides the "open interest switch Method" that rolls over to the back month

[4] We follow Hsu and Kuan (2005) to compute the consistent estimator of σ_k^2 based on the bootstrap resample: $\widehat{\sigma}_k^2 = \frac{1}{B}\sum_{b=1}^{B}\left(\overline{\mu}_k^b - \overline{\overline{\mu}_k^b}\right)^2$, where $\overline{\overline{\mu}_k^b}$ is the average of $\overline{\mu}_k^b$ over b.

[5] The number of bootstrap samples B may influence the accuracy of the estimated p-values. However, Brock et al. (1992) and Kho (1996) show that their estimated bootstrap p-values are insensitive to the bootstrap size B when the number of bootstrap samples goes beyond 500.

[6] The list of futures markets that we choose is close to that of Park and Irwin (2010). However, we exclude the pork bellies and Mark futures due to data availability and include in addition two financial futures (E-mini S&P and E-mini NASDAQ) and two currency futures (EUR and AUD). The selected nineteen actively traded futures markets represent each major group of futures contracts: grains (corn, soybeans, and wheat), a meat (live cattle), softs (cocoa, sugar, and lumber), metals (silver and copper), an energy (oil), currencies (YEN, GBP, EUR, and AUD), interest rate (treasury-bills and the Eurodollar), and three equity index (S&P 500, E-mini S&P, and E-mini NASDAQ). Moskowitz et al. (2012) include a boarder data set in attempt to construct a cross-sectional time-series momentum (TSM) factor and a diversified TSM strategy across all futures markets. However, our paper differs Moskowitz et al. (2012) in that we focus on technical indicators that are usually applied to high-frequency data. Also, we evaluate the performance of SBTR for each futures market. It turns out that the set of technical indicators used to form the vector of quantitative characteristics of the best SBTR for each futures market are different from each other. Unlike Moskowitz et al. (2012), it is hard to find a unified trading rule applicable to each futures market under the similarity-based approach. Therefore, our paper focuses on examining the applicability and the profitability of the similarity-based approach with technical indicators for each futures market rather than making attempt to construct a cross-sectional or a diversified similarity-based strategy.

Table 1
Descriptive statistics of daily futures returns.

Sample period	Full sample period				Sub-period 1				Sub-period 2			
Market	Mean	Std. Dev.	*t*-stat	No.	Mean	Std. Dev.	*t*-stat	No.	Mean	Std. Dev.	*t*-stat	No.
Corn	7.04	25.28	1.28	5266	5.05	20.67	0.81	2766	9.23	29.56	0.99	2500
Soybean	14.08	22.59	2.86	5268	12.63	21.22	1.98	2769	15.70	24.02	2.07	2499
Wheat	−18.93	24.93	−3.44	5142	−8.47	22.57	−1.25	2768	−31.12	27.42	−3.50	2374
Live Cattle	−6.80	13.05	−2.39	5263	1.18	13.18	0.30	2767	−15.64	12.88	−3.84	2496
Lumber	−30.29	25.10	−5.54	5266	−12.23	24.30	−1.68	2773	−50.39	25.90	−6.14	2493
Cocoa	10.90	25.58	1.95	5229	20.21	25.80	2.59	2738	0.67	25.32	0.08	2491
Sugar	−0.66	31.06	−0.10	5231	25.43	30.03	2.80	2739	−29.34	32.05	−2.89	2492
Copper	12.56	20.03	2.08	2747	30.45	19.20	3.90	1508	−9.23	20.92	−0.98	1239
Silver	−2.86	21.69	−0.60	5247	2.33	15.47	0.50	2751	−8.58	26.92	−1.01	2496
Oil	6.61	30.89	0.98	5246	16.97	29.77	1.89	2750	−4.81	32.06	−0.47	2496
S&P500	4.29	16.71	1.18	5271	6.09	16.89	1.20	2770	2.29	16.51	0.44	2501
E-mini S&P	6.28	19.64	1.06	2752	0.70	22.63	0.08	1512	13.08	15.23	1.91	1240
E-mini NASDAQ	7.05	18.00	1.30	2751	3.41	19.10	0.44	1512	11.48	16.58	1.54	1239
T-Bills	3.54	5.16	3.11	5125	3.10	5.42	1.90	2754	4.06	4.85	2.58	2371
Eurodollar	0.22	0.68	1.47	5253	0.26	0.78	1.10	2749	0.18	0.56	1.00	2504
YEN	−0.84	10.74	−0.36	5274	−2.16	11.40	−0.63	2771	0.62	9.96	0.20	2503
GBP	−0.20	8.59	−0.11	5275	0.89	8.02	0.37	2772	−1.41	9.18	−0.48	2503
EUR	−2.37	9.67	−0.81	2755	−0.32	10.09	−0.08	1515	−4.87	9.14	−1.19	1240
AUD	3.41	13.52	0.84	2753	7.23	15.52	1.15	1513	−1.26	10.58	−0.26	1240

The table presents the summary statistics for the unconditional daily returns on futures. The full sample period tested is from 1995/01/01 to 2015/12/31 for the following futures markets: corn, soybean, wheat, live cattle, lumber, cocoa, sugar, silver, oil, S&P 500, T-Bills, Eurodollar, YEN and GBP (G1 sample), and the sample period is from 2005/01/01 to 2015/12/31 for copper, E-mini S&P, E-mini NASDAQ, EUR and AUD (G2 sample). We also divide the full sample period into two sub-periods with roughly equal lengths to examine the robustness of the SBTR returns. The two sub-periods for G1 sample include 1995–2005 and 2006–2015, and they are 2005–2010 and 2011–2015 for G2 sample. The mean returns and the standard deviations are annualized and expressed as percentages. The number of observations is denoted by No.

contract (second shortest time to expiry) when the open interest of the back month contract exceeds that of the front contract (the contract which has the shortest time to expiry on any date). However, our weekly strategies assume that investors always enter a position on the first trading day in the next week following the buy/sell signals. If the roll-over day of the open interest switch method is not the first trading day in a week, the investors would open and close the positions with different futures contracts.

To address this problem, we construct a new futures prices series by applying two continuous futures prices obtained from the Quandl database. Specifically, we assume that when the investors observe that the open interest of the back month contract exceeds that of the front contract, they close the position of the front contract on the last trading day of the current week, and then open a new position of the back month contract on the first trading day of the next week. This roll-over method is applicable in practice and assures that the investors open and close the positions of the same futures contracts.

Table 1 reports summary statistics for the annualized means and standard deviations of unconditional daily returns across the nineteen futures markets and across the two sub-periods. Daily returns are calculated as the log differences between the opening and closing prices of the same trading day, so as to comply with the daily strategies of SBTRs. Differential characteristics in the return distributions therein, across the futures markets, can clearly be identified: The annualized mean returns range from −30.29 percent for lumber to 14.08 percent for soybean; and the annualized standard deviations range from 0.68 percent for the Eurodollar to 31.06 percent for sugar. Within each market, the statistical properties of the return distributions across different sub-periods also vary. Sugar futures, for example, have their annualized mean returns ranging from −29.34 percent to 25.43 percent while their annualized standard deviations range from 30.03 percent to 32.05 percent across the sub-periods.

4.2. *Performance evaluation*

Table 2 presents, for each futures market, the annualized mean returns of the best-performing daily SBTRs identified using the whole sample period. The second column of Table 2 shows the quantitative characteristics of these selected strategies, which include the types of technical indicators, and the adopted time lengths for the moving windows. For example, the winning SBTR for corn futures exhibits the following quantitative characteristics: it uses a 10-year moving window, and adopts a multivariate strategy that involves an MA indicator defined by the difference between the past 10-day (short-term) MA and the past 150-day (long-term) MA, the past 150-day RSI, the difference between the closing price and the past 50-day maximum price, and the difference between the closing price and the past 50-day minimum price.

According to Table 2, the best SBTR for corn futures generates a positive annualized mean return of 24.29 percent with a 25.24 percent annualized standard deviation. The unconditional annualized mean return following the buy (sell) signals generated by the stochastic averaging predictor is 26.70 percent (−20.86 percent). The total number of buy (sell) signals comes to 3089 (2177), and the fraction of buy (sell) signals followed by positive unconditional returns is 53.32 percent (50.30 percent). The winner across the markets is the SBTR applied to lumber futures, which generates the best annualized mean return (39.61 percent) with an annualized standard deviation of 25.05 percent. Such outperformance relies on a multivariate strategy that facilitates the combination of one MA, one VMA,

Table 2
Performance of the best daily SBTRs selected during the whole sample period.

