INTERNATIONAL
REVIEW OF FINANCE

International Review of Finance, 19:1, 2019: pp. 191–206
DOI: 10.1111/irfi.12161

Technical Analysis Profitability Without Data Snooping Bias: Evidence from Chinese Stock Market*

FUWEI JIANG[†], GUOSHI TONG[‡] AND GUOKAI SONG[†]
[†]School of Finance, Central University of Finance and Economics, Beijing, China and
[‡]Hanqing Advanced Institute of Economics and Finance, Renmin University of China, Beijing, China

ABSTRACT

We perform a comprehensive analysis on the profitability of a large number of technical analysis based trading rules in Chinese stock market. To counter data snooping bias, we employ a stepwise superior predictive ability test to identify genuinely profitable trading rules among more than 28,000 technical signals. Using 19 years of daily data on Chinese aggregate stock market return, we find substantial evidence on the profitability of technical trading rules measured by either the market timing ability or Sharpe ratio gain. Our results on the profitability of technical rules hold during different subperiods and remain valid under the presence of transaction costs.

JEL Codes: C12; C52; G14

Accepted: 15 September 2017

I. INTRODUCTION

Technical analysis involves a set of trading rules that make buy and sell decisions on the underlying security based on its past price patterns, trading volumes and potentially other public information. Technical analysis is widely adopted among security analysts, covered in financial news media and easily accessible to most investors through various trading platforms. From a theoretical perspective, the use of technical analysis to forecast future return is justified in a number of equilibrium models that feature heterogeneity in investors'

* We gratefully acknowledge the helpful comments from the Editor, an anonymous referee, and feedbacks from Huafeng Chen, Po-Hsuan Hsu, Guofu Zhou, and seminar participants at Renmin University and Central University of Finance and Economics. We also thank Prof. Po-Hsuan Hsu for sharing with us a series of MATLAB and Fortran codes on superior predictive ability tests. This article is supported by the National Natural Science Foundation of China (Nos. 71602198, 71572052), Beijing Natural Science Foundation (No. 9174045), and the Program for Innovation Research in Central University of Finance and Economics.

access and response to information or feedback trading (e.g., Cespa and Vives 2012; Han et al. 2016). Empirically, however, evidence tends to be inconclusive. While previous studies have found profitability of using technical analysis tools in aggregate stock markets (e.g., Brock et al. 1992; Gencay 1998b; Lo et al. 2000), in foreign exchange and bond markets (e.g., Gencay 1999; Goh et al. 2013; Neely et al. 2014) and for individual stocks and portfolios (e.g., Glabadanidis 2015, 2017), an influential work by Sullivan et al. (1999) documented the absence of out-of-sample profitability and thus raised concerns on the genuine predictiveness of technical analysis signals.

In this article, we add to the above studies by examining the profitability of technical analysis trading rules using Chinese aggregate stock market data. Complementary to many existing works that focus on various moving average rules, we perform a comprehensive investigation on a large number of commonly used technical signals. In particular, we consider five categories of technical indicators: channel break rules; filter rules; moving average rules; oscillator rules and support resistance rules. These five categories combined with a range of plausible parameters setting provide us with 28,909 distinct technical trading rules, which encompass the 2049 moving average rules considered in Brock et al. (1992) and 7846 trading rules in Sullivan et al. (1999). We then evaluate jointly all these trading rules against the performance metrics of market timing ability and Sharpe ratio gain against a buy and hold benchmark.

We emphasize that since our empirical analysis relies on a single time series data to test the profitability of a large number of trading rules, data snooping bias becomes a concern.[1] To address this concern, we employ a stepwise superior predictive ability (step-SPA) test following a series of methodological studies by White (2000), Romano and Wolf (2005), Hansen (2005) and Hsu et al. (2010). This up-to-date inference procedure extends White's reality check test and allows to identify all genuinely profitable trading rules among the large number of technical signals considered while controlling for data snooping bias.

We apply this Step SPA test to gauge the predictiveness of technical analysis in Chinese aggregate stock market. Using 19 years (1997–2015) of daily data on all A-share index, we find that although the majority of technical rules considered seem to be profitable based on traditional *t*-test, less than 1% are genuinely significant while eliminating data snooping bias. In particular, we identify 170 and 54 significantly profitable trading rules, respectively, under the metrics of market timing ability and Sharpe ratio gain. These numbers drop to 144 (142) and 54 when we consider a one way transaction cost of 0.25% (0.5%). We then summarize the parameters setting of all the identified rules and list the specific forms of the top 10 strategies accounting for transaction

1 Since searching among competing trading rules implicitly involve multiple hypothesis testing using a single data-set, the likelihood of incorrectly rejecting at least one of the null hypothesis (Type I error) will increase.

costs. We find that Moving Average category dominates the top 10 list, providing an average annual excess return of around 65% (or 48%), and achieving an average Sharpe ratio of about 2.6 (1.8) under a 0.25% (or 0.5%) transaction cost.

