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THE SIGNIFICANCE OF TECHNICAL TRADING-RULE PROFITS IN THE FOREIGN EXCHANGE MARKET: A BOOTSTRAP APPROACH

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ABSTRACT

In this paper, we present new evidence on the profitability and statistical significance of technical trading rules in the foreign exchange market. We utilize a new data base, currency futures contracts for the period 1976-1990, and we implement a new testing procedure based on bootstrap methodology. Using this approach, we generate thousands of new exchange rate series constructed by random reordering of each original series. We then measure the profitability of the technical rules for each new series. The significance of the profits in the original series is assessed by comparison to the empirical distribution of results derived from the thousands of randomly generated series. Overall, our results suggest that simple technical trading rules have very often led to profits that are highly unusual. Splitting the entire 15-year sample period into three 5-year periods reveals that on average the profitability of some trading rules declined in the 1986-1990 period although profits remained positive (on average) and significant in many cases.

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I. Introduction and Motivation

Since the advent of floating exchange rates in the early 1970s, numerous empirical studies have investigated the time series behavior of exchange rates and the empirical distribution of exchange rates. A null hypothesis that features prominently in these studies is whether exchange rates can be characterized as serially independent drawings from a stationary distribution. Alongside these studies, tests of foreign exchange market efficiency have examined the profitability of various trading rules. A null hypothesis in these studies has been that mechanical rules for generating trading signals should not result in unusual (risk-adjusted) profits.

A variety of empirical studies (reviewed in Section II) support the notion that mechanical trading rules are often profitable when applied in the spot foreign exchange market. A drawback to these studies is that most do not measure the statistical significance of their results, while others measure statistical significance assuming that the volatility of exchange rates is constant. The latter assumption is questionable since recent evidence rejects the hypothesis that exchange rates can be described as random, independent drawings from a stationary distribution. Evidence is more consistent with the view that exchange rates are drawn from non-stationary distributions.

The purpose of this paper is to undertake new tests of the random behavior of exchange rates and the profitability of mechanical trading rules. Our tests do not rely on assumptions regarding the distribution of the process underlying exchange rate changes. Our approach involves the application of bootstrap methods -- i.e. the generation of thousands of new series of pseudo exchange rates, each new series constructed from random reordering of the original series. We measure the profitability of the mechanical trading rules for each new series. The significance of the results from the original series can be assessed by comparison to the empirical distribution of results derived from the thousands of randomly generated series.

Overall, our empirical results suggest that mechanical trading rules have very often led to profits that are highly unusual relative to the profits earned by the same rules when applied to the randomly generated time series of exchange rates. Based on a sample of five currencies over the period January 1, 1976 - December 31, 1990 and nine trading rules, we find that in 31 cases the original exchange rate series produced profits in the top 1% of all times series, in eight cases the original series produced profits in the top 5% of all time series, and the remaining six cases produced profits that were positive but not significant. Splitting the entire 15-year sample period into three 5-year periods revealed that on average the profitability of mechanical trading rules has declined in the 1986-1990 period, although profits remained positive (on average) and significant in many cases.

The plan for the remainder of the paper is to review some of the earlier research on spot exchange rates and market efficiency in Section II. We present our own methodology and data sources in Section III. Our empirical results are presented in the following section. A summary and conclusions are in the final section.

II. Previous Research

A. Efficient Market Theory

There are now a substantial number of empirical studies testing the efficiency of the foreign exchange market. Surveys of this literature have been prepared by Levich (1985, 1989) and Hodrick (1987). A critical point in the formulation of these studies is that all tests of market efficiency are tests of a joint hypothesis -- first, the hypothesis that defines market equilibrium returns as some function of the available information set, and second, the hypothesis that market participants set actual prices or returns to conform to their expected values.

To be more specific, if we define $r_{j,t+1}$ as the actual one-period rate of return on asset *j* in the period ending at time *t+1*, and $E(r_{j,t+1}|I_t)$ as the expected value of that return conditional on the information set available at time *t*, then the excess market return can be written as

$$Z_{j,t+1} = r_{j,t+1} - E(r_{j,t+1}|I_t) \quad . \tag{1}$$

The market is efficient if the expectational errors follow a fair game process such that $E(Z_{j,t+1}|I_t)=0$ and $Z_{j,t}$ is uncorrelated with $Z_{j,t+k}$ for any value of *k*. In words, the market is efficient if, on average, expectational errors are zero, and these errors follow no pattern that might be exploited to produce profits.

In the case of speculative trading in spot or forward foreign exchange markets, risk is present but a risk premium may or may not be characteristic of equilibrium pricing and returns.[1] For example, in the monetary model of exchange rates, domestic and foreign currency bonds are assumed to be perfect substitutes once the interest differential between foreign and domestic assets offsets the foreign exchange rate change. In this case, there is no foreign exchange risk premium -- any sustained speculative trading profits would be deemed unusual and a violation of market efficiency. However, in the portfolio balance model of exchange rates, domestic and foreign currency bonds are assumed to be imperfect substitutes, and in equilibrium investors require a risk premium (which could vary over time) in addition to the expected exchange rate change to compensate them for the uncertainty of exchange rate changes. In this case, some positive level of profits from trading rules would be consistent with an equilibrium. Since the equilibrium expected return in foreign exchange speculation could be zero or positive and time varying, it has been difficult to gauge what constitutes unusual or excessive profits as would be characteristic of an inefficient market.

The primary technique for testing spot market efficiency has been to compute the profitability of various mechanical trading

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[1] Asset models of exchange rates are discussed in Levich (1985) and Branson and Henderson (1985).

strategies. One popular technique for generating buy and sell signals is the filter rule.[2] An x percent filter rule leads to the following strategy: 'Buy a currency whenever it rises by x percent above its most recent trough; sell the currency and take a short position whenever the currency falls x percent below its most recent peak.' In the spot foreign exchange market, the expected profit (P) from a long foreign currency (FC) position over the period (t,t+1) is

$$E(P_{t,t+1}) = E\,[\ln\,(S_{t+1}/S_t)] - (i_\$ - i_{FC}) \qquad (2)$$

where i_{FC} represents the interest earned on the long FC position, $i_\$$ is the interest expense of the short \$ position and S is the spot exchange rate in \$/FC.[3] The right-hand-side of equation (2) is the uncovered interest parity condition (also known as the Fisher Open effect). Accordingly, under the joint null hypothesis of market efficiency and no foreign exchange risk premium, expected profits will be zero. Spot speculation of the sort described can be conducted using lines of credit secured by Treasury Bills that earn

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[2] Filter rules were used by Alexander (1961) to test for trading profits in American equity markets. Follow up tests by Fama and Blume (1966) found that no profits were available after adjusting for transaction costs, dividends paid during short sales, and pricing discontinuities.