Market	Best strategy	Strategy return			Buy			Sell			Intercept						Sharpe ratio	SPA *p*-value
		Mean	Stdev	*t*-stat	Mean	No.	Buy > 0	Mean	No.	Sell > 0	α_{trad}	*t*-stat	α_{plain}	*t*-stat	α_{TSM}	*t*-stat		
Corn	MA10-150, RSI150, TRB50, 10Y	24.29	25.24	4.37	26.70	3089	53.32	−20.86	2177	50.30	21.19	3.92	22.73	4.17	20.32	3.89	0.96	3.4
Soybean	CS, MA1-20, VMA5-20, RSI50, TRB150, 10Y	24.43	22.56	4.93	21.11	4805	54.09	−58.86	463	46.65	24.68	5.00	14.04	4.00	24.70	5.06	1.08	0.2
Wheat	RSI5, VMA1-5, 1Y	24.64	24.91	4.55	11.33	1295	52.51	−29.11	3847	48.35	24.21	4.47	15.40	3.25	25.90	4.78	0.99	0.4
Live Cattle	MA10-20, VMA1-10, RSI20, TRB50, 1Y	13.80	13.03	4.88	8.95	2058	53.26	−16.91	3205	48.17	12.85	4.62	12.27	4.44	13.02	4.73	1.06	0.4
Lumber	MA1-5, VMA20-50, RSI50, TRB5, 3Y	39.61	25.05	7.24	27.44	894	53.91	−42.10	4372	46.29	39.18	7.18	18.00	4.71	39.08	7.16	1.58	0
Cocoa	MA1-5, VMA1-10, RSI10, TRB20, 10Y	25.91	25.54	4.68	22.32	4312	53.94	−42.80	917	45.58	25.28	4.56	19.14	4.40	25.29	4.62	1.01	0.2
Sugar	MA100-150, VMA50-100, RSI10, TRB50, 3Y	34.32	30.98	5.07	28.36	3104	55.25	−43.02	2127	46.22	30.62	4.61	34.38	5.09	29.42	4.40	1.11	0
Copper	CS, MA5-50, VMA20-100, RSI5, TRB5, 3Y	26.90	19.97	4.51	25.71	2108	64.37	−30.84	639	49.30	26.72	4.51	19.95	3.96	25.45	4.40	1.35	1.4
Silver	MA1-20, VMA1-150, RSI20, TRB10, 3Y	15.66	21.67	3.33	12.72	2640	71.63	−18.64	2607	65.67	13.47	3.05	15.51	3.33	16.39	3.58	0.72	40.2
Oil	MA5-20, VMA5-100, RSI50, TRB20, 10Y	30.41	30.83	4.59	22.75	4269	53.27	−63.91	977	46.37	23.56	3.80	27.29	4.58	26.20	4.15	0.99	0.6
S&P500	CS, MA10-20, VMA1-5, RSI100, TRB100, 3Y	12.31	16.69	3.37	12.96	3374	55.10	−11.14	1897	51.77	12.20	3.33	12.04	3.27	12.64	3.55	0.74	61.2
E-mini S&P	MA1-5, VMA1-5, RSI100, TRB100, 5Y	15.53	19.62	2.67	13.69	2192	56.20	−22.74	560	54.29	15.09	2.61	14.12	2.41	15.19	2.66	0.79	48.2
E-mini NASDAQ	MA1-5, VMA10-20, 5Y	15.76	17.98	2.81	13.11	2393	55.24	−33.48	358	50.28	15.91	2.86	11.58	2.47	15.50	2.78	0.88	36.4
T-Bills	MA1-10, VMA1-5, RSI20, TRB5, 5Y	5.09	5.16	4.48	4.86	4551	55.92	−6.89	574	49.83	4.96	4.40	2.50	3.05	5.15	4.56	0.99	1.4
Eurodollar	CS, MA50-150, VMA20-150, RSI150, TRB20, 3Y	0.44	0.68	2.94	0.41	4178	64.77	−0.53	1075	56.84	0.28	2.04	0.49	2.55	0.41	3.08	0.64	43.0
YEN	MA5-10, VMA20-50, RSI5, TRB50, 1Y	5.49	10.74	2.35	4.93	2489	52.95	−5.99	2785	48.08	4.92	2.17	5.53	2.36	4.78	2.23	0.51	90.6
GBP	MA50-100, VMA5-20, RSI20, TRB5, 10Y	4.59	8.58	2.46	3.37	3438	51.54	−6.88	1837	48.45	3.56	1.92	4.63	2.51	4.51	2.40	0.53	86.0
EUR	MA10-20, VMA5-20, RSI150, TRB150, 5Y	7.25	9.66	2.50	3.62	1856	51.83	−14.74	899	47.94	7.04	2.44	7.92	2.88	6.90	2.41	0.75	64.6
AUD	MA1-50, VMA5-150, RSI50, TRB5, 5Y	12.59	13.50	3.07	9.41	2340	54.15	−30.62	413	48.67	10.96	2.81	11.17	2.90	12.32	3.08	0.93	27.2

This table reports the annualized mean returns of the best SBTRs selected during the whole sample period for each futures market. The daily SBTRs assume that investors enter a long or short position at the opening price on the next day according to the signal generated by the similarity-based predictors and close the position at the closing price of the same day. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs. The fractions of buy (sell) signals followed by positive unconditional returns are denoted by Buy(Sell) > 0 and expressed as percentages. The mean returns and the standard deviations are annualized and reported as percentages. The *p*-values of Hansen's (2005) SPA test are also expressed as percentages. The number of days on which the similarity-based predictors generate buy (sell) signals is denoted by No. The *t*-statistics are all adjusted for serial dependence using the Newey and West's (1987) method. The α_{trad},α_{plain}, andα_{TSM} defined by Eq. (9) are the intercepts from regressing the returns of the best SBTR onto the returns of the corresponding non-similarity-based technical strategy, the corresponding naïve long-only strategy, and the corresponding TSM strategy of Moskowitz et al. (2012), respectively.

Table 3
Performance of the best weekly SBTRs with the MYR exit strategy selected during the whole sample period.

Market	Best strategy	Strategy return			Buy			Sell			Intercept						Sharpe ratio	SPA *p*-value
		Mean	Stdev	*t*-stat	Mean	No.	Buy > 0	Mean	No.	Sell > 0	α_{trad}	*t*-stat	α_{plain}	*t*-stat	α_{TSM}	*t*-stat		
Corn	MA1-150, VMA5-20, RSI20, TRB150, 1Y	11.13	22.15	2.31	13.08	410	53.34	−9.86	627	50.11	10.94	2.27	11.06	2.30	10.11	2.14	0.50	81.4
Soybean	MA5-20, VMA5-50, 3Y	8.99	19.91	2.09	7.97	773	51.95	−11.96	263	50.04	9.31	2.19	7.47	2.06	8.63	2.04	0.45	72.8
Wheat	MA1-5, VMA10-50, RSI5 TRB100, 1Y	21.35	25.49	3.89	10.12	335	52.27	−26.71	701	47.53	20.49	3.77	18.34	3.36	21.75	4.00	0.84	7.4
Live Cattle	CS, MA1-150, VMA5-150, RSI100 TRB150, 10Y	13.32	12.63	4.84	6.97	478	51.36	−18.80	554	48.52	13.33	4.84	13.17	4.79	13.23	4.82	1.05	0.4
Lumber	MA100-150, VMA1-100, 5Y	34.14	24.70	6.36	17.50	123	53.75	−36.38	910	46.43	33.78	6.40	10.77	3.26	33.91	6.36	1.38	0
Cocoa	MA1-10, VMA10-20, RSI10, TRB10, 1Y	18.24	25.40	3.31	21.24	603	53.22	−14.00	427	49.67	18.23	3.30	17.86	3.24	18.36	3.35	0.72	25.8
Sugar	MA20-100, RSI10,1Y	30.60	29.42	4.76	22.49	437	53.75	−36.58	593	48.50	27.87	4.39	28.72	4.56	27.39	4.36	1.04	1.0
Copper	CS, MA1-5, VMA10-20, RSI50, TRB20, 3Y	35.81	27.27	4.37	35.05	348	54.77	−37.27	180	46.90	28.11	3.75	32.88	4.10	29.60	3.90	1.31	2.0
Silver	CS, MA10-100, VMA1-5, RSI5, TRB10, 5Y	12.46	24.29	2.33	10.34	724	60.66	−17.48	305	53.70	12.27	2.30	11.51	2.46	12.44	2.33	0.51	70.2
Oil	MA20-50, VMA5-20, RSI10, TRB150, 1Y	40.74	31.29	6.03	34.94	664	55.12	−51.18	369	47.07	36.78	5.54	40.72	6.01	33.09	5.14	1.30	0
S&P500	MA5-10, VMA20-100, 1Y	12.86	18.76	3.21	14.89	729	55.95	−7.94	302	50.80	13.00	3.25	13.12	3.24	12.78	3.30	0.69	10.6
E-mini S&P	MA1-20, VMA20-50, RSI5, TRB10, 3Y	15.01	19.53	2.63	12.91	466	56.95	−27.75	77	52.73	15.01	2.63	15.43	2.67	14.91	2.76	0.77	25.4
E-mini NASDAQ	CS, MA50-100, VMA10-20, RSI20, TRB150, 3Y	15.09	20.68	2.46	12.33	502	55.60	−48.40	42	49.04	10.79	1.94	13.01	2.19	13.81	2.31	0.73	22.8
T-Bills	MA20-100, VMA5-20, RSI100, TRB100, 10Y	4.35	5.52	3.59	3.93	990	54.83	−14.17	43	52.31	4.35	3.60	1.54	2.60	4.26	3.51	0.79	5.6
Eurodollar	MA10-100, VMA1-100, 10Y	0.48	0.62	3.53	0.45	1010	59.26	−2.11	20	59.80	0.48	3.50	0.11	2.16	0.47	3.48	0.78	7.8
YEN	MA1-50, VMA1-10, RSI50, TRB50, 1Y	5.37	7.35	3.36	5.09	425	58.44	−5.56	610	48.59	5.10	3.28	5.19	3.26	5.37	3.37	0.73	28.6
GBP	CS, MA1-10, VMA100-150, RSI5, TRB5, 10Y	5.98	6.34	4.28	5.74	941	58.73	−8.43	90	57.14	5.98	4.45	2.32	2.83	6.00	4.29	0.94	2.0
EUR	MA1-10, VMA10-20, RSI50, TRB150, 3Y	6.74	9.59	2.30	4.12	321	52.46	−10.68	214	48.04	6.99	2.40	7.06	2.46	5.30	1.96	0.70	58.8
AUD	MA5-10, VMA1-5, RSI10, TRB10, 5Y	10.06	8.81	3.70	6.69	467	67.78	−32.91	69	53.20	9.30	3.49	9.33	3.81	8.98	3.51	1.14	5.6

This table reports the annualized mean returns of the best weekly SBTRs with the MYR exit strategy selected during the whole sample period for each futures market. The weekly SBTRs with the MYR exit strategy assume that investors enter a long or short position at the opening price on the start date of the next week according to the signal generated by the similarity-based predictors and close the position at the closing price at the end of that week. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs. The fractions of buy (sell) signals followed by positive unconditional returns are denoted by Buy(Sell) > 0 and expressed as percentages. The mean returns and the standard deviations are annualized and reported as percentages. The *p*-values of Hansen's (2005) SPA test are also expressed as percentages. The number of days on which the similarity-based predictors generate buy (sell) signals is denoted by No. The *t*-statistics are all adjusted for serial dependence using the Newey and West's (1987) method. The α_{trad},α_{plain}, and α_{TSM} defined by Eq. (9) are the intercepts from regressing the returns of the best SBTR onto the returns of the corresponding non-similarity-based technical strategy, the corresponding naïve long-only strategy, and the corresponding TSM strategy of Moskowitz et al. (2012), respectively.

