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BANK POSITIONS AND FORECASTS OF EXCHANGE RATE MOVEMENTS

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ABSTRACT

Using data on the foreign exchange positions of five leading financial institutions, this paper attempts to determine whether the recent profitability of banks' foreign exchange trading is due to superior abilities to forecast exchange rate movements. Overall, the position data provide evidence that the performances of some financial institutions are 1) better than one might expect if their forecasts were purely random and 2) consistent with the possibility that they may possess information that would be valuable in forecasting changes in exchange rates. The conclusions are limited, however, by the possibility that there exists a time-varying risk premium which is correlated with the positions.

Bank Positions and Forecasts of Exchange Rate Movements

Michael P. Leahy[1]

Introduction

The profitability of banks' foreign exchange trading has been trending upward in recent years, prompting questions about the source of those profits. In particular, do the profits arise from providing market-making services in an environment where the demand for those services is growing? Or do the profits arise from savvy position-taking and superior abilities to forecast exchange rate movements?

This paper investigates the second question. Its specific objective is to study whether the position data reported on the form FFIEC 035, our best source of information on the positions banks take, indicate any special abilities on the part of the reporting financial institutions in predicting exchange rate changes. A bank will be successful in its position-taking to the extent that it takes long positions in currencies that eventually appreciate and short positions in currencies that eventually depreciate (more than the interest rate differential). If the reporting financial institutions have a better-than-average ability to forecast changes in exchange rates, their

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positions, and ultimately trading profits, would presumably reflect that ability.

Overall, the position data appear to provide some evidence that the performances of some financial institutions are 1) better than one might expect if their forecasts were purely random and 2) consistent with the possibility that they may possess information that would be valuable in forecasting changes in exchange rates. These results are suggested in the analysis of individual currency performances by the fact that some institutions appear more often in the top tenth of the performance distributions than one might expect if the top performances were merely the outcome of good luck. Furthermore, when the performances are evaluated for a group of currencies rather than for individual currencies, the number of institutions that appears in the top tenth of the performance distributions seems to be relatively high, with the same institutions again appearing relatively frequently.

These results are consistent with other findings of persistently good performances in financial markets[2] and are intriguing because they seem to indicate that some institutions may have either monopolisitic access to information, such as private information about order flows, or superior insight into the implications of publicly available information. On the other hand, if the institutions' positions are correlated with a time-varying risk premium, the superior performances can be interpreted as compensation for bearing risk rather than as an indication of any special abilities to forecast movements in exchange rates.

There are at least two problems one must recognize in linking the results of this study with the profitability of banks' foreign exchange trading. First, the position data may not be representative of the positions that the financial institutions actually take when they make their

2. See, for example, Grinblatt and Titman (1992).

profits. The FFIEC 035 position data are measures as of the close of business on one day per month. Even if position-taking taking has made a significant contribution to the profits of these institutions, one might not detect it with this sample. Banks whose profits are made largely on intra-day positions or on positions taken on other days of the month will not show strong performances here. Second, the usefulness of these data in determining the profitability of position-taking in general by these institutions is severely hampered by our ignorance of the horizons over which the positions are held. The reported positions might well be profitable over a horizon not considered in this analysis.

Two types of statistical approaches are used in this paper. One is a nonparametric approach that focuses on the frequency with which the signs of the positions match the signs of changes in exchange rates. The other is a parametric approach that uses logit models to incorporate information on the magnitude of positions as well as their signs and to determine how well the position data predict the direction of currency movements. A third approach, not presented here, involves fitting a linear regression model that includes information on the magnitudes and signs of not only the position but also the change in the exchange rate. The results of this third approach are described in a companion paper by Ammer and Brunner (1994).