[3] To avoid Siegel's Paradox, the interest rate $i_\$$ and i_{FC} should be compounded continuously. Contrary to results suggested by Black (1990) we view the Siegel Paradox as a nominal effect. By using continuous compounding, expected profits are zero from the standpoint of both the \$ and FC based investor.

interest for the speculator. It follows that the entire realized profit from following a mechanical signal

$$P_{t,t+1} = \ln (S_{t+1}/S_t) - (i_\$ - i_{FC}) \qquad (3)$$

should be interpreted as an unusual return -- a risk premium, over and above the risk free rate of interest. However, under the joint null hypothesis of market efficiency and a time varying exchange risk premium (RP_t), expected profits from currency speculation will be positive. In this case, only the excess profit

$$\pi_{t,t+1} = P_{t,t+1} - RP_t \qquad (4)$$

should conform to the conditions of a fair game if the market is efficient. The conundrum, then, in interpreting the empirical series of profits as in equation (3) is that occasional profits may be the result of chance, but sustained profits could either be indicative of market inefficiency or fair compensation for an exchange risk premium. The empirical support for a non-trivial exchange risk premium is mixed.[4] In practice, most empirical studies have not taken an exchange risk premium explicitly into account.

B. Empirical Evidence on Exchange Markets

Studies by Dooley and Shafer (1976, 1983) report the filter

[4] See Froot and Thaler (1990) for a discussion of the evidence on the foreign exchange risk premium.

rule trading profits for nine currencies using daily spot rates over the 1973-1981 period. Their calculations are adjusted to reflect the interest expense and interest income of long and short positions (as in equation [3]) and transaction costs are incorporated by using bid and asked foreign exchange quotations. Their results indicate that small filters ($\underline{x}$ = 1, 3, or 5 percent) would have been profitable for all currencies over the entire sample period. The authors also reported results for 10, 15, 20 and 25 percent filters. These filters were profitable in more than one-half of the sub-periods but the results were more variable than for the smaller filters. However, even with the small filters there appears to be some element of riskiness in these trading rules since each filter would have generated losses in at least one currency during at least one sub-period. Even so, for three currencies (Yen, Guilder, and Pound sterling) every small filter was profitable in every sub-period. The authors did not report any measures of statistical or economic significance of these profits.

A study by Sweeney (1986) used a similar filter rule technique on daily exchange rates for ten currencies over the April 1973 - December 1980 sample period and reached similar conclusions.[5] Filters of 0.5, 1, 2, 3, 4, 5, and 10 percent led to trading profits in more than 80% of the cases. The results for the smaller

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[5] Sweeney imposes a restriction on short FC positions. From and initial position in $, a buy signal triggers a move into FC while a sell signal results in a move back into $. Profits from this trading rule are evaluated vis-a-vis the benchmark of buying and holding the FC. The same methodology was used by Cornell and Dietrich (1978) in an analysis of five currencies over the March 1973 - September 1975 period.

filters (0.5, 1, and 2 percent) were again superior. Sweeney divided his sample into a 2.5-year estimation period followed by a 5-year post-sample period. Filter rules that were profitable in the first period tended to be profitable in the second. Under the assumption of constant exchange rate volatility, Sweeney calculated that in about one-third of the cases, the profits from filter trading were statistically significant. Again, the results were more pronounced for the smaller filters.

Schulmeister (1987,1988) conducted an in-depth analysis of the $/DM rate over the April 1973 - September 1986 period using several technical models in addition to the simple filter model.[6] In particular, Schulmeister tested a popular moving average rule that generates signals based on a cross-over between short-term and long-term moving average of past exchange rate. According to this rule, when the short-term moving average penetrates the long-term moving average from below (above) a buy (sell) signal is generated. Results for the 3 day-10 day, 5 day-10 day, and 4 day-16 day combinations are reported.

Schulmeister's results suggest that most of these technical models would have resulted in profitable trading strategies even after adjusting for interest expense and transaction costs. In particular, the moving average rules are profitable in each of the 10 sub-periods analyzed. Schulmeister suggests that the reason for his results is that exchange rate changes and speculative profits

[6] He also tested a momentum model, based on the rate of change in past exchange rate, and a combination model involving both moving average and momentum models.

appear to be non-normally distributed. There are too many small exchange rate changes (relative to a normal distribution) but also too many large exchange rate swings (also relative to the normal). The implication from the latter is that once an exchange rate move has started, it is likely to proceed more or less uninterrupted, which allows market technicians time to identify a profitable investment opportunity.[5]

Two papers that analyze the statistical properties of exchanges rates are also worth noting. In an analysis of daily spot exchange rates over the period 1974-1983, Hsieh (1988) rejects the hypothesis exchange rates are independently drawn from a fat-tailed distribution that remains fixed over time. While the usual tests do reveal the presence of serial correlation in exchange rates, Hsieh argues that this may be the result of heteroskedasticity. Once heteroskedasticity is removed from the data, very little serial correlation remains. Exchange rates appear more accurately characterized as drawings from distributions that vary over time with changing means and variances.[6]

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[5] A trend following rule in which the investor buys more as the currency goes up and sells more as the currency goes down is a dynamic call replicating strategy. As the strategy produces a synthetic currency call option, the profits from this strategy should be skewed. By comparison, the trading rules here entail a fixed position that is held until the next signal of opposite sign appears.

[6] This result underlies the generalized autoregressive conditional heteroskedasticity (GARCH) model that includes the specification of a time-varying and serially correlated error term. An autoregressive integrated moving average (ARIMA) process is a more restricted representation of a time series process with constant variance and time invariant parameters.

