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Profitability of technical analysis in financial and commodity futures markets — A reality check

Stéphane Meng-Feng Yen [a,*], Ying-Lin Hsu [b]

[a] Department of Accountancy and Institute of Finance and Banking, National Cheng Kung University, 1 University Rd., East District, Tainan 701, Taiwan
[b] Department of Applied Mathematics and Institute of Statistics, National Chung Hsing University, 250 Kuo Kuang Rd., Taichung 402, Taiwan

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ABSTRACT

Based on the SPA test (test for superior predictive ability), Sortino and reversed Sortino ratios, we examined the profitability of a universe of 8061 technical trading rules in ten futures markets including five financial and five commodity underlying assets. We tested whether the best performing rule really beats its buy-and-hold benchmark strategy in bullish and bearish markets, respectively, during the in-sample testing period. The best rules' performance relative to the benchmark is also tested during the one-year out-of-sample period for all ten sets of data. A novel set of multi-indicator rules, MFI–RSI, and four popular categories of single-indicator rules, filter rules, moving averages, on-balance volume averages and momentum strategy in volume, were employed to form our universe of trading rules. The results on the SPA test suggest market efficiency in nine of the ten futures markets, while the results on the Sortino and reversed Sortino ratios reveal persistent outperformance of the best 'downside' and 'upside' rules relative to the buy-and-hold benchmark across time in four and three futures markets, respectively.

1. Introduction

Technical analysis has been one of the popular trading techniques among others in the futures markets for years. An excerpt from a report in BusinessWeek on March 19, 2001 [11] emphasizes the prevalence of technical analysis in futures markets: '…Most of the futures managers trade on the basis of technical, rather than fundamental, analysis, looking at such measures as price movements and changes in trading volume. They have developed analytical models based on the behavior of different futures markets over the years. "It's a systematic approach, and the systems are designed to profit when the futures products move through certain designated levels," says Sol Waksman, president of Barclay Trading Group, which researches and tracks futures funds….'

Despite its importance in the futures markets, the profitability of technical analysis might be subject to the so-called data-snooping bias, a stylized fact that is common to research on repetitively discovering the best model to explain an economic or financial time series. When the same set of data is tested using a chunk of models, we will always find that one or two of them are able to explain the data to a satisfactory extent, but only by chance rather than by any specific ability of the models themselves. Such a search for the best model from an enormous union constitutes the so-called data-snooping bias. An implication of the data-snooping bias is that any previous evidence of the profitability of technical analysis might be subject to questions. Without taking into account the data-snooping bias, such a conclusion might be fairly due to the mere luck, which is not robust to variability in sample periods or in variables.

Sullivan, Timmermann and White [23] tested five categories[1] of simple trading rules each based on one single technical indicator, amounting to 7846 rules in total, for the S&P 500 index futures. STW's[2] sample period is from 1984 through 1996 for the S&P 500 futures. Using White's [25] BRC to control for the data-snooping bias, STW found that, though some of the trading rules are able to beat the benchmark model (i.e. holding cash and staying out of the market) during the sample period above, the best rule of them is not able to show statistically significant outperformance relative to the benchmark with a possibility of 90.8%. STW concluded that profitability of technical analysis in the S&P 500 futures market might be due to the mere luck.

In this article we aimed to extend STW's work by using more futures contracts, a more powerful test than the BRC to alleviate the data-snooping bias, adding a more sophisticated type of trading rules as well as improving on the way to calculate daily trading returns. In particular, we examined ten futures contracts consisting of five financials and five commodities. To alleviate the significant reduction

[1] Filter rule, moving average, support and resistance, channel breakout and on-balance volume average.

[2] Acronyms STW and HK refer to, two groups of authors: Sullivan, Timmermann and White, and Hsu and Kuan. BRC stands for *bootstrap reality check*, while SPA test is abbreviated from *test for superior predictive ability*.

* Corresponding author. Tel.: +886 6 275 7575x53443; fax: +886 6 274 4104.
E-mail addresses: yenmf@mail.ncku.edu.tw (S.M.-F. Yen), ylhsu@amath.nchu.edu.tw (Y.-L. Hsu).

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in the rejection rate of the null hypothesis under the BRC due to too many poorly performing trading rules, we followed Hsu and Kuan [14] and employed the more powerful SPA test introduced by Hansen [13]. All five categories of trading rules in STW were based on a single indicator of different parameter sets, while we modified this simple universe by including a category of technical analysis based on a multi-indicator strategy, the *MFI–RSI* rules, in our universe of trading rules. Adding more complex trading rules to the set of rules tested would reduce the gap between previous academic studies and what the futures market practitioners have been gradually and really doing. STW and previous studies all ignored the issue of calculating the rate of return for futures trading in a more practical manner. On the contrary, we computed the return for a trading rule using both the futures margin account and the risk-free current account. Without taking into account the market practices in calculating returns for trading futures, the profits or losses will be underestimated which then leads to an underestimated standard deviation of the daily returns. The results of the SPA test, based on the studentized average daily return in our context, will also be biased. Moreover, STW and previous studies did not separate the trading rules' performance during downside markets from during upside markets. We responded to this issue by applying the SPA test to bull and bear markets separately and comparing the (reversed) Sortino ratio of the trading rules with their buy-and-hold benchmark counterpart. Last but not the least, we replaced the benchmark of 'null' system (i.e. always staying out of the market) in STW by the buy-and-hold strategy.[3]

The ten futures contracts are CME Euro/USD FX futures (EUR/$ FX, hereafter), LIFFE FTSE 100 Index futures (FT-100, hereafter), EUREX DJ Euro Stoxx 50 Index futures (Stoxx-50, hereafter), SIMEX MSCI Taiwan Index futures (TW, hereafter), CBOT/CME US 30-year T-Bond futures (T-Bond, hereafter), CME live cattle futures (Cattle, hereafter), COMEX gold futures (Gold, hereafter), NYMEX/CME New York light sweet crude oil futures (Crude oil, hereafter), NYBOT/ICE coffee futures (Coffee, hereafter) and CBOT/CME soybean futures (Soybean, hereafter).[4] The five categories of technical trading rules are, firstly, a hybrid of the money flow index and the relative strength index (hereafter MFI–RSI), followed by the filter rules (hereafter FR), the moving averages (hereafter MA), the on-balance volume averages (hereafter OBV) and the momentum strategies in volume (hereafter MSV). The MFI–RSI category is formed by coupling the money flow index with the relative strength index, a novel application in the academic literature. The MFI tracks the flow of money into and out of a market, which is often used to warn of trend weakness and likely reversal points. The RSI measures price strength by comparing upward and downward close-to-close movements, which is often used to indicate whether a security has been overbought or oversold and thus a likely reversal. Both indicators are formulated to fluctuate between 0 and 100, enabling prespecified overbought or oversold levels. Mixing these two indicators will efficiently reduce the number of noisy trading signals and increase the percentage of successful trades.

Based on the SPA test to control for the data-snooping bias, we found that, the *MFI–RSI* and *MSV* types of technical trading rules tend to be identified as the best rule which significantly outperforms the benchmark in as many as seven futures markets, four financial and three commodity contracts. Nine of the fifteen sub-testing periods leading to a significant, best rule are in a bearish market, suggesting that the elites from the universe of our 8061 rules tend to perform better in a downside market than in an upside market. However, these 'real' outperformers selected from the most recent in-sample testing period generally fail to consistently provide a relatively good performance during the out-of-sample period. What is worse is that most of them generate a negative cumulative excess return, an evidence of no performance persistence among these in-sample 'real' outperformers. The only exception appears in the case of live cattle futures, in which the best trading rule selected from the last testing period, an *MSV* rule, still significantly beats the benchmark and generates a relatively large cumulative excess return over the one-year out-of-sample period. These results suggest that the remaining nine futures markets conform to the weak form of efficient market hypothesis, a finding in accord with what STW found with the S&P 500 index futures market.

Our results based on the Sortino and reversed Sortino ratios calculated for the entire in-sample period tend to suggest performance superiority of the best 'downside' rule over the best 'upside' rule in that the Sortino ratio of the former is larger than the reversed Sortino ratio of the latter across all ten contracts. Unlike the results on the SPA test, the best 'downside' rule consistently outperforms the benchmark in more than half the eight futures markets where the best rule generated trading signals during the one-year out-of-sample period. In contrast, the best 'upside' rule keeps beating the benchmark in less than half the ten futures markets where the best rule generated trading signals in the out-of-sample period. However, most of these persistent 'downside' and 'upside' outperformers tend to give a cumulative excess return larger than what their benchmark brings about. Our results based on the Sortino and reversed Sortino ratios indicate an evidence of better profitability relative to the benchmark from using the best technical trading rule out of the universe of our 8061 rules in the Eur/$ FX, Stoxx-50, T-Bond and Crude oil futures markets.

The rest of the paper is organized as follows. Section 2 presents the material and methods on the reality check of technical analysis' profitability, involving the trading rules, the SPA test, the (reversed) Sortino ratio and the data used. Section 3 details the practical issues of transaction cost and return calculation. Section 4 discusses the results, while Section 5 concludes.

