Technical Trading Rules and Regime Shifts in Foreign Exchange

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ABSTRACT

This paper performs tests on several different foreign exchange series using a methodology inspired by technical trading rules. Moving average based rules are used as specification tests on the process for foreign exchange rates. Several models for regime shifts and persistent trends are simulated and compared with results from the actual series. The results show that these simple models can not capture some aspects of the series studied. Finally, the economic significance of the trading rule results are tested. Returns distributions from the trading rules are compared with returns on risk free assets and returns from the U.S. stock market.

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I. Introduction

Techniques for using past prices to forecast future prices has a long and colorful history. Since the introduction of floating rates in 1973 the foreign exchange market became another potential target for "technical" analysts who attempt to predict potential trends in pricing using a vast repertoire of tools with colorful names such as channels, tumbles, steps and stumbles. These market technicians have generally been discredited in the academic literature since their methods are sometimes difficult to put to rigorous tests. This paper attempts to settle some of these discrepancies through the use of bootstrapping techniques.

For stock returns many early studies generally showed technical analysis to be useless, while for foreign exchange rates there is no early study showing the techniques to be of no use. Dooley and Shafer(1983) found interesting results using a simple filter rule on several daily foreign exchange rate series. In later work Sweeney(1986) documents the profitability of a similar rule on the Deutsche Mark. In an extensive study, Schulmeister(1987) repeats these results for several different types of rules. Also, Taylor(1990) finds that technical trading rules do about as well as some of his more sophisticated trend detecting methods.

While these tests were proceeding, other researchers were trying to use more traditional economic models to forecast exchange rates with much less success. The most important of these was Meese and Rogoff(1983). These results showed the random walk to be the best out of sample exchange rate forecasting model. Recently, results using nonlinear techniques have been mixed. Hsieh (1989) finds most of the evidence for nonlinearities in daily exchange rates is coming from changing conditional variances. Diebold and Nason(1990) and Meese and Rose(1990) found no improvements using nonparametric techniques in out of sample forecasting. However, LeBaron(1990) and Kim(1989) show small out of sample forecast improvements. During some periods LeBaron(1990) found forecast improvements of over 5 percent in mean squared error for the German Mark. Both these papers relied on some results connecting volatility with conditional serial correlations of the series.

This paper breaks off of the traditional time series approaches and uses a technical trading rule methodology. With the bootstrap techniques of Efron(1979), some of the technical rules can be put to a more thorough test. This is done for stock returns in Brock, Lakonishok, and LeBaron(1990).[1] This paper will use similar methods to study exchange rates. These allow not only the testing of simple random walk models,

[1] Recently, Levich and Thomas(1991) have obtained some related results for several foreign exchange futures series.

but the testing of any reasonable null model that can be simulated on the computer. In this sense the trading rule moves from being a profit making tool to a new kind of specification test. The trading rules will also be used as moment conditions in a simulated method of moments framework for estimating linear models.

Finally, the economic significance of these results will be explored. Returns from the trading rules applied to the actual series will be tested. Distributions of returns from the exchange rate series will be compared with those from risk free assets and stock returns. These tests are important in determining the actual economic magnitude of the deviations from random walk behavior that are observed.

Section II will introduce the simple rules used. Section III describes the null models used. Section IV will present results for the various specification tests. Section V will implement the trading rules and compare return distributions and section VI will summarize and conclude.

II. Technical Trading Rules

This section outlines the technical rules used in this paper. The rules are closely related to those used by actual traders. All the rules used here are of the moving average or oscillator type. Here, signals are generated based on the relative levels of the price series and a moving average of past prices,

$$ma_t = (1/L) \sum_{i=0}^{L-1} p_{t-i}.$$

For actual traders this rule generates a buy signal when the current price level is above the moving average and a sell signal when it is below the moving average.[2] This paper will use these signals to study various conditional moments of the series during buy and sell periods. Estimates of these conditional moments are obtained from foreign exchange time series, and these estimates are then compared with those from simulated stochastic processes. Section IV of the paper differs from most trading rule studies which look at actual trading profits from a rule. Actual trading profits will be explored in section V.

III. Null Models for Foreign Exchange Movements

This section describes some of the null models which will be used for comparison with the actual exchange rate series. These models will be run through the same trading rule systems as the actual data and then compared with those series. Several of these models will be bootstrapped in the spirit of Efron(1979)

[2] There are many variations of this simple rule in use. One is to replace the price series with another moving average. A second modification is to only generate signals when the price differs from the moving average by a certain percentage. Many other modifications are discussed in Schulmeister(1987), Sweeney(1986), and Taylor(1990).

using resampled residuals from the estimated null model. This closely follows some of the methods used in Brock et. al. (1990) for the Dow Jones stock price series.

The first comparison model used is the random walk,

$$log(p_t) = log(p_{t-1}) + \epsilon_t.$$

Log differences of the actual series are used as the distribution for ϵ_t and resampled or scrambled with replacement to generate a new random walk series. The new returns series will have all the same unconditional properties as the original series, but any conditional dependence will be lost.

The second model used is the GARCH model (Engle(1982) and Bollerslev(1986)). This model attempts to capture some of the conditional heteroskedasticity in foreign exchange rates.[3] The model estimated here is of the form

$$r_t = a + b_1 r_{t-1} + b_2 r_{t-2} + \epsilon_t \qquad \epsilon_t = h_t^{1/2} z_t$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}$$

$$z_t \sim N(0,1).$$

This model allows for an AR(2) process in returns. The specification was identified using the Schwartz(1978) criterion. Only the Japanese Yen series required the two lags, but for better comparisons across exchange rates the same model is used.[4] Estimation of this model is done using maximum likelihood.

Simulations of this model follow those for the random walk. Standardized residuals of the GARCH model are estimated as,

$$\frac{\epsilon_t}{\sqrt{h_t}}.$$

These residuals are then scrambled and the scrambled residuals are then used to rebuild a GARCH representation for the data series. Using the actual residuals for the simulations allows the residual distribution to differ from normality. Bollerslev and Woldridge(1990) have shown that the previous parameter estimates

[3] For more extensive descriptions of these results on exchange rates see Hsieh(1988,1989) and other references contained in Bollerslev et. al.(1990).

[4] Other specifications with changing conditional means related to volatility (GARCH-M) were also tried, but these turned out insignificant. This agrees with some of the results found in Domowitz and Hakio(1985).

will be consistent under certain deviations from normality. Therefore the estimated residuals will also be consistent.[5]

The third model has been proposed for foreign exchange markets in a paper by Engle and Hamilton(1990). It suggests that exchange rates follow long persistent swings following a 2 state markov chain. It is given by,

$$r_t = (\mu_0 + \mu_1 S_t) + (\alpha_0 + \alpha_1 S_t) z_t$$

$$P(S_t = 1 | S_{t-1} = 1) = p$$

$$P(S_t = 0 | S_{t-1} = 1) = 1 - p$$

$$P(S_t = 0 | S_{t-1} = 0) = q$$

$$P(S_t = 1 | S_{t-1} = 0) = 1 - q$$

$$z_t \sim N(0, 1).$$

This model allows both the mean and variance for exchange rate returns to move between two different states. Since this model is capable of generating persistent trends it presents a strong possibility for generating the results seen using the trading rules. Estimation is done using maximum likelihood. For this model the simulations will use normally distributed random numbers from a computer random number generator.

IV. Empirical Results

A. Data Summary

The data used in this paper are all from the EHRA macro data tape from the Federal Reserve Bank. Weekly exchange rates for the British Pound (BP), German Mark (DM), and Japanese Yen (JY) are sampled every Wednesday from January 1974 through February 1991 at 12:00pm EST.

Returns are created using log first differences of these weekly exchange rates quoted in dollars/fx. Table 1 presents some summary statistics for these return series. All three series show little evidence of skewness and are slightly leptokurtic. These properties are common for many high frequency asset returns series. The first 10 autocorrelations are given in the rows labeled, ρ_n. The Bartlett asymptotic standard error for these

[5] The convergence of the bootstrap distribution has not been shown for GARCH models. Brock, Lakonishok, and LeBaron(1990) use a similar technique for stock returns. Their results are supported through large computer simulations.

series is 0.033. The BP shows little evidence of any autocorrelation except for lags 4 and 8, while the DM shows some weak evidence of correlation, and the JY shows strong evidence for some autocorrelation. The Ljung-Box-Pierce statistics are shown on the last row. These are calculated for 10 lags and are distributed $\chi^2(10)$ under the null of i.i.d. The p-values are included for each in parenthesis. The BP and JY series reject independence while the DM series does not.

The interest rate series used are also from the EHRA macro data tape. For the dollar the weekly eurodollar rate is used. For the pound, the international money market call money rate is used. For the mark, the Frankfurt interbank call money rate is used, and for the yen, the Tokyo unconditional lender rate. Weekly rates are constructed expost from the compounded rates from Wednesday through Tuesday. These rates can only be viewed as proxies for the desirable situation of having a set of interest rates from the same offshore market at the same maturity. At this time that is not available.

B. Random Walk Comparisons

In this section simulations are performed comparing conditional moments from the technical trading rules with a bootstrapped random walk generated from the actual returns time series scrambled with replacement. Three moving average rules will be used, the 20 week, 30 week, and 50 week moving averages. These are fairly common lengths used by traders. We will see that the results are not very sensitive to the lengths used. The moving average rules force us to start the study after a certain number of weeks have gone by. For this paper all tests for all the rules begin after week fifty. This gives the same number of weekly observations for all three rules.

Table 2 presents the results comparing the actual series for the British Pound with 500 simulated random walks. Six comparison statistics are computed in this table. First, the column labeled Buy refers to the conditional mean during buy periods. This is,

$$m_b = (1/N_b)\sum_{t=0}^{N-1} r_{t+1} I_t^b,$$

where N_b are the number of buy signals in the sample and I_t^b is a indicator variable for a buy signal at time t. The second column, labeled σ_b, looks at the standard deviation of this same set of returns. This is,

$$\left((1/N_b)\sum_{t=0}^{N-1} (r_{t+1} - m_b)^2 I_t^b\right)^{1/2}.$$

This gives a simple idea of how risky the buy or sell periods might be, and tells us something about what is happening to conditional variances. The third column, labeled Fraction Buy, is just the fraction of buy weeks, N_b/N. The next two columns, Sell and σ_s repeat the previous descriptions for the sell periods. Let m_s be the mean during the sell periods. The final column, Buy-Sell, refers to the difference between the buy and sell means, $m_b - m_s$.

This table presents several results for each test. The first is the fraction of simulated random walks that generate a given statistic greater than that for the original series. This can be thought of as a simulated p-value. For the 20 week moving average rules this result is given in the first row of the table. For the BP series we see that 8 percent of the simulations generated a mean return greater than that from the actual series. The next row, Simulation Mean, shows the mean of m_b for the 500 simulated random walks, and the third row, Xrate Mean, shows m_b for the exchange rate series. For the BP series the table reports a mean 1 week buy return of 0.091 percent which is greater than the simulated mean of -0.012 percent. The simulations show that this difference is weakly significant with 8 percent of the simulations generating a m_b greater than 0.091 percent.

