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Market efficiency and the returns to simple technical trading rules: new evidence from U.S. equity market and Chinese equity markets

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Abstract

Numerous studies in the finance literature have investigated technical analysis to determine its validity as an investment tool. This study is an attempt to explore whether some forms of technical analysis can predict stock price movement and make excess profits based on certain trading rules in markets with different efficiency level. To avoid using arbitrarily selected 26 trading rules as did by Brock, Lakonishok and LeBaron (1992) and later by Bessembinder and Chan (1998), this paper examines predictive power and profitability of simple trading rules by expanding their universe of 26 rules to 412 rules. In order to find out the relationship between market efficiency and excess return by applying trading rules, we examine excess return over periods in US markets and also compare the excess returns between US market and Chinese markets. Our results found that there is no evidence at all supporting technical forecast power by these trading rules in US equity index after 1975. During the 1990's break-even costs turned to be negative, -0.06%, even failing to beat a buy-holding strategy in US equity market. In comparison, our results provide support for the technical strategies even in the presence of trading cost in Chinese stock markets.

Keywords

evidence, rules, u, equity, chinese, markets, simple, returns, technical, efficiency, trading, market

Disciplines

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Market Efficiency and the Returns to Simple Technical Trading Rules: New Evidence from US Equity Market and Chinese Equity Markets

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Abstract:

Numerous studies in the finance literature have investigated technical analysis to determine its validity as an investment tool. This study is an attempt to explore whether some forms of technical analysis can predict stock price movement and make excess profits based on certain trading rules in markets with different efficiency level. To avoid using arbitrarily selected 26 trading rules as did by Brock, Lakonishok and LeBaron (1992) and later by Bessembinder and Chan (1998), this paper examines predictive power and profitability of simple trading rules by expanding their universe of 26 rules to 412 rules. In order to find out the relationship between market efficiency and excess return by applying trading rules, we examine excess return over periods in US markets and also compare the excess returns between US market and Chinese markets. Our results found that there is no evidence at all supporting technical forecast power by these trading rules in US equity index after 1975. During the 1990's break-even costs turned to be negative, -0.06%, even failing to beat a buy-holding strategy in US equity market. In comparison, our results provide support for the technical strategies even in the presence of trading cost in Chinese stock markets.

JEL classification: G14

Keywords: Technical analysis; Return forecastality; Transaction costs; Equity markets

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Market Efficiency and the Returns to Simple Technical Trading Rules: New Evidence from US Equity Index

I. Introduction

Technical analysis is essentially the search for recurrent and predictable patterns in stock prices. Rules under technical analysis (so called technical trading rules), while many and varied, aim in general to identify the initiation of new trends. Some of the simple rules include filter rules (buy when the price rises by a given proportion above a recent trough), trading range breaks (buy when the price rises by a given proportion above a recently established trading range) and moving average crossovers (buy when a shorter moving average penetrates a longer moving average from below). For each rule, the analyst chooses the time horizon over which troughs and peaks are to be identified and moving averages calculated, as well as the threshold before a decision is made (Beechey et al. 2000).

Although the vast majority of the professional traders use technical analysis, most academics, until recently, had not recognized the validity of these methods. They prefer the much more theoretical fundamental analysis. However, since the article of Brock, Lakonishok and LeBaron (1992), showing that simple forms of technical analysis contain significant predictive power for US equity index returns, many studies in the finance literature have investigated technical analysis to determine its validity as an investment tool. Among others, based on the same universe of 26 trading rules, however, Bessembinder and Chan (1998) argued that although the technical trading rules do have predictive ability in US data, their use would not allow investors to make excess returns in the presence of costly trading.

However, these methods of testing for successful technical trading rules were considered to suffer from the potential problem of data mining because the rules are imposed ex post by the testers. There will be a possibility that bias in choice of rule remains. Skouras argues that Brock's "single" arbitrarily selected rule found to be effective is lack of justification given that real technical analysts use different rules in different times and in different markets (2001, p. 214).

To avoid using arbitrarily selected 26 trading rules as did by Brock, Lakonishok and LeBaron (1992) and later by Bessembinder and Chan (1998), this paper examines predictive power and profitability of simple trading rules by expanding their universe of 26 rules to 412 rules. In order to find out the relationship between market efficiency and excess return by applying trading rules, we examine excess return over periods in US markets when the markets tended to be more efficient and also compare the excess returns between US market and Chinese markets during 1990s. Chinese stock markets that have been purposely segmented since they were firstly opened in the early 1990s are less efficient than US market during the same period. The segmentation of the Chinese stock markets can be observed in following three respects. First, dual listing is not allowed so that each company's issue is restricted to one of the two exchanges, the Shenzhen Stock Exchange and the Shanghai Stock Exchange. Second, a listed company in either exchange can issue two types of shares: 'A Shares' are issued only to domestic investors and 'B Shares' are sold only to foreign investors, though both of these two type shares are identical. The last but not the least importance, the amount of outstanding B Shares is always smaller within the limit set by the central government, making foreign investors minority shareholders.

This paper progresses as follows: in the following section we provide the reader with a review of some of the empirical literature; Section III sets out the data, technical rules and measurement of returns, Section IV demonstrates empirical results, and finally, in Section V conclusions are presented.

