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An Analysis of the Performance of European Foreign Exchange Forecasters

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AN ANALYSIS OF THE PERFORMANCE OF EUROPEAN FOREIGN EXCHANGE FORECASTERS*

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Abstract: A database of individual forecasters' exchange rate predictions is analyzed. We demonstrate that only a small minority can be classed as rational, that most forecasts are inferior to easily available alternatives, and that relatively good performance in one period is not a reliable indicator of relatively good performance in subsequent periods.

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Introduction

The failure of standard economic models to display any out-of-sample forecasting ability over horizons of up to one year "continues to exert a pessimistic effect on the field of empirical exchange rate modeling in particular and international finance in general" (Frankel and Rose, 1994).[1] As a result of this lack of success, many economists have turned to alternative approaches to modelling exchange rates over shorter horizons.

One important line of research considers the effect that technical analysts or noise traders may have on the market. Technical analysts ignore fundamental variables (such as money supplies, income levels or interest rates) and instead use statistical, graphical or, in some cases, astrological techniques to predict exchange rates. The widespread use of these methods is well documented (see Allen and Taylor, 1990) and many economists argue that dealing by noise traders may be sufficient to drive a wedge between the market price and the 'true' fundamental price. The market price only returns to the fundamental price in the long run when the random effects of the supposedly irrational noise traders wash out. It is argued, therefore, that economic models may only display long run forecasting ability.

Rather than examine academic models of exchange rates based on fundamental or technical analysis, this chapter investigates the performance of a large number of European-based exchange rate forecasters. The panel includes individuals employed in (i) large eminent commercial and investment banks based in Europe's key financial sectors, (ii) major multinational corporations, and (iii) independent private and public sector forecasting agencies. All panellists are close to the currency market and are well aware of the many factors which can affect the exchange rate. These practitioner forecasts therefore probably incorporate both fundamental and technical analysis, together with expectations of other potentially important influences on exchange rates such as the actions of central banks and foreign currency order flows. Examining forecasts based on a wider information set than just fundamental or technical determinants is a more powerful test of predictive performance: if economic fundamentals, technical analysts and central bank actions all affect the exchange rate to some significant extent, forecasting on the basis of just some of the relevant information will clearly be inferior.

This investigation of a sample of forecasters' ability to predict exchange rates has three

[1] Considerable evidence exists which suggests that economists can say something useful about the exchange rate over horizons in excess of one year (see MacDonald, 1995).

main components. First, the forecasts are analyzed to determine whether they can be described as rational, using two simple regression-based tests. Second, the accuracy of each individual forecaster is measured and compared to a simple but robust benchmark. Third, this chapter investigates whether the performance of each forecaster is a useful guide to their future forecasting ability. In other words, are forecasters who have been more accurate than their peers in the past likely to be more accurate in the future? Before the data are tested, however, the next section describes the survey data in more detail.

1. Data Description

The forecasts analyzed in this chapter are taken from the database of Consensus Economics Inc. of London (hereafter Consensus). Consensus contact over 200 economists, traders and executives from leading commercial and investment banks, public and private sector forecasting agencies and multinational corporations each month. The panellists are requested to return by facsimile, *inter alia*, their point estimates of the spot exchange rate of the Deutschmark, pound sterling and Japanese yen against the US dollar in three calendar months' time (the date for which the forecasts are made is termed the forecast date). The mean and standard deviation of the forecasts are compiled by Consensus and sent to clients shortly after the survey is conducted.

The survey began in September 1989, but due to slightly lower coverage in the initial months the first forecasts used in this chapter are those made in January 1990. A total of 60 three-month forecast periods are available. The survey covers the G7 nations plus Australia but for this chapter we shall only examine the European-based forecasters' predictions. Over the five years of the survey 110 European-based organisations have provided at least one exchange rate forecast. Of these 43 are British-based, 29 are from Germany, 23 from France and 15 from Italy. To maintain anonymity, the panellists are identified in the database by a mnemonic which only reveals their nationality.[2]

Response rates to the survey are typically high but imperfect. To ensure sufficient observations for reliable estimation of the performance of each forecaster, a minimum response rate of 40 (out of a possible 60) forecasts is initially imposed. This reduces the panel to 53, 49,

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[2] The same mnemonics have been used in previous studies of this database to facilitate comparison. See MacDonald and Marsh (1994), MacDonald and Marsh (1996) and Marsh and Power (1996).

and 47 forecasters for the Deutschmark, pound and yen respectively. Nevertheless, as Table 1 shows, these panellists which remain account for a disproportionately high share of the forecasts for each currency; the coverage therefore appears sufficiently comprehensive for the results to be considered representative of European foreign exchange forecasters as a whole.

