Trading Rules Profitability in the Emerging FX Market: Danger of Data Snooping*

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Abstract

We study the profitability of technical trading rules (hereafter "TTR") for the emerging foreign exchange markets, which are usually perceived to be less efficient. We find little supportive evidence for TTR once we control for data snooping bias, as opposed to conventional wisdom that technical analysis is more likely to be useful in less efficient market. Data snooping bias is intrinsic in searching for profitable trading rules by researchers and practitioners. We quantify the danger of data snooping bias using formal test with data snooping check. If we ignore the data snooping bias, we do find thousands of profitable rules for every considered emerging currency exchange rates. The profitability disappears in most cases, however, when data snooping bias is taken into account. We use an universe of 25,988 trading strategies for 10 emerging market currencies, consisting of simple rules, charting rules with kernel smoothing and complex trading rules. Most of these strategies are popular in the trading practice, but have not yet been studied for emerging market currencies in the literature. We also find that in the charting rules with kernel smoothing, those based on the under-smoothed spot series perform better than over-smoothed and original spot series, confirming that under-smoothing mimics better the eyeball smoothing of professional traders.

Keywords: foreign exchange, technical trading, data snooping, reality check, SPA test, StepM test, SSPA test, emerging market.

EFM Classification: 610, 620

*We are grateful to Andreas Schrimpf, Waldmar Rotfuss for their helpful discussions. We thank Jonas Vogt for excellent research assistance. Funding support from Deutsche Bank is gratefully acknowledged. Errors and omissions remain the responsibility of the authors.

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1 Introduction

The profitability of technical trading rules (hereafter "TTR") is a conundrum. On the one hand, technical analysis only needs public available information like asset prices. If the market is (weakly) efficient, as widely believed among financial economists, rational investors should quickly arbitrage away the profits, and therefore leave no room for technical analysis. On the other hand, if TTR cannot generate persistent profits, why do at least 90% percent of experienced traders place some weight on it in costly trading activity [Taylor and Allen (1992)]?

Empirical evidence is more supportive for the TTR, which seems to resolve this conundrum to a high extend. For example, Park and Irwin (2007) surveys 95 modern studies and finds that 56 studies report profitability, 20 studies report negative results, while the rest indicate mixed results. These results, when taken at face value, tend to reject the market efficiency hypothesis and lend support for the traders' practice. However, there are at least two caveats. One is the publication bias. It arises when the researchers and editor tend to produce/publish results that appear significant, in particular those against common beliefs (market efficient hypothesis in the current context). The other is the data snooping (also called "data mining") bias. A given market typically has only a single history for studying the phenomena of interest. Trying hard and long enough in searching along almost all conceivable dimensions makes it very likely to find seemingly profitable but in fact wholly spurious trading strategies[1]. This bias, if not correctly accounted for, invalidates the classical statistical inference, as those conducted in the majority of previous literature. The publication bias reinforces the data mining bias in favor of publishing such results, casting doubt on the validity of most academic evidences. Thus, despite of researchers' endeavors, the conundrum remains a conundrum.

To shed new light into the conundrum, we test the profitability of TTR on emerging FX market while controlling for data snooping bias. The FX market has substantial supportive evidence for the profitability of technical analysis[2]. Most of these studies, however, confined themselves to

[1]For a detailed and more general discussion of this issue, see Sullivan, Timmermann, and White (1999), White (2000) and Hansen (2005)

[2]Examples are Sweeney (1986), Levich and Thomas (1993), Neely (1997), Chang and Osler (1999), LeBaron (1999), Osler (2000), and Qi and Wu (2006). There are also several studies showing the opposite [see Lee and Mathur (1996) and Neely and Weller (2003)].

currencies of developed economies. It is unclear whether their findings can be carried over to those from the emerging markets, which themselves are heterogeneous. In fact, three components contribute to the profitability of TTR: spot exchange rate movement, interest rate differential and transaction cost. All these components can differ significantly from emerging FX market to developed FX market for the following reasons: First, spot exchange rate in emerging market are usually more volatile, and are more likely to have currency crisis. If the TTR captures the risk premium of spot exchange rate movement, then it is likely to be more profitable in emerging market than developed market, ceteris paribus; Second, the emerging countries have on average higher nominal interest rates, which has direct implications on the profitability of TTR; Third, emerging markets tend to have stricter regulation and capital control. These regulation differences make the speculation more difficult to arbitrage away the profits; Fourth, the bid-ask spreads are usually two to four times larger in emerging markets than in developed countries [Burnside, Eichenbaum, and Rebelo (2007)], indicating a higher transaction cost for emerging currency speculations; Fifth, many authors conjectured that the trading rules profitability are results of central bank interventions [Sweeney (1986); Levich and Thomas (1993); LeBaron (1999); Saacke (2002)]. One the one hand, the central banks from emerging markets tend to intervene more often, the trading rules on these countries' currencies are more likely to be profitable. On the other hand, the exchange rates with emerging market may not be deemed as important enough to merit the intervention from the major central banks, which can reduce the profitability.

Among the few studies on the profitability of technical trading rules on emerging FX markets, Martin (2001) investigates moving average rules using daily data between 1993 and 1995 for 12 emerging markets, and finds significant improvement in the mean excess return, but not in the Sharpe ratio; Lee, Gleason, and Mathur (2001) examine the profitability of moving average and channel rules in 13 Latin American countries over the period 1992-99 and find mixed results; Pojarliev (2005) documents profitability of moving average rule using monthly data for the period of 1999-2004. It is still premature to conclude whether technical trading rules can generate sizable profits based on these mixed results. Furthermore, these studies do not formally control for the effect of data snooping bias, which is a critical concern in this line of research (which this paper will address). The data snooping concern is more difficult to address for emerging market currencies given that the time span of exchange rate series is usually short, such that researchers can hardly use out-of-sample test[3] to avoid data snooping bias.

Data snooping arises when the same data is used repeatedly by one or many researchers for the purpose of inference or model selection. It has long been considered by academic researchers [Jensen (1967), Jensen and Bennington (1970), Lo and MacKinlay (1990) and Brock, Lakonishok, and LeBaron (1992)]. However, rigorously founded and generally applicable test is not available until White (2000) introduced the Reality Check[4]. Searching for the optimal trading rule is a prominent example where data snooping can occur, as investors keep exploiting the possibility of detecting trading rules for easy profits. Reality Check can directly quantify the effect of data snooping when testing the best trading rule from the "full universe" of trading strategies. Since then a couple of studies [e.g., Sullivan et al. (1999), White (2000), Hsu and Kuan (2005) and Qi and Wu (2006)] have applied Reality Check and found mixed results. In particular, Qi and Wu (2006) are the first to study the TTR profitability with Reality Check for developed countries' currencies. They consider a universe of 2127 technical trading rules and find that data snooping biases do not change the conclusion of profitability of trading rules in full sample. But in the second half of the sample the data snooping bias is more serious.

Reality Check however, is known to suffer from some drawbacks. Hansen (2005) points out that the power of Reality Check can be reduced, and even be driven to zero when too many poor and irrelevant rules are included in the set of alternatives. Simply excluding poor performing alternatives does not lead to valid inference in general either. To solve this problem, Hansen (2005) proposes a new test statistic for superior predictive ability (hereafter "SPA"), which invokes a sample-dependent distribution under the null hypothesis. This "SPA" test is more powerful compared to White's Reality Check and less sensitive to the inclusion of poor and irrelevant alternatives.

The question of interest for both Reality Check and SPA test is whether the best trading rule beats

[3]see Neely, Weller, and Ulrich (forthcoming) as an example for applying out-of-sample test.

[4]Alternative ways of handling data snooping bias includes testing on different but comparable data set, or by pseudo out of sample test, which splits sample periods into in-sample and out-of-sample periods, or by genetic programming approach. In practice, however, comparable data might be difficult to find, sample splitting is more or less arbitrary while out of sample test can have as serious data mining bias as in-sample test [Inoue and Kilian (2004)], and genetic programming can be inadequate due to inefficient ways of learning and due to the search domain is still constrained to some degree in practice.

the benchmark. An investor might want to know whether a particular trading rule is profitable. A researcher may want to test whether a certain trading rule found profitable in the literature indeed outperforms the market. Furthermore, as pointed out by Timmermann (2006), choosing the forecast with the best track record is often a bad idea, and combination of forecasts dominates the best individual forecast in out-of-sample forecasting experiments. So we may want to know all or some of the profitable trading strategies and combine them for decision making (this is what the complex trading rules we study in this paper do)[5]. We may also want to avoid worse strategies when combining trading rules. Romano and Wolf (2005) modify Reality Check and proposes a stepwise multiple test (hereafter "StepM"), which can detect as many profitable trading rules as possible for a given significance level. Hsu and Hsu (2006) propose a stepwise SPA (hereafter "SSPA") test combining the SPA test and StepM test together, which is more powerful in identifying all good trading strategies.

We consider three groups of trading rules in this paper. The first group consists of the simple rules (including for example, filter rules and moving average rules), which are the most frequently studied rules in the literature. These simple rules we study nests all trading rules studied by Qi and Wu (2006), the previously largest trading rule universe in FX market studied. We also study the charting rules with kernel smoothing (including for example, Head and Shoulders and Rectangle rules), as studied by Lo, Mamaysky, and Wang (2000). These charting rules are the most frequently used trading rules by traders. They are applied to smoothed spot series because the professional traders eyeball smooth the price series to filter out noise in practice too. Lo et al. (2000) advocate kernel smoothing can mimic the eyeball smoothing of professional traders. The key issue of kernel smoothing is the choice of the bandwidth, which determines the degree of smoothing. Unlike Lo et al. (2000) who choose an ad hoc bandwidth, we consider 3 different bandwidth (scaling the optimal bandwidth with 0.3, 1 and 4), as well as the original series, in order to see the effect from under-smoothing, over-smoothing and no-smoothing. The last group of trading rules we study consists of the complex trading rules. Complex trading rules combine some information from simple rules to reach its own trading signal. Combing signals of different rules is important since

[5]Some evidence of unstable performance of the trading strategy is provided in Sullivan et al. (1999). They find that the best trading rule applying to DJIA for the period of 1897-1986 does not outperform the benchmark for the period of 1987-1996.

there is no sure-fire rule [Edwards and Magee (1997)] and hence it is necessary to use some rules together to build up a consensus [Pring (1991)]. We consider three classes of complex trading rules as in Hsu and Kuan (2005). We also propose a voting by learning strategy (VLS) of our own.