II. Review

Most of technical trading rules are simple and fairly inexpensive to implement. One would therefore not expect such rules to generate excess profits in an efficient market. Most academic studies of technical analysis, including Fama and Blume (1966) and Jensen and Benington (1970), conclude that technical analysis is not useful. In the last few years, increasing evidence that a relatively simple set of technical trading rules possess significant forecast power for equity returns (Brock, et al, 1992; Hudson et al., 1996) has renewed interest in technical analysis. Bessembinder and Chan (1998) further investigate and provide interpretation for the intriguing Brock et al (1992) finding. Undertaking additional empirical analysis of the same technical rules examined by Brock et al (1992), Bessembinder and Chan (1998) document that the forecast ability is partially, but not solely, attributable to return measurement errors arising from nonsynchronous trading. They argue that the evidence supporting technical forecast power need not be inconsistent with market efficiency. “Break-even” one-way trading costs are computed to be 0.39% for the full sample and 0.22% since 1975, which are small compared to recent estimate of actual trading costs.

However, these methods of testing for successful technical trading rules were considered to suffer from the potential problem of data mining because the rules are imposed ex post by the testers. There will be a possibility that bias in choice of rule remains. Skouras argues that Brock’s “single” arbitrarily selected rule found to be effective is lack of justification given that real technical analysts use different rules in different times and in different markets (2001, p. 214). He further argues that these limited rules are chosen according to non-rigorous and often implicit criteria makes results drawn from them subject to standard data-mining criticisms, which diminish their forcefulness. Theoretically this could be a problem that would be avoided if the rules considered are the choices of an Artificial technical Analyst which are by construction explicit and can be expected to be robust with respect to reasonable variations in the agent’s design. The preferred strategy to test technical trading rules is to formulate the rules ex ante, thus eliminating potential bias (Fyfe et al, 1999) through the introduction of artificial intelligence techniques such as genetic algorithm. However, a degree of arbitrariness still remains in the selection of the rule class to be tested even in the artificial intelligence case. In addition, the arbitrariness involved in the specification of learning schemes is an additional problem.

While there is no perfect solution to arbitrariness of selection of rules or rule class, this paper focuses on simple technical trading rules which are fairly inexpensive to implemented and test the hypothesis that these simple rules should not generate excess profits in an efficient market. Therefore, moving averages and trading breakout rules should be a right selection for the test. A solution to the problems of too few rules which are arbitrarily selected and tested by Brock et al (1992) and Bessembinder and Chan (1998) is offered by including most rules which are possibly implemented by traders. We actually exhausted all rules until that the rule generates only few trades. We realize that our list of 412 trading rules does not completely exhaust the set of rules that were considered historically, such as channel break-outs, on-balance volume averages etc. However, our list of rules is vastly larger than those compiled in previous studies and we actually focused on these simple rules, which can be implemented by normal investors without additional costs.

We also evaluate the possibility that the return forecastability document by Brock et al. could simply reflect measurement errors in portfolio returns arising due to nonsynchronous reporting of prices which induces spurious positive autocorrelation in index price change (Scholes and Williams, 1977). The technical trading rules we evaluate exploit positive serial dependence. Typically, the technical rules initially emit a buy (sell) signal on a day characterised by an unusually large upward (downward) market movement. The partial adjustment of index values resulting from nonsynchronous trading of the component securities implies that the measured next day return will tend to be biased in the same direction as the prior day price change. This bias implies that profits from the technical rules will tend to be overstated. As a simple control for the effects of nonsynchronous trading, we compare buy and sell day returns while implementing a one-day lag between the initial emission of a signal and the resulting trade.

Recently, Sullivan, Timmermann and White (1997) utilize White's reality check bootstrap methodology to evaluate simple technical trading rules while quantifying the data-snooping bias and fully adjusting for its effect in the context of the full universe from which the trading rules were drawn (Sullivan, et al, 1997). However, our paper actually focused on different issues mainly the relationship between market efficiency and returns on simple trading rules and relationship between different efficient equity markets with richer background, while we have run the bootstrap tests to largely fix the data-snooping problem.

III. The Data, Technical Rules and Measurement of Returns

(1) Data

The data include 17740 daily observations for US Dow Jones Industrial Average (DJIA) index and 2469 for Shanghai “A” (ShA), 2178 for the Shanghai “B” (ShB), 1997 for the Shenzhen “A” (SzA) and 1995 for the Shenzhen “B” (SzB). All of these indices are based on closing prices. The data are obtained from Datastream International and cover the period October 6, 1992 to December 15, 2000 for ShA, ShB, SzA and SzB. DJIA data are covered for the period January 2, 1926 to December 15, 2000. Stock index returns are calculated using the continuously compounded formula.

(2) Technical Rules

We now describe the technical rules evaluated by Brock et al. (1992) and Bessembinder and Chan (1998) and address some issues related to these rules chosen by these authors.

Two of the simplest and most popular classes of technical trading rules, moving average crossover rules and trading-range breakout rules are examined by both Brock et al. (1992) and Bessembinder and Chan (1998). These 26 trading rules include ten variable-length-moving-average (VMA) rules, ten fixed-length-moving-average (FMA) rules, and six trading-range-break (TRB) rules. The moving average rules involve comparison of a short-term moving average of prices to a long-term moving average. Buy (sell) signals are emitted when the short-term average exceeds (is less than) the long term average by at least a pre-specified percentage band. The most popular moving average rule is considered to be 1-200, where the short average is one day (today’s price) and the long average is 200 days. Other variations that they evaluate include 1-50, 1-150, 5-150, and 2-200. Each rule is evaluated with bands of 0 and 1%, making for ten moving average combinations in total. Once a single is emitted, VMA rules call for the position to be maintained until the short and long moving averages cross again, while FMA rules hold the position for a fixed number of days. Bessembinder and Chan (1998) evaluate FMA strategies with fixed holding periods of ten and thirty days.

