A Dynamic Trading Strategy Approach to Deviations from Uncovered Interest Parity *

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Abstract

Foreign exchange predictability is explored from the standpoint of generating explicit dynamic strategies. These are used to assess the economic significance and economic magnitude of the predictability present in exchange rates. It is found that considering the true out of sample behavior of certain dynamic foreign exchange strategies greatly reduces the magnitude of previously reported puzzles.

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1 Introduction

The presence of significant predictability has been documented for many financial time series. Converting this predictability into a useful dynamic trading strategy involves many hurdles that often weeds out many candidate predictors. However, this hurdle is crucial for judging economic significance, and directing future theoretical explorations. This paper analyzes some of the predictable features of foreign exchange rates with these features in mind.

Earlier studies on converting predictability into dynamic strategies in foreign exchange markets include Hodrick & Srivastava (1984), Bilson (1981), and Bilson & Hsieh (1987).[1] A related area of research has looked into the properties of certain ad hoc technical trading forecasts. Among some of the papers in this area are Sweeney (1986), LeBaron (1998), Levich & Thomas (1993), and Taylor (1992). Technical trading rules are by their very nature trading decision rules, so they are generally tested by running an actual strategy.

There are many potential pitfalls that can come between a prediction and implementing it. These include parameter instability, transactions costs, and possibilities that the strategy may expose the trader to some unusual idiosyncratic risks. Also, the actual algorithm in use may have bad stability properties which are not readily apparent ex ante.

This paper concentrates on only one small aspect of predictability, that of predicting future exchange rates. The fact that exchange rates have predictable components that should not be there in a risk neutral world is well known, and has a long history.[2] Puzzles concerning exchange rates are interesting for several reasons. First, predictability is at the center of the issue. There is no puzzling static return behavior in foreign exchange alone. Second, some estimates of this predictability are very large relative to other puzzles in finance. This demands some kind of exploration to see if this one type of predictability could be so large as to dominate many other known asset pricing puzzles.

This paper explores the predictability from uncovered parity, by building dynamic strategies. The resulting portfolios will be analyzed to see in what way they may be an additional piece in asset pricing puzzles, and in which ways some of this predictability may have been overstated.

[1]Another recent paper looking at the overall robustness of this predictability is Bekaert & Hodrick (1993), and Neely & Weller (1997) addresses recent parameter instabilities in the VAR regressions.

[2]See Engel (1996) and Lewis (1995) for recent surveys.

2 Dynamic Trading Strategies

The strategies considered are based on the Hansen & Jagannathan (1990) bounds derived from scaled returns. Let x_t be an excess return at time t, and m_t the marginal rate of substitution. It is well known that this implies that,

$$E_t(m_{t+1}x_{t+1}) = 0. \quad (1)$$

Using the definition of covariance, the law of iterated expectations, and the fact that the absolute value of m_t is always positive gives,

$$cov(m_{t+1}, x_{t+1}) = E(m_{t+1})E(x_{t+1}) \quad (2)$$

$$|cov(m_{t+1}, x_{t+1})| = E(m_{t+1})|E(x_{t+1})|. \quad (3)$$

It is then a simple application of the Cauchy-Schwartz inequality to get the traditional bounds given by

$$\frac{\sigma_m}{E(m)} > \frac{|E(x)|}{\sigma_x}. \quad (4)$$

The right hand side of this inequality is simply the Sharpe ratio for the excess return, x. The key issue for dynamic strategies is there is nothing special about x_t except that it can be implemented at zero cost. This might be a static return or any feasible dynamic strategy. Any of these will set a hurdle for the variability of the marginal rate of substitution.[3]

This paper will consider strategies of the form,

$$x_{t+1}^p = g(I_t)x_{t+1}, \quad (5)$$

where I_t is any piece of information that is available at time t. These clearly meet the conditions of feasibility and zero cost. Scaled returns consider the case where g is a linear function. Assume that I_t is a real valued variable at time t, and the strategy recommends holding $w_t = a + bI_t$ of the asset giving a total return of,

$$x_{t+1}^p = (a + bI_t)x_{t+1}. \quad (6)$$

It is clear from this writing of the strategy that estimating (a, b) is equivalent to traditional N security