Table 4
Performance of the best weekly SBTRs with the CL exit strategy selected during the whole sample period.

Market	Best strategy	Strategy return			Buy			Sell			Intercept						Sharpe ratio	SPA *p*-value
		Mean	Stdev	*t*-stat	Mean	No.	Buy > 0	Mean	No.	Sell > 0	α_{trad}	*t*-stat	α_{plain}	*t*-stat	α_{TSM}	*t*-stat		
Corn	MA10-20, VMA10-50, RSI50, TRB100, 1Y	30.40	15.43	9.41	38.26	437	63.62	−25.01	637	39.25	30.40	9.50	30.44	9.42	30.42	9.50	1.97	0
Soybean	MA5-10, VMA5-20, RSI50, TRB150, 1Y	27.55	13.70	9.59	26.82	658	63.07	−28.71	416	37.50	27.55	9.58	26.46	9.02	27.54	9.58	2.01	0
Wheat	MA5-10, VMA5-20, RSI100, TRB150, 1Y	30.91	17.19	8.68	37.89	329	61.40	−27.83	745	37.45	30.91	8.67	29.16	8.06	30.92	8.67	1.80	0
Live Cattle	MA10-150, VMA20-50, 1Y	18.01	8.11	10.43	17.43	500	63.20	−18.51	574	40.42	18.01	10.36	17.85	10.31	17.75	10.36	2.22	0
Lumber	MA20-50, VMA10-50, 1Y	41.77	17.36	11.29	26.03	412	57.52	−51.56	662	35.35	41.77	11.16	36.02	9.46	41.46	11.16	2.41	0
Cocoa	CS, MA10-20, VMA1-20, RSI50, TRB100, 10Y	20.46	18.22	5.17	21.59	622	57.72	−18.89	447	43.18	20.46	5.19	19.45	4.98	20.40	5.19	1.12	0
Sugar	MA5-10, RSI5, TRB20, 10Y	34.41	18.62	8.31	27.84	566	58.30	−41.80	503	37.18	34.41	8.30	34.23	8.31	34.39	8.30	1.85	0
Copper	MA1-10, VMA50-100, RSI50, TRB50, 1Y	30.18	17.87	5.82	29.84	274	59.49	−30.53	272	40.81	30.18	5.92	30.17	5.81	29.33	5.92	1.69	0.2
Silver	MA20-50, VMA50-100, 1Y	25.85	17.21	7.13	24.31	531	61.02	−27.36	541	43.81	25.85	7.34	25.98	7.25	26.14	7.34	1.50	0
Oil	MA50-100, VMA10-50, RSI50, TRB5, 1Y	35.01	20.13	8.08	26.30	679	57.44	−50.09	392	38.78	35.01	7.99	35.04	8.15	33.89	7.99	1.74	0
S&P500	MA10-20, VMA20-50, 1Y	21.75	10.90	8.96	18.07	778	61.83	−31.45	295	37.97	21.75	8.95	21.67	8.43	21.04	8.95	1.99	0
E-mini S&P	MA1-20, VMA20-50, RSI100, TRB20, 3Y	18.94	11.43	5.46	13.71	460	57.39	−45.97	89	34.83	18.94	5.46	18.92	5.04	18.61	5.46	1.66	0
E-mini NASDAQ	MA1-10, RSI50, TRB5, 1Y	19.66	12.22	5.33	16.24	438	58.68	−33.15	111	43.24	19.66	5.26	18.73	4.46	18.64	5.26	1.61	0.4
T-Bills	MA20-50, VMA20-50, 1Y	6.70	3.48	9.11	5.94	826	62.11	−9.21	248	35.89	6.70	8.97	5.51	7.83	6.72	8.97	1.92	0.2
Eurodollar	MA5-20, VMA20-100, RSI150, TRB100, 1Y	0.87	0.42	9.44	0.79	842	61.16	−1.20	232	36.21	0.87	9.40	0.72	6.64	0.87	9.40	2.08	0
YEN	CS, MA20-50, VMA50-150, RSI5, TRB20, 1Y	8.81	6.05	6.46	9.96	457	57.77	−7.95	616	40.10	8.81	6.64	8.84	6.50	8.72	6.64	1.46	0
GBP	MA5-10, VMA20-50, RSI150, TRB150, 1Y	7.49	4.95	6.71	7.30	685	61.17	−7.83	389	42.16	7.49	6.60	7.15	6.09	7.44	6.60	1.51	0
EUR	MA50-100, VMA20-50, RSI5, TRB150, 1Y	11.34	6.25	6.12	9.91	288	60.42	−12.92	259	36.29	11.34	6.46	11.14	6.25	11.60	6.46	1.81	0
AUD	MA50-100, VMA20-150, RSI5, TRB50, 1Y	12.44	7.67	5.51	11.98	358	62.57	−13.29	189	42.33	12.44	5.54	12.56	5.46	12.52	5.54	1.62	0.6

This table reports the annualized mean returns of the best weekly SBTRs with the CL exit strategy selected during the whole sample period for each futures market. The weekly SBTRs with the CL exit strategy assume that investors enter a long or short position with n futures contracts at the opening price on the start date of the next week according to the signal generated by the similarity-based predictors, and then close them out one by one at the closing price on each day in that week, where n equals the number of trading days in that week. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs. The fractions of buy (sell) signals followed by positive unconditional returns are denoted by Buy(Sell) > 0 and expressed as percentages. The mean returns and the standard deviations are annualized and reported as percentages. The *p*-values of Hansen's (2005) SPA test are also expressed as percentages. The number of days on which the similarity-based predictors generate buy (sell) signals is denoted by No. The *t*-statistics are all adjusted for serial dependence using the Newey and West's (1987) method. The α_{trad},α_{plain}, and α_{TSM} defined by Eq. (9) are the intercepts from regressing the returns of the best SBTR onto the returns of the corresponding non-similarity-based technical strategy, the corresponding naïve long-only strategy, and the corresponding TSM strategy of Moskowitz et al. (2012), respectively.

one RSI, and one TRB indicator to identify scenario resemblances of the present and to carry out stochastic averaging predictions based on a 3-year moving window.

The Intercept column of Table 2 shows the values of three intercepts, α_{trad}, α_{plain}, and α_{TSM} to test the added value of similarity-based approach. For each futures market, we regress the returns of the best SBTR onto the returns of the corresponding non-similarity-based technical strategy, the corresponding naive long-only strategy, and the corresponding time-series momentum (TSM hereafter) strategy of Moskowitz et al. (2012), respectively. For the corresponding non-similarity-based strategy, we select from the elements of the vector of quantitative characteristics of the best SBTR the technical indicator that delivers the best performance. For the corresponding naive long-only strategy, we use the unconditional returns on futures defined by Eqs. (3), (4), and (5) for the daily SBTRs, the weekly SBTRs with the MYR exit strategy, and the weekly SBTRs with the CL exit strategy, respectively. For the corresponding TSM strategy, we first calculate the past 60-days (for the daily strategies in Table 2) and 20-weeks (for the weekly strategies in Tables 3 and 4) cumulative returns at time t ($r_{past,t}$) for each futures market. If the sign of the past cumulative return is positive, we enter a long position and otherwise, a short position. The return of TSM strategy is then calculated as $r_{TMS,t} = sign(r_{past,t}) * y_t$, where y_t is defined by Eqs. (3), (4), and (5) in Tables 2–4, respectively. Specifically, for each futures market we estimate the following regression:

$$r_{\mathrm{SBTR},t} = \alpha + \beta r_t + \varepsilon_t \tag{9}$$

where $r_{SBTR,t}$ is the return of the best SBTR at time t. α is α_{trad}, α_{plain}, and α_{TSM}, when r_t refers to $r_{trad,t}$, $r_{plain,t}$, and $r_{TSM,t}$, respectively.

Table 2 also reports the Sharpe ratio of the best SBTR for each futures market. The Sharpe ratio is calculated as the annualized mean return of the best SBTR divided by its annualized standard deviation. All the t-statistics in Tables 2–10 are adjusted for the serial dependence according to the Newey and West's (1987) method. The t-statistics following the Mean and Stdev columns of the strategy return in Tables 2–10 are for the null hypothesis that the mean return of each strategy is zero. The t-statistics following the α_{trad}, α_{plain}, and α_{TSM} in Tables 2–4 are for the null hypothesis that these intercepts are zero, respectively.