Engel and Hamilton (1990) model the time-varying nature of exchange rate distributions as a Markov switching process between state 1 and state 2 where exchange rate movements are drawn from distributions

$$N\ (\mu_1\ ,\ \sigma_1^2)\quad \text{in state 1, and}$$

$$N\ (\mu_2\ ,\ \sigma_2^2)\quad \text{in state 2 .}$$

Assume that these states evolve so that

$$\Pr(s_t = 1 \mid s_{t-1} = 1) = p_{11}$$

$$\Pr(s_t = 2 \mid s_{t-1} = 1) = 1 - p_{11}$$

$$\Pr(s_t = 1 \mid s_{t-1} = 2) = 1 - p_{22}$$

$$\Pr(s_t = 2 \mid s_{t-1} = 2) = p_{22}\ .$$

If p_{11} and p_{22} are high, and μ_1 and μ_2 have opposite signs, then there will be "long swings" (i.e. uninterrupted trends) in exchange rates -- the sort that might be susceptible to mechanical trading rules. Analyzing quarterly data for the period 1973:4 - 1988:1, Engel and Hamilton conclude that the long swings hypothesis (p_{11} and p_{22} high, and μ_1 and μ_2 with opposite signs) fits the data significantly better than a state independent model of a single distribution.

III. Data and Methodology

A characteristic of exchange rates is that while it might be possible to model a series from one period as drawings from a fixed distribution, it is not possible to "turn the clock back" and draw additional samples from the same time period. Instead, researchers typically "turn the clock forward" and draw additional observations from an extended sample period. This technique may confound the analysis if the sampling distribution itself varies over time.

In classical statistics, statistical statements about population parameters are based only on the sample of data actually drawn in the context of an assumption about the distribution function that generated the sample. An alternative is the bootstrap approach, which assumes nothing about the distribution generating function.[7] The distribution generating function is determined empirically using numerical simulation. By drawing numerous random samples (with replacement) of size n from the original data itself, these new samples generate an empirical distribution. Probability statements regarding the original data (for example, the mean, standard deviation, or other moments) can now be made with reference to the empirical distribution.

In this paper, we have collected data on futures prices for five currencies (British pound [BP], Canadian dollar [CD], German mark [DM], Japanese yen [JY], and Swiss franc [SF]) for the period January 1, 1976 through December 31, 1990, or approximately 3800 daily observations. Our data source is I.P. Sharpe & Co., now a part of Reuters. Quotations are on closing settlement prices from the International Monetary Market of the Chicago Mercantile Exchange. A single time series is assembled by bringing together quotations on successive near-term contracts. For example, futures prices in January and February of 1976 reflect the March 1976

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[7] For more on the bootstrap method, see Efron (1979, 1982) and Hinkley (1988). For an application of bootstrap techniques to technical trading rules in the stock market, see Brock, Lakonishok and LeBaron (1991).

contract; futures prices in March, April and May of 1976 reflect the June 1976 contract; and so forth.[8] Since futures prices reflect the contemporaneous interest differential between the foreign currency and the U.S. dollar, price trends and profits can be measured simply by

$$P_{t,t+1} = \ln (F_{t+1}/F_t) \qquad (5)$$

where F_t is the currency futures price at time $\underline{t}$.[9]

By the use of futures contracts, we eliminate the need for overnight interest rates on spot interbank deposits and we also obtain a reliable and consistent data set. However, each individual futures contract displays a deterministic decline in maturity from roughly 110 days to 20 days as we follow its price movements. Samuelson (1976) has proved that "near futures contracts show more variability than (sufficiently far) distant ones," so there is some possibility that return variances may be rising as our contracts move toward maturity and then falling abruptly as we roll into the next futures contract. However, Samuelson (1976) also shows that for some stationary price generating processes, variance may rise over some intervals as time to maturity (T) rises, even though in

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[8] The June 1976 Japanese yen contract had extremely light trading volume and so there are no observations for yen during the months of March, April and May 1976. Data for the yen begin in June 1976 with prices for the September contract.

[9] In this assumption, we rely on the interest rate parity relationship that is well established in the empirical literature. See Frenkel and Levich (1988).

the limit, variance of futures price changes is zero as $T \to \infty$. Thus, whether variance rises as our futures contracts move from T=110 to 20 days to maturity remains an empirical question. As a practical matter, however, volatility in futures price changes, $\sigma^2(P_{t,t+1})$, will be heavily dominated by spot price changes (See Appendix). Our analysis of futures price changes reveals that there is no significant difference between volatility for 'far' maturities ($80 \leq T_f \leq 110$) and 'near' maturities ($20 \leq T_n \leq 50$).

In order to generate a vector of buy and sell trading signals, we utilize filter rules of size $\underline{x}$ = 0.5%, 1%, 2%, 3%, 4%, and 5% and three moving average cross-over rules: 1 day/5 day, 5 day/20 day, and 1 day/200 day. Each vector of signals is then applied to the original series of futures prices to measure the actual profitability of using these mechanical rules on the original sequence of price changes given in equation (5). As noted earlier, technical models employing filter rules and moving averages are popular models that have been analyzed in earlier studies. The filter sizes and moving average lengths are selected as they have been applied in earlier studies. Other filter sizes and moving average lengths along with other technical models could, of course, be analyzed. Data-mining exercises of this sort must be avoided. Rather than torture the data until a profitable rule materializes, we will report our empirical results for all of the popular models that we test.

We now describe our simulation technique. Each series of futures prices of length N+1 corresponds to a series of log price changes of length N. These N observations could be arranged in M = N! separate sequences, each sequence (m = 1, ... M) corresponding to a unique profit measure (X[m,r]) under trading rule r for r = 1, ... R.[10] For each currency, we generate a new comparison series (a shuffled series), by making a random rearrangement of price changes in the original series. By operating on the sequence of price <u>changes</u>, the starting and ending price <u>levels</u> of the new series are constrained to be exactly as their values in the original data. And by randomly rearranging the original data, the new series is constrained to have identical distributional properties as the original series. However, the time series properties of the new data are made random. Our simulation, therefore, generates one of the many paths that the exchange rate might have followed from its level on the starting day of the sample until the ending day holding constant the original distribution of price changes.

This process of randomly shuffling the series of returns is repeated 10,000 times for each currency, thereby generating 10,000 i.i.d. drawings from all m = 1, ... M possible sequences. Each of the 10,000 notional paths bears the same distributional properties as the original series, but the time series properties have been scrambled with each path, by construction, drawn independently of the other notional paths. Each technical rule (all filters and moving averages) is then applied to each of the 10,000 random series and the profits, X[m,r], are measured. This procedure

[10] In our case with N approximately 3800, M is, conservatively speaking, a huge number. With N=50, for example, $M = 3.04 \times 10^{64}$.

generates an <u>empirical distribution</u> of profits. The profits of the original series can then be compared to the profits from the randomly generated, shuffled series. Under the null hypothesis, if there is no information or signals in the original sequence of data, then the profits obtained from trading in the original series should not be significantly different from the profits available in the shuffled series. The null hypothesis that there is no information in the original time series of data is rejected at the α percent level if the profits obtained in the original series are greater than the α percent cutoff level of the empirical distribution.