Since the performance of these technical rules can be uneven over time, we gauge the robustness of their predictiveness over different historical episodes. In particular, we reconduct the Step SPA test using a variety of sample periods with starting time ranging from 1992 to 2007. We document that as we postpone the sample starting time, the number of identified rules tends to decrease. This finding is consistent with the adaptive markets hypothesis proposed in Lo (2004) and the empirical evidence on foreign exchange market predictability by Neely et al. (2009). For the post-2007 period, we further break it into a global financial crisis (2007–2008) and a post crisis (2009–2015) episode. We document that the average trading profit during the global financial crisis is much larger than that in other periods, echoing Rapach et al. (2010), among others, who found equity risk premium forecast to be stronger during business cycle trough. Yet, we show that the profitability of technical rules remains economically large in the aftermath of the global financial crisis. Finally, our findings on the profitability of technical rules are still valid when we apply these rules to the Shanghai Stock Exchange Composite Index.

II. DATA AND METHODOLOGY

A. Data and summary statistics

We consider daily data on Chinese aggregate stock market. We download value weighted aggregate return data directly from the RESSET database[2], which includes all normal A-share stocks listed in Shanghai and Shenzhen stock exchanges. The risk-free interest rate is also obtained from RESSET in order to construct excess returns. While our main focus is on the excess return of this All-A index, we also download the Shanghai Stock Exchange Composite Index from RESSET for our robustness check exercises. The majority of our results are based on a sample period between January 2, 1997 till December 31, 2015, which amounts to 4599 trading days, yet we also conduct our empirical analysis using sample periods with a variety of starting time ranging from 1992 to 2007.[3]

Table 1 illustrates the summary statistics of daily return on Chinese aggregate stock market. As can be seen, during the past 19 years (1997–2015, 4599

2 RESSET database is a major vendor of financial data in China and is available at http://www3.resset.cn:8080/product/common/main.jsp

3 The Chinese Securities Regulatory Committee (CSRC) implemented a 10% daily price change limit policy on December 26, 1996 since stock market was very speculative and volatile during the early stage of its re-establishment in 1991. Besides, there were not many stocks traded then.

Table 1 Descriptive statistics: Chinese aggregate stock market returns

Means	Min	Max	Std	$AR(1)$	Sharpe	Number of observations
0.0475%	0.0992	–0.0944	0.0180	0.0408	0.0264	4599

trading days), the daily return has an average of 0.0475%; a standard deviation of 1.8% and a first order autocorrelation of 0.0408.

B. Construction of technical indicators

Following the works of Brock et al. (1992), Sullivan et al. (1999) and Hsu et al. (2016), we construct five categories of technical trading rules that use the time series of past price data. These include channel break rules, which attempt to identify channel fluctuations of prices and detect its break; filter rules, which generate buy or sell signals when current price exceeds or falls by a given percentage; moving average rules, which compares current price with its past moving average; oscillator rules, which provide over-bought or oversold signals; and support resistance rules, which seek to identify new trend when price breaches a support or resistance level. For each category, we then consider several variants of a trading rule with a range of plausible parameter settings. This will lead us to a total of 28,909 distinct technical rules, including 10,000 channel break rules; 2562 filter rules; 13,695 moving average rules; 1500 oscillator rules, and 1152 support resistance signals. We provide more details on the construction of technical rules below:

1 Channel breakout (CB) rules: We define a trading channel of range c% as occurring when the high level of the daily closing stock market index over the previous j days is within c% of the low over the previous j days. The upper bound of the trading channel on a particular day will be c% above the low of the previous j days and the lower bound will be c% below the high of the previous j days. We denote the following two types of rules, where the second type allows for a neutral position.

CB1: If a c% trading channel exists and if the daily closing stock index moves up (down) at least x percent above (below) the upper (lower) bound of the channel and remains so for d days, go long (short).

CB2: If a c% trading channel exists and if the daily closing stock index moves up (down) at least x percent above (below) the upper (lower) bound of the channel and remains so for d days, go long (short) for k days. For parameters setting, we let $x = \{0.05, 0.1, 0.25, 1, 2.5, 5, 10, 15, 25\}$; $d = \{0, 1, 2, 5\}$; $j = \{2, 5, 10, 15, 20, 25, 50, 100, 200, 250\}$; $c = \{0.1, 0.5, 1, 5, 10\}$, and $k = \{1, 5, 10, 25\}$, which will give us a total of 10,000 CB rules.

2 Filter (F) rules: We define two types of filter rules as follows.

F1: If the daily closing stock index moves up (down) at least x percent above (below) its most recent low (high) over the previous j days and remains so for d days, go long (short).

F2: If the daily closing stock index moves up (down) at least x percent above (below) its most recent low (high) over the previous j days and remains so for d days, go long (short) for k days. We parameterize $d = \{0, 1, 2, 3, 4, 5\}$; $x = \{0.05, 0.1, 0.5, 1, 5, 10, 20\}$; $k = \{5, 10, 15, 20, 25\}$, and $j = \{1, 2, 5, 10, 20, 25, 50, 100, 150, 250\}$ to get a total of 2562 F rules.