Trading range break rules involve comparing the current price to the recent minimum and maximum. TRB rules emit buy singles when the current price exceeds the recent maximum by at least a pre-specified band, and emit sell signals when the current price falls below the recent minimum by at least the pre-specified band. Bessembinder and Chan and Brock et al. both evaluate separate TRB rules over the period 50, 150 and 200 days, respectively. They use bands of 0 and 1%, making for a total of six TRB combinations.

Skouras argued that these arbitrarily selected rules found to be effective are lack of justification given that real Technical Analysts use different rules in different times and in different markets (p. 214). Based on the literature of charting, we found simple trading rules implemented by traders and practitioners are much more than only these 10 VMA and 10 FMA rules. These are numerous variations and modifications of moving average crossover rules. For example, usually more than one moving average have been used to trading signals instead of only one moving average (cross-over with a current stock closing price (such as 1-50, 1-150 and 1-200 they use)).

There are two types of filters we will impose on the moving average rules and trading break. The filters are said to assist in filtering out false trading signals (ie. Those signals that would result in losses). The fixed percentage band filter requires that the buy or sell signal exceed the moving average by a fixed multiplicative amount. Traders may not only use bands of 0 and 1% but also use some higher bands, such as 2%. More importantly, arbitrarily determined fixed 10-day holding period for FMA is most unreal. We consider holding a given long or short position for a pre-specified number of days, which are based on previous academic studies and the technical analysis literate.

Among eighty-four VMA rules we evaluated, we find the rule with the highest break-even costs (1.52%) is (short mv=13, long mv=200, band=0%), which is much higher than the eighty-four-VMA rule portfolio's average break-even costs (0.514%) (See Table 1). The FMA rule with the highest break-even cost actually is (short mv=7, long mv= 20, band=1%, holding period =50 days). Its break-even cost is 5.6% compared with 0.13% of the one for the average 288-FMA-rule portfolio. It is important to note that these two rules are not one of the rules arbitrarily selected by Bessembinder and Chan and Brock et al. To avoid any arbitrary selection of these simple rules, we include most the rules, which generate at least few trades during the period concerned.

[Table 1]

In this paper, for VMA rules, short –term moving averages include 1, 4, 7, 10, 13, 16 and 19 days, while long-term moving averages consist of 50, 100, 150 and 200 days. Each rule is evaluated with bands of 0, 1% and 2%, making for eighty-four variable-moving average combinations in total. For FMA rules, much more rules we included in our selection to reflect more real situation in trader's world. Short-term moving averages include 1, 3, 5 and 7 days, while long-term moving averages include 50,100,150, and 200 days. We also include different holding days including 10, 15, 20, 25, 30, 35, 40, 45 and 50 days. Each rule is evaluated with bands of 0 and 1%, making for 288 fixed moving average combinations in total. For Trading range break (TRB) rules, while the short term moving average is always only 1, the TRB range includes 50, 100, 150 and 200 days. We also include different holding days including 10, 20, 30, 40, and 50 days. Each rule is evaluated with bands of 0 and 1%, making for 40 fixed moving average combinations in total.

(3) Methodology

To evaluate the effect of transaction costs on the profitability of trading rules, we simulate a "double-or-out" strategy. Under this strategy, an investor borrows to double the stock investment upon buy signals, sells stock to hold cash on sell signals, but holds a standard long stock position in the absence of a signal. Let R_t denote the index return on day t and i_t is the daily risk-free interest rate and $r_t = R_t - i_t$ denote the index return excess of the interest rate. Let π_{it} denote the additional (pre-trading cost) day t return earned by a trader relying on technical rule i as compared to that earned by an investor who passively holds the index. Under this strategy, a trader reacts to buy signals by borrowing money to double their equity investment. This gives a pre-transactions cost trading return on buy days of $TR_t = 2R_t - i_t$, which exceeds the buy and hold return by r_t, so $\pi_{it}= r_t$. During sell signals, the trader reacts to sell signals by liquidating any equity holdings and purchasing interest bearing instruments, leading to sell day trading returns of $TR_t = i_t$, which exceeds the return from passively holding the index by - r_t , so π_{it}= -r_t. On days where no signal is emitted the trader simply holds a long equity position, giving a trading return of $TR_t = R_t$, so $\pi_{it} = 0$. Let π_i^B denote the sum of π_{it} across the subset of sample days for which rule i emits by buy signals, π_i^S denote the sum of π_{it} across the subset of sample days for which rule i emits by sell signals and let $\pi_i = \pi_i^B + \pi_i^S$.

In the absence of transaction costs, the additional return (π_i) earned by technical trading relative to a buy-and-hold strategy is given as: $\pi_i = \Sigma\, TR_t - \Sigma\, R_t = N_B\, r_B - N_S r_S$, where N_B is the number of days the double (buy) position is held, N_S is the number of days the out (sell) position is held. Daily interest rate for these markets is not available to us. We approximate π_i as $N_B R_B - N_S\, R_S$ where R_B and R_S are mean raw returns on buy and sell days, respectively. If N_B differs from N_S, our excess profit measure will typically be biased. However Bessembinder and Chan (1998) noticed that for typical interest rates this bias is small relative to the magnitude of buy versus sell day returns.

Of course, a trader would incur transaction costs. Let C denote the percentage one-way round-trip cost of buying and selling. For new signals that shift the position from “double” to “out” or vice versa, 200% of the portfolio much be traded immediately. New trading signals that arrive while the trader is holding a standard long position generate a trading most of C%, plus another C% when the position is eventually reversed. Let N_i denote the number of position taken in response to newly emitted rule i buy and sell signals during the sample interval. Accumulated trading costs exactly consume the excess return to using technical rule i instead of buy-and-hold if $\pi_i = 2N_iC$, so the break-even one-way trading cost for rule i is $C_i = \pi_i / N_i$.