The data used in this analysis come from several sources. The position data are drawn from the monthly FFIEC 035 reports of five leading financial institutions over a period from June 1990 to March 1994. Because these reports are confidential, the institution names are suppressed in this paper; the five banks are referred to only by letters of the alphabet chosen at random (G, P, R, W, and Y). Data are available for other institutions, but it was determined that due to various reporting problems the data for those institutions would not be appropriate for this study. Line 11 in the FFIEC 035 report, the net reported dealing position, is used for the position data. According to the report instructions, the net reported dealing position is "the actively managed net dealing position for currencies . . . as reported to senior management for internal risk management purposes." The 035 report provides positions for six major currencies--the Australian dollar, Canadian dollar, mark, yen, Swiss franc, and U.K. pound. The exchange rate changes are derived from 4 p.m. exchange rates in New York, as reported by the Federal Reserve Bank of New York, and they are adjusted for interest rate differentials using eurocurrency deposit rates maintained by the BIS for all currencies except the Australian dollar. For the Australian dollar, we used the domestic cash rate. The changes in the six exchange rates, adjusted for interest rate differentials, are calculated over eight horizons extending from 1 to 20 business days.[3]

Nonparametric Analysis

One of the simplest ways to measure the performance of the position data in forecasting exchange rate changes is to calculate the proportion of times the signs of the position data match the signs of the change in the exchange rates. If the positions were taken randomly, with an equal probability of being long or short, one would expect that roughly half the time the signs would match. If, however, the positions taken reflect some ability to predict exchange rate changes, the proportion of correct sign matches would be greater than half. Under the assumption that the sign of position is independent of the sign of the change in the exchange rate, the number of correct guesses has a binomial distribution. Using this distribution, we can test whether the number of correct forecasts is significantly better than what we might expect if the positions were taken at random. Outcomes that appear in the higher end of the distribution, which would be represented by a percentile ranking, say, between 90 and 100,

3. The horizons considered are 1, 2, 3, 4, 5, 10, 15, and 20 business days.

are more likely to be indicative of better-than-random performance. In those cases, the position data might have some positive value as a forecasting tool. On the contrary, outcomes that appear in the middle of the distribution would show little support for the hypothesis that the position data indicate any significant information value.[4]

Table 1 shows the number of individual performances that score a percentile ranking of 90 or better.[5] The maximum number of performances that could appear for any one institution is 48, which would occur if the institution earned percentiles of 90 or above in all six currencies at each of the eight horizons. If the performances were purely random draws from the interval between 0 and 100, we might expect that 10 percent or about 4 or 5 of the outcomes to be at 90 or better for each institution. Table 1 shows an average of less than 3 outcomes in the top tenth for each institution. In addition, the frequency with which the various institutions appear in the top decile is not uniform. Institutions W and Y appear relatively more frequently than the others, although not more than one might reasonably expect if their performances were random.

Merton (1981) has criticized the use of this test, arguing that the proportion of correct forecasts may not be useful in determining whether the forecasts reflect any special abilities or information not already available to the market. For example, suppose that a particular currency is expected to appreciate more often than it depreciates during some period but that the timing of the ups and downs is not known. An investor with no special

4. Ironically, outcomes in the lower tail of the distribution are also indicative of information value, i.e., consistently wrong forecasts also contain useful information.

5. With about 45 observations at each horizon, the sign of the position would have to match the sign of the change in the exchange rate at least 60 percent of the time to be in the top decile. Also, because the outcomes and associated probabilities in this analysis are discrete, there will always be some spanning of percentiles. In an attempt to avoid biasing the results one way or the other, I report the mid-point of the probability interval as the percentile.

information about the timing could take a long position in the currency throughout the period. This position will correctly forecast the changes in the exchange rate more than half the time if the currency does indeed appreciate more often than it depreciates. However, those position data would not provide any information to market participants that they do not already have.

In an efficient-market equilibrium, the high score associated with this forecasting strategy can be thought of as an indicator of the return to bearing risk in the presence of a risk premium. Under the assumption that the risk premium is known to investors, the fact that one investor takes a risky position and is compensated for bearing that risk is not a sign of any special forecasting ability. To determine whether the FFIEC 035 position data offer information useful in forecasting exchange rate changes, we would like to exclude from our tests, to the extent possible, successful forecasts associated merely with compensation for bearing risk.