[3]The Sharpe ratio is also a generally used measure for performance. See Sharpe (1994) for a survey. Recent work by Lettau & Uhlig (1997) has shown a direct connection between the Sharpe ratio and preference parameters under certain assumptions.

portfolio optimization. The optimal (a, b) that maximizes the Sharpe ratio of the dynamic strategy is given by

$$z = (a, b)' = \Omega^{-1} E(x_{t+1}, I_t x_{t+1})', \tag{7}$$

where Ω is the variance covariance matrix of $(x_{t+1}, I_t x_{t+1})$. [4] Substituting this in for x^p gives the traditional multiasset HJ bound

$$\frac{\sigma_m}{E(m)} > E(x_{t+1}, I_t x_{t+1}) \Omega^{-1} E(x_{t+1}, I_t x_{t+1})'. \tag{8}$$

In the asymptotic stationary world the timing of all this does not matter much. However, in this paper it will be crucial. The methods introduced below will consider various methods for estimating the optimal dynamic strategy using in sample, or realized observations. This gives a fair appraisal of the extension of the bound coming from an actually usable real time strategy.

3 Empirical Results

3.1 Data Summary

The data used will be monthly foreign exchange rates measured on the London close for the last trading day of the month. The time period covers January 1981 through April 1998 for a total of 208 months. These are aligned with one month eurorate bid prices from the same close. The data are from Datastream, and their original source is Natwest Bank. Excess returns will be constructed as the continuously compounded rates of return with interest rate adjustments.

$$p_t = \log(P_t)$$

$$x_{t+1} = p_{t+1} - p_t - (i_t - i_t^*) \tag{9}$$

Covered interest parity with the 1 week forward rate is given by,

$$f_t - p_t = i_t - i_t^* = I_t, \tag{10}$$

where I_t is the forward discount, and will be used as the information variable for the scaled strategies. Covered parity shows that the strategies used here can either be thought of as a dynamic borrowing and lending strategy in the two currencies, or a simple long or short speculation in the forward market.

[4] See any basic finance book, for example, Elton & Gruber (1991).

Summary statistics for the interest adjusted series are given in table 1. The series labeled, DM, JY, BP, refer to the German Mark, Japanese Yen, and British Pound, respectively. There is very little leptokurtosis, and no significant autocorrelation. None of the series show much evidence for skew, and the unconditional means are close to zero.

Description	DM	JY	BP
Mean*100	-0.07	-0.05	0.02
Std.*100	3.40	3.49	3.46
Skew	-0.15	0.42	-0.01
Kurtosis	2.99	3.39	4.64
ρ_1	0.076	0.137	0.076
ρ_2	0.072	0.041	0.072
ρ_3	-0.039	0.093	0.039
ρ_4	0.000	0.030	0.007
ρ_5	0.007	0.065	0.070
(std)	(0.069)	(0.069)	(0.069)

Table 1: Summary statistics for monthly foreign exchange excess returns, January 1981 through April 1998. Observations are taken at the end of the month London close for a total of 208 observations. ρ_n refers to the autocorrelation at lag n, and the (std) refers to the Bartlett standard errors for the autocorrelations.

3.2 Benchmark tests

The first set of tests will implement the strategies on the full sample for comparisons with previous studies. The entire sample is used to estimate Ω, and the expected values going into the estimation of the dynamic strategies. This is exactly the (HJ) scaled return bound for the full sample. Results of this procedure are given in table 2.

The column labeled 81-89* is taken from Bekaert & Hodrick (1992) (BH), and refers to monthly scaled HJ bounds on the different currencies using the same forward discount scaling information. The two comparison series are shown first from a subsample corresponding to BH, and then from the full sample. All further reported bounds will use the adjusted weekly returns for comparison.

