

Can Political Variables Really Predict Exchange Rate Movements ?*

S. Brock. Blomberg and Andrew Mountford †
Wellesley College University of London,
 Royal Holloway College

11 September, 1999

Abstract

This paper argues that Blomberg and Hess's (*Journal of International Economics 1997*) finding that political variables can be used to predict exchange rate movements better than the random walk model must be seen in the context of the decade and half of previous research which failed to beat this benchmark. This paper uses White's "Reality Check" methodology to test whether political variables remain as significant predictors of the exchange rate when a host of alternative competing models are taken into account. It finds that they do not.

JEL Classification Numbers: F31, G12, H8.

Keywords: Exchange Rates, Forecasting,

*We thank Joe Joyce for a very useful discussion regarding this paper.

†Addresses for correspondence: A. Mountford, Dept. Economics, Royal Holloway College, University of London, Egham, Surrey TW20 OEX, U.K. **email:** A. Mountford@rhnc.ac.uk. and S. Brock Blomberg, Economics Dept., Wellesley College, Wellesley, MA 02481 U.S.A & Weatherhead Ctr for Intl Affairs, Harvard University **email:** sblomberg@wellesley.edu

1 Introduction

One of the most robust empirical findings in all of international macroeconomics is that no theoretically-based model can out-perform a random walk in out-of-sample forecasting.¹ That is why the recent finding by Blomberg and Hess (1997) is so intriguing. Blomberg and Hess showed that linear empirical exchange rate models which included political variables out-performed the random walk model in terms of predicting out of sample exchange rates. Blomberg and Hess showed that their results held over different countries, in different sub-samples and for different forecast horizons, yet intuitively their results were a little unsettling since they found that a more popular government forecasted a future depreciation of the currency. Their results thus behoved further research either to show that the results were soundly based or to find an alternative explanation for the findings. This is precisely what this paper does.

In this paper we use the recently derived “Reality Check” procedure of White (2000) to deal with the problem of determining the significance of an empirical model employing a repeatedly used dataset. This problem has come to be known as “data snooping”, see Campbell, Lo and MacKinlay (1997). Data snooping is a problem when the same dataset becomes the basis of an intense research debate about competing models. In this case it is possible that the ‘best’ model which emerges from this debate performs well due to chance correlation with the particular dataset, rather than due to a deeper connection to the ‘true’ underlying model. This problem is inherent in time series econometrics where essentially there is only one dataset, e.g. history only happens once.

White’s (2000) procedure, following on from the work of Diebold and Mariano (1995) and West (1996), deals with this problem by using the bootstrap resampling methods of Politis and Romano (1994), and has been employed in

¹See Meese and Rogoff (1983) for a seminal paper in the area.

Sullivan, Timmermann and White (1998,1999) to test whether stock market trading rules significantly outperform market forecasts or 'beat the market'. They found that after correcting for dat snooping biases they do not.

It is only natural then to consider a similar strategy to see if political models really do 'beat the random walk'. This is an important question not only because there are persuasive theoretical reasons for believing in the significance of political variables for movements in the exchange rate, see for example Alesina et al (1997), but also because the in-sample performance of models with political variables is extremely good, see Blomberg and Hess (1997), and because political factors have been shown to play a large role in explaining the sustainability of currency pegs, see Blomberg, Frieden and Stein (1999).

This paper is organized into two sections. In the first section we briefly describe the methodology, the dataset and the selection of alternative competing models of the exchange rate. In the second section we present and discuss the results.

2 Description of the Data, Methodology and Models

This section will be brief because more detailed descriptions of the data and methodology can be found in Blomberg and Hess (1997) and White (1997) respectively.