Table 1.

Response Rates of Consensus Panel Forecasters

	Deutschmark	Pound Sterling	Japanese Yen
All Forecasts	6611	5891	6349
European Forecasts	4035	3688	3458
of which, Selected Forecasts	2920	2682	2587
Coverage (Selected/European)	72.4%	72.7%	74.8%

One limitation of the survey is that the forecasts are collected from organisations rather than from individuals. Therefore, for example, should the chief economist change job or take a vacation during which his assistants make the forecasts the nature of the forecasts might change. We have made no attempt to correct for this potential problem due to the obvious difficulties of keeping track of the employment and holiday plans of around two hundred people.

A second problem is that the Consensus panellists are asked to forecast ‘the’ exchange rate prevailing on the specified forecast date rather than, say, the New York closing rate. We have chosen the mid-afternoon London rates as the most appropriate due to London’s dominance of the foreign exchange market and its central position in the daily trading pattern.[3] These data are collected from the Barclays Bank International pages on Datastream, and are the middle market rates prevailing at a time between 3:30 and 4:00pm in London. Experimentation with alternative actual values made no substantive differences to our conclusions.

The three currencies behaved very differently over the period under study. The Deutschmark-US dollar rate exhibited large swings throughout the period, the pound-dollar rate swung wildly in the first two years, dropped sharply in mid 1992 and subsequently traded in a narrow range, while the yen appreciated relatively consistently throughout the sample period.

[3] See the regular Bank of England Quarterly Bulletin surveys on foreign exchange trading.

The spot exchange rates are plotted in Figures 1 through 3. As a rough guide to the accuracy of the forecasters, for each month the range of highest and lowest forecasts is also plotted as a vertical line together with the rate prevailing on the forecast date. From all three graphs it is apparent that forecasters as a whole failed to predict many of the major swings in the currencies (i.e. the actual exchange rate lies outside the forecast range). Following such unexpected movements in the exchange rates the range of forecasts often widened considerably (e.g. the Deutschmark in mid-1991). Conversely, when the markets were more stable the range of forecasts narrowed appreciably (e.g. sterling from mid-1993).

2. Forecaster Rationality

Increasingly in economics, models are specified which assume agents have rational expectations. Survey data on expectations allow us to test for rationality by seeing whether they obey two properties (see, for example, MacDonald, 1992); forecasts should be unbiased predictors of the actual price, and the implied forecast error should be orthogonal to the conditioning information set.[4] These properties may be summarised with reference to regression equations (1) and (2)

$$\Delta s_{t+k} = \alpha + \beta \Delta s^{e}_{t+k} + \varepsilon_{t+k} \quad \textbf{(1)}$$

$$s^{e}_{t+k} - s_{t+k} = \Phi_0 + \Phi_1 X_t + \varepsilon_{t+k} \quad \textbf{(2)}$$

where s denotes the natural logarithm of the exchange rate, the superscript e denotes an expectation, k is the forecast horizon $\Delta s_{t+k} = s_{t+k} - s_t$, and X_t is the period t information set available to agents at the time their forecasts were formed. If agents form optimal forecasts of the future spot rate, then in equation (1) α should equal zero and β should equal 1 (the unbiasedness property) and furthermore in equation (2), the Φ coefficients should jointly equal zero (the error orthogonality property).[5] Forecast series for which all properties hold are said to be rational forecasts. Note that equation (1) is specified in difference form because of the non-

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[4] Froot and Ito (1989) examine a third efficiency property, namely the consistency of expectations but this is not investigated in this chapter.

