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EXCHANGE RATE PROBABILITY DISTRIBUTIONS AND FUNDAMENTAL VARIABLES

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Abstract

This study attempts to increase fundamental variables ability to explain exchange rate price changes. To do this fundamental variables from the various theoretical models are linked with the distributional characteristics of exchange rate changes. Models are developed that relate fundamental economic variables to the specific forms of the distributions of exchange rate changes. Data sets are developed to isolate the effects of alternative distributional models. Regression models are applied to explain observed results for jump processes, for jumps based on the GARCH(1,1) model and to examine shifts between normals for the mixture of 2 normals process. The regression results indicate that explanatory power is increased by isolating the jumps. Implications of results and improvements in methodology are discussed.

INTRODUCTION

Published research, reports weak linkages between exchange rates and fundamental economic variables. Estimates of exchange rate equations have not fit the data well, and the out-of-sample predictions of these models are no better than the simplest naive alternative predictions. Single equation structural models have dominated the literature. The single equation structural models subjected to the most extensive testing are: the flexible price monetary model (Frenkel (1976) and Bilson (1978)), the sticky price monetary model (Dornbusch (1976) and Frankel (1979)), and the sticky price asset model (Hooper and Morton (1982)). These models are basically the logarithm of the exchange rate price change regressed against various fundamental variables, U.S. and Foreign: money supply, short and long term interest rates, industrial production, and cumulative trade balances, each model putting different restrictions on some of the parameters.

One of the first rigorous tests of these structural models was conducted by Meese and Rogoff (1983a,1983b,1988). Out-of-sample tests of the models were compared to a benchmark random walk model. Previous tests of the predictive accuracy of the models used in-sample tests. Predictions based on estimates from the structural models failed to outperform predictions of the simple random walk models. Even when a lagged adjustment was added to the model the random walk model was superior.

Although Meese and Rogoff found that the lagged adjustment did not improve results, more recent research supports the addition of lags to the specification. For example papers by Woo (1985), Boughton (1987), and Schinasi and Swamy (1989) find that addition of lags to the specification allowed the models to outperform a random walk (Schinasi and Swamy (1989) also include time- varying parameters).

Further improvements in the performance of the reduced-form structural models occurred when the coefficients of the independent variables were allowed to be stochastic and error correction regressors were included (See, Alexander and Thomas (1987), Boothe and Glassmen (1987), Sheen (1989), Baille and Bollerslev (1989), Gandolfo, Pandoan, and Palandino (1990), and Edison (1991)).

Meese and Rose (1989) tested a nonlinear model and found that forecasts from this model were no better than a random walk model. Diebold, Gardeazabel, and Yilmaz (1994) using improved methodology that allows for drift in the estimated model, find no evidence for cointegration among spot exchange rates.

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MacDonald and Taylor (1995) using a monetary error correction model, find that there are up to 3 statistically significant cointegrating variables between the pound-dollar exchange rate and domestic and foreign money supplies, industrial production, and long-term interest. MacDonald and Taylor's results conflict with previous research. They attribute their findings to improved estimation methodology. Their error correction model is found to be superior to the random walk, in 5 different forecasting horizons. The improvement increased as the forecast horizon lengthens. These results are consistent with Nelson (1995). He regresses multiple-period changes in the log exchange rate on the deviation of the log exchange rate from its fundamental value, Nelson finds that the R-squares increase with the forecast horizon and that out of sample predictions at long horizons, out performed the random walk.

To date there is no model, using daily data, that is consistently superior to the random walk model, based on *exante* predictive performance.

Recent studies on the form of the probability distribution of exchange rate price changes support a mixture of normals, a GARCH type model, or the mixed jump diffusion model (See: Tucker and Pond (1988), Taylor (1986), Akgiray and Boothe (1988), McCurdy and Morgan (1988), Kugler and Lenz (1990), Fujihara and Park (1990), Bollerslev, Chou and Kroner (1992), and Bollerslev and Ghysels (1996)).

This study combines these two lines of research by developing models that relate the specific form of the distribution of exchange rate price changes to the fundamental variables.

Although the link between fundamental variables and daily exchange rate price changes is weak, we hope to improve this link by focusing on the distributional characteristics of exchange rate price changes. Specifically, we use the form of the probability distribution to isolate a jump or distributional switch. The fundamental variables are examined to determine if they can explain this jump or switch. The fundamental variables include information on trade balances, relative interest rate changes, money supply changes, relative inflation changes, and changes in stock market indices.