2. Material and methods

2.1. Trading rules

Since the word 'technical analysis' itself concerns an enormous variety of simple or complex rules and strategies, it is unlikely to cover all candidates that were or are being used. However, it is possible to discuss the effectiveness of technical analysis from the perspectives of academics. In particular, we reviewed all past studies in the literature of this regard and summarized all previously discussed rules and strategies. Although we attempted to include all important rules, we recognized that we cannot exhaust all possible rules. As a result, we focused on Brock et al. [5], STW [23] and HK [14] which nearly covered all past efforts in this regard and selected those relatively good rules identified by these studies. In addition, we included a type of double-indicator trading rules in our universe to test whether the use of multi-indicators would help increase profitability. In total, we tested five categories of trading rules: money flow index coupled with relative strength index, filter rules, moving averages, on-balance volume averages, and momentum strategy in volume. Since all five categories were constructed based upon simple arithmetic calculation of the historical prices and/or trading volumes, a trade-off between

[3] Since futures investors are able to go long and go short a futures contract recurrently, staying out of the market or the risk-free rate seems to be a natural benchmark. However, futures investors are not supposed to use the risk-free reward to benchmark their trading performance because speculative trading in high-leveraged derivatives itself aims to earn a higher rate of return than trading spot assets. If the buy-and-hold strategy is conventionally regarded as the performance benchmark for trading spot assets, speculative futures investors would surely go after something better than what the buy-and-hold strategy brings.

[4] To explore a wider sample period than the S&P 500 index futures in STW, we included the 30-year US T-bond, live cattle and soybean futures contracts in the ten contracts, which all started trading earlier than 1984.

the responsiveness of a trading rule and its signal-to-noise ratio resulted. This is why we chose a large set of parameter combinations to form each category of technical rules.

When a trading rule generated a buy signal, we went long a futures contract, which was held in the position until an exit signal appeared. Similarly, we went short a futures contract when a short signal occurred and the position was held until an exit signal showed. Following STW,[5] any contract held in position was switched to the next nearest month contract seven calendar days prior to the last trading date of the expiring contract to avoid market illiquidity and the roll-over effect prior to contract maturity.

2.1.1. A hybrid from money flow index and relative strength index (MFI–RSI)

Although single-indicator trading rules are straightforward to construct and easy to understand, market professionals are in favor of multi-indicator trading rules. For example, Altucher, a Wall Street trader, advocated the use of 20 strategies and techniques which have been greatly implemented in the stock markets [3]. Many of them involve using more than one technical indicator. The ways in which market professionals such as Altucher uses technical indicators are very different from those studied in the academic literature.

As regards complex strategies, STW examined a 'cumulative wealth rule' while HK studied a learning strategy, which both concern regularly updating the best single-indicator rule according to all competitors' performance during the preceding sample period of a fixed range. However, regular substitution of a new indicator or strategy for the current one will lead to adverse position changes and thus incur costs of transaction larger than otherwise. STW and HK both found that this complex type of technical rules is not among the best rules as expected.

One advantage of using multi-indicator trading rules is their ability to filter out noisy trading signals which cause unwanted losses. In this article, we suggested mixing the Money Flow Index (MFI, pioneered by Birinyi, Jr.) with the Relative Strength Index (RSI, introduced by Wilder, Jr.) [26]. The rationale of using these two indicators together has been mentioned in Section 1. The construction of this type of rules is detailed in Appendix A. In total, we have 2916 members for the MFI–RSI category.

2.1.2. Filter rules (FR)

The FR is one of the most commonly-adopted trading rules in the literature [2,9,14,23,24]. This category of rules was proved profitable with statistical significance by [17] for currency futures. The FR-type of technical indicators is used to detect a possible reversal of the trend in the underlying asset price. How this type of rules is constructed is discussed in Appendix B. We have a total of 1560 rules for this category.

2.1.3. Moving averages (MA)

In parallel to the FR, the MA has also been popular for long among practitioners in many financial markets, in particular, the currency [16] and stock markets [5,14,22,23]. This type of technical indicators is used to confirm the start of an upcoming trend of the asset price, either downward or upward. A literature survey was provided by STW. We refer the details of their construction to Appendix C. The MA was found to be profitable by [5] and HK for stock indexes and by [17] for currency futures with statistical significance. We thus included this category in our union. In total, we have 840 rules for this category.

2.1.4. On-balance volume averages (OBV)

Trading rules based on the trading volume have not attracted much attention in the literature. One of such examples is the OBV based on the sum of positive momentum (i.e. the trading volume when the closing price rises) and negative momentum (i.e. the trading volume when the closing price declines). The OBV rules were introduced by [12], which are used to confirm price moves and detect a trend weakness and thus a likely reversal point. STW found the 2-day OBV to be the best performer for the DJIA index during two in-sample subperiods, and both the 30-day and 75-day OBV the best performers for the S&P 500 futures for the 1984–1996 period. We thus included this category in our universe (see Appendix D for further details). The number of OBV rules amounts to 105 in this study.

2.1.5. Momentum strategy in volume (MSV)

The MSV is a category that has been largely discussed in the literature [6–8,10,21,22]. In contrast to the OBV which is based on both the price and the trading volume, the MSV is based on the trading volume solely. Details of its rule construction are discussed in Appendix E. While the MSV rules do not generate significant performance relative to the buy-and-hold benchmark strategy in HK, they found that the best trading rule for the DJIA spot market falls within this category. As a result, we included this category in our universe of trading rules. Totally, we have 2640 MSV rules.

All parameter settings are summarized in Appendix F. We have a total of 8061 rules in our union for the subsequent reality check based on the SPA test and the (reversed) Sortino ratio.

2.2. Evaluation of the trading rules' performance

We employed two approaches in evaluating the performance of the trading rules. One is the SPA test applied to control for the data-snooping bias given such a large universe of competing trading rules. The other is the Sortino ratio which aims to differentiate how each trading rule (in particular, the best trading rule) performs during downside markets from upside markets.

2.2.1. SPA test for technical analysis

To avoid drawing a misleading conclusion given the data-snooping bias common to sizable unions of models, trading strategies, or technical rules, one must statistically mitigate the possibility that good performance comes from sampling variation rather than real skill. The literature substantially implements the bootstrap methods such as White's BRC to control for the data-snooping bias.

However, White's BRC suffers a loss of test power when too many poor models are included in the universe tested. Stated otherwise, even if there are indeed some models that really outperform their benchmark, the null hypothesis that the best model of all is not better than the benchmark cannot be rejected. Including too many poor models that are unable to explain the underlying data substantially increases the critical value of the bootstrapped empirical distribution of the test statistic under the null hypothesis given the same p-value. Under such a circumstance, it fails to reject the false null hypothesis that the best model cannot outperform the benchmark model. In light of this drawback, the SPA test was devised to increase the rejection rate of the null hypothesis by re-centering and standardizing the test statistic of the BRC, which increases the test power.

In the context of reality check with the efficacy of technical analysis in the futures markets, a natural benchmark would be the buy-and-hold strategy. The SPA test can be applied in this context to test the null hypothesis that none of the trading rules of a large union is superior to the benchmark. In other words, define the relative

[5] STW switched their trading rules' positions in the S&P 500 index futures on the 9th calendar day of the contract month (March, June, September and December), which is 6, 7, or 8 calendar days prior to the last trading day (the third Thursday of the contract month). We averaged these three possibilities and chose the dates 7 calendar days prior to the last trading days as our position-switching dates for all ten contracts in this article.

performance measure of the kth trading rule as its return in excess of its benchmark performance, i.e.

$$r_{k,t} \equiv R_{k,t} - R_{0,t}, \text{ for } k = 1, \ldots, m \tag{1}$$

where $R_{k,t}$ denotes the day-t return of the kth trading rule and $R_{0,t}$ the day-t return of the buy-and-hold benchmark strategy. The null hypothesis can then be formulated by

$$H_0 : \boldsymbol{\mu} \leq \mathbf{0}, \text{ where } \boldsymbol{\mu} \equiv E(\boldsymbol{r}_t) \text{ and } \boldsymbol{r}_t = (r_{1,t}, \ldots, r_{m,t})'. \tag{2}$$

Testing this hypothesis is not straightforward when the number of rules tested, m, is large. Basing on White's BRC, Hansen proposed a more powerful test to control for the data-snooping bias. To test the null hypothesis in Eq. (2), in particular, Hansen proposed a new test statistic based on the non-negative studentized average abnormal return:

$$\Lambda_T^{SPA} = \max\left(\max_{k=1,\ldots,m} \sqrt{T}\, \bar{r}_k / \hat{\sigma}_k, 0\right), \tag{3}$$

where $\hat{\sigma}_k$ is a consistent estimate of the standard deviation of $\sqrt{T}\bar{r}_k$.

To avoid using the least favorable configuration in White [25] (i.e. imposing $\boldsymbol{\mu} = \boldsymbol{0}$ in Eq. (2)) and to reduce the adverse influence of the rules with large negative average returns on the rejection rate of the null hypothesis, Hansen suggested a different way to bootstrap the distribution of Λ_T^{SPA} [13]. For the kth rule, let $\bar{z}_k^{*,b}$ denote the sample average of the bth bootstrapped realization of the centered returns:

$$Z_{k,t}^{*,b} = r_{k,t}^{*,b} - \bar{r}_k \mathbf{1}_{\left\{\sqrt{T}\bar{r}_k \geq -\hat{\sigma}_k \sqrt{2 \log \log T}\right\}}, \text{ where } \mathbf{1}_{\{\}} \text{ is the indicator function.} \tag{4}$$

The condition contained in the indicator function above is used to re-center the bootstrapped distribution of the test statistic in Eq. (3) away from $\boldsymbol{\mu} = \boldsymbol{0}$ given very poorly performing trading rules in the union. Employing $\hat{\sigma}_k$ in Eq. (3) to studentize $\sqrt{T}\,\bar{r}_k$ reduces the possibility of fat tails in the empirical distribution of $\max_{k=1,\ldots,m} \sqrt{T}\,\bar{r}_k$ due to trading rules with a large return variability. Both re-centering in Eq. (4) and studentization in Eq. (3) increase the rejection rate of the null hypothesis in Eq. (2).

