

# **Technical Trading-Rule Profitability, Data Snooping, and Reality Check: Evidence from the Foreign Exchange Market\***

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## **Abstract**

This paper reports evidence on the profitability and statistical significance of a large number of technical trading rules in the foreign exchange market. Using standard tests, our results indicate significant profitability of moving average and channel breakout rules for seven dollar exchange rates. We then apply White's (2000) Reality Check bootstrap methodology to evaluate these rules and to characterize the effects of potential data-snooping biases. We find that data-snooping biases are in general quite large, but do not change the basic conclusion on the significance of profitability for five currencies using the benchmark of buying and holding foreign exchange. Using the benchmark of holding the dollar, we find significant profitability at the one percent level for all seven currencies even after data-snooping biases are properly taken into account. Employing the Japanese yen and the Deutsche mark respectively as a vehicle currency yields stronger results. The excess returns remain significant after accounting for reasonable transaction costs and cannot be easily explained by a systematic risk factor. Our findings suggest that certain rules might indeed have merit.

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# **Technical Trading-Rule Profitability, Data Snooping, and Reality Check: Evidence from the Foreign Exchange Market**

## **Abstract**

This paper reports evidence on the profitability and statistical significance of a large number of technical trading rules in the foreign exchange market. Using standard tests, our results indicate significant profitability of moving average and channel breakout rules for seven dollar exchange rates. We then apply White's (2000) Reality Check bootstrap methodology to evaluate these rules and to characterize the effects of potential data-snooping biases. We find that data-snooping biases are in general quite large, but do not change the basic conclusion on the significance of profitability for five currencies using the benchmark of buying and holding foreign exchange. Using the benchmark of holding the dollar, we find significant profitability at the one percent level for all seven currencies even after data-snooping biases are properly taken into account. Employing the Japanese yen and the Deutsche mark respectively as a vehicle currency yields stronger results. The excess returns remain significant after accounting for reasonable transaction costs and cannot be easily explained by a systematic risk factor. Our findings suggest that certain rules might indeed have merit.

## Introduction

Since the breakdown of the Bretton Woods System in early 1973, many major currencies have floated against the U.S. dollar. Since then, a large body of research has been devoted to studying the time series properties of exchange rates and to testing the efficiency of the foreign exchange market. One strand of such literature examines the profitability of technical trading rules. The central idea underlying this research is that if the foreign exchange market is efficient, one should not be able to use publicly available information to predict changes in exchange rate in the future and hence to make an abnormal (risk-adjusted) profit.<sup>1</sup> In particular, popular technical trading strategies, which use current and past price and volume data and are guided by mechanical algorithms, should not be able to beat the market. This suggests a simple and robust test for the weak form efficient market hypothesis. Hence, a researcher can apply numerous rules to a given data set and a finding of significant profitability of a technical trading rule is often interpreted as evidence of violation of the weak form market efficiency. Cornell and Dietrich (1978) are the first to document large profits of filter rules and moving average rules for the Dutch guilder, the Deutsche mark and the Swiss franc using the post-Bretton Wood data. Sweeney (1986) applies simple filter rules to the dollar-Deutsche mark exchange rate and finds significant profitability of these rules. He also shows that filter rule profits cannot be easily explained by risk. Levich and Thomas (1993) examine the profitability of filter rules and moving average rules using futures prices for five currencies. Using a bootstrap re-sampling method to evaluate the statistical significance of their results, they report that some rules may be

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<sup>1</sup> A complementary literature studies the forecasting accuracy of exchange rates using either fundamental analysis or time-series techniques. See, for example, Meese and Rogoff (1983, 1988), Baillie and Bollerslev (1989, 1994), Diebold, Gardeazabal and Yilmaz (1994), and Mark (1995). In contrast to the literature on technical analysis with high-frequency data, these researchers employ lower-frequency data (monthly or quarterly) and find that exchange rates are in general unforecastable at the 1 to 12 months horizons.

significantly profitable. Kho (1996) also reports profitability of moving averages rules in currency markets and demonstrates that part of excess returns can be accounted for by a time-varying risk premium. Other studies in this area include Gencay (1999), Lee and Mathur (1996), Neely *et al.* (1997), Taylor (1994), and Sweeney (1988).

It is unclear, however, whether the profitability of mechanical trading rules will be significant out of sample. In practice, a researcher can examine many trading rules for a given data set and there is a high probability that one such rule will yield superior performance *ex post* even if it does not provide any useful economic signal *ex ante*. In other words, there is a possibility that any superior results obtained may be due to pure luck rather than due to any merit of the trading rules designed. This is the so-called data-snooping problem, whose importance has been recognized by researchers in finance. For example, Brock *et al.* (1992) apply 26 technical trading rules to 90 years of daily data for the Dow Jones Industrial Average index and find that these rules are capable of outperforming a benchmark of holding cash. Using bootstrap method, they show that the returns obtained from the trading strategies are inconsistent with any of the null models that they explored. However, as they examine many rules which are not independent, their method does not provide a comprehensive test across all rules. In a recent paper, White (2000) develops a novel procedure, called Reality Check, which takes care of data-snooping biases and thereby permits computation of such a test. The idea of the White procedure is to generate the empirical distribution from the full set of models (in our case, trading strategies) that lead to the best-performing trading strategy and to draw inference from this distribution for certain performance measures. Sullivan *et al.* (1999) apply White's Reality Check methodology to the Brock *et al.* (1992) data set, and find that certain trading rules indeed outperform the benchmark. However, after adjusting for data-snooping biases, there is

insufficient evidence that technical trading strategies are of any economic value for predicting the U.S. stock market returns for the most recent 10-year period.

The purpose of this paper is to study the profitability of numerous technical trading rules in the foreign exchange market and to examine the biases due to data snooping. Our paper is the first study to formally investigate the data-snooping biases of technical rules in the foreign exchange market using White's (2000) Reality Check methodology. We employ four types of popular trading strategies: filter rules, moving average rules, trading range break rules, and channel breakout rules. For each type of rules, we consider various parameterizations. Overall, we investigate the universe of 2,127 parameterizations of trading rules. We employ daily dollar exchange rate data for seven currencies for the period between April 2, 1973 and December 31, 1998. Our evaluation is based on two performance measures: average return and Sharpe ratio, where the latter criterion accounts for total (stand-alone) risk.

We find that over the 26-year period, certain rules do indeed outperform the market even after adjustments are made for data-snooping biases. In particular, using White's bias-adjusted  $p$ -values, we find that the best-performing trading strategies produce both higher mean returns and higher Sharpe ratios than the benchmark of buying and holding foreign currency at the five percent significance level for the Canadian dollar, the French franc, the Italian lira and the British pound; and at the 10 percent level for the Japanese yen. Furthermore, for all seven currencies, the best-performing strategies outperform the benchmark of just holding the U.S. dollar at the one percent significance level. The excess returns generated by these rules are not only statistically significant, but also economically important and cannot be easily explained by a systematic risk factor. The basic results are not altered when reasonable levels of transaction

costs are incorporated. Furthermore, using the Japanese yen and the Deutsche mark respectively as a vehicle currency produces stronger results on the significance of technical analysis.

The remainder of the paper is organized as follows. Section I describes the universe of technical trading rules that we explored in this study. Section II explains the bootstrap methodology that we adopt to investigate data-snooping biases in trading-rule profitability in the foreign exchange market. The main empirical results are reported in Section III. Section IV carries out various checks for the robustness of results. Concluding remarks are contained in the final section.

## **I. Technical Trading Rules**

Technical trading rules have been very popular tools used by traders in financial markets for many decades and the study on their performance has been a subject of extensive research. For applications of technical trading rules in the foreign exchange market, in a survey of major foreign exchange dealers based in London in 1990, Taylor and Allen (1992) report that at least 90 percent of the respondents place some weight on technical analysis when forecasting currency prices. In order to obtain meaningful estimate of data-snooping biases, we must provide a comprehensive coverage of the trading rules in use. Four popular types of trading rules are considered in this study. Following Sullivan *et al.* (1999), for each type, we experiment with numerous parameterizations. The notations and specific parameter values used in our experiments are spelled out in the Appendix. The four types of rules are described below. In each case, we assume that the speculator initially does not hold currency positions, neither foreign nor domestic, but he does have the necessary initial wealth to be used as margins to trade foreign exchange contracts.

### A. Filter Rules

A filter rule strategy is specified as follows. If the daily closing price (in U.S. dollars) of a foreign currency goes up by  $x$  percent or more from its most recent low, then the speculator borrows the dollar and uses the proceeds to buy the foreign currency. When the closing price of the foreign currency drops by at least  $y$  percent from a subsequent high, the speculator short sells the foreign currency and uses the proceeds to buy the dollar. We define the subsequent high as the highest price over the  $e$  most recent days and the subsequent low as the lowest price over the  $e$  most recent days. Following Sullivan *et al.* (1999), we also consider the case where a given long or short position is held for  $c$  days during which time all other signals are ignored.

### B. Moving Average Rules

The moving average of a currency price for a given day is computed as the simple average of prices over the previous  $n$  days, including the current day. Under a 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  $b$  percent, the speculator borrows the dollar to buy the foreign currency. Similarly, when the short moving average is below the long moving average by  $b$  percent, the speculator short sells the foreign exchange to buy the dollar. In addition to this fixed percentage band filter, we also implement the moving average rules with a time delay filter, which requires that the long or short signals remain valid for  $d$  days before he takes any action. As in the filter rule case, we also consider the case where a given long or short position is held for  $c$  days during which time all other signals are ignored.