The second row shows the results for the standard deviations of the buy returns, σ_b. The column shows that 56 pecent of the simulations had standard deviations greater than that in the original series. This clearly shows no significant difference between the simulations and the original series. In other words, while the buys generate a larger mean they do not have a larger variance. The next column reports that the fraction of buys to sells for the actual series, row 3, is 0.486. This does not appear to be unusually large or small relative to the simulated random walks.

For the sells, m_s for the British pound series is -0.134 percent which compares with -0.014 percent for the simulation. Table 1 shows that 98 percent of the simulated random walks generated m_s statistics larger than -0.134 indicating that the sell period returns for the original series are unusually small when compared with the random walk. The next column, σ_s, shows that these returns are not different from the entire sample in terms of volatility.

The final column reports the difference $m_b - m_s$. For this rule the difference is about 0.2 percent, and none of the simulated random walks generated such a large difference between buy and sell returns.

The next 6 rows of the table repeat the same results for the other two rules, the 30 and 50 week moving average rules. The results for these rules are similar to the first two with the buy means unusually large and the sell means unusually small. There still appears to be no effect in volatility.[6]

The final set of tests perform a joint test based on all three rules. An average is taken for the statistics generated from each of the three rules. For the mean buys this would be,

$$m_b = 1/3\big(m_b(1,20) + m_b(1,30) + m_b(1,50)\big).$$

Finding the distribution of this statistic would require knowing the joint distribution across all the rules. The results for each rule are clearly far from independent so this would be a difficult job. With the simulated random walks the rules can now be compared with results for the same average statistics over the 500 simulated random walks. This section of the table shows that the pattern for each of the individual rules is repeated in the average rules.

A good question to ask at this point is how general these results are for different moving averages. This paper has used only 3 different moving average rules. These are chosen to be close to those used by actual traders. It is quite possible that there may be some data snooping problems here in that these rules have already been chosen because of their past performance in the data. This problem is partially accounted for in figure 1 which displays the buy-sell differences for several different lengths of moving averages. It is clear from this figure that the results are not overly sensitive to the length of the moving average chosen.

The next two tables, 3 and 4, repeat the results for the DM and JY series. Turning to the average rows we see very similar results to table 2. The buy-sell differences are large for both with p-values of 0.

For the JY series the standard deviations during the buy and sell periods are not unusually small or large. For the DM series some weak differences appear between the standard deviations during the buy and sell periods. For the average across the rules using the buy standard deviations the simulated p-value is 0.87, indicating that 87 percent of the simulations were more volatile than the actual exchange rate series. For the sells this value is 0.12, indicating that 12 percent of the simulations were more volatile than the original series. This shows some weak evidence that the buy periods were less volatile than average and the sells were more volatile than average. The results are pretty weak for the average rule, but checking the individual rules stronger rejections are found for the 30 and 50 week moving averages individually. This result moves

[6] This is generally the case for all the exchange rate tests used here. It differs from some of the results in Brock et. al. (1990) where stock returns were found to be more volatile during sell periods than during buy periods.

counter to a simple mean variance connection for the exchange rate from a dollar perspective. The higher conditional returns from the buy period should be compensating for more risk, but these results show that for the DM the risk (in terms of own standard deviation) is lower. While this is puzzling, measuring the riskiness of a foreign exchange series is more complicated than estimating the standard deviation, so strong conclusions about risk premia require more adequate modeling of the exact risk-return trade off.

Another check for changes in the conditional distributions of returns is performed in table 5. In this table skewness and kurtosis are estimated for the returns during the buy and sell periods. It is possible that these higher moments might give a better indication of the riskiness of returns during each of the periods. This table combines the results for the 3 series into one table. The individual tests are summarized with a single row entry giving their simulated p-value and the averages are presented in three rows for each exchange rate. This table shows little difference in the higher moments from the actual series buy and sell periods and their simulation counterparts.

Table 6 considers the stability of these results over various subsamples. It is quite possible that these rules may be picking up certain nonstationarities in the data series. The rules themselves are probably very good at checking for changes in regime. If these regime changes are relatively infrequent then splitting the sample into two and repeating the tests makes it less likely that the rules will detect any differences between the buy and sell periods. Table 6 presents results for such an experiment, where each series is broken in half and the previous random walk simulations are repeated for each subsample.

For the BP, the results are basically unchanged across the subsamples. However, the trading rule results look slightly less significant in the second subsample. The simulated p-value for the average buy-sell difference moves from 0 to 0.052. Also, the average buy-sell difference falls from 0.37 percent to 0.195 percent. The DM series shows similar results for the buy and sell means in the two different subsamples. The p-value for the average buy-sell difference moves from 0.004 in the first subsample to 0 in the second subsample. The average buy-sell difference increases from 0.26 percent to 0.34 percent. For the standard deviations the results look different. For the standard deviations, the small volatility during buy periods is coming entirely from the first subperiod. For the average standard deviations the p-value for σ_b is 0.994 for the first subsample and 0.330 for the second subsample. The results on σ_s also are much stronger during the first subsample with a p-value of 0.01 during the first subsample and 0.566 during the second subsample. The results for the JY series change very little from the first to the second subsample. The mean buy-sell difference falls from 0.4 percent to 0.3 percent. The p-value for this number goes from 0 to 0.012.

C. GARCH Comparisons

Table 7 shows the parameter estimates for GARCH(1,1)-AR(2) model for each of the 3 exchange rate series. The estimates show very similar estimates for the variance parameters, β and α_1, for the three exchange rate series. The AR(2) parameters show some significant persistence in exchange rate movements for all three series, but both the Yen and the Mark show a somewhat larger amount of persistence with both the AR(1), and AR(2) parameters significant.

Standardized residuals from this model are run back through the same model to generate simulated time series for the three exchange rate series. Results of these simulations are presented in table 8. This table shows that the GARCH model combined with the AR(2) causes some increase in the mean buys and some decrease in the mean sells. Most of this is probably coming from the persistence in the AR(2). However, the magnitude of these differences is not as great as that for the actual series.

For the BP the average buy-sell difference for the three tests is 0.07 percent which compares with 0.29 percent for the actual series. The simulated p-value here is 0.01. For the BP the GARCH model leaves the previous results unchanged. Also, there are no effects on volatility as previously mentioned.

For the DM and JY series the GARCH model has a slightly stronger effect. The simulations generate average buy-sell differences of 0.10 and 0.13 percent respectively. The "p-values" for these differences are now 0.054, and 0.028 respectively. The added persistence of the AR(2) has caused a large buy-sell difference for these series. While this does have a small impact on the results from the simulations the differences remain small relative to the buy-sell difference for the actual series.

D. Regime Shift Bootstrap

Some of the results for the GARCH model suggest that while this model is moving in the right direction, the persistence generated is not strong enough to generate the trading rule results that are seen in the data. The rules used continue to generate buy or sell signals after the price has cut through the moving average, not just in the neighborhood of the moving average.

Long range persistence could be generated using the regime shifting model used by Engle and Hamilton(1990). In this model conditional means and variances follow a two state markov process. The parameter estimates for this model are given in table 9. For only one of the three series, the JY, are both the conditional mean parameters significantly different from zere. For the BP series they are both insignificantly different from zero. There is also a sign pattern reversal on the JY series. For this series high variance periods are high mean periods. For the other two series this result is reversed.

It seems doubtful that the magnitudes of the regime shift parameters will be large enough to generate the conditional mean differences. For example, for the BP series the conditional mean for $S_t = 0$ is 0.05 percent, and for the $S_t = 1$ period it is -0.02 percent. It is difficult to see how this will generate a buy-sell spread of 0.29 percent. This is confirmed in table which shows the results for simulations of this model using a normal random number generator to generate errors. There is little evidence of this model capturing what the trading rules are picking up for any of the series. For the DM and BP series the buy-sell differences are actually negative. For all the series the "p-values" for the buy-sell differences are all close to zero.

This should not rule out this model in general, but at these relatively high frequencies (weekly) it does not seem to capture what is going on. There may be some numerical problems in estimation as the probabilities, p and q, are close to 1 at this time horizon. In Engle and Hamilton(1990) the conditional mean estimates are significant and larger than those found here. This may be due to the use of quarterly data. It remains to be seen whether other estimation techniques can help repair these results for the regime shift model.

E. Interest Rate Differentials

The use of the previous simple processes for foreign exchange movements ignores much of the information available in world financial markets. This section incorporates some of this information into further simulations.

The relation that will be used here is uncovered interest parity. This relation can be written as

$$E_t(s_{t+1}) - s_t = i_t - i_t^*,$$

where i and i^* are the domestic and foreign interest rates and s_t is the log of the exchange rate. In a risk neutral world the interest rate differential over the appropriate horizon should be equal to the expected drift of the exchange rate.

While uncovered parity, and theories closely related to it, have been rejected by several studies it is important to see if this long range persistent drift could be causing what the trading rules are picking up. For this test a model of the form,

$$s_{t+1} = s_t + i_t - i_t^* + \epsilon_t$$

where ϵ_t is i.i.d. noise will be used. One major problem is getting the interest rates and their timing correct. This is a problem which is extremely difficult to get exactly right. For the weekly exchange rates used here weekly eurorates would be the most useful series to have. This study is constrained by what is available on the EHRA tapes. For the dollar weekly eurorates are available at daily frequency and will be used as the risk free dollar rate for each week beginning at the close on Wednesday. Unfortunately, the other currencies do not have such rates available. The weekly rates are constructed from daily expost overnight rates from Wednesday to the following Tuesday. Assuming the expectations hypothesis holds at the very short end of the term structure,

$$i_{t,7} = \sum_{i=0}^{6} E_t i_{t+i,1}$$

or,

$$i_{t,7} = \sum_{i=0}^{6} i_{t+i,1} + e_t,$$

where $E_t(e_t) = 0$. The expected drift term $i_t - i_t^*$ is therefore $i_t - \tilde{i}^* + e_t$ and where $\tilde{i}^*$ is the expost rate constructed from the overnight rates. Therefore

$$s_{t+1} - s_t = i_t - \tilde{i}_t^* + \eta_t,$$

where $E_t(\eta_t) = 0$.

The time period studied is shortened due to data availability. For the BP and DM the series now start in January 1975, and for the JY the series begins in October 1977. The lengths of the BP, DM, and JY series are 832, 832, and 690 weeks respectively.

Rather than immediately adjusting these series for the interest differential, a slightly different approach is taken at first. Representative series of the form,

$$s_{t+1} = s_t + \mu_t + \epsilon_t$$

will be simulated. The drift, μ_t is obtained from the appropriate interest differential. An estimate of the residual series, $\hat{\epsilon}_t$ is obtained by removing the drift from the actual exchange rate changes. This is then scrambled with replacement, and a new series is generated using the original drift series and the scrambled residuals. This gives us representative exchange rate series reflecting the appropriate information from the interest rates.