All the Newey and West's (1987) adjusted t-statistics under the Strategy return column of Table 2 are larger than 2.326, implying that the returns of the best SBTRs are all positive at the 1 percent significance level after the serial dependence adjustment. The t-statistics for the α_{trad} under the Intercept column are generally larger than 2.326, except for the Eurodollar, YEN and GBP futures markets. These results indicate that the best SBTRs generally add value to the traditional non-similarity-based technical trading rules. In addition, the t-statistics for the α_{plain} and α_{TSM} are larger than 2.326, except for the YEN futures, suggesting that the best SBTRs are also value-added comparing to the corresponding naive long-only strategies and the TSM of Moskowitz et al. (2012).

The rightmost column presents the p-values of Hansen's (2005) SPA test for those best-performing daily SBTRs. The results show that in ten out of the nineteen futures markets, the best-performing daily SBTRs are robust to the data-snooping adjustments at the 5 percent significance level.

Tables 3 and 4 examine the return predictive ability of the best-performing weekly SBTRs under the MYR and CL exit strategies, respectively. Table 3 shows that among six out of the nineteen futures markets, the best-performing weekly SBTRs with the MYR exit strategy generate positive returns at the 5 percent significance level based on Hansen's SPA test (ten out of the nineteen futures markets if we use a 10 percent significance level), which are weaker than the results for the daily SBTRs in Table 2. The t-statistics for the α_{trad}, α_{plain}, and α_{TSM} also suggest a less significant added value of the weekly SBTRs with the MYR exit strategy than the daily SBTRs. For example, while most of the best-performing daily SBTRs are value-added strategies at the 1 percent significance level according to their t-statistics for the α_{trad}, the t-statistics of α_{trad} for four out of the nineteen best-performing weekly SBTRs with the CL exit strategy are lower than 2.326. Across the markets, the best-performing SBTR is found for oil futures where a multivariate strategy with one MA, one VMA, one RSI and one TRB indicator is adopted under a moving window of 1 years.

Table 4 reports the annualized mean returns of the best-performing weekly SBTRs with the CL exit strategy. All strategies generate profits that are significant at the 1 percent level after the adjustment of the data-snooping biases. Compared to the results in Tables 2 and 3, the weekly SBTRs with the CL exit strategy seem to generate the most profound returns and add the most significant value to the traditional non-similarity-based technical trading rules, the naive long-only strategies, and the TSM strategies of Moskowitz et al. (2012). This finding, consistent with Lu et al. (2015), is likely to be a direct consequence of strategy returns exhibiting lower standard deviations—pointing to the role played by the CL exit strategy as a mechanism for risk sharing.

Several interesting findings can be drawn from Tables 2–4. First, the ways in which different types of trading indicators synergize in order to search (resemblances), identify (similarities) and predict (stochastic averaging returns) seem to vary across markets. However, we find that common to most of the futures markets, the outperforming SBTRs seem to rely on multivariate strategies that exploit different combinations of the MA, VMA, RSI, and TRB indicators in order to construct the vector of quantitative characteristics. For example, there are twelve futures markets in Table 2 where the best-performing daily SBTRs use the combinations of the MA, VMA, RSI, and TRB indicators. In addition, in four futures markets, the best-performing daily SBTRs exploit the 5-day Candlestick patterns combined with the MA, VMA, RSI, and TRB indicators. For the rest of the markets, the outperforming SBTRs also rely on multivariate strategies of heterogeneous indicator types. This finding suggests that similarity-based traders may consider it unwise, or even brutal, to rely solely on a single type of trading indicator to trade. The similarity-based technical trading mentality is likely to be at its best upon for those decision makers whose mental capacity allows them to process information based on a multitude of technical indicators.

Second, the fraction of buy signals followed by positive unconditional returns exceeds the fraction of sell signals followed by positive unconditional returns for all futures markets. For example, Table 2 shows that the fraction for buy signals ranges from 51.54 percent to 71.63 percent, while the fraction for sell signals ranges from 45.58 percent to 65.67 percent. According to Brock et al. (1992), the fraction of positive unconditional returns should be the same for both buy and sell signals if the signals generated by technical rules are indeed useless. Using binomial tests, we confirm that the differences in the fraction of positive returns following buy

Table 5
In- and out-of-sample performance of the best daily SBTRs selected during the first sub-period.

Market	In-sample					Out-of-sample		
	Best strategy	Annualized mean return	Stdev	*t*-stat	SPA *p*-value	Annualized mean return	Stdev	*t*-stat
Corn	MA10-20, RSI150, TRB10, 10Y	25.40	20.61	4.03	7.6	10.83	29.56	1.14
Soybean	MA50-150, VMA1-150, RSI150, TRB50, 10Y	27.52	21.16	4.28	4.6	16.62	24.03	2.20
Wheat	MA100-150, VMA1-20, RSI5, TRB50, 1Y	26.44	22.51	3.99	2.8	18.73	27.47	2.10
Live Cattle	CS, MA100-150, VMA1-150, RSI5, TRB100, 1Y	13.57	13.16	3.47	27.8	–	–	–
Lumber	MA50-150, VMA20-50, RSI50, TRB5, 10Y	31.19	24.23	4.35	1.2	48.60	25.91	5.73
Cocoa	MA5-10, VMA1-50, RSI10, TRB5, 10Y	32.67	25.75	4.28	0.0	6.60	25.33	0.82
Sugar	MA50-100, VMA1-5, RSI150, TRB5, 3Y	35.44	29.99	3.92	2.0	15.79	32.07	1.55
Copper	MA1-5, VMA5-10, RSI10, TRB150, 5Y	34.34	19.18	4.38	0.2	-7.12	20.92	-0.81
Silver	RSI150, VMA100-150, 10Y	11.08	15.46	2.43	82.8	–	–	–
Oil	CS, MA20-100, VMA5-50, RSI20, TRB10, 10Y	42.85	29.67	4.83	0.2	2.73	32.07	0.27
S&P500	CS, MA10-20, VMA1-100, RSI100, TRB5, 1Y	17.18	16.86	3.37	20.6	–	–	–
E-mini S&P	MA1-5, VMA1-10, RSI10, TRB100, 5Y	20.19	22.60	2.18	79.4	–	–	–
E-mini NASDAQ	MA1-5, VMA10-20, 5Y	19.87	19.05	2.46	51.4	–	–	–
T-Bills	MA1-5, VMA1-5, RSI10, TRB20, 3Y	5.52	5.41	3.41	18.4	–	–	–
Eurodollar	MV50-150, RSI10, TRB150, 10Y	0.55	0.78	2.36	30.0	–	–	–
YEN	MA5-10, VMA20-50, RSI5, TRB50, 1Y	8.17	11.39	2.40	91.8	–	–	–
GBP	MA10-50, VMA1-5, RSI50, TRB150, 1Y	6.44	8.01	2.74	69.8	–	–	–
EUR	MA1-10, VMA1-150, RSI150, TRB150, 3Y	9.88	10.07	2.38	68.4	–	–	–
AUD	CS, MA20-150, VMA1-10, RSI10, TRB10, 3Y	22.51	15.47	3.48	9.2	−4.98	10.57	−1.05

This table reports the performance of the best daily SBTRs selected during the first sub-period (in-sample) and the performance of these SBTRs in the second sub-period (out-of-sample). The daily SBTRs assume that investors enter a long or short position at the opening price on the next day according to the signal generated by the similarity-based predictors and close the position at the closing price of the same day. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs selected during the first sub-period. For the in-sample performance, we report the annualized mean returns, the standard deviations, the Newey and West (1987) adjusted *t*-statistics, and the SPA *p*-values. For the out-of-sample performance, we only report the annualized mean returns, the standard deviations, and the Newey and West (1987) adjusted *t*-statistics of the significant rules selected during the first sub-period. All results are expressed as percentages, except for the *t*-statistics.

and sell signals are significant, thereby rejecting the null hypothesis for their equality. This result indicates that the trading signals generated by SBTRs are of predictive ability over future probable returns.

Third, Tables 2–4 provide supportive evidence for the predictive ability of stochastic averaging predictors over future probable returns. Consistent with Park and Irwin (2010), we document favorable results of technical trading rules applied to commodity futures relative to financial futures. In particular, Table 2 shows that the best-performing daily SBTR among financial futures markets yields an annualized mean return of 15.76 percent for E-mini Nasdaq futures. On the other hand, the best-performing daily SBTR traded among commodity futures generates an annualized mean return of 39.61 percent for lumber futures. In addition, the average mean return across financial futures markets is 8.78 percent, while the average mean return across commodity futures is 25.99 percent.

Finally, when searching for past market scenario-resemblances of the present, we find that the adopted time length in fact varies across different markets. Similar experiences of the recent past—rather than those of the distant past—seem to induce greater impacts on the similarity-based traders' decision making. For example, Table 2 shows that the best-performing SBTRs for wheat, live cattle, and Yen futures utilize a moving window based on recent 1-year period (relative to a 5-year maximum), whilst for lumber, sugar, copper, silver, the S&P 500, and the Eurodollar, the best-performing SBTRs entail conducting a similarity search based on a moving window for the recent 3-year period (relative to a 10-year maximum).

Table 6
In- and out-of-sample performance of the best weekly SBTRs with the MYR exit strategy selected during the first sub-period.