3 Moving average (MA) rules: We denote the simple moving average of the stock index (SI) over j days at time t as $MA_t(j) = \frac{1}{j}\sum_{i=0}^{j-1} SI_{t-i}$, and define five types of single, double and triple moving average trading rules.

MA1: If the daily closing stock index moves up (down) at least x percent above (below) $MA_t(q)$ and remains so for d days, go long (short).

MA2: If the daily closing stock index moves up (down) at least x percent above (below) $MA_t(q)$ and remains so for d days, go long (short) for k days.

MA3: If $MA_t(p)$ moves up (down) at least x percent above (below) $MA_t(q)$ and remains so for d days, go long (short).

MA4: If $MA_t(p)$ moves up (down) at least x percent above (below) $MA_t(q)$ and remains so for d days, go long (short) for k days.

MA5: If the daily closing stock index moves up (down) at least x percent above (below) any two of $MA_t(n)$, $MA_t(p)$ and $MA_t(q)$ and remains so for d days, go long (short) with one-third of the risk budget. If the daily closing stock index moves up (down) at least x percent above (below) all three of $MA_t(n)$, $MA_t(p)$ and $MA_t(q)$ and remains so for d days, go long (short).

We set $q = \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250\}$; $p = \{2, 5, 10, 15, 20, 25, 50, 100, 150, 200\}$; n = $\{2, 5, 10, 15, 20, 25, 50, 100, 150\}$; $x = \{0, 0.05, 0.1, 0.5, 1, 5\}$; $d = \{0, 2, 3, 4, 5\}$, and $k = \{5, 10, 25\}$ to get a total of 13,659 MA rules.

4 Oscillator (O) rules: Construct relative strength index (RSI) as $RSI_t(h) = 100\left[\frac{U_t(h)}{U_t(h)+D_t(h)}\right]$, where $U_t(h) = \sum_{j=1}^{h} I\left(SI_{t-j} - SI_{t-j-1} > 0\right)\left(SI_{t-j} - SI_{t-j-1}\right)$ denotes the cumulated up movement over the previous h days and $U_t(h) = \sum_{j=1}^{h} I\left(SI_{t-j} - SI_{t-j-1} < 0\right) \mid SI_{t-j} - SI_{t-j-1} \mid$ the cumulated down movement over the previous h days. We define two types of reversal indicator and two types of trend following indicators as follows.

O1: If $RSI_t(h)$ moves above 50 + v for at least d days and subsequently moves below 50 + v then go short and if $RSI_t(h)$ moves below 50 – v for at least d days and subsequently moves above 50 + v then go long.

O2: If $RSI_t(h)$ moves above 50 + v for at least d days and subsequently moves below 50 + v then go short for k days and if $RSI_t(h)$ moves below 50 – v for at least d days and subsequently moves above 50 + v then go long for k days.

O3: If $RSI_t(h)$ moves above $50 + v$ for at least d days go long and if $RSI_t(h)$ moves below $50 - v$ for at least d days go short.

O4: If $RSI_t(h)$ moves above $50 + v$ for at least d days go long for k days and if $RSI_t(h)$ moves below $50 - v$ for at least d days go short for k days.

We set $h = \{5, 10, 15, 20, 25, 50, 100, 150, 200, 250\}$; $v = \{1, 2, 5, 10, 15, 20, 25\}$; $d = \{1, 2, 5\}$, and $k = \{1, 5, 10, 25\}$ to get 1500 O rules.

5 Support resistance (SR) rules: Denote a resistance level as the highest daily closing stock index over the j previous days and a support level as the lowest daily closing stock index over the j previous days, we define two types of rules.

SR1: If the daily closing stock index moves up (down) at least x percent above (below) the resistance (support) level and remains so for d days, go long (short).

SR2: If the daily closing stock index moves up (down) at least x percent above (below) the resistance (support) level and remains so for d days, go long (short) for k days.

We set $d = \{0, 1, 2, 3, 4, 5\}$; $x = \{0.05, 0.1, 0.5, 1, 2.5, 5, 10\}$; $k = \{1, 5, 10, 25\}$, and $j = \{2, 5, 10, 15, 20, 25, 50, 100, 250\}$ to get 1152 SR rules.

C. Performance metrics

In order to evaluate the profitability of technical rules, we define trading rules return and performance metrics as follows. Let $r_{m,t} = \log(1 + R_{m,t}) - \log(1 + R_{f,t})$ be the log excess return of holding the value weighted market portfolio at day t, where $R_{f,t}$ is the daily risk free rate. Denote $S_{j,t-1}$ to be the trading signal generated by strategy j at the beginning of day t using data up to day $t - 1$. We assume that $S_{j,t-1}$ can take the values of 1, 0, −1 for long, neutral, short positions, respectively. The realized return for strategy j at each day t is then computed as:

$$r_{j,t} = S_{j,t-1} r_{m,t}. \tag{1}$$

In terms of performance metric, we start by looking at the mean excess return of each technical trading rule, simply defined as,