These simulations are then run through the same trading rule tests run in previous sections. Results of these tests are presented in table 11. The results are comparable to those found for the random walk simulations in tables 2 through 4. For all three series none of the rules generate buy-sell differences which are as large as those generated from the original series. The adjustment for the interest differential appears to have had little effect on the trading rule results.

Table 12 repeats some of the earlier GARCH simulations accounting for interest differentials. In this case the more traditional approach of subtracting the expected drift from the exchange rate returns is done. A GARCH model is then fit to these "zero drift" terms and simulated back using scrambled standardized residuals as in section IV C. Comparing table 12 with table 8 shows very few differences. Adjusting the exchange rate series using the expected drift has very little impact on the GARCH simulations. The large (small) returns during buy (sell) are still not replicated well by the simulated null model.

F. Simulated Method of Moments Estimates

The previous tests have not incorporated the trading rule diagnostic tests into the estimation procedure. This section presents a method where the two can be brought together in one combined procedure.

One problem with the trading rule measures is that it is difficult to derive analytic results for these measures. One technique for estimating parameters using conditions which can only be simulated is simulated method of moments. This technique was developed for cross section data by McFadden(1989) and Pakes and Pollard(1989). It is extended to time series cases in Duffie and Singleton(1989) and Ingram and Lee(1991).

We will follow the procedure of fitting a linear process to the data using a set of moment conditions which includes the trading rules. The trading rules must first be modified to fit into a moment condition framework. Define r_t as the returns series of interest. Also, let p_t be the price at time t where

$$r_t = log(p_t) - log(p_{t-1}).$$

Again, use the moving average of length L at time t,

$$ma_t(L) = (1/L) \sum_{i=0}^{L-1} p_{t-i}.$$

One first guess for trading rule related moment might be,

$$E\{S(\frac{p_{t-1}}{ma_{t-1}})r_t\}$$

where $S(x) = 1$ if $x \geq 1$ and $S(x) = -1$ if $x < 1$. This will not do for simulated method of moments since the first derivatives of this moment will not necessarily be continuous in the parameters of the process r_t. The condition must be replaced with a "smooth substitute". The hyperbolic tangent does a good job of being just such a function.[7] Replace the above condition with

$$E\{tanh((1/\mu)(\frac{p_{t-1}}{ma_{t-1}} - 1))r_t\}.$$

This condition can now be added to a more standard set of moment conditions.[8]

The estimation procedure will attempt to fit an AR(2) to each of the exchange rate series. When using any method of moments estimator, choosing the moment conditions to use is not always a trivial procedure. Here, the choice of moments will follow the goal of trying to see whether a linear model does of good job of replicating some properties of the data (autocovariances) as well as the trading rule results. This goal does not intend to get the tightest estimates of the parameters on the model. For this reason the set of moment condtitions will be rather small relative to other studies. The actual data will be aligned to simulated data using the mean, variance, the first three lagged autocovariances, and one trading rule moment. This gives a total of six moment conditions. For the trading rule moment condition the 30 week moving average is used. The results are generally similar across the other rules.[9]

There are two final details left for estimation. The variance covariance matrix is estimated using the Newey-West(1987) weighting using 10 lags. The lag length has been moved from 5 to 50 and the results have not changed greatly. This is important for this case since the moving average may generate very long range dependence in the estimated moments. Lastly, the number of simulations is set to 50 times the sample size. For most of these series this gives simulation samples in the range of 40,000 to 45,000.

Results of the estimation are given in table 13. This table shows the estimated parameters and the chi-squared goodness of fit estimate for the AR(2). For the BP series the results show a weak, but insignificant

7

$$\tanh(x) = \frac{-e^{-x} + e^{x}}{e^{-x} + e^{x}}$$

8 This condition brings in the problem of a free parameter, μ. This parameter is set to 1/10 the standard deviation of the price-moving average ratio. Experiments with this parameter have show the results to be insensitive to changes in the paramater ranging from 1 to 1/100 standard deviations.

9 This technique also allows the use of several trading rule conditions simultaneously. Dependence across rules is captured in the variance covariance matrix.

AR(1) parameter combined with a rejection of the moment conditions as indicated by the χ^2 test. The AR(2) is not able to match up with both the covariances and the trading rule results. The next rows present results for similar estimation removing the trading rule moment condition. Similar parameter estimates are obtained but now the goodness of fit statistic is only significant at the 18 percent level. The trading rule condition has clearly added an important restriction for this time series.

The row labeled DM repeats this procedure for the DM series. In this case the model estimates two larger AR coefficients and the goodness of fit test is only significant at the 13 percent level. The AR(2) is not strongly rejected here. Part of the reason for this can be seen in table 1. There is some correlation in this series at the first two lags which allows the estimated AR coefficients to be larger. When the rule is removed the chi-square statistic still remains small with a significance level of 73 percent.

For the JY series the AR(2) specification is rejected at the 3 percent level. In this case the model is estimating the largest AR parameters of the three series. However, these appear to not be enough to match the trading rule condition. This is again demonstrated by removing this condition. After this is done the chi-squared statistic drops to 2.1 which has a significance level of 0.15. The next rows in the table repeat these results for the zero drift series. These series generate results similar to those for the original series.

The simulated method of moments procedure has added to the earlier results. The procedure rejected the simple linear specification for 2 of the 3 foreign exchange series. This rejection followed from a procedure that combined standard autocovariance moments with conditions based on the trading rules.

V. Economic significance of Trading Rule Profits

The tests run in the previous section have shown the moving average trading rules to be able to detect periods of high and low returns. These returns are statistically large when compared with several different stochastic processes for the exchange rate series. These results are interesting in attempting to model the exact dynamics in the foreign exchange market, but they do not give us the economic significance of these rules. This section will make an attempt to measure the trading rule results. Transactions costs and interest rates will be accounted for, and some attempts will be made to measure the riskiness of the strategies relative to other assets.

The moving average trading rules will be implemented as suggested by the previous tests. When the current price is above the long moving average a buy is indicated and when it is below a sell is indicated. The implementation tests performed here will concentrate on the 30 day moving average alone. When a buy is indicated in a currency the trader takes a long position in that currency and deposits this in foreign bonds. In the rules used here the trader also will borrow dollars and invest these funds in the foreign currency. The trader will take a 50% leveraged position.[10] This generally follows the procedure used in Dooley and Shafer(1983). Sweeney(1986) takes a slightly more cautious route of never borrowing and moving only from domestic bonds to foreign bonds conditional on the signal. This strategy leaves the trader exposed to foreign exchange risk only part of the time. There is obviously a continuous range of adjusting the leverage parameter which moves the outcome of the strategy both in terms of risk and return. In this study the 50% leverage strategy will used for comparability with other studies and for the purpose of risk comparisons with the stock market.

Trading is done once a week. When the rule signals a change in position a trade is made. Transactions costs are assumed to be 0.1 % of the size of the trade. This appears to be a reasonable estimate and is used in Dooley and Shafer(1983). Some studies are slightly above this number (Sweeney(1984) uses 1/8%), while others claim that this is a maximum for foreign exchange trading. The weekly eurodollar rate series and daily call money overnight rates are used again with compounding occurring at daily frequencies for the daily series. An interest rate differential of 3% per year is used to estimate the borrowing rates from the lending rates from the tape. This is probably an upper bound on the borrowing and lending spread and is estimated from the current prime rate - CD spread. Results will be compared with those from buying and holding stocks in the U.S. market. The CRSP value weighted index including dividends will be used to represent this asset. All tests begin in October 1977 and end in December 1989.

Table 14 presents some summary statistics comparing the results for the various assets. The row labeled BP gives the trading strategy for the pound. The table shows that the strategy executed 36 trades and yielded an average return of 16.7 percent per year continuously compounded. It had a weekly standard deviation over the period of 2.25 percent. The column labeled β estimates the CAPM beta for the dynamic strategy using the CRSP portfolio as the market proxy. While a static CAPM based only on domestic securities is probably not a good representation of risk it is still interesting to observe how correlated the strategy is with the stock market, and how much potential there is for diversification. For all currency strategies the β is negative and very close to zero. The last three columns present results for a buy and hold strategy in the foreign currency and bonds. For the pound this is 9.9 percent with a weekly standard deviation of 1.57

[10] This means that an investor with \$1 who receives a buy signal will borrow \$1 domestically and invest \$2 in the foreign currency. The reverse is followed for a sell.

percent. This should be compared with the return to only holding dollar bonds (reported in the last row) of 9.5 percent with a weekly standard deviation of 0.05 percent.

The next three rows present results for the DM, JY, and CRSP series respectively. All the series have similar standard deviation and beta risk characteristics. The DM underperforms CRSP by about 2.6 percent, and the JY exceeds the CRSP series by about 5 percent. In each case the strategies dramatically dominate the buy and hold portfolios.

Two currencies give returns in excess of the CRSP return. The important economic question is whether these dynamic strategies offer an important new security in terms of risk and return. This a difficult question to answer without an appropriate model for risk or the exact stochastic process for either foreign exchange or stocks. A fairly straight forward technique will be used to try to get some initial answers to this question. Returns will be measured over fixed horizons choosen at random out of the entire sample. In other words fix the horizon at 1 year and estimate returns at randomly choosen 1 year periods during the sample. This will generate a joint distribution of stock and exchange rate returns which can be compared.[11]

Results for 500 simulations at the 1 year horizon are presented in table 15. For the BP series the simulations gave an average annual return of 19.5 percent with a standard deviation of 13.7 percent. This compares with a return of 16.2 percent with a standard deviation of 18 percent for the CRSP series. The table also presents some other risk measures. The first, prob($< RF - 5$%), reports the estimated probability of getting a return of less than 5% below the risk free rate. This number attempts to capture some aspect of draw down risk. For the BP series this happens in 15 percent of the the simulations as compared with 29 percent for the CRSP series. The next column reports the probability of the exchange rate return falling below CRSP. This is 46 percent for the BP. The next column, T$<$RF, estimates the fraction of time that the compounded return on the strategy was below the compounded return on a risk free bond. For the BP series this is 34 percent. The final column reports the average beta and the standard deviation of the estimated beta across the simulations. Beta is estimated weekly for each simulation. This again shows that there is very little correlation between the strategy and the CRSP series. Results for the buy and hold strategy for the BP

[11] One drawback of this technique is that the first and last part of the series will be under represented in simulations. One solution might be to think of the series as rolling around back onto itself on a circle. However, this imposes a severe pasting together of disjoint parts of the series. Another solution might be to use the m-dependent bootstrap of Kunsch(1989). Both of these possibilities are left for the future. For the present the reader should realize that the simulation does not adequately sample some parts of the series.

are shown in the next row. This gives a mean return of 11.0 with a standard deviation of 15.7. Buy and hold falls below the dynamic strategy in mean return, and it shows little improvement in riskiness.