III. Empirical Results

Brock et al. (1992) emphasize the danger of obtaining spurious empirical results if trading rules are both discovered and tested in the same data set. They note that there is no complete remedy for “data-snooping” biases, but attempt to mitigate the problem by using long data series and by reporting results for all rules evaluated. We therefore report results for all rules tested as follows. Meanwhile, We use bootstrap methodologies to assess the statistical significance of our various point estimates. We have run a hypothesis that $\pi_i = \pi_i^B + \pi_i^S = 0$, which states that the technical rules in the aggregate have no predictive power for returns. If the hypothesis that the technical rule as a group possesses no forecast power cannot be rejected statistically based on our extended rules, then the conclusion made by previous authors that technical trading rules possess forecast power for US markets should be rejected at first place.

In Table 1, we report returns to technical trading, numbers of trades and break-even costs for 84 VMA rules and 84 VMA portfolio. The results for 288 FMA rules and 40 TRB rules will be provided upon request. Outcomes of hypothesis tests for the full sample and for each individual rule and for portfolios is reported besides. P-values for the "Buy-Sell = 0" hypothesis report the proportion of outcomes in 500 simulations where the buy-sell differential is as large as or larger than observed in the actual data.

Technically we find annually excess return of buy or sell position by converting its relevant daily buy or sell return as follows: Annual excess buy (sell) return = $\exp^{(\text{mean daily buy (sell) return} * 250 * \text{proportion of buy (sell) position in a year})}$ [1] – 1. This procedure should result in more accurate outcome than ones obtained by Bessembinder and Chan (1998) in which each total buy (sell) return has been annualized by dividing by the number of years in the sample. We find percentage break-even costs by dividing annual buy-sell return by trades per year for rule i. The columns labeled "Buy", "Sell" and "Buy-sell" reflect the quantities the annual excess buy return, annual excess sell return and the difference between annual excess buy and sell return and break-even costs.

In Table 2, we report results for each of four sub-periods of approximately equal length (exactly the same as Bessembinder and Chan (198)), 1926-1943, 1944-59, 1960-1975 and 1976-1991, the last of which is chosen to represent the period of reduced transaction costs following the deregulation of brokerage commissions in the US in May 1975. To economise

[1] Note that the reported returns are those that accumulated during periods when buy and sell signals were in effect, and that they do not represent annualised returns. As such, they reflect the relative scarcity of FMA signals. On average the FMA rules generated 1.72 signals per year, accompanied by an average 30-day holding period. Thus, no FMA signal is in effect during most of the 269 actual trading days per year. TRB has a similar situation with FMA. A trader relying on VMA rules would take a position most days; the only days a position is not taken are those where the short moving average differs from the long moving average by less than the pre-specified band.

on space, subperiod results are reported for portfolio but not individual rules. Table 1 and Table 2 report results obtained when trading returns are measured beginning with the closing index value that initially generate a signal, while in Table 3 we report portfolio results obtained when a one-day lag is imposed to allow for the effects of nonsynchronous trading. In both Table 2 and 3 we report returns to technical trading, number of trades and break-even costs from our test and ones from Bessembinder and Chan (1998).

For the full sample, aggregation across all rules gives a buy-sell differential of 1.50% per year, and ex post break-even one-way transactions costs of 0.29%, which is smaller than that (0.39%) of Bessembinder and Chan (1998). Ex post profitability and break-even costs vary across rules. As a group, the VMA rules provided the largest buy-sell return differential, 5.12% per year, allowing the highest break-even costs, 0.51% per year. The FMA and TRB rules generated buy-sell differentials of only 0.46% and 1.37% per year, respectively, allowing break-even costs of 0.13% and 0.19% respectively. However, in the absence of ex ante reasons to prefer some rules, we view the break-even cost computed across all evaluated rules as providing the most appropriate benchmark. Imposition of a one-day lag reduces break-even costs aggregated across all rules to 0.22% from 0.29%.

Break-even costs have declined over time substantially. Aggregated across all rules, the buy-sell differential for the 1926 to 1943 subsample was 3.32%, which allowed break-even cost of 0.58%. The annual buy-sell differential has declined since, to 0.80% in the 1944 to 1959 interval, 0.94% in the period between 1960 and 1975 and 0.45% in the most recent 1976 to 1991 period. As a consequence, break-even costs declined continuously to 0.09% for the most recent subsample. With a one-day lag impose, break-even costs for the post 1976 sample become negligible, only 0.01%. This number is substantially smaller than that (0.11%) obtained by Bessembinder And Chan (1998). This result suggests that the forecast ability is partially attributed to return measurement errors arising from nonsynchronous trading before 1975, and solely attributable to the return measurement errors for the post-1975 period.

Combining the estimates of effective bid-ask spreads and commissions give estimated one-way equity trading costs of 0.25% plus market impact for institutional traders (Bessembinder and Chan (1998)) for post-1975 period. This estimated trading cost is much higher than the ex post break-even costs for the most recent subperiod. The estimated one-way transaction cost of 1.35% for the period between 1960 and 1975 is also higher than the ex post break-even costs for the same period, which are 0.20% without any trading lag or 0.10% if a one-day lag is imposed. There is no reason to believe that trading costs prior to 1960 were lower than earlier decades. We conclude that it is more unlikely that traders could have used our much more extensive simple trading rules to improve returns net of trading costs comparing with those rules originally evaluated by Brock et al. (1992) and Bessembinder and Chan (1998) for the full sample of the data.