Comparing the two shorter samples shows a very close correspondence between the two estimated bounds, and shows that this data set gives comparable results. Also, this table reports bootstrap standard errors which will be used throughout the paper. They are determined by resampling returns series with replacement, and estimating the Sharpe ratio on each of the redrawn data sets.[5] The procedure treats the returns series and the scaled returns series as a return vector cross section. These are redrawn together to maintain the

[5]These standard errors should be viewed with some trepidation since it will be shown that the dynamic strategies are nonnormal. They are presented for comparison with the previous estimates, but the bootstrap should be used to estimate other measures of significance.

cross sectional dependence. This computer generated distribution is used to estimate the standard error. Given that there is some evidence for dependence in foreign exchange time series, a stationary bootstrap is also tried. This generates new time series that try to capture some of the dependence by drawing random blocks of points rather than individual points.[6] In general the stationary and iid bootstraps give similar results, so the iid bootstrap numbers alone will be used in future tables. [7]

Comparing to the full sample shows some interesting changes. While the JY stays at about the same level, both the DM and BP fall quite dramatically. However, they are still at an interesting level relative to other benchmarks. BH also estimate bounds for many other securities including U.S. equity at 0.112, and a U.S., Japanese, U.K, and German portfolio, 0.237. Relative to these numbers we are still in an interesting range.[8]

Description	81-89*	81-89	81-98(4/30)
DM	0.319	0.284	0.137
Bootstrap	(0.066)	(0.074)	(0.067)
Stationary		(0.077)	(0.069)
JY	0.320	0.323	0.296
Bootstrap	(0.082)	(0.103)	(0.073)
Stationary		(0.083)	(0.056)
BP	0.394	0.415	0.231
Bootstrap	(0.068)	(0.069)	(0.065)
Stationary		(0.069)	(0.090)
BP+JY+DM	0.477	0.467	0.321
Bootstrap	(0.097)	(0.111)	(0.078)
Stationary		(0.083)	(0.071)
Stocks	0.237	0.202	0.127
Bootstrap	(0.105)	(0.097)	(0.071)
Stationary		(0.114)	(0.069)
FX+Stocks		0.529	0.367
Bootstrap		(0.094)	(0.075)
Stationary		(0.102)	(0.069)

Table 2: Comparison FX scaled HJ bounds. Monthly * numbers are taken from BH. Estimates are from a restricted time series that lines up with theirs, and on the full sample. BH standard errors use a Taylor expansion with 3 Newey-West lags. Bootstrap refers to iid bootstrap, and stationary refers to a stationary bootstrap with an average block size of 10.

The last two tests look at aggregate portfolios combining different dynamic strategies. The first replicates BH's test of the combined 3 foreign exchange strategies. The value of 0.467 obtained in column two is very

[6]See Politis & Romano (1994) for development of the stationary bootstrap.

[7]Dependence in the stationary bootstrap is determined by one number which sets the average size for blocks of points. This was tested out to an average size of 20 without any major differences.

[8]This crude comparison is not a formal test of whether investors would be interested in the dynamic FX strategies. This depends on covariance properties with the benchmark portfolio, or other risk factors. The purpose of the test here, is to see how large some of these dynamic strategies are relative to the more traditional security classes.

close to the BH value, but again the full sample value is much lower at 0.321. The final row is a slightly different test. It adds the 4 country stock excess returns to the set of dynamic foreign exchange strategies. This is a diversified international investment strategy where the amount of foreign exchange exposure can be adjusted conditional on the time t information. It differs slightly from the strategies in BH which also add dividend price ratios to the information set. The row labeled "stocks" presents the value for the optimally mixed equity portfolio on its own with no dynamic trading. The estimated bounds of 0.202, and 0.127 for the BH sample, and full sample respectively are somewhat lower than the dynamic foreign exchange strategies, indicating the importance of understanding how much these values are moved to by the dynamic strategies. The final rows show the results of adding the stock portfolios to the foreign exchange portfolios. The inequality bands do expand, but not by a large amount relative to the three foreign exchange series combined.

3.3 Out of sample tests

The previously estimated scaled HJ bounds have the problem of using in sample information to estimate portfolio weights. This section will move to out of sample portfolio weights. To align with the previous table the restricted sample is presented along with the full sample.