[5] In the presence of non-overlapping data the error terms in equations (1) and (2) should also be serially uncorrelated, but our use of monthly sampled three month forecasts makes this further test invalid.

stationarity of the exchange rate series. Since the observational frequency of our data is greater than the forecast horizon this imparts a moving average error of order equal to k-1 (i.e. 2 when examining three month forecasts). Whilst OLS estimation produces unbiased and consistent coefficient estimates they are inefficient. We therefore use Hansen's (1982) Generalised Method of Moments (GMM), in its heteroscedasticity-consistent form, to correct the coefficient covariance matrix.

The results of these tests of the rationality of our panellists' forecasts are summarised in Table 2. For the error orthogonality tests in equation (2) the information set is potentially limitless, but to illustrate the panellists' performance we include only the one period lagged change in the exchange rate (i.e. Δs_{t-1}).

Only nine forecasters prove to be rational, all when forecasting the pound sterling exchange rate. No forecasters can be said to be unbiased for the yen, and the two that appear to be unbiased when forecasting the Deutschmark fail the orthogonality condition. Indeed for a total of 69 forecaster-currency combinations, simply incorporating the previous period's change in the exchange rate would have improved forecasting accuracy (a clear case of irrationality). Including other equally simple elements in the information set resulted in even more failures of the orthogonality condition (although these results are not reported here to conserve space). In the majority of cases the point estimate of β is negative. This indicates that the forecasters even got the direction of change (weighted by the square of their forecast error) wrong.

Table 2

Unbiasedness, Error Orthogonality and Rationality

	Number	Unbiasedness	β>0	Orthogonality	Rational
Deutschmark	53	2	22	27	0
Pound Sterling	49	11	25	38	9
Japanese Yen	47	0	11	15	0

Notes: The first column gives the number of forecasters tested. Figures in the column headed Unbiasedness give the number of forecasters for which the null hypothesis that α=0 and β=1 in equation (1) cannot be rejected. The third column gives the number of forecasters which returned a positive estimate of β (regardless of significance), while the column headed Orthogonality gives the number of forecasters for which the null of Φ_0=Φ_1=0 in equation (2) cannot be rejected. The final column gives the number of forecasters for which both unbiasedness and error orthogonality cannot be rejected.

Despite this apparent crushing indictment of the forecasting ability of our panellists it should be noted that these tests of rationality are particularly stringent. They require that the unbiasedness and error orthogonality propositions hold within what is a relatively short sample period. For example, suppose that in reality forecasters are rational. Randomly distributed, unforecastable shocks to the key determinants of exchange rates would be captured by the error term in equation (1) and would not affect the coefficient β. However, suppose that within the sample period these shocks do not arrive randomly. Even with truly rational forecasters, rejection of the unbiasedness hypothesis may occur. To get a further impression of the performance of the forecasters we now examine a measure of their predictive accuracy

3. Forecaster Accuracy

Several competing approaches exist for calculating the accuracy of forecasts. Engel (1994) argues that ideally a loss function should be specified by the evaluator or end-user of the predictions and alternative forecasts compared by how well they minimise this function. Specifying this objective function is seldom a simple task, however and the literature on foreign exchange rate forecast evaluation follows three different approaches. The majority of papers compare forecasts on the basis of statistical measures of accuracy such as the root mean squared error (RMSE). The primary advantage of this measure is that it is very simple to compute. Its main disadvantage, however, is that within Engel's framework it imposes a quadratic loss function on the end user, which may or may not be appropriate.

A second, widespread approach is to use some form of profitability measure (see Boothe, 1983). Since a major use for exchange rate forecasts is currency speculation, evaluating predictions on the basis of profits earned has immediate appeal. The main problem here is that a rule needs to be specified which determines the size of any speculative positions taken. The Consensus data are point forecasts with no measure of uncertainty or risk attached. It is difficult to then determine time-varying position sizes, and is certainly less than plausible to impose a fixed position size irrespective of expected profits. A portfolio-based approach to this problem has been suggested by Marsh and Power (1996) but their method is dependent upon such high survey response rates that it would not be possible to provide a meaningful evaluation of sufficient forecasters here.

The third approach is closely related to that of profitability, and is based upon directional forecasting ability (see Leitch and Tanner, 1991). Both its main advantage and disadvantage is that it assumes that the direction of the predicted change in the exchange rate is the only thing that matters. Clearly a speculator who can trade costlessly is solely interested in whether a currency will appreciate or depreciate. This speculator only wants to know which side of the market to be on. However, once trading costs are introduced the speculator will need to know whether any expected profits will cover the expense of trading. Similarly, an importer wondering whether to hedge currency exposure will be interested in the magnitude of any potential exchange rate losses, since retail foreign exchange trading is certainly not costless and ties up valuable credit lines.