IV. <u>Empirical Results</u>

In Table 1, we present descriptive statistics on the original times series of futures price returns. The mean daily return for all currencies is small and averages near zero. The largest (absolute) mean return was negative four basis points per day for the BP in the second sub-period, or roughly 10% per annum. The daily standard deviation varies from 0.27% for the CD to 0.79% for the SF. For the CD and the JY, the standard deviation of returns is fairly constant across the three sub-periods. However, for the other three currencies, volatility rises sharply in the second sub-period.

The autocorrelation of daily returns for lags 1-10 are reported in Table 2.[11] The estimates reveal a considerable amount of significant autocorrelation. For the DM, SF, and CD we find evidence of significant positive autocorrelation at lags 1 and/or 2. In more general tests for autocorrelation, we find significant Box-Pierce Q statistics for the DM and CD (over the full sample) and the JY and SF over the 1976-1980 subperiod.[12] No Q statistics are significant for the BP, or for any currency in the final 1986-1990 subperiod.

Sample autocorrelation may be spurious in the presence of heteroskedasticity.[13] Given the empirical evidence reviewed earlier on heteroskedasticity in currency movements, we follow the methodology of Hsieh (1988) and compute heteroskedasticity-consistent estimates of the standard error for each autocorrelation coefficient, $s(k) = \sqrt{(1/n)(1+\gamma(x^2,k)/\sigma^4)}$, where n is the sample size, $\gamma(x^2,k)$ is the sample autocovariance of the squared data at lag k, and σ is the sample standard deviation of the original data. As expected, this adjustment reduces the number of significant autocorrelation coefficients. None of the adjusted Box-Pierce Q

[11] Autocorrelations at lags 11-30 were computed but they are not reported here.

[12] The Box-Pierce Q(k) statistic tests the joint hypothesis that the first k autocorrelation coefficients are zero. We also computed Ljung-Box Q^* statistics which gave nearly identical results.

[13] See Maddala (1988, pp. 218-9)

statistics are significant at the 5% level.[14]

The profits associated with the generation of buy and sell signals using filter rules and moving average rules are reported in Tables 3A and 3B respectively. Over the entire 15-year sample period, every size filter results in positive profits for every currency. Average profit in the Canadian dollar across all filters is 2.0%, substantially less than the average for other currencies where results range between 6.9% and 8.1% . The results are much the same for the moving average rules which led to average profits of 2.7% for the CD, and between 7.0% and 9.0% for the other currencies.

As expected, small filters and trading rules based on short-term moving averages result in considerably more trading signals than larger filters and rules embodying long-term moving averages. The most 0.5% filter traded 901 times in 15 years, or about 60 trades per year; the 1/5 moving average rule for the Canadian dollar produced 987 trades or about 65 trades per year. We calculate that the likely cost of transacting in the currency futures market is about 2.5 basis points (0.025%) per transaction for a large institution. A more conservative estimate would be roughly 4.0 basis points.[15] At 65 trades per year, a speculator

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[14] The adjusted Box-Pierce Q(K) statistic is calculated as $\Sigma^{K}_{k=1}[\rho(k)/s(k)]^2$, which is asymptotically distributed as X^2 with K degrees of freedom.

[15] We consider two elements in the cost of transacting: first, the bid/ask spread which we take as $0.0002 or $0.0001 per transaction, and second, the brokerage commission estimated at $11.00 per round-trip transaction. Since the sizes of currency

would have his trading profits reduced by 1.62% per year or 2.60% per year if we take our more conservative measure. Transaction costs of this magnitude would nearly decimate the 3.3% annual return for the 1/5 moving average rule in the Canadian dollar and take a considerable bite out of the other transaction generating rules. For the other trading rules we consider, the volume of trading is considerably smaller, and transaction costs do not significantly affect profits.

The rank of the filter rule profits for the actual series in comparison to the 10,000 randomly generated series is also reported in Table 3A. The results are quite striking. In nineteen of the cases, the profits of the actual series rank in the top 1% (9900 and above) of all the simulated series. In six further cases, the rank is in the top 5% (9500 - 9899). The remaining five cases rank lower, but in no case lower than the top 21% of the simulated series (rank 7900 and above). Thus in 25 of our 30 cases, we can reject the hypothesis that there is no information in the original series that can be exploited for profit by our filter rules.

The results are much the same for the moving average rules. We find twelve cases in which the profits of the actual series rank in the top 1% of all of the simulated series and two additional cases that are significant at the 5% level. The remaining case ranks

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futures contract are fixed and futures prices are variable, the percentage cost of transacting varies somewhat across currencies and over time. Our likely estimate reflects an average across these dimensions.

lower, but still in the top 6% of the simulated series (rank 9400 and above). Again, these results imply a strong rejection of the hypothesis that there is no information in the original series that can be exploited for profit by our moving average rules.

Summary statistics for the simulated series and filter rule trading strategies are shown in Table 4A. In all thirty cases, the average profit is very small and insignificantly different from zero. In only one case (the 0.5% filter rule for the British pound) is the average profit positive for the sample of 10,000 simulated series. The other sample statistics for the simulated series suggest that average profits are normally distributed without skewness or kurtosis.

These results strongly suggest that the actual exchange rate series contained significant departures from serial independence that allowed technical trading rules to be profitable. If the actual series had been generated randomly, our simulations suggest that average profits would be close to zero. Gauged against these simulations, the actual path of exchange rates is seen to embody a significant degree of serial dependence.