Merton (1981) offers an alternative measure that can, in principle, detect special forecasting ability in the presence of a risk premium. In the context of exchange rate forecasting, this measure is the sum of the probability of a correct forecast when the currency is appreciating and the probability of a correct forecast when the currency is depreciating. The sum of these conditional probabilities indicates the value of the position data as a forecasting tool. A position that is always positive would always correctly forecast the upward movements of the currency and never correctly forecast the downward movements. In this case, the sum of the probabilities would equal one, identical to the sum had random positions been chosen that would correctly forecast only half the upward movements and half the downward movements. Merton demonstrates that the sum of these conditional probabilities must be greater than one for the forecasts to have any positive value to agents interested in timing the movements of market prices.[6]

Henriksson and Merton (1981) provide a nonparametric test of the hypothesis that these conditional probabilities sum to one. If the forecasts are purely random, the number of times the position data correctly forecast an upward movement in the price of a currency follows a hypergeometric distribution. Cumby and Modest (1987) note that this test is an application of Fisher's (1935) exact test of the independence of row and column classifications in a two-by-two contingency table. Cumby and Modest also demonstrate that the Henriksson-Merton test is biased when there is a time-varying risk premium that is correlated with the forecasts. A constant risk premium, however, which could create problems for the simpler binomial test, would not bias the Henriksson-Merton test of market timing abilities.

Table 2 shows the number of individual performances that score a percentile of 90 or better under the assumption that the forecasts are purely random. The results are similar to those in table 1, although the performance of institution G looks better in this analysis, while the performance of institution P looks a bit worse. Still, there is little evidence overall of any better-than-random forecasting ability across all the banks--with an average of less than 3 performances appearing for each institution. As before, the frequency with which the various institutions appear in the top decile is not uniform.

Logit Analysis

One might think that the confidence an institution attaches to its belief about exchange rate movements is related to the size of the position

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6. In the special case in which the probability of a correct forecast in an up-market is equal to the probability of a correct forecast in a down-market, Merton's model is equivalent to the simple binomial model presented above. However, Merton's more general model allows these conditional probabilities to be equal without imposing that equality by assumption.

it takes. An institution might take a large position when it is more confident about its forecast of an exchange rate and a small position when it is less confident. To incorporate information about the confidence with which a bank might forecast an exchange rate change, one can consider a logit model of the probability that a currency will appreciate. In this framework, if the position data do contain information useful in predicting exchange rates, a larger (more positive or less negative) position would imply a larger probability that a currency would appreciate. The estimated distribution of the coefficient on the position variable is used to determine how well the position data perform. A coefficient that is positive and significantly different from zero at a 90 percent confidence level is interpreted as signaling a better-than-random performance by the bank. As with the nonparametric test of Henriksson and Merton, a good performance in the logit estimation may be indicative of an ability to forecast exchange rates not generally available to the market. Such a conclusion is warranted, however, only if one is willing to assume that any risk premium that might exist is either constant or uncorrelated with the positions taken.

As shown in table 3, 27 individual performances earned a percentile ranking of 90 or better. While this is a considerable increase from the number of performances that appeared in tables 1 and 2, it is still only a bit more than the 5 per institution one might expect with purely random forecasting. The frequency with which individual institutions appear in the top decile remains uneven, although three institutions--Y, P, and G--appear somewhat more frequently than one might expect with just random forecasting.

Additional Analysis

Additional analysis of the distribution of performance percentiles over the bottom, middle, and top thirds of the interval between 0 and 100 is shown in tables 4 and 5. Table 4 reports on results from the nonparametric estimation suggested by Henriksson and Merton; table 5 reports on the results of the logit estimation. If the positions taken by the institutions were random, the distribution of the percentiles would be roughly even across the thirds, as appears to be the case on average in table 4. The last two columns on the tables display information on more formal statistical tests of the uniformity of the distribution of results. Pearson's Q statistic, which is distributed as a chi-squared random variable with 2 degrees of freedom under the null hypothesis that the distribution of the percentiles is uniform, supports a rejection of the null hypothesis only at a horizon of three days in table 4. However, this rejection occurs because of the large number of performances in the middle third of the distribution, not because of an inordinately large number of good performances. In addition, the Kolmogorov-Smirnov statistic fails to come in large enough to reject the null hypothesis at any horizon. The logit estimation analyzed in table 5 shows a bit more promising results at the horizon of two days, with both the Q-statistic and the Kolmogorov-Smirnov test detecting a statistically significant (at the 10 percent level, at least) deviation from uniformity that corresponds to a large number of performances in the top third of the distribution. While table 4 provides little support for the hypothesis that the top performances in table 2 are indicative of anything more than good luck, tables 3 and 5 support the better-than-random hypothesis at one horizon at least.