Our paper contributes to the analysis of trading strategies in FX market along several important ways. First, we provide the first comprehensive documentation of trading rules profitability for emerging markets currencies, which becomes more important but is still poorly understood; Second, we consider a large universe of trading rules, including simple rules, charting rules with kernel smoothing and complex trading rules, most of which have not yet been studied for emerging market currencies in academic research; Third, we conduct the StepM test [Romano and Wolf (2005)] and SSPA test [Hsu and Hsu (2006)]. These tests detect as many profitable trading rules as possible from the universe, while accounting for the data snooping bias. These tests also allow us to compare the findings from the literature directly with ours, since they can test whether the specific trading rules considered in the literature are still profitable after controlling for data snooping bias.

Our analysis reveals a number of interesting results. First, the data snooping bias is substantial: if we ignore the data snooping bias, we do find thousands of profitable rules for every emerging currencies considered. The profitability disappears in most cases, however, when data snooping bias is taken into account. Second, we find little supportive evidence for technical analysis in emerging FX markets, though conventional wisdom postulates that this is more likely to happen for less efficient market like emerging market. Third, we find that in the charting rules with kernel smoothing, those based on the under-smoothed spot series perform better than over-smoothed and original spot series, confirming that under-smoothing mimics better the eyeball smoothing of professional traders. We also find that Head and Shoulders strategies from under-smoothed spot rate series are often among the best performing rules.

The remainder of this paper is structured as follows. Section 2 provides the description of the universe of the trading rules considered in our paper. Section 3 discusses the methodology for accounting for the effect of data snooping bias and for identifying the best strategies as well as the profitable strategies. Section 4 documents briefly our data and then reports our main empirical findings for trading on the currencies from emerging market. Section 5 concludes. Detailed documentation of the trading rules considered can be found in the appendix.

2 Universe of Trading Rules

Defining the universe of trading rules is a key step for obtaining valid inference in superior predictive test. Although the power of White's Reality Check can be reduced by including too many irrelevant trading rules, Hansen (2005) emphasizes that excluding them does not lead to valid inference in general either. Of course, to define a complete and exhaustive universe of trading rules is neither possible nor viable. So we expand the trading rule to a large universe while keeping it computationally feasible. In total we have 25,988 trading rules, consisting of simple rules, charting rules with kernel smoothing and complex trading rules. We document the trading rules considered in this paper in the following section. Table I gives an overview of the universe of trading rules we considered. The parameters used here are described in detail in the appendix.

[Insert Table I About Here]

2.1 Simple trading rules

Our descriptions of simple trading rules draw heavily from Sullivan et al. (1999), Qi and Wu (2006), and in particular, Hsu and Kuan (2005), though we make some modifications to avoid ambiguities.

2.1.1 Filter Rules

The filter rule strategy for generating trading signal follows Sullivan et al. (1999) and Qi and Wu (2006). The basic filter rule could be stated as follows: if the daily closing price (in British Pound) of a foreign currency moves up by $x\%$ or more from its most recent low, the speculator borrows the British Pound and uses the proceeds to buy and hold the foreign currency until its price moves down at least $x\%$ from a subsequent high, at which time the speculator short sells the foreign currency and uses the proceeds to buy the British Pound. Two definitions of the subsequent high (low) are considered. One is the highest (lowest) closing price over the period of holding a particular long (short) position. The alternative high (low) refers to the most recent closing price that is greater (less) than e previous closing price. We also consider that a given long or short position is held for prespecified c days during which time all other signals are ignored.

2.1.2 Moving Average Rules

Moving averages are among the oldest trading rules used by chartist. The (equally weighted) moving average of a currency price for a given day t over the n days is $\frac{1}{n}\sum_{i=0}^{n-1} s_{t-i}$. Under a simple single moving average rule, when the current price is above the moving average by an amount larger than the band with $b\%$, the speculator borrows the British Pound to buy the foreign currency. Similarly, when the current price is below the moving average by $b\%$, the speculator short sells the foreign currency to buy the British Pound. Under dual moving average rule, when the short moving average of a foreign currency price is above the long moving average by an amount larger than the band with $b\%$, the speculator borrows the British Pound to buy the foreign currency. If the short moving average of a foreign currency price penetrates the long moving average from above, the speculator short sells the foreign currency to buy the British Pound. Follows Sullivan et al. (1999) and Qi and Wu (2006), we implement the moving average rules with a time delay filter in addition to the fixed percentage band filter as described above. The time delay filter requires that the long or short signals remain valid for d days before action is taken. Similar to the filter rule case, we also consider holding a given long or short position for c days during which period all other signals are ignored.

2.1.3 Trading Range Break (or Support and Resistance) Rules

The support and resistance level refers to certain price levels acting as barriers to prevent traders from pushing the price of an underlying asset in a certain direction. Under a trading range break rule, when the price of a foreign currency moves above the maximum price (resistance level) over the previous n days by $b\%$, the speculator borrows the British Pounds to buy the foreign currency. When the price goes below the minimum price over the previous n days by $b\%$, the speculator sells short the foreign currency and buy the British Pound. Alternatively, we use the local maximum (minimum), which is the most recent closing price higher (lower) than the e previous closing prices, as the definition for the resistance level. Here we also allow a time delay filter, d, as well as the holding period of *c* days to be included, as in the case of moving average rules.

2.1.4 Channel Breakout Rules

A channel is defined to be the one that occurs when the high price of a foreign currency over the previous *n* days is within *x*% of the low over the previous *n* days. Under a channel breakout rule, when the closing price of the foreign currency goes above the channel by *b*%, a signal is generated for the speculator to borrow the British Pound and buy the foreign currency; when the closing price of the foreign currency drops below the channel by *b*%, a signal is generated for the speculator to short sells the foreign currency and buys the British Pound. Again, we consider a holding period of *c* days.

2.1.5 Momentum strategies

A momentum strategy tries to predict the strength or weakness of the current market based on an "oscillator" constructed from a momentum measure. We follow Hsu and Kuan (2005) to use the rate of change (ROC) as the momentum measure. The m-day ROC at time t is defined as the change of spot exchange rate divided by the closing spot exchange rate at time $t - m$. Two oscillators are considered: simple oscillator (which is just m-day ROC), and moving average oscillator (which is the w-day moving average of m-day ROC with $w \leq m$). An overbought/oversold level *k* (say 5% or 10%) is needed to determine whether a position should be initiated. When the oscillator penetrates the overbought level from below, the speculator borrows the British Pound to buy the foreign currency. If the oscillator crosses the oversold level from above, the speculator sells short the foreign currency and buy the British Pound. Once again, we consider a holding period of *c* days.

2.2 Charting rules with kernel smoothing

Similar to Lo et al. (2000), we consider 5 pairs of technical patterns applying to kernel smoothed spot series: Head and Shoulders (HS) and Inverse Head and Shoulders (IHS), Triangle (TA), Rectangle (RA), Double Tops and Bottoms (DTB) and Broadening Tops and Bottoms (BTB). Using non-parametric smoothing does not mean we are considering so complicated rules that investor cannot use. On the contrary, we do this because investors filter out noise when using these non-linear rules. In this sense they are doing smoothing in their trading practice. Kernel smoothing is an ideal way to smooth the spot rates. The critical issue in kernel smoothing is the choice of bandwidth. The aim here is to find which degree of smoothing can mimic the eyeball smoothing adopted by investors. Lo et al. (2000) recommend to use a bandwidth equals to $0.3\times$*(optimal band width)*, which is calculated from a cross validation method (Lo et al. (2000), see also Härdle (1990) for detailed discussion of kernel smoothing and cross validation). Lo et al. (2000) advocate to use this under-smoothed stock price series since they are neither too volatile nor too smooth, and the professional technical analysts they interviewed feel such a smoothing is more acceptable than other versions of smoothed series. They admit, however, such an approach is ad hoc. Commenting on that paper, Jegadeesh (2000) recommends to use different choice of bandwidth to assess whether their results are sensitive to these choices. Gene Savin and Zvingelis (2007) considers the following multiples 1, 1.5, 2 and 2.5 of the optimal bandwidth. We use 3 different bandwidth (scaling the optimal bandwidth with 0.3, 1 and 4), as well as the original series, in order to see the effect from under-smoothing, optimal smoothing, over-smoothing and no smoothing. Therefore, for each pair of charting rules in this class, we apply them to four versions of spot rates depending on the smoothing parameters used.

2.2.1 Head and Shoulders and Inverted Head and Shoulders

Head and Shoulders is one of the most popular, and one of the most trusted chart patterns by practitioners in technical analysis. It occurs when the second (head) of three consecutive peaks is higher than the first (left shoulder) and the third (right shoulder). The minima between left (right) shoulder and the head are called left (right) troughs. We require the two shoulders (troughs) to be approximately equal such that their differences are no more than a differential rate x. The HS pattern is completed when the adjacent local minimum of the right shoulder penetrates the neckline and the band. Short position in foreign currency is taken exactly on the day when price crosses the neckline and band. Following Chang and Osler (1999), two exit rules for HS strategy are considered, namely endogenous and exogenous. For the endogenous one, we distinguish two kinds of situation. We define a cutoff as y times standard deviation of daily exchange rate change. If the price falls by *d* percent times difference between head and average trough(the difference referred as "measuring objective" or "price objective" in technical manual), we exit on the day when the price has risen above a local minimum by the cutoff percentage that implies the price has conclusively stopped moving in the predicted direction. In the second case, if the price does not fall by such an amount, we allow for a possible bounce or interruption, that is, the price may temporarily move back toward the neckline. When the second trough goes below the aforementioned *d* percent line, we are back to the former case. Otherwise, we liquidate the position at the second trough. In both situations, in order to limit the loss, a stop-loss line is incorporated whenever the price goes in the wrong direction sufficiently far. An exogenous exit rule means we close our position after holding for an exogenous specified number of days f. The inverted Head and Shoulders is just an inverse version of Head and Shoulders, and once the IHS is completed, the speculator expects a upward trend in the future spot exchange rate. So he will borrow the British Pound to buy the foreign currency.