To measure the stability of these results over time, we split the sample period into three, five-year sub-periods and repeated our analysis. We decided to split the sample in this arbitrary way rather than based on foreign currency strength and weakness, since the latter might exaggerate the profitability of trend-following rules. Our results for filter rules (in Table 5A) show that out of ninety cases (5 currencies x 6 filter rules x 3 periods) the application of filter rules to the original data resulted in profits in 80 cases and losses in the remaining ten cases. Across all currencies, the average profitability of filter rules rose from 7.2% in 1976-1980 to 7.3% in 1981-1985, but fell to 4.0% in 1986-1990. Smaller filters appeared to be most profitable in the first two sub-periods, while in the final sub-period, the 3%, 4%, and 5% filters appeared to be more profitable on average. The recent decline in profitability is most apparent for the DM and SF, for which 0.5%, 1% and 2% filters generally would have produced losses. Nevertheless, of the ninety cases in Table 5A, profits significant at the 10% level were found in more than half of the cases.

A similar set of results for moving average rules during the three sub-periods is reported in Table 5B. All 45 cases (5 currencies x 3 rules x 3 periods) result in positive profits. On average, there is some deterioration over time in the profitability of these rules, but the overall decline is small. The most pronounced decline was for the 1 day/5 day rule in the third sub-period for DM and SF. Despite this, more than half of the cases held significant profits at the 10% level.

These results for five-year sub-periods illustrate some of the risks that are entailed in technical trading, although it appears that some of these risks can be diversified by not operating in a single currency with a single technical rule.

V. Summary and Conclusions

The purpose of this paper was to update earlier evidence on the profitability of simple technical trading rules and to extend these results using a new statistical test. Our results show that the profitability of simple technical models that was documented on data from the 1970s has continued on into the 1980s. Moreover, our statistical tests suggest that the profitability of these technical rules is highly significant in comparison to the empirical distribution of profits generated by thousands of bootstrap simulations.

The profitability of trend following rules strongly suggests some form of serial dependency in the data, but the nature of that dependency remains unclear.[16] Oddly, the BP series does not reveal any significant autocorrelation, yet the trading profits in the BP are similar to other currencies. Our technical rules for the DM, CD and SF are most profitable during subperiods when there is no significant autocorrelation, rather than in other subperiods when serial correlation is present. Only the JY has its most profitable subperiod when its autocorrelation is significant.

The persistence of trading profits over the 15-year sample period is itself a striking result. However, we also found evidence that these profits have declined somewhat over the most recent five-year sub-period. Possible explanations for the persistence of trading profits are the presence of central bank intervention that tends to lean against the wind and retard exchange rate movements. The profitability of trend following rules may be the result of

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[16] Bilson (1990) models the relationship between past and future exchange rate changes as a non-linear function of observable variables.

excessive speculation that cause prices to follow, at least temporarily, a speculative bubble path away from their fundamental equilibrium values. It is also, of course, possible that too little capital is committed to currency speculation making market prices slow to adjust to their equilibrium values. While commercial banks are exceedingly active in interbank market trading and intra-day positions may be large, far less capital is committed to overnight and longer-term currency positions.

The results presented here could be extended in several worthwhile directions. One would be to specify alternative models for generating exchange rates such as a univariate ARIMA time series model, a Markov switching model as discussed in Section II, or a GARCH model. Each specification could itself be taken as the null model, and we could then generate numerous simulated series using bootstrap techniques. Comparing the profitability of the original series with the empirical distribution of profits (and distributions of other sample statistics) would determine whether we can reject any null model.[17] While this technique could clarify which statistical model (or models) were consistent with the generation of currency prices, because these null models are not necessarily equilibrium economic models, they would not necessarily tell us whether the profits earned by technical trading rules were unusual in an economic, risk-adjusted sense.

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[17] Brock, Lakonishok and LeBaron use technical models in concert with bootstrap simulation techniques to test the adequacy of alternative null models for the generation of stock market prices.

APPENDIX

Using the notation from the text, we can write the interest rate parity relation with continuous compounding as

$$F_t = S_t \exp[i_{\$,t} - i_{FC,t}] = S_t \exp[D_t] \tag{A1}$$

At time (t-1), equation (A1) can be re-written as

$$F_{t-1} = S_{t-1} \exp[D_{t-1}] \tag{A2}$$

Dividing A1 by A2 and taking logarithms, we have

$$\ln (F_t/F_{t-1}) = \ln (S_t/S_{t-1}) + (D_t - D_{t-1}) \tag{A3}$$

or

$$f_t = s_t + d_t \tag{A4}$$

where f_t is the price trend or the daily profit as defined in equation (5) in the text. The variance of f_t is

$$\sigma^2(f_t) = \sigma^2(s_t) + \sigma^2(d_t) + 2 \operatorname{Cov}(s_t, d_t) \tag{A5}$$

As an empirical matter, it is well documented (see Levich [1989]) that the volatility of the interest differential, d_t, is far less than the volatility of the spot rate. Practically speaking, then, volatility in futures contracts will tend to be dominated by contemporaneous volatility in spot contracts rather than by changes in interest rates as the contract matures.

References

Alexander, Sydney S. "Price Movements in Speculative Markets: Trends or Random Walks," Industrial Management Review, 2 (May 1961): 7-26.

Bilson, John F.O. "Technical Currency Trading," in L. Thomas (ed.), The Currency Hedging Debate, (London: International Financing Review), 1990.

Black, Fischer. "Equilibrium Exchange Rate Hedging," Journal of Finance, 45, No. 3 (July 1990): 899-907.

Branson, William H. and Dale Henderson. "The Specification and Influence of Asset Markets," in R. Jones and P. Kenen (eds.), Handbook of International Economics, (Amsterdam: North-Holland Publishing), 1985.

Brock, William, Josef Lakonishok and Blake LeBaron. "Simple Technical Rules and the Stochastic Properties of Stock Returns," University of Wisconsin, Social Science Research Institute, Working Paper #9022, January 1991.

Cornell, W. Bradford and J. Kimball Dietrich. "The Efficiency of the Market for Foreign Exchange Under Floating Exchange Rates," Review of Economics and Statistics, 60, No. 1 (February 1978): 111-20.

Dooley, Michael P. and Jeffrey Shafer. "Analysis of Short-Run Exchange Rate Behavior: March 1973 - September 1975," International Finance Discussion Papers, No. 76. Washington, D.C., Federal Reserve System, 1976.

Dooley, Michael and Jeffrey Shafer. "Analysis of Short-Run Exchange Rate Behavior: March 1973 - November 1981," in D. Bigman and T. Taya (eds.), Exchange Rate and Trade Instability, (Cambridge, Mass.: Ballinger Publishing), 1983.