$$\bar{r}_j = \frac{1}{T}\sum_{t=1}^{T} r_{j,t}. \tag{2}$$

However, since a high mean return could be driven by either a precise predictive power or simply a high average risk taking behavior, we also decompose the trading rule performance into a “tilting” and a “market timing” component. While “tilting” refers to the average position of a trading rule, which can be replicated by statically being long or short on the asset, "market timing" component is driven purely by the trading rule's ability to predict the market. Following the literature, we first decompose each period's realized return as,

$$r_{j,t} = r_{j,t}^{tilt} + r_{j,t}^{tim}, \tag{3}$$

where $r_{j,t}^{tilt} = \left(\frac{1}{T}\sum_{t=1}^{T} s_{j,t-1}\right) r_{m,t}$ represents the "tilting" component. We then subtract this tilting component from the realized returns and compute the mean excess return based only on the "timing" component of the decomposed return as $\bar{r}_j^{tim} = 1/T\sum_{t=1}^{T} r_{j,t}^{tim}$. Note that $\bar{r}_j^{tim}$ is very similar to the X-statistics introduced in Sweeney (1986), which penalizes trading rules that simply collect risk premium by riding a long trend.

While the above metric ignores the riskyness of the market timing returns, an alternative yet more conventional performance measure which adjusts risk in the sense of return volatility is the Sharpe ratio. Following standard practice in Sullivan et al. (1999), Faber (2007), Moskowitz et al. (2012), Pätäri and Vilska (2014), and Zakamulin (2014), among others, we compute the Sharpe ratio gain of each technical rule against that of the buy and hold benchmark.

D. Step SPA testing methodology

Our primary goal is to test whether there exit any technical trading rules that generate superior profit based on the performance metrics defined above. However, as we are searching among over 28,000 trading rules on the same historical data, the likelihood of incorrectly finding a profitable rule due to its luck would increase. To account for such data snooping bias, a number of important development has been made in the literature. In particular, White (2000) proposes a joint testing method known as reality check, in which the joint distribution of test statistics is approximated through bootstrap. Hansen (2005) note that White's test tend to be conservative (i.e., have low power when many poor models are involved) and suggest an improvement based on recentering and weighting the test statistics in conducting reality check. While both White (2000) and Hansen (2005) tests help to examine the existence of outperforming trading rules, we are also interested in identifying all these rules. To this end, we follow Romano and Wolf (2005) and Hsu et al. (2010) to perform a stepwise multiple SPA test as below.

- Let R be a J by T matrix with element, $r_{j,t}$, be the realized return for strategy j at day t.
- Compute the vector of performance metrics $f = (f_1, \ldots, f_J)$ for all trading rules based on the return matrix R.

- Resample R for B times using the stationary bootstrap method of Politis and Romano (1994) and for each resample R^*, recompute the vector of performance metrics $f^* = \left(f_1^*, \ldots, f_J^*\right)$.
- For a prespecified level α_0, a bootstrap critical value for J rules is determined by

$$q_{\alpha_0}(J) = \inf\left\{q \mid P^*\left[\sqrt{T}\max_{j=1:J}\left(f_j^* - f_j + \mu_j\right) < q\right] > (1-\alpha_0)\right\},$$

the $(1 - \alpha_0)$th quantile of the recentered empirical distribution under the bootstrap probability measure p^*, where $\mu_j = f_j I\left(\sqrt{T} f_j < -\sigma_j [2\log T]\right)$, $I(\cdot)$ is the indicator function and σ_j denotes the standard deviation of the original return series by trading rule j.

- Rearrange f_j in descending order and record (reject) trading rule j if $\sqrt{T} f_j > q_{\alpha_0}(J)$.
- Remove the rejected rules and repeat the above steps with the remaining K rules under the critical value $q_{\alpha_0}(K)$, where $K < J$, until no more rules can be rejected.

As shown in Hsu et al. (2010), this step SPA test is consistent under the null hypothesis of $E(f_j) \leq 0$, $\forall j$, and identifies as many significant rules as possible given a prespecified significance level, while minimizing the influence of many poor rules on the power of the test. Following their convention, we set $B = 500$ and a random block length sampling parameter of 0.9 for the implementation of stationary bootstrap.

III. EMPIRICAL FINDINGS

In this section, we provide empirical evidence on the predictiveness and profitability of a large number of technical trading rules in Chinese aggregate stock market. We focus on the number of trading rules that are profitable and the performance they can achieve.

A. Predictiveness of technical analysis without data-snooping bias

To have an intuitive sense on the impact of data snooping bias, we first conduct a standard t-test on the significance of profitability generated by each of the individual technical rule. As documented in Panel B of Table 2, among the 28,909 rules we consider, 23,068 of them exhibit strong market timing ability $\bar{r}^{tim}$ and 5612 of them achieve significant Sharpe ratio gains ΔSR at 1% significance level. The numbers further increase to 23,204 and 11,717 when we base our inference on a 95% confidence. These results imply that a majority of the

Table 2 Number of identified technical trading rules based on ΔSR and $\bar{r}^{tim}$