Given the bootstrap above, Hansen suggested using [19]'s HAC-consistent kernel estimator for the standard deviation of $\sqrt{T}\,\bar{r}_k$:

$$\hat{\sigma}_k \equiv \sqrt{\hat{\omega}_{0,k} + 2\sum_{i=1}^{T-1} \kappa(T,i)\hat{\omega}_{i,k}}, \tag{5}$$

where $\hat{\omega}_{i,k}$ and $\kappa(T,i)$ denote, respectively, the i^{th} autocovariance of r_k and its weight. In particular,

$$\hat{\omega}_{i,k} \equiv T^{-1} \sum_{t=1}^{T-i} (r_{k,t} - \bar{r}_k)(r_{k,t+i} - \bar{r}_k) \text{ for } i = 0, \ldots, T-1, \text{ and} \tag{6}$$

$$\kappa(T,i) \equiv (T - i/T)(1-q)^i + (i/T)(1-q)^{T-i}, \tag{7}$$

where q refers to the smooth parameter of the geometric distribution assumed for the block size under the stationary bootstrap framework [19].

The consistent p-values of Λ_T^{SPA} are determined by the empirical distribution of $\Lambda_T^{*,SPA}$ whose realizations are

$$\Lambda_T^{*,SPA}(b) = \max\left(\max_{k=1,\ldots,m} \sqrt{T}\, \bar{Z}_k^{*,b} / \hat{\sigma}_k, 0\right), \; b = 1, \ldots, B. \tag{8}$$

When such p-values are used, the test Eq. (3) is referred to as the SPA_C test.

Moreover, Hansen considered the averages $\bar{z}_k^{L*}(b)$ and $\bar{z}_k^{U*}(b)$ based on the following respective bootstrapped returns: $Z_{k,t}^{L*}(b) = r_{k,t}^{*,b} - \max(\bar{r}_k, 0)$ and $Z_{k,t}^{U*}(b) = r_{k,t}^{*,b} - \bar{r}_k$.

It is straightforward to see that $\bar{z}_k^{L*}(b) \leq \bar{z}_k^{*,b} \leq \bar{z}_k^{U*}(b)$. The bootstrapped distributions of $\Lambda_T^{L^*,SPA}$ and $\Lambda_T^{U^*,SPA}$ are now computed as Eq. (8), with $\bar{z}_k^{*,b}$ replaced by $\bar{z}_k^{L*}(b)$ and $\bar{z}_k^{U*}(b)$, respectively. The test Λ_T^{SPA} will be referred to as the SPA_L and SPA_U tests if its p-values are determined by the distributions of $\Lambda_T^{L*,SPA}$ and Λ_T^{U*SPA}, respectively. Although these p-values are inconsistent, they serve as the lower and upper bounds for the consistent p-values.

To tell how the best trading rule performs relative to the buy-and-hold benchmark strategy during the bull markets and bear markets separately, we divided each in-sample testing period into three subperiods: (i) from the day immediately following the end of the signal-generating period to the day with the highest closing price (if it appeared earlier than the lowest closing price), (ii) from the day immediately following the highest closing price to the day immediately preceding the lowest closing price, and (iii) from the day with the lowest closing price to the end of the in-sample testing period. If this

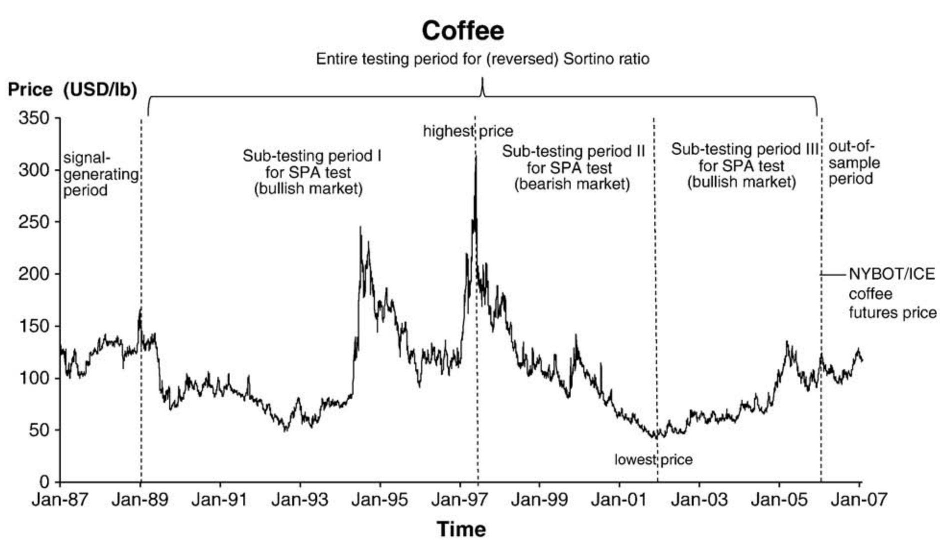

Fig. 1. An example of how to divide the entire sample period into different components — NYBOT/ICE coffee futures market. Plotted using the daily closing price of this coffee futures contract, the figure illustrates how the entire sample period is divided into a signal-generating period, an in-sample period for performance reality check and an out-of-sample period for performance persistence test. The in-sample testing period is further divided into three sub-testing periods under the SPA test.

was the case, we would have a bullish market in the beginning, followed by a bearish market and then another bullish market. If the lowest closing price occurred prior to the highest closing price, we would have a bearish market in the beginning, followed by a bullish market and then another bearish market. Fig. 1 illustrates how the division of our futures data is conducted.

2.2.2. Sortino ratio

Another approach to evaluating the trading rule's performance during the bear and bull markets independently is to use the Sortino and reversed Sortino ratio.[6] The former is used to measure how a trading rule performs in downside markets, while the latter is applied for upside markets. In particular, the two ratios of the kth trading rule are given by

$$SR_k^-\,(\text{Sortino ratio}) \equiv \bar{r}_k / \omega_k^- \quad \text{and} \tag{9}$$

$$SR_k^+\,(\text{reversed Sortino ratio}) \equiv \bar{r}_k / \omega_k^+, \tag{10}$$

where $\bar{r}_k$ denotes the average of $r_{k,t}$ defined in Eq. (1) with $R_{0,t}$ replaced by the risk-free rate $R_{f,t}$[7]. ω_k^- and ω_k^+ denote, respectively, the downside and upside semi-standard deviations given by

$$\omega_k^- \equiv \sqrt{\left[1 / \sum_{t=1}^{T} I_{\{r_{k,t}<0\}}\right] \sum_{t=1}^{T} I_{\{r_{k,t}<0\}} (r_{k,t} - \bar{r}_k)^2}, \text{ and} \tag{11}$$

$$\omega_k^+ \equiv \sqrt{\left[1 / \sum_{t=1}^{T} I_{\{r_{k,t}>0\}}\right] \sum_{t=1}^{T} I_{\{r_{k,t}>0\}} (r_{k,t} - \bar{r}_k)^2}. \tag{12}$$

2.3. Data

We studied ten futures markets: five financial contracts and five commodity contracts. The five financial contracts are EUR/$ FX, FT-100, Stoxx-50, TW and T-Bond. The five commodity futures contracts are Cattle, Gold, Crude oil, Coffee and Soybean. It is typical of a futures market to have the largest liquidity for its near-month contract. We thus focused the study on the near-month contracts. Similar to HK, the sample period for each market is composed of a signal-generating period, an in-sample testing period and an out-of-sample performance evaluation period. The out-of-sample period spans one year for all ten markets. We calculated the Sortino and reversed Sortino ratios for the in-sample period and tested how the best trading rules (i.e. the one with the largest Sortino ratio or reversed Sortino ratio) perform relative to the buy-and-hold benchmark strategy during the out-of-sample period. In the context of the SPA test, however, the in-sample testing period is further divided into three subperiods detailed in Section 2.2.1. The data on these ten sets of futures contracts are from the Institute for Financial Markets. Since the data on trading volume had not been available until the electronic trading system was initiated in mid-2003 for most of the ten products, we followed [4] and replaced the data on the daily trading volume by the daily total tick count, which equals the sum of upticks and downticks in a trading day. The initial and maintenance margin requirements for each exchange are as of April 10, 2007.

In order to allow the average trader enough time to execute his/her order after the signals are generated, we replaced the daily closing price and the daily total tick count upon market close by the price 5 min before the market close and the daily tick count cumulated until then, respectively. Once a signal is initiated 5 min before the market closes, we assume that each trade can be completed using the closing price, which is usually the transaction price for orders presented during the last 5 min.

3. Calculation

3.1. Transaction cost

It is estimated that the average futures transaction cost for financial and commodity futures ranges from 0.0004% to 0.033% of the nominal value per contract for each round-trip trade [18]. The actual commission rate depends on whether the investor is an institutional customer, an individual customer or a market maker. Due to the competition in the futures brokerage business among online brokers and main-street securities houses, moreover, the commissions charged for their customers are subject to a great variety and it is not likely to track the variation of the transaction cost from the past. As a result of the complications above, we turned to a local futures broker, Fubon Futures Corporation,[8] in Taiwan for information on the commissions charged for individual customers for all ten contracts as of April 10, 2007. The commissions for all ten contracts are contained in the third bottom row of Table 1, which amount to a proportion of the nominal value from 0.0003% to 0.0284% on a per-contract-per-side basis. This is equivalent to a range from 0.0006% to 0.0568% per contract for a round-trip trade, similar to the range estimated by [18] above.