### C. Trading Range Break (or Support and Resistance) Rules

Under a trading range break rule, when the price of a foreign currency exceeds the maximum price (resistance level) over the previous  $n$  days by  $b$  percent, the speculator borrows the dollar to buy the foreign currency. When the price goes below the minimum price over the previous  $n$  days by  $b$  percent, the speculator sells short the foreign exchange to buy the dollar. We also consider an alternative definition for the resistance level, i.e., the local maximum (minimum), which is the most recent closing price higher (lower) than the  $e$  previous closing prices. As with the moving average rules, we implement the rules with a time delay filter,  $d$ , and as well we consider the case where a given long or short position is held for  $c$  days during which time all other signals are ignored.

### D. Channel Breakout Rules

A channel is defined to be one that occurs when the high price of a foreign currency over the previous  $n$  days is within  $x$  percent of the low over the previous  $n$  days. Under a channel breakout rule, the speculator borrows the dollar to buy foreign exchange when the closing price of the foreign currency goes above the channel by  $b$  percent and sells short the foreign exchange to buy the dollar when the closing price goes below the channel by  $b$  percent. Once again, we consider holding a given long or short position for  $c$  days during which all other signals are ignored.

## II. The Bootstrap Experiment to Study Data-Snooping Biases

In the past, data snooping has been prevalent due to the lack of practical methods that are capable of assessing its potential dangers in a given situation. Recently, White (2000) proposes a



patent-pending procedure, called Reality Check, for testing the null hypothesis that the model selected in a specification search has no predictive superiority over a given benchmark model. It allows aggressive model searching to be undertaken with confidence that one will not mistake results that could have been generated by chance for genuinely good results.

White's (2000) procedure was developed based on Diebold and Mariano's (1995) and West's (1996) methods to test whether a given model has predictive superiority over a benchmark model after taking into consideration the effects of data snooping. The test evaluates the distribution of a performance measure, accounting for the full set of models that lead to the best-performing model, and is based on the  $L \times 1$  performance statistic

$$\bar{f} = N^{-1} \sum_{t=P}^T f_t \quad (1)$$

where  $L$  is the number of models,  $N$  is the number of prediction periods indexed from  $P$  through  $T$  so that  $N = T - P + 1$ ,  $f_t = f(X_{t-1}, \hat{\theta}_{t-1})$  is the observed performance measure for period  $t$  (such as the difference in returns between a trading rule and a benchmark),  $\hat{\theta}_{t-1}$  is a vector of estimated parameters, and  $X$  is a vector of observed dependent and predicting variables that satisfy certain regularity conditions.<sup>2</sup> In this study, there is no parameter to be estimated. The performance measures are calculated from returns generated by trading rules  $(\theta_k, k = 1, \dots, L)$ .

Our full sample of daily exchange rates starts on April 2, 1973 and ends on December 31, 1998, with a total of 6463 observations for each currency studied. The first trading signal is generated for the 256<sup>th</sup> observation for all trading rule specifications because some rules require

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<sup>2</sup> See Diebold and Mariano (1995) and West (1996) for details on the regularity conditions.

255 days of previous data in order to provide a trading signal. Therefore,  $P$  is 256,  $T$  is 6463, and  $N$  is 6208. We investigate 69 filter rules, 858 moving average rules, 560 trading range break rules, and 640 channel breakout rules. Thus the total number of trading rules ( $L$ ) is 2127.

Sweeney (1986) shows that the excess returns from filter rules are primarily dependent on exchange rate variations, and not much on interest-rate differentials. Since it is difficult to obtain high-quality daily interest rate data, following the general practice in the literature (e.g., Sweeney (1986), Lee and Mathur (1996), and Szakmary and Mathur (1997)), we ignore interest-rate differentials in calculating returns.<sup>3</sup> Thus, the rate of return ( $r$ ) of the  $k^{\text{th}}$  trading rule at time  $t$  is computed as

$$r_{k,t} = (s_t - s_{t-1})I_{k,t-1} - \text{abs}(I_{k,t-1} - I_{k,t-2})g, \quad k = 1, \dots, L; \quad t = 256, \dots, T \quad (2)$$

where  $s_t$  is the natural logarithm of exchange rate (domestic currency price of one unit foreign currency);  $I_{k,t}$  represents the trading signal generated by the  $k^{\text{th}}$  trading rule using information available at time  $t$  and this dummy variable may take three values: 1 represents a long position, 0 represents a neutral position, and -1 represents a short position; and  $g$  is a one-way transaction cost. We consider three scenarios:  $g = 0, 0.025$  and  $0.05$  percent. Two benchmarks are used to assess the excess return from each trading rule studied: “always long” and “always neutral.” In the “always long” position, the investor buys and holds the foreign currency for the entire

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<sup>3</sup> We have tried to get an estimate of the daily interest rate differentials based on monthly data of the three-month Euro currency interest rates. We find that the daily mean *absolute* interest rate differential between the dollar and the other currencies lies between 0.006 percent to 0.013 percent in our sample period. In contrast, the daily mean *absolute* exchange rate change lies between 0.18 percent to 0.55 percent (see Table I). Furthermore, Bessembinder (1994) documents that the bid-ask spreads for major currencies in the spot markets are in the order of 0.05 percent to 0.08 percent. The above observations suggest that interest rate differentials are much lower than exchange rate changes and typical bid-ask spreads, and should not be a significant factor in influencing daily currency trading decisions.

forecasting period. In the “always neutral” position, the investor does not take a position (either long or short) and simply holds the dollar throughout the investment horizon. It can be seen from (2) that when the benchmark trading rule is “always long”, the excess return is

$$f_{k,t} = r_{k,t} - (s_t - s_{t-1}), \quad (3)$$

and when the benchmark is “always neural,”

$$f_{k,t} = r_{k,t}. \quad (4)$$

When assessing whether there exists a superior rule, the null hypothesis to be tested is that the performance of the best rule is no better than the benchmark, i.e.,

$$H_0 : \max_{k=1,\dots,L} \{E(f_k)\} \leq 0, \quad (5)$$

where the expectation is evaluated with the simple arithmetic average  $\bar{f}_k = N^{-1} \sum_{t=P}^T f_{k,t}$ .

Rejection of this null hypothesis will lead to the conclusion that the best trading rule achieves performance superior to the benchmark.

White (2000) shows that this null hypothesis can be tested by applying the stationary bootstrap method of Politis and Romano (1994) to the observed values of  $f_{k,t}$ . The procedure is implemented in the following steps. Step 1, for each trading rule  $k$ , we resample the realized

excess return series  $f_{k,t}$ , one observation at a time with replacement, and denote the resulting series by  $f_{k,t}^*$ . This process is repeated  $B$  times. Step 2, for each replication  $i$ , we compute the sample average of the bootstrapped returns, denoted by  $\bar{f}_{k,i}^* \equiv N^{-1} \sum_{t=P}^T f_{k,t}^*$ ,  $i = 1, \dots, B$ . Step 3, we construct the following statistics:

$$\bar{V} = \max_{k=1, \dots, L} \{\sqrt{N}(\bar{f}_k)\}, \quad (6)$$

$$\bar{V}_i^* = \max_{k=1, \dots, L} \{\sqrt{N}(\bar{f}_{k,i}^* - \bar{f}_k)\}, \quad i = 1, \dots, B. \quad (7)$$

Step 4, White's Reality Check  $p$ -value is obtained by comparing  $\bar{V}$  to the quantiles of  $\bar{V}_i^*$ . By employing the maximum value over all  $L$  models, the Reality Check  $p$ -value incorporates the effects of data snooping from the search over the  $L$  technical trading rules. To keep the amount of computation manageable, we choose  $B = 500$ .

With some slight modification, the same method can be used to evaluate the superiority of the best trading rules based on the Sharpe ratio which measures the average excess return per unit risk. In this case, the null hypothesis becomes

$$H_0 : \max_{k=1, \dots, L} \{G(E(r_k))\} \leq G(E(r_0)) \quad (8)$$

where  $G$  is the Sharpe ratio:  $G(E(r_{k,t})) = \frac{E(r_{k,t})}{\sqrt{E(r_{k,t}^2) - (E(r_{k,t}))^2}}$ .<sup>4</sup> The expectations are evaluated

with arithmetic averages, and the relevant sample statistics are

$$\bar{f}_k = G(\bar{r}_k) - G(\bar{r}_0), \quad (9)$$

where  $\bar{r}_0$  and  $\bar{r}_k$  are average rates of return over the prediction sample for the benchmark and the  $k^{\text{th}}$  trading rule, respectively. Again, the Politis and Romano (1994) bootstrap procedure can be applied to yield  $B$  bootstrapped values of  $\bar{f}_k$ , denoted as  $\bar{f}_{k,i}^*$ . Equations (6) and (7) can then be used to obtain  $\bar{V}$  and  $\bar{V}_i^*$ , based on which White's Reality Check  $p$ -value can be computed.

### III. Empirical Evidence from Seven Dollar Exchange Rates

#### A. Data and Summary Statistics

We obtain daily data from the Federal Reserve Board's website for the following currency prices relative to the U.S. dollar: the Canadian dollar (CAN), the Deutsche mark (GER), the French franc (FRA), the Italian lira (ITA), the Japanese yen (JAP), the Swiss franc (SWI), and the pound sterling (UK). Table I reports some summary statistics of the daily returns (changes in the logarithm of exchange rates). The mean return rates show that *on average* the dollar appreciates against the Canadian dollar, the French franc, the Italian lira and the British pound, while depreciates against the other three currencies over the sample period. The mean *absolute* daily changes in exchange rates are quite large, ranging from 0.18 to 0.55 percent. With

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<sup>4</sup> Recall that because interest rate differentials are ignored, in computing the Sharpe ratio, the risk-free rate (or interest rate differential in this case) is not subtracted.

the exception of the Canadian dollar, all exchange rates display substantial daily volatility with the standard deviation of daily change in the range of 0.62 percent to 0.76 percent. The maximum daily appreciation of the dollar relative to these six currencies lies between 3.8 percent (British pound) to 6.69 percent (Italian lira), while the maximum depreciation of the dollar ranges between 4.04 percent (Deutsche mark) to 5.63 percent (Japanese yen). The corresponding numbers are much smaller for the Canadian dollar. On the other hand, the Canadian dollar has the smallest Sharpe ratio (average return per unit risk) among all seven currencies. All daily return distributions have excess kurtosis relative to the normal distribution (3) and all distributions appear to skew to the left with the exception of the Japanese yen. The standard Jarque-Bera test (not reported) overwhelmingly rejects the null hypothesis of normality for all currencies. The first-order serial correlation ranges between 0.0331 to 0.0628. Serial correlation at higher orders is far smaller for all currencies.