Furthermore, a look at the whole distribution of outcomes reveals a slight tendency for there to be more outcomes in the top and bottom thirds of the distribution than in the middle third. This kind of result might occur when banks take positions in all currencies against the dollar, essentially betting that the dollar will move one way or the other against them all. When the bet turns out to be correct, the bank could get credit for up to six correct forecasts instead of one; when the bet turns out to be incorrect, the bank could show as many as six incorrect forecasts rather than one. In this case, even random forecasting would tend to generate more outcomes at the extremes of the distribution than one might otherwise expect.

Multinomial Logit Estimation

To attempt to deal with this problem, a multinomial logit model was estimated for trios of currencies and corresponding positions. In the simple logit estimation conducted above, there were only two categories of outcomes--the currency either rose against the dollar or fell. In the multinomial logit model, the number of categories of outcomes can be larger than two. With three exchange rates, the number of categories can be as large as eight--all three currencies can appreciate, all three can depreciate, two can appreciate and one depreciate (in 3 different ways), and one can appreciate and two depreciate (in 3 different ways). In both the simple and multinomial logit estimation, the purpose of the estimation is see whether the position data have any power to predict the probability of being in a category. With the multinomial categorization of the outcomes, correctly guessing a decline of the dollar against three currencies counts as one correct forecast, not three.

More currencies were not used in the multinomial logit analysis because of data limitations. With as many as six currencies, up to 64 categories can be generated. There are, however, only about 45 monthly observations in sample currently available. Even with only three currencies, it is often difficult to estimate the coefficients on the position data with any precision. Nonetheless, it is possible to test hypotheses about groups of coefficients with some precision even when individual coefficient estimates are imprecise. In particular, the hypothesis considered here is whether the position data as a group contribute to the explanatory power of the model over and above the constant terms. More formally, the null hypothesis is that the vector of coefficients on the positions are all zero. Under the null, the position data have no explanatory power. In this case, the likelihood ratio has a chi-squared distribution.

Table 6 shows individual institution performances that fall into the top decile of the chi-squared distribution for the mark-yen-U.K. pound trio. An additional complication arises because of the multivariate nature of this analysis. The percentile test cannot distinguish performances that are very good from those that are very bad, because a consistently bad performance is just as useful a predictor as a consistently good one. Consequently, the table reports only those performances that fall into the top decile and show a successful prediction history. A prediction history is defined as the sum over the sample period of the product of the position and the sign of the exchange rate change at a given horizon (adjusted for interest rate differentials). A successful prediction history is a positive sum. As noted in the table, Institution R is not listed as a top performer in the table, even though its performance shows up in the top decile as many as four times on the basis of the likelihood ratio test, because its position data generate unsuccessful prediction histories.

If all five banks had successful prediction histories and delivered performances that were in the top decile, the table would list a total of 40 appearances. Under the assumption that the forecasts are random, however, one would expect to see only about ten percent or about four listed in the table. Thus, the fact that 25 percent of the total are in the top decile and have successful prediction histories appears to be a rejection of randomness, particularly for some institutions. Institutions P and G appear much more frequently than one might expect, and Institution Y appears somewhat more frequently. While one should keep in mind that the sample size in this exercise is not large for this type of estimation procedure, the multinomial logit estimation appears to reveal that the position data for these banks show better-than-random performances and may be indicative of some predictive power.