3.2. Calculation of returns

Unlike most previous studies, we focused our study on the futures markets whereby trading is exercised on margins instead of the nominal amount of the underlying asset. In calculating the rate of return, as a result, we needed to take into account the margin requirement and the margin call when the balance of the trading account fell below the maintenance margin. Any gain or loss based on the futures price itself should be multiplied by the relevant contract multiplier, i.e. the dollar value each index point is worth. The resulting gain or loss was then added to or subtracted from the margin balance of the previous day. However, real-life trading is more complicated than this. When the margin balance falls below the maintenance margin, which is about 75% of the initial margin, the futures exchange would require the investor to deposit more cash to restore the balance to equal at least the size of the initial margin. The current position would be terminated by an offsetting transaction exercised by the exchange on behalf of the investor, otherwise. As a result, we also needed to consider the day-to-day activity of the average investor's borrowing (the amount of variation margin when faced with a margin call) from the risk-free current account, and withdrawing excess margin from the futures margin account (after making a profit) and depositing it into the risk-free current account. The rate of return of day t is therefore given by

$$r_t = \frac{\delta_{t-1} \times (p_t^c - p_{t-1}^c) \times CM - TC}{MB_{t-1}} \times \frac{MB_{t-1}}{|MB_{t-1}| + |CB_{t-1}|} + R_{f,t} \times \frac{CB_{t-1}}{|MB_{t-1}| + |CB_{t-1}|}, \tag{13}$$

where δ_{t-1} equals 1 for a long position, 0 for a neutral position and -1 for a short position held at day $t-1$. CM and TC, respectively, refer to contract multiplier and transaction cost. p_t^c (p_{t-1}^c), MB_t (MB_{t-1}), and CB_t (CB_{t-1}) denote, respectively, the closing price, the margin account balance and the current account balance of day t (day $t-1$), and $R_{f,t}$ the risk-free rate of day t.[9] In Eq. (13), we assume the same risk-free rate for

[6] We thank an anonymous referee for his/her valuable suggestions on how to distinguish the performance of the trading rule during bearish markets from during bullish markets. Our application of the SPA test separately for the bearish and bullish markets in Section 2.2.1 also resulted from those suggestions.

[7] The data on the risk-free rates are from the Datastream. In particular, we employed the Singapore 3-month T-bill rate for TW, UK 3-month T-bill rate for FT-100, 1-month euro Euribor for Stoxx-50, and US 3-month T-bill rate for the remaining seven futures contracts.

[8] Since what we aimed to discover is the performance of the best technical trading rule relative to the buy-and-hold benchmark, ignoring the historical variation of the commission and the difference between the transaction costs incurred by institutional and individual investors should be innocuous.

[9] The same set of risk-free rates mentioned in footnote 7 was used here for Eq. (13).

Table 1
The sample periods and the contract profiles of all ten futures markets.

Markets (category)	EUR/$ FX (currency)	Stoxx-50 (equity)	FT-100 (equity)	TW (equity)	T-Bond (interest rate)	Cattle (meat)	Gold (metal)	Crude oil (energy)	Coffee (food)	Soybean (grain)
Signal-generating period	04/Jan/99– 29/Dec/00	01/Jul/98– 20/Jun/00	01/Jul/98– 26/Jun/00	01/Apr/97– 21/Apr/99	01/Oct/82– 28/Sep/84	02/Dec/74– 29/Nov/76	03/Jan/84– 23/Jan/86	02/Jan/87– 10/Jan/89	05/Jan/87– 30/Jan/89	01/Jul/82– 12/Sep/84
Testing period For SPA test I:	02/Jan/01– 05/Jul/01 (bearish)	21/Jun/00– 04/Sep/00 (bullish)	27/Jun/00– 04/Sep/00 (bullish)	22/Apr/99– 17/Feb/00 (bullish)	01/Oct/84– 03/Oct/84 (bearish)	30/Nov/76 ~ 14/Jan/77 (bearish)	24/Jan/86 ~ 25/Aug/99 (bearish)	11/Jan/89 ~ 10/Dec/98 (bearish)	31/Jan/89 ~ 29/May/97 (bullish)	13/Sep/84– 27/Jun/88 (bullish)
II:	06/Jul/01– 29/Dec/04 (bullish)	05/Sep/00– 11/Mar/03 (bearish)	05/Sep/00– 11/Mar/03 (bearish)	18/Feb/00– 02/Oct/01 (bearish)	04/Oct/84– 02/Oct/98 (bullish)	17/Jan/77– 14/Oct/03 (bullish)	26/Aug/99– 31/Jan/06[a] (bullish)	11/Dec/98– 29/Aug/05 (bullish)	30/May/97– 03/Dec/01 (bearish)	28/Jun/88– 07/Jul/99 (bearish)
III:	30/Dec/04– 31/Jan/06 (bearish)	12/Mar/03– 31/Jan/06 (bullish)	12/Mar/03– 31/Jan/06 (bullish)	03/Oct/01– 24/Jan/06 (bullish)	05/Oct/98– 31/Jan/06 (bearish)	15/Oct/03– 31/Jan/06 (bearish)		30/Aug/05– 31/Jan/06 (bearish)	04/Dec/01– 31/Jan/06 (bullish)	08/Jul/99– 31/Jan/06 (bullish)
For (reversed) Sortino ratio	02/Jan/01– 31/Jan/06	21/Jun/00– 31/Jan/06	27/Jun/00– 31/Jan/06	22/Apr/99– 24/Jan/06	01/Oct/84– 31/Jan/06	30/Nov/76– 31/Jan/06	24/Jan/86– 31/Jan/06	11/Jan/89– 31/Jan/06	31/Jan/89– 31/Jan/06	13/Sep/84– 31/Jan/06
Out-of-sample period	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	03/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07	01/Feb/06– 31/Jan/07
Contract multiplier	$0.0001/€ = $12.50	1 pt = €10.0	0.5 pt = £5.00	0.1 pt = $10	1/32 pt = $31.25	$0.0001/lb = $4	$0.10/oz = $10	$0.01/ barrel = $10	$0.05/ lb = $18.75	$0.0025/ bushel = $12.50
Initial margin	$2970	€3600	£4100	$2000	$4860	$1080	$5400	$8100	$3780	$4725
Maintenance margin	$2200	€2880	£3280	$1600	$3600	$800	$4000	$6000	$2700	$3500
Commission per-contract-per-side	$12	€12	£12	$8	$12	$12	$12	$12	$12	$12
Commission/notional value[b]	0.0074%	0.0284%	0.0194%	0.0255%	0.0109%	0.0003%	0.0184%	0.0206%	0.0272%	0.0003%
Exchange	CME	EUREX	LIFFE	SIMEX	CBOT/CME	CME	COMEX	NYMEX/CME	NYBOT/ICE	CBOT/CME

[a] The second subperiod of the gold futures market lasts until the end of the entire in-sample period for the SPA test, which explains why the third subperiod is not available.
[b] The commission/notional value entry in the second bottom row refers to the proportion of the commission per-contract-per-side to the notional value in percentage.

the average investor for borrowing from and depositing into his/her current account. More and more futures brokers offer investors the so-called combo account which is composed of one margin account for trading futures and one current account for withdrawing variation margins due and depositing excess margin. Such an account would automatically restore the margin balance to the initial margin level when faced with a margin call as long as there is enough money in the account, and withdraw the excess margin and deposit it at the risk-free rate when making a profit. Although the average investor cannot borrow at the risk-free rate, such an assumption is not far from reality since he/she would usually deposit an amount in the combo account more than what the initial margin requires. As a result, any withdrawal from the current account unit of the combo account due to a margin call should be regarded as a loss of opportunity of depositing excess capital at the rate of return offered by the combo account, which is close to the risk-free rate. Such an opportunity cost can be demonstrated by a negative return of the current account if we set its initial balance to zero.

Another important issue in calculating the trading returns concerns the roll-over practice. To accurately compute the return for each round-turn trade which might involve switching the position across months, any position-switching gain or loss was subtracted from or added back to the margin balance. To evaluate the out-of-sample performance of the best trading rules selected from the testing period relative to the benchmark, we reset the margin balance of both the best trading rules and the buy-and-hold benchmark strategy to the level of initial margin and the risk-free current account balance to zero at the end of the testing period. Table 1 reports the summary statistics of all ten sets of futures contracts investigated.

4. Results and discussion

4.1. Results on the SPA test

4.1.1. In-sample performance of the best rules

We examined the ten futures markets based on four values of q of the stationary bootstrap method under the SPA test, each corresponding to 1000 resamples. Table 2 contains the traditional t-test p-values for the best trading rules and their SPA test counterparts. The best rule under the traditional t-test refers to those whose studentized average daily returns in excess of their benchmark performance are largest. The results on Table 2 tend to suggest that the data-snooping unadjusted p-values of the best trading rules are much less than their SPA_c counterparts in most of the scenarios tested. This finding appears to indicate that the traditional t-test overstates the statistical significance of the best trading rules' performance relative to what the SPA test suggests. Moreover, the null hypothesis that the best trading rule cannot beat the buy-and-hold benchmark is rejected under the SPA test in seven out of the ten markets for at least one sub-testing period: EUR/$ FX, Stoxx-50, FT-100, TW, Cattle, Crude oil and Coffee. This finding contrasts STW who found statistically insignificant results based on their universe of 7846 rules for the S&P 500 futures market. The results on Table 2 also tend to show that the null hypothesis is more frequently rejected in bearish markets than in bullish markets. In particular, we found statistically significant SPA p-values for the best rules in nine bearish periods but in only four bullish periods.