We will use the root mean squared error, a statistical measure of forecast accuracy, for the simple reason that since the seminal work of Meese and Rogoff (1983) on exchange rate forecasting, it has remained the most widely used metric. The root mean squared error of a series of forecasts is calculated as

$$RMSE = \sqrt{\frac{\sum (s^{e}_{t+k} - s_{t+k})^2}{n}} \qquad \textbf{(3)}$$

where in addition to terms already defined, n is the number of forecasts in the sample. Since the exchange rates are expressed in logarithmic form, the RMSE statistic gives approximate percentage errors. In principle, this measure allows us to compare the accuracy of any two (or more) forecasts. It does not in itself say that one forecaster is significantly more accurate than another, although this can be tested using a variety of procedures (see Diebold and Mariano, 1995).

Comparing the relative accuracy of competing forecasters is interesting. However, an absolute measure, or benchmark, against which forecasters can be measured is essential to evaluate their performance in practice; *X* may be more accurate than *Z*, but this is of limited interest if both are inferior to a simple alternative measure. The choice of appropriate benchmark was simplified once Meese and Rogoff (1983) concluded that none of the exchange rate models they examined were more accurate than a random walk (that is, a naive prediction of no change). The random walk has become the primary benchmark against which currency forecasts are judged.[6]

Since forecasters provide predictions over different samples, the random walk benchmark is computed for each permutation of response records. Thus, if forecaster B1 replies to all questionnaires with the exception of January 1992, a random walk RMSE statistic is also calculated over all months except January 1992. The ratio of forecaster RMSE to the corresponding random walk measure is then calculated. A value less than unity indicates that the forecaster 'beats' a random walk. Note that this procedure only compares the performance of each forecaster with the random walk alternative. Two forecasters can only be compared when their response records are identical.

Table 3

Forecaster Accuracy

	Number of Forecasters	RMSE Ratio < 1
Deutschmark	53	1
Pound Sterling	47	1
Japanese Yen	45	0

Notes: The first column gives the number of forecasters analyzed for each currency. The second column gives the number of forecasters whose RMSE was less than that of a random walk over a corresponding period.

These ratios of forecaster accuracy are presented graphically in Figures 4 through 6, and in tabular form in Table 3. It is quite clear that few forecasters manage to provide more accurate predictions than the random walk model. The results of this study are therefore consistent with the findings of Meese and Rogoff (1983) and several subsequent authors, who have concluded that fundamental models do not appear to be able to predict exchange rates over horizons of less than one year. They are also in apparent agreement with the conclusions of Levich and Thomas (1993), who found that although the ability of technical trading rules to predict future changes in the exchange rate were initially promising, their ability had diminished substantially in the late 1980s. Even the additional information that the panellists could have brought to the forecasts,

[6] The forward rate is sometimes suggested as an alternative benchmark. However, given the large literature that documents substantial bias in the forward rate, and the fact that it too proved inferior to a random walk in Meese and Rogoff's study (1983), the more common benchmark is maintained here.

such as order flow information or expectations of central bank operations, were not sufficient to improve their comparative accuracy.

We noted above that we could not strictly compare the performance of forecasters with different response records. Nevertheless, the RMSE ratios will provide some guide as to who are the better performers even if precise rankings are not possible. The individual results for each currency reveal some interesting relationships. Foremost among these is the consistently good performance of forecaster F6, who proves to have the lowest RMSE ratio for the Deutschmark, second lowest for the pound sterling and sixth lowest for the yen. In previous work using this database, G9 has consistently ranked in the top quartile for all three currencies (see Marsh, 1994, and Marsh and Power, 1996). Based on the longer data sample analyzed in this chapter, G9 still appears to be the most accurate forecaster of the pound and comes a creditable seventh for the Deutschmark, but is among the least accurate of yen forecasters with a RMSE ratio in excess of two. These contrasting fortunes raise the interesting question of whether the best forecasters remain accurate over time. In the next section we examine whether the better forecasters are able to maintain their relatively good performance, or whether a good track record in predicting exchange rates in the past is no guide to future success.