2.2.2 Triangle

Triangle is one of the reverse pattern based also on pricing movements showing five consecutive local extrema. Triangle tops (TTOP) is characterized with 3 descending local maxima and two ascending local minima. Triangle bottoms (TBOP) is characterized with 3 ascending local minima and two descending local maxima. Once a triangle is completed, it will be a signal for taking a long (short) position in foreign currency if the future closing spot exchange rate exceeds the latest top (or falls below the latest bottom) by a fixed proportion x, known as the "trend filter". We consider similar liquidation methods as HS.

2.2.3 Rectangle

The rectangle pattern is also characterized by five consecutive local extrema. Rectangle tops (RTOP) requires three tops and two bottoms lie in near an upper horizontal lines, that is, within x percent of their average, respectively. Moreover, we require that the lowest top is higher than the highest bottom. Similarly, the rectangle bottoms (RBOT) requires two tops and three bottoms lie in near an upper horizontal lines. Signals are generated in a similar way as the Triangle rule, so do the liquidation methods considered.

2.2.4 Double Tops and Bottoms

The double tops(bottoms) are characterized by two tops(bottoms) lie in near an upper horizontal lines, with one bottom (top) lie in between. Following Lo et al. (2000), we require that the two tops (bottoms) occur at least a month, or 22 trading days, apart. In addition, the second top (bottom) should be higher (lower) than all the local maxima (minima) in between.

2.2.5 Broadening Tops and Bottoms

Similar to Triangle class, the Broadening Tops and Bottoms are characterized by five consecutive local extrema. Broadening Tops (BTOP) requires 3 descending local maxima and two ascending local minima. Broadening Bottoms requires 3 descending local minima and two ascending local maxima. Compared to the Triangle class, this class correspondences a "divergence" shape, while Triangle class requires a "convergence" shape.

2.3 Complex trading rules

Single rule can generate false signals when prices fluctuate in a broad sideways pattern. Relying on a single rule can be a dangerous practice, even for the best rule found historically. Technical analyst can combine other trading rules to confirm the prediction of price direction. Follow Hsu and Kuan (2005), we consider three classes of complex trading rules: the learning strategy (LS), the voting strategy (VS), and the fractional position strategy (FPS). Besides of these complex trading rules, we also propose a new class of complex rules, voting by learning strategy (VLS), which combines the voting and learning rules together.

2.3.1 Learning Strategy (LS)

A learning strategy assumes that an investor learn from the past *m* days (memory span) the strategies' performances within the certain class, he then switch his position by following the best strategy found during the memory span. After his switch, he waits for *r* days (review span) and then evaluates the past *m* days (memory span) the strategies' performances again to decide whether to switch. For evaluation of the trading rules, we use mean return and Sharpe ratio during the memory span as the performance. measure.

2.3.2 Voting Strategy (VS)

Voting strategy is a system of voting by trading rules within each class. Each rule is assigned one vote for recommending a ballot. We consider the three choice ballot, where long, no, or short position can be voted. The decision follows the recommendation of majority votes. To avoid the voting result is dominated by the class with a large number of rules, we consider every class of simple rules separately but not the one consists of all rules.

2.3.3 Fractional Position Strategy (FPS)

Note that both learning strategy and voting strategy yield signal as integer. The fractional position strategy, in contrast, allows to take the position of a non-integer between -1 and 1. The fraction of a position is determined by an "evaluation index", in our case is just the faction of winning votes recommending same positions relative to all votes within the same class.

2.3.4 Voting by Learning Strategy(VLS)

Under this strategy we consider the best n trading rules evaluated from the memory span within each class of simple rules, and then assign votes to these rules as in the voting strategy class. The decision follows the recommendation of majority votes from these best n trading rules. In addition, we consider the case that the top n trading rules are selected from the set of all simple trading rules .

3 Test with Data Snooping Check

In this section we discuss the aforementioned four tests (Reality Check, SPA, SRC and SSPA) in a consistent manner and with notations similar to Hansen (2005). Although these tests are applicable to the general superior predictive ability of forecasting models, we focus our discussion on their applications to test profitable trading rules in foreign exchange rate market.

Suppose our universe of trading rules includes m rules. Let δ^k_{t-1} be a "signal" function which generates trading signal by the k^{th} trading rule using information up to $t-1$. This signal function can take three values that instructs a trader to take a short position ($\delta_{k,t-1} = -1$), a long position ($\delta_{k,t-1} = 1$), or no position ($\delta_{k,t-1} = 0$) in a foreign currency at time $t-1$. The k^{th} trading rule yields the profit as:

$$R^k_t = (s_t - s_{t-1} + r^*_t - r_t)\delta^k_{t-1} - abs(\delta^k_{t-1} - \delta^k_{t-2})g \tag{1}$$

where R^k_t is the excess return from trading on the currency in period t using k^{th} trading rule, s_t is the logarithm of the spot exchange rate (British Pound price of one unit foreign currency) at time t; r_t and r^*_t are, respectively, domestic and foreign interest rates from time t-1 to t; g is a one way transaction cost.

We consider two performance measures. One is the mean excess return, and the other is the Sharpe ratio [6]. We use a natural benchmark that the investor does not take position in the foreign

[6] The Sharpe ratio used here is in fact information ratio, defined as the mean excess return divided by the standard deviation. In practice, people do not make strict distinction of these two measures. So we still use the name "Sharpe ratio" here. We calculate robust Sharpe ratio with studentization and HAC standard errors. Please see Wolf (2007) for details.

exchange market and hence earns a zero excess return (alternatively, zero Sharpe ratio). Therefore our performance measure is in fact a relative performance measure [$d_{k,t}$ in the notation of Hansen (2005)] of k^{th} trading strategy compared to the benchmark.

3.1 Reality check

White (2000) tests the null hypothesis that the benchmark is not inferior to any of the alternative trading rules:

$$\mathbf{H_0} : \mu \leq \mathbf{0}, \tag{2}$$

where $\mu = E(\mathbf{d_t})$ and is a $m \times 1$ vector ($\mu \in \mathbb{R}^m$), while $\mathbf{d_t} = (d_{1,t}, \cdots, d_{m,t})$ is the $m \times 1$ vector of relative performance measures. Rejecting equation 2 implies there exists at least one trading rule that beats the benchmark. White proceeds to construct the reality check from the test statistics,

$$T_n \equiv max(n^{1/2}\overline{d}_1, \cdots, n^{1/2}\overline{d}_m), \tag{3}$$

The complication of this test is that the true distribution of T_n depends on nuisance parameters such that the null distribution is not unique. The typical way to handle the ambiguity is to use the "least favorable configuration(LFC)", also known as "the point least favorable to the alternative". That means, it assumes $\mu_k = 0$ for all k, even though all negative values of μ_k also conform the null hypothesis. White's reality check follows LFC to simplify the null hypothesis.

To calculate the p-value for the null hypothesis, White (2000) recommends the stationary bootstrap method of Politis and Romano (1994) to first obtain the empirical distribution of T_n^*:

$$T_n^*(b) = max[n^{1/2}(\overline{d}_1(b) - \overline{d}_1), \cdots, (n^{1/2}\overline{d}_m(b) - \overline{d}_m)], \qquad b = 1, \cdots, B \tag{4}$$

The p-value is obtained by comparing the T_n with the quantiles of the empirical distribution of $T_n^*(b)$. If the p-value is smaller than a given significance level, the null hypothesis is rejected.

3.2 SPA test

The null hypothesis of SPA test [Hansen (2005)] is the same as in White's Reality Check. Hansen (2005) points out some drawbacks of White's Reality Check. First, the test statistic is not studentized. Second, the LFC-based approach followed by Reality Check can affect the power adversely by adding poor and irrelevant alternatives, in some extreme cases the power can even be driven to zero. The SPA test uses the studentized test statistic, which typically will improve the power. Hansen (2005) provides a concrete example for highlighting the advantage of studenting the individual statistics, since it avoids a comparison of the performance measured in different "units of standard deviation". To avoid the reduction of power due to the application of LFC, the SPA test invokes a sample-dependent distribution under the null hypothesis, which can discard the poor models asymptotically. The test statistics for SPA is given as the following:

$$T_n^{SPA} = max[max_{k=1,\cdots,m} \frac{n^{1/2}\overline{d}_k}{\hat{\omega}_k}, 0], \tag{5}$$

where $\hat{\omega}_k^2$ is some consistent estimator of $\omega_k^2 = var(n^{1/2}\overline{d}_k)$. Then an estimator $\hat{\mu}^c$ for μ is chosen such that it conforms with the null hypothesis based on $N_m(\hat{\mu}^c, \hat{\Omega})$. The particular $\hat{\mu}^c$ suggested by Hansen (2005) is $\hat{\mu}_k^c = \overline{d}_k \mathbb{I}_{\{n^{1/2}\overline{d}_k/\hat{\omega}_k \leq -\sqrt{2loglogn}\}}$ for $k = 1, \cdots, m$, where $\mathbb{I}$ is the indicator function. It can be shown that for poor trading rule $\mu_k < 0$, it has little effect on the distribution, and for sufficient large n, it will be discarded eventually. The improvement of the power of the SPA test over the Reality Check is further confirmed by the simulation experiment conducted in Hansen (2005). The p-value of T_n^{SPA} is calculated by bootstrapping its empirical distribution and then compares the T_n^{SPA} with the quantiles of the empirical distribution of $T_n^{SPA*}(b, n)$. That is:

$$\hat{p}^{SPA} \equiv \sum_{b=1}^{B} \frac{\mathbb{I}_{\{T_n^{SPA*}(b,n) > T_n^{SPA}\}}}{B} \tag{6}$$

Furthermore, Hansen (2005) defines another two p-values, which are not consistent, but can serve as the upper and lower bound for the consistent p-value. It imposes the null by recentering the bootstrap variables about $\hat{\mu}^l$ or $\hat{\mu}^u$, instead of $\hat{\mu}^c$. That is:

$$Z^*_{k,b,t} \equiv d^*_{k,b,t} - g_i(\overline{d}_k), \tag{7}$$

where $i = l, c, u$, $g_l(x) = max(0, x)$, $g_u(x) = x$, and $g_c(x) = x \times \mathbb{I}_{\{x \geq -\sqrt{(\hat{\omega}_k^2/n)2loglogn}\}}$. One can show that $E(Z^*_{k,b,t}) = \hat{\mu}^i$ for $i = l, c, u$.