Table 7 refers to the out of sample HJ bounds for the dynamic returns. The first column, labeled 82-89 replicates the previous results using only previous data to estimate portfolio weights. The first year is used as an initial estimation period, and data points are added by month after that. DM scaled, JY scaled, and BP scaled give the scaled HJ bounds for the 3 FX series. There is a drop off in all three from the extremely high values of the in sample tests, to much more moderate levels. Actually, only the BP bound is greater than two standard deviations from zero. Another very interesting result is that the strategy for all currencies generates a very modest bound of 0.094.

The two other columns repeat the experiments for the full sample. The first column shows that the reductions in the estimated bounds continue when using the full sample. Estimated bounds for both the DM and BP show further reductions going to 0.085 and 0.128, respectively. One possible cause for these large reductions is the fact that early observations use very little data, 1 year, in estimating optimal portfolio weights at the start. To check this, the initial start was moved ahead one year to give 24 months of data to start with. The last column, labeled "83-98", refers to these experiments. Little improvement is seen except for some minor changes in the JY series.[9]

[9]Experiments were also tried with a 5 year starting period, but they also gave little differences from the 1 year starting

The final rows in the table again add stock portfolios to the picture. The row labeled "Stocks" reports out of sample results for a static stock portfolio alone. A very surprising result is that these portfolios actually generate negative (very close to zero) bounds. This unusual result was checked by looking at an equal weighted portfolio. The equal weighted portfolio gave a bound of 0.096 which is not as unusual as the very low numbers given by the explicit out of sample optimization.

The final row reports results from adding the static stock holdings along with the dynamic foreign exchange strategies. As with the previous tests the bounds are again not very impressive.

Description	82-89	82-98(4/30)	83-98 (4/30)
DM scaled	0.176 (0.113)	0.085 (0.081)	0.074 (0.086)
JY scaled	0.118 (0.158)	0.153 (0.108)	0.242 (0.079)
BP scaled	0.238 (0.133)	0.128 (0.080)	0.105 (0.079)
DM+JY+BP	0.094 (0.126)	0.074 (0.088)	0.121 (0.085)
Stocks	-0.051 (0.103)	-0.053 (0.071)	-0.006 (0.076)
Stocks+FX	0.010 (0.114)	0.013 (0.079)	0.125 (0.079)

Table 3: Out of sample bounds. Scaled returns use interest differential as information variables. Numbers in parenthesis are an iid bootstrap using 1000 replications.

3.4 Dynamic Properties

The out of sample values for the variance bounds are only one part of the story. This section analyzes the properties of these dynamic trading strategies. Table 4 presents summary statistics on four of the foreign exchange dynamic trading strategies. The table gives means, standard deviations, skewness, and kurtosis estimates for each dynamic strategy.

The numbers are estimated using the 1983-1998 (4/30) sample with a two year start up period. In the first column it is easy to see that the mean returns for all but the JY are insignificantly different from zero. This repeats the message from the previous table about the overall weakness of these types of strategies when using out of sample portfolio weights.

The table presents some further problems with these strategies. The column labeled kurtosis shows that they generate very nonnormal returns with a few very large outliers. For the DM series the kurtosis shows

values.

a value over 22, but for all the exchange rate strategies outliers appear to be important. Even the combined strategy across the 3 exchange rates still gives a kurtosis measure of 11.76. A histogram of these returns is shown in figure 1, and a time series of the returns is displayed in figure 2. They show clearly the fact that a few large returns are present in the tails.

Description	Mean	Std.	Kurtosis	Skew	Max	Min
DM scaled	0.026 (0.025)	0.342 (0.057)	22.29 (7.99)	-2.76 (1.27)	0.97	-2.55
JY scaled	0.055 (0.017)	0.227 (0.018)	5.878 (1.21)	-0.278 (0.451)	0.76	-0.97
BP scaled	0.036 (0.025)	0.344 (0.037)	9.371 (1.42)	-1.315 (0.541)	1.15	-1.57
DM+JY+BP	0.054 (0.032)	0.445 (0.053)	11.76 (2.49)	-1.830 (0.606)	1.35	-2.39

Table 4: Dynamic strategy properties. Numbers in parenthesis are bootstrap standard errors from 1000 replications.