METHODOLOGY

To test any model that relies on fundamental variables to explain either the GARCH(1,1) based jumps, the mixed jump diffusion jump arrivals, or shifts between mixtures of normals one must first isolate the effects of the candidate process. Here, we develop operational measures to represent the components of the assumed distributional models.

To test a model that uses fundamental variables to explain the mixed jump diffusion model jumps, the raw spot exchange data must be divided into jump and nonjump categories. Since the mixed jump diffusion model does not tell you which data points are jumps, boxplots are used to isolate the jumps. A jump is operationally defined to be any point greater than 1.5 times the interquartile range. While, the arbitrary multiple can be criticized, this method of isolating the jumps does not impose any distributional form on the jump distribution. For dates where these jumps occur, the change in the spot exchange value and the values of the fundamental variables on the same date were used as the jump data subset. Regression models are estimated using this subset of the data.

The dependent variable is the change in the log of the spot rate on the jump date. The fundamental variables used include unrestrictive forms of the variables from the monetary models, plus a variable for stock price movements. Only the unexpected component of the fundamental variables is used as independent variables since the expected component should already be incorporated in the exchange rate. A naive approach is used to determine the unexpected component. The most recent previous value is used as the expected.

For variables with daily data, the value for the previous day is the expected value for the current day. Dummy variables are used for fundamental variables with longer time intervals between the release of information. For example, money supply, cumulated trade balance, and industrial production information does not change on a daily basis. Therefore dummy variables are used to represent days when new information is released. The model tested for the jump data is:

Equation 1

$$j_t = \alpha_0 + \alpha_1 Uis_t + \alpha_2 Fis_t + \alpha_3 Uil_t + \alpha_4 Fil_t + \alpha_5 Umd_t + \alpha_6 Fmd_t + \alpha_7 Utd_t + \alpha_8 Ftd_t + \alpha_9 Uid_t + \alpha_{10} Fid_t + \alpha_{11} Indu_t + \alpha_{12} Indf + u$$

where *U* denotes U.S. currency and *F* denotes the foreign currency, the subscript *t* denotes time, and *j* = the logarithm of the change in the dollar price of foreign currency on the jump date, *is* = % change in the short term interest rate, *il* = the unexpected portion of long run inflation, proxied by the % change in long term interest rates, *md* = the dummy variable for a countries money supply announcement, *td* = the dummy variable for the announcement of the trade balance figures, *id* = the dummy variable for the announcement of the industrial production figures, *ind* = % change in the stock market index, and *u* = disturbance term.

To determine if the fundamental variables can explain the mixture of normals, maximum likelihood estimation is first applied to the exchange rate data to determine the parameter estimates for two normal distributions. We use an IMSL subroutine (*DNCONG*), which conducts constrained optimization. Based on these estimates, each spot exchange rate is classified by evaluating the estimated posterior probability for each normal distribution; the observation is then assigned to the distribution with the largest estimated posterior probability. The classification rule is to select the distribution j for generating observation t that has the largest posterior probability, that is:

Equation 2

$$\underset{j}{Max}\ \tau_j p(S(t)|(\alpha_j,\sigma^2_j))$$

where τ_j is the sample proportion of the total observations from distribution *j*, and $p(S(t)|(\alpha_j,\sigma^2_j))$ is a normal probability density function with mean α_j and variance σ^2_j. The spot exchange rates are each assigned to a group representing one of the normal distributions. The result is a time series of spot exchange rate changes with information on which normal distribution it is likely to come from. Examining this time series we can isolate the days when there is a distributional switch or jump (from normal 1 to normal 2 or from normal 2 to normal 1). This jump data is then regressed on the fundamental variables relating to the jump days using equation 1.

The GARCH(1,1) model assumes a normal distribution with conditional variances that change over time, as function sums of past squared deviations from the mean and past variances. The GARCH model is designed to account for persistence of shocks to the conditional variance process. Therefore the estimated GARCH(1,1) volatility equation for each currency is used in an attempt to isolate the jump data. Using each currencies volatility equation the daily percentage increase in volatility is estimated as, $(\sigma_t - \sigma_{t-1})/ \sigma_{t-1} \times 100$. A cutoff rate is chosen for each currency so that the number of jumps exactly matches the number of jumps from the boxplot approach. Assuming we have the relevant regressors, with this comparison, we can determine if the conditional variance approach is superior to the arbitrary boxplot approach in determining a true jump.

Once the jumps have been isolated using the conditional variance equation, regression (1) is run where the dependant variable is the logarithm of the change in the dollar price of foreign currency on the jump date determined by the volatility equation.