3.3 StepM test

Both the Reality Check and the SPA test seek to answer whether the best trading strategy beats the benchmark. As discussed in section 1, it is often more interesting to identify all outperforming trading rules, or to know whether a particular trading rule improves upon the benchmark. The Reality Check can be modified easily for identifying potential strategies beating the benchmark, but Romano and Wolf (2005) show that this is only suboptimal, and amounts to only the first step of StepM test of Romano and Wolf (2005), which can detect more good strategies from the second step on. The StepM test is therefore more powerful than the Reality Check in detecting superior trading rules. The aim of the StepM test is to find as many profitable trading rules as possible. Their null hypothesis is considered as the individual hypothesis test:

$$H_0^k : \mu_k \leq 0, \tag{8}$$

The individual decisions are taken in a manner that asymptotically controls for the familywise error rate (FWE) at the significance level α. The FWE is defined as the probability of incorrectly identifying at least one strategy as superior. The joint confidence region is constructed to have nominal joint coverage probability of $1 - \alpha$ in each stage. In the first stage it is of the form,

$$[d_1 - c_1, \infty) \times \cdots \times [d_m - c_1, \infty) \tag{9}$$

If $0 \notin [d_k - c_1, \infty)$, then the k^{th} trading rule is detected as profitable. This first step can detect more than one profitable rules. For the second step, all the profitable rules found in the first step are dropped from the universe and only remaining rules are used to form the new universe. Forming similar confidence interval as in (9), though replace c_1 by c_2, one can detect the profitable trading rules, if any, from the remaining rules by checking whether the individual confidence interval $[d_k - c_1, \infty)$ contains zero or not. If no profitable rules found, stop, otherwise continue this way until no profitable rules can be detected. Since typically the individual confidence interval in the joint confidence interval shrinks with the increasing number of testing steps, more profitable trading rules can be detected than relying on only the first step.

Romano and Wolf (2005) also propose the use of studentization to improve the power and level properties of the StepM test.

3.4 Stepwise SPA test

The Stepwise SPA test of Hsu and Hsu (2006) aims at combining the advantage of both the SPA test and the StepM test, to improve upon the White's Reality Check in two different ways. In this setting, the null hypothesis is similar to the StepM test, though the null will be imposed to center the bootstrap variables around $\hat{\mu}^c$ as in the SPA test, such that poor and irrelevant trading rules will be discarded asymptotically. They provide formal proofs and simulation results to demonstrate that the SSPA test is more powerful than the Reality Check, SPA test, and StepM test.

4 Empirical Results

4.1 Data and Summary Statistics

We collect daily spot exchange rate data from Datastream, which covers the period from January 1981 to July 2007. The spot exchange rate is quoted as foreign currency units per British pound (hereafter GBP). We study the countries which have both spot exchange rate and overnight interest rate (if no overnight interest rate available, we use other daily short rate instead) available. In total we include 10 currencies from emerging markets, which represent various geographic regions. The data for most of them starts in the 1990s. The detail of the currencies we consider and their data availability are reported in table II.

[Insert Table II About Here]

Table III reports the summary statistics of daily returns (defined as the log difference of spot exchange rates). The mean return shows the average depreciation of individual emerging market currency against the GBP. Almost all the emerging market currencies on average depreciate relative to the GBP, with only one currency [Czech Republic (Koruny)] appreciates. The highest daily depreciation happens to the India Rupees, with an amount of 12.8 percent. The highest appreciation happens to the South Africa Rand (16.82 percent). The standard deviations are usually higher than those commonly found in developed countries'exchange rate [see Qi and Wu (2006) for comparison]. The skewness for India (Rupees) is 2.36, and small for other currencies. The large kurtosis found in most of these currencies shows extreme depreciation/appreciation occurred. Lee et al. (2001) also report extremely high kurtosis, consistent with our findings. Overall the summary statistics illustrates the more volatile exchange rate in emerging market than their developed countries' counterparts.

[Insert Table III About Here]

4.2 Profitable trading rules: full sample results

In this section we report the performance of trading rules using the full sample, with the whole universe of (25,988) trading rules, and with or without taking the transaction cost into account.

4.2.1 Most profitable trading rules

Table IV shows the performance of the best trading rules (in terms of best past performance) found under the mean excess return (panel A) and Sharpe Ratio (panel B) criteria for each currency, assuming no transaction cost. According to mean excess return, the best trading rule of each currency yields all positive but highly heterogeneous mean excess return across currencies, ranging from a low of 6% (India Rupees) to a high of 32% (Brazil Reais).

Interestingly, 6 out of 10 best trading rules reported are charting rules based on an under-smoothed version of spot rate series[7]. These spot rates are first smoothed using the kernel smoothing method, and then apply the charting rules for obtaining the trading signals. 4 best trading rules are Heads and Shoulders and the other two are Rectangle rules. We discuss the merit of under-smoothing in the later section. Filter rules are found to be most profitable for 3 currencies.

Panel A also reports four p-values (one p-value from Reality Check and three p-values from the SPA test, including the upper bound and lower bound p-values)[8]. We also calculate the nominal value by applying Reality Check to each trading rule. The smallest nominal P-values are all found very close to zero for every currency. So we do not report it in the table. Note that the best performing rule is not necessarily the most significant rule which has the smallest nominal p-value. The reported four p-values can be compared to the smallest nominal p-value, which is an easy but rigorous way of quantifying the effect of data-snooping bias. Unsurprisingly, all the p-values with data snooping check are bigger than the smallest nominal p-values which ignores data snooping bias. 3 out of 10 currencies have a p value (SPA_c) less than 0.05, indicating that at least one trading rule found to be significantly profitable (at 5% significance level) if one ignores transaction costs. For the other 7 currencies, no trading rules are found to be profitable even in the absence of transaction cost.

The Sharpe ratios of the best rules reported in panel B are all positive and large in the absence of transaction costs, ranging from 0.95 to 1.81. 6 out of 10 currencies are detected to have profitable rules, which is twice more than those found according to the mean excess return criteria. The majority of the best performing rules (7 out of 10) are charting rules with kernel smoothing, among which 6 are heads and shoulders rules and one is Rectangle rule. Two complex rules are also among

[7] In the table, the number follows directly after the abbreviation of the charting rules with kernel smoothing indicates the degree of smoothing. "1" stands for smoothing with 0.3 multiple of optimal bandwidth. Similarly, "2" and "3" stand for 1 and 4 multiple of optimal bandwidth, respectively. "4" stands for no smoothing.

[8] To calculate the p-values, we apply circular block bootstrap with a block length of 2 and 500 bootstrap replications. Our results change little when we use different block length or other bootstrap procedures like stationary bootstrap and moving block bootstrap.

the best performing rules, both of which are voting by learning rules based on Rectangle rules class. Still, the smallest nominal p-value for every currencies is close to zero. When comparing them to the p-values of Reality Check and SPA test, they are much smaller in most cases, indicating that the data snooping bias is large. Though the results so far show that some of currencies have at least one profitable trading rule in the absence of transaction costs, it is still premature to conclude there are profitable rules in practice where non-zero transaction cost is involved.

[Insert Table IV About Here]

We consider a 0.1% one-way transaction cost[9]. Table V documents the performance of best trading rules with such a cost.

[Insert Table V About Here]

Not surprisingly, both the mean excess returns and Sharpe ratio are smaller than in the previous case. They are still positive and large for all currencies, however. The annual mean excess return ranges from 0.05 (Thailand Baht) to 0.30 (Brazil Reais). The annualized Sharpe ratio is between 0.78 (Poland Zlotych) and 1.72 (Brazil Reais). The number of transactions is also smaller. For the mean excess return criteria, half of the best rules are simple rules, 4 are the charting rules with under smoothing (3 are head and shoulders rules) and one is the learning rule based on the filter rule class. Under the Sharpe ratio criteria, half of the best performing rules are head and shoulders applied to under smoothed spot rates, and 3 are learning rules and voting by learning rule. The remaining two are the momentum rule in price and the filter rule.

A close look at p-values of reality check and SPA tests shows no profitable rules according to the mean excess return criteria. The smallest p-value with data-snooping check is 0.11 (South Africa

[9]Lee et al. (2001) uses the same transaction costs for Latin American Countries' currencies. Burnside et al. (2007) mentions that the emerging countries' bid-ask spreads are usually 2-4 times higher than the developed counties' currencies. Qi and Wu (2006) uses transaction costs of 0.04%. So we choose 0.1% percent as one way transaction costs here.

Rand). For the Sharpe ratio, we find 2 out of 10 currencies (Brazil Reais and Mexico Pesos) have profitable rules, even after the data-snooping bias is controlled for. In general, since we still have the smallest nominal P-value close to zero for every currency, we will find profitable rules if the data snooping bias is not considered. Therefore, ignoring the data snooping effect leads to a significant bias.