## B. Results for the Maximum Mean Return Criterion

Table II reports the performance of the best trading rules under the mean return criterion. Column (2) displays the best rules selected, Columns (4)-(6) reports the performance when the benchmark is buying and holding foreign exchange (“always long”), while Columns (7)-(9) show the performance when the benchmark is holding the dollar (“always neutral”). The nominal  $p$ -value is computed by applying the Reality Check methodology to the best trading rule only, thereby ignoring the effects of data-snooping. The White  $p$ -value, on the other hand, is computed by applying the Reality Check procedure to the universe of all trading rules and therefore corrects for the biases due to data-snooping. All simulations are obtained through Politis and

Romano's (1994) stationary bootstrap technique with the value of the smoothing parameter,  $q$ , set to 0.5.

Two currencies (the Japanese yen and the Swiss franc) choose channel breakout as the best-performing rule, while the remaining five currencies select moving average as the best-performing rule. The moving averages chosen are relatively short (between 15 to 25 days). Both channel breakout rules use the shortest period (5 days) to form a channel. With the benchmark of buying and holding foreign exchange, the mean excess returns are all positive but vary substantially, from a low of 5.51 percent per annum for the Canadian dollar to a high of 13.94 percent per annum for the Italian lira. The nominal  $p$ -values are all smaller than the five percent level. When taken at face value, these numbers imply that technical trading rules do significantly outperform the buy-and-hold strategy for all seven currencies if data-snooping biases are ignored. However, when the White's Reality Check procedure is applied to correct for data-snooping biases, the  $p$ -values are in general much larger. Nevertheless, the null hypothesis that technical analysis does not have genuine merit can be rejected at the five percent level for the Canadian dollar, the French franc, the Italian lira, and the British pound. The null hypothesis can nearly be rejected at the 10 percent level for the Japanese yen, but cannot be rejected even at the 10 percent level for the Deutsche market and the Swiss franc.

With the strategy of always holding the dollar as an alternative benchmark, we also find some data-snooping biases in that the White  $p$ -values are in general larger than the corresponding nominal  $p$ -values. However, because all nominal  $p$ -values are extremely small, the White  $p$ -values are small as well so that the null hypothesis can be rejected at the one percent level for all seven currencies. It is interesting to note that for the Deutsche mark and the Swiss franc, the

excess returns under the “always neutral” benchmark are larger than those under the “always long” benchmark, making the White  $p$ -values significant at the one percent level.

It may be premature, however, to say that the best-performing rules identified above are actually profitable because we have not considered the effects of transaction costs on the performance of the trading strategies. These effects can indeed be significant when the trading frequencies of the preferred rules are high. Column (3) of Table II reports the total number of one-way trades for each best trading rule. Over the 25-year period with 6208 trading days, there are trades for between 13 and 19 percent of the days for these currencies. While the percentage transaction costs per trade for foreign currencies are in general much lower than those for stocks, frequent trading can accumulate the small costs per trade into a substantial number.

To get a rough idea on how high the one-way transaction cost per trade can be so that the trading rules can still survive to make a profit, consider the five currencies where the best trading rules produce significant White  $p$ -values at the 10 percent level with the benchmark of “always long.” Let  $x$  be the maximum transaction cost per one-way trade for a rule to be breaking even over the 25 trading years, we find that  $x = 25 * 5.51 / 1178 = 0.12$  percent for the Canadian dollar. Similarly, we find  $x = 0.27$  percent for the French franc, 0.32 percent for the Italian lira, 0.25 for the Japanese yen and 0.27 percent for the British pound. With the exception of the Canadian dollar, these threshold transaction costs are indeed much larger than the actual transaction costs incurred in major foreign exchange markets. For example, Bessembinder (1994) documents that the *round-trip* transaction costs in the interbank market, as measured by bid-ask spreads, lie between 0.05 percent to 0.08 percent for the Deutsche mark, the Japanese yen, the Swiss franc, and the British pound. The bid-ask spreads for currencies less heavily traded and with greater



volatility can be larger (Shapiro, 1999, p.148-157).<sup>5</sup> Thus the one-way costs are in the range of 0.025 to 0.04 percent, which are not in the same order of magnitude compared to the threshold transaction costs estimated above. Using a more conservative 0.04 percent one-way cost, we find that the *after-cost* profit for the Canadian dollar is 3.63 percent ( $5.51 - 1178 \cdot 0.04 / 25$ ); 9.36 percent for the French franc; 12.17 percent for the Italian lira; 7.22 percent for the Japanese yen; and 9.37 percent for the British pound. Except for the Canadian dollar, these *after-cost* profit numbers are clearly economically significant. Furthermore, in practice, one can incorporate the transaction cost when computing the rate of returns from each trading rule so that the optimal trading rule chosen will reflect the impact of the cost. It is expected that *ceteris paribus*, the higher the transaction cost, the smaller number of transactions the optimal trading rule will have. We conduct an experiment to confirm this assertion in Section IV.

### C. Market Risk Factor

While the excess returns reported above are in general both statistically and economically significant, they may simply be a compensation for risk. To investigate to what extent excess returns can be explained by a systematic risk factor, we estimate the following simple one-factor model:

$$f_t = \alpha + \beta(r_{m,t} - r_{f,t}) + \varepsilon_t \quad (10)$$

where  $f_t$  is the daily excess return from the best-performing rule relative to the “always long” benchmark,  $r_{m,t}$  is the market rate of return, and  $r_{f,t}$  is the risk-free rate. We use returns on the

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<sup>5</sup> Neely, Weller and Dittmar (1997) also claim that 0.05 percent is a reasonable cost per round-trip trade.

value-weighted U.S. stock market index and on the S&P500 index as proxies for the market return, and the three-month U.S. Treasury bill rate as the risk-free rate. The market indexes are obtained from the CRSP tape, while the Treasury bill rate is obtained from the Federal Reserve Board's website. Table III reports the estimation results. Interestingly, we find that the estimate of  $\beta$  has the unexpected negative sign, is very small in magnitude in all cases, and is significantly different from zero at the five percent level only for the Canadian dollar. On the other hand, the value of the pricing error  $\alpha$ , which is expressed in annualized percentage, is always statistically significant, very large in magnitude and captures most of the excess return from the best-performing trading rule. These results show that the market risk factor is unlikely going to explain the excess return. We do not intend to fully explore the possibilities of explaining the excess returns on the trading strategies as a payment for systematic risk. Our point here is only that the beta risk does not provide a simple explanation. In the following subsection, we employ an alternative criterion to select trading rules: the Sharpe ratio, which incorporates total (stand-alone) risk.

#### D. Results for the Maximum Sharpe Ratio Criterion

Table IV summarizes the results on the performance of the best trading rules under the Sharpe ratio criterion, which adjusts for total risk. Compared to the results in Table II, the most striking finding is that all the best-performing rules identified under the Sharpe ratio criterion are identical to those under the mean return criterion. These results are in sharp contrast with those in Sullivan *et al.* (1999), who report that when their full universe of trading rules are considered, the best trading rule under the Sharpe ratio criterion is never the same as the one generated under the mean return criterion using the Dow Jones Industrial Average index and the S&P500 futures

index for all the sample periods that they investigate. These results indicate that there may exist important differences in the statistical distributions between daily equity prices and daily exchange rates.

The statistical significance of the best trading rules as well as the nature of data-snooping biases under the Sharpe ratio criterion are also very similar to those under the mean return criterion. When the “always long” strategy is used as a benchmark, the nominal  $p$ -values are lower than the five percent level for all seven currencies. However, the White  $p$ -values are far greater than the corresponding nominal  $p$ -values and are above the 10 percent level for the Deutsche mark, the Japanese yen, and the Swiss franc. When the “always neutral” strategy is used as a benchmark, the White  $p$ -values are all smaller than or equal to the one percent level, implying that technical trading rules do yield superior Sharpe ratios than the benchmark of holding the dollar even after data-snooping biases are properly accounted for.

#### E. Frequency Distribution of Excess Returns of Trading Rules

It may be interesting and useful to see among the universe of 2127 trading rules, how many of them actually make a positive excess return (winning rules) and how many of them lose money (losing rules) relative to a benchmark. To this end, for each currency we construct the frequency distribution of excess returns of all 2127 rules.

Figures 1(A)-(G) exhibit the frequency distributions of excess returns relative to the benchmark of buying-and-holding foreign exchange. Evidently, the distribution heavily skews to the right for the Canadian dollar, the French franc, the Italian lira and the British pound. In particular, for the Canadian dollar, among all 2127 rules, there are only 6 losing rules (yielding negative mean excess return relative to the benchmark), with the highest frequency occurring at

the return rate of around 2 percent. The respective number of losing rules and return rate of highest frequency are 154 rules and 2 percent for the French franc; 14 rules and 4 percent for the Italian lira; and 83 rules and 2 percent for the British pound. It is also interesting to note that for the Deutsche mark, there are as many as 714 losing rules with the highest frequency occurring at around -2 percent of return. For the Japanese yen, 905 rules are losing rules and the highest frequency occurs at around -4 percent. Similarly, the Swiss franc has 980 losing rules with the highest frequency at around -3 percent. These graphs provide an intuitive explanation for why the White  $p$ -values reported in Table II are significant at the five percent level only for the former four currencies.