Market	In-sample					Out-of-sample		
	Best strategy	Annualized mean return	Stdev	*t*-stat	SPA *p*-value	Annualized mean return	Stdev	*t*-stat
Corn	MA20-100, VMA1-100, RSI10, TRB10, 10Y	15.54	17.66	2.93	40.8	–	–	–
Soybean	MA5-10, VMA1-10, RSI20, TRB10, 5Y	18.10	19.54	3.08	21.0	–	–	–
Wheat	MA10-20, RSI100, TRB5, 1Y	22.48	21.95	3.41	7.2	−4.57	29.05	−0.49
Live Cattle	CS, MA10-20, VMA5-10, RSI5, TRB5, 10Y	15.71	13.08	3.99	3.8	8.94	12.10	2.29
Lumber	MA5-20, VMA20-50, 5Y	22.30	24.43	3.03	34.4	–	–	–
Cocoa	MA1-50, VMA10-50, RSI100, TRB50, 1Y	28.40	25.31	3.71	2.4	−10.97	25.48	-1.34
Sugar	MA20-100, VMA20-50, RSI10, TRB150, 1Y	31.98	27.40	3.86	7.2	−4.63	31.61	-0.46
Copper	MA20-50, VMA5-20, RSI10, TRB150, 3Y	54.26	31.17	4.25	1.0	−7.43	21.13	−0.75
Silver	MA1-5, VMA10-20, RSI100, TRB5, 5Y	16.60	20.55	2.67	64.5	–	–	–
Oil	MA5-20, VMA5-20, RSI10, TRB150, 1Y	47.91	29.21	5.43	0	32.22	33.48	3.00
S&P500	MA5-10, VMA20-100, 1Y	18.91	17.42	3.61	0.4	5.84	20.20	0.89
E-mini S&P	MA50-100, VMA10-20, RSI150, TRB10, 3Y	17.64	22.45	1.95	51.4	–	–	–
E-mini NASDAQ	MA1-150, VMA5-10, RSI10, TRB10, 3Y	18.02	23.62	1.90	47.8	–	–	–
T-Bills	MA20-150, VMA5-10, RSI100, TRB100, 10Y	4.15	5.81	2.37	43.0	–	–	–
Eurodollar	MA1-150, VMA1-150, RSI5, TRB150, 10Y	0.77	0.63	4.06	2.2	0.08	0.62	0.41
YEN	MA10-50, VMA1-100, RSI50, TRB50, 1Y	6.63	7.17	3.07	27.2	–	–	–
GBP	CS, MA1-5, VMA1-5, RSI20, TRB100, 10Y	8.66	6.44	4.45	0	2.40	6.22	1.20
EUR	MA5-100, VMA5-50, RSI50, TRB150, 5Y	9.48	9.98	2.34	50.6	–	–	–
AUD	MA10-20, VMA1-150, RSI10, TRB20, 3Y	14.66	9.69	3.73	4.4	0.54	7.48	0.15

This table reports the performance of the best weekly SBTRs with the MYR exit strategy selected during the first sub-period (in-sample) and the performance of these SBTRs in the second sub-period (out-of-sample). The weekly SBTRs with the MYR exit strategy assume that investors enter a long or short position at the opening price on the start date of the next week according to the signal generated by the similarity-based predictors and close the position at the closing price at the end of that week. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs selected during the first sub-period. For the in-sample performance, we report the annualized mean returns, the standard deviations, the Newey and West (1987) adjusted *t*-statistics, and the SPA *p*-values. For the out-of-sample performance, we only report the annualized mean returns, the standard deviations, and the Newey and West (1987) adjusted *t*-statistics of the significant rules selected during the first sub-period period. All results are expressed as percentages, except for the *t*-statistics.

4.3. Sub-sample analysis

For robustness checks, we perform sub-sample analyses over two sub-periods of approximately equal lengths. In the case of G1 sample, the two sub-periods are 1995–2005 and 2006–2015. For G2 sample, the two sub-periods are 2005–2010 and 2011–2015.[7]

We first follow Qi and Wu (2006) and Park and Irwin (2010) to conduct in- and out-of-sample tests. We use the first sub-period to select the best strategies for each futures market and then evaluate the performance of these best strategies during the second sub-period. Table 5 presents the in- and out-of-sample performance for the best-performing daily SBTRs selected from the first sub-period. The second column reports the quantitative characteristics of the winning strategies, including the types of technical indicators in use and the length of time adopted for the moving windows. We also report annualized mean returns, standard deviations, and the *p*-values based on Hansen's (2005) test for each best-performing SBTR in the first sub-period. Table 5 shows that the best-performing daily SBTRs generate significant profits in nine futures markets during the first sub-period at the 10 percent

[7] We follow Park and Irwin (2010) to perform the sub-sample analyses over two sub-periods of approximately equal lengths. Therefore, in the case of G1 sample, the breakpoint is 2005/12/31, and for G2 sample, it is 2010/12/31. We also consider different breakpoints (for example, 2006, 2007, 2008, 2009, or 2010 for G1 sample) to perform the in- and out-of-sample analyses and the results are qualitatively the same as the current results. The results are available from the authors upon request.

Table 7
In- and out-of-sample performance of the best weekly SBTRs with the CL exit strategy selected during the first sub-period.

Market	In-sample					Out-of-sample		
	Best strategy	Annualized mean return	Stdev	*t*-stat	SPA *p*-value	Annualized mean return	Stdev	*t*-stat
Corn	MA10-20, VMA50-100, RSI5, TRB5, 10Y	25.28	12.70	6.75	0	10.58	18.77	1.10
Soybean	MA20-50, VMA5-10, RSI150, TRB50, 1Y	26.51	13.04	6.89	0	22.80	14.65	5.07
Wheat	MA10-100, VMA5-20, RSI50, TRB100, 1Y	22.21	14.21	5.30	0.2	38.25	20.10	6.30
Live Cattle	MA10-100, VMA20-50, 1Y	18.08	8.51	7.19	0	17.66	7.65	7.83
Lumber	MA5-10, VMA5-10, RSI5, TRB50, 1Y	44.13	17.90	8.36	0	31.71	17.04	5.83
Cocoa	CS, MA100-150, VMA1-50, 10Y	25.49	17.42	4.95	0	7.17	19.16	1.20
Sugar	CS, MA5-10, RSI20, TRB20, 5Y	30.55	17.74	5.83	0	14.51	20.25	2.17
Copper	MA1-10, VMA50-100, RSI50, TRB50, 1Y	45.19	20.34	5.55	0.2	10.17	13.45	1.79
Silver	VMA5-10, TRB5, 1Y	20.25	14.71	4.67	0.6	17.66	20.06	2.88
Oil	MA20-100, VMA5-50, RSI5, TRB5, 1Y	35.56	19.47	6.18	0	23.91	21.18	3.68
S&P500	MA5-20, VMA5-20, RSI150, TRB150, 1Y	19.99	10.17	6.65	0	22.66	11.74	5.90
E-mini S&P	MA50-100, VMA1-10, RSI20, TRB5, 1Y	22.13	13.08	4.23	4.8	7.90	8.97	2.23
E-mini NASDAQ	MA1-10, RSI150, TRB5, 1Y	25.37	13.61	4.66	2.6	12.14	10.04	2.75
T-Bills	MA10-50, VMA20-50, 1Y	7.17	3.49	6.97	0	5.64	3.50	5.13
Eurodollar	MA10-50, VMA5-20, RSI20, TRB100, 1Y	0.91	0.41	7.53	0	0.54	0.44	3.76
YEN	CS, MA20-50, VMA5-100, RSI5, TRB20, 1Y	10.51	6.30	5.66	0.2	3.63	5.81	1.88
GBP	CS, MA10-150, VMA1-20, RSI150, TRB20, 1Y	7.69	4.54	5.74	0	5.87	5.42	3.21
EUR	MA50-100, VMA20-50, RSI5, TRB150, 1Y	14.84	6.58	5.63	0	6.68	5.74	2.59
AUD	MA50-100, VMA20-100, RSI5, TRB50, 1Y	17.08	8.57	4.98	0.6	5.82	6.21	2.04

This table reports the performance of the best weekly SBTRs with the CL exit strategy selected during the first sub-period (in-sample) and the performance of these SBTRs in the second sub-period (out-of-sample). The weekly SBTRs with the CL exit strategy assume that investors enter a long or short position with *n* futures contracts at the opening price on the start date of the next week according to the signal generated by the similarity-based predictors, and then close them out one by one at the closing price on each day in that week, where *n* equals the number of trading days in that week. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs selected during the first sub-period. For the in-sample performance, we report the annualized mean returns, the standard deviations, the Newey and West (1987) adjusted *t*-statistics, and the SPA *p*-values. For the out-of-sample performance, we only report the annualized mean returns, the standard deviations, and the Newey and West (1987) adjusted *t*-statistics of the significant rules selected during the first sub-period period. All results are expressed as percentages, except for the *t*-statistics.

significance level. For the out-of-sample results, we present the annualized mean returns, standard deviations, and *t*-statistics of those significant best-performing daily SBTRs selected during the first sub-period. We find that there are four out of the nine futures markets where the best daily SBTRs selected during the first sub-period can generate significant profits in the out-of-sample period at the 10 percent significance level.[8]

Tables 6 and 7 report the in- and out-of-sample results for the weekly SBTRs with the MYR and CL exit strategies, respectively. In Table 6, there are ten best-performing weekly SBTRs with the MYR exit strategy selected from the first sub-period that pass Hansen's (2005) SPA test at the 10 percent significance level. Most of the strategies cannot generate significant profits in the second sub-period. On the other hand, the weekly SBTRs with the CL exit strategy in Table 7 produce robust results in all the futures markets in the first sub-period, and in seventeen futures markets, the best-performing SBTRs selected from the first sub-period still generate profits in the second sub-period at the 10 percent significance level. The results of the in- and out-of-sample experiments suggest that the weekly SBTRs with the CL exit strategy dominate the daily SBTRs and the weekly SBTRs with the MYR exit strategy.[9]

[8] For a one-sided test, a t-statistic has to be greater than 1.29 (1.64) to be claimed significantly greater than zero at 10 percent (5 percent) significance level.