2.1 The Data

We use the same data as Blomberg and Hess (1997). Thus we have monthly data for three economies, the USA, UK and Germany, which starts for all countries in 1973:1 and ends in 1994:6, 1991:12 and 1989:12 respectively. The economic variables for each economy are the trade weighted exchange rate

and bilateral exchange rates, (s), the growth rate of industrial production, (ip), the inflation rate, (inf), the short term interest rate, (i) and the change in the balance of trade figures, ($trad$). In addition the overnight eurodollar rate, (i^w), and weighted averages of the G7 countries' inflation rates, (inf^w), and growth rates of industrial production, (ip^w) are also used. The political variables for each economy are the government approval ratings, (app) and dummy variables for recent changes in government ideology, ($part$), (right to left or left to right) and for upcoming elections, (ele).

2.2 Methodology

The aim of White's (2000) procedure is to take into account of the search for the best model, in determining the significance of the predictive superiority of the best model vis-a-vis a benchmark model. Thus for this paper, we aim to determine whether the predictive superiority of Blomberg-Hess's political models is significant after we have taken account of the previous large research effort put into beating the random walk.

White's procedure compares the predictive accuracy of a number, C , of 'Candidate Models' relative to a benchmark model. For this paper the selection of a benchmark model is simple task. Meese and Rogoff's (1983) demonstration that the random walk model outperforms all others in out-of-sample forecasting, firmly established the random walk model as the benchmark for exchange rate models. Candidate models are then selected from a broad range of possible theories ranging from trade-based to political-based models. To measure predictive accuracy we will use the Mean Squared Error (M.S.E), which is calculated in a recursive manner whereby the parameters of models are updated with the addition of each new observation.

Ideally we would like to obtain the p value of the best model's M.S.E. relative to the random walk by looking at the distribution of 'the relative M.S.E. of the best candidate model'.² Unfortunately we do not know this

²Intuitively, consider tossing 100 fair coins a 1000 times each and then taking the coin

distribution. However, White (2000) shows that one can obtain a consistent p value by comparing the relative M.S.E of the best model in the sample with the distribution of the performance of the best model in bootstrapped resamples. Appendix A describes White’s procedure for generating this p value. Intuitively, White’s technique allows one to obtain the distribution using a bootstrapping technique by appealing to asymptotic theory.

2.3 The Candidate Models

In this subsection, we show how we developed our candidate models. The candidate models are a proxy for the academic community’s cumulative search for a predictive exchange rate model. We set up 92 alternative, “candidate” models for predicting the exchange rate using the available data. All ‘92’ models are basic autoregressive models of the form,

$$\Delta s_t = \alpha + \sum_{i=1}^k \sum_{j=1}^l \beta_{ij} X_{i,t-j}$$

where, the X_i variables are those described in section 2.1 ranging from traditional economic factors to political ones.

It is clear that there are an enormous quantity of possible candidate models with many different combinations of variables and lag lengths to choose from and so the choice of 92 is extremely conservative and arbitrary, however it must be emphasized that this does **NOT** effect the conclusions of this paper. If one increases the number of candidate models then if the extra models do not improve on the predictive accuracy of the ‘best’ model, then the p value for the ‘best’ model will increase since it must take into account that the ‘best’ model was obtained after a search over more ‘candidate’ models with the most uneven outcome in terms of heads and tails. If one tested this coin for bias using the standard t distribution then one would probably find this coin to be biased. This is because one shouldn’t be using the t distribution, one should be using the ‘distribution for the most uneven coin from a sample of a 100 fair coins’.

els. Alternatively if the extra models do improve on the predictive accuracy then they will have beaten Blomberg and Hess's model.

The precise method of generating the 92 models is described in Appendix B, but it is useful to highlight and track some particular models to compare various theories predictive performance. (The numbering of the models is chosen entirely for convenience in writing the computer code and does not have any economic foundation).

Model 4: Uncovered Interest Parity (UIP) In this model the only X_i are lags the domestic and foreign interest rate.

Model 27: Economic 'Fundamentals' Model. This is where all the non-political variables described in Section 2.1 are included as regressors.

Model 91: Blomberg and Hess's Political Model 2 This model uses just the political variables in Section 2.1, as regressors.