Rules	Total number	Panel A: step-SPA test				Panel B: traditional *t*-test			
		ΔSR		$\bar{r}^{tim}$		ΔSR		$\bar{r}^{tim}$	
		$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 1\%$	$\alpha = 5\%$
CB1	2000	0	0	0	0	428	874	1468	1474
CB2	8000	0	0	0	0	1091	2597	5716	5773
Sum	10,000	0	0	0	0	1519	3471	7184	7247
F1	462	0	0	0	4	88	183	381	381
F2	2100	0	0	0	1	243	735	1251	1272
Sum	2562	0	0	0	5	331	918	1632	1653
MA1	495	31	36	40	47	208	331	425	429
MA2	1650	0	0	0	1	286	839	1530	1534
MA3	1650	11	18	28	32	278	727	1626	1628
MA4	4950	0	0	0	0	480	1840	4823	4828
MA5	4950	0	0	2	71	1914	2512	3837	3860
Sum	13,695	42	54	70	151	3166	6249	12,241	12,279
O1	150	0	0	0	0	0	17	80	82
O2	600	0	0	0	0	13	49	298	307
O3	150	0	0	0	0	69	114	150	150
O4	600	0	0	0	0	149	328	593	594
Sum	1500	0	0	0	0	231	508	1121	1133
SR1	72	0	0	0	0	16	30	50	50
SR2	1080	0	0	3	14	349	541	840	842
Sum	1152	0	0	3	14	365	571	890	892
Total sum	28,909	42	54	73	170	5612	11,717	23,068	23,204

considered technical rules do seem to be profitable if we ignore the data snooping issue articulated above. However, when we apply the stepwise SPA test, we find that although the predictiveness of technical analysis remains, the number of profitable trading rules drops sharply. In particular, Panel A of Table 2 shows that only 170 rules possess significant market timing ability $\bar{r}^{tim}$ at 95% confidence, among which 151 fall into the moving average category, 14 belong to the support resistance category, and 5 are the Filter rules. While under the metric of ΔSR, 54 rules stay significant and all of them belong the moving average category. At 1% significance level, total number of identified rules will further decrease to 73 and 42 under the performance measures of $\bar{r}^{tim}$ and ΔSR, respectively. Yet, the moving average category remains to occupy a majority of these identified rules. Overall, our evidence suggests that technical analysis indeed generates profitable trading rules, although data snooping bias does add a lot of noise on which rules are genuinely profitable.

B. Transaction cost

We next quantify the effect of transaction cost on the performance of technical trading rules. Specifically, we reidentify technical rules that exhibit significant market timing ability and Sharpe ratio gains under a one way transaction cost of either 0.25% or 0.5%. We document in Table 3 that, under a 0.25% (0.5%)

Table 3 Number of identified rules under transaction cost

Rules		Total number	tc = 0.25%		tc = 0.5%	
			$\bar{r}^{tim}$	ΔSR	$\bar{r}^{tim}$	ΔSR
Channel	CB1	2000	0	0	0	0
Break	CB2	8000	0	0	0	0
	Sum	10,000	0	0	0	0
Filter	F1	462	4	0	4	0
	F2	2100	1	0	1	0
	Sum	2562	5	0	5	0
Moving	MA1	495	47	36	47	36
Average	MA2	1650	1	0	1	0
	MA3	1650	32	18	32	18
	MA4	4950	0	0	0	0
	MA5	4950	45	0	43	0
	Sum	13,695	125	54	123	54
Oscillator	O1	150	0	0	0	0
	O2	600	0	0	0	0
	O3	150	0	0	0	0
	O4	600	0	0	0	0
	Sum	1500	0	0	0	0
Support	SR1	72	0	0	0	0
resistance	SR2	1080	14	0	14	0
	Sum	1152	14	0	14	0
	Total sum	28,909	144	54	142	54

Table 4 Number of identified rules applied to SSE composite index and under transaction cost

Rules		Total number	tc = 0.25%		tc = 0.5%	
			$\bar{r}^{tim}$	ΔSR	$\bar{r}^{tim}$	ΔSR
Channel	CB1	2000	0	0	0	0
Break	CB2	8000	0	0	0	0
	Sum	10,000	0	0	0	0
Filter	F1	462	2	0	2	0
	F2	2100	0	0	0	0
	Sum	2562	2	0	2	0
Moving	MA1	495	45	37	45	37
Average	MA2	1650	0	0	0	0
	MA3	1650	29	20	29	20
	MA4	4950	0	0	0	0
	MA5	4950	5	0	5	0
	Sum	13,695	79	57	79	57
Oscillator	O1	150	0	0	0	0
	O2	600	0	0	0	0
	O3	150	0	0	0	0
	O4	600	0	0	0	0
	Sum	1500	0	0	0	0
Support resistance	SR1	72	0	0	0	0
	SR2	1080	0	0	0	0
	Sum	1152	0	0	0	0
	Total sum	28,909	81	57	81	57

transaction cost, 5 Filter rules; 125 (123) Moving Average rules and 14 Support Resistance rules remain to deliver significant timing ability $\bar{r}^{tim}$ at 5% significance level. Whereas under the metric of Sharpe ratio gain ΔSR, the number of identified rules stays at 54. As a robustness check, we also apply the technical rules to Shanghai Stock Exchange Composite Index and summarize the results in Table 4.[4] Below, we still focus on the value weighted aggregate market.