[9] The results of the daily SBTRs and the weekly SBTRs with the MYR exit strategy in Tables 2, 3, 5, and 6 show that there is an inconsistency between the results drawn from SPA *p*-values and those from in- and out-of-sample tests. That is, although Tables 2 and 3 report that most of the best SBTRs are robust after adjusting data-snooping biases, these strategies cannot profit in the out-of-sample period. While both the daily SBTRs and the weekly SBTRs with the CL exit strategy are capable of generating profits after we control for the data-snooping biases, we highlight the fact that only the weekly SBTRs with the CL exit strategy are robust to the sub-period and out-of-sample tests.

Table 8
Performance of the best daily SBTRs selected during the second sub-period.

Market	Best strategy	Annualized mean return	Stdev	*t*-stat	SPA *p*-value
Corn	MA20-150, VMA100-150, RSI50, TRB100, 3Y	32.36	29.50	3.47	23.4
Soybean	CS, MA1-5, VMA5-10, RSI50, TRB150, 10Y	31.81	23.96	4.12	1.8
Wheat	CS, MA5-50, VMA5-20, RSI150, TRB150, 10Y	38.66	27.38	4.29	0.6
Live Cattle	MA5-20, VMA10-20, RSI150, TRB50, 1Y	20.28	12.86	4.91	0.4
Lumber	MA20-50, VMA1-5, RSI150, TRB20, 1Y	60.99	25.81	7.34	0
Cocoa	MA10-20, VMA5-150, 5Y	27.37	25.26	3.43	47.4
Sugar	MA100-150, VMA20-50, RSI150, TRB50, 5Y	40.70	32.00	3.92	6.8
Copper	CS, MA1-20, VMA20-100, RSI10, TRB5, 3Y	24.04	20.87	2.61	77.2
Silver	CS, MA10-20, VMA1-150, RSI20, TRB5, 3Y	28.65	26.87	3.48	43.2
Oil	MA5-20, VMA5-100, RSI20, TRB5, 10Y	25.12	32.02	2.52	78.4
S&P500	MA1-20, VMA50-100, RSI10, TRB10, 3Y	13.18	16.49	2.50	91.2
E-mini S&P	MA10-20, VMA5-150, RSI5, TRB5, 3Y	22.60	15.19	3.32	21.2
E-mini NASDAQ	MA100-150, VMA1-5, RSI20, TRB20, 1Y	22.54	16.54	3.04	24.8
T-Bills	CS, MA1-10, VMA20-100, RSI20, TRB5, 5Y	6.65	4.84	4.15	1.4
Eurodollar	CS, MA1-10, VMA5-50, RSI20, TRB100, 5Y	0.74	0.56	4.14	8.0
YEN	CS, MA10-20, VMA5-50, RSI20, TRB150, 10Y	6.27	9.95	2.00	97.4
GBP	MA5-10, VMA5-20, RSI150, TRB5, 10Y	7.79	9.16	2.66	84.2
EUR	MA10-150, VMA5-20, RSI10, TRB150, 5Y	10.73	9.11	2.72	65.4
AUD	MA20-50, VMA5-150, RSI20, TRB50, 5Y	8.62	10.56	1.80	94.2

This table presents the performance of the best daily SBTRs selected during the second sub-period for each futures market. The daily SBTRs assume that investors enter a long or short position at the opening price on the next day according to the signal generated by the similarity-based predictors and close the position at the closing price of the same day. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs. The mean returns and the standard deviations are annualized and reported as percentages. The Newey and West (1987) adjusted *t*-statistics are denoted by *t*-stat. The *p*-values of Hansen's (2005) SPA test are expressed as percentages.

Table 9
Performance of the best weekly SBTRs with the MYR exit strategy selected during the second sub-period.

Market	Best strategy	Annualized mean return	Stdev	*t*-stat	SPA *p*-value
Corn	CS, MA20-150, RSI5, 3Y	23.56	26.33	2.78	43.2
Soybean	MA1-5, VMA10-150, RSI100, TRB10, 5Y	14.89	20.28	2.28	3.4
Wheat	MA20-150, VMA50-150, RSI10, TRB10, 3Y	30.08	28.99	3.22	10.8
Live Cattle	CS, MA10-150, VMA1-5, RSI20, TRB10, 3Y	14.60	12.08	3.75	43.6
Lumber	MA20-50, VMA1-20, RSI10, TRB50, 10Y	56.08	24.92	6.98	0
Cocoa	MA1-5, VMA50-100, RSI100, TRB20, 10Y	26.93	25.43	3.29	52.2
Sugar	MA10-100, VMA5-10, RSI20, TRB50, 10Y	47.78	31.46	4.72	14.2
Copper	MA1-150, VMA5-50, RSI5, TRB150, 5Y	23.48	21.08	2.39	99.4
Silver	MA1-5, VMA50-100, RSI10, TRB5, 1Y	20.64	27.92	2.29	79.6
Oil	MA50-150, VMA5-20, RSI10, TRB10, 3Y	42.88	33.43	3.99	15.8
S&P500	CS, MA1-10, VMA5-100, RSI20, TRB10, 10Y	16.04	20.17	2.46	90.4
E-mini S&P	MA1-100, VMA5-100, RSI5, TRB50, 5Y	20.13	14.81	2.94	32.8
E-mini NASDAQ	MA1-20, VMA10-20, RSI50, TRB20, 1Y	17.46	15.99	2.36	24.2
T-Bills	MA10-100, VMA1-20, RSI50, TRB10, 5Y	5.57	5.17	3.35	6.2
Eurodollar	MA10-100, VMA1-5, RSI100, TRB5, 5Y	0.31	0.62	1.54	6.8
YEN	CS, MA1-150, VMA1-10, RSI150, TRB20, 3Y	7.18	7.55	2.95	64.2
GBP	CS, MA50-100, VMA1-5, RSI50, TRB150, 3Y	5.13	6.21	2.57	59.2
EUR	MA50-150, VMA1-10, RSI150, TRB100, 5Y	9.35	9.03	2.23	63.4
AUD	MA1-100, RSI20, TRB50, 3Y	7.51	7.47	2.16	97.8

This table presents the performance of the best weekly SBTRs with the MYR exit strategy selected during the second sub-period for each futures market. The weekly SBTRs with the MYR exit strategy assume that investors enter a long or short position at the opening price on the start date of the next week according to the signal generated by the similarity-based predictors and close the position at the closing price at the end of that week. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs. The mean returns and the standard deviations are annualized and reported as percentages. The Newey and West (1987) adjusted *t*-statistics are denoted by *t*-stat. The *p*-values of Hansen's (2005) SPA test are expressed as percentages.

We also perform a sub-sample analysis to examine the profitability of the best-performing SBTRs selected during the second sub-period. Table 8 presents the performance of the best-performing daily SBTRs selected during the second sub-period. There are seven futures markets where the best-performing SBTRs generate profits at the 10 percent significance level. Tables 9 and 10 report the sub-sample analyses for the weekly SBTRs with the MYR and CL exit strategies, respectively. Based on Hansen's (2005) nominal *p*-value, there are only four futures markets in which the best-performing weekly SBTRs with the MYR exit strategy generate profits at the 10 percent significance level during the second sub-period, and there are nineteen when the CL exit strategy is applied. The performances of the weekly SBTRs with the CL exit strategy are still the most robust based on the sub-sample analysis, which is consistent with the

Table 10
Performance of the best weekly SBTRs with the CL exit strategy selected during the second sub-period.

Market	Best Strategy	Annualized mean return	Stdev	*t*-stat	SPA *p*-value
Corn	MA5-100, VMA20-50, 1Y	43.72	17.72	7.82	0
Soybean	MA20-100, VMA10-50, 1Y	31.74	14.32	7.19	0
Wheat	MA5-20, VMA10-20, RSI5, TRB150, 1Y	45.35	19.80	7.49	0
Live Cattle	MA10-150, VMA20-50, 1Y	18.73	7.60	8.25	0
Lumber	MA5-50, VMA50-100, 1Y	44.01	16.48	8.38	0
Cocoa	MA1-5, VMA10-20, 1Y	26.48	18.82	4.37	1.8
Sugar	MA5-10, VMA10-100, 10Y	50.99	19.03	8.63	0
Copper	MA20-50, VMA5-150, RSI10, TRB20, 5Y	23.40	13.11	4.01	5.6
Silver	MA20-50, VMA50-100, 1Y	36.74	19.53	6.29	0
Oil	MA50-100, VMA10-50, RSI50, TRB10, 1Y	40.91	20.65	6.59	0.4
S&P500	MA10-20, VMA10-50, RSI100, TRB150, 1Y	24.61	11.66	6.23	1.4
E-mini S&P	MA20-100, VMA5-20, RSI50, TRB20, 5Y	19.35	8.61	4.78	0.6
E-mini NASDAQ	MA1-5, VMA1-5, RSI20, TRB20, 1Y	19.71	9.79	4.60	0.2
T-Bills	MA20-50, VMA5-50, 1Y	7.23	3.44	6.59	0.2
Eurodollar	MA10-20, VMA10-100, RSI100, TRB150, 1Y	0.92	0.43	6.42	0.2
YEN	CS, MA20-50, VMA1-5, RSI50, TRB50, 10Y	11.04	5.62	6.06	0
GBP	CS, MA5-20, VMA100-150, RSI50, TRB150, 5Y	10.49	5.28	5.91	0.4
EUR	CS, MA20-50, VMA5-10, RSI10, TRB10, 5Y	12.86	5.52	4.84	0.8
AUD	MA50-150, VMA5-20, RSI5, TRB100, 3Y	9.61	6.11	3.37	4.4

This table presents the performance of the best weekly SBTRs with the CL exit strategy selected during the second sub-period for each futures market. The weekly SBTRs with the CL exit strategy assume that investors enter a long or short position with *n* futures contracts at the opening price on the start date of the next week according to the signal generated by the similarity-based predictors, and then close them out one by one at the closing price on each day in that week, where *n* equals the number of trading days in that week. The second column presents the combinations of technical indicators constructing the vector of qualitative characteristics and the lengths of the moving window adopted by the best SBTRs. The mean returns and the standard deviations are annualized and reported as percentages. The Newey and West (1987) adjusted *t*-statistics are denoted by *t*-stat. The *p*-values of Hansen's (2005) SPA test are expressed as percentages.

results of the data-snooping test in Table 4.