Efron, B. "Bootstrap Methods: Another Look at the Jackknife," The Annals of Statistics, Vol. 7, No. 1 (1979): 1-26.

Efron, B. The Jackknife, the Bootstrap and Other Resampling Plans, Philadelphia: Society for Industrial and Applied Mathematics, 1982.

Engel, Charles and James D. Hamilton. "Long Swings in the Dollar: Are They in the Data and Do Markets Know It?" American Economic Review, Vol. 80, No. 4 (September 1990): 689-713.

Fama, Eugene F. and Marshall Blume. "Filter Rules and Stock Market Trading Profits," Journal of Business, 39 (1966): 226-41.

Froot, Kenneth A. and Richard H. Thaler. "Anomalies: Foreign Exchange," Journal of Economic Perspectives, 4, No. 3 (Summer 1990): 179-92.

Frenkel, Jacob A. and Richard M. Levich. "Foreign Exchange Markets: Spot and Forward," in the New Palgrave: A Dictionary of Economic Thought and Doctrine, London: Macmillan, 1988.

Hinkley, David V. "Bootstrap Methods," Journal of the Royal Statistical Society 50, No. 3 (1988): 321-37.

Hodrick, Robert. The Empirical Evidence of the Efficiency of Forward and Futures Foreign Exchange Markets, (Chur Switzerland: Harwood Academic Publishers), 1987.

Hsieh, David A. "The Statistical Properties of Daily Foreign Exchange Rates: 1974-1983," Journal of International Economics 24 (1988): 129-45.

Levich, Richard M. "Empirical Studies of Exchange Rates: Price Behavior, Rate Determination and Market Efficiency," in R. Jones and P. Kenen (eds.), Handbook of International Economics, (Amsterdam: North-Holland Publishing), 1985.

Levich, Richard M. "Is the Foreign Exchange Market Efficient?" Oxford Review of Economic Policy, Vol. 5, No. 3, (Fall 1989): 40-60.

Maddala, G.S. Introduction to Econometrics, New York: Macmillan, 1988.

Samuelson, Paul A. "Is Real-World Price a Tale Told by the Idiot of Chance?" Review of Economics and Statistics, (February 1976):120-24.

Schulmeister, Stephan. "An Essay on Exchange Rate Dynamics," unpublished working paper, Austrian Institute of Economic Research, 1987.

Schulmeister, Stephan. "Currency Speculation and Dollar Fluctuations," Quarterly Review, Banca Nazionale del Lavoro, No. 167 (December 1988): 343-65.

Sweeney, Richard. "Beating the Foreign Exchange Market," Journal of Finance, (March 1986): 163-82.

Table 1. Sample statistics of daily returns: Foreign exchange

Currency	Variable	Full Sample	1976-80	1981-85	1986-90
DM	N	3786	1258	1264	1264
	Mu	0.000012	0.000073	-0.000338	0.000302
	Sigma	0.006740	0.005170	0.007579	0.007204
	T-value	0.11	0.50	-1.58	1.49
	Skewness				
	Kurtosis				
BP	N	3786	1258	1264	1264
	Mu	0.000077	0.000273	-0.000418	0.000379
	Sigma	0.007065	0.005626	0.008170	0.007137
	T-value	0.67	1.72	-1.82	1.88
	Skewness				
	Kurtosis				
CD	N	3785	1257	1264	1264
	Mu	0.000019	-0.000100	-0.000090	0.000246
	Sigma	0.002696	0.0025122	0.002571	0.002968
	T-value	0.43	-1.40	-1.25	2.95
	Skewness				
	Kurtosis				
JY	N	3533	1006	1263	1264
	Mu	0.000072	0.000230	-0.000190	0.000208
	Sigma	0.006964	0.007113	0.006532	0.007248
	T-value	0.61	1.02	-1.03	1.02
	Skewness				
	Kurtosis				
SF	N	3786	1258	1264	1264
	Mu	-0.000007	0.000045	-0.000345	0.000280
	Sigma	0.007856	0.006778	0.008517	0.008153
	T-value	-0.05	0.24	-1.44	1.22
	Skewness				
	Kurtosis				

Note: N = number of logarithmic returns
Sample period for JY is 1977-1990

Table 2. Autocorrelation functions of daily returns - Foreign exchange

	1	2	3	4	5	6	7	8	9	10	Sample Size
DM											
Full Sample	-0.0044	0.0270	0.0205	-0.0304	0.0113	0.0254	0.0039	0.0383a	0.0137	0.0028	3786
1976-1980	0.0478	0.0644a	-0.0375	-0.0420	0.0058	0.0434	0.0103	0.0511	0.0248	0.0658a	1258
1981-1985	-0.0266	0.0724b	0.0429	-0.0386	0.0029	0.0464	-0.0116	0.0430	0.0132	-0.0266	1264
1986-1990	-0.0107	-0.0430	0.0208	-0.0155	0.0153	-0.0138	0.0138	0.0170	0.0097	-0.0071	1264
BP											
Full Sample	0.0282	-0.0074	-0.0148	-0.0055	-0.0113	0.0183	-0.0027	0.0136	0.0288	-0.0180	3786
1976-1980	0.0292	-0.0176	-0.0143	-0.0212	-0.0227	0.0196	0.0157	0.0112	0.0544	0.0242	1258
1981-1985	0.0156	0.0351	-0.0016	-0.0222	-0.0418	0.0346	-0.0009	0.0160	0.0187	-0.0637a	1264
1986-1990	0.0368	-0.0628b	-0.0440	0.0238	0.0282	-0.0134	-0.0209	-0.0012	0.0266	0.0036	1264
CD											
Full Sample	0.0665b	-0.0310a	-0.0209	0.0196	0.0317a	0.0170	0.0183	0.0156	0.0149	-0.0215	3785
1976-1980	0.0449	-0.0176	0.0498	0.0237	0.0450	0.0099	0.0750b	0.0393	0.0194	0.0047	1257
1981-1985	0.1044b	-0.0296	-0.0656a	-0.0014	0.0447a	0.0551	0.0017	0.0454	0.0230	-0.0432	1264
1986-1990	0.0451	-0.0508	-0.0436	0.0245	0.0025	-0.0157	-0.0179	-0.0345	-0.0062	-0.0361	1264
JY											
Full Sample	0.0087	-0.0032	0.0324a	0.0078	0.0123	0.0215	-0.0044	0.0424b	0.0421b	0.0332a	3533
1976-1980	0.0184	-0.0401	0.0172	0.0072	0.0108	0.0137	-0.0210	0.0206	0.0839b	0.1083b	1006
1981-1985	-0.0207	0.0266	0.0485	0.0417	0.0108	0.0575a	-0.0051	0.0459	0.0419	-0.0382	1263
1986-1990	0.0230	-0.0019	0.0263	-0.0225	0.0166	-0.0025	0.0076	0.0550a	0.0113	0.0290	1264
SF											
Full Sample	0.0112	0.0234	0.0102	-0.0181	0.0033	0.0061	0.0025	0.0128	0.0225	0.0016	3786
1976-1980	0.0921b	0.0719a	-0.0018	-0.0055	-0.0113	0.0063	0.0188	-0.0060	0.0495	0.0516	1258
1981-1985	-0.0322	0.0620a	0.0127	-0.0273	0.0080	0.0272	-0.0115	0.0291	0.0120	-0.0310	1264
1986-1990	0.0007	-0.0518	0.0124	-0.0177	0.0037	-0.0206	0.0039	-0.0001	0.0155	-0.0050	1264