To get a more direct perception on the identified rules, we report in Table 5 the range of parameter settings of all the identified technical rules at 95% confidence and under transaction cost. Furthermore, we list below the particular forms of the top 10 trading strategies along with their performance. In fact, we identify the same set of top 10 strategies under the metrics of $\bar{r}^{tim}$ and ΔSR and report the results in Table 6. We observe that under a 0.25% (0.5%) one way transaction cost, the first type of moving average rules dominate the top 10 list, with an average turnover per year ranging from 41 to 151 (41–76). The after transaction cost average annual excess returns of these top 10 rules range from 61% to 70% (46.7–50.7%) and their Sharpe ratios lie between 2.4 and 2.9 (1.8–1.9). The average cumulative returns of these top 10 technical rules under

4 As shown in the Table 4, for Shanghai Stock Exchange Composite Index and a sample period of 1997–2015, 81 and 57 rules are identified to be profitable at a 95% confidence under transaction cost and the performance metrics of $\bar{r}^{tim}$ and ΔSR.

Table 5 Parameters space of identified rules under transaction cost

Rules	Parameters ranges				
Panel A: $\bar{r}^{tim}$					
Filter	d	x	j	k	
F1	2	[0.05,0.5]	[20,25]	—	
F2	0	5	20	15	
MA	q	p	n	x	d
MA1	[2100]	—	—	[0,2.5]	[0,2]
MA2	20	0.05	0	5	—
MA3	[5,50]	[2,5]	—	[0,1]	0
MA5	[25,250]	[20,50]	[15,25]	[0,0.5]	0
SR	d	x	j	k	
SR2	[0,1]	[0.5,1]	[5100]	[5,25]	
Panel B: ΔSR					
MA	q	p	x	d	
MA1	[2,50]	—	[0,2.5]	0	
MA3	[5,25]	2	[0,1]	0	

Table 6 Top 10 technical rules under transaction cost

Rule	Parameters			Before TC	Annual trading #	After TC	After TC
	q	x	d	$\bar{r}$		$\bar{r}$	SR
Panel A: tc = 0.25%							
MA1	5	0.05	0	0.9275	92.0526	0.6973	2.9140
MA1	5	0	0	0.9306	93.3684	0.6971	2.9025
MA1	5	0.1	0	0.9112	90.0526	0.6861	2.8674
MA1	5	0.5	0	0.8483	76.1579	0.6579	2.7961
MA1	10	0.1	0	0.7876	57.8947	0.6429	2.6042
MA1	10	0.05	0	0.7868	58.9474	0.6394	2.5892
MA1	10	0	0	0.7811	60.6316	0.6295	2.5500
MA1	2	0.5	0	0.8742	100.9474	0.6218	2.7560
MA1	2	0.1	0	0.9939	151.3684	0.6155	2.4079
MA1	15	0.1	0	0.7157	41.7368	0.6113	2.3705
Panel B: tc = 0.5%							
MA1	15	0.1	0	0.7157	41.7368	0.5070	1.9340
MA1	10	0.1	0	0.7876	57.8947	0.4981	1.9689
MA1	15	0	0	0.7145	43.3158	0.4979	1.8941
MA1	10	0.05	0	0.7868	58.9474	0.4920	1.9420
MA1	15	0.05	0	0.7040	43.5263	0.4863	1.8513
MA1	20	0	0	0.6619	36.5263	0.4793	1.8072
MA1	10	0	0	0.7811	60.6316	0.4779	1.8848
MA1	20	0.05	0	0.6566	36.3158	0.4750	1.7937
MA1	20	0.1	0	0.6500	36.1053	0.4694	1.7735
MA1	5	0.05	0	0.8483	76.1579	0.4675	1.9144

Entries for each row are the type of technical rule; its parameters setting; turnover per year; mean excess return and Sharpe ratio.

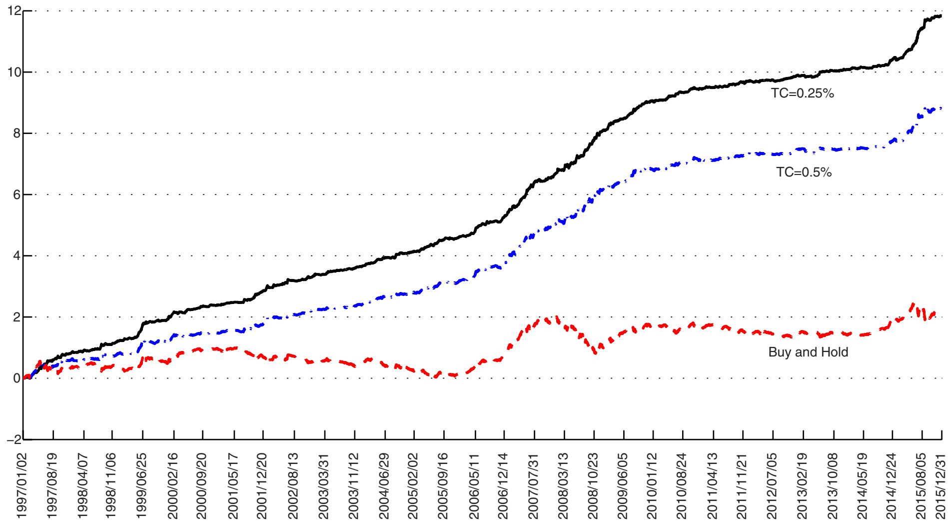

Figure 1 Cumulative Excess Return of an Equal Weighted Portfolio Using the Top 10 Rules. [Color figure can be viewed at wileyonlinelibrary.com]