Table 3 reports the titles of the best trading rules, which statistically significantly outperform the buy-and-hold benchmark strategy according to Table 2. After accounting for the risk (i.e., the standard deviation of the daily return differential), stated otherwise, Table 3 contains those statistically significant, best outperformers against the buy-and-hold strategy. We found that the best rules are mainly in the categories of MFI–RSI and MSV for all ten markets under all four choices of the expected block size ($1/q$). Among the 24 best trading rules on Table 3, in particular, the MFI–RSI category contains 15 of them, while the MSV category includes the remaining nine. On the other hand, none of the best trading rules comes from the other three types of rules. This result

Table 2
Traditional *t*-test *p*-values for the best rules Vs. their SPA *p*-values.

Panel A: Financial futures									
EUR/$ FX									
Market condition *traditional t-test*	Bearish (02/Jan/01–05/Jul/01) *p*-value = 0.009***[b]			Bullish (06/Jul/01–29/Dec/04) *p*-value = 0.148			Bearish (30/Dec/04–31/Jan/06) *p*-value = 0.018**		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	**0**[d]	**0**	**0**	0.800	0.958	0.964	**0.061**	**0.073**	**0.076**
$q = 0.1$	**0.083**	**0.098**	**0.098**	0.948	1	1	0.312	0.366	0.366
$q = 0.25$	0.222	0.255	0.258	0.926	0.985	0.987	0.422	0.493	0.495
$q = 0.5$	0.428	0.499	0.499	0.898	0.984	0.985	0.515	0.577	0.580
Stoxx-50[a]									
Market condition *traditional t-test*	Bullish (21/Jun/00–04/Sep/00) *p*-value = 0.018**			Bearish (05/Sep/00–11/Mar/03) *p*-value = 0.003***			Bullish (12/Mar/03–31/Jan/06) *p*-value = 0.004***		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	Not enough data[c]			**0**	**0**	**0**	0.532	0.698	0.736
$q = 0.1$	**0.016**	**0.017**	**0.018**	**0.037**	**0.037**	**0.037**	0.508	0.721	0.744
$q = 0.25$	0.099	0.131	0.138	0.119	0.120	0.120	0.269	0.476	0.492
$q = 0.5$	0.289	0.401	0.420	0.183	0.187	0.187	0.218	0.406	0.422
FT-100									
Market condition *traditional t-test*	Bullish (27/Jun/00–04/Sep/00) *p*-value = 0.027**			Bearish (05/Sep/00–11/Mar/03) *p*-value = 0.000***			Bullish (12/Mar/03–31/Jan/06) *p*-value = 0.002***		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	Not enough data			**0.001**	**0.001**	**0.001**	**0.029**	**0.046**	**0.054**
$q = 0.1$	0.110	0.131	0.143	**0.050**	**0.050**	**0.050**	0.166	0.254	0.263
$q = 0.25$	0.428	0.559	0.595	0.106	0.107	0.107	0.191	0.280	0.290
$q = 0.5$	0.522	0.677	0.701	0.114	0.115	0.115	0.214	0.321	0.327
TW									
Market condition *traditional t-test*	Bullish (22/Apr/99–17/Feb/00) *p*-value = 0.080*			Bearish (18/Feb/00–02/Oct/01) *p*-value = 0.001***			Bullish (03/Oct/01–24/Jan/06) *p*-value = 0.001***		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	0.125	0.152	0.162	**0**	**0**	**0**	**0.027**	**0.042**	**0.042**
$q = 0.1$	0.578	0.704	0.705	**0.039**	**0.039**	**0.039**	0.262	0.363	0.366
$q = 0.25$	0.722	0.824	0.826	**0.065**	**0.066**	**0.066**	0.259	0.352	0.355
$q = 0.5$	0.721	0.811	0.811	0.129	0.131	0.131	0.212	0.315	0.318
T-bond									
Market condition *traditional t-test*	Bearish (01/Oct/84–03/Oct/84) Not enough data			Bullish (04/Oct/84–02/Oct/98) *p*-value = 0.199			Bearish (05/Oct/98–31/Jan/06) *p*-value = 0.003***		
SPA Test				SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	Not enough data			0.994	1	1	0.210	0.253	0.257
$q = 0.1$				1	1	1	0.473	0.574	0.583
$q = 0.25$				1	1	1	0.453	0.563	0.569
$q = 0.5$				1	1	1	0.501	0.623	0.633
Panel B: Commodity futures									
Cattle									
Market condition *traditional t-test*	Bearish (30/Nov/76–14/Jan/77) *p*-value = 0.009***			Bullish (17/Jan/77–14/Oct/03) *p*-value = 0.021**			Bearish (15/Oct/03–31/Jan/06) *p*-value = 0.004***		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	Not enough data			0.455	0.733	0.774	**0.045**	**0.056**	**0.063**
$q = 0.1$	**0.043**	**0.048**	**0.048**	0.785	0.960	0.971	0.516	0.655	0.671
$q = 0.25$	0.160	0.169	0.169	0.862	0.990	0.991	0.608	0.772	0.780
$q = 0.5$	0.225	0.238	0.238	0.846	0.975	0.982	0.512	0.652	0.658
Gold									
Market condition *traditional t-test*	Bearish (24/Jan/86–25/Aug/99) *p*-value = 0.011**			Bullish (26/Aug/99–31/Jan/06) *p*-value = 0.211					
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u			
$q = 0.01$	0.169	0.188	0.188	0.801	0.954	0.962			
$q = 0.1$	0.396	0.428	0.428	0.942	0.996	0.996			
$q = 0.25$	0.401	0.442	0.442	0.948	0.998	0.998			
$q = 0.5$	0.415	0.467	0.467	0.948	0.994	0.994			

Table 2 (*continued*)

Panel B: Commodity futures									
Crude oil									
Market condition *traditional t-test*	Bearish (11/Jan/89–10/Dec/98) p-value = 0.012**			Bullish (11/Dec/98–29/Aug/05) p-value = 0.259			Bearish (30/Aug/05–31/Jan/06) p-value = 0.009***		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	0.738	0.824	0.824	0.957	0.999	1	**0**	**0**	**0**
$q = 0.1$	0.454	0.549	0.549	0.98	1	1	**0.041**	**0.055**	**0.055**
$q = 0.25$	0.341	0.419	0.419	0.986	0.998	0.998	0.265	0.316	0.318
$q = 0.5$	0.380	0.477	0.477	0.990	0.999	0.999	0.401	0.489	0.494
Coffee									
Market condition *traditional t-test*	Bullish (31/Jan/89–29/May/97) p-value = 0.011**			Bearish (30/May/97–03/Dec/01) p-value = 0.000***			Bullish (04/Dec/01–31/Jan/06) p-value = 0.005***		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	0.423	0.460	0.463	**0**	**0**	**0**	**0.028**	**0.036**	**0.038**
$q = 0.1$	0.624	0.670	0.670	**0.082**	**0.083**	**0.083**	0.358	0.457	0.462
$q = 0.25$	0.626	0.668	0.669	**0.082**	**0.085**	**0.085**	0.395	0.516	0.522
$q = 0.5$	0.568	0.620	0.621	**0.099**	**0.101**	**0.101**	0.419	0.549	0.553
Soybean									
Market condition *traditional t-test*	Bullish (13/Sep/84–27/Jun/88) p-value = 0.081*			Bearish (28/Jun/88–07/Jul/99) p-value = 0.027**			Bullish (08/Jul/99–31/Jan/06) p-value = 0.043**		
SPA test	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
$q = 0.01$	0.306	0.329	0.329	0.288	0.305	0.305	0.457	0.581	0.581
$q = 0.1$	0.681	0.769	0.769	0.464	0.501	0.501	0.680	0.767	0.767
$q = 0.25$	0.722	0.803	0.804	0.568	0.593	0.593	0.642	0.724	0.724
$q = 0.5$	0.731	0.823	0.823	0.624	0.650	0.650	0.668	0.748	0.748

[a] For the first testing period in the case of Stoxx-50, 9 rules, *FR*(40, 15, 10), *FR*(40, 20, 10), *FR*(40, 15, 15), *FR*(40, 20, 15), *FR*(40, 15, 20), *FR*(40, 20, 20), *MA*(10, 125, 5), *MA*(15, 125, 4) and *MA*(30, 125, 2), generated the same sets of trading signals as the buy-and-hold benchmark. We thus deleted these 9 rules in order to let the SPA test to work in this particular scenario.

[b] ***, ** and * denote, respectively, 1%, 5% and 10% significance level for the traditional *t*-test.

[c] 'Not enough data', indicates insufficient data for the SPA test under the specified q. For a given value of q (e.g. 0.01), the stationary bootstrap requires at least $1/q$ (= 100) data observations for the bootstrap to work.

[d] All the SPA p-values in bold denote statistical significance at the 10% level.

Table 3
The significant best trading rules according to the market and the value of q under the SPA test.