Finally one should note that the models 89-92 only contain political variables and that the benchmark model is just the above equation with no X_i regressors.

3 Results

We look at the significance of the political model for predicting changes in future trade weighted exchange rates in Section 3.1 and for predicting bilateral exchange rates in Section 3.2. We expect the results for the bilateral models to be superior than the trade-weighted models because there is more political and economic information available. We do indeed find this to be true but do not find evidence that any model 'beats' the random walk using White's technique.³

³The bootstrapping and calculations of p values were done using the "Forecaster's Reality Check Basic" of QuantMetrics Corporation.

3.1 Predicting Trade Weighted Exchange Rates

The results for the best candidate models are summarized in Table 1, while the results for the highlighted candidate models are displayed in Table 2. In each table, the columns denote the appropriate currency and step-ahead forecast. The forecast horizons are based on data availability and directly follow Blomberg and Hess. For Table 2, we show the appropriate MSE for the candidate models relative to the random walk. For Table 1, we show the p values denoting the probability that the best candidate model is significantly different than the random walk.

Tables 1 and 2 Here

Table 1 shows that for neither economy are the improvements of the best model significantly better than the random walk model of any forecast horizon. Most p values are greater than 0.50 which means that it is as likely as not that the best model's predictive superiority over the random walk stems from chance. The only dataset and forecast horizon that is very different from 0.50 is the one period ahead forecast for the US dollar.

Nevertheless Table 2 shows that political models do tend to have lower M.S.E.'s than models without political variables. The Blomberg Hess Political Model 2 beats the random walk model more times than not, which is better than the performance of the UIP and economic fundamentals' models. However this paper is **NOT** testing the relative merits of political versus traditional economic models. The question that this paper addresses is the relevant standard error of the predictive performance of the best model and whether the predictive performance of the best model is significantly better than the random walk. The results of this paper suggest that the predictive

superiority of Blomberg-Hess's models are not significantly different from the random walk after taking into account the 'data snooping' bias.

Figure 1 Here

This last point nicely illustrated in Figure 1. This graphs the MSE of all the 92 candidate models relative to the benchmark for the 1 period ahead forecasts of the US\$ 1986:1-1989:12.⁴ Note that certain models do have low MSE's such as those that incorporate lagged s (9 - 36) and in fact the best model (number 19) does have the presidential approval rating as a regressor. However its performance is not very different from model 9 which has only the lagged exchange rate and domestic and world industrial production as regressors.

The other line on the graph shows the p value for the best model that you would get if you stopped the experiment after each particular model. After some models this p values drops near .10 but it would be misleading to consider this value since it does not take into account the bias surrounding model selection. This is precisely the point of our paper. **The only p value that counts is the p value after all 92 models have been considered.**

Tables 3 and 4 Here

⁴This is the exchange rate and forecast horizon with the best p value.

3.2 Predicting Bilateral Exchange Rates

In this subsection, we extend the analysis to examine the bilateral case. The results for the best model are summarized in Table 3, while the results for the highlighted candidate models are displayed in Table 4. As expected, Table 3 shows that for bilateral exchange rates the best model fares better than when considering trade weighted exchange rates. However in each case, regardless of forecast horizon or currency the p value is above 0.10. Furthermore, it is also the case that the best model is not the same model for each individual currency although it is noticeable that for each exchange rate the best model for the 1 period ahead forecast is also the best model for the 6 period ahead forecast.

Figure 2 Here

In addition, as with the trade weighted exchange rate, the best models almost always include a political variable with Table 4 showing that political models have lower MSE's than the UIP and fundamental models. Finally, it is again illustrative to graph the MSE of all the 92 candidate models relative to the benchmark for the best predicted forecast horizon for some exchange rate and forecast horizon as we did in Figure 1. This is done in Figure 2 for the 1 step ahead prediction errors for the *DM : US* exchange rate which gives the best results in the original Blomberg-Hess paper.⁵ This shows that almost all models beat the random walk for this case with real variables and political variables playing significant roles. Again the best model, (number 64) includes a political variable as a regressor (the difference of governmental

⁵The general results are not sensitive to exchange rate or horizon.

approval ratings). However again its performance is similar to model 16 which has only the lagged exchange rate, industrial production and inflation figures as regressors. Thus the p value for model 64 is not statistically significant.