either level of transaction cost are then plotted in Figure 1, which graphically shows their out-performance relative to a buy and hold benchmark.

C. Subperiods and global financial crisis

Since the out-performance delivered by trading rules can be uneven over time, we gauge the robustness of the predictiveness by technical indicators at different sample periods and historical episodes. We first reconduct the step-SPA test with varying starting date ranging from 1992 to 2007. Table 7 reports the number of identified trading rules at 95% confidence under a one way transaction cost of 0.25% for a list of sample ranges. Observe that, as we postpone the sample starting date, the number of identified rules tends to decrease. For example, when we set the starting date to be 1992, the total number of identified rules under $\bar{r}^{tim}$ reaches 545. Yet, it drops to 153 (sample starts at 1995) and gradually decrease to 53 (sample starts at 2007). Similarly, under the metric of ΔSR, the number of identified rules decreases from 62 to 31. These findings are consistent with the adaptive markets hypothesis proposed in Lo (2004) and the empirical evidence on foreign exchange market predictability by Neely et al. (2009). For the post-2007 period, we further break it into a 2007–2008 global financial crisis episode and a 2009–2015 post-crisis episode. We document in Table 8 that, the profitability of identified rules during the 2007–2008 crisis is larger than in other episodes, reaching as high as an annual excess return of 147% (119%) and a Sharpe ratio of 3.9 (3.1) under a 0.25% (0.5%) transaction cost. These results echo Rapach et al. (2010), among others, who showed that equity risk premium forecasts are stronger during business cycle

Table 7 Number of identified rules at various subperiods

Rules	Sample period				
	92–15	95–15	97–15	02–15	07–15
Panel A: $\bar{r}^{tim}$					
Channel break	50	6	0	0	0
Filter	60	6	5	0	0
Moving average	374	138	125	71	53
Oscillator	30	2	0	0	0
Support resistance	31	1	14	0	0
Panel B: ΔSR					
Channel break	0	0	0	0	0
Filter	0	0	0	0	0
Moving average	62	55	54	47	31
Oscillator	0	0	0	0	0
Support resistance	0	0	0	0	0

Entries are the number of identified rules at 95% confidence and under a 0.25% one way transaction cost.

troughs. While the average profitability of technical rules decreases in the aftermath of the global financial crisis, we find it remains economically large with an average annual excess return of 47% (30%) and a Sharpe ratio of 2 (1.25) under a 0.25% (0.5%) transaction cost.

IV. CONCLUDING REMARKS

In this article, we examine the predictiveness of technical analysis in Chinese aggregate stock market. We consider five commonly used categories of technical indicators and investigate more than 28,000 number of trading rules. To account for data snooping bias, we employ an up-to-date step-SPA test following the works of White (2000); Romano and Wolf (2005); Hansen (2005); Hsu et al. (2010). Our empirical results indicate that data snooping bias has a large

Table 8 Average performance of identified rules during and after the global financial crisis

	Avg $\bar{r}$ before TC	Avg $\bar{r}$ after TC		Avg SR before TC	Avg SR after TC	
		tc = 0.25%	tc = 0.5%		tc = 0.25%	tc = 0.5%
Panel A: $\bar{r}^{tim}$						
2007–2008	1.5966	1.3818	1.1669	5.3716	3.6075	2.9946
2009–2015	0.6319	0.4671	0.3022	2.0821	2.0032	1.2501
Panel B: ΔSR						
2007–2008	1.7409	1.4669	1.1929	5.9913	3.8987	3.1026
2009–2015	0.6238	0.4621	0.3004	2.0576	1.9849	1.2457

impact on the identification of profitable rules. While a majority of technical rules seem to be profitable based on traditional *t*-test, less than 200 are significant at 1% significance level after removing data snooping bias. However, among these identified rules, the top performing ones could achieve economically large profits. And these profits are mainly driven by the rules' market timing ability and predictiveness would remain during different subperiods and in the presence of transaction costs. Potential extensions in future works include the consideration of real time trading models under higher frequency data (e.g., Gencay et al. 2002, 2003); nonlinear predictability by technical signals (e.g., Gencay 1996; Gencay and Stengos 1997, 1998); and optimal technical trading rules that maximize expected performance (e.g., Gencay 1998a).