4.2.2 Profitable trading rules

It is often desirable to know all profitable trading rules, as discussed in the previous sections. We detect all the profitable rules according to the individual nominal p-value, the StepM test and the the SSPA test. These detailed results are not reported here for the sake of space (available upon request). Instead, we report the total number of profitable trading rules detected by nominal p-value and compare them to those found by the StepM or the SSPA test. This comparison can serve as an alternative way of quantifying the danger of data snooping. It provides additional information for the extend of data snooping bias than just comparing the nominal P-value (of best performing rule or most significant rule) with the P-value from the SPA test or Reality check. The latter shows only that the extend of data snooping bias for the best performing rule or most significant rule, while the former tells also the data snooping bias beyond those two rules, since it shows that how many rules are falsely detected as profitable rules once the data snooping bias is taken into account.

[Insert Table VI About Here]

Table VI reports the number of profitable trading rules without transaction costs (panel A) and with one way transaction costs of 0.1% (panel B) under both the mean excess return and Sharpe ratio criteria. In the absence of transaction cost, and ignoring data snooping bias (nominal p-value), we find for every currency more than 2000 profitable trading rules for each criteria. The extreme case happens to Mexico Pesos, where almost every trading rule (25,983 out of 25,988) is profitable under Sharpe ratio criteria. When the data snooping bias is taken into account, we find only 3 out of 10 currencies have profitable rules according to mean excess return, and 6 out of 10 according to the Sharpe ratio. These findings are consistent with the results in table IV and V. Furthermore, the total number of trading rules detected is quite small compared to those found by individual nominal p-values. For the mean return criteria, the largest number of profitable trading rules found is 41 (Hungary Forint by SSPA test) while a test based on nominal p-value finds 3376 profitable rules, and for the Sharpe criteria, the detected number of profitable rules is at most 134 (Mexico Pesos by SSPA test) and a test based on nominal p-value finds 2464 profitable rules. These results are striking, highlighting the enormous danger of data snooping.

When we have one-way transaction costs of 0.1%, we find fewer profitable trading rules (Panel B). Even in this case, we can still find thousands of profitable trading rules according to both criteria when we consider the individual nominal P-value. The StepM test on the contrary, finds no profitable rules. Only under the Sharpe ratio criteria, does the SPA test find 1 profitable rule for Brazil the Reais and 24 profitable rules for the Mexico Pesos. Again, these striking results indicate that the data snooping bias is substantial.

Both panels also show that the SSPA test can detect more, but not less profitable trading rules than the StepM test, confirming that the SSPA test does have higher power than the StepM test.

4.3 Trading rule profitability in sub-sample

Trading rule performance is often not stable. Today's profitable rule does not guarantee sure profits for tomorrow. For example, Sullivan et al. (1999) find that the best trading rule applying to DJIA for the period of 1897-1986 does not outperform the benchmark for the period of 1987-1996. Qi and Wu (2006) find the profitability declines in recent periods. For that reason, we document the trading rule profitability in two subperiods of our sample. The second subperiod is between 08/2002 and 07/2007 for each currency. Having the same length of second subperiods facilitates a comparison across currencies. We report the results which assumes 0.1% one way transaction costs. The results with zero transaction costs are qualitatively similar and are available from the authors upon request.

[Insert Table VII About Here]

Table VII reports the results for the first subperiod. Most of the best performing rules (8 out of 10) are found to be simple rules like channel breakout rules, and the remaining 2 are head and shoulders rules with under smoothing for mean excess return (panel A). Under the Sharpe ratio criteria (panel B) the best trading rules disperse over the simple rules, charting rules with kernel smoothing and complex rules. For both criteria, we find extreme high performance for Brazil Reais (annual mean excess return of 0.76 and Sharpe ratio of 2.97). We still find thousands of profitable trading rules according to an individual nominal p-value (results not reported), but we find no profitable trading rules according to SPA test.

[Insert Table VIII About Here]

We report the results for the second sample period in table VIII. Unlike Qi and Wu (2006), we do not find a uniform decline of mean excess return and Sharpe ratio relative to the first subsample. Indeed, we find that 3 currencies under mean excess return criteria and 5 currencies under Sharpe ratio criteria have higher profits than their first subperiod counterparts. We also find that the performance of best rule for Brazil Reais is not that extreme (annual mean excess return of 0.23 and Sharpe ratio of 1.57). The best performing rules are most often found to be simple rules like support and resistance and momentum strategy in price. There are also charting rules applied to under smoothed spot rates and complex rules however. When looking at the p values with data snooping check, we find again no profitable rules. Nearly all these p-values are equal to or larger than those in the first sub-sample though.

4.4 Further results

4.4.1 Reduced universe of trading rules

Our universe of trading rules is the largest in number in the FX trading rule literature so far. This however raises the question on the power of the test as the number of trading rules are usually 5 times higher than the number of the observations. To address this issue, we consider reduced universe, which contains the trading rules in each class[10]. The size of these universes ranges from 497 (filter rule) to 3,384 (head and shoulders for example). By doing this, we assume that the professional traders and researchers search profitable rules only within each class.

We report the results for the filter rule and the moving average rule, which are the most often studied classes in the FX trading rules literature. Results based on other classes of trading rules are similar, and are available from the authors upon request.

[Insert Table IX About Here]

Panel A of table IX shows that even assuming no transaction cost, and in a universe as small as of only 497 trading rules, no profitable trading rules are detected according to the StepM and SSPA test for 9 currencies. For South Africa rand, at most 3 rules are found profitable. Ignoring the data snooping bias involved, however, one can find much more trading rules profitable based on the nominal p-value. The extend of data snooping bias is substantial. Similarly for moving average rule in panel B, we find some profitable trading rules according to nominal p-value. Once the data snooping bias is controlled, we found no profitable rules in moving average class, even we assume zero transaction cost. Given the results in these two examples and similar results for unreported classes, we conclude that our major conclusions are robust to using smaller universe of trading rules.

4.4.2 Charting rules with kernel smoothing

Our previous results indicate that under-smoothing the spot rates can lead to improvement of charting rules relative to over-smoothing or the original series. We show here in more detail whether this holds true in general. We do this by reporting the best trading rules among all the charting rules with kernel smoothing.

Table X in the appendix shows that, with the whole sample of the observations, all the best rules are

[10]We do not consider complex rules here, since they are based on simple rules and charting rules with kernel smoothing, which search in large universe implicitly.

found to be based on the under-smoothed spot series, disregarding to whether transaction costs are assumed. The sub-sample results are similar, with only few exceptions[11]. These results strongly support the view of Lo et al. (2000) that such an under-smoothing can mimic the eyeball smoothing of the professional technical analysts well. The results here also show that the majority of them are the head and shoulders rules according to both criteria. Gene Savin and Zvingelis (2007) consider the multiples 1, 1.5, 2 and 2.5 of the optimal bandwidth for head and shoulders rules. They do not consider under-smoothing. Our results show that, however, it is the under-smoothing that performs relatively well.

5 Conclusion

Nowadays the emerging FX market becomes increasingly important, though few research has been done to examine the profitability of technical analysis in this market. We conduct a first comprehensive test of technical trading rule profitability with 25,988 trading rules for 10 emerging markets currencies' spot exchange rates. These trading rules include simple rules, charting rules with kernel smoothing and complex trading rules. Although popular among professional traders, the majority of these trading rules have not been studied in the literature for emerging FX markets. Our results provide the first evidence on the profitability of these rules. However, we find little supportive results.

Our results control for data-snooping bias, which is intrinsic in the search for the profitable rules. We apply the Reality Check (White (2000)), the SPA test (Hansen (2005)), the StepM test (Romano and Wolf (2005)) as well as the SSPA test (Hsu and Hsu (2006)) to quantify the effect of data snooping bias. We find thousands of profitable trading rules for each currency, and for both mean excess return and Sharpe ratio criteria, when we ignore the data snooping bias. Once the data snooping bias is controlled for, we find very few profitable trading rules. Our results highlight that the danger of data snooping is indeed substantial, and should be carefully controlled for when testing for profitable trading rules.

[11] Sub-sample results are not reported here for the sake of space, but are available from the authors upon request

We modify the charting rules (Head and Shoulders, Triangle, Rectangle, Double Tops and Bottoms, as well as Broadening Tops and Bottoms) considered by Lo et al. (2000) and apply different bandwidths for smoothing the spot rate series. We find that under-smoothing (with bandwidth 0.3 times the optimal bandwidth) yields higher profits than over-smoothing or no-smoothing. These results show that under-smoothing mimics the eyeball smoothing by the professional technical analysts.

Our major findings are robust to the inclusion of transaction costs, to the sub-sample analysis, and to the reduced universe of trading rules. Overall we find rare evidence against the efficiency of emerging FX markets. Investors have to be careful when applying technical analysis to these markets, given the substantial data snooping bias likely involved. Further research, like investigating economic explanations of trading rules' profitability or determinants of its cross country variation, needs also to account for the danger of data snooping.

A Trading Rules Documentation

Notations

S_t: Exchange rate (British Pound price of one unit foreign currency), $t = 1, 2, ..., T$

s_t : lnS_t

g: transaction cost adjustment factor, $g = 0, 0.025\%, 0.05\%$

r_t: domestic interest rate

r_t^* : foreign interest rate

I_t: signal= 1: long; = 0:neutral; = -1: short

R_t: rate of return from a trading rule

$R_t = (s_t - s_{t-1} + r_t^* - r_t)I_{t-1} - abs(I_{t-1} - I_{t-2})g$

Benchmark: $I = 0$, no participation in the FX market.