4.4. Transaction costs

Although testing the profitability of technical trading rules against index prices would seem to benefit from the data's longer available time series, testing against the futures markets generates more convincing results because the associated transactions costs are transparent and hence easy to control. Furthermore, the complications imposed by short-sale constraints (Brock et al., 1992; Sullivan et al., 1999) can be avoided.

To assess the impact of transaction costs on the best-performing SBTRs, we consider two measures of transaction cost, namely, the break-even transaction costs and the applicable commissions per round-trip trade. For the break-even transaction costs, we follow Qi and Wu (2006) to calculate the maximum one-way transaction costs for the best-performing SBTRs to break even, i.e., to eliminate all possible returns or performance (Bessembinder and Chan, 1998). The first four columns of Table 11 report the annualized mean returns, the number of round-trip trades and the maximum one-way transaction cost of the strategies for the best daily SBTRs selected from the whole sample period. The length of the whole sample period is 11 years for copper, E-mini S&P, E-mini NASDAQ, EUR and AUD futures (G2 sample) and 21 years for the rest of the futures markets (G1 sample). Taking the corn futures as an example, the annualized mean return and the number of round-trip trades for the best daily SBTR are 24.29 percent and 5266, respectively. The number of round-trip trades is equal to the number of trading days during the sample period. The maximum one-way cost to break even is 21 * 24.29 percent/(5266 * 2) = 0.0484 percent, where 5266 multiplied by 2 is the number of trades. That is, if the one-way trading cost for an investor is greater than 0.0484 percent, the SBTR may not generate a positive return. To test the profitability of technical strategies in currency markets, Qi and Wu (2006) adopt one-way costs in the range of 0.025–0.04 percent as suggested by Bessembinder (1994) who measures the bid-ask spread in the inter-bank market. We find that the range of the one-way cost is also applicable to the futures market, as Wang et al. (1997) and Wang and Yau (2000) also report a similar range of the one-way cost for seven futures markets. The fifth and sixth columns report the annualized mean returns after the transaction costs of 0.025 percent and 0.04 percent, respectively. The daily SBTRs are still profitable if the transaction cost is 0.025 percent in thirteen out of the nineteen futures markets, and the after-cost returns are still positive in eight futures markets when the transaction cost is assumed to be 0.04 percent.

Alternatively, we can consider the commission per round-trip trades to account for the transaction costs. Park and Irwin (2010) consider a range of commission costs of $12.5-$100 per futures 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 a low transaction cost 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 commission costs to the percentage deducted, we first estimate the average prices of these futures markets during the whole sample period and calculate the average contract sizes as the average prices multiplied by the point value of the contract. Then we divide the one-way commission cost (which is the commission per round-trip trade divided by 2) by the average contract size to obtain the ratio of the one-way commission to average contract size. For example, since the average price of the soybean futures during the whole sample period is

Table 11
Transaction cost and after-cost performance of the best daily SBTRs.

Markets	Annualized mean return	No. of round-trips	Trading years	Maximum one-way cost	After-cost return		Point value	Average price	Average contract size	Ratio of one-way commission to average contract size	
					0.025%	0.04%				$50	$6.25
Corn	24.29	5266	21	0.0484	11.75	4.23	50	353.86	17,693	0.2826	0.0353
Soybean	24.43	5268	21	0.0487	11.89	4.36	50	846.92	42,346	0.1181	0.0148
Wheat	24.64	5142	21	0.0503	12.40	5.05	50	470.55	23,527	0.2125	0.0266
Live Cattle	13.80	5263	21	0.0275	1.27	−6.25	400	90.69	36,276	0.1378	0.0172
Lumber	39.61	5266	21	0.0790	27.07	19.55	110	291.45	32,060	0.1560	0.0195
Cocoa	25.91	5229	21	0.0520	13.46	5.99	10	1926.10	19,261	0.2596	0.0324
Sugar	34.32	5231	21	0.0689	21.87	14.39	112,000	12.83	14,372	0.3479	0.0435
Copper	26.90	2747	11	0.0539	14.41	6.92	25,000	3.05	76,183	0.0656	0.0082
Silver	15.66	5247	21	0.0313	3.17	−4.33	5000	12.34	61,683	0.0811	0.0101
Oil	30.41	5246	21	0.0609	17.92	10.43	1000	53.28	53,279	0.0938	0.0117
S&P500	12.31	5271	21	0.0245	−0.24	−7.77	250	1226.70	306,675	0.0163	0.0020
E-mini S&P	15.53	2752	11	0.0310	3.02	−4.48	50	1410.80	70,540	0.0709	0.0089
E-mini NASDAQ	15.76	2751	11	0.0315	3.26	−4.25	20	2400.20	48,004	0.1042	0.0130
T-Bills	5.09	5125	21	0.0104	−7.11	−14.43	1000	114.67	114,673	0.0436	0.0055
Eurodollar	0.44	5253	21	0.0009	−12.07	−19.57	2500	97.01	242,516	0.0206	0.0026
YEN	5.49	5274	21	0.0109	−7.07	−14.60	125,000	0.95	119,150	0.0420	0.0052
GBP	4.59	5275	21	0.0091	−7.97	−15.51	62,500	1.64	102,708	0.0487	0.0061
EUR	7.25	2755	11	0.0145	−5.27	−12.79	125,000	1.32	165,188	0.0303	0.0038
AUD	12.59	2753	11	0.0252	0.08	−7.43	100,000	0.87	87,110	0.0574	0.0072

This table presents the annualized mean return, the maximum one-way cost to break even, a range of transaction costs and the after-cost performance for the best-performing daily SBTRs identified during the whole sample period. The number of round-trips is the number of the actual trading days on which the SBTR generates a signal. The maximum one-way cost is the cost that makes the after-cost returns of the SBTRs become zero. The after-cost return is the annualized mean return after-cost of the SBTRs when the one-way cost is assumed to be 0.025 percent and 0.04 percent. The point value is the change in the value of the futures contracts when the underlying spot prices increase by one point. The average price is the average of the futures opening prices during the whole sample period. The average contract size is the average futures price multiplied by the point value, which refers to the average contract value during the whole sample period. The rightmost two columns present the transaction costs as percentages when the one-way commission is assumed to be $50 and $6.25. The annualized mean return, the maximum one-way cost, the after-cost return and the ratio of one-way commission to average contract size are expressed as percentages.

Table 12
Transaction cost and after-cost performance of the best weekly SBTRs with the MYR exit strategy.

Markets	Annualized mean return	No. of round-trips	Trading years	Maximum one-way cost	After-cost return		Point value	Average price	Average contract size	Ratio of one-way commission to average contract size	
					0.025%	0.04%				$50	$6.25
Corn	11.13	1,072	21	0.1679	8.58	7.05	50	353.47	17,673	0.2829	0.0354
Soybean	8.99	1072	21	0.2274	6.44	4.91	50	846.34	42,317	0.1182	0.0148
Wheat	21.35	1048	21	0.1781	18.85	17.36	50	469.76	23,488	0.2129	0.0266
Live Cattle	13.32	1074	21	0.0957	10.76	9.23	400	90.01	36,003	0.1389	0.0174
Lumber	34.14	1048	21	0.3221	31.64	30.15	110	292.92	32,222	0.1552	0.0194
Cocoa	18.24	1070	21	0.1995	15.69	14.16	10	1905.60	19,056	0.2624	0.0328
Sugar	30.6	1070	21	0.3407	28.05	26.52	112000	12.81	14,346	0.3485	0.0436
Copper	35.81	547	11	0.2561	33.32	31.83	25000	3.07	76,770	0.0651	0.0081
Silver	12.46	1073	21	0.1033	9.91	8.37	5000	12.27	61,333	0.0815	0.0102
Oil	40.74	1067	21	0.3331	38.20	36.68	1000	53.34	53,345	0.0937	0.0117
S&P500	12.86	1074	21	0.0780	10.30	8.77	250	1215.30	303,825	0.0165	0.0021
E-mini S&P	15.01	549	11	0.1346	12.51	11.02	50	1393.60	69,680	0.0718	0.0090
E-mini NASDAQ	15.09	549	11	0.1130	12.59	11.10	20	2390.90	47,818	0.1046	0.0131
T-Bills	4.35	1048	21	0.0492	1.85	0.36	1000	114.46	114,464	0.0437	0.0055
Eurodollar	0.48	1070	21	0.0027	−2.07	−3.60	2500	96.97	242,427	0.0206	0.0026
YEN	5.37	1074	21	0.0673	2.81	1.28	125000	0.95	119,338	0.0419	0.0052
GBP	5.98	1073	21	0.0562	3.43	1.89	62500	1.65	102,813	0.0486	0.0061
EUR	6.74	549	11	0.0685	4.24	2.75	125000	1.33	165,938	0.0301	0.0038
AUD	10.06	549	11	0.1038	7.56	6.07	100000	0.88	87,550	0.0571	0.0071