Guoshi Tong
Hanqing Advanced Institute of Economics and Finance
Renmin University of China
Beijing 100872
China
gstong@ruc.edu.cn

REFERENCES

Brock, W., J. Lakonishok, and B. LeBaron (1992), 'Simple Technical Trading Rules and the Stochastic Properties of Stock Returns', *Journal of Finance*, 47, 1731–64.

Cespa, G., and X. Vives (2012), 'Dynamic Trading and Asset Prices: Keynes vs. Hayek', *Review of Economic Studies*, 79, 539–80.

Faber, M. T. (2007), 'A Quantitative Approach to Tactical Asset Allocation', *Journal of Wealth Management*, 9, 69–79.

Gencay, R. (1996), 'Non-Linear Prediction of Security Returns With Moving Average Rules', *Journal of Forecasting*, 15, 165–74.

Gencay, R. (1998a), 'Optimization of Technical Trading Strategies and the Profitability in Security Markets', *Economics Letters*, 59, 249–54.

Gencay, R. (1998b), 'The Predictability of Security Returns with Simple Technical Trading Rules', *Journal of Empirical Finance*, 5, 347–59.

Gencay, R. (1999), 'Linear, Non-linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules', *Journal of International Economics*, 47, 91–107.

Gencay, R., and T. Stengos (1997), 'Technical Trading Rules and the Size of the Risk Premium in Security Returns', *Studies in Nonlinear Dynamics & Econometrics*, 2, 1–14.

Gencay, R., and T. Stengos (1998), 'Moving Average Rules, Volume and the Predictability of Security Returns with Feedforward Networks', *Journal of Forecasting*, 17, 401–14.

Gencay, R. et al. (2002), 'Real-time Trading Models and the Statistical Properties of Foreign Exchange Rates', *International Economic Review*, 43, 463–91.

Gencay, R., M. Dacorogna, R. Olsen, and O. Pictet (2003), 'Foreign Exchange Trading Models and Market Behavior', *Journal of Economic Dynamics and Control*, 27, 909–35.

Glabadanidis, P. (2015), 'Market Timing with Moving Averages', *International Review of Finance*, 15, 387–425.

Glabadanidis, P. (2017), 'Timing the Market with a Combination of Moving Averages', *International Review of Finance*. Forthcoming.

Goh, J., F. Jiang, J. Tu, and G. Zhou (2013), 'Forecasting Government Bond Risk Premia Using Technical Indicators,' Working Paper.

Han, Y., G. Zhou, and Y. Zhu (2016), 'A Trend Factor: Any Economic Gains from Using Information Over Investment Horizons?', *Journal of Financial Economics*, 122, 352–75.

Hansen, P. R. (2005), 'A Test for Superior Predictive Ability', *Journal of Business and Economic Statistics*, 23, 365–80.

Hsu, P.-H., Y.-C. Hsu, and C.-M. Kuan (2010), 'Testing the Predictive Ability of Technical Analysis Using a New Stepwise Test Without Data Snooping Bias', *Journal of Empirical Finance*, 17, 471–84.

Hsu, P.-H., M. P. Taylor, and Z. Wang (2016), 'Technical Trading: Is it Still Beating the Foreign Exchange Market?', *Journal of International Economics*, 102, 188–208.

Lo, A. W. (2004), 'The Adaptive Markets Hypothesis', *Journal of Portfolio Management*, 30, 15–29.

Lo, A. W., H. Mamaysky, and J. Wang (2000), 'Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation', *Journal of Finance*, 55, 1705–70.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012), 'Time Series Momentum', *Journal of Financial Economics*, 104, 228–50.

Neely, C. J., P. A. Weller, and J. M. Ulrich (2009), 'The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market', *Journal of Financial and Quantitative Analysis*, 44, 467–88.

Neely, C. J. et al. (2014), 'Forecasting the Equity Risk Premium: The Role of Technical Indicators', *Management Science*, 60, 1772–91.

Pätäri, E., and M. Vilska (2014), 'Performance of Moving Average Trading Strategies Over Varying Stock Market Conditions: The Finnish Evidence', *Applied Economics*, 46, 2851–72.

Politis, D. N., and J. P. Romano (1994), 'The Stationary Bootstrap', *Journal of the American Statistical Association*, 89, 1303–13.

Rapach, D. E., J. K. Strauss, and G. Zhou (2010), 'Out-of-sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy', *Review of Financial Studies*, 23, 821–62.

Romano, J. P., and M. Wolf (2005), 'Stepwise Multiple Testing as Formalized Data Snooping', *Econometrica*, 73, 1237–82.

Sullivan, R., A. Timmermann, and H. White (1999), 'Data-Snooping, Technical Trading Rule Performance, and the Bootstrap', *Journal of Finance*, 54, 1647–91.

Sweeney, R. J. (1986), 'Beating the Foreign Exchange Market', *Journal of Finance*, 41, 163–82.

White, H. (2000), 'A Reality Check for Data Snooping', *Econometrica*, 68, 1097–126.

Zakamulin, V. (2014), 'The Real-life Performance of Market Timing with Moving Average and Time-Series Momentum Rules', *Journal of Asset Management*, 15, 261–78.