4. Hot Hands in Foreign Exchange Forecasting

The term 'hot hands' was coined in the finance literature to characterise investors who exhibit above average performance which persists for some time. If hot hands exist, above average performance in one period would indicate that above average performance in the subsequent period is likely. Similarly, the phenomenon of 'cold hands' can be defined based on below average performance. Malkiel (1995) and Kahn and Rudd (1995) look for evidence of hot or cold hands in the US mutual fund management industry with little success. More positive findings are reported by Grinblatt and Titman (1992) and Hendricks, Patel and Zeckhauser (1993). Kahn and Rudd (1995) find persistence in the US fixed income fund management sector.

The same principle can be applied to the Consensus database of foreign exchange forecasters - does relatively (in)accurate performance in one period indicate that relatively (in)accurate performance can be expected in the subsequent period? To our knowledge, this is the first time that this 'hot hands' phenomenon has been explicitly tested for in the foreign exchange market.

The main practical difficulty in testing for hot hands again relates to the imperfect response rates of panellists. Simply using the average forecast error over those months for which each panellist provides a prediction implicitly assumes that each month is equally difficult to forecast. This may not be the case since during periods of relative economic instability exchange rates may be relatively difficult to predict. This problem can be dealt with by means of a fixed effects model.

The fixed effects model computed is given in equation (4)

$$|e_{it}| = \mu_i + \delta_t + \varepsilon_{it} \qquad \textbf{(4)}$$

where μ_i and δ_t are termed forecaster and month effects respectively. The dependent variable is a column of absolute errors stacked by forecaster. The forecaster effects dummies take the form of i column vectors, one for each forecaster. Forecaster j's dummy vector contains a one if the element of the dependent variable is an absolute error of forecaster j and a zero otherwise. The month effect dummy for period k contains a one if the element of the dependent variable is an error relating to a forecast made in period k and a zero otherwise. Note that this is not a seasonal dummy in the usual sense since a forecast made in January 1990 needs a different dummy to one made in January 1991.

The estimates of μ_i can be interpreted as the average accuracy of forecaster i, conditional on the months in his or her sample of predictions. The inclusion of month effects controls against attributing superior forecasting ability to a panel member who, by chance or design, only provides forecasts for relatively easy months. Forecasters who chose not to provide predictions for a currency during turbulent months derive no advantage over the average of those that did.

Estimates of μ_i are calculated for each forecaster using data from the first half of the sample, and the forecasters are ranked. A forecaster is defined as a 'Winner' ('Loser') if he or she is more (less) accurate than the median forecaster. The same procedure is repeated using data from the second half of the sample.[7]

[7] Since the forecasts are over three month horizons the two central months are excluded from the analysis to ensure the two sub-samples are fully independent. The first half of the sample is therefore limited to the period January 1990-May 1992, and the second half is limited to August 1992-December 1994. To ensure both sub-samples contained sufficient observations to accurately assess performance the sample was further limited to those panellists that provided at least 18 forecasts in each. In practice this only excluded one or two panellists for each currency.

The existence of hot hands can then be tested by means of the z-statistic, defined as:

$$z = \frac{Y - np}{\sqrt{np(1-p)}} \quad \textbf{(5)}$$

where Y is the number of persistently winning forecasters, n is the number of winning forecasters in the first half of the sample, and p is the probability that a winner from the first half of the sample will be a winner in the second (see Malkiel, 1995). Under the null hypothesis of no persistence p should equal one-half (i.e. even though a forecaster may have been a winner in the first period he or she still has only a fifty-fifty chance of being a winner in the second period). The z-statistic tests whether the probability p of consistently winning is different to one-half. It is approximately normally distributed with mean zero and standard deviation one for large n.[8]

An alternative test for performance persistence is the standard χ^2 test of a 2×2 contingency table (see Kahn and Rudd, 1995). The four cells of the table categorize forecasters as persistent winners, persistent losers, winners who become losers, or losers who become winners. Persistence would clearly be indicated by higher numbers in the persistent winner and persistent loser cells. This approach tests for general performance persistence (i.e. hot and cold hands at the same time). The test statistic χ, which is distributed $\chi^2(1)$, is calculated as:

$$\chi = \sum \frac{(O_j - E_j)^2}{E_j} \quad \textbf{(6)}$$

where O_j is the observed number of forecasters in cell j, and E_j is the expected number of forecasters in cell j. Under the null hypothesis of no persistence of performance the same number of forecasters would be expected to fall in each cell, since we are ranking winners and losers with respect to the median forecaster.