Table 4 and Table 5 reports mean break-even cost for the double and out strategies between US and Chinese stock markets. Despite the substantial recent growth of Chinese stock markets, as one of the most important emerging markets, their institutional structure has led some to question whether they are as informational efficient as their US counterparts. The ownership of majority of Chinese listed companies is concentrated in the hands of a small number of investors (legal person ownership), and the incidence of insider trading is relatively high. Also, requirements for financial disclosures are less stringent, leading to a scarcity of publicly available information. If Chinese stock markets are in fact relatively inefficient, technical analysis may be able to exploit the inefficiencies. We found that the rules are quite successful in predicting stock price movements in Chinese markets where excess annual return 5.92% which allowed break-even costs of 1.31 %. Although this break-even costs are slightly lower than estimated actual trading costs of about 1.5% for individual investors during the 1990s, this result provides support for the technical strategies even in the presence of costly trading in Chinese stock markets at least for institution investors during the 1990s.

By contrast, aggregated across all rules, the buy-sell differential in Dow Jones Industrial Average for the same period was –0.33%, which allowed break-even cost of –0.12%. This result is similar to the one obtained by Professor LeBaron recently (New York Time, 2000). There are a number of reasons these trading systems failed to beat the index in the US market. First, a large part of the failure of such approaches likely has to do with increasing market efficiency in the US markets. Investors in the 1990's witnessed the growth of two important forces: personal computers and discount brokerage commissions. The PC lets individuals learn about and act quickly upon statistical patterns in price and volume data. Cheap trading, particularly online, has let investors exploit technical strategies far more easily. Secondly, as more investors try their hands at technical analysis, trying to take advantage of pricing anomalies, the anomalies evaporate and the strategy loses its advantage. That is market efficiency at work. Think about that when you next read about such an approach in your favorite chat room. One example of this is classic moving average crossover systems. The premise is that the system is a trend-following system and you buy when the short-term average crosses above the long-term average and sell when the short-term average crosses below the long-term average. The problem with this premise is that the market only trends about 10% to 20% of the time and spends the rest of the time oscillating in narrow ranges. If we look more closely at cycle theory, the moving average crossover system will be 180 degrees out of phase with the market if we use a half-cycle and full-cycle length moving averages. This means the system will be buying when it should be selling and vice versa (see "Moving violation," right). When the half-cycle average crosses the full cycle average, the market is topping, and the opposite is true at bottoms (Ruggiero, 2001).

IV. Conclusion

Overall, for the period prior to 1991, we find that simple forms of technical analysis contain a declining forecast power for US equity index. We further found that the forecast ability is partially attributed to return measurement errors arising from nonsynchronous trading for that period before 1975, and solely attributable to the return measurement errors for the period 1975-91. Break-even one-way trading costs are computed to be 0.3% for full sample and declined from 0.59% during the period 1926-43 to only 0.09% during 1975-91. With a one-day lag imposed, break-even costs for the period between 1975-91 become negligible, only 0.01%.

As Bailey et al. (1990) discuss, mis-pricings that are smaller than transactions costs need not be immediately eliminated even in an efficiency market. We argue that the evidence of technical forecast power need not be inconsistent with market efficiency for US market even before 1975, when break-even costs are small compared to recent estimate of actual trading costs for each individual sub-period. We also found technical forecast power by these popular trading rules in US market had been disappeared during the 1990s.

We also find that these simple trading rules are quite successful in predicting stock price movements in Chinese markets and allowing traders make possible excess profits in 1990s, while trading systems based on these simple trading rules even does not beat the US index during the same period.

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Appendix 1: Trading Rule Parameters

This appendix describes the parameterizations of the 412 trading rules used to generate the full universe of rules under consideration.

A. Variable Moving Averages

N = fast moving average
M = slow moving average
B = fixed band multiplicative value

N = 1, 4, 7, 10, 13, 16, 19 [7 values]
M= 50, 100, 150, 200 [4 values]
B= 0, 0.01, 0.02 [3 values]
There will be a combined VMA 84 rules.

B. fixed moving averages

N = fast moving average
M = slow moving average

B = fixed band multiplicative value

C = number of days a position is held, ignoring all other signals during that time

N= 1, 3, 5, 7 [4 values]

M=50, 100, 150, 200 [4 values]

B=0, 0.01 [2 values]

C= 10, 15, 20, 25, 30, 35, 40, 45, 50 [9 values]

There will be a combined FMA 288 rules.

c. Trend Range Band (TRB) support and resistance

n= number of days in the support and resistance range

b= fixed band multiplicative value

c= number of days a position is held, ignoring all other signals during that time

n = 50, 100, 150, 200 [4 values]

b= 0, 0.01 [2 values]

c = 10, 20, 30, 40, 50 [5 values]

There will be a combined 40 TRB rules.

Appendix 2. Computation of the Bootstrap P-Values

We use bootstrap methodologies to assess the statistical significance of our various point estimates. We test the hypotheses that $\pi_i = \pi_i^B + \pi_i^S = 0$, which represent the null hypotheses that rule i individually and a set of rules in the aggregate have no power to improve the technical trader's pre-trading-cost returns, using a procedure very similar to Brock et al, The set of actual index returns is scrambled, which eliminates any serial dependence in the returns so that the bootstrap distribution conforms to the null hypothesis of no forecast power, and a simulated index is created by linking the scrambled returns. Each of the 412 technical rules is fit to the simulated index, and returns to each rule and to the portfolios are recorded. This procedure is repeated 500 times. The proportion of simulation outcomes where the computed π_i exceed the point estimates from the actual sample comprise bootstrap p-values for the hypotheses that π_i equal zero.