Table 2 - Continuation. Autocorrelation functions of daily returns - Foreign exchange

	Original Autocorrelations				Heteroskedasticity Consistent Autocorrelations			
	No. Significant	Box-Pierce			No. Significant	Box-Pierce		
	in 30 lags	Q(10)	Q(20)	Q(30)	in 30 lags	Q(10)	Q(20)	Q(30)
DM								
Full Sample	4	17.21	37.97	52.19	3	11.46	26.91	38.55
1976-1980	5	24.13	31.96	52.13	3	12.44	18.54	35.20
1981-1985	3	18.07	26.92	40.18	3	12.64	19.54	30.96
1986-1990	2	4.66	21.33	36.06	2	4.09	18.94	33.57
BP								
Full Sample	1	10.99	29.21	41.97	1	7.22	20.25	30.08
1976-1980	0	8.33	17.32	22.57	0	6.23	13.31	18.10
1981-1985	2	12.11	21.14	40.41	1	7.27	13.87	28.76
1986-1990	3	12.56	31.40	37.32	3	11.58	27.41	32.83
CD								
Full Sample	3	33.17	48.46	63.25	2	18.78	29.59	42.96
1976-1980	3	18.92	29.81	45.45	3	14.20	24.23	39.88
1981-1985	4	32.31	52.59	62.77	1	15.19	27.89	35.94
1986-1990	1	12.92	26.43	33.42	1	8.79	19.38	25.73
JY								
Full Sample	3	22.96	32.70	38.87	2	17.30	25.82	31.32
1976-1980	3	22.36	34.22	45.02	2	16.40	25.93	34.81
1981-1985	1	17.68	25.31	33.33	0	12.65	20.12	26.77
1986-1990	0	7.67	16.62	25.05	0	5.85	14.00	22.64
SF								
Full Sample	1	6.94	25.95	37.00	1	5.14	19.49	28.66
1976-1980	4	24.35	34.71	59.65	2	11.64	18.49	35.76
1981-1985	2	10.96	19.09	30.35	1	8.13	14.59	24.25
1986-1990	2	4.89	20.54	33.59	2	4.46	18.73	32.23

Note: Q(10) - $X^2(10)$ with critical values 25.2, 20.5 and 18.3 at the 1%, 5% and 10% significance levels
Q(20) - $X^2(20)$ with critical values 40.0, 34.2 and 31.4 at the 1%, 5% and 10% significance levels
Q(30) - $X^2(30)$ with critical values 53.7, 47.0 and 43.8 at the 1%, 5% and 10% significance levels

a: significant at 5% level with standard error = $1/\sqrt{N}$
b: significant as above and with heteroskedasticity consistent standard error

Table 3A: Profitability of Filter Rules, Percent Per Annum
(Sample Period, January 1976 - December 1990)

Currency Sample Size	Filter Size (in %) 0.5	1.0	2.0	3.0	4.0	5.0	Average Profit
DM (N=3786)							
Actual Profit	2.2	9.3	5.5	7.9	8.1	8.2	6.9
No. of Trades	825	409	195	97	62	41	
Rank in 10,000	7929	9997	9792	9987	9989	9988	
BP (N=3786)							
Actual Profit	9.9	7.5	7.4	8.4	8.0	4.3	7.6
No. of Trades	791	424	188	106	65	55	
Rank in 10,000	9998	9957	9942	9990	9977	9344	
CD (N=3785)							
Actual Profit	3.3	3.4	1.7	0.9	1.6	1.1	2.0
No. of Trades	305	121	51	28	15	11	
Rank in 10,000	9992	9989	9521	8246	9528	8887	
JY (N=3693)							
Actual Profit	7.5	8.3	7.0	7.1	10.1	8.4	8.1
No. of Trades	784	410	174	98	60	44	
Rank in 10,000	9962	9985	9938	9943	10000	9990	
SF (N=3786)							
Actual Profit	8.1	6.8	3.7	7.2	10.1	6.7	7.1
No. of Trades	901	533	253	127	78	62	
Rank in 10,000	9928	9854	8844	9896	9990	9852	

Table 3B: Profitability of Moving Average Rules, Percent Per Annum
(Sample Period, January 1976 - December 1990)

Currency Sample Size	Moving Average: Short-term (days)/Long-term(days) 1/5	5/20	1/200				Average Profit
DM (N=3786)							
Actual Profit	6.4	11.2	8.1				8.6
No. of Trades	964	215	75				
Rank in 10,000	9907	10000	9981				
BP (N=3786)							
Actual Profit	7.4	10.5	8.7				8.9
No. of Trades	943	187	60				
Rank in 10,000	9950	10000	9988				
CD (N=3785)							
Actual Profit	3.3	2.7	2.3				2.7
No. of Trades	987	196	81				
Rank in 10,000	9993	9950	9834				
JY (N=3693)							
Actual Profit	7.3	10.6	9.2				9.0
No. of Trades	929	191	85				
Rank in 10,000	9957	9998	9996				
SF (N=3786)							
Actual Profit	5.2	8.9	6.9				7.0
No. of Trades	980	211	81				
Rank in 10,000	9857	9472	9975				

Table 4A: Statistics on the Profitability of Filter Rules Over 10,000 Simulated Sample Periods (1976-1990 Period, Percent Per Annum)