A1. Simple Rules

A1.1 Filter Rules (FR)

x: increase in the log pound value of foreign currency required to generate a "buy" signal

y: decrease in the log pound value of foreign currency required to generate a "sell" signal

e: the number of the most recent days needed to define a low (high) based on which the filters are applied to generate "long" ("short") signal

c: number of days a position is held during which all other signals are ignored

$x = 0.0005, 0.001, 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3$ (24 values)

$y = 0.0005, 0.001, 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.04, 0.05, 0.075, 0.1$ (12 values)

$e = 1, 2, 3, 4, 5, 10, 15, 20$ (8 values)

$c = 5, 10, 25, 50$ (4 values)

Noting that y must be less than x, there are 185 (x,y) combinations

Number of rules in FR class = $x + x \times e + x \times c +$ ((x,y) combinations)) = $24 + 192 + 96 + 185 = 497$

A1.2. Moving Average Rules (MA)

n: number of days in a moving average

m: number of fast-slow combinations of n

b: fixed band multiplicative value

d: number of days for the time delay filter

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

$n = 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250$ (15 values)

$m = \sum_{i=1}^{n-1} i = 105$

$b = 0.0005, 0.001, 0.005, 0.01, 0.02, 0.03, 0.04, 0.05$ (8 values)

$d = 2, 3, 4, 5$ (4 values)

$c = 5, 10, 25, 50$ (4 values)

Number of rules in MA class: $= n + m + b \times (n + m) + (d \times (n + m) + c \times (n + m) + 9 = 15 + 105 + 960 + 480 + 480 + 9 = 2049$

A1.3. Support and Resistance (SR, or Trading Range Break) Rules

n: number of days in the support and resistance range;

e: used for an alternative definition of extrema where a low (high) can be defined as the most recent closing price that is less (greater) than the n previous closing prices;

b: fixed band multiplicative value;

d: number of days for the time delay filter;

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

$n = 5, 10, 15, 20, 25, 50, 100, 150, 200, 250$ (10 values);

$e = 2, 3, 4, 5, 10, 20, 25, 50, 100, 200$ (10 values);

$b = 0.0005, 0.001, 0.005, 0.01, 0.02, 0.03, 0.04, 0.05$ (8 values);

$d = 2, 3, 4, 5$ (4 values);

$c = 5, 10, 25, 50$ (4 values);

Number of rules in SR class $= [(1 + c) \times (n + e)] + [b \times (n + e) \times (1 + c)] + [d \times c \times (n + e)] = 100 + 800 + 320 = 1220$

A1.4. Channel Breakout Rules (CBO)

n: number of days for a channel

x: difference between the high price and the low price ($x \times$low price) required to form a channel

b: fixed band multiplicative value ($b < x$)

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

$n = 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250$ (15 values)

$x = 0.001, 0.005, 0.01, 0.02, 0.03, 0.05, 0.075, 0.10$ (8 values)

$b = 0.0005, 0.001, 0.005, 0.01, 0.02, 0.03, 0.04, 0.05$ (8 values)

$c = 1, 5, 10, 25$ (4 values)

Noting that b must be less than x. There are 43 (x,b) combinations.

Number of rules in CBO class = $n \times x \times c + n \times c \times$((x,b) combinations)= 320 + 1720 = 2040

A1.5. Momentum Strategies in Price (MSP)

m: number of days rate of change in price;

w: number of days in moving average;

k: overbought/oversold level;

f: fixed holding days;

$m = 2, 5, 10, 20, 30, 40, 50, 60, 125, 250$ (10 values);

$w = 2, 5, 10, 20, 30, 40, 50, 60, 125, 250$ (10 values);

$k = 0.05, 0.10, 0.15, 0.2$ (4 values);

$f = 5, 10, 25, 50$ (4 values);

Noting that w must be less than or equal to m, there are 55 $w - m$ combinations.

Number of rules in MSP class = $m \times k \times f$+ ((m,w) combinations)$\times k \times f$ = 160 + 880 = 1040

A2. Charting Rules with Kernel Smoothing

A2.1. Head-and-Shoulders (HS)

x: differential rate of shoulders or troughs

k: fixed band multiplicative value;

f: fixed holding days;

r: stop loss rate;

d: parameter for fixed liquidation price;

y: multiple of standard deviation of daily exchange-rate changes used to liquidate the position;

b: multiple of optimal bandwidth of kernel regression;

$x = 0.015, 0.03, 0.05$; (3 values)

$k = 0, 0.005, 0.01$; (3 values)

$f = 1, 5, 10, 25$ (4 values)

$r = 0.005, 0.0075, 0.01$; (3 values)

$d = 0.25, 0.5, 0.75$; (3 values)

$y = 1, 1.25, 1.5, 1.75, 2.00, 2.5, 3.00, 3.50, 4.00, 4.50$ (10 values)

$b = 0.3, 1, 4$ (3 values)

Number of rules in HS class = $(x \times k \times r \times d \times y + x \times k \times f) \times (1 + b)$= $(810 + 36) \times 4 = 3384$

Remark: In subsample analysis, we have to change the value of standard deviation to respective time periods.

A2.2. Triangle (TA)

k: fixed band multiplicative value;

f: fixed holding days;

r: stop loss rate;

d: parameter for fixed liquidation price;

y: multiple of standard deviation of daily exchange-rate changes used to liquidate the position;

b: multiple of optimal bandwidth of kernel regression;

$k = 0, 0.005, 0.01$; (3 values)

$f = 1, 5, 10, 25$ (4 values)

$r = 0.005, 0.0075, 0.01$; (3 values)

$d = 0.25, 0.5, 0.75$; (3 values)

$y = 1, 1.25, 1.5, 1.75, 2.00, 2.5, 3.00, 3.50, 4.00, 4.50$ (10 values)

$b = 0.3, 1, 4$ (3 values)

Number of rules in TA class: = $(k \times r \times d \times y + k \times f) \times (1 + b)$= $(270 + 12) \times 4 = 1128$

A2.3. Rectangle (RA)

x: differential rate of shoulders or troughs

k: fixed band multiplicative value;

f: fixed holding days;

r: stop loss rate;

d: parameter for fixed liquidation price;

y: multiple of standard deviation of daily exchange-rate changes used to liquidate the position;

b: multiple of optimal bandwidth of kernel regression;

$x = 0.015, 0.03, 0.05$; (3 values)

$k = 0, 0.005, 0.01$; (3 values)

$f = 1, 5, 10, 25$ (4 values)

$r = 0.005, 0.0075, 0.01$; (3 values)

$d = 0.25, 0.5, 0.75$; (3 values)

$y = 1, 1.25, 1.5, 1.75, 2.00, 2.5, 3.00, 3.50, 4.00, 4.50$ (10 values)

$b = 0.3, 1, 4$ (3 values)

Number of rules in RA class = $(x \times k \times r \times d \times y + x \times k \times f) \times (1 + b)$= $(810 + 36) \times 4 = 3384$

A2.4. Double Tops and Bottoms (STB)

x: differential rate of shoulders or troughs

k: fixed band multiplicative value;

f: fixed holding days;

r: stop loss rate;

d: parameter for fixed liquidation price;

y: multiple of standard deviation of daily exchange-rate changes used to liquidate the position;

b: multiple of optimal bandwidth of kernel regression;

n: least day differential between two tops/bottoms;

$x = 0.015, 0.03, 0.05$; (3 values)

$k = 0, 0.005, 0.01$; (3 values)

$f = 1, 5, 10, 25$ (4 values)

$r = 0.005, 0.0075, 0.01$; (3 values)

$d = 0.25, 0.5, 0.75$; (3 values)

$y = 1, 1.25, 1.5, 1.75, 2.00, 2.5, 3.00, 3.50, 4.00, 4.50$ (10 values)

$b = 0.3, 1, 2$; (3 values)

$n = 22$ (1 value);

Number of rules in DTB class: = $(x \times k \times r \times d \times y \times n + x \times k \times f \times n) \times (1 + b) = (810 + 36) \times 4 = 3384$

A2.5. Broadening Tops and Bottoms (BTB)

k: fixed band multiplicative value;

f: fixed holding days;

r: stop loss rate;

d: parameter for fixed liquidation price;

y: multiple of standard deviation of daily exchange-rate changes used to liquidate the position;

b: multiple of optimal bandwidth of kernel regression;

$k = 0, 0.005, 0.01$; (3 values)

$f = 1, 5, 10, 25$ (4 values)

$r = 0.005, 0.0075, 0.01$; (3 values)

$d = 0.25, 0.5, 0.75$; (3 values)

$y = 1, 1.25, 1.5, 1.75, 2.00, 2.5, 3.00, 3.50, 4.00, 4.50$ (10 values)

$b = 0.3, 1, 4$ (3 values)

Number of rules in BTB class: $= (k \times r \times d \times y + k \times f) \times (1 + b) = (270 + 12) \times 4 = 1128$

A3. Complex Rules

A3.1. Learning strategies (LS)

m: memory span;

r: review span;

$m = 2, 5, 10, 20, 40, 60, 125, 250$ (8 values);

$r = 1, 5, 10, 20, 40, 60, 125, 250$ (8 values);

Noting that $r \leq m$, there are 36 (m,r) combinations.

We have 2 performance measures: the sum of m daily returns, and the sharpe ratio.

In addition, including class with kernel smoothed series and learning on all simple rules, there are $5 + 5 \times 4 + 1 = 26$ simple classes of trading rules.

Number of rules in LS class $= 36 \times 2 \times 26 = 1872$

A3.2. Voting Strategies (VS)

Number of rules in VS class: $= 26$

A3.3. Fraction Position Strategies (FRS)

Noting that there are 25 simple classes of trading rule.