The distribution of these returns along with the CRSP distribution is shown in figure 2. These are the 1 year holding period simulated returns. This figure clearly shows strong evidence that the BP series may first order stochastically dominate its equivalent buy and hold position. The comparison with CRSP is more difficult, but the graph suggests that the pound strategy may second order stochastic dominate CRSP. Both these comparisons await more detailed statistical testing.[12]

Results for the DM series are given in the next two rows of table 15. This series gives a mean return less than CRSP with similar risk characteristics. Its returns are again much larger than the equivalent buy and hold strategy. Figure 3 plots the distribution for the DM strategies. There is again a clear indication that the strategy first order stochastically dominates the buy and hold strategy. No simple comparisons can be made between the DM strategy and CRSP.

Results for the JY are given in the next two rows. The JY outperforms CRSP by 6 percent and its buy and hold by 10 percent. It has a larger standard deviation, but its other risk measures are equivalent to CRSP. Figure 4 shows the distributions. Once again it appears that the strategy first order stochastically dominates buy and hold. The strategy appears close to first order dominating CRSP except for a small section. However, it shows strong evidence for second order stochastic dominance.

For all three currencies the betas are very low. This suggests the possibility for diversification. The next row in table 15, labeled CRSP+BP, presents results for a porfolio formed by starting out invested half in stocks and half in the BP dynamic strategy. The portfolio increases returns and reduces standard deviation over the original CRSP portfolio. It is easy to select an optimal portfolio using currencies determined by looking at the results expost. The next row tests a strategy that might have been followed had the investor not known the relatively poor performance of the DM. In this strategy wealth is split equally between a buy

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[12] First order stochastic dominance is obtained when

$$F(x) - G(x) \geq 0 \qquad \forall \qquad x$$

for the distribution functions F and G, where the inequality is strict over a set of positive measure. Any consumer prefering more to less will prefer the distribution G. Second order stochastic dominance is obtained when

$$\int_{-\infty}^{x} (F(s) - G(s))ds \geq 0 \qquad \forall \qquad x.$$

In this case only risk averse consumers will prefer G, Rothschild and Stiglitz(1970).

and hold CRSP portfolio and the dynamic portfolios. The half in the dynamic foreign exchange portfolios is split 1/3 to each currency. This strategy performs similarly to the BP+CRSP portfolio showing that there is probably little diversification gain across foreign exchange strategies themselves.

Results for all these strategies and CRSP are plotted in figure 5. The two dynamic strategies are close to each other and appear close to second order dominating the CRSP returns alone. This is consistent with the properties of the dynamic foreign exchange strategies which suggested that they were zero beta securities exhibiting similar risk-return characteristics to the stock portfolio.

These results are further tested in table 16. This table compares the previous distributions using a myopic 1 year investor with crra utility. The coefficient of relative risk aversion is set to 4. The table finds α that sets

$$Eu(\alpha W\tilde{R}_1) = Eu(W\tilde{R}_2),$$

$$u(x) = \frac{1}{(1-\gamma)}x^{1-\gamma},$$

where R_1 is the return given by the labels on the left side of the rows, and R_2 is the return given in the columns. For each currency it is clear that the this consumer would willing to give up close to 8 percent of the invested wealth to shift to the dynamic strategy from BH. Comparisons with CRSP suggest the consumer would be willing to give up 4-5 percent of wealth for each strategy except for the DM where CRSP is preferred. This improvement holds for the three exchange rate CRSP portfolio. The last column compares the diversified portfolio with each of the strategies. Interestingly, the portfolio shows little improvement over the BP and JY strategies separately.

Finding an optimal portfolio expost is not a confirmation of an inefficient market. It should always be easy to find portfolios which dominate the market portfolio in an expost data search. The evidence shows some performance improvements for currency and currency-stock portfolios when compared to the stock portfolio. This should be viewed with some caution as it awaits further statistical testing. All the trading rules do offer similar performance characteristics to the market portfolio with no beta risk. To the stock market investor wondering whether to speculate in the foreign exchange market the evidence at this point appears somewhat uncertain. However, for any economic agent whose job requires some amount of liquidity in various foreign exchange markets the recommendation is clear. These agents are comparing the risk free rates of return in all markets and will have to maintain some exposure to foreign exchange risk. There are very dramatic improvements in moving from buy and hold strategies to the trading rules for these agents.[13]

There are several problems that could move these conclusions in either direction. First, the data used may not represent interest rates that traders could actually use. Also, there may be some timing problems in terms of settlements. For example, the rules as implemented, assume that traders can get the closing price on the day of the signal. This may not always be the case. Also, settlement procedures are not considered here.[14] Finally, measurement of risk with respect to a U.S. stock portfolio probably misses much of the exposure to international portfolio risk that the exchange rate portfolios are exposed to. Estimating betas on a world portfolio or using a multifactor model might be more appropriate here.

There are some problems in the analysis which work in favor of the trading rules. First, the rules used are very simple compared to what most traders use. Also, most traders would operate at the daily frequency or higher.[15] Second, the comparison series, the CRSP index, may be difficult to obtain in practice. No attempt was made to adjust for transactions costs on this series even though using the CRSP index implies that dividends are being continuously reinvested. The ability of the average investor to track this index should be more carefully considered.

There has been some recent evidence that the usefulness of technical trading strategies has diminished over time (Sweeney and Surarjaras(1989)). To check the possibility of a trend in trading rule profits over time a plot is made of the trading rule returns measured over two year horizons for the three currencies rolling the horizon forward 1 quarter for each point plotted. This is plotted in figure 6. There is some evidence for a drop off in profits in recent years. However, when analyzing the entire series it is unclear whether this period is at all unusual. There have been earlier periods when the rules did not perform very well. The time period around 1982-1983 appears to have also been relatively poor. It is interesting that these might be periods in which the 2 year horizon is reaching into periods just after the Plaza Agreement when the dollar changed direction.

[13] This may explain the extensive use of technical trading advice by many market participants.

[14] An experiment was performed to test the robustness of the results to timing. The testing programs were modified so that investors could not get the interest rates at time t, but could get the rates given one day later. Results of this experiment are not presented since they are almost identical to those from the original series.

[15] Most of the rules used here were repeated at daily frequency with little change in the results.

VI. Conclusions

This paper has presented evidence supporting the premise that exchange rates do not follow a random walk. Moreover, these deviations are detected by simple moving average trading rules. These rules find that, in general, returns during buy periods are higher than returns during sell periods. Volatility appears to be indistinguishable during these two periods. Also, skewness and kurtosis show no discernible patterns over buy and sell periods.

These results are supportive of earlier work in Dooley and Shafer(1983), Schulmeister(1987), Sweeney(1986), Taylor(1980), Taylor(1986), and more recently Taylor(1990). These other authors perform extensive tests on the profitability of these tests and find that in general the rules make money even when adjusted for transactions costs, interest rate differentials, and very simple measures of risk.

In this paper the rules are first used as specification tests for several different processes. The GARCH, regime shifting, and interest rate adjusted models are unable to generate results consistent with the actual series. In each case it is still possible that a modified version of the model could be capable of generating results consistent with the actual data, but this awaits further experimentation. Two answers for these results are the following. First, it is possible that the series are nonstationary and are punctuated by strong changes in regime that cannot be captured by these simple models. Second, none of the models considered here allow for any connection between trend and volatility changes. This possibility is considered in Taylor(1986), and results in Bilson(1990), Kim(1989), and LeBaron(1990) suggest that there may be some connection.

The final section of the paper runs some experiments to test the economic significance of these results. The trading rules are implemented on the data as they would be used in practice. Estimates for transaction costs and interest rate spreads are used to measure the realized returns from the strategies. For the three currencies tested the trading rule strategies generated return distributions similar to those from the CRSP stock index with very low correlation with the market. This suggests portfolios formed by combining the strategies with the CRSP index may dominate the stock index on its own.

While these results are interesting they should still be viewed with some caution. There are still several interest rate and timing issues that are not exactly worked out. Also, the use of other risk factors than CAPM beta may be important. As in any trading rules test there are further questions about the parameters used and whether the prices used were actually tradeable. Given these issues and the lack of a statistical test on the distribution comparisons the results can not be taken as clear evidence that every economic agent is missing a big opportunity. However, for one group of agents the results are pretty strong. For people who are involved in foreign exchange markets, either in trading goods or securities, and who maintain positions in foreign currencies there appear to be major gains over buy and hold strategies. This is easily seen in table 15 by comparing the buy and hold strategies with those for the rules. This may explain the large number of technical trading services available in the foreign exchange market.[16]

The results in this paper may eventually lead to some better explanations for several effects in foreign exchange markets. Among these are the movements in forward and futures markets for foreign exchange.[17] Also, results from survey data found in Dominguez(1986) and Frankel and Froot(1990) may be relevant to some of the results found here.[18] Lastly, foreign exchange markets differ from stock markets in that central banks play an important role. The behavior of these large economic agents may differ greatly from that of ordinary traders. These agents may even be willing to lose money to satisfy other objectives.

This paper has shown that technical trading rules may provide a useful specification test for examining foreign exchange markets. This paper uses these rules to demonstrate some of the shortcomings of common parametric models for foreign exchange movements. Some evidence is given on the economic significance of these results, and shows that the strategies generate returns similar to those from a domestic stock portfolio. Further tests will be necessary to completely answer the questions raised about the economic significance of these results.

[16] See Frankel and Froot(1990) for some evidence on the number of chartists.

[17] See Hodrick(1987) for a survey of these results.

[18] These papers, using survey data, find that short range forecasts are more trend following while longer range forecast are more mean reverting.

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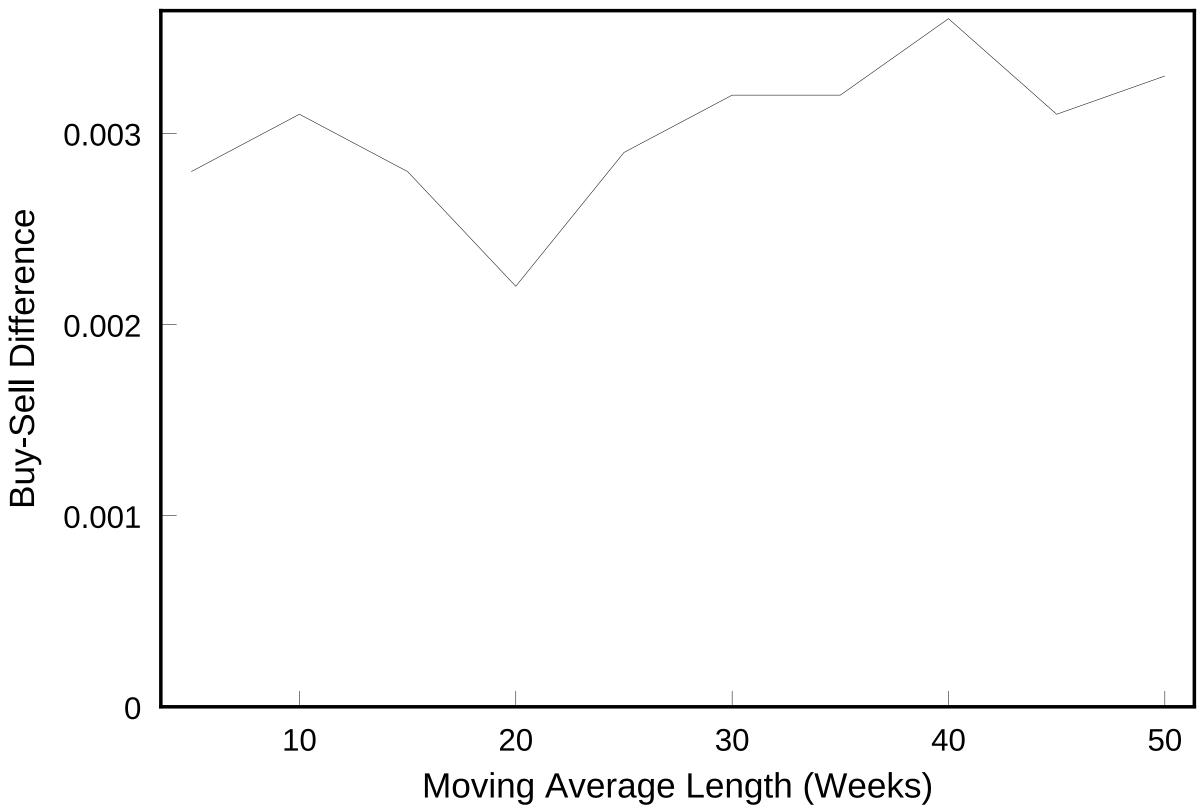