SAMPLE DATA

The exchange rate data consists of the daily closing spot prices for the British pound, Canadian dollar, German mark, and Japanese yen versus the U.S. dollar from the Merrill Lynch debt markets group's fixed income research data base for the years 1988 to 1992. The daily stock market indices are also from Merrill Lynch. The money supply (*M1*), trade balance, cumulative capital movements and industrial production monthly figures are from national sources. The short term interest rates are represented by three month Eurodeposit rates. The long term interest rates consist of yields on long term government bonds with a maturity of 10 years. The interest rate data is also from Merrill Lynch. The daily series represents changes between business days with no adjustment for holidays.

REGRESSION RESULTS

The regression results are summarized in Tables 1 through 4.[1] For all regressions, Whites (1980) correction for heterscedasticity is used, correcting for possible 1st order heteroscedasticity. This procedure did not significantly change the results and therefore is not shown . First order autocorrelation is tested using the Durbin Watson test. This test indicates no significant autocorrelation at the .05 level of significance for any currency.

Examining the Canadian regression results, Table 1, for the four regressions, the F Statistic is significant. Therefore the models have some explanatory power.

Examination of R^2 indicates that the fundamental variables do a much better job explaining the changes in the three jump subsets than they do explaining the overall data. The R^2 increases from .07 for the overall sample, to .13 for the 2 normal jump regression, .30 for the GARCH based jump regression, and to .34 for the boxplot jump regression.

All three jump regressions have Canadian long term interest rates significant. There is no consistency in terms of additional significant variables across the jump models. The Boxplot jump regression has the U.S. industrial dummy variable and the Canadian stock market index significant. The GARCH jump regression has the U.S. trade balance dummy variable and the U.S. stock market index significant. The additional significant variables in the 2 normal jump regression are the U.S. and Canadian trade balance dummy variables.

The explanatory power of the GARCH jump regression is no better than the boxplot jump regression. This indicates that for the Canadian data, the conditional variance approach is no better than the arbitrary boxplot approach in determining a jump.

Table 2 shows the Japanese regression results, the F statistic is significant for all four models. Similar to the Canadian results, the explanatory power of the jump regressions far exceeds that of the overall regression. The R^2 increases from .04 for overall, to .08 for the 2 normal jump regression, to .29 for the boxplot jump regression, and to .33 for the GARCH jump regression.

Japanese long term interest rates are significant for all four models. Again, there is no consistency in additional significant variables across the jump regressions. The additional variables significant in the Boxplot jump regression are the U.S. and the Japanese money supply dummy variables, and the Japanese industrial production dummy variable. The GARCH regression additional significant variables are both countries money supply dummy variables, the Japanese trade balance dummy variable, and the U.S. industrial production dummy variable. The additional significant variables for the 2 normal regression are the U.S. trade balance dummy variable, and the U.S. stock market index. The explanatory power of the GARCH jump regression is only slightly superior to the boxplot jump regression.

For the British regression, Table 3, the R^2 increases from the overall regression .05 to the jump regressions .11, .24, and .25 for the 2 normals, boxplot jump and GARCH regressions respectively. The F statistic is found not to be significant for the boxplot and GARCH jump regressions. The insignificant F statistic occurs in spite of the increased R^2 because the results are based on such a small sample. There are 12 independent variables and the increase in R^2 of using just the jumps is not large enough in this case to overcome only 64 data points. When a jump is determined using the 2 normal data (592 data points), the F statistic is significant. This gives support to small sample size being the problem with the other jump models. For the significant 2 normal jump regression, four variables are found to be significant, British long term interest rates, U.S. money supply dummy variable, U.S. trade balance dummy variable, and both countries stock market indexes.

The German regression results, Table 4, like the British, only the 2 normal jump regression has the only significant F statistic for the jump regressions, although the R^2 for all jump regressions are higher than the R^2 for the overall .03. Again, these results can occur with small sample sizes. Five variables are found to be significant in the 2 normal jump regressions. They are U.S. short and long term interest rates, German long term interest rates, U.S. trade balance dummy variable and the U.S. stock market index.

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1. As part of model estimation, variance inflation factors were estimated and used to detect multicollinearity. This method is more powerful than correlation analysis since it will pick up associations between two or more regressors. As a rule of thumb, Myers (1990), Kennedy (1992) suggest that a variance inflation factor exceeding 10 indicates that collinearity may be a problem. Variance inflation factors are run for the three models, for each currency (in addition to the jump, 2 normals and GARCH regressions, an overall regression is run for comparison purposes). None of the variance inflation factors are near 10. The highest value found is 2.684. Therefore, multicollinearity should not be a problem here.