Market	Testing period (market condition)	q	Trading rule
EUR/$ FX	I. 02/Jan/01–05/Jul/01 (bearish)	0.01	*MFI–RSI*(15,5,30,30,60,60)
		0.10	*MFI–RSI*(15,5,30,30,60,60)
	III. 30/Dec/04–31/Jan/06 (bearish)	0.01	*MFI–RSI*(5,10,30,30,60,70)
Stoxx-50	I. 21/Jun/00–04/Sep/00 (bullish)	0.10	*MFI–RSI*(5,5,30,20,80,60)
	II. 05/Sep/00–11/Mar/03 (bearish)	0.01	*MSV*(250,20,30,5,5)
		0.10	*MSV*(250,10,30,20,25)
FT-100	II. 05/Sep/00–11/Mar/03 (bearish)	0.01	*MSV*(60, 2, 10, 5, 5)
		0.10	*MSV*(50, 5, 50, 5, 10)
	III. 12/Mar/03–31/Jan/06 (bullish)	0.01	*MFI–RSI*(5,30,20,30,60,80)
			MFI–RSI(10,30,20,30,60,80)
			MFI–RSI(15,30,30,30,60,80)
TW	II. 18/Feb/00–02/Oct/01 (bearish)	0.01	*MSV*(250,2,10,20,10)
		0.10	*MFI–RSI*(5,10,20,30,70,60)
		0.25	*MFI–RSI*(5,10,20,30,70,60)
	III. 03/Oct/01–24/Jan/06 (bullish)	0.01	*MFI–RSI*(30, 30, 30, 30, 80, 70)
Cattle	I. 30/Nov/76–14/Jan/77 (bearish)	0.10	*MSV*(50, 30, 50, 5, 50)
	III. 15/Oct/03–31/Jan/06 (bearish)	0.01	*MSV*(250, 5, 50, 20, 50)
Crude oil	III. 30/Aug/05–31/Jan/06 (bearish)	0.01	*MSV*(40, 10, 20, 10, 10)
		0.10	*MSV*(40, 10, 20, 10, 10)
Coffee	II. 30/May/97–03/Dec/01 (bearish)	0.01	*MFI–RSI*(5, 5, 40, 30, 60, 80)
		0.10	*MFI–RSI*(5, 5, 30, 30, 60, 80)
		0.25	*MFI–RSI*(20, 5, 20, 30, 80, 80)
		0.50	*MFI–RSI*(20, 5, 20, 30, 80, 80)
	III. 04/Dec/01–31/Jan/06 (bullish)	0.01	*MFI–RSI*(30, 40, 20, 40, 70, 80)

The consistent estimate of the standard deviation of the normalized average abnormal return, $\sqrt{T}\ \bar{r}_k$, depends on the value of the smooth parameter of the geometric distribution assumed for the block size under the stationary bootstrap (i.e. q in Eq. (7) in Section 2.2.1). As a result, the best trading rule might not be the same across the four choices of q, which leads to different p-values under the SPA test. Moreover, we found that, in some circumstances such as during the 2nd subperiod in the Stoxx-50 market with q of 0.01 and 0.1, more than one trading rules generate the same best set of trading signals. Therefore, they equally became the best trading rule with the same p-value under the SPA test.

tends to indicate that the trading rules constructed based on volume only or on volume plus price dominate those based on price only. Although the best trading rules concentrate in the MFI–RSI category, however, we cannot find a single best trading rule which applies to all ten markets.

Another issue that has been ignored by the literature involves the effect of the expected block size of the stationary bootstrap, $1/q$, on the SPA test results. Setting q to be 0.25 under the SPA test, Hansen conducted an empirical study to evaluate a large number of competing linear regression models used to forecast the annual U.S. inflation rate [13]. However, our results contained in Tables 2 and 3 suggest that the SPA test results tend to be subject to the choice of q. Since the true level of autocorrelation in the performance of the average trading rule relative to the benchmark is unknown, there is no criterion to determine the most appropriate value for q. It is thus best to say that the null hypothesis of no superiority of our 8061 rules over their benchmark is rejected only when the SPA_c p-values under all four choices of q are less than or equal to 0.1. In our context, only in the bearish testing periods for FT-100 (05/Sep/00–11/Mar/03) and for Coffee (30/May/97–03/Dec/01), the best trading rules 'really' outperform the buy-and-hold benchmark.[10]

[10] The SPA_c p-values are trivially larger than 0.1 under q of 0.25 and 0.5 for FT-100 during the second subperiod and under q of 0.5 for Coffee during the second subperiod, as shown in Table 2.

Table 4
Out-of-sample performance of the best in-sample 'real' outperforming rules according to the SPA test.

Market	In-sample performance				Out-of-sample performance					
	Market condition of the last sub-testing period	q	Title of best rule	Studentized mean abnormal return of best rule[a]	Studentized mean abnormal return of best rule[a]	Nominal p-values of best rule[b]			Cumulative excess return of best rule[c]	Cumulative excess return of buy-and-hold[c]
						SPA_l	SPA_c	SPA_u		
EUR/$ FX	Bearish	0.01	*MFI–RSI*(5, 10, 30, 30, 60, 70)	3.312	−0.453	0.277	0.448	0.448	−81.66%	94.13%
			MFI–RSI(5, 30, 20, 30, 60, 80)						−18.06%	−18.06%
FT-100	Bullish	0.01	*MFI–RSI*(10, 30, 20, 30, 60, 80)	3.708	Equal performance[d]				−18.06%	−18.06%
			MFI–RSI(15, 30, 30, 30, 60, 80)						−18.06%	−18.06%
TW	Bullish	0.01	*MFI–RSI*(30, 30, 30, 30, 80, 70)	3.815	Equal performance				−72.59%	−72.59%
Cattle	Bearish	0.01	*MSV*(250, 5, 50, 20, 50)	3.562	1.830	**0.042**	**0.042**	**0.042**	**317.07%**	**−99.85%**
Crude oil	Bearish	0.01	*MSV*(40, 10, 20, 10, 10)	8.414	0.577	0.237	0.237	0.237	−74.31%	−88.80%
		0.10	*MSV*(40, 10, 20, 10, 10)	3.426	0.526	0.300	0.300	0.300	−74.31%	−88.80%
Coffee	Bullish	0.01	*MFI–RSI*(30, 40, 20, 40, 70, 80)	3.723	Equal performance				−86.78%	−86.78%

[a] The studentized mean abnormal returns were calculated using $\sqrt{T}\ \bar{r}_k/\hat{\sigma}_k$ in Eq. (3).
[b] The nominal p-values for the out-of-sample performance results were obtained by applying the SPA test to the best rule only. Since there is only one rule tested during the out-of-sample period, there is no data-snooping bias.
[c] Cumulative excess returns are calculated by compounding the daily returns in excess of the risk-free rate over the one-year out-of-sample period for both the best rule and the benchmark.
[d] 'Equal performance' denotes the best trading rule generating the same series of signals as does the buy-and-hold benchmark during the out-of-sample period. The SPA test cannot be applied to this context since the day-to-day returns generated by the trading rule are identical to those by the benchmark. As a result, the p-values of the SPA test and their upper and lower bounds are not available.

4.1.2. Out-of-sample performance of 'real' in-sample best rules

What the in-sample results reported on Tables 2 and 3 do not necessarily guarantee persistence of the relatively good performance of those significant, best rules across time. We thus conducted an out-of-sample test for those significant best rules selected from the last in-sample testing period. Only 6 out of the 10 markets lead to a significant, best rule under the SPA test as shown by Table 4, namely, EUR/$ FX, FT-100, TW, Cattle, Crude oil and Coffee. Despite their good performance relative to the buy-and-hold benchmark during the last testing period of the six markets, all these best rules except the one for the contract of Cattle fail to consistently outperform the benchmark during the one-year out-of-sample period according to their nominal SPA p-values. What is worse is that these in-sample outperforming rules generate negative cumulative excess returns during the out-of-sample period. This result indicates that the best rules selected from the universe of technical trading rules tested in this study are not able to enhance traders' profits relative to the buy-and-hold benchmark although they have been proved useful and profitable in the most recent past for the six futures markets above. In general, the ten futures markets seem to be efficient at least in a weak form. The only exception appears for the contract of Cattle in that the best trading rule selected from the last testing period, an *MSV* (250, 5, 50, 20, 50), keeps beating the benchmark in the out-of-sample period, as suggested by the nominal SPA_c p-value of 0.042. It generates an economically large cumulative excess return, 317.07%, which dwarfs the buy-and-hold counterpart, −99.85%. Coincidentally, the last testing period for the Cattle futures market is also a bearish one.

4.2. Results on Sortino and reversed Sortino ratios

To differentiate the performance of the 8061 trading rules in a downside market from that in an upside market, we calculated both the Sortino and reversed Sortino ratios for each contract according to Eqs. (9) to (12). Table 5 reports the largest values of these two ratios (i.e. the best rule) among the 8061 rules for all ten contracts during the entire testing period and their out-of-sample counterparts. The two ratios for the benchmark strategy are also reported. Although the difference between the (reversed) Sortino ratios of the best rule and of the benchmark cannot be tested in the framework of the SPA test,[11] its size for both ratios in both the in-sample and out-of-sample periods seems to be economically large and non-negligible for all ten contracts.

[11] Since the Sortino (reversed Sortino) ratio is based on the lower (upper) semi-standard deviation of negative (positive) returns and it is impossible for the trading rule and the benchmark to generate only negative (positive) returns on the same series of dates, the SPA test is thus not applicable due to lack of a common sample period.