This table presents the annualized mean return, the maximum one-way cost to break even, a range of transaction costs and the after-cost performance for the best-performing weekly SBTRs with the MYR exit strategy identified during the whole sample period. The number of round-trips is the number of the actual trading days on which the SBTR generates a signal. The maximum one-way cost is the cost that makes the after-cost returns of the SBTRs become zero. The after-cost return is the annualized mean return after-cost of the SBTRs when the one-way cost is assumed to be 0.025 percent and 0.04 percent. The point value is the change in the value of the futures contracts when the underlying spot prices increase by one point. The average price is the average of the futures opening prices during the whole sample period. The average contract size is the average futures price multiplied by the point value, which refers to the average contract value during the whole sample period. The rightmost two columns present the transaction costs as percentages when the one-way commission is assumed to be $50 and $6.25. The annualized mean return, the maximum one-way cost, the after-cost return and the ratio of one-way commission to average contract size are expressed as percentages.

Table 13
Transaction cost and after-cost performance of the best weekly SBTRs with the CL exit strategy.

Markets	Annualized mean return	No. of round-trips	Trading years	Maximum one-way cost	After-cost return		Point value	Average price	Average contract size	Ratio of one-way Commission to average contract size	
					0.025%	0.04%				$50	$6.25
Corn	30.40	5266	21	0.0606	17.86	10.34	50	353.86	17,693	0.2826	0.0353
Soybean	27.55	5268	21	0.0549	15.01	7.48	50	846.92	42,346	0.1181	0.0148
Wheat	30.91	5142	21	0.0631	18.67	11.32	50	470.55	23,527	0.2125	0.0266
Live Cattle	18.01	5263	21	0.0359	5.48	−2.04	400	90.69	36,276	0.1378	0.0172
Lumber	41.77	5266	21	0.0833	29.23	21.71	110	291.45	32,060	0.1560	0.0195
Cocoa	20.46	5229	21	0.0411	8.01	0.54	10	1926.10	19,261	0.2596	0.0324
Sugar	34.41	5231	21	0.0691	21.96	14.48	112000	12.83	14,372	0.3479	0.0435
Copper	30.18	2747	11	0.0604	17.69	10.20	25000	3.05	76,183	0.0656	0.0082
Silver	25.85	5247	21	0.0517	13.36	5.86	5000	12.34	61,683	0.0811	0.0101
Oil	35.01	5246	21	0.0701	22.52	15.03	1000	53.28	53,279	0.0938	0.0117
S&P500	21.75	5271	21	0.0433	9.20	1.67	250	1226.70	306,675	0.0163	0.0020
E-mini S&P	18.94	2752	11	0.0379	6.43	−1.07	50	1410.80	70,540	0.0709	0.0089
E-mini NASDAQ	19.66	2751	11	0.0393	7.16	−0.35	20	2400.20	48,004	0.1042	0.0130
T-Bills	6.70	5125	21	0.0137	−5.50	−12.82	1000	114.67	114,673	0.0436	0.0055
Eurodollar	0.87	5253	21	0.0017	−11.64	−19.14	2500	97.01	242,516	0.0206	0.0026
YEN	8.81	5274	21	0.0175	−3.75	−11.28	125000	0.95	119,150	0.0420	0.0052
GBP	7.49	5275	21	0.0149	−5.07	−12.61	62500	1.64	102,708	0.0487	0.0061
EUR	11.34	2755	11	0.0226	−1.18	−8.70	125000	1.32	165,188	0.0303	0.0038
AUD	12.44	2753	11	0.0249	−0.07	−7.58	100000	0.87	87,110	0.0574	0.0072

This table presents the annualized mean return, the maximum one-way cost to break even, a range of transaction costs and the after-cost performance for the best-performing weekly SBTRs with the CL exit strategy identified during the whole sample period. The number of round-trips is the number of the actual trading days on which the SBTR generates a signal. The maximum one-way cost is the cost that makes the after-cost returns of the SBTRs become zero. The after-cost return is the annualized mean return after-cost of the SBTRs when the one-way cost is assumed to be 0.025 percent and 0.04 percent. The point value is the change in the value of the futures contracts when the underlying spot prices increase by one point. The average price is the average of the futures opening prices during the whole sample period. The average contract size is the average futures price multiplied by the point value, which refers to the average contract value during the whole sample period. The rightmost two columns present the transaction costs as percentages when the one-way commission is assumed to be $50 and $6.25. The annualized mean return, the maximum one-way cost, the after-cost return and the ratio of one-way commission to average contract size are expressed as percentages.

846.92 and the point value is $50, the average contract size is therefore $42,346. If the commission per round-trip trade is $12.5, the percentage of the one-way commission is $6.25/$42,346 = 0.0148 percent, which is lower than the maximum one-way cost for the best SBTR to break even over the sample period. When the one-way commission is $6.25, all the SBTRs still have positive returns because the ratios of one-way commission to average contract size are all lower than the maximum one-way cost for each futures market with the exception of the Eurodollar futures. However, when we assume a one-way commission of $50, then none of the best SBTRs generates positive returns except for the S&P 500 futures.

Table 12 reports the performance of the best weekly SBTRs with the MYR exit strategy after the transaction cost is considered. The maximum one-way costs that are tolerable are much higher than those of the daily SBTRs in Table 11, since the trading frequency of the weekly SBTRs with the MYR exit strategy is much lower. Almost all strategies are profitable after we consider the one-way transaction costs in the range of 0.025-0.04 percent or the one-way commission of $6.25. When the one-way commission is $50, there are thirteen futures markets where the ratio of the one-way commission to the average contract size is lower than the maximum one-way cost. Although the after-cost performance of the weekly SBTRs with the MYR exit strategy seems better than that of the daily SBTRs, the performance is not robust to the sub-sample and out-of-sample analyses.

Table 13 shows that the after-cost performance of the best weekly SBTRs with the CL exit strategy is similar to the results of the daily SBTRs as their trading frequencies are similar. In ten out of the nineteen futures markets, the weekly SBTRs with the CL exit strategy generate positive profits under the assumption of a 0.04 percent one-way cost, and when the one-way cost is 0.025 percent, the SBTRs are profitable in thirteen futures markets. When the one-way commission is $6.25, all strategies survive. However, when the one-way commission is $50, none of the best SBTRs can generate positive returns except for the S&P 500 futures.

5. Conclusion

By proposing the SBTR, this paper adds to the technical trading literature a novel prospective depicting how technical-trading decision making relates to similarity-based analogical reasoning. The SBTR, while allowing for a univariate setting as its degenerate case, is a multivariate technical trading strategy. In this paper, the trading signals generated by technical indicators alone do not initiate a similarity-based trader's trading decisions. Yet the loss-gain experiences of past returns, which bring about pain and pleasure, have impacts on his/her decision making. The buy (sell) decisions of traders are determined by the stochastic averaging predictor—an indicator-assisted forecasting process of probable future returns—whose positivity (negativity) triggers a buy (sell) signal.

Our key findings are as follows. First, both the daily SBTRs and the weekly SBTRs with the CL exit strategy are capable of generating profits in most of the futures markets at the 5 percent significance level even after accounting for data-snooping bias. The performance of the weekly SBTRs with the CL exit strategy, in particular, is robust to the sub-period and out-of-sample tests. The results indicate the predictive ability of the SBTR. Second, the outperforming SBTR strategies are multivariate strategies based on different types of technical indicators. That is, to trade and win under reasoning by similarity/analogy seems to entail exploiting feasible combinations of the MA, RSI, TRB, and VMA indicators in the construction of the vector of quantitative characteristics. Third, we find that the trader's adopted time lengths of moving time windows in conducting similarity searches indeed matter. The optimal choice of time lengths for the moving window is seldom the distant past. Instead, the quantitative characteristics of the recent past play a major role in decision making process of the similarity-based traders. Fourth, transactions costs are as important as anticipated in prior studies. After considering a wide range of one-way transaction costs, most of the best-performing SBTRs remain profitable when the maximum one-way transaction cost to break even is 0.025 percent, or when the commission per round-trip trade is assumed to be $6.25.

Authors' contribution

Mi-Hsiu Chiang: Conceptualization, Project administration, Writing – Review and editing. Hsin-Yu Chiu: Software programming, Empirical analysis, Data curation, Writing-first draft. Wei-Yu Kuo: Conceptualization, Methodology, Supervision, Writing-Review and editing.

Acknowledgements

We are grateful for helpful comments from Yu-Chin Hsu (Institute of Economics, Academia Sinica, Taiwan) and seminar participants at the 2017 Financial Management Association Asia Pacific Conference, the 2017 Taiwan Finance Association Annual Meeting, and the 2017 Financial Engineering Association of Taiwan Annual Meeting. We would like to acknowledge the financial support from the Ministry of Science and Technology of Taiwan (Nos. 108-2410-H-153-025-MY2, 106-2410-H-004-058, and 105-2410-H-004-033-MY3).

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