It is difficult to evaluate the impact of these deviations from normality on performance, but there are several diagnostics which can give an impression how far these distributions are from normal. Table 5 shows the empirical left tail quantiles for the dynamic strategy on the three exchange rates as compared with the actual quantiles from a gaussian with the same mean and standard deviation. Similar sorts of tail estimates are made when doing value at risk calculations. It is clear that if one was using a normal approximation, the probability of a large loss could be greatly underestimated. This table should still be viewed with some caution since the empirical quantile estimates are derived from one observation. Table 3.4 repeats

Left Tail	DM+JY+BP	Gaussian
0.010	-2.14	-0.98
0.025	-1.14	-0.82
0.050	-0.58	-0.68
0.100	-0.27	-0.52

Table 5: Tail quantile comparisons: DM+JY+BP strategy

the previous exercise for the Japanese Yen dynamic strategy. The lower kurtosis levels reported earlier are reflected in that quantile values are much closer to the gaussian comparisons than for the 3 exchange rate strategy.

Just how these outliers affect the evaluation of the strategies is not clear. From the standpoint of HJ bounds, there is no change. The only impact on those might be a suggestion that second moments might not exist, in which case the HJ procedure would be invalid. From a performance evaluation perspective these

Left Tail	JY	Gaussian
0.010	-0.71	-0.47
0.025	-0.42	-0.39
0.050	-0.34	-0.31
0.100	-0.17	-0.23

Table 6: Tail quantile comparisons: JY strategy

outliers may be important. They show intuitively the potential weaknesses of looking only at the first two moments when evaluating risk measures. What might be surprisingly large risk adjusted returns in mean variance space, look less so when the full distribution is considered.

4 Time stationarity

There may actually be several causes for the drop off in HJ bounds observed so far. One is the simple effect of in sample bias which has been emphasized so far. However, it appears a second mechanism might be at work. There has been some indication in the earlier tables that there was a reduction in of predictability over time. Figure 3 shows estimates of the coefficient for the standard unbiasedness regression,

$$s_{t+1} - s_t = \beta_0 + \beta_1(f_t - s_t) \tag{11}$$

where the forward discount is replaced by the interest rate differential,

$$s_{t+1} - s_t = \beta_0 + \beta_1(i_t - i_t^*). \tag{12}$$

The figure shows a 4 year rolling estimate of β_1 with the x-axis marking the first year of the estimation period. Under the uncovered parity condition, these estimates should be 1. It appears from the figure that deviations have been getting weaker over time.

A more precise test is given in table 7 which looks at the sample from 1985-1998(4/30) only. The first column looks at the in sample optimized HJ bounds, while the second column examines out of sample results using a 2 year start period. For the DM and BP individual series even in sample estimates report relatively low HJ bounds, but the JY stays pretty large at 0.287. The 3 exchange rate portfolio still compares relatively well to the previous numbers with an estimated bound of 0.318. However, moving out of sample, all of the results change, and the 3 exchange rate series drops dramatically to 0.094 which is insignificantly different from zero.

Description	In	Out
DM scaled	0.074 (0.089)	0.013 (0.104)
JY scaled	0.287 (0.085)	0.191 (0.098)
BP scaled	0.110 (0.085)	0.083 (0.095)
DM+JY+BP	0.318 (0.087)	0.094 (0.098)

Table 7: Out of sample bounds. Scaled returns use interest differential as information variables. Numbers in parenthesis are an iid bootstrap using 1000 replications. 1985-1998 (4/30)

5 Conclusions

This paper further documents the predictability in foreign exchange markets from the standpoint of building simple dynamic strategies, and using the information in current interest differentials. Several interesting features are uncovered. First, the performance of dynamic strategies is greatly reduced by considering true out of sample, and therefore tradable, experiments. Second, the returns from the dynamic strategies are far from normal, with several large outliers.

This suggests that researchers investigating scaled HJ bounds should be cautious in their interpretations. Even better, out of sample estimates should be reported. Also, the large tails cause a slight difference in interpretation for the Sharpe ratio and HJ bounds. Obviously, there is no real impact on HJ bound interpretations except for possible questions about moment existence. It greatly affects Sharpe ratio interpretations since these are based on a mean variance world. If certain risks from a strategy are hiding in higher order moments, then they may coexist with anomalously large Sharpe ratios even though traders are being correctly reimbursed for the extra risk.