Figures 2(A)-(G) present the frequency distributions of mean excess returns relative to the benchmark of always holding the U.S. dollar. The distributions profoundly skew to the right, with the highest frequency occurring at the territory of positive returns in all seven cases. The Italian lira has the most losing trading rules (271), but even that accounts for only 13 percent of all the rules investigated.

#### F. Wealth Accumulation over Time

Over the 26-year sample period, the foreign exchange market experienced several unusual episodes of instability. These include, for example, the drastic appreciation of the dollar in the early 1980s and its abrupt drop in the mid 1980s, and more recently the 1992 EMS currency crisis, the 1994 Mexican peso crisis, and the 1997 Asian currency crisis. A strategy that works well for one episode may not work well at all for another episode and it will be of interest to see how the best strategy performs over time. Suppose that on the first trading day (April 9, 1974) an investor invests 100 dollars. We examine how this investor's total wealth accumulates

over time if the best-performing strategy is employed. This cumulative wealth is to be compared with the two benchmarks: buying-and-holding foreign exchange and just holding the dollar.

Figures 3(A)-(G) present the results, where in each panel the thick line shows the cumulative wealth from the best trading strategy while the thin line represents the cumulative wealth from buying and holding foreign exchange. Because we ignore interest rate differentials, the cumulative wealth from holding the dollar is the 100-dollar horizontal line. We make several interesting remarks from these plots. First, the best-performing strategy displays a clear trend of steady growth in wealth over time for all cases. However, the ending level of wealth differs drastically across currencies, ranging from around 250 dollars in the case of the Canadian dollar to 2,000 dollars in the case of the Japanese yen. Second, the thick line always lies above the thin line for all currencies except for the Swiss franc at the early part of the sample where the two lines cross. Furthermore, the thick line never crosses the 100-dollar horizontal line. These observations combined imply that the best trading rule yields a higher total wealth than either benchmark regardless of the length of the investment horizon. Third, for all currencies, the cumulative wealth level of the best trading strategy displays a great deal of fluctuations over the sample period, indicating that there are substantial risks involved if the investment horizons are relatively short. Furthermore, it is also interesting to note that the cumulative wealth level is far more volatile in the 1990's than in the first two decades of the sample except for the Canadian dollar and the French franc.

In summary, we find that even after adjustments for data-snooping biases are made, the best-performing technical rules generate significantly higher mean returns and higher Sharpe ratios than the benchmark of buying and holding foreign exchange for five out of seven currencies. Furthermore, the best-performing rules significantly beat the benchmark of holding

the dollar for all seven currencies. The excess returns cannot be easily attributed to systematic market risk of trading rules. The frequency distributions of excess returns of all trading strategies and the comparison in cumulative wealth levels of the best-performing rule with two benchmarks provide additional insights on the significance of the findings.

#### **IV. Robustness of Results**

The proceeding section demonstrates that when technical trading rules are applied to the foreign exchange market, data-snooping problems are significant and can lead to incorrect inference. Our results also show that even after correcting for such biases, there exists substantial evidence that mechanical strategies yield superior performance than passive strategies. In this section, we conduct a number of sensitivity analyses to examine the robustness of these results. As can be seen in the previous section, the statistical results based on the Sharpe ratio criterion are very similar to those based on the mean return criterion. To economize on space, in this section, we only report the robustness check results based on the mean return criterion.

##### **A. The Impact of Transaction Cost**

Section III shows that the best-performing rules imply relatively frequent trading for all seven currencies. In practice, it is not rational to trade if the expected excess return (relative to the current holding position) implied by the trading signal is not as high as the transaction cost per trade. In this subsection, we consider the impact of transaction cost on the profitability of various trading rules. As can be seen from Equation (2), a larger transaction cost imposes a greater penalty on the trading rules that generate more frequent switching signals. Therefore, with a transaction cost we expect to see that a rule with less frequent trading will be selected as

the optimal rule. We consider two levels of transaction cost per one-way trade in our experiment: 0.025 percent and 0.05 percent.

Panel A of Table V reports results on the best trading rules and their performance based on the mean return criterion with a 0.025 percent transaction cost. Compared to the baseline results in Table II, we find that this cost filter has a relatively small effect on the overall performance of the trading rules. In particular, the best-performing rule is identified to be of the same type for each currency, with the exact parameterization being chosen for the French franc, the Deutsche mark, and the British pound. Yet, the number of trades is significantly reduced for the Canadian dollar, the Italian lira and the Swiss franc.

The degree of data-snooping biases is also found to be fairly serious in that the White  $p$ -values are in general much larger than the nominal  $p$ -values. When the “always long” strategy is used as a benchmark, the nominal  $p$ -value is significant at the one percent level for all currencies except the Swiss franc which is significant at the five percent level. When the White  $p$ -values are used to account for data-snooping biases, the null hypothesis can be rejected at the five percent level for the Canadian dollar, the French franc and the British pound, and at the one percent for the Italian lira. For these currencies, although the *after-cost* excess returns are somewhat lower than the respective ones in Table II with zero transaction cost, they are not only statistically significant, but also economically important.

Using “always neutral” as a benchmark, we find that after biases are accounted for, the null hypothesis can be rejected at the 10 percent level for the Canadian dollar, and at the five percent level for the remaining six currencies. The excess returns after transaction costs lie in the range of 8.5-11.4 percent per annum for these six currencies, which are economically non-trivial.

Panel B of Table V exhibits the performance of the best trading rules with a 0.05 percent transaction cost. The number of trades is dramatically reduced except the French franc and the Japanese yen. Using the “always long” benchmark, the null hypothesis can be rejected at the five percent level for the Canadian dollar and the Italian lira; and at the 10 percent level for the French franc and the British pound. With the “always neutral” benchmark, the Canadian dollar is the only currency that does not reject the null hypothesis at the 10 percent level. The null can be rejected at the 10 percent level for the Swiss franc, and at the five percent level for the other five currencies. Compared to the 0.025 percent filter, the 0.05 percent transaction cost leads to less frequent trading and produces only slightly lower *after-cost* profits in all cases.

#### B. Evidence from Cross Exchange Rates

One distinct characteristic of the dollar exchange rates over the post-Bretton Woods period is that they show very long swings. In particular, the dollar exhibits persistent appreciation in the early 1980s and deep depreciation starting in the mid 1980s. The simple trading rules work perhaps because of the trend-like behavior of the dollar, making it relatively easy for the rules to identify the general pattern. In this subsection, we employ the Japanese yen and the Deutsche mark respectively as a vehicle currency and apply the trading rules to exchange rates relative to the yen and the mark. This experiment is warranted because it allows us to examine whether the profitability of technical rules is purely a dollar event or a phenomenon in the foreign exchange market in general.

Panel A of Table VI reports the results when the Japanese yen is used as a vehicle currency. With the “always long” benchmark and using the nominal  $p$ -value, the null hypothesis is rejected at the one percent level for all currencies. Even after adjusting for data-snooping



biases, the null hypothesis is rejected at the five percent level for all currencies except the Swiss franc. Furthermore, the excess return measures are all economically significant. These results are in general stronger than those when the U.S. dollar is used as a vehicle currency. When the “always neutral” benchmark is used, we also find strong support for the profitability of trading rules. The null hypothesis can be rejected at the five percent level for all six currencies even after data-snooping biases are corrected. The excess returns are economically important as well.

Panel B of Table VI shows the results for five Deutsche mark exchange rates. Based on the “always long” benchmark and after accounting for data-snooping biases, the null hypothesis can be rejected at the one percent level for all currencies except the Swiss franc.<sup>6</sup> Using the “always neutral” benchmark, the null hypothesis can be rejected at the one percent for all currencies.

The above results suggest that the profitability of mechanical trading signals is pronounced not only for the dollar exchange rates but can also be important for other exchange rates.

### C. Sensitivity of White’s $p$ -value to Changes in the Smoothing Parameter

The Politis and Romano’s (1994) stationary bootstrap re-samples blocks of varying length from the original data, where the block length follows the geometric distribution with mean block length  $1/q$ . A larger value of  $q$  generates shorter block length and is appropriate for data with little dependence, and vice versa. Thus far, we have chosen  $q = 0.5$  for all experiments. As a different  $q$  value implies a different sampling distribution of exchange rates generated, it can in turn affect both the nominal  $p$ -value and the White  $p$ -value of the test. Our last experiment

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<sup>6</sup> The fact that there are relatively small variations in the exchange rate between the Swiss franc and the Deutsche mark due to their pegging may partly explain the insignificance of the trading-rule profitability.

is to examine whether our results are sensitive to the choice of the  $q$  value. We consider two additional values,  $q = 1$  and  $0.1$ , where the former case corresponds to the uniform distribution and is popularly used (see, for example, Brock *et al.* (1992), and Levich and Thomas (1993)).

Table VII reports the nominal  $p$ -values and the White  $p$ -values under the mean return criterion without transaction cost for  $q=1, 0.1$ , where our baseline case of  $q=0.5$  is also displayed for ease of comparison. Overall, we find that the White  $p$ -values are not greatly affected by the choice of the smoothing parameter  $q$ . The White  $p$ -values associated with  $q=1$  and  $0.1$  deviate from our baseline case ( $q=0.5$ ) typically by one to three percentage points using either benchmark. In none of the cases do the results change qualitatively.