4.2.1. Best rules of downside and upside markets

The left half of Table 5 shows that the Sortino ratio of the best trading rule is larger than the reversed Sortino ratio of the best trading rule for all ten contracts. This result tends to suggest that the best trading rule selected from the universe of our 8061 candidates tends to perform better in a downside market than in an upside market. Except for the three contracts of FT-100, Crude oil and Soybean, the best rule is not the same across the two ratios. Moreover, there is not a single category of rules which dominate the others for downside markets. Certainly, MA category seems to trail its four competitors in finding the best rule from both market conditions for all ten contracts. For upside markets, however, the best trading rules lie mainly in the categories of MSV and MFI–RSI, a finding consistent with our SPA test results for the in-sample data. As for the benchmark, the two ratios seem to be very close to each other for all ten contracts, which suggests that each of the ten futures markets is as volatile in an upside market condition as in a downside market condition during the entire in-sample period. This provides a fair setting for us to compare the performance of the best trading rule during different market conditions.

4.2.2. Out-of-sample performance of in-sample rules with largest (reversed) Sortino ratio

In parallel with the analysis in Section 4.1.2, we discuss here whether the relatively good performance of the trading rules with the largest (reversed) Sortino ratio persists through the one-year out-of-sample period. The right half of Table 5 shows that the Sortino and the reversed Sortino ratios of the in-sample best rules are larger than their benchmark counterparts in only five and four markets, respectively. In particular, the best in-sample 'downside' trading rule consistently outperforms the benchmark for five out of the eight contracts where the best rules generate signals during the out-of-sample period: EUR/$ FX, Stoxx-50, T-Bond, Cattle and Crude oil. Measured by the reversed Sortino ratio, on the other hand, the best in-sample 'upside' trading rule outperforms the benchmark for only four out of the ten contracts where the best rules generate signals during the out-of-sample period: T-Bond, Cattle, Crude oil and Coffee. This result tends to suggest a percentage of persistent best 'downside' rules higher than that of persistent best 'upside' rules. Unlike the results based on the SPA test, moreover, both persistent 'downside' and 'upside' best rules tend to bring forth a cumulative excess return better than the benchmark does. The only

Table 5
Out-of-sample performance of the best in-sample outperforming rules according to the Sortino and reversed Sortino ratios.

Market	In-sample performance						Out-of-sample performance							
	Downside performance			Upside performance			Downside performance				Upside performance			
	Title of best rule	*Sortino ratio*		Title of best rule	*reversed Sortino ratio*		*Sortino ratio*		Cumulative excess return		*Reversed Sortino ratio*		Cumulative excess return	
		Best rule	Buy-and-hold		Best rule	Buy-and-hold	Best rule	Buy-and-hold	Best rule	Buy-and-hold	Best rule	Buy-and-hold	Best rule	Buy-and-hold
EUR/$FX	*FR*(6, 0.5, 10)	0.116	0.035	*MSV*(250, 2, 5, 15, 50)	0.098	0.034	**0.168**	**0.081**	**105.16%**	**94.13%**	−0.087	0.074	−99.86%	94.13%
Stoxx-50	*MFI–RSI*(5,5,30,20,60,60)	0.081	−0.023	*MSV*(40, 2, 40, 15, 5)	0.066	−0.024	**0.055**	**0.041**	**34.33%**	**7.95%**	−0.070	0.045	−79.39%	7.95%
FT-100	*MSV*(40, 2, 5, 20, 25)	0.081	−0.028	*MSV*(40, 2, 5, 20, 25)	0.067	−0.029	−0.051	0.034	−81.05%	−18.06%	−0.049	0.039	−81.05%	−18.06%
TW	*FR*(30, 0.5, 3)	0.492	−0.010	*MSV*(40, 5, 20, 15, 10)	0.064	−0.011	No signal	0.024	−4.56%	−72.59%	−0.027	0.027	−95.04%	−72.59%
T-Bond	*MSV*(250, 40, 60, 20, 25)	0.055	0.030	*MFI–RSI*(20, 15, 40, 20, 80, 80)	0.045	0.030	**0.082**	**−0.048**	**121.82%**	**−73.91%**	**0.045**	**−0.051**	**30.18%**	**−73.91%**
Cattle	*OBV*(25, 50)	0.041	0.022	*MFI–RSI*(5, 15, 20, 30, 70, 80)	0.039	0.022	**0.009**	**−0.078**	−100.27%	−99.85%	**−0.016**	**−0.093**	−100.06%	−99.85%
Gold	*MFI–RSI*(20,15, 30, 40, 80, 70)	0.039	0.005	*MSV*(50, 10, 20, 20, 25)	0.034	0.005	−0.048	0.070	−94.93%	61.14%	−0.115	0.078	−96.44%	61.14%
Crude oil	*MSV*(250, 2, 20, 20, 10)	0.056	0.023	*MSV*(250, 2, 20, 20, 10)	0.043	0.023	**0.096**	**−0.042**	**173.72%**	**−88.80%**	**0.085**	**−0.046**	**173.72%**	**−88.80%**
Coffee	*FR*(30, 5, 1)	0.106	−0.017	*MFI–RSI*(30, 15, 20, 30, 60, 80)	0.039	−0.018	No signal	−0.019	−4.59%	−86.78%	**0.018**	**−0.020**	**−60.60%**	**−86.78%**
Soybean	*MSV*(125, 2, 10, 15, 50)	0.040	−0.004	*MSV*(125, 2, 10, 15, 50)	0.036	−0.004	0.010	0.077	−29.89%	100.89%	0.008	0.075	29.89%	100.89%

[a] Numbers in bold are results for those best rules which outperfom the buy-and-hold strategy during the out-of-sample period.

exception occurs in the case of Cattle where both the best 'downside' rule, an *OBV*(25, 50), and the best 'upside' rule, an *MFI–RSI*(5, 15, 20, 30, 70, 80), fail to generate a cumulative excess return better than the benchmark counterpart. While not reported here, a careful scrutiny of the day-to-day returns of these two rules over the out-of-sample period reveals the reason: a single large, negative daily return of about 250% in size hinders these two rules from outperforming their benchmark.

5. Conclusions

Our SPA test results tend to suggest market efficiency in that the universe of our 8061 trading rules is generally unable to beat the buy-and-hold strategy although they were selected from among the most-profitable types of technical trading rules in previous studies. Only one of the nine 'real' (i.e. statistically significant) outperformers identified from the most recent testing period, i.e. an MSV rule in the live cattle futures market, consistently beats the benchmark over the one-year out-of-sample period. However, the results based on the Sortino and reversed Sortino ratios are not completely in accord with what we found with the SPA test. The best 'downside' rule and the best 'upside' rule selected from the entire in-sample testing period are both able to generate a rate of return exceeding the benchmark over the one-year out-of-sample period for a few contracts. Despite the inconsistency between the two sets of results on performance persistence of the trading rules, we found that the best rules screened by both methods come from the MFI–RSI and MSV categories, both using the volume information.

Although our empirical results tend to deny the profitability of our 8061 rules in many of the ten futures markets, it might be overreaching to imply the deficiency of technical analysis in the futures markets. As technical analysis continues to develop rapidly, new trading rules and strategies employed by futures market practitioners might have been much more complicated than those used in this study. It is worthwhile to reexamine this issue when more techniques are revealed to the public. Moreover, the SPA test used to control for the data-snooping bias can be improved to examine not only the most-profitable rule but also all others which significantly outperform the benchmark. Testing the performance persistence of all outperformers in the out-of-sample period will give a more general picture of the profitability of technical analysis in the futures markets. Two recently developed statistical techniques, the stepwise reality check (SRC) [20] and the stepwise test for superior predictive ability (SSPA test) [15], might contribute to this issue.

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Appendix A. Money flow index with relative strength index

We first define *RSI* and *MFI* respectively. Let $U_t \equiv p_t - p_{t-1}$ if $p_t > p_{t-1}$ and 0 otherwise, and $D_t \equiv p_{t-1} - p_t$ if $p_t < p_{t-1}$ and 0 otherwise, where p_t refers to the day-t closing price. An N-day *RSI* on day t is given by

$$RSI_t(N) = 100 - 100 / (1 + RS_t(N)), \tag{A.1}$$

where

$$RS_t(N) = \sum_{i=0}^{N-1} U_{t-i} / \sum_{i=0}^{N-1} D_{t-i}, \tag{A.2}$$

Eq. (A.1) gives the first RSI_N of the entire data, i.e. $t=N$. From there, we continue to build $RSI_t(N)$ for $t>N$. To avoid extreme values of RS_N such as positive (negative) infinity following an N-day continuous rise (decline) in p_t, (A.2) should be replaced by

$$RS_t(N) = EMA_t^N(U) / EMA_t^N(D), \tag{A.3}$$

where $EMA_t^N(U)$ and $EMA_t^N(D)$ denote, respectively, the N-day exponential moving average of U_t and D_t. In particular, they are given by $EMA_t^N(U) = \alpha^* U_t + (1-\alpha)^* EMA_{t-1}^N(U)$ and $EMA_t^N(D) = \alpha^* D_t + (1-\alpha)^* EMA_{t-1}^N(D)$, where $\alpha \equiv 2/(1+N)$. Note that the initial values of $EMA_t^N(U)$ and $EMA_t^N(D)$ are given by the average of U_t and D_t, respectively, over the first N days.