The tests performed should be taken as only a crude estimate of the magnitude of the predictability puzzles in foreign exchange. They simply show some of the strengths and weakness of various types of predictors. More complete tests would involve fully developed global risk models, and cross correlations with other international assets.

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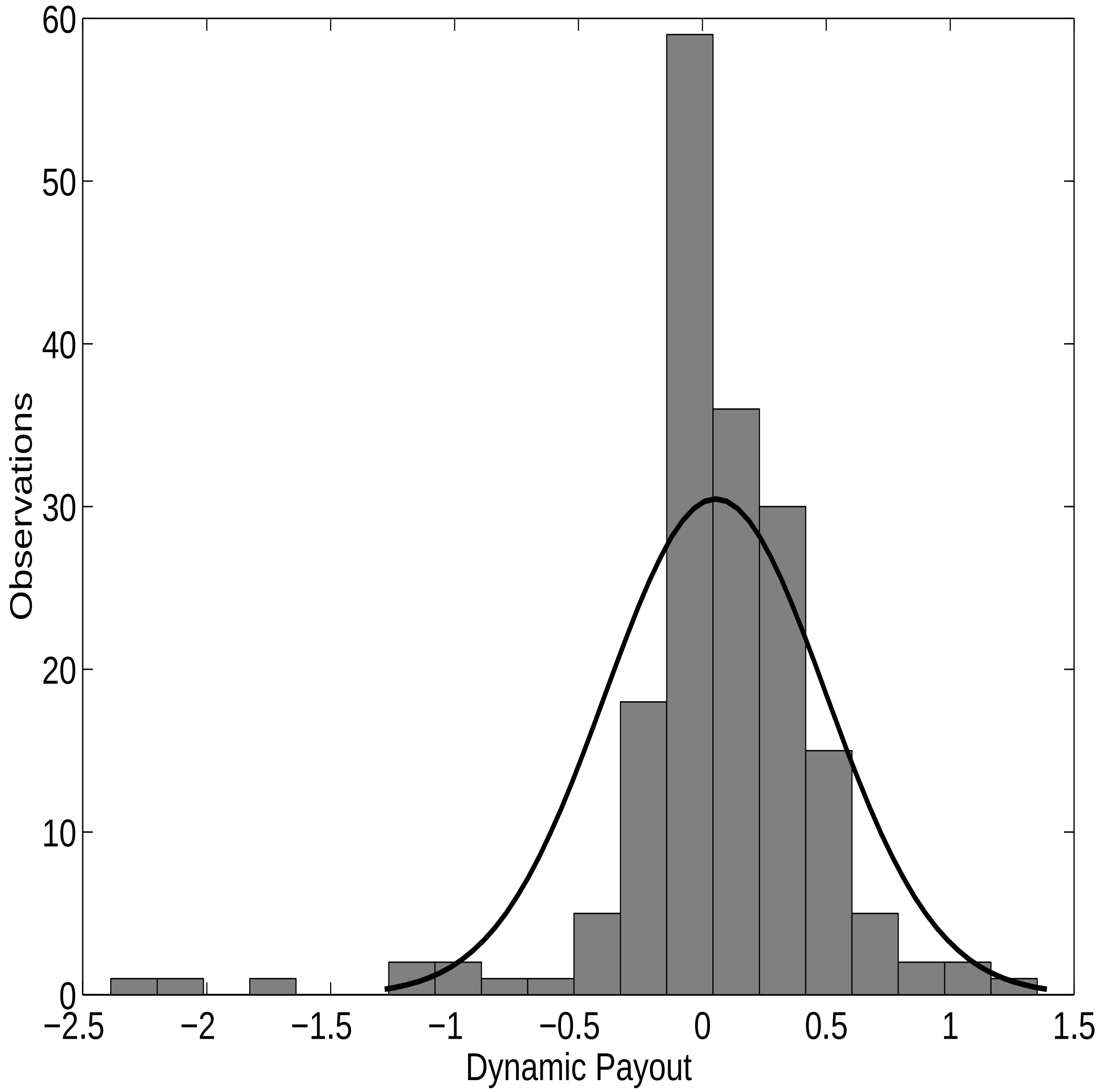