4 Conclusions

In this paper we have subjected the empirical findings of Blomberg and Hess to White's 'Reality Check' and found that they are not significantly better predictors than the random walk for any exchange rate at any forecast horizon when considering data snooping bias. Nevertheless models with political variables do seem to have lower MSE's than purely economic models and so political models may well be a good direction in which to search for a better predictor than the random walk model.

Wellesley College.

University of London, Royal Holloway College.

Appendix A

White's Reality Check Procedure

This appendix simply paraphrases relevant sections of White (2000).

Assume we have the squared prediction errors of the C candidate models for N 'out of sample' periods. Suppose also we have B bootstrap resamples of these squared prediction errors generated according to the Politis and Romano (1994) stationary bootstrap algorithm⁶. Now proceed as follows.

1.) Calculate the M.S.E. for the random walk model, MSE_{rw} , and the M.S.E for candidate model 1, MSE_1 . Define $\bar{f}_1 \equiv (MSE_1 - MSE_{rw})$, and $\bar{V}_1 \equiv N^{1/2}\bar{f}_1$. Now for each of the bootstrap resamples calculate $\bar{f}_{1,i^*} \equiv (MSE_{1,i^*} - MSE_{rw,i^*})$ and $\bar{V}_{1,i^*} \equiv N^{1/2}(\bar{f}_{1,i^*} - \bar{f}_1)$ for $i^* = 1, \dots, B$.

2.) Calculate the M.S.E for candidate model 2, MSE_2 . Define $\bar{f}_2 \equiv MSE_2 - MSE_{rw}$, and $\bar{V}_2 \equiv \max\{N^{1/2}\bar{f}_2, \bar{V}_1\}$. Now for each of the bootstrap resamples calculate $\bar{f}_{2,i^*} \equiv (MSE_{2,i^*} - MSE_{rw,i^*})$ and then define $\bar{V}_{2,i^*} \equiv \max\{N^{1/2}(\bar{f}_{2,i^*} - \bar{f}_2), \bar{V}_{1,i^*}\}$ for $i^* = 1, \dots, B$.

3.) Continue on in this way for all C candidate models. This results in final values $\bar{V}_C \equiv \max\{N^{1/2}\bar{f}_C, \bar{V}_{C-1}\}$ and $\bar{V}_{C,i^*} \equiv \max\{N^{1/2}(\bar{f}_{C,i^*} - \bar{f}_C), \bar{V}_{C-1,i^*}\}$ for $i^* = 1, \dots, B$.

4.) Compute the p value by sorting \bar{V}_{C,i^*} $i^* = 1, \dots, B$ into ascending order and then find M such that $\bar{V}_{C,M^*} \leq \bar{V}_C \leq \bar{V}_{C,(M+1)^*}$. Then the p value is given by $1 - M/B$.

⁶The bootstrapping and calculations of p values were done using the "Forecaster's Reality Check Basic" of QuantMetrics Corporation. We used 500 bootstrap resamples with a bootstrap smoothing parameter of 0.25. The results were not sensitive to different values of these parameters.

Appendix B

The Selection of the Candidate Models

The section details how the 92 candidate models were generated. The choice of 92 is extremely arbitrary but it must be noted that, as argued in the text (i.) 92 is an extremely conservative modeling of the search for models that perform better than the random walk, and

(ii) Adding more “candidate” models can only be bad for the Blomberg-Hess result.