Conclusions

In general, these results are consistent with the hypothesis that the FFIEC 035 position data contain some information that would be helpful in forecasting movements of exchange rates, but it is difficult to provide outright support. The nonparametric analyses, which consider how well the signs of the positions predict the signs of changes in the exchange rate, seem to provide little or no support for the hypothesis. However, the logit analyses, which incorporate the magnitudes of positions as well as their signs into models that predict the signs of changes in the exchange rate, appear to provide more support. In particular, the relatively frequent appearance of two or three institutions in the top tenth of the performance distributions under the logit estimations is indicative of some better-than-random forecasting ability by those institutions and possibly some special forecasting ability. However, these conclusions are limited by the possibility that there exits a time-varying risk premium which is correlated with the positions taken by the top performers. In that case, what appears to be special forecasting ability may be only normal compensation for bearing risk.

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Table 1

Simple Matching of Signs of Positions and Exchange Rate Changes:

Frequency of Appearance of Individual Institutions
in the Top Decile of the Binomial Distribution
(48 appearances per institution are possible)

Institution	Number of Appearances
G	0
P	3
R	0
W	5
Y	5
total	13

Table 2

Conditional Matching of Signs of Positions and Exchange Rate Changes:

Frequency of Appearance of Individual Institutions
in the Top Decile of the Hypergeometric Distribution
(48 appearances per institution are possible)

Institution	Number of Appearances
G	4
P	1
R	0
W	5
Y	4
total	14

Table 3

Logit Estimation of Extent to which Sign and Magnitude of Position
Predict Direction of Exchange Rate Change:

Frequency with which an Institution's Performance
Appears in the Top Decile of the t-Distribution
(48 appearances per institution are possible)

Institution	Number of Appearances
G	6
P	7
R	4
W	1
Y	9
total	27

Table 4

Distribution of Performances In Individual Currencies
by horizon
based on results of nonparametric estimation (Henriksson-Merton test)

Horizon (days)	Number of Cases in: Bottom Third	Middle Third	Top Third	Q	K-S
1	10	10	10	0.0	0.62
2	10	6	14	3.2*	0.98
3	7	16	7	5.4	0.80
4	8	9	13	1.4	0.63
5	13	7	10	1.8	0.81
10	9	9	12	0.6	0.89
15	12	9	9	0.6	0.77
20	10	12	8	0.8	0.67
average	9.9	9.7	10.4		
average share	.33	.32	.35		

Table 5

Distribution of Performances In Individual Currencies
by horizon
based on results of logit estimation

Horizon (days)	Number of Cases in: Bottom Third	Middle Third	Top Third	Q	K-S
1	7	12	11	1.4*	0.72*
2	8	6	16	5.6	1.25
3	11	6	13	2.6	0.78
4	11	9	10	0.2	0.46
5	12	11	7	1.4	0.77
10	12	6	12	2.4	0.67
15	15	7	8	3.8	1.12
20	12	8	10	0.8	0.62
average	11.0	8.1	10.9		
average share	.37	.27	.36		

Notes for tables 4 and 5: Column headed Q contains Pearson's Q-statistic; under the null hypothesis that the distribution of outcomes is uniform, a Q-statistic for three-celled decomposition is distributed chi-squared with 2 degrees of freedom. Column headed K-S contains the Kolmogorov-Smirnov statistic. An * indicates that the test rejects the hypothesis of uniform distribution at 10 percent level.

Table 6

Multinomial Logit Estimation
of Extent to which Signs and Magnitudes of Positions
in Marks, Yen, and U.K. pounds
Predict Directions of Corresponding Dollar Exchange Rate Changes:

Frequency with which Individual Institutions
Exhibit Successful Prediction Histories and
Performances that appear in the Top Decile of Chi-Squared Distribution
(8 appearances per institution are possible)

Institution	Number of Appearances
G	3
P	4
R	0
W	1
Y	2
total	10

Note: The position data for Institution R delivered performances that ranked in the top decile at four horizons, but these performances were not reported in the table because the data show an unsuccessful prediction history. A prediction history is defined as the sum over the sample period of the product of the sign of the exchange rate rate change at a given horizon (adjusted for interest rate differentials) and the position taken. A successful prediction history is defined as a positive sum. All the performances reported in the table had successful prediction histories.

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