While the *RSI* is solely based on the closing price, the *MFI* also takes into account the trading volume. This might explain why the literature calls the latter a volume-weighted version of the *RSI*. According to Achelis [1], let p_t^H, p_t^L and p_t^C denote the highest, lowest and closing prices, the typical price is given by $TP_t \equiv (p_t^H + p_t^L + p_t^C)/3$. Let Vol_t denote the trading volume of day t, $MF_t^+ = TP_t \times Vol_t$ if $TP_t > TP_{t-1}$ and 0 if otherwise, and $MF_t^- = TP_t \times Vol_t$ if $TP_t < TP_{t-1}$ and 0 if otherwise, an N-day *MFI* on day t is given by

$$MFI_t(N) = 100 - 100 / (1 + MR_t(N)), \tag{A.4}$$

where $MR_t(N) = PMF_t(N) / NMF_t(N)$, $PMF_t(N) \equiv \sum_{i=0}^{N-1} MF_{t-i}^+$ and $NMF_t(N) \equiv \sum_{i=0}^{N-1} MF_{t-i}^-$.Let BO_{MFI}, SO_{MFI}, BO_{RSI}, SO_{RSI}, $MFI(N_1)$ and $RSI(N_2)$ denote, respectively, the overbought and oversold levels for *MFI*, the overbought and oversold levels for *RSI*, an N_1-day *MFI* and an N_2-day *RSI*, trading signals are given by the following rules.

A. *Long entry (short exit)*: Whenever one of the following three conditions is satisfied, we go long a futures contract (close out the short position).

a.1. $MFI(N_1)$ crosses SO_{MFI} from below and simultaneously $RSI(N_2)$ crosses SO_{RSI} from below.
a.2. $MFI(N_1)$ crosses SO_{MFI} from below if $RSI(N_2)$ crossed SO_{RSI} from below and stays above SO_{RSI}.
a.3. $RSI(N_2)$ crosses SO_{RSI} from below if $MFI(N_1)$ crossed SO_{MFI} from below and stays above SO_{MFI}.

B. *Long exit (short entry)*: Whenever one of the following three offsetting signals appears, we close out the long position above (go short a futures contract).

b.1. $MFI(N_1)$ crosses BO_{MFI} from above and simultaneously $RSI(N_2)$ crosses BO_{RSI} from above.
b.2. $MFI(N_1)$ crosses BO_{MFI} from above if $RSI(N_2)$ crossed BO_{RSI} from above and stays below BO_{RSI}.
b.3. $RSI(N_2)$ crosses BO_{RSI} from above if *MFI* crossed BO_{MFI} from above and stays below BO_{MFI}.

An entry signal for a new short position appears just when an exit signal for closing out an existing long position is confirmed by any of the three long exit rules above. Similarly, an exit signal for closing out an existing short position emerges when an entry signal for a new long position occurs under any of the three long entry rules above. Details are not repeated here.

Appendix B. Filter rules

Long entry: When the current closing price rises from the most recent lowest closing price over the past N days by a% or more, we go long a futures contract.

Long exit: We close out the long position when the current closing price drops by b% or more from the latest highest closing price over the past N days following the most recent lowest closing price above, where b is prespecified to be equal to or less than a.

Short entry: When the current closing price drops from the most recent highest closing price over the past N days by a% or more, we go short a futures contract.

Short exit: We close out the short position when the current closing price recovers by b% or more from the latest lowest closing price over the past N days following the most recent highest closing price above, where b is prespecified to be equal to or less than a.

Appendix C. Moving averages

Let $MA_t(N)$ be the N-day simple moving average of the closing prices calculated on day t. It is given by

$$MA_t(N) = \left(\sum_{i=1}^{N-1} p_{t-i} \right) / N, \tag{C.1}$$

where p_t denotes the closing price of day t. Given a short $MA_t(N_1)$ and a relatively long $MA_t(N_2)$, where N_1 is less than N_2, the trading signals are generated as follows.

Long entry (short exit): When $MA_t(N_1)$ crosses $MA_t(N_2)$ from below to the extent that $MA_t(N_1)$ is larger than $MA_t(N_2)$ by b% of $MA_t(N_2)$ or more, we go long a futures contract (close out the short position).

Long exit (short entry): When $MA_t(N_1)$ crosses $MA_t(N_2)$ from above to the extent that $MA_t(N_1)$ is less than $MA_t(N_2)$ by b% of $MA_t(N_2)$ or more, we close out the long position (short sell a futures contract).

Appendix D. On-balance volume averages

Let OB_t, called *OB*-indicator, be the cumulative trading volume calculated on day t and be dependent on the price movements. It is given by

$$OB_t = OB_{t-1} + Vol_t \text{ if } p_t > p_{t-1}, \quad OB_{t-1} \text{ if } p_t = p_{t-1}, \text{ and} \tag{D.1}$$

$$OB_{t-1} - Vol_t \text{ if } p_t < p_{t-1},$$

where Vol_t and p_t denote, respectively, the trading volume and the closing price of day t. Note that the initial point for OB_t, i.e. the zero point, is arbitrary. We set the beginning of the 1-year signal-generating period as the initial point. An N-day *OBV* indicator is the N-day simple moving average of the *OB*-indicator above. In particular,

$$OBV_t(N) \equiv \left(\sum_{i=0}^{N-1} OB_{t-i} \right) / N. \tag{D.2}$$

Given a short $OBV_t(N_1)$ and a relatively long $OBV_t(N_2)$, where N_1 is less than N_2, the trading signals are generated as follows.

Long entry (short exit): When $OBV_t(N_1)$ crosses $OBV_t(N_2)$ from below, we go long a futures contract (close out the short position).

Long exit (short entry): When $OBV_t(N_1)$ crosses $OBV_t(N_2)$ from above, we close out the long position (short sell a futures contract).

Appendix E. Momentum strategy in volume

Let $ROC_t(e)$ denote the rate of change in the current day's trading volume with respect to the trading volume e days ago. In other words, $ROC_t(e) = (Vol_t - Vol_{t-e}) / Vol_{t-e}$, where e is an integer larger than 1.

An MSV indicator is given by a simple moving average of the $ROC_t(e)$. In particular, an N-day $MSV_t(N)$ is given by

$$MSV_t(N) \equiv \left(\sum_{i=0}^{N-1} ROC_{t-i}(e) \right) / N. \tag{E.1}$$

Given a short $MSV_t(N_1)$ and a relatively long $MSV_t(N_2)$, where $N_1 < N_2 \le e$, the trading signals are generated as follows.

Long entry: When $MSV_t(N_1)$ crosses $MSV_t(N_2)$ from below to the extent that $MSV_t(N_1)$ is larger than $MSV_t(N_2)$ by b% of $MSV_t(N_2)$ or more, we go long a futures contract.

Long exit: We close out the long position g days after it is established, ignoring all signals during the period between.

Short entry: When $MSV_t(N_1)$ crosses $MSV_t(N_2)$ from above to the extent that $MSV_t(N_1)$ is less than $MSV_t(N_2)$ by b% of $MSV_t(N_2)$ or more, we short sell a futures contract.

Short exit: We close out the short position g days after it is established, ignoring all signals during the period between.

Appendix F. Summary of parameters used in all rules

Category	Parameter	Value	No. of rules
MFI–RSI	N_1	5, 10, 15, 20, 30, 40	2916
	N_2	5, 10, 15, 20, 30, 40	
	SO_{MFI}	20, 30, 40	
	SO_{RSI}	20, 30, 40	
	BO_{MFI}	60, 70, 80	
	BO_{RSI}	60, 70, 80	
FR	a	0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 6, 7, 8, 9, 10, 12, 14, 16, 18, 20, 25, 30, 40, 50	1560
	b	0.5, 1, 1.5, 2, 2.5, 3, 4, 5, 7.5, 10, 15, 20	
	N	1, 2, 3, 4, 5, 10, 15, 20	
MA	N_1	2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200	840
	N_2	2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250	
	b	0.1, 0.5, 1, 1.5, 2, 3, 4, 5	
OBV	N_1	2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200	105
	N_2	2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250	
MSV	e	2, 5, 10, 20, 30, 40, 50, 60, 125, 250	2640
	N_1	2, 5, 10, 20, 30, 40, 50, 60, 125	
	N_2	2, 5, 10, 20, 30, 40, 50, 60, 125, 250	
	b	5, 10, 15, 20	
	g	5, 10, 25, 50	

Note: N_1 and N_2 for *MFI–RSI* are selected arbitrarily to contain a reasonable size of window for calculating the two component indicators' values. The settings for SO_{MFI}, SO_{RSI}, BO_{MFI}, and BO_{RSI} are fixed at the levels commonly used by market practitioners. The parameter settings used for FR, MA and OBV are from STW [23], while those for MSV are from HK [14]. Definitions for all parameters listed in the second column are detailed in Appendices A through E.

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Stéphane M.F. Yen received his Ph.D. degree in Finance from the ICMA Centre at the University of Reading, U.K. in 2005. Since Aug. 2006, he has been an assistant professor with the Department of Accountancy and the Institute of Finance and Banking at the National Cheng Kung University, Tainan, Taiwan. His research interests involve mainly financial econometrics, funds performance evaluation and socially responsible investing.

Ying-Lin Hsu received his Ph.D. degree in Statistics from the National Chiao Tung University, Taiwan in 2002. He is currently an associate professor with the Department of Applied Mathematics and the Institute of Statistics at National Chung Hsing University, Taichung, Taiwan. His major research interests include statistical applications in industrial engineering, finance and bioinformatics.