Figure 1: Dynamic trading payout: 3 currencies

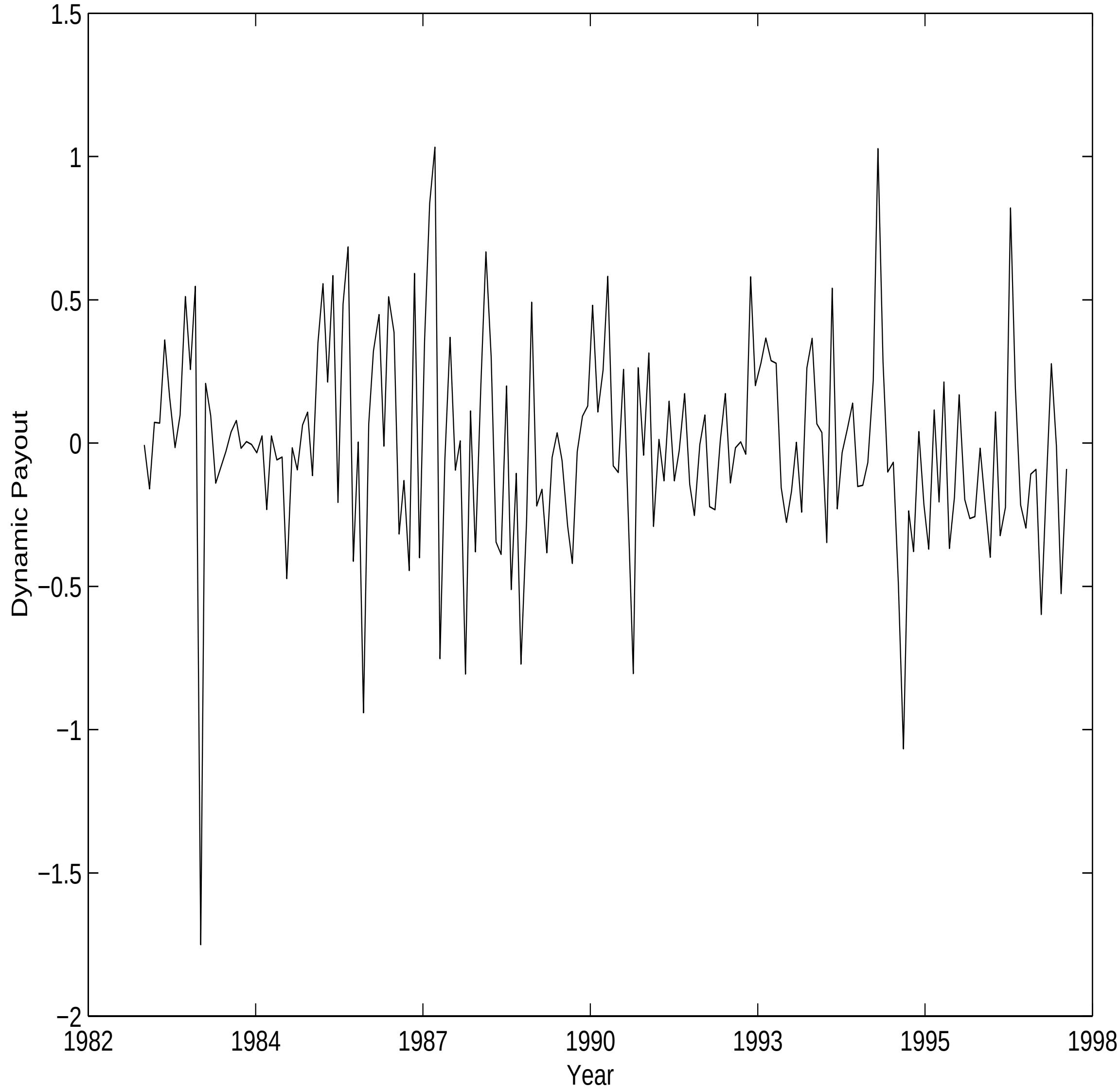

Figure 2: Dynamic trading