The results with different values of the smoothing parameter under the Sharpe ratio criterion are very similar. Also, the White's  $p$ -values are not sensitive to the choice of the smoothing parameter when a 0.025 or 0.05 percent transaction cost is imposed. These results are not reported to economize on space.

In summary, our simulation results seem to be robust to alternative values of the smoothing parameter  $q$ .

## V. Conclusion

Researchers have long been interested in examining whether technical trading strategies can predict the changes in exchange rates and beat the market. While numerous studies document significant profitability of certain rules, it is unclear whether their superior performance is due to their genuine economic information, or is due to pure luck. The fundamental problem is that a researcher often applies more than one trading rule to a particular

data set and there is almost always a possibility that some rules may work by pure chance regardless of their information contents. This is the serious data-snooping problem in finance.

By employing White's (2000) Reality Check methodology, our paper makes a first attempt to characterize the data-snooping biases of various popular mechanical algorithms in the foreign exchange market and to re-examine the profitability of these rules. Evidence from seven dollar exchange rates shows that the data-snooping problem is in general rather serious. Nevertheless, even after data-snooping biases are properly accounted for, we find that the null hypothesis that trading rules do not beat the benchmark of buying and holding foreign currency can be rejected at the five percent significance level for the Canadian dollar, the French franc, the Italian lira and the British pound; and at the 10 percent level for the Japanese yen. Furthermore, the null hypothesis can be rejected at the one percent level for all seven currencies based on the benchmark of holding the U.S. dollar. The excess returns generated by these trading rules are not only statistically significant, but economically important as well. They cannot be easily explained by a systematic risk factor. Imposing reasonable transaction costs does not greatly affect our basic results. Using the Japanese yen and the Deutsche mark as vehicle currencies produces stronger results.

These reasonably robust results suggest that it is not easy to totally attribute the excess profitability of technical trading strategies to pure luck. Certain rules might indeed be meritorious. Why the potential profit opportunity is not fully exploited in the most heavily traded market is an important issue, which is beyond the scope of this paper and is left for future research.

## Appendix

### Trading Rules Investigated

#### Notations:

$S_t$ : Exchange rate (U.S. dollar price of one unit foreign currency),  $t = 1, 2, \dots, T$   
( $T=6463$ )

$s_t$ :  $\ln S_t$

$g$ : transaction cost adjustment factor

$r$ : rate of return from trading rules

$I$ : signal = 1: long; = 0: neutral; = -1: short

$$r_t = (s_t - s_{t-1})I_{t-1} - \text{abs}(I_{t-1} - I_{t-2})g, t = 256, 257, \dots, 6463, n = 6208, g = 0, 0.001$$

Benchmarks:  $I = 1$  always long;  $I = 0$  always neutral

#### A. Filter Rules

$x$ : percentage increase in the dollar value of foreign currency required to generate a “buy” signal

$y$ : percentage decrease in the dollar 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

$x = 0.0005, 0.001, 0.005, 0.01, 0.05, 0.10$  (6 values)

$y = 0.0005, 0.001, 0.005, 0.01, 0.05$  (5 values)

$e = 1, 2, 5, 10, 20$  (5 values)

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

Total number of filter rules =  $x \cdot c + x \cdot e + x \cdot y = 24 + 30 + 15 = 69$

(Note: As in Sullivan et al. (1999), we do not consider all possible combinations of  $x, y, e, c$ )

#### B. 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

$n = 2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250$  (11 values)

$$m = \sum_{i=1}^{10} i = 55$$

$b = 0, 0.0005, 0.001, 0.005, 0.01, 0.05$  (6 values)

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

$c = 5, 10, 25$  (3 values)

$$\begin{aligned} \text{Total number of MA rules} &= nb + mb + nd + md + nc + mc \\ &= 66 + 330 + 44 + 220 + 33 + 165 = 858 \end{aligned}$$

### C. Trading Range Break (TRB, or Support and Resistance) Rules

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

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

$b$ : 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

$n = 5, 10, 15, 20, 25, 50, 100$  (7 values)

$e = 2, 3, 4, 5, 10, 25, 50$  (7 values)

$b = 0.0005, 0.001, 0.005, 0.01, 0.05$  (5 values)

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

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

Total number of TRB rules =

$$nc + ec + nbc + ebc + ncd + ecd = 28 + 28 + 140 + 140 + 112 + 112 = 560$$

### D. 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

$n = 5, 10, 15, 20, 25, 50, 100, 200$  (8 values)

$x = 0.001, 0.005, 0.01, 0.05, 0.10$  (5 values)

$b = 0.0005, 0.001, 0.005, 0.01, 0.05$  (5 values)

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

Note that  $b$  must be less than  $x$ . There are 15  $x$ - $b$  combinations.

$$\text{Total number of CBO rules} = n \cdot x \cdot c + n \cdot c \cdot (xb \text{ combinations}) = 160 + 480 = 640$$

$$\text{Total number of trading rules} = 69 + 858 + 560 + 640 = 2127$$

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**Table I**  
**Descriptive Statistics for Daily Changes in the Logarithm of Exchange Rates**

The table reports summary statistics for daily changes in the logarithm of exchange rates for the period between April 2, 1973 to December 31, 1998, with 6463 observations for each currency. Exchange rate is defined as the U.S. dollar price of one unit foreign currency;  $s_t$  is the logarithm of exchange rate;  $\rho(k)$  is the  $k$ -<sup>th</sup> order serial correlation of  $(s_t - s_{t-1})$ .

$s_t - s_{t-1}$	CAN	FRA	GER	ITA	JAP	SWI	UK
Mean*100	-0.0067	-0.0031	0.0083	-0.0161	0.0132	0.0134	-0.0062
Mean Absolute*100	0.1841	0.4505	0.4757	0.4215	0.4388	0.5487	0.4323
Min	-0.0190	-0.0587	-0.0587	-0.0669	-0.0626	-0.0583	-0.0384
Max	0.0186	0.0416	0.0414	0.0404	0.0563	0.0441	0.0459
Standard Deviation	0.0026	0.0065	0.0066	0.0062	0.0065	0.0076	0.0062
Sharpe Ratio	-0.0259	-0.0048	0.0125	-0.0259	0.0204	0.0176	-0.0099
Skewness	-0.1843	-0.1911	-0.0680	-0.5281	0.4251	-0.0184	-0.1421
Kurtosis	4.3654	5.5238	3.5506	8.0005	6.3622	3.4030	3.9643
$\rho(1)$	0.0552	0.0323	0.0333	0.0374	0.0443	0.0353	0.0630
$\rho(2)$	-0.0069	-0.0067	-0.0052	0.0022	0.0122	-0.0089	0.0014
$\rho(3)$	0.0015	0.0120	0.0137	0.0110	0.0061	0.0032	-0.0047
$\rho(4)$	-0.0028	0.0085	0.0002	-0.0133	0.0082	-0.0074	0.0019
$\rho(5)$	0.0128	0.0196	0.0193	0.0134	0.0176	0.0052	0.0331
$\rho(6)$	-0.0055	-0.0206	-0.0004	0.0008	-0.0054	0.0084	-0.0089



**Table II**  
**Performance of the Best Trading Rules under the Mean Return Criterion without Transaction Cost**

The table reports the performance of the best trading rule from the universe of 2127 trading rules for each currency under the mean return criterion in the absence of transaction cost. The “always long” benchmark means buying and holding foreign currency, while the “always neutral” benchmark means holding the U.S. dollar. The “mean return” is the annualized percentage average return rate of the best trading rule minus the return rate of the benchmark. The “White’s  $p$ -value” is computed by applying the Reality Check methodology to the universe of 2127 trading rules and incorporates the effects of data-snooping biases. The “nominal  $p$ -value” is calculated by applying the Reality Check methodology to the best trading rule only, thereby ignoring the effects of data-snooping.

Currency	Best Trading Rule	Number of Trade	Benchmark: Always Long			Benchmark: Always Neutral		
			Mean Return	Nominal $p$ -value	White’s $p$ -value	Mean Return	Nominal $p$ -value	White’s $p$ -value
CAN	MA(n=20,b=0)	1178	5.51	0.0000	0.0080	3.65	0.0000	0.0060
FRA	MA(n=20,b=0)	1016	10.99	0.0000	0.0160	10.42	0.0000	0.0000
GER	MA(n=25,b=.001)	780	8.08	0.0060	0.1760	9.80	0.0000	0.0000
ITA	MA(n=20,b=0)	1104	13.94	0.0000	0.0000	10.05	0.0000	0.0000
JAP	CBO(n=5,x=.01,c=1)	842	8.57	0.0000	0.1060	12.22	0.0000	0.0000
SWI	CBO(n=5,x=.05,b=.0005,c=1)	1192	6.75	0.0160	0.4320	10.01	0.0000	0.0080
UK	MA(n=15,b=.001)	1026	11.01	0.0000	0.0100	9.53	0.0000	0.0020

**Table III**  
**Parameter Estimates of One-Factor Model for Excess Returns of Best Trading Rules**

The table reports estimate of the one-factor model:

$$f_t = \alpha + \beta(r_{m,t} - r_{f,t}) + \varepsilon_t$$

where  $f_t$  is the daily excess return from the best-performing rule relative to the “always long” benchmark,  $r_{m,t}$  is the market rate of return, and  $r_{f,t}$  is the risk-free rate. We use the returns on the value-weighted U.S. stock market index and on the S&P500 index as proxies for the market return, and the three-month U.S. Treasury bill rate as the risk-free rate. The market indexes are obtained from CRSP daily files, while the Treasury bill rate is obtained from the Federal Reserve’s website. A  $p$ -value denotes the statistical significance level at which the estimated parameter is different from zero. The values of  $\alpha$  are in annualized percentage.