To generate the 92 candidate models for the trade weighted exchange rate, we defined 8 sets of regressors: $X_1 = 4$ lags of s , $X_2 = 4$ lags of ip and ip^w , $X_3 = 4$ lags of inf and inf^w , $X_4 = 4$ lags of i and i^w , $X_5 = 4$ lags of $trad$, $X_6 = 4$ lags of app , $X_7 = part$, $X_8 = ele$.

The 92 models are the following :-

Models 1-8 are constant plus X_i for $i=1, \dots, 8$.
Models 9-15 are constant, X_1 plus X_i for $i=2, \dots, 8$.
Models 16-21 are constant, X_1, X_2 plus X_i for $i=3, \dots, 8$.
Models 22-26 are constant, X_1, X_2, X_3 plus X_i for $i=4, \dots, 8$.
Models 27-30 are constant, X_1, X_2, X_3, X_4 plus X_i for $i=5, \dots, 8$.
Models 31-33 are constant, X_1, X_2, X_3, X_4, X_5 plus X_i for $i=6, \dots, 8$.
Models 34-35 are constant, $X_1, X_2, X_3, X_4, X_5, X_6$ plus X_i for $i=7, 8$.
Model 36 is constant, $X_1, X_2, X_3, X_4, X_5, X_6, X_7$ and X_8 .
Models 37-42 are constant, X_2 plus X_i for $i=3, \dots, 8$.
Models 43-47 are constant, X_2, X_3 plus X_i for $i=4, \dots, 8$.
Models 48-51 are constant, X_2, X_3, X_4 plus X_i for $i=5, \dots, 8$.
Models 52-54 are constant, X_2, X_3, X_4, X_5 plus X_i for $i=6, \dots, 8$.
Models 55-56 are constant, X_2, X_3, X_4, X_5, X_6 plus X_i for $i=7, 8$.
Model 57 is constant, $X_2, X_3, X_4, X_5, X_6, X_7$ and X_8 .
Models 58-62 are constant, X_3 , plus X_i for $i=4, \dots, 8$.
Models 63-66 are constant, X_3, X_4 plus X_i for $i=5, \dots, 8$.
Models 67-69 are constant, X_3, X_4, X_5 plus X_i for $i=6, \dots, 8$.
Models 70-71 are constant, X_3, X_4, X_5, X_6 plus X_i for $i=7, 8$.
Model 72 is constant, X_3, X_4, X_5, X_6, X_7 and X_8 .
Models 73-76 are constant, X_4 plus X_i for $i=5, \dots, 8$.

Models 77-79 are constant, X_4, X_5 plus X_i for $i=6, \dots, 8$.
 Models 80-81 are constant, X_4, X_5, X_6 plus X_i for $i=7, 8$.
 Model 82 is constant, X_4, X_5, X_6, X_7 and X_8 .
 Models 83-85 are constant, X_5 plus X_i for $i=6, \dots, 8$.
 Models 86-87 are constant, X_5, X_6 plus X_i for $i=7, 8$.
 Model 88 is constant, X_5, X_6, X_7 and X_8 .
 Models 89-90 are constant, X_6 plus X_i for $i=7, 8$.
 Model 91 is constant, X_6, X_7 and X_8 .
 Model 92 is constant, X_7 and X_8 .

Models 36 and 91 correspond to Model's 1 and 2 in Blomberg and Hess (1997).

The procedure to generate the 92 candidate models for the bilateral exchange rate is essentially the same. We defined 8 sets of regressors: $X_1 = 4$ lags of s , $X_2 = 4$ lags of ip^1 and ip^2 , $X_3 = 4$ lags of inf^1 and inf^2 , $X_4 = 4$ lags of i^1 and i^2 , $X_5 = 4$ lags of $trad^1$ and $trad^2$, $X_6 = 4$ lags of $(app^1 - app^2)$, $X_7 = part^1 - part^2$, $X_8 = ele^1 - ele^2$, where the superscripts 1 and 2 refer to the two countries whose bilateral exchange rate we are predicting. We then proceeded as in the trade weighted exchange rate case.