The third approach used is to regress the estimates of μ_i from the second sub-period on the μ_i estimates from the first period (see Kahn and Rudd, 1995):

$$\mu_i(2) = \alpha + \beta \mu_i(1) + \varepsilon \quad \textbf{(7)}$$

8 An equivalent procedure tests for cold hands.

Persistence of performance would be indicated by a significantly positive estimate of β since performance in the first sub-period would help predict performance in the second period.

The distributions of forecasters into contingency tables of winners and losers in the two periods are detailed in Table 4.

Table 4a

Deutschmark

		Sub-Period 2 W	Sub-Period 2 L
Sub-Period 1	W	14	11
	L	10	14

Table 4b

Pound Sterling

		Sub-Period 2 W	Sub-Period 2 L
Sub-Period 1	W	13	10
	L	10	13

Table 4c

Japanese Yen

		Sub-Period 2 W	Sub-Period 2 L
Sub-Period 1	W	14	7
	L	8	14

Table 4a, for example, indicates that of the 25 forecasters categorized as winners in the first period, 14 remained winners while 11 became losers. Similarly, 14 of the 24 losers remained as such. At first glance, this would appear to indicate that performance does tend to persist. The tests detailed above will allow us to determine whether these tendencies are significant or not.

The results of the alternative tests for persistence of performance are presented in Table 5. Only two test statistics are significant at the five percent level: the regression-based test for the pound and the χ test for the yen. The results for the pound are heavily influenced by one forecaster who is outstandingly poor in both sub-samples (plotted on the extreme right of Figure 7). Excluding this single observation from the regression removes all statistical significance (rotating the fitted relationship clockwise), and leads to the conclusion that good or bad performance in the first 29 month period could not be relied upon as an indicator of similar performance in the second 29 month period for the Deutschmark or pound sterling.

For the yen, however, all four tests show at least weak evidence that performance persists, including a very strong indication of persistence from the χ-test.[9] One might therefore conclude that there is evidence that relatively good (bad) yen forecasters remain relatively good (bad).

Table 5

Tests of Performance Persistence

	z-test - hot hands	*z*-test - cold hands	χ-test	β-test
Deutschmark	0.60	0.82	1.01	0.41
Pound Sterling	0.63	0.63	0.78	2.03*
Japanese Yen	1.53	1.28	3.95*	1.34

Notes: See text for details of each test statistic. An asterisk denotes significance at the five percent level.

5. Conclusions

The main findings of our investigation into the performance of European-based foreign exchange forecasters presented in this chapter can be summarised as follows:

(1) Evidence of irrationality was found for the vast majority of forecasters, primarily because of bias in their predictions.

(2) Over the full sample only two forecasters were more accurate than the simple alternative

9 The *z*- and β-test statistics are all significant at the ten percent level or better for a one-sided test.

of a random walk; the remainder were considerably worse. Some forecasters, notably F6, were consistently among the most accurate for all currencies, although, particularly in the case of G9, good performance for some currencies does not indicate good performance for all.

(3) No significant evidence which suggested that the past records of forecasters provide reliable indication of their future performance for the Deutschmark or pound sterling. Good yen forecasters, on the other hand, do tend to remain relatively accurate. This may be related to the behaviour of the yen over the sample period.

The practical conclusion of this chapter is that even professionals in the currency markets, who are able to incorporate fundamental determinants, technical analysis and other factors into their forecasts, seem unable to out-perform a naive prediction of no change. The best prediction of the exchange rate in three months' time still appears to be today's rate.

Finally, it should be noted that this conclusion is based on forecasts over a three month horizon. Considerable evidence exists that simply using fundamental factors can help predict the exchange rate over long horizons (i.e. in excess of twelve months), while there have been no studies to date of ultra-short horizon forecasts. This latter area of one day, one hour or even one minute forecast horizons should be investigated if we are to gain a better insight into the operation of the foreign exchange market.

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