Currency	$\alpha$	$t$ -statistic	( $p$ -value)	$\beta$	$t$ -statistic	( $p$ -value)
Value-Weighted Stock Index Return as Market Factor						
CAN	5.70	4.45	(0.0000)	-0.03	-5.52	(0.0000)
FRA	11.25	3.89	(0.0001)	-0.02	-1.87	(0.0619)
GER	8.19	2.87	(0.0041)	-0.02	-1.30	(0.1931)
ITA	14.11	4.64	(0.0000)	-0.01	-0.98	(0.3287)
JAP	8.56	3.04	(0.0024)	-0.02	-1.30	(0.1927)
SWI	6.88	2.15	(0.0316)	-0.01	-0.83	(0.4061)
UK	11.21	3.88	(0.0001)	-0.02	-1.49	(0.1361)
S&P500 Index Return as Market Factor						
CAN	5.55	4.33	(0.0000)	-0.02	-4.57	(0.0000)
FRA	11.15	3.86	(0.0001)	-0.02	-1.79	(0.0731)
GER	8.12	2.84	(0.0045)	-0.01	-1.21	(0.2282)
ITA	14.04	4.62	(0.0000)	-0.01	-0.76	(0.4489)
JAP	8.48	3.01	(0.0026)	-0.01	-1.04	(0.2964)
SWI	6.83	2.14	(0.0328)	-0.01	-0.81	(0.4156)
UK	11.13	3.85	(0.0001)	-0.02	-1.32	(0.1864)

**Table IV**  
**Performance of the Best Trading Rules under the Sharpe Ratio Criterion without Transaction Cost**

The table reports the performance of the best trading rule from the universe of 2127 trading rules for each currency under the Sharpe ratio criterion in the absence of transaction cost. The “always long” benchmark means buying and holding foreign currency, while the “always neutral” benchmark means holding the U.S. dollar. The “White’s  $p$ -value” is computed by applying the Reality Check methodology to the universe of 2127 trading rules and incorporates the effects of data-snooping biases. The “nominal  $p$ -value” is calculated by applying the Reality Check methodology to the best trading rule only, thereby ignoring the effects of data-snooping. The best trading rule under the Sharpe ratio criterion is the same as under the mean return criterion for all seven currencies.

Currency	Best Trading Rule	Number of Trade	Sharpe Ratio	Benchmark: Always Long		Benchmark: Always Neutral	
				Nominal $p$ -value	White’s $p$ -value	Nominal $p$ -value	White’s $p$ -value
CAN	MA(n=20,b=0)	1178	.0554	0.0000	0.0080	0.0000	0.0060
FRA	MA(n=20,b=0)	1016	.0653	0.0000	0.0200	0.0000	0.0000
GER	MA(n=25,b=.001)	780	.0596	0.0060	0.1760	0.0000	0.0000
ITA	MA(n=20,b=0)	1104	.0642	0.0000	0.0000	0.0000	0.0000
JAP	CBO(n=5,x=.01,c=1)	842	.0746	0.0040	0.1160	0.0000	0.0000
SWI	CBO(n=5,x=.05,b=.0005,c=1)	1192	.0526	0.0200	0.4400	0.0000	0.0100
UK	MA(n=15,b=.001)	1026	.0604	0.0000	0.0100	0.0000	0.0020

**Table V**  
**Performance of the Best Trading Rules under the Mean Return Criterion with Transaction Costs**

The table reports the performance of the best trading rule from the universe of 2127 trading rules for each currency under the mean return criterion in the presence of transaction cost. The “always long” benchmark means buying and holding foreign currency, while the “always neutral” benchmark means holding the U.S. dollar. The “mean return” is the annualized percentage average return rate (after transaction cost) of the best trading rule minus the return rate of the benchmark. The “White’s  $p$ -value” is computed by applying the Reality Check methodology to the universe of 2127 trading rules and incorporates the effects of data-snooping biases. The “nominal  $p$ -value” is calculated by applying the Reality Check methodology to the best trading rule only, thereby ignoring the effects of data-snooping. Panel A reports the results with a 0.1 percent transaction cost while Panel B presents the case with a 0.05 percent transaction cost.

Panel A. One-Way Transaction Cost = 0.025 percent

Currency	Best Trading Rule	Number of Trade	Benchmark: Always Long			Benchmark: Always Neutral		
			Mean Return	Nominal $p$ -value	White’s $p$ -value	Mean Return	Nominal $p$ -value	White’s $p$ -value
CAN	MA(n=20,b=.001)	690	4.81	0.0000	0.0260	2.94	0.0000	0.1000
FRA	MA(n=20,b=0)	1016	9.95	0.0000	0.0440	9.38	0.0000	0.0000
GER	MA(n=25,b=.001)	780	7.29	0.0060	0.2720	9.00	0.0000	0.0060
ITA	MA(n <sub>1</sub> =2,n <sub>2</sub> =25,b=.0005)	652	13.13	0.0000	0.0000	9.24	0.0000	0.0000
JAP	CBO(n=5,x=.01,b=.0005,c=1)	758	7.76	0.0080	0.2020	11.41	0.0000	0.0000
SWI	CBO(n=5,x=.05,b=.005,c=1)	692	5.95	0.0380	0.5860	9.21	0.0000	0.0260
UK	MA(n=15,b=.001)	1026	9.97	0.0000	0.0340	8.49	0.0000	0.0080

Panel B. One-Way Transaction Cost = 0.05 percent

Currency	Best Trading Rule	Number of Trade	Benchmark: Always Long			Benchmark: Always Neutral		
			Mean Return	Nominal $p$ -value	White’s $p$ -value	Mean Return	Nominal $p$ -value	White’s $p$ -value
CAN	TRB(n=5,c=10,d=5)	29	4.69	0.0000	0.0320	2.83	0.0000	0.1320
FRA	MA(n=20,b=.0005)	904	9.02	0.0000	0.0840	8.44	0.0000	0.0020
GER	MA(n=25,b=.005)	472	6.61	0.0080	0.3420	8.33	0.0000	0.0180
ITA	MA(n <sub>1</sub> =2,n <sub>2</sub> =25,b=.0005)	652	12.46	0.0000	0.0040	8.57	0.0000	0.0040
JAP	CBO(n=5,x=.01,b=.0005,c=1)	758	6.99	0.0160	0.3060	10.64	0.0000	0.0000
SWI	MA(n=10,b=.01)	560	5.34	0.0540	0.6900	8.60	0.0000	0.0680
UK	CBO(n=5,x=.005,c=10)	46	9.42	0.0020	0.0580	7.94	0.0000	0.0220

**Table VI**  
**Performance of the Best Trading Rules under the Mean Return Criterion, Cross Exchange Rates**  
**(Transaction Cost = 0,  $q = 0.5$ )**

The table reports the performance of the best trading rule from the universe of 2127 trading rules for each currency under the mean return criterion in the absence of transaction cost when the Japanese yen and the Deutsche mark are respectively used as the vehicle currency. The “always long” benchmark means buying and holding foreign currency, while the “always neutral” benchmark means holding the Japanese yen. The “mean return” is the annualized percentage average return rate of the best trading rule minus the return rate of the benchmark. The “White’s  $p$ -value” is computed by applying the Reality Check methodology to the universe of 2127 trading rules and incorporates the effects of data-snooping biases. The “nominal  $p$ -value” is calculated by applying the Reality Check methodology to the best trading rule only, thereby ignoring the effects of data-snooping.

Panel A. Japanese Yen as Vehicle Currency

Currency	Best Trading Rule	Number of Trade	Benchmark: Always Long			Benchmark: Always Neutral		
			Mean Return	Nominal $p$ -value	White’s $p$ -value	Mean Return	Nominal $p$ -value	White’s $p$ -value
CAN	CBO( $n=5, x=.01, b=.0005, c=1$ )	790	17.34	0.0000	0.0000	11.83	0.0000	0.0000
FRA	Filter( $x=.01, e=10$ )	2722	14.12	0.0000	0.0040	9.90	0.0000	0.0000
GER	MA( $n=15, b=0$ )	1354	12.19	0.0000	0.0080	10.26	0.0000	0.0040
ITA	MA( $n_1=5, n_2=25, c=1$ )	460	19.23	0.0000	0.0000	11.69	0.0000	0.0000
SWI	Filter( $x=.001, c=1$ )	5122	9.02	0.0000	0.1220	8.62	0.0000	0.0240
UK	Filter( $x=.001, e=2$ )	6334	16.65	0.0000	0.0000	11.52	0.0000	0.0000