SUMMARY AND CONCLUSIONS

This study examines relationships between forms of probability distributions for exchange rate price changes and fundamental variables. The form of the probability distribution is used to isolate a jump or distributional switch. The GARCH(1,1) model, a mixture of 2 normals and a jump process are used to isolate data representing a jump. All regression results indicate that explanatory power increases by isolating the jump data. The use of the volatility equation of the GARCH(1,1) model to isolate a jump, is found to be no better than the arbitrary boxplot approach.

For two of the four exchange rates examined, the increases in R^2 are significant compared to the overall data. With the other two currencies the overall F statistic increases significantly only for the 2 normal jump regressions, although the R^2 in each case increases. This result is due to the small sample sizes for the boxplot and GARCH(1,1) jump regressions.

A few significant coefficients have theoretically incorrect signs. Complex interactions between currencies and fundamental variables and the inability of independent single equation regression models to pick up these relationships could account for the observed inconsistencies. Simultaneous equations models could improve results and eliminate some of the observed inconsistencies.

Overall, we find significant links between distributional patterns of exchange rate changes and fundamental economic variables. Distributional switching or jumps seem to be affected by different fundamental variables than the non-jump data. For example, the dummy variables for government announcements of money supply, cumulated trade balance, and industrial production, did not generally play a significant role in the overall sample regressions. Alone, this information indicates that the market efficiently incorporates this information into exchange rates. For the significant jump regressions these dummy variables play a much more significant role, especially trade balance and money supply dummy variables. The jump data reveals that the market does not always incorporate this information efficiently. The market can be overly optimistic or pessimistic towards these figures. These results have important implications for specification and testing of exchange rate models.

REFERENCES

[1] Alexander, D., and L. Thomas, "Monetary/Asset Models of Exchange Rate Determination: How Well Have They Performed in the 80s?" *International Journal of Forecasting*, 1987, pp. 53-64.

[2] Akgiray, V., and G. Booth, "Mixed Diffusion-Jump Process Modeling of Exchange Rate Movements," *Review of Economics and Statistics*, November, 1988, pp. 631-637.

[3] Baillie, R., and T. Bollerslev, "Common Stochastic Trends in a System of Exchange Rates," *Journal of Finance* 44, 1989, pp. 167-181

[4] Bilson, J., "The Current Experience with Floating Exchange Rates: An Appraisal of the Monetary Approach," *American Economic Review: Papers and Proceedings*, 1978, pp. 392-397.

[5] Bollerslev, T., R. Chou, and K. Kroner, "ARCH Modeling in Finance," *Journal of Econometrics*, 1992, pp. 5-59.

[6] Bollerslev, T., and E. Ghysels, "Periodic Autoregressive Conditional Heteroscedasticity," *Journal of Business and Economic Statistics*, 1996, pp. 139-151.

[7] Boothe, P., and D. Glassman, "Off the Mark: Lessons for Exchange Rate Modelling" *Oxford Economic Papers*, 1987, pp. 443-423.

[8] Boughton, J., "Tests of the Performance of Reduced-Form Exchange Rate Models," *Journal of International Economics*, 1987, pp. 41-52.

[9] Diebold, F., J. Gardeazabal, and K. Yilmaz, "On Cointegration and Exchange Rate Dynamics," *Journal of Finance* 2, 1994, pp. 727-735.

[10] Dornbusch, R., "Expectations and Exchange rate Dynamics," *Journal of Political Economy*, 1976, pp. 1161-1176.

TABLE 1
Canadian Regression Results

	Overall	**Boxplot**	**GARCH**	**2 Normals**
F-Statistic	7.473	2.584	1.994	2.574
R-Square	.067	.341	.303	.131
Adj R-Square	.058	.209	.151	.081
Significant Variables at 5% Level				
Uis				
Uil	-.00034 (6.75)			
Cis	.00010 (5.32)			
Cil	.00094 (47.21)	.00294 (30.57)	.00362 (14.85)	.00119 (11.52)
Umd				
Cmd				
Utd	-.00066 (3.62)		-.00409 (6.45)	-.004430 (41.65)
Ctd				.006334 (18.48)
Uid		.00660 (270.08)		
Cid				
Indu	.00024 (3.90)		.00197 (4.49)	
Indc		-.00426 (28.65)		
Number of Observations	1262	67	67	217

#is: Short Term Interest Rate, *#il*: Long Term Interest Rate, *ind#*: Stock Market Index, *#md*: Money Supply Dummy, *#td*: Trade Balance Dummy, *#id*: Industrial Production Dummy. *#=C*:Canadian, B:British, U:United States, J:Japan, G:German.