Figure 1: British Pound Buy-Sell Differences

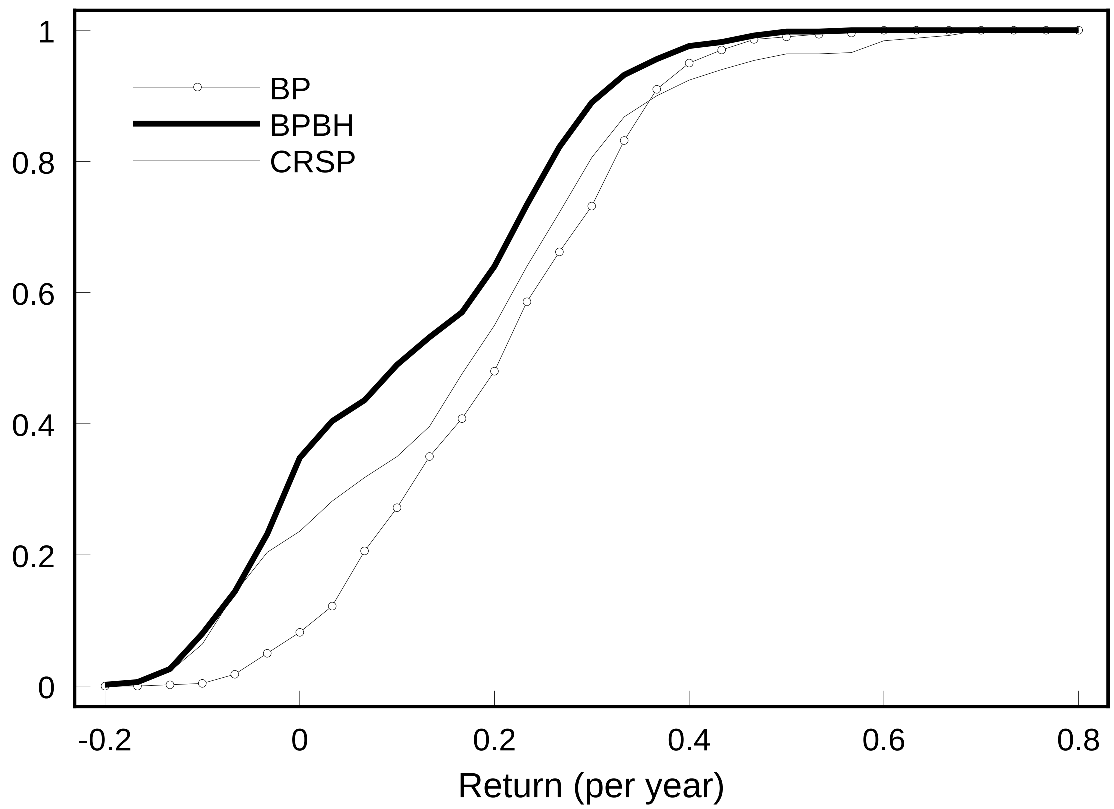

Figure 2: Simulated Return Distribution - 1 Year Period

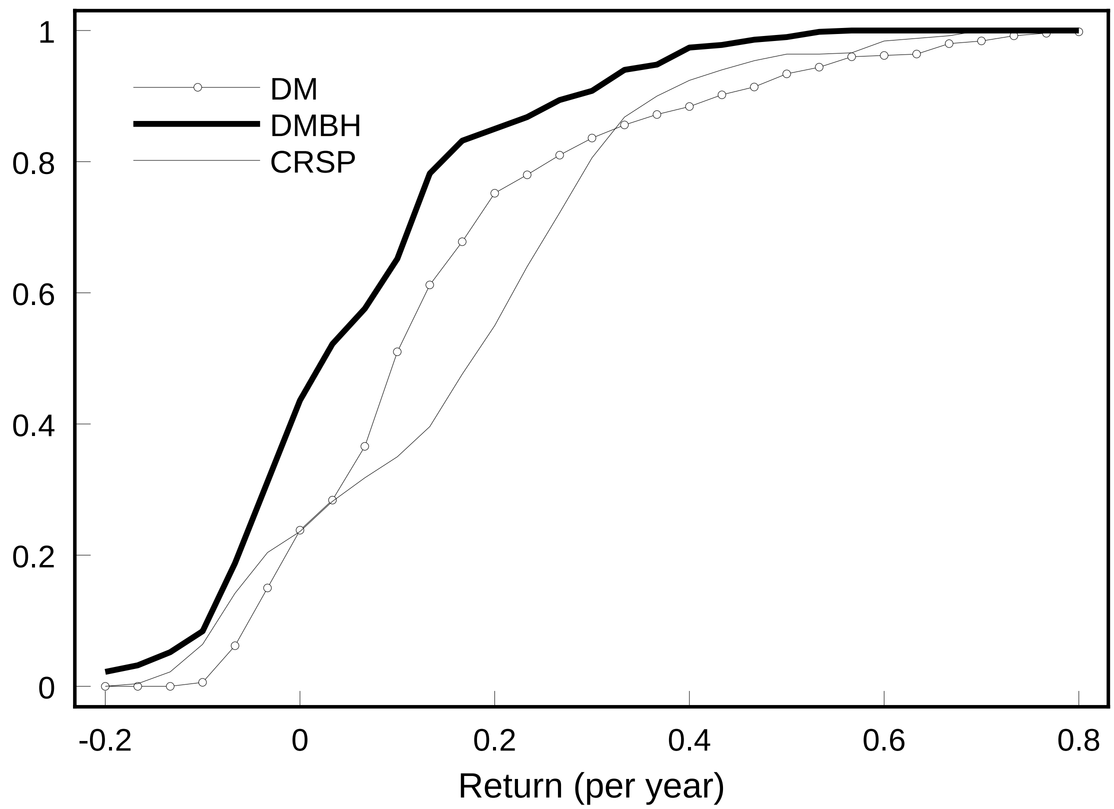

Figure 3: Simulated Return Distribution - 1 Year Period

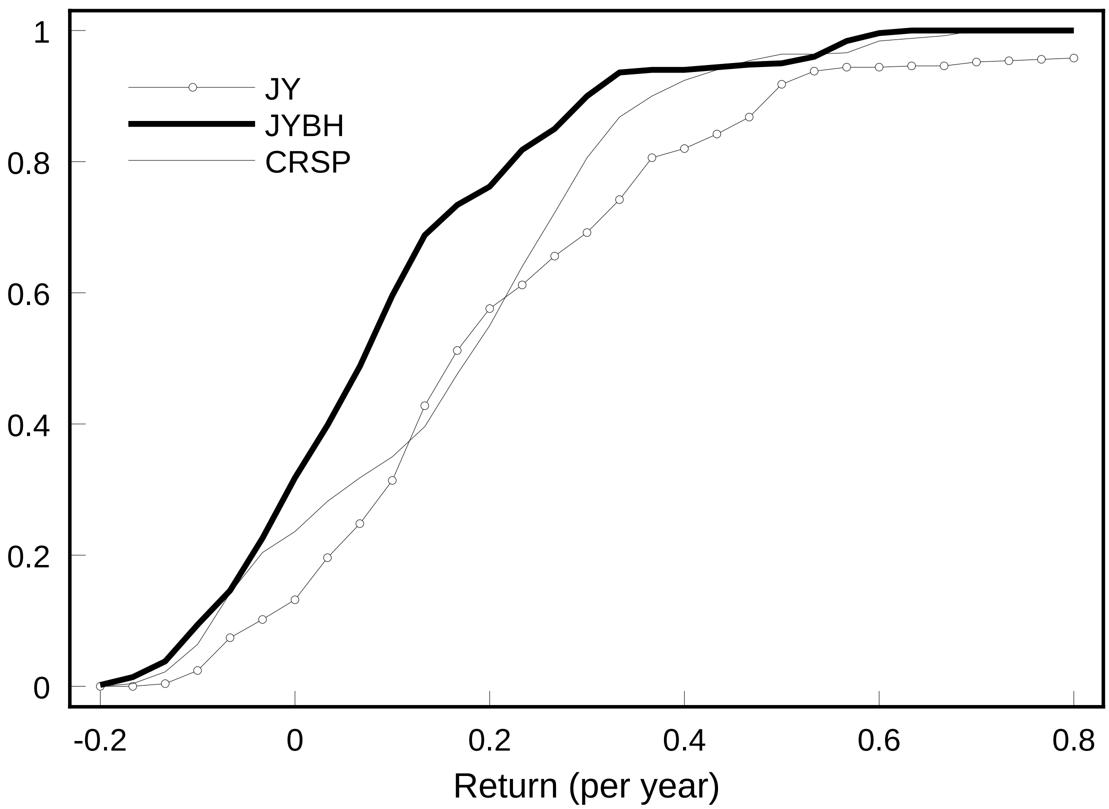

Figure 4: Simulated Return Distribution - 1 Year Period

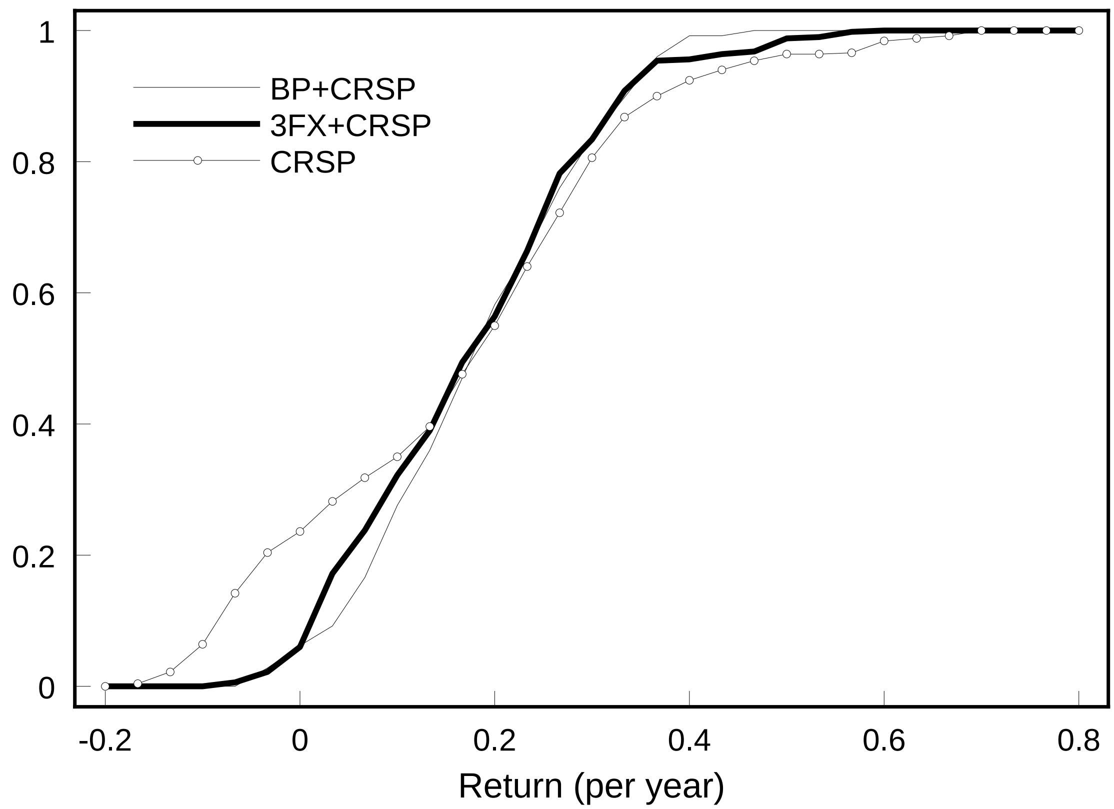

Figure 5: Simulated Return Distribution - 1 Year Period

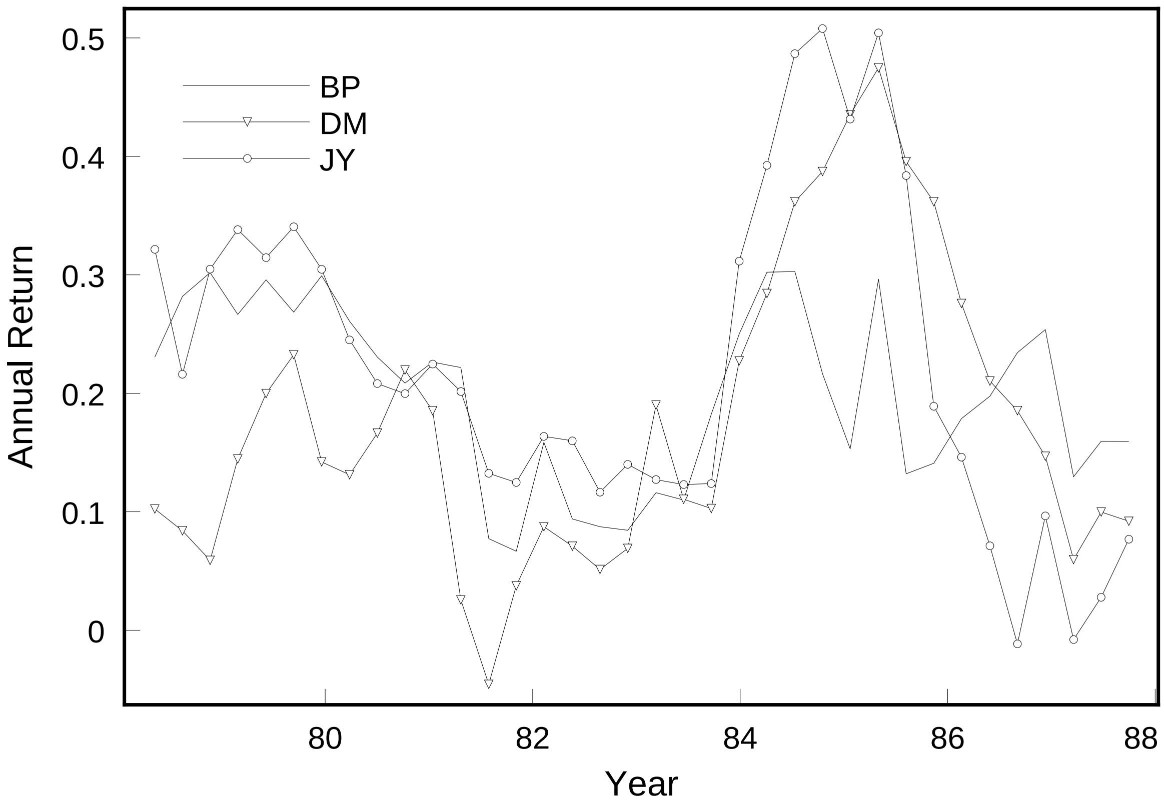

Figure 6: Rolling Strategy Returns: 2 Year Periods

Table 1
Summary Statistics

Description	BP	DM	JY
Sample Size	893	893	893
Mean*100	-0.0162	0.0686	0.0875
Std.*100	1.4398	1.4350	1.4012
Skewness	0.2107	0.3532	0.3785
Kurtosis	5.5931	4.3735	5.1425
ρ_1	0.0488	0.0636	0.1105
ρ_2	-0.0248	0.0609	0.0962
ρ_3	0.0367	0.0060	0.0592
ρ_4	0.0959	0.0414	0.0446
ρ_5	0.0164	-0.0200	0.0338
ρ_6	-0.0135	-0.0570	-0.0002
ρ_7	0.0070	-0.0028	-0.0359
ρ_8	0.0862	0.0625	0.0060
ρ_9	-0.0305	0.0146	-0.0036
ρ_{10}	-0.0047	0.0414	-0.0833
Bartlett	0.0335	0.0335	0.0335
LBP	20.16	15.53	26.41
p-values $(\chi^2(10))$	(0.027)	(0.115)	(0.003)

Summary statistics for BP (British Pound), DM (German Mark), JY (Japanese Yen) weekly exchange rates from 1974-February 1991.

Table 2
BP Random Walk Bootstrap

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
(1,20)	Fraction > Xrate	0.08000	0.56000	0.46000	0.98000	0.42000	0.00000
	Simulation Mean	-0.00012	0.01434	0.47810	-0.00014	0.01429	0.00002
	Xrate Mean	0.00091	0.01426	0.48624	-0.00134	0.01442	0.00225
(1,30)	Fraction > Xrate	0.01000	0.63000	0.34000	1.00000	0.37000	0.00000
	Simulation Mean	-0.00018	0.01438	0.47364	-0.00010	0.01427	-0.00007
	Xrate Mean	0.00135	0.01421	0.50406	-0.00184	0.01452	0.00319
(1,50)	Fraction > Xrate	0.01000	0.64000	0.37000	1.00000	0.18000	0.00000
	Simulation Mean	-0.00019	0.01436	0.46809	-0.00011	0.01425	-0.00009
	Xrate Mean	0.00145	0.01410	0.49466	-0.00182	0.01487	0.00327
Average	Fraction > Xrate	0.01000	0.66000	0.39000	0.99000	0.32000	0.00000
	Simulation Mean	-0.00016	0.01436	0.47333	-0.00012	0.01427	-0.00005
	Xrate Mean	0.00124	0.01419	0.49496	-0.00166	0.01460	0.00290