Number of rules in FRS class $= 25 + 1 = 26$

A3.4. Voting by learning strategies (VLS)

m: memory span;

r: review span;

n: number of top trading rules chosed within a class;

$m = 1, 2, 5, 10, 20, 40, 60, 125, 250$ (9 values);

$r = 1, 5, 10, 20, 40, 60, 125, 250$ (8 values);

$n = 2, 3, 5, 10, 50$ (5 values)

Number of rules in VLS class: $= 37 \times 26 \times 5 = 4810$

Total number of trading rules = 497 + 2049 + 1220 + 2040 + 1040 + 3384 + 1128 + 3384 + 3384 + 1128 + 1872 + 26 + 26 + 4810 = 25988

B Tables and Figures

Table I
The universe of trading rules

Trading Rules	Number of rules
Simple trading rules	
Filter Rules (FR)	497
Moving Averages (MA)	2049
Support and Resistance (SR)	1220
Channel Break-Outs (CB)	2040
Momentum Strategies in Price (MSP)	1040
Chart rules with kernel smoothing	
Head and Shoulders (HS, IHS)	3384
Triangle (TA)	1128
Rectangle (RA)	3384
Double Tops and Bottoms (DTB)	3384
Broadening Tops and Bottoms (BTB)	1128
Complex trading rules	
Learning Strategies (LS)	1872
Voting Strategies (VS)	26
Fraction Position Strategies (FPS)	26
Voting by Learning Strategies (VLS)	4810
Total number of trading rules	25988

Table II
Data used for testing the profitability of trading rules

All data are from Datastream, individual exchange rate is included into the sample whenever both the daily spot exchange rate and overnight interest rate are available.

Currency	Symbol	Available data	Out-of-Sample test period
Brazil, Reais	BRL	01/2000-07/2007	08/2002-07/2007
Czech Republic, Koruny	CZK	01/1998-07/2007	08/2002-07/2007
Hungary, Forint	HUF	09/1995-07/2007	08/2002-07/2007
India, Rupees	INR	01/1991-07/2007	08/2002-07/2007
Indonesia, Rupiahs	IDR	01/1999-07/2007	08/2002-07/2007
Mexico, Pesos	MXN	01/1995-07/2007	08/2002-07/2007
Poland, Zlotych	PLN	01/1995-07/2007	08/2002-07/2007
South Africa, Rand	ZAR	01/1981-07/2007	08/2002-07/2007
Thailand, Baht	THB	01/1999-07/2007	08/2002-07/2007
Turkey, New Lira	TRY	08/2002-07/2007	n.a.

Table III
Summary statistics for daily changes in the logarithm of exchange rates

This table reports the daily returns, defined as the log difference of spot exchange rates

Currency	Observation	Mean (%)	Std (%)	Min (%)	MAX (%)	Skewness	Kurtosis
BRL	1975	0.0119	1.09	-10.87	9.08	-0.11	13.57
CZK	2498	-0.0127	0.55	-2.49	2.66	-0.01	4.52
HUF	3107	0.0198	0.54	-2.42	4.89	0.36	6.92
INR	4325	0.0202	0.67	-4.18	12.80	2.36	43.82
IDR	2237	0.0156	1.05	-8.70	7.96	-0.20	12.62
MXN	3281	0.0323	1.02	-15.56	11.39	-0.49	45.37
PLN	3281	0.0119	0.60	-3.02	4.19	0.42	6.70
ZAR	6933	0.0302	0.88	-16.82	10.21	-0.30	34.29
THB	2237	0.0057	0.62	-7.50	8.92	0.59	32.76
TRY	1303	0.0002	0.88	-5.61	6.34	0.64	8.67

Table IV
Performance of the Best FX Trading Rules in Emerging Market (without transaction cost)

Panel A: Mean Return Criteria

Currency	Best Trading Rule	Nr. of Trades	Mean Excess Return	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	RA1(y= 4.50, k=0.000, r=0.0100, d= 0.50, x=0.030)	126	0.32	0.18	0.22	0.24	0.26
CZK	FR(x=0.0005, e=2)	1151	0.07	1.00	0.50	0.54	0.55
HUF	FR(x=0.0005, e=2)	1477	0.08	1.00	0.04	0.04	0.04
INR	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	230	0.06	1.00	0.14	0.16	0.16
IDR	MA(n=10, m=5, c=5)	311	0.17	0.99	1.00	1.00	1.00
MXN	HS1(y= 3.50, k=0.000, r=0.0100, d= 0.50, x=0.050)	188	0.16	0.03	0.03	0.04	0.04
PLN	FR(x=0.0250, c=25)	79	0.08	1.00	1.00	1.00	1.00
TRY	RA1(y= 1.25, k=0.000, r=0.0075, d= 0.75, x=0.030)	72	0.20	1.00	0.98	0.99	1.00
THB	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	146	0.06	1.00	0.70	0.72	0.73
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	322	0.14	0.02	0.03	0.03	0.03

Panel B: Sharpe Ratio Criteria

Currency	Best Trading Rule	Nr. of Trades	Sharpe Ratio	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	VLS_RA(x=2, m=250, r=250)	82	1.81	0.06	0.02	0.02	0.05
CZK	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.030)	140	1.46	0.11	0.62	0.62	0.72
HUF	HS1(y= 1.50, k=0.000, r=0.0050, d= 0.75, x=0.015)	166	1.59	0.00	0.00	0.00	0.00
INR	HS1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.030)	280	1.22	0.01	0.01	0.01	0.03
IDR	RA1(y= 1.75, k=0.000, r=0.0050, d= 0.75, x=0.015)	158	1.34	0.80	0.21	0.21	0.77
MXN	HS1(y= 1.50, k=0.000, r=0.0100, d= 0.50, x=0.030)	190	1.45	0.00	0.00	0.00	0.01
PLN	MSP(m=2, f=5, k= 0.01)	119	0.95	1.00	0.99	0.99	1.00
TRY	VLS_RA(x=5, m=125, r=40)	54	1.66	1.00	0.33	0.33	0.94
THB	HS1(y= 1.75, k=0.000, r=0.0100, d= 0.75, x=0.050)	148	1.59	0.08	0.04	0.04	0.54
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	322	0.97	0.01	0.01	0.01	0.03

Results are based on the whole universe contains 25988 trading rules, Detailed description of the parameters listed in the best trading rule can be found in the appendix. The mean excess return and Sharpe ratio are both annualized.

Table V
Performance of the Best FX Trading Rules in Emerging Market (with 0.1% one way transaction cost)

Panel A: Mean Return Criteria

Currency	Best Trading Rule	Nr. of Trades	Mean Excess Return	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	RA1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.030)	114	0.30	0.43	0.27	0.30	0.37
CZK	SR(n=5, c=25)	75	0.05	1.00	1.00	1.00	1.00
HUF	MA(n=200, m=125)	15	0.05	1.00	0.81	0.89	0.94
INR	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	230	0.05	1.00	0.98	1.00	1.00
IDR	MA(n=15, m=2, b=0.030)	23	0.14	1.00	1.00	1.00	1.00
MXN	HS1(y= 3.50, k=0.000, r=0.0100, d= 0.50, x=0.030)	188	0.14	0.21	0.14	0.17	0.21
PLN	FR(x=0.0250, c=25)	79	0.08	1.00	1.00	1.00	1.00
TRY	LS_FR1(m=125, r=40)	57	0.19	1.00	1.00	1.00	1.00
THB	CB(n= 100, x=0.100, c= 50)	3	0.05	1.00	1.00	1.00	1.00
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	322	0.13	0.11	0.08	0.11	0.13

Panel B: Sharpe Ratio Criteria

Currency	Best Trading Rule	Nr. of Trades	Sharpe Ratio	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	VLS_RA(x=2, m=250, r=250)	60	1.72	0.12	0.04	0.04	0.12
CZK	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	140	1.02	1.00	1.00	1.00	1.00
HUF	HS1(y= 1.25, k=0.000, r=0.0050, d= 0.75, x=0.030)	168	1.12	0.75	0.16	0.16	0.64
INR	LS_MSP2(m=250, r=250)	62	0.91	0.94	0.28	0.28	0.93
IDR	MSP(m=50, f=5, w=50, k=0.01)	14	1.18	1.00	0.48	0.49	0.98
MXN	HS1(y= 1.50, k=0.000, r=0.0100, d= 0.75, x=0.015)	154	1.29	0.07	0.02	0.02	0.09
PLN	FR(x=0.0250, c=25)	79	0.78	1.00	1.00	1.00	1.00
TRY	VLS_RA(x=5, m=125, r=40)	50	1.51	1.00	0.92	0.92	0.99
THB	HS1(y= 1.75, k=0.000, r=0.0100, d= 0.75, x=0.030)	148	1.08	1.00	1.00	1.00	1.00
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	322	0.88	0.11	0.08	0.08	0.15

Results are based on the whole universe contains 25988 trading rules, Detailed description of the parameters listed in the best trading rule can be found in the appendix. The mean excess return and Sharpe ratio are both annualized.

Table VI
Number of profitable trading rules

All profitable trading rules detected at 5% level. The universe of trading rules contains 25988 rules. The whole sample data are used for detecting the profitable rules.