Currency	Filter Size (in %) 0.5	1.0	2.0	3.0	4.0	5.0
DM						
Average Profit	-0.008	-0.006	-0.014	-0.030	-0.035	-0.043
Median Profit	-0.006	-0.007	-0.023	-0.029	-0.030	-0.037
Standard Dev.	0.418	0.416	0.408	0.405	0.412	0.411
BP						
Average Profit	0.005	-0.006	-0.013	-0.013	-0.014	-0.013
Median Profit	0.003	-0.011	-0.016	-0.016	-0.016	-0.014
Standard Dev.	0.433	0.434	0.429	0.425	0.424	0.424
CD						
Average Profit	-0.005	-0.010	-0.017	-0.022	-0.025	-0.029
Median Profit	-0.003	-0.011	-0.018	-0.022	-0.024	-0.029
Standard Dev.	0.166	0.165	0.164	0.162	0.158	0.152
JY						
Average Profit	-0.013	-0.008	-0.007	-0.010	-0.010	-0.015
Median Profit	-0.011	-0.009	-0.008	-0.013	-0.009	-0.016
Standard Dev.	0.412	0.411	0.410	0.411	0.406	0.407
SF						
Average Profit	0.000	-0.016	-0.023	-0.026	-0.030	-0.038
Median Profit	0.002	-0.014	-0.020	-0.030	-0.029	-0.036
Standard Dev.	0.475	0.482	0.481	0.480	0.478	0.474

Table 4B: Statistics on the Profitability of Moving Average Rules Over 10,000 Simulated Sample Periods (1976-1990 Period, Percent Per Annum)

Currency	Moving Average: Short-term (days)/Long-term(days)		
	1/5	5/20	1/200
DM			
Average Profit	-0.008	-0.005	-0.018
Median Profit	0.000	-0.003	-0.017
Standard Dev.	0.409	0.409	0.404
BP			
Average Profit	0.005	-0.006	-0.013
Median Profit	0.003	-0.011	-0.016
Standard Dev.	0.433	0.434	0.429
CD			
Average Profit	-0.005	-0.010	-0.017
Median Profit	-0.003	-0.011	-0.018
Standard Dev.	0.166	0.165	0.164
JY			
Average Profit	-0.013	-0.008	-0.007
Median Profit	-0.011	-0.009	-0.008
Standard Dev.	0.412	0.411	0.410
SF			
Average Profit	0.000	-0.016	-0.023
Median Profit	0.002	-0.014	-0.020
Standard Dev.	0.475	0.482	0.481

Table 5A: Profitability of Filter Rules, Percent Per Annum.
Three Sample Sub-Periods

Currency	Filter Size (in %)						Average
	0.5	1.0	2.0	3.0	4.0	5.0	Over All Filters
DM							
1976-1980	5.4c	8.3a	5.4c	5.4c	5.2b	5.1b	5.8
1981-1985	6.4	17.9a	13.6a	10.9b	7.5	8.0c	10.7
1986-1990	-5.0	2.3	-2.7	5.8	9.8b	8.7c	3.1
BP							
1976-1980	8.3b	10.3a	9.0b	9.6b	11.4a	6.5c	9.2
1981-1985	12.4b	9.1c	7.0	8.8c	9.4c	2.7	8.2
1986-1990	9.0c	3.7	6.4	8.2c	1.3	1.6	5.0
CD							
1976-1980	4.3a	6.2a	1.8	-0.6	-1.4	0.1	1.7
1981-1985	3.1c	1.9	3.2b	0.4	0.2	-1.1	1.3
1986-1990	2.6	2.3	-0.1	1.6	5.4	5.3	2.8
JY							
1976-1980	7.5c	5.1	8.7b	10.9b	8.7b	7.5c	8.1
1981-1985	5.2	10.8b	5.5	3.6	10.8a	10.8a	7.8
1986-1990	9.8b	8.7b	6.9c	6.4	9.8b	6.0	7.9
SF							
1976-1980	17.5a	11.2a	7.1c	13.9a	12.6a	5.2	11.2
1981-1985	8.3	12.2b	6.3	7.1	8.0	8.5c	8.4
1986-1990	-1.3	-2.6	-1.6	-0.4	7.8c	4.1	1.0
All Currencies							
1976-1980	8.6	8.2	6.4	7.9	7.3	4.9	7.2
1981-1985	7.1	10.4	7.1	6.2	7.2	5.8	7.3
1986-1990	3.0	2.9	1.8	4.3	6.8	5.1	4.0

Note: a - Significant at 1% level, rank>9900: 13 entries
b - Significant at 5% level, rank>9500: 17 entries
c - Significant at 10% level, rank>9000: 18 entries
not significant at 10% level, rank<9000: 42 entries

90 entries total

Table 5B: Profitability of Moving Average Rules, Percent Per Annum.
Three Sample Sub-Periods

Currency	Moving Average: Short-term (days)/Long-term(days)			Average Over All MA Rules
	1/5	5/20	1/200	
DM				
1976-1980	7.2b	9.4a	6.6b	7.7
1981-1985	10.9b	12.5b	5.4	9.6
1986-1990	2.1	11.0b	5.5	6.2
BP				
1976-1980	5.3	12.9a	5.0	7.7
1981-1985	8.5c	5.1	7.5	7.1
1986-1990	8.2c	14.0a	8.6c	10.3
CD				
1976-1980	3.8	5.3a	0.9a	3.4
1981-1985	2.9c	1.4	1.4	1.9
1986-1990	2.6	1.4	5.4c	3.2
JY				
1976-1980	4.7	15.3a	12.9a	10.9
1981-1985	9.1b	7.7c	5.4	7.4
1986-1990	8.5b	9.7b	3.5	7.2
SF				
1976-1980	8.5b	2.7	6.0c	5.7
1981-1985	12.3b	7.0	7.1	8.8
1986-1990	1.4	6.5	7.2	5.0
All Currencies				
1976-1980	5.0	8.9	6.1	6.9
1981-1985	8.7	6.7	5.4	6.9
1986-1990	4.6	8.5	6.0	6.4

Note:
a - Significant at 1% level, rank>9900: 7 entries
b - Significant at 5% level, rank>9500: 10 entries
c - Significant at 10% level, rank>9000: 7 entries
not significant at 10% level, rank<9000: 21 entries

45 entries total