Buy refers to the mean 1 week return during buy periods, σ_b, the standard deviation of these returns, and Fraction Buy is the fraction of buy weeks out of total weeks. Sell and σ_s are the same for the sell returns. Buy-Sell is the difference between the buy mean and sell mean. The row labeled Fraction $>$ Xrate shows the fraction of the 500 simulations which generate a value for the statistic larger than that from the actual series. Simulation mean is the mean value for the statistic for the simulated random walks, and Xrate Mean is the value from the original series.

Table 3
DM Random Walk Bootstrap

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
(1,20)	Fraction > Xrate	0.03000	0.68000	0.32000	0.99000	0.31000	0.00000
	Simulation Mean	0.00070	0.01431	0.56273	0.00065	0.01422	0.00005
	Xrate Mean	0.00177	0.01398	0.58601	-0.00112	0.01454	0.00288
(1,30)	Fraction > Xrate	0.04000	0.90000	0.27000	1.00000	0.08000	0.00000
	Simulation Mean	0.00067	0.01434	0.57816	0.00070	0.01421	-0.00003
	Xrate Mean	0.00169	0.01352	0.61877	-0.00112	0.01526	0.00281
(1,50)	Fraction > Xrate	0.05000	0.96000	0.55000	0.96000	0.01000	0.00000
	Simulation Mean	0.00069	0.01434	0.60050	0.00066	0.01417	0.00003
	Xrate Mean	0.00164	0.01330	0.59786	-0.00095	0.01555	0.00259
Average	Fraction > Xrate	0.03000	0.87000	0.43000	1.00000	0.12000	0.00000
	Simulation Mean	0.00068	0.01433	0.58024	0.00067	0.01420	0.00002
	Xrate Mean	0.00170	0.01360	0.60085	-0.00106	0.01512	0.00276

Table 4
JY Random Walk Bootstrap

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
(1,20)	Fraction > Xrate	0.00000	0.52000	0.73000	1.00000	0.59000	0.00000
	Simulation Mean	0.00087	0.01395	0.59132	0.00100	0.01392	-0.00013
	Xrate Mean	0.00250	0.01388	0.54817	-0.00114	0.01368	0.00363
(1,30)	Fraction > Xrate	0.00000	0.49000	0.79000	1.00000	0.53000	0.00000
	Simulation Mean	0.00089	0.01397	0.61437	0.00100	0.01388	-0.00012
	Xrate Mean	0.00260	0.01391	0.55156	-0.00116	0.01372	0.00376
(1,50)	Fraction > Xrate	0.01000	0.40000	0.74000	0.98000	0.45000	0.00000
	Simulation Mean	0.00086	0.01393	0.64814	0.00105	0.01392	-0.00018
	Xrate Mean	0.00213	0.01402	0.59431	-0.00071	0.01397	0.00284
Average	Fraction > Xrate	0.00000	0.47000	0.72000	1.00000	0.52000	0.00000
	Simulation Mean	0.00087	0.01395	0.61761	0.00102	0.01390	-0.00014
	Xrate Mean	0.00241	0.01394	0.56439	-0.00100	0.01379	0.00341