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Currency	Forecast Horizon	Forecast Period	P Value (Best Model)	Variables in Best Model
\$	1	86:1-89:12	0.202	s, ip, ipw, app
\$	1	88:7-92:6	0.314	s, i, iw
\$	6	86:1-89:12	0.646	i, iw, trad, app, part
\$	6	88:7-92:6	0.660	i, iw, trad, app, ele
\$	12	86:1-89:12	0.660	i, iw, trad, app, part
\$	12	88:7-92:6	0.486	i, iw, trad, app, part, ele
£	1	86:1-89:12	0.750	s, ip, ipw, part
£	1	88:1-91:12	0.992	s, ip, ipw, part
£	6	86:1-89:12	0.672	trad, ele
£	6	88:1-91:12	0.994	i, iw, part
£	12	86:1-89:12	0.822	s, ip, ipw, part
£	12	88:1-91:12	0.982	s, ip, ipw
DM	1	86:1-89:12	0.784	s
DM	6	86:1-89:12	0.954	app, ele
DM	12	86:1-89:12	0.982	app, ele

Table 1: *Predictions for the Trade Weighted Exchange Rates. (The second out of sample forecasting period is different for the UK due to lack of political data after 91:12) The results show that for no forecasting horizon and sample period is the predictive superiority of the best model significantly better than the random walk. The variables of the best model are described in Appendix B.*

Forecast Horizon & Currency	Forecast Period	M.S.E. Random Walk	M.S.E. Best Model	M.S.E. UIP Model	M.S.E. Fund. Model	M.S.E. Blom-Hess Model 2
\$, 1	86:1-89:12	0.00056	0.00046	0.00058	0.00054	0.00051
\$, 1	88:7-92:6	0.00060	0.00051	0.00059	0.00054	0.00061
\$, 6	86:1-89:12	0.00056	0.00050	0.00053	0.00060	0.00051
\$, 6	88:7-92:6	0.00057	0.00052	0.00056	0.00056	0.00056
\$, 12	86:1-89:12	0.00060	0.00054	0.00058	0.00066	0.00056
\$, 12	88:7-92:6	0.00059	0.00052	0.00058	0.00058	0.00055
£, 1	86:1-89:12	0.00033	0.00030	0.00034	0.00034	0.00033
£, 1	88:1-91:12	0.00024	0.00024	0.00025	0.00030	0.00025
£, 6	86:1-89:12	0.00030	0.00026	0.00032	0.00042	0.00027
£, 6	88:1-91:12	0.00022	0.00022	0.00023	0.00057	0.00024
£, 12	86:1-89:12	0.00025	0.00022	0.00030	0.00044	0.00024
£, 12	88:1-91:12	0.00023	0.00022	0.00024	0.00074	0.00024
DM, 1	86:1-89:12	0.000062	0.000054	0.000062	0.000085	0.000061
DM, 6	86:1-89:12	0.000066	0.000063	0.000066	0.000103	0.000065
DM, 12	86:1-89:12	0.000065	0.000062	0.000065	0.000131	0.000065

Table 2: *M.S.E.'s of Notable Models for the Trade Weighted Exchange Rates.* The models refer to those described in section 2.3. The table confirms the results of Blomberg and Hess that the political model has a good M.S.E. performance relative to the UIP and Fundamentals models although it is never the best model. The variables of the best model are described in Appendix B.

Currency	Forecast Horizon	Forecast Period	P Value (Best Model)	Variables in Best Model
DM:\$	1	86:1-89:12	0.168	inf, i, app
DM:\$	6	86:1-89:12	0.214	inf, i, app
DM:\$	12	86:1-89:12	0.22	inf, i, app
$\mathcal{L} : \$$	1	86:1-89:12	0.346	i, trad, part
$\mathcal{L} : \$$	6	86:1-89:12	0.164	i, trad, part
$\mathcal{L} : \$$	12	86:1-89:12	0.20	s,ip, inf, trad, app, part
$DM : \mathcal{L}$	1	86:1-89:12	0.34	s, ip, inf, part
$DM : \mathcal{L}$	6	86:1-89:12	0.724	s, ip, inf, part
$DM : \mathcal{L}$	12	86:1-89:12	0.798	s, ip