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Table 1: Annual Returns, Break-Even Trading Costs: Technical Trading Rules (84 Variable-Length Moving Average Rules) Implemented on DJIA Stocks from 1926-1991, No Trade Lag, Total Data Length = 17740

	Annual Excess Returns					Bootstrap P-Values
(Item1, Item2, factor)	Buy	Sell	Buy - Sell	Trades per year	Breakeven Costs	
(1, 50, 0.0)	0.068	-0.024	0.092	15.636	0.003	0.002
(1, 100, 0.0)	0.064	-0.020	0.084	10.818	0.004	0.001
(1, 150, 0.0)	0.064	-0.020	0.084	8.152	0.005	0.635
(1, 200, 0.0)	0.066	-0.021	0.088	5.879	0.007	0.041
(4, 50, 0.0)	0.050	-0.007	0.057	10.212	0.003	0.001
(4, 100, 0.0)	0.054	-0.010	0.064	6.636	0.005	0.000
(4, 150, 0.0)	0.060	-0.016	0.076	4.667	0.008	0.125
(4, 200, 0.0)	0.058	-0.014	0.073	3.303	0.011	0.632
(7, 50, 0.0)	0.041	0.002	0.039	8.000	0.002	0.042
(7, 100, 0.0)	0.048	-0.005	0.053	5.333	0.005	0.000
(7, 150, 0.0)	0.055	-0.011	0.065	3.879	0.008	0.009
(7, 200, 0.0)	0.052	-0.008	0.060	2.879	0.010	0.555
(10, 50, 0.0)	0.039	0.004	0.035	7.091	0.002	0.075
(10, 100, 0.0)	0.043	0.000	0.043	4.636	0.005	0.006
(10, 150, 0.0)	0.046	-0.003	0.048	3.303	0.007	0.000
(10, 200, 0.0)	0.052	-0.009	0.061	2.424	0.013	0.693
(13, 50, 0.0)	0.032	0.010	0.022	6.500	0.002	0.003
(13, 100, 0.0)	0.042	0.001	0.041	4.106	0.005	0.005
(13, 150, 0.0)	0.041	0.002	0.039	3.076	0.006	0.025
(13, 200, 0.0)	0.055	-0.011	0.065	2.152	0.015	0.000
(16, 50, 0.0)	0.027	0.016	0.011	6.106	0.001	0.225
(16, 100, 0.0)	0.033	0.010	0.023	3.621	0.003	0.007
(16, 150, 0.0)	0.039	0.004	0.036	2.833	0.006	0.006
(16, 200, 0.0)	0.051	-0.008	0.059	2.015	0.015	0.005
(19, 50, 0.0)	0.025	0.018	0.007	6.045	0.001	0.325
(19, 100, 0.0)	0.033	0.010	0.023	3.439	0.003	0.000
(19, 150, 0.0)	0.040	0.003	0.037	2.591	0.007	0.000
(19, 200, 0.0)	0.048	-0.005	0.053	1.833	0.014	0.015
(1, 50, 0.01)	0.071	-0.025	0.096	14.788	0.003	0.000
(1, 100, 0.01)	0.070	-0.016	0.086	9.985	0.004	0.063
(1, 150, 0.01)	0.062	-0.025	0.087	8.000	0.005	0.352
(1, 200, 0.01)	0.065	-0.025	0.090	6.030	0.007	0.001
(4, 50, 0.01)	0.048	-0.012	0.060	9.091	0.003	0.000
(4, 100, 0.01)	0.052	-0.009	0.061	5.727	0.005	0.085
(4, 150, 0.01)	0.053	-0.020	0.072	4.439	0.008	0.000
(4, 200, 0.01)	0.064	-0.015	0.079	3.439	0.012	0.000
(7, 50, 0.01)	0.040	0.000	0.040	7.621	0.003	0.000
(7, 100, 0.01)	0.051	-0.007	0.058	4.758	0.006	0.961
(7, 150, 0.01)	0.048	-0.009	0.057	3.606	0.008	0.852