Table 5
Skewness Kurtosis

Rule	Result	Buy Skew	Buy Kurt.	Sell Skew	Sell Kurt. 1
BP					
(1,20)	Fraction > Xrate	0.57200	0.26600	0.33600	0.48000
(1,30)	Fraction > Xrate	0.50400	0.30600	0.42200	0.48800
(1,50)	Fraction > Xrate	0.61800	0.33000	0.26600	0.48000
Average	Fraction > Xrate	0.56400	0.29600	0.32600	0.48000
	Simulation Mean	0.19899	5.41680	0.21749	5.45927
	Xrate Mean	0.13446	5.94169	0.33541	5.51124
DM					
(1,20)	Fraction > Xrate	0.32800	0.20200	0.44600	0.61800
(1,30)	Fraction > Xrate	0.30000	0.16800	0.35400	0.66600
(1,50)	Fraction > Xrate	0.30600	0.07600	0.34600	0.79800
Average	Fraction > Xrate	0.31200	0.13600	0.35000	0.72400
	Simulation Mean	0.34152	4.28222	0.35344	4.27991
	Xrate Mean	0.44344	5.55364	0.39410	3.43740
JY					
(1,20)	Fraction > Xrate	0.34000	0.52800	0.31400	0.62000
(1,30)	Fraction > Xrate	0.36400	0.52400	0.33400	0.62800
(1,50)	Fraction > Xrate	0.35400	0.54200	0.39200	0.70800
Average	Fraction > Xrate	0.33000	0.53000	0.34600	0.66800
	Simulation Mean	0.38354	5.08946	0.40757	5.05235
	Xrate Mean	0.49069	4.96434	0.54188	4.63171

Table 6
Subsamples: Random Walk

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
BP First Half							
(1,20)	Fraction $>$ Xrate	0.02200	0.97600	0.16000	0.99800	0.09000	0.00200
(1,30)	Fraction $>$ Xrate	0.01200	0.94600	0.10600	0.99800	0.05800	0.00000
(1,50)	Fraction $>$ Xrate	0.01000	0.88800	0.12400	1.00000	0.05200	0.00000
Average	Fraction $>$ Xrate	0.00600	0.95200	0.11800	1.00000	0.06400	0.00000
	Simulation Mean	-0.00080	0.01168	0.39614	-0.00059	0.01172	-0.00022
	Xrate Mean	0.00103	0.01025	0.51048	-0.00267	0.01288	0.00370
BP Second Half							
(1,20)	Fraction $>$ Xrate	0.20600	0.20000	0.61200	0.69400	0.69400	0.18400
(1,30)	Fraction $>$ Xrate	0.07000	0.24400	0.46200	0.83400	0.64800	0.05000
(1,50)	Fraction $>$ Xrate	0.07400	0.36600	0.49800	0.80400	0.51000	0.04400
Average	Fraction $>$ Xrate	0.09400	0.24600	0.51800	0.78800	0.63000	0.05200
	Simulation Mean	0.00011	0.01647	0.52470	0.00050	0.01652	-0.00038
	Xrate Mean	0.00148	0.01719	0.51900	-0.00047	0.01609	0.00195
DM First Half							
(1,20)	Fraction $>$ Xrate	0.10800	0.96000	0.18000	0.99200	0.05800	0.00800
(1,30)	Fraction $>$ Xrate	0.19600	0.99600	0.12200	0.96600	0.00800	0.02000
(1,50)	Fraction $>$ Xrate	0.13400	0.99600	0.20600	0.99400	0.00200	0.00600
Average	Fraction $>$ Xrate	0.13400	0.99400	0.17400	0.99200	0.01000	0.00400
	Simulation Mean	0.00008	0.01259	0.52143	0.00026	0.01265	-0.00018
	Xrate Mean	0.00101	0.01067	0.61935	-0.00164	0.01476	0.00264
DM Second Half							
(1,20)	Fraction $>$ Xrate	0.10400	0.25400	0.45000	0.95000	0.69800	0.03000
(1,30)	Fraction $>$ Xrate	0.04600	0.39200	0.45400	0.99600	0.60000	0.00200
(1,50)	Fraction $>$ Xrate	0.04000	0.40000	0.73400	0.94800	0.41600	0.00600
Average	Fraction $>$ Xrate	0.04800	0.33000	0.56200	0.98600	0.56600	0.00000
	Simulation Mean	0.00103	0.01569	0.62656	0.00141	0.01577	-0.00037
	Xrate Mean	0.00255	0.01599	0.60792	-0.00084	0.01549	0.00339

Table 6 continued

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
JY First Half							
(1,20)	Fraction > Xrate	0.00200	0.75400	0.52800	0.99800	0.51600	0.00200
(1,30)	Fraction > Xrate	0.00000	0.78200	0.53600	0.99800	0.41400	0.00000
(1,50)	Fraction > Xrate	0.01200	0.79200	0.41000	0.98200	0.21000	0.00000
Average	Fraction > Xrate	0.00000	0.79200	0.48800	0.99800	0.33000	0.00000
	Simulation Mean	0.00007	0.01246	0.52896	0.00039	0.01243	-0.00032
	Xrate Mean	0.00217	0.01178	0.53548	-0.00185	0.01274	0.00402
JY Second Half							
(1,20)	Fraction > Xrate	0.10000	0.43200	0.69000	0.95800	0.90800	0.01600
(1,30)	Fraction > Xrate	0.11400	0.46400	0.79800	0.94000	0.91400	0.03200
(1,50)	Fraction > Xrate	0.08200	0.26000	0.80200	0.96400	0.94200	0.01400
Average	Fraction > Xrate	0.08800	0.38600	0.77200	0.97200	0.95000	0.01200
	Simulation Mean	0.00139	0.01521	0.67445	0.00185	0.01532	-0.00046
	Xrate Mean	0.00262	0.01550	0.60469	-0.00033	0.01355	0.00295

Table 7
GARCH(1,1) Parameter Estimates

$$x_t = a + b_1 x_{t-1} + b_2 x_{t-2} + \epsilon_t \qquad \epsilon_t = h_t^{1/2} z_t$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}$$

$$z_t \sim N(0,1)$$

Xrate	α_0	β	α_1	b_1	b_2	a
BP	2.2940	0.7287	0.1680	0.0832	0.0324	-3.4473
	(0.3504)	(0.0363)	(0.0303)	(0.0391)	(0.0393)	(4.5733)
DM	1.4131	0.7539	0.1889	0.0604	0.0935	6.8368
	(0.3480)	(0.0319)	(0.0289)	(0.0378)	(0.0349)	(4.2092)
JY	1.3460	0.7610	0.1875	0.1179	0.0832	6.3114
	(0.2403)	(0.0321)	(0.0308)	(0.0380)	(0.0389)	(4.1427)

Estimation is by maximum likelihood. Numbers in parenthesis are asymptotic standard errors.

Table 8
GARCH Bootstrap

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
BP							
(1,20)	Fraction $>$ Xrate	0.17600	0.55200	0.39400	0.81800	0.53000	0.09400
(1,30)	Fraction $>$ Xrate	0.04800	0.57400	0.27600	0.95800	0.50400	0.00800
(1,50)	Fraction $>$ Xrate	0.02000	0.58800	0.30400	0.97000	0.42400	0.00800
Average	Fraction $>$ Xrate	0.05600	0.57000	0.31600	0.94400	0.48600	0.01000
	Simulation Mean	0.00008	0.01474	0.46559	-0.00058	0.01492	0.00066
	Xrate Mean	0.00124	0.01419	0.49496	-0.00166	0.01460	0.00290
DM							
(1,20)	Fraction $>$ Xrate	0.28400	0.78200	0.40400	0.92800	0.64600	0.07600
(1,30)	Fraction $>$ Xrate	0.25800	0.85800	0.32200	0.94200	0.49400	0.07000
(1,50)	Fraction $>$ Xrate	0.23200	0.87800	0.55600	0.93400	0.42200	0.05000
Average	Fraction $>$ Xrate	0.25000	0.85000	0.42600	0.94400	0.52200	0.05400
	Simulation Mean	0.00122	0.01582	0.58933	0.00021	0.01558	0.00101
	Xrate Mean	0.00170	0.01360	0.60085	-0.00106	0.01512	0.00276
JY							
(1,20)	Fraction $>$ Xrate	0.13400	0.73400	0.68200	0.92000	0.64200	0.04600
(1,30)	Fraction $>$ Xrate	0.08600	0.71800	0.73800	0.94400	0.60600	0.02600
(1,50)	Fraction $>$ Xrate	0.13200	0.67000	0.63400	0.89600	0.56800	0.03800
Average	Fraction $>$ Xrate	0.11400	0.71000	0.69200	0.93200	0.60200	0.02800
	Simulation Mean	0.00146	0.01611	0.59672	0.00016	0.01519	0.00130
	Xrate Mean	0.00241	0.01394	0.56439	-0.00100	0.01379	0.00341

Results from simulations of 500 GARCH models. These models are generated from estimated parameters and standardized residuals from maximum likelihood.

Table 9
Regime Shift Parameter Estimates

$$x_t = (\mu_0 + \mu_1 S_t) + (\alpha_0 + \alpha_1 S_t) z_t$$
$$P(S_t = 1 | S_{t-1} = 1) = p$$
$$P(S_t = 0 | S_{t-1} = 1) = 1 - p$$
$$P(S_t = 0 | S_{t-1} = 0) = q$$
$$P(S_t = 1 | S_{t-1} = 0) = 1 - q$$
$$z_t \sim N(0,1)$$

Xrate	$\alpha_0 * 1000$	$\alpha_1 * 1000$	$\mu_0 * 1000$	$\mu_1 * 1000$	p	q
BP	2.7811	12.2139	0.4923	-0.7119	0.9933	0.9260
	(0.2447)	(0.3578)	(0.3851)	(0.6374)	(0.0033)	(0.0342)
DM	6.7422	9.0407	1.1889	-0.6388	0.9940	0.9738
	(0.4188)	(0.5350)	(0.5313)	(0.7815)	(0.0034)	(0.0136)
JY	4.8973	11.8531	-0.7646	2.4587	0.9387	0.8773
	(0.2892)	(0.5093)	(0.3632)	(0.7655)	(0.0157)	(0.0266)

Estimation is by maximum likelihood. Numbers in parenthesis are asymptotic standard errors.

Table 10
Regime Shift Bootstrap

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
BP							
(1,20)	Fraction > Xrate	0.04800	0.48200	0.53800	0.97200	0.56600	0.02000
(1,30)	Fraction > Xrate	0.00400	0.51200	0.39400	0.99400	0.49400	0.00200
(1,50)	Fraction > Xrate	0.00400	0.62000	0.42400	0.99800	0.27000	0.00000
Average	Fraction > Xrate	0.00800	0.53000	0.43000	0.99400	0.44200	0.00000
	Simulation Mean	-0.00025	0.01420	0.48442	-0.00007	0.01449	-0.00018
	Xrate Mean	0.00124	0.01419	0.49496	-0.00166	0.01460	0.00290
DM							
(1,20)	Fraction > Xrate	0.03600	0.53200	0.53800	0.99600	0.60000	0.00000
(1,30)	Fraction > Xrate	0.04200	0.70000	0.43400	0.99600	0.32600	0.00600
(1,50)	Fraction > Xrate	0.05600	0.78000	0.64400	0.98200	0.23000	0.00800
Average	Fraction > Xrate	0.02800	0.68400	0.55200	0.99400	0.37000	0.00000
	Simulation Mean	0.00064	0.01405	0.60895	0.00080	0.01481	-0.00016
	Xrate Mean	0.00170	0.01360	0.60085	-0.00106	0.01512	0.00276
JY							
(1,20)	Fraction > Xrate	0.00800	0.73400	0.64200	1.00000	0.42800	0.00000
(1,30)	Fraction > Xrate	0.00400	0.65000	0.73200	0.99800	0.45200	0.00000
(1,50)	Fraction > Xrate	0.02400	0.57200	0.66600	0.97800	0.41200	0.00400
Average	Fraction > Xrate	0.00400	0.63000	0.68400	0.99600	0.42200	0.00200
	Simulation Mean	0.00089	0.01422	0.59701	0.00087	0.01364	0.00002
	Xrate Mean	0.00241	0.01394	0.56439	-0.00100	0.01379	0.00341

Results from simulations of 500 regime-shift models. These models are generated from estimated parameters and computer generated normal random numbers.