Table 3: *Predictions for the Bilateral Exchange Rates. The results are better than for the trade weighted exchange rate but still for no forecasting horizon and sample period is the predictive superiority of the best model significantly better than the random walk. The variables of the best model are described in Appendix B.*

Forecast Horizon & Currency	Forecast Period	M.S.E. Random Walk	M.S.E. Best Model	M.S.E. UIP Model	M.S.E. Fund. Model	M.S.E. Blom-Hess Model 2
DM:\$,1	86:1-89:12	0.000823	0.000647	0.000777	0.000743	0.000663
DM:\$,6	86:1-89:12	0.000835	0.000669	0.000803	0.000812	0.000700
DM:\$,12	86:1-89:12	0.00885	0.000700	0.000865	0.000910	0.000760
\mathcal{L} : \$,1	86:1-89:12	0.000763	0.000630	0.000669	0.000691	0.000736
\mathcal{L} : \$,6	86:1-89:12	0.000806	0.000641	0.000728	0.000697	0.000772
\mathcal{L} : \$,12	86:1-89:12	0.000922	0.000735	0.000827	0.000785	0.000870
DM : \mathcal{L} ,1	86:1-89:12	0.000399	0.000297	0.000482	0.000401	0.000427
DM : \mathcal{L} ,6	86:1-89:12	0.000389	0.000348	0.000465	0.000499	0.000408
DM : \mathcal{L} ,12	86:1-89:12	0.000300	0.000267	0.000414	0.000496	0.000427

Table 4: *M.S.E.'s of Notable Models for Bilateral Exchange Rates. The models refer to those described in section 2.3. The table confirms the results of Blomberg and Hess that the political model has a relatively good M.S.E. performance although again it is never the best model.*