Panel A: without transaction cost

	Mean Excess Return Criteria			Sharpe Ratio Criteria		
Currency	Nominal P-value	StepM	SSPA	Nominal P-value	StepM	SSPA
BRL	4806	0	0	2403	1	1
CZK	3432	0	0	5110	0	0
HUF	3376	32	41	25983	103	121
INR	3594	0	0	2586	3	13
IDR	3838	0	0	2508	0	0
MXN	4286	18	22	2464	102	134
PLN	3220	0	0	2707	0	0
TRY	5388	0	0	4271	0	0
THB	3708	0	0	3194	0	5
ZAR	4474	1	1	2884	2	9

Panel B: with one way transaction cost of 0.1%

	Mean Excess Return Criteria			Sharpe Ratio Criteria		
Currency	Nominal P-value	StepM	SSPA	Nominal P-value	StepM	SSPA
BRL	4006	0	0	1407	0	1
CZK	3112	0	0	2995	0	0
HUF	2466	0	0	2128	0	0
INR	2537	0	0	2189	0	0
IDR	2761	0	0	2365	0	0
MXN	3603	0	0	2464	0	24
PLN	2426	0	0	2103	0	0
TRY	4939	0	0	4259	0	0
THB	3033	0	0	2769	0	0
ZAR	2612	0	0	1639	0	0

Table VII
Performance of the Best FX Trading Rules in first sub-period (with 0.1% one way transaction cost)

Panel A: Mean Return Criteria

Currency	Best Trading Rule	Nr. of Trades	Mean Excess Return	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	CB(n=5, x=0.025, c=5, b=0.0050)	13	0.76	0.92	0.99	0.99	0.99
CZK	MA(n=15, m=5, b=0.015)	5	0.12	1.00	1.00	1.00	1.00
HUF	SR(e=4, d=2, c=25)	49	0.07	1.00	1.00	1.00	1.00
INR	CB(n= 5, x=0.005, c= 25)	93	0.06	1.00	1.00	1.00	1.00
IDR	CB(n=10, x=0.050, c=10, b=0.0010)	17	0.36	1.00	1.00	1.00	1.00
MXN	HS1(y= 4.00, k=0.000, r=0.0075, d= 0.50, x=0.030)	108	0.15	1.00	0.61	0.69	0.83
PLN	FR(x=0.0250, c=25)	39	0.12	1.00	1.00	1.00	1.00
THB	MA(n=10, m=5, c=50)	13	0.11	1.00	1.00	1.00	1.00
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	256	0.14	0.12	0.09	0.10	0.13

Panel B: Sharpe Ratio Criteria

Currency	Best Trading Rule	Nr. of Trades	Sharpe Ratio	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	CB(n=5, x=0.025, c=5, b=0.0050)	13	2.97	0.72	0.28	0.28	0.47
CZK	MA(n=15, m=5, b=0.015)	5	1.27	1.00	1.00	1.00	1.00
HUF	HS1(y= 2.00, k=0.000, r=0.0050, d= 0.75, x=0.015)	76	1.07	1.00	1.00	1.00	1.00
INR	LS_MSP2(m=250, r=250)	48	1.06	0.99	0.24	0.24	0.92
IDR	MSP(m=50, f=5, k= 0.01)	8	1.76	1.00	0.95	0.95	1.00
MXN	VLS_HS(x=50, m=60, r=40)	78	1.51	0.47	0.09	0.09	0.42
PLN	MSP(m=5, f=10, w=5, k=0.02)	6	1.17	1.00	0.93	0.93	1.00
THB	DTB2(f= 5, k=0.005, n= 22, x=0.030)	18	1.39	1.00	1.00	1.00	1.00
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	256	0.99	0.08	0.06	0.06	0.13

Results are based on the whole universe contains 25988 trading rules, Detailed description of the parameters listed in the best trading rule can be found in the appendix. The mean excess return and Sharpe ratio are both annualized. The first sub-sample periods for each currencies are defined in the table II

Table VIII
Performance of the Best FX Trading Rules in second sub-period (with 0.1% one way transaction cost)

Panel A: Mean Return Criteria

Currency	Best Trading Rule	Nr. of Trades	Mean Excess Return	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	RA1(y= 4.00, k=0.000, r=0.0075, d= 0.75, x=0.030)	78	0.23	1.00	1.00	1.00	1.00
CZK	MA(n=10, c=25)	39	0.06	1.00	1.00	1.00	1.00
HUF	SR(e=5, b=0.0050, c=50)	15	0.11	1.00	1.00	1.00	1.00
INR	LS_SR1(m=60, r=60)	63	0.12	1.00	1.00	1.00	1.00
IDR	MA(n=2, b=0.015)	5	0.12	1.00	1.00	1.00	1.00
MXN	SR(n=100, b=0.0050, c=50)	5	0.13	1.00	1.00	1.00	1.00
PLN	CB(n=5, x=0.025, c=10, b=0.0010)	15	0.10	1.00	1.00	1.00	1.00
THB	FR(x=0.0100, c=50)	9	0.10	1.00	1.00	1.00	1.00
ZAR	SR(e=2, d=4, c=10)	91	0.17	1.00	1.00	1.00	1.00

Panel B: Sharpe Ratio Criteria

Currency	Best Trading Rule	Nr. of Trades	Sharpe Ratio	P-value (RC)	P-value (SPA_l)	P-value (SPA_c)	P-value (SPA_u)
BRL	RA1(y= 3.00, k=0.000, r=0.0075, d= 0.75, x=0.050)	78	1.57	1.00	1.00	1.00	1.00
CZK	HS1(y= 2.00, k=0.000, r=0.0100, d= 0.75, x=0.030)	76	1.43	1.00	1.00	1.00	1.00
HUF	SR(e=5, b=0.0050, c=50)	15	1.24	1.00	1.00	1.00	1.00
INR	MSP(m=250, f=10, w=20, k=0.05)	4	1.47	1.00	0.96	0.96	1.00
IDR	VLS_RA(x=5, m=125, r=20)	58	1.45	1.00	1.00	1.00	1.00
MXN	MSP(m=40, f=50, w=20, k=0.01)	2	1.41	1.00	1.00	1.00	1.00
PLN	MSP(m=250, f=5, k= 0.02)	10	1.46	1.00	0.89	0.89	1.00
THB	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.030)	98	1.14	1.00	1.00	1.00	1.00
ZAR	MSP(m=60, f=50, w=40, k=0.01)	2	1.19	1.00	1.00	1.00	1.00

Results are based on the whole universe contains 25988 trading rules, Detailed description of the parameters listed in the best trading rule can be found in the appendix. The mean excess return and Sharpe ratio are both annualized. The sample period is 08/2002-07/2007.

Table IX
Number of profitable trading rules (reduced universe)

All profitable trading rules detected at 5% significance level. We assume no transaction cost involved.

Panel A: Filter Rule class (total number of trading rules: 497)

	Mean Excess Return Criteria			Sharpe Ratio Criteria		
Currency	Nominal P-value	StepM	SSPA	Nominal P-value	StepM	SSPA
BRL	168	0	0	89	0	0
CZK	154	0	0	169	0	0
HUF	142	0	0	494	0	0
INR	110	0	0	96	0	0
IDR	127	0	0	109	0	0
MXN	38	0	0	32	0	0
PLN	160	0	0	139	0	0
TRY	144	0	0	112	0	0
THB	136	0	0	137	0	0
ZAR	140	1	3	34	1	1

Panel B: Filter Rule class (total number of trading rules: 2049)

	Mean Excess Return Criteria			Sharpe Ratio Criteria		
Currency	Nominal P-value	StepM	SSPA	Nominal P-value	StepM	SSPA
BRL	482	0	0	6	0	0
CZK	72	0	0	366	0	0
HUF	70	0	0	2048	0	0
INR	11	0	0	4	0	0
IDR	121	0	0	14	0	0
MXN	25	0	0	12	0	0
PLN	146	0	0	56	0	0
TRY	26	0	0	15	0	0
THB	62	0	0	62	0	0
ZAR	381	0	0	5	0	0

Table X
Best Charting Rules with Kernel Smoothing

This table documents the best charting rules among all the charting rules with kernel smoothing. HS1 refers to Head and Shoulder Rule applied to under-smoothed spot series with the chosen bandwidth equals to 0.3 times the optimal bandwidth from the cross validation.

Panel A: without transaction cost

Currencies	Best trading rule (Mean Excess Return)	Best trading rule (Sharpe Ratio)
BRL	RA1(y= 4.50, k=0.000, r=0.0100, d= 0.50, x=0.030)	RA1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.030)
CZK	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.030)	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)
HUF	HS1(y= 1.50, k=0.000, r=0.0050, d= 0.75, x=0.050)	HS1(y= 1.25, k=0.000, r=0.0050, d= 0.75, x=0.015)
INR	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	HS1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.030)
IDR	DTB1(y= 2.50, k=0.010, r=0.0100, d=0.50, n=22, x=0.050)	RA1(y= 2.50, k=0.000, r=0.0050, d= 0.75, x=0.015)
MXN	HS1(y= 3.50, k=0.000, r=0.0100, d= 0.50, x=0.030)	HS1(y= 1.50, k=0.000, r=0.0100, d= 0.50, x=0.050)
PLN	RA1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.050)	RA1(y= 1.00, k=0.000, r=0.0050, d= 0.75, x=0.050)
TRY	RA1(y= 1.25, k=0.000, r=0.0075, d= 0.75, x=0.050)	RA1(y= 1.25, k=0.000, r=0.0050, d= 0.75, x=0.050)
THB	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	HS1(y= 1.75, k=0.000, r=0.0100, d= 0.75, x=0.030)
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)

Panel B: with one way transaction cost of 0.1%

Currencies	Best trading rule (Mean Excess Return)	Best trading rule (Sharpe Ratio)
BRL	RA1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.030)	RA1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.030)
CZK	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.030)	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.030)
HUF	HS1(y= 1.50, k=0.000, r=0.0050, d= 0.75, x=0.050)	HS1(y= 1.50, k=0.000, r=0.0050, d= 0.75, x=0.030)
INR	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	HS1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.050)
IDR	DTB1(y= 2.50, k=0.010, r=0.0100, d= 0.50, n= 22, x=0.050)	RA1(y= 1.25, k=0.000, r=0.0050, d= 0.75, x=0.015)
MXN	HS1(y= 3.50, k=0.000, r=0.0100, d= 0.50, x=0.050)	HS1(y= 1.50, k=0.000, r=0.0100, d= 0.75, x=0.015)
PLN	RA1(y= 1.25, k=0.000, r=0.0100, d= 0.75, x=0.050)	RA1(f= 50, k=0.000, x=0.015)
TRY	RA1(y= 1.25, k=0.000, r=0.0075, d= 0.75, x=0.050)	RA1(y= 1.25, k=0.000, r=0.0075, d= 0.75, x=0.050)
THB	HS1(y= 4.50, k=0.000, r=0.0100, d= 0.75, x=0.050)	HS1(y= 1.75, k=0.000, r=0.0100, d= 0.75, x=0.050)
ZAR	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)	HS1(y= 1.00, k=0.000, r=0.0100, d= 0.75, x=0.050)

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