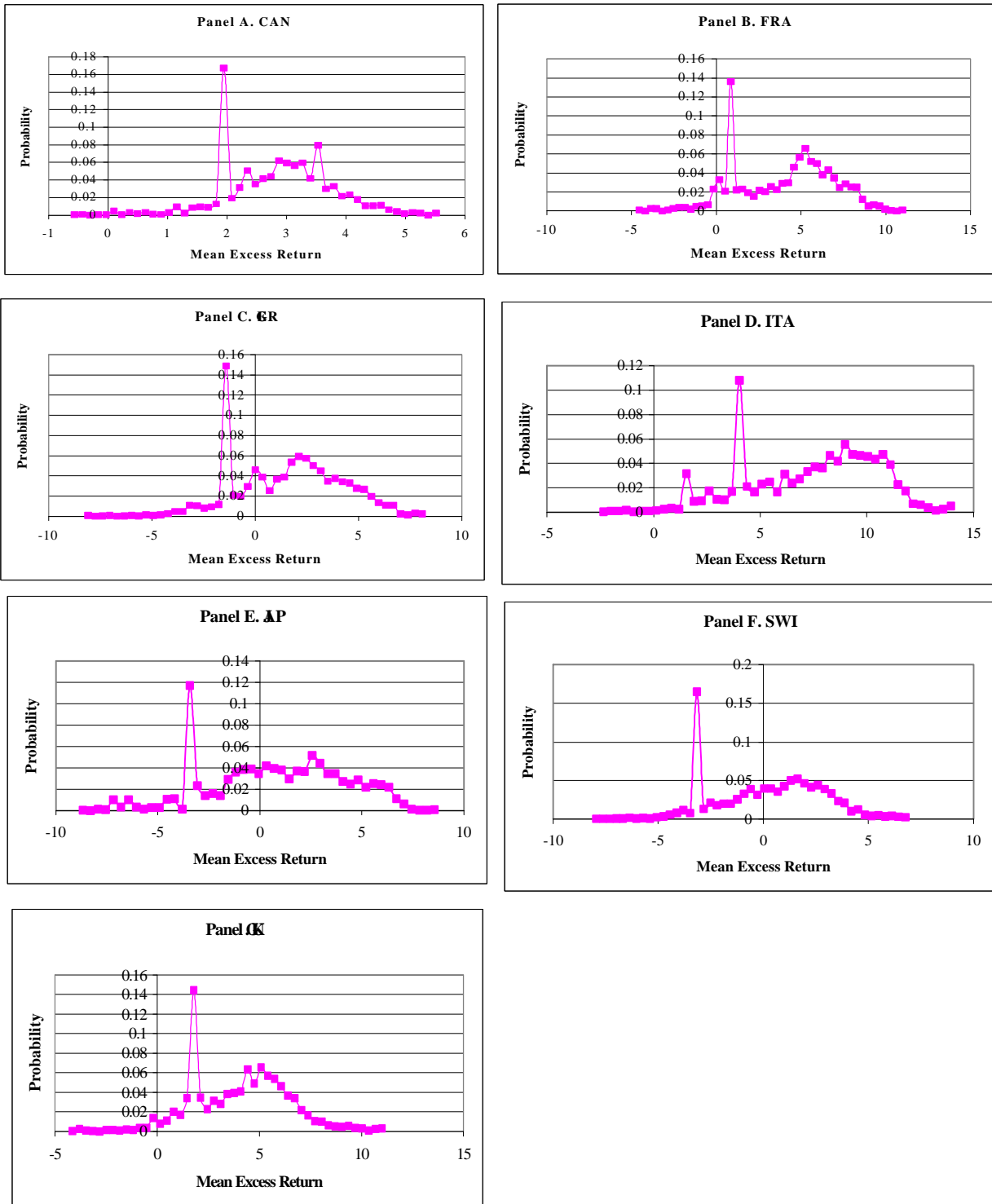
Panel B. Deutsche Mark as Vehicle Currency

Currency	Best Trading Rule	Number of Trade	Benchmark: Always Long			Benchmark: Always Neutral		
			Mean Return	Nominal $p$ -value	White’s $p$ -value	Mean Return	Nominal $p$ -value	White’s $p$ -value
CAN	MA( $n=5, b=.005$ )	1208	14.53	0.0000	0.0000	10.95	0.0000	0.0000
FRA	MA( $n_1=2, n_2=50, c=5$ )	390	6.10	0.0000	0.0000	3.81	0.0000	0.0040
ITA	MA( $n_1=2, n_2=50, b=.05$ )	2	12.43	0.0000	0.0000	6.82	0.0000	0.0000
SWI	MA( $n_1=15, n_2=20, d=3$ )	610	2.93	0.0140	0.4140	4.47	0.0000	0.0100
UK	MA( $n_1=20, n_2=50, b=0$ )	230	10.55	0.0000	0.0000	7.36	0.0000	0.0000

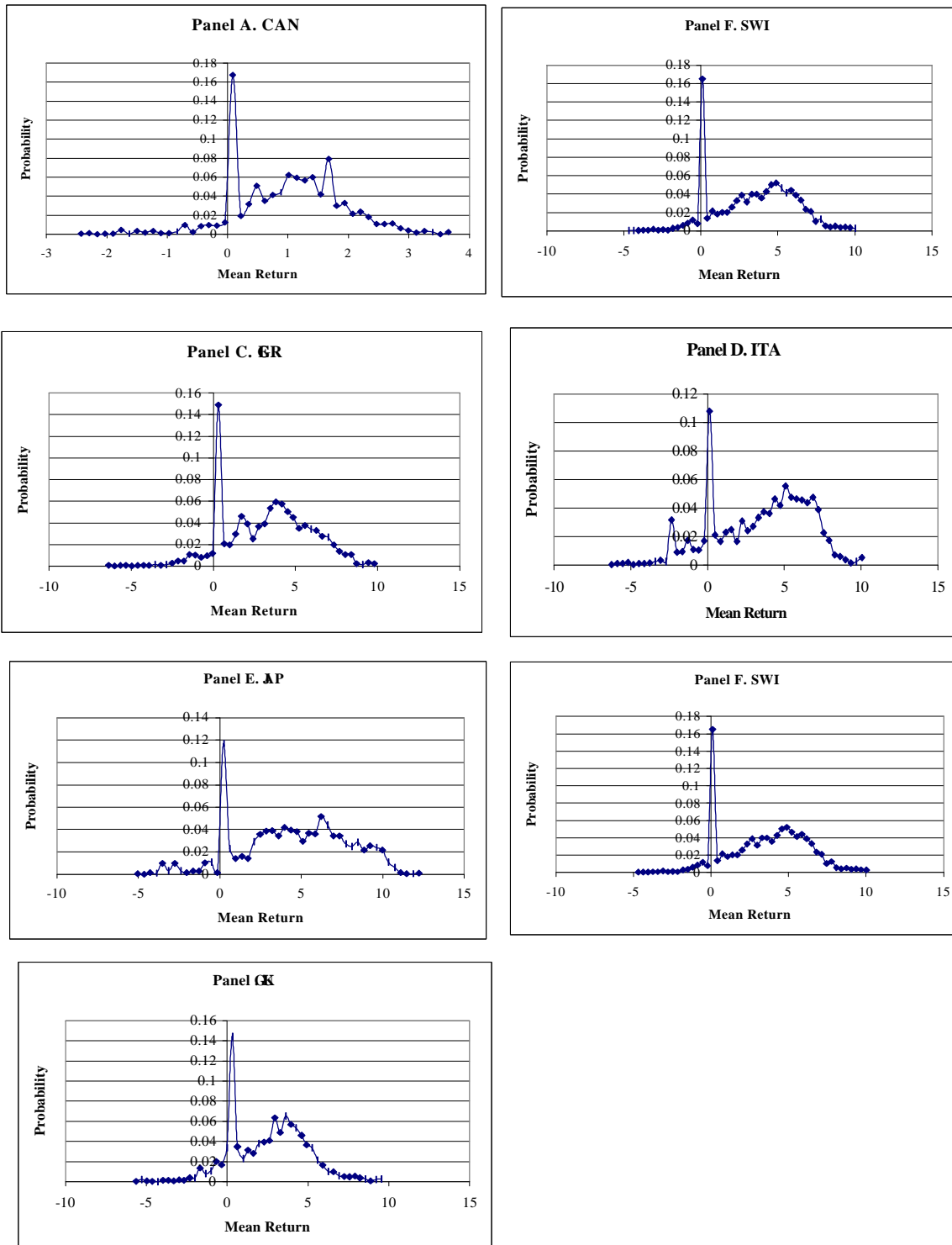
**Table VII**  
**White's  $p$ -value with Different Smoothing Parameter ( $q$ ) under the Mean Return Criterion without Transaction Cost**

The table reports the performance of the best trading rule from the universe of 2127 trading rules for each currency under the mean return criterion for alternative values of the smoothing parameter  $q$  in the absence of transaction cost. The “always long” benchmark means buying and holding foreign currency, while the “always neutral” benchmark means holding the U.S. dollar. The “White's  $p$ -value” is computed by applying the Reality Check methodology to the universe of 2127 trading rules and incorporates the effects of data-snooping biases. The “nominal  $p$ -value” is calculated by applying the Reality Check methodology to the best trading rule only, thereby ignoring the effects of data-snooping.

Currency	Benchmark: Always Long						Benchmark: Always Neutral					
	q=0.5		q=1		q=0.1		q=0.5		q=1		q=0.1	
	Nominal p-value	White's p-value	Nominal p-value	White's p-value	Nominal p-value	White's p-value	Nominal p-value	White's p-value	Nominal p-value	White's p-value	Nominal p-value	White's p-value
CAN	0.0000	0.0080	0.0000	0.0020	0.0000	0.0020	0.0000	0.0060	0.0000	0.0020	0.0000	0.0120
FRA	0.0000	0.0160	0.0000	0.0200	0.0000	0.0240	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GER	0.0060	0.1760	0.0020	0.1540	0.0020	0.1720	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ITA	0.0000	0.0000	0.0000	0.0060	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
JAP	0.0000	0.1060	0.0020	0.0920	0.0020	0.1340	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SWI	0.0160	0.4320	0.0160	0.4080	0.0080	0.4740	0.0000	0.0080	0.0000	0.0100	0.0000	0.0100
UK	0.0000	0.0100	0.0000	0.0100	0.0000	0.0300	0.0000	0.0020	0.0000	0.0000	0.0000	0.0020