(7, 200, 0.01)	0.053	-0.011	0.063	2.773	0.011	0.000
(10, 50, 0.01)	0.030	0.001	0.029	6.758	0.002	0.230
(10, 100, 0.01)	0.046	-0.004	0.050	4.152	0.006	0.041
(10, 150, 0.01)	0.040	-0.006	0.046	3.091	0.007	0.063
(10, 200, 0.01)	0.052	-0.010	0.062	2.439	0.013	0.071
(13, 50, 0.01)	0.030	0.002	0.029	6.030	0.002	0.542
(13, 100, 0.01)	0.040	0.004	0.036	3.864	0.005	0.000
(13, 150, 0.01)	0.039	-0.008	0.047	2.833	0.008	0.023
(13, 200, 0.01)	0.048	-0.012	0.060	2.152	0.014	0.003
(16, 50, 0.01)	0.027	-0.002	0.029	5.424	0.003	0.005
(16, 100, 0.01)	0.034	0.009	0.025	3.682	0.003	0.000
(16, 150, 0.01)	0.035	-0.009	0.045	2.606	0.009	0.007
(16, 200, 0.01)	0.052	-0.005	0.057	1.939	0.015	0.001
(19, 50, 0.01)	0.024	0.000	0.024	5.212	0.002	0.000
(19, 100, 0.01)	0.032	0.008	0.023	3.394	0.003	0.004
(19, 150, 0.01)	0.036	-0.006	0.042	2.500	0.008	0.524
(19, 200, 0.01)	0.050	0.001	0.048	1.894	0.013	0.074
(1, 50, 0.02)	0.055	-0.020	0.076	14.394	0.003	0.654
(1, 100, 0.02)	0.063	-0.018	0.081	9.939	0.004	0.037
(1, 150, 0.02)	0.056	-0.028	0.084	7.470	0.006	0.541
(1, 200, 0.02)	0.053	-0.025	0.077	6.803	0.006	0.000
(4, 50, 0.02)	0.035	-0.004	0.039	8.470	0.002	0.007
(4, 100, 0.02)	0.054	-0.014	0.068	5.970	0.006	0.032
(4, 150, 0.02)	0.049	-0.015	0.064	4.379	0.007	0.652
(4, 200, 0.02)	0.050	-0.015	0.064	3.652	0.009	0.000
(7, 50, 0.02)	0.028	-0.007	0.036	6.848	0.003	0.180
(7, 100, 0.02)	0.047	-0.005	0.052	4.636	0.006	0.040
(7, 150, 0.02)	0.044	-0.008	0.052	3.530	0.007	0.056
(7, 200, 0.02)	0.048	-0.012	0.061	2.894	0.010	0.256
(10, 50, 0.02)	0.027	-0.006	0.033	5.955	0.003	0.532
(10, 100, 0.02)	0.044	-0.001	0.045	4.136	0.005	0.103
(10, 150, 0.02)	0.041	-0.004	0.044	3.076	0.007	0.050
(10, 200, 0.02)	0.045	-0.009	0.054	2.576	0.010	0.070
(13, 50, 0.02)	0.022	-0.011	0.033	5.258	0.003	0.000
(13, 100, 0.02)	0.035	-0.001	0.036	3.591	0.005	0.855
(13, 150, 0.02)	0.036	-0.006	0.042	2.621	0.008	0.875
(13, 200, 0.02)	0.039	-0.002	0.041	2.379	0.009	0.646
(16, 50, 0.02)	0.020	-0.012	0.033	4.758	0.003	0.365
(16, 100, 0.02)	0.034	-0.001	0.034	3.318	0.005	0.000
(16, 150, 0.02)	0.033	-0.005	0.039	2.530	0.008	0.412
(16, 200, 0.02)	0.039	-0.003	0.042	2.197	0.009	0.085
(19, 50, 0.02)	0.017	-0.012	0.030	4.333	0.003	0.000
(19, 100, 0.02)	0.033	0.004	0.029	3.076	0.005	0.015
(19, 150, 0.02)	0.027	-0.004	0.031	2.470	0.006	0.252
(19, 200, 0.02)	0.040	-0.003	0.042	2.076	0.010	0.012
84 VMA Portfolio	4.443	-0.677	5.120	4.985	51.354	0.000

Table 2. Annual Returns, Break-Even Trading Costs: Technical Trading Rules Implemented on DJIA Stocks from 1926-1991, No Trade Lag

Annual Excess Returns							
	Buy	**Sell**	**Buy-Sell**	**Trades Per Year**	**Break-Even Costs(%)**	**Bootstrap P-values**	**Costs(%) By B&C**
Full Sample 1926-1991							
84 VMA Rules	4.44	-0.68	5.12	4.98	0.51	0.001	0.57
288 FMA Rules	0.54	0.08	0.46	1.71	0.13	0.000	0.25
40 TRB Rules	1.51	0.15	1.37	3.55	0.19	0.060	0.14
All 412 Rules	1.43	-0.07	1.50	2.56	0.29	0.000	0.39
Subperiods:							
1926-1943							
84 VMA Rules	4.57	-4.95	9.53	5.44	0.88	0.154	0.71
288 FMA Rules	0.47	-1.05	1.53	1.95	0.39	0.008	0.29
40 TRB Rules	1.72	-1.47	3.18	4.15	0.38	0.006	0.43
All 412 Rules	1.43	-1.89	3.32	2.88	0.58	0.000	0.54
1944-1959							
84 VMA Rules	6.51	1.82	4.69	4.79	0.49	0.018	0.59
288 FMA Rules	0.70	1.08	-0.38	1.59	-0.12	0.004	0.14
40 TRB Rules	2.66	1.50	1.16	3.11	0.19	0.000	0.18
All 412 Rules	2.07	1.27	0.80	2.39	0.17	0.000	0.39
1960-1975							
84 VMA Rules	2.44	-0.80	3.23	4.68	0.35	0.004	0.52
288 FMA Rules	0.20	-0.05	0.25	1.58	0.08	0.658	0.30
40 TRB Rules	0.75	-0.39	1.14	3.20	0.18	0.021	0.10
All 412 Rules	0.71	-0.23	0.94	2.37	0.20	0.000	0.36
1976-1991							
84 VMA Rules	3.79	2.66	1.13	5.15	0.11	0.018	0.40
288 FMA Rules	0.95	0.56	0.39	1.72	0.11	0.008	0.28
40 TRB Rules	0.73	1.29	-0.57	3.70	-0.08	0.654	-0.20
All 412 Rules	1.51	1.06	0.45	2.61	0.09	0.000	0.22

Table 3. Annual Returns, Break-Even Trading Costs: Technical Trading Rules Implemented on DJIA Stocks from 1926-1991, One-day Trade Lag