Table 11
Interest Rate Drift

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
BP							
(1,20)	Fraction > Xrate	0.01200	0.31200	0.40600	0.98200	0.65000	0.00200
(1,30)	Fraction > Xrate	0.01000	0.61600	0.28400	0.99200	0.29600	0.00000
(1,50)	Fraction > Xrate	0.00600	0.71400	0.32800	0.99400	0.15200	0.00000
Average	Fraction > Xrate	0.00600	0.55200	0.32000	0.99400	0.33000	0.00000
	Simulation Mean	-0.00014	0.01468	0.47660	-0.00011	0.01461	-0.00002
	Xrate Mean	0.00155	0.01457	0.50731	-0.00165	0.01491	0.00320
DM							
(1,20)	Fraction > Xrate	0.03200	0.46200	0.54400	0.99000	0.60600	0.00400
(1,30)	Fraction > Xrate	0.11000	0.75600	0.54000	0.96000	0.21200	0.02400
(1,50)	Fraction > Xrate	0.04600	0.82200	0.75000	0.97200	0.16600	0.00800
Average	Fraction > Xrate	0.04000	0.70400	0.63000	0.98200	0.29400	0.00400
	Simulation Mean	0.00028	0.01541	0.53898	0.00048	0.01544	-0.00020
	Xrate Mean	0.00157	0.01505	0.51050	-0.00135	0.01582	0.00292
JY							
(1,20)	Fraction > Xrate	0.02200	0.35400	0.76200	0.99600	0.63800	0.00200
(1,30)	Fraction > Xrate	0.00200	0.35000	0.86600	0.99600	0.66400	0.00000
(1,50)	Fraction > Xrate	0.12400	0.57600	0.81200	0.97800	0.59400	0.01200
Average	Fraction > Xrate	0.02400	0.42400	0.81400	0.99200	0.64200	0.00000
	Simulation Mean	0.00077	0.01521	0.59642	0.00098	0.01533	-0.00021
	Xrate Mean	0.00226	0.01531	0.52717	-0.00121	0.01502	0.00348

Results from simulations of 500 replications of series generated with conditional drift equal to given interest rate differentials. $r_t = \mu_t + \epsilon_t$ where μ_t corresponds to the interest rate differential at time t.

Table 12
GARCH Zero Drift

Rule	Result	Buy	σ_b	Fraction Buy	Sell	σ_s	Buy-Sell
BP							
(1,20)	Fraction > Xrate	0.06400	0.36800	0.36200	0.90200	0.66000	0.03600
(1,30)	Fraction > Xrate	0.03000	0.51400	0.27800	0.93400	0.42000	0.00600
(1,50)	Fraction > Xrate	0.01400	0.54800	0.34200	0.97800	0.33200	0.00400
Average	Fraction > Xrate	0.02400	0.48000	0.31800	0.94400	0.44400	0.00600
	Simulation Mean	0.00051	0.01480	0.51214	-0.00035	0.01519	0.00085
	Xrate Mean	0.00197	0.01462	0.54196	-0.00149	0.01502	0.00346
DM							
(1,20)	Fraction > Xrate	0.15600	0.69800	0.27000	0.91600	0.60800	0.05000
(1,30)	Fraction > Xrate	0.13800	0.79200	0.18200	0.89400	0.48600	0.05400
(1,50)	Fraction > Xrate	0.03400	0.78800	0.38800	0.95000	0.46600	0.00800
Average	Fraction > Xrate	0.09200	0.76200	0.29800	0.92400	0.52600	0.02600
	Simulation Mean	0.00052	0.01576	0.47758	-0.00069	0.01513	0.00121
	Xrate Mean	0.00159	0.01385	0.51942	-0.00176	0.01462	0.00335
JY							
(1,20)	Fraction > Xrate	0.02400	0.36000	0.56800	0.96200	0.52800	0.00600
(1,30)	Fraction > Xrate	0.01600	0.43600	0.55600	0.97000	0.47800	0.00200
(1,50)	Fraction > Xrate	0.19400	0.35200	0.59800	0.93200	0.63600	0.04000
Average	Fraction > Xrate	0.05000	0.37200	0.57600	0.97000	0.54600	0.00000
	Simulation Mean	0.00060	0.01522	0.49250	-0.00052	0.01513	0.00112
	Xrate Mean	0.00201	0.01543	0.47334	-0.00193	0.01499	0.00394

Results from simulations of 500 GARCH models. These models are generated from estimated parameters and standardized residuals from maximum likelihood. Models are estimated and simulated using foreign exchange returns series with interest rate differentials removed.

Table 13
SMM Estimation

$$r_t = \mu + \rho_1(r_{t-1} - \mu) + \rho_2(r_{t-2} - \mu) + \sigma\epsilon_t$$
$$\epsilon_t \sim N(0, 1)$$

Series	Condition	μ	σ	ρ_1	ρ_2	χ^2
BP	Rule	-0.046	1.407	0.043	-0.017	8.261
		(0.054)	(0.074)	(0.035)	(0.041)	(0.016)
BP	No Rule	-0.023	1.450	0.031	-0.029	1.793
		(0.057)	(0.073)	(0.034)	(0.039)	(0.181)
DM	Rule	0.099	1.410	0.051	0.042	3.989
		(0.052)	(0.061)	(0.031)	(0.043)	(0.136)
DM	No Rule	0.071	1.427	0.052	0.045	0.120
		(0.054)	(0.062)	(0.031)	(0.043)	(0.729)
JY	Rule	0.152	1.364	0.104	0.103	6.819
		(0.055)	(0.062)	(0.039)	(0.042)	(0.033)
JY	No Rule	0.125	1.405	0.100	0.088	2.066
		(0.059)	(0.062)	(0.039)	(0.040)	(0.150)
BPZD	Rule	0.075	1.463	0.063	-0.017	8.540
		(0.059)	(0.078)	(0.035)	(0.041)	(0.014)
BPZD	No Rule	0.043	1.492	0.043	-0.022	1.773
		(0.063)	(0.078)	(0.035)	(0.040)	(0.183)
DMZD	Rule	0.021	1.404	0.063	0.047	3.035
		(0.055)	(0.063)	(0.031)	(0.045)	(0.219)
DMZD	No Rule	0.011	1.428	0.063	0.048	0.009
		(0.058)	(0.063)	(0.031)	(0.045)	(0.924)
ZYZD	Rule	0.061	1.501	0.098	0.113	5.734
		(0.070)	(0.062)	(0.040)	(0.043)	(0.057)
JYZD	No Rule	0.006	1.509	0.100	0.083	1.230
		(0.073)	(0.064)	(0.042)	(0.044)	(0.541)

Parameters estimated by simulated method of moments. Numbers in parenthesis are asymptotic standard errors for the parameters and the p-value for the chi-squared goodness of fit test. Moments used are the mean, variance, 3 autocovariances and the 30 day moving average trading rule. The chi-squared statistic has 6-4 = 2 degrees of freedom when the trading rule is used and 5-4 = 1 degrees of freedom when it is not used. The variance-covariance matrix is estimated using the Newey-West(1987) technique with 10 lags.

Table 14
Rule Implementation Summary

Series	Trades	Return/year	Return/week	Std/week	β	BH	BH/week	BH(std)
BP	36	16.7	0.35	2.25	-0.07	9.9	0.20	1.57
DM	43	12.6	0.26	2.19	-0.08	6.2	0.13	1.54
JY	26	20.1	0.41	2.17	-0.03	8.4	0.17	1.52
CRSP VW		15.2	0.32	2.18				
$ RF		9.5	0.18	0.05				

This table summarizes the results of the trading rules over the full sample. β is the estimated CAPM beta for the trading strategy estimated using weekly data. t(return-CRSP) is a t-statistic for equality of the returns for the strategy and CRSP. BH stands for the the buy and hold strategy in the foreign currency holding foreign bonds.

Table 15
1 Year Horizon

Series	Return/year	Std	Prob(<RF-5%)	Prob(<CRSP)	T<RF	β
BP	19.5	13.7	0.15	0.46	0.34	-0.04
					(0.31)	(0.26)
BP BH	11.0	15.7	0.42	0.59	0.50	0.06
					(0.39)	(0.16)
DM	14.3	18.7	0.32	0.50	0.46	-0.06
					(0.34)	(0.18)
DM BH	5.6	14.7	0.55	0.65	0.62	0.07
					(0.37)	(0.19)
JY	22.2	24.0	0.19	0.37	0.39	-0.04
					(0.35)	(0.21)
JY BH	9.4	16.6	0.45	0.59	0.56	0.03
					(0.37)	(0.17)
CRSP	16.2	18.0	0.29		0.41	
					(0.35)	
CRSP+BP	17.9	11.2	0.14	0.46	0.36	0.47
					(0.32)	(0.13)
3FX+CRSP	17.4	12.8	0.18	0.38	0.37	0.47
					(0.32)	(0.10)

Simulation results for one year trading horizon. Results of 1000 simulation of randomly selected 2 year intervals during the sample. Prob(<RF-5%) is the probability of underperforming the domestic risk free rate by more that 5%. Prob(<CRSP) is the probability that the strategy underperforms the CRSP index. T<RF is the fraction of time that the cumulative return on the strategy spends below the cummulative return on the risk free asset. β is again the beta estimated against the CRSP index. CRSP+BP is a portfolio which is started with portfolio weights of 1/2 and 1/2 on CRSP and the trading strategy respectively. 3FX+CRSP is a portfolio which is started with weights of 1/2 on a buy and hold stock position, and 1/2 on a equally weighted position in the three foreign exchange strategies.

Table 16
Utility Distribution Comparisons: 1 Year Horizon

Series	BH	CRSP	3FX+CRSP
BP	0.92	0.95	0.99
DM	0.93	1.01	1.05
JY	0.91	0.96	1.00
BP+CRSP		0.96	0.99
3FX+CRSP		0.96	

Utility comparisons of myopic 1 year crra investors. Fraction of wealth α that would make an investor indifferent between the row rule used on αW and the column rule on W. Degree of relative risk aversion is fixed at 4.