Figure 1

US \$ Trade Weighted Exchange Rate:
Relative Prediction errors

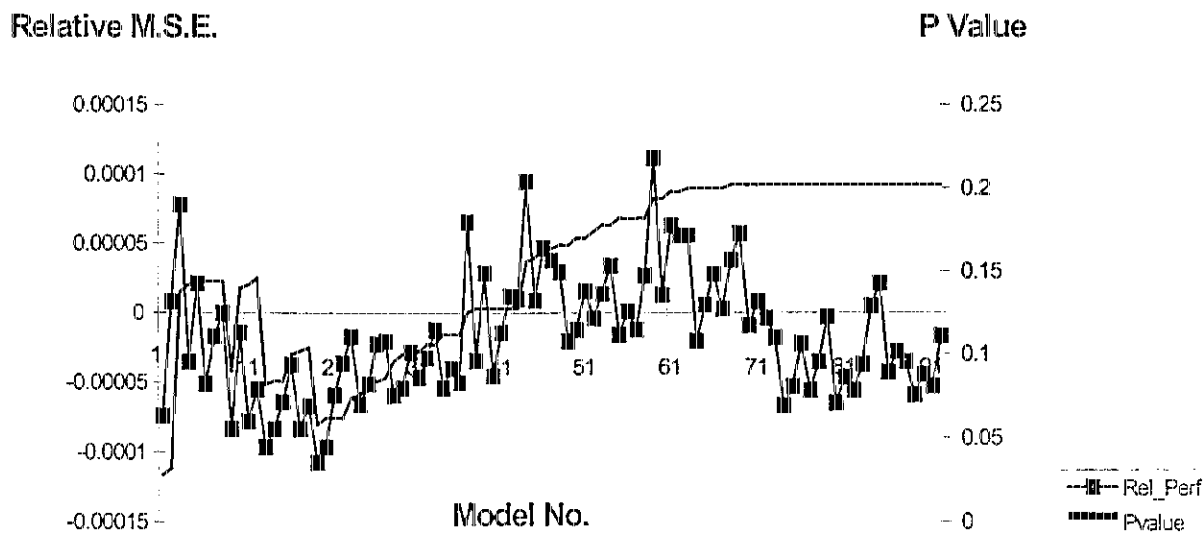


Figure 1. This shows the mean squared errors (M.S.E.'s) of all 92 models described in Appendix B, relative to the M.S.E. of the random walk model. It shows that for this particular exchange rate and forecast horizon, models with a lagged exchange rate (Models 9-36) and models with only political variables (models 89-92) tend to have relatively low M.S.E.'s. The secondary axis relates to the solid line. This gives the p value you would get if you stopped the experiment after each particular model. Thus if you stopped after model 19 you might conclude that model 19 is significantly better than the random walk. This would be incorrect since this p value does not take into account that the experiment is searching over 92 models. The only p value that counts is the final p value.

Figure 2

DM:US\$ Bilateral Exchange Rate:
Relative Prediction errors

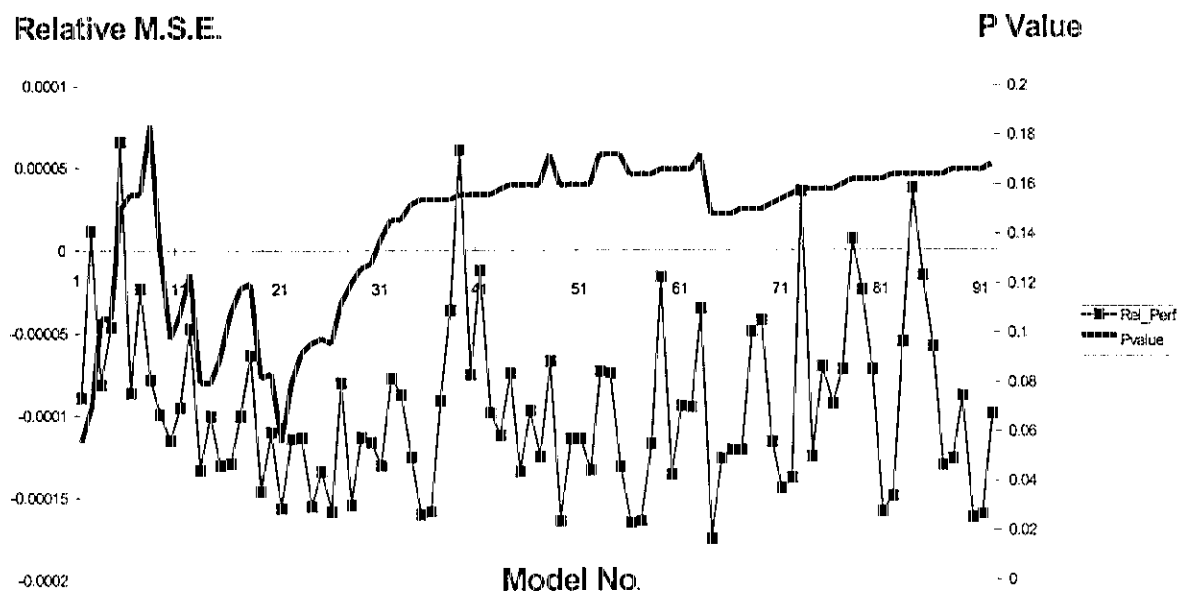


Figure 2. This shows the mean squared errors (M.S.E.'s) of all 92 models described in Appendix B, relative to the M.S.E. of the random walk model. It shows that for this particular exchange rate and forecast horizon almost all models beat the random walk. The secondary axis relates to the solid line. This gives the p value you would get if you stopped the experiment after each particular model. Thus if you stopped after model 21 you might conclude that model 21 is significantly better than the random walk. This would be incorrect since this p value does not take into account that the experiment is searching over 92 models. The only p value that counts is the final p value.