Annual Excess Returns							
	Buy	**Sell**	**Buy-Sell**	**Trades Per Year**	**Break-Even Costs(%)**	**Bootstrap P-values**	**Costs(%) By B&C**
Full Sample 1926-1991							
84 VMA Rules	3.97	-0.25	4.22	4.98	0.42	0.000	0.42
288 FMA Rules	0.43	0.14	0.28	1.71	0.08	0.015	0.17
40 TRB Rules	1.23	-0.13	1.36	5.59	0.12	0.001	0.12
All 412 Rules	1.23	0.04	1.19	2.76	0.22	0.000	0.29
Subperiods:							
1926-1943							
84 VMA Rules	4.14	-4.49	8.64	5.44	0.79	0.016	0.57
288 FMA Rules	0.33	-1.16	1.50	1.95	0.38	0.012	0.23
40 TRB Rules	3.06	-1.68	4.74	6.31	0.38	0.052	0.38
All 412 Rules	1.37	-1.89	3.27	3.09	0.53	0.000	0.44
1944-1959							
84 VMA Rules	6.16	2.08	4.08	4.79	0.43	0.004	0.50
288 FMA Rules	0.63	1.08	-0.46	1.59	-0.14	0.006	0.12
40 TRB Rules	2.04	0.95	1.09	4.97	0.11	0.000	0.11
All 412 Rules	1.89	1.27	0.62	2.57	0.12	0.000	0.32
1960-1975							
84 VMA Rules	1.89	-0.20	2.10	4.68	0.22	0.032	0.32
288 FMA Rules	0.09	0.05	0.04	1.58	0.01	0.254	0.21
40 TRB Rules	-0.39	-0.80	0.41	5.05	0.04	0.000	0.04
All 412 Rules	0.41	-0.09	0.50	2.55	0.10	0.000	0.23
1976-1991							
84 VMA Rules	3.18	3.08	0.09	8.23	0.01	0.065	0.21
288 FMA Rules	0.78	0.86	-0.08	1.72	-0.02	0.000	0.11
40 TRB Rules	2.18	0.93	1.25	5.62	0.11	0.009	-0.10
All 412 Rules	1.41	1.32	0.08	3.42	0.01	0.000	0.11

Table 4. Annual Returns, Break-Even Trading Costs: Technical trading rules implemented on DJIA Stocks compared with Chinese stocks during 1991-2000, No Trade Lag

	Annual Excess Returns					
Rules	**Buy**	**Sell**	**Buy-Sell**	**Trades per year**	**Breakeven costs(%)**	**Bootstrap P-values**
DJIA						
84 VMA	6.49	6.02	0.47	5.62	0.04	0.254
288 FMA	1.25	1.92	-0.67	1.84	-0.18	0.058
40 TRB	2.97	2.47	0.50	3.52	0.07	0.000
Total 412 Rules	2.48	2.81	-0.32	2.78	-0.06	0.000
Shanghai A						
84 VMA	12.30	47.81	-35.51	4.64	-3.82	0.063
288 FMA	5.42	1.11	4.31	2.04	1.06	0.087
40 TRB	10.96	61.03	-50.07	3.49	-7.18	0.000
Total 412 Rules	7.36	16.45	-9.09	2.71	-1.68	0.000
Shanghai B						
84 VMA	7.73	-11.22	18.95	3.79	2.50	0.005
288 FMA	5.40	-4.84	10.24	1.75	2.92	0.630
40 TRB	7.73	-5.75	13.47	2.82	2.39	0.004
Total 412 Rules	6.10	-6.23	12.33	2.27	2.72	0.000
ShenZhen A						
84 VMA	14.98	-2.60	17.58	4.08	2.15	0.652
288 FMA	1.49	-0.36	1.85	1.68	0.55	0.023
40 TRB	13.32	0.54	12.77	2.91	2.20	0.012
Total 412 Rules	5.39	-0.73	6.12	2.29	1.34	0.000
ShenZhen B						
84 VMA	13.01	-19.44	32.45	2.82	5.75	0.074
288 FMA	4.96	-3.13	8.09	1.31	3.10	0.365
40 TRB	10.81	-10.37	21.18	2.91	3.65	0.000
Total 412 Rules	7.17	-7.16	14.33	1.77	4.05	0.036
China Portfolio	6.50	0.58	5.92	2.26	1.31	0.000

Table 5. Annual Returns, Break-Even Trading Costs: Technical trading rules implemented on DJIA Stocks compared with Chinese stocks during 1991-2000, one-day Lag

	Annual Excess Returns					
Rules	**Buy**	**Sell**	**Buy-Sell**	**Trades per year**	**Breakeven costs(%)**	**Bootstrap P-values**
DJIA						
84 VMA	6.59	6.04	0.54	5.61	0.05	0.002
288 FMA	1.25	1.92	-0.67	1.85	-0.18	0.000
40 TRB	3.17	2.81	0.36	4.15	0.04	0.064
Total 412 Rules	2.53	2.85	-0.32	2.84	-0.06	0.000
Shanghai A Shares						
84 VMA	31.27	5.24	26.03	4.64	2.80	0.965
288 FMA	4.18	-1.58	5.76	2.06	1.40	0.002
40 TRB	19.05	3.96	15.09	4.39	1.72	0.006
Total 412 Rules	11.14	0.34	10.80	2.82	1.92	0.000
Shanghai B Shares						
84 VMA	5.60	-9.79	15.39	3.79	2.03	0.065
288 FMA	4.89	-4.31	9.19	1.77	2.60	0.851
40 TRB	2.92	-5.44	8.36	3.47	1.21	0.000
Total 412 Rules	4.84	-5.54	10.38	2.34	2.21	0.000
ShenZhen A Shares						
84 VMA	15.27	-2.67	17.93	4.08	2.20	0.000
288 FMA	1.48	-0.37	1.84	1.69	0.55	0.085
40 TRB	12.87	1.73	11.14	3.30	1.69	0.361
Total 412 Rules	5.40	-0.63	6.03	2.33	1.29	0.000
ShenZhen B Shares						
84 VMA	11.71	-19.00	30.71	2.82	5.45	0.652
288 FMA	5.28	-3.27	8.54	1.31	3.26	0.002
40 TRB	7.61	-11.37	18.98	3.20	2.97	0.004
Total 412 Rules	6.81	-7.26	14.08	1.80	3.91	0.085
China Portfolio	7.05	-3.27	10.32	2.32	2.22	0.000