payout: 3 currencies

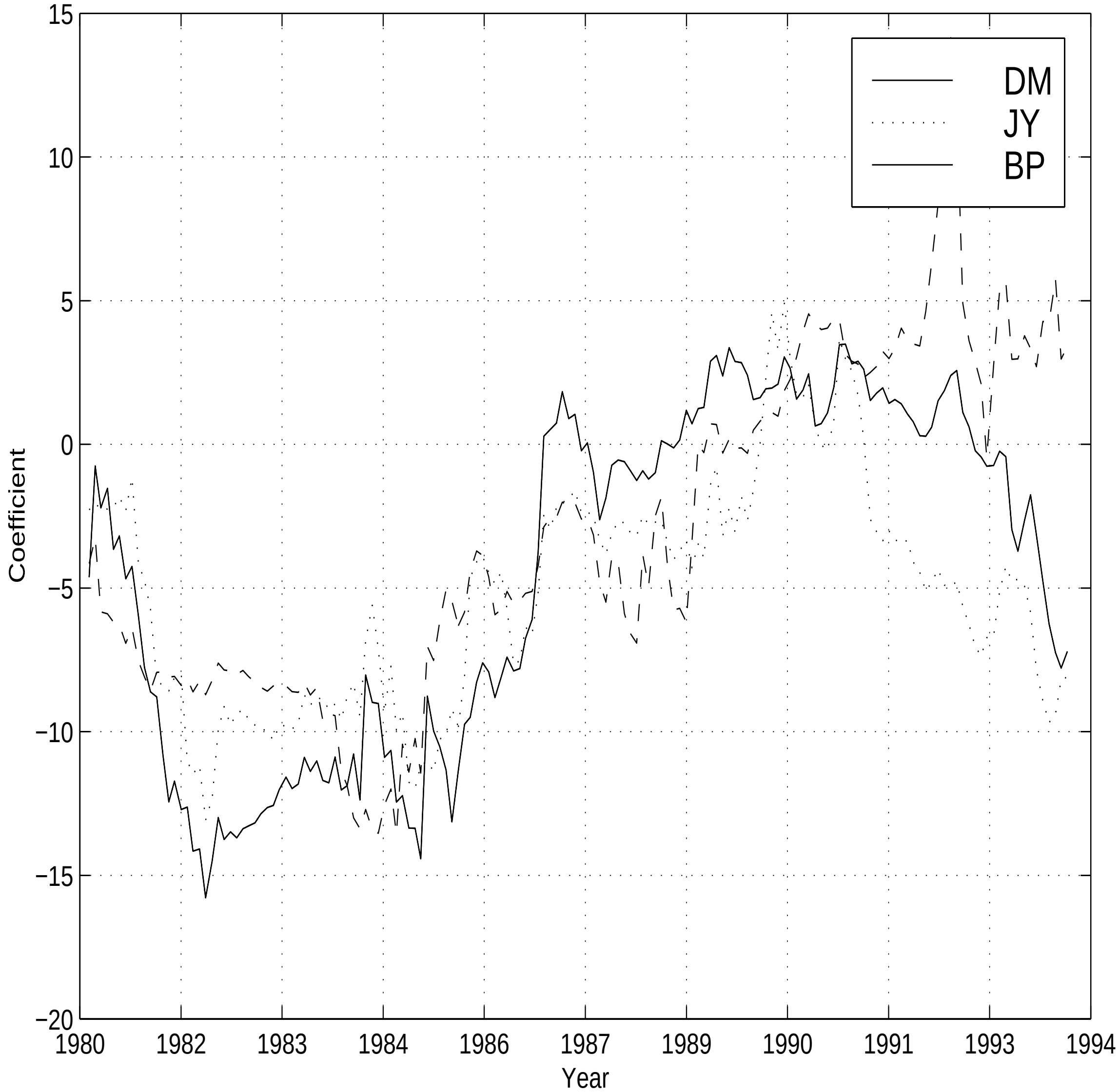

Figure 3: Rolling 4 year regression coefficients