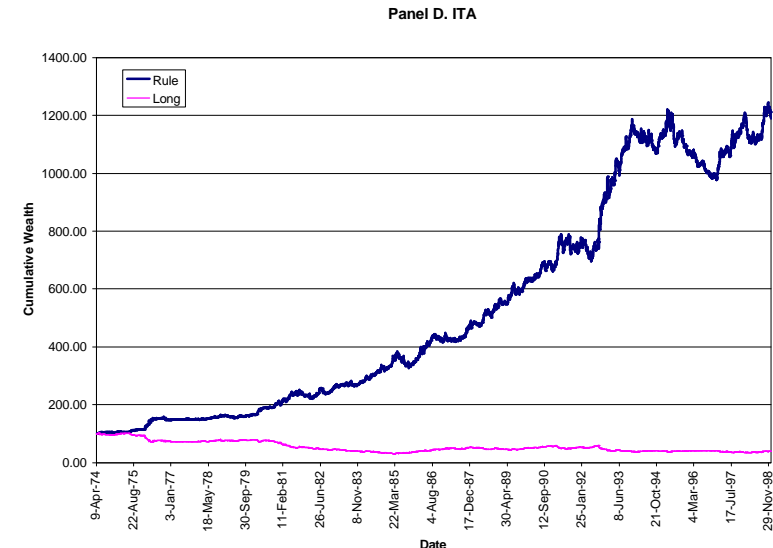
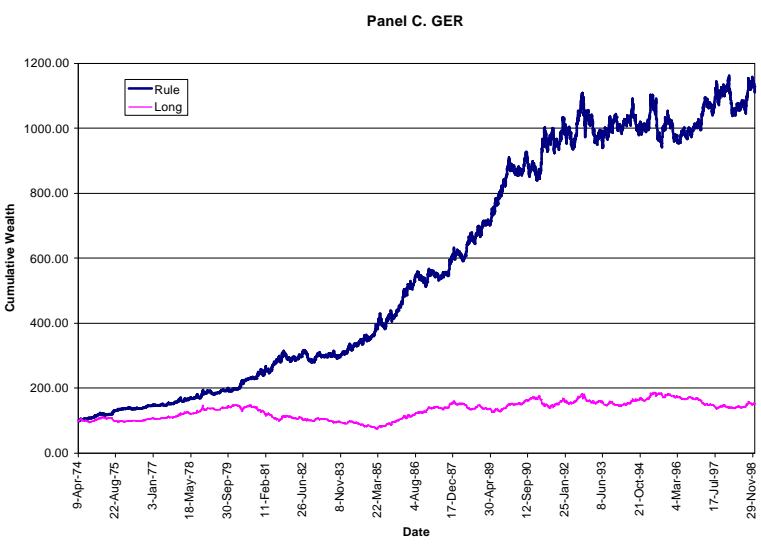
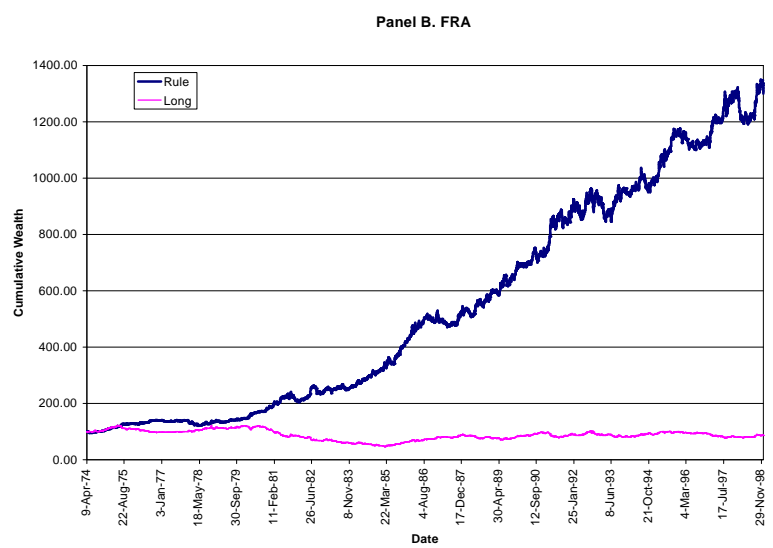
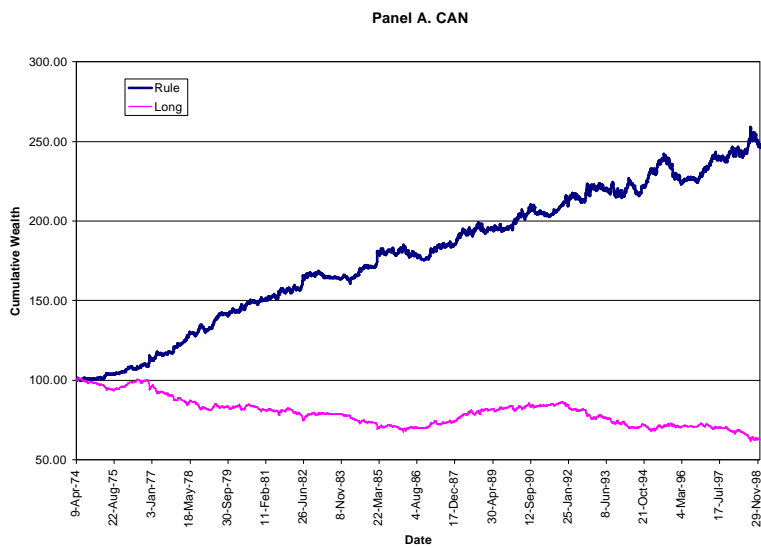


**Figure 1 Distribution of mean excess returns across trading rules.**  
 These figures plot the frequency distributions of mean excess returns relative to the benchmark of buying-and-holding foreign currency for each of the seven exchange rates.

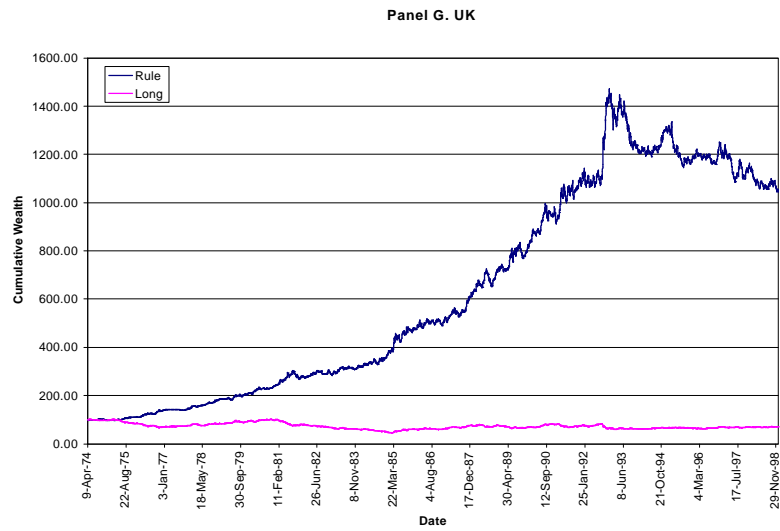
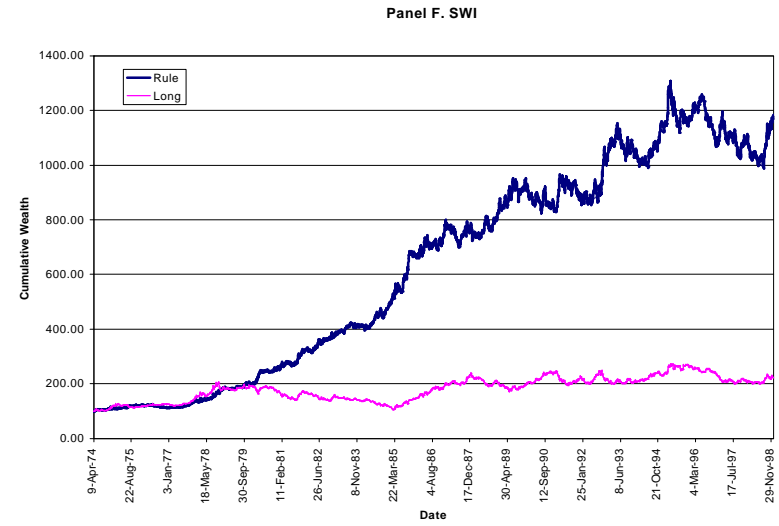
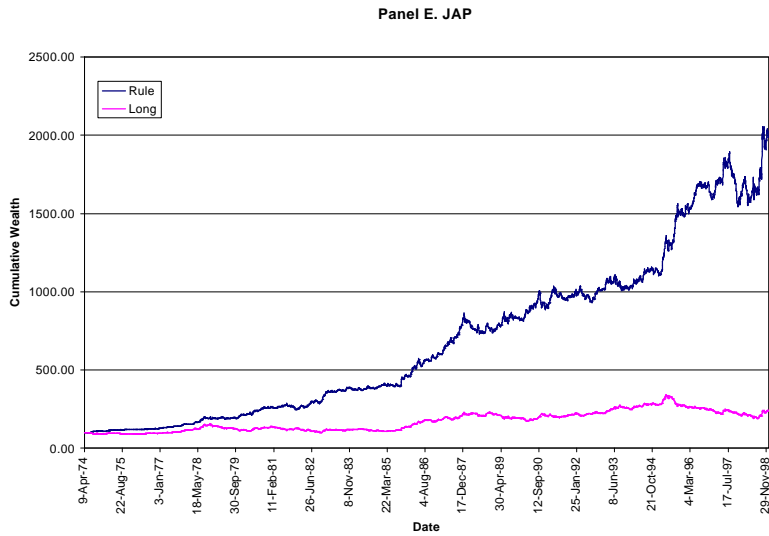


**Figure 2** Distribution of mean return across Trading rules. These figures plot the frequency distributions of mean excess returns relative to the benchmark of always holding the US dollar for each of the seven exchange rates.





**Figure 3 Cumulative wealth.** These figures plot the cumulative wealth over time for each of the seven exchange rates. The thick line is for the best the trading strategy, and the thin line is for the strategy of buying-and-holding foreign currency.



**Figure 3 Cumulative wealth (continue)**