TABLE 2
Japanese Regression Results

	Overall	**Boxplot**	**GARCH**	**2 Normals**
F-Statistic	4.336	2.064	2.175	3.290
R-Square	.040	.293	.330	.084
Adj R-Square	.031	.133	.178	.064
Significant Variables at 5% Level				
Uis				
Uil	.00050 (10.86)			
Jis				
Jil	.00102 (10.86)	.00628 (5.02)	.00678 (6.28)	.00110 (7.26)
Umd	-.00224 (5.04)	.02387 (13.65)	-.02293 (9.52)	
Jmd		-.10064 (5.18)	-.01724 (11.35)	
Utd				.00365 (5.46)
Jtd			-.00701 (4.79)	
Uid			.02180 (8.02)	
Jid		.01508 (3.56)		
Indu	.00054 (7.29)			.00088 (7.73)
Indj				
Number of Observations	1262	66	66	592

#is: Short Term Interest Rate, *#il*: Long Term Interest Rate, *ind#*: Stock Market Index, *#md*: Money Supply Dummy, *#td*: Trade Balance Dummy, *#id*: Industrial Production Dummy. *#=C*:Canadian, B:British, U:United States, J:Japan, G:German.

TABLE 3
British Regression Results

	Overall	Boxplot	GARCH	2 Normals
F-Statistic	5.449	1.366	1.457	3.789
R-Square	.050	.243	.252	.105
Adj R-Square	.041	.075	.079	.076
Significant Variables at 5% Level				
Uis				
Uil	.00103 (3.36)			
Bis	.00050 (3.82)			
Bil	.00107 (3.27)			.00202 (2.73)
Umd	-.03384 (-2.26)			-.00733 (-2.98)
Bmd				
Utd		.01733 (2.22)		.00585 (2.64)
Btd				
Uid				
Bid				
Indu	.00052 (2.02)			.00134 (2.39)
Indb	.00113 (4.10)			.00199 (3.13)
Number of Observations	1262	64	64	407

#is: Short Term Interest Rate, *#il*: Long Term Interest Rate, *ind#*: Stock Market Index, *#md*: Money Supply Dummy, *#td*: Trade Balance Dummy, *#id*: Industrial Production Dummy. *#=C*:Canadian, B:British, U:United States, J:Japan, G:German.

TABLE 4
German Regression Results

	Overall	Boxplot	GARCH	2 Normals
F-Statistic	3.520	.663	1.107	3.278
R-Square	.033	.194	.287	.109
Adj R-Square	.023	.000	.028	.076
Significant Variables at 5% Level				
Uis	.00044 (2.50)			.00090 (2.19)
Uil	.00104 (3.40)			.00154 (2.06)
Gis				
Gil				.00226 (2.45)
Umd				
Gmd				
Utd				.00535 (2.30)
Gtd				
Uid				
Gid				
Indu	.00082 (3.87)			.00186 (3.05)
Indg				
Number of Observations	1262	46	46	334

#is: Short Term Interest Rate, *#il*: Long Term Interest Rate, *ind#*: Stock Market Index, *#md*: Money Supply Dummy, *#td*: Trade Balance Dummy, *#id*: Industrial Production Dummy. *#=C*:Canadian, B:British, U:United States, J:Japan, G:German.

[11] Edison, H., "Forecast Performance of Exchange Rate Models Revisited," *Applied Economics*, 1991, pp. 187-196.

[12] Fujihara, R., and K. Park, "The Probability Distribution of Futures Prices in the Foreign Exchange Market: A Comparison of Candidate Processes," *Journal of Futures Markets*, 1990, pp. 623-641.

[13] Frankel, J., " On the Mark: A Theory of Floating Exchange Rates Based on Real Interest Differentials," *American Economic Review*, 1979, pp. 610-622.

[14] Frenkel, J., " A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence," *Scandinavian Journal of Economics*, 1976, pp. 200-224.

[15] Gandolfo, G., P. Padoan, and G. Paladino, "Exchange Rate Determination: Single-Equation or Economy-Wide Models?" *Journal of Banking and Finance*, 1990, pp. 965-992.

[16] Hooper, P., and J. Morton, "A Model of Nominal and Real Exchange Rate Determination." *Journal of International Money and Finance*, 1982, pp. 39-56.

[17] Kugler, P., and C. Lenz, "Chaos, ARCH and the Foreign Exchange Market: Empirical Results from Weekly Data," Unpublished Manuscript, 1990, Volkswirtschaftliches Institut, Zurich.

[18] MacDonald, R, and M. Taylor, "The Monetary Model of the Exchange Rate: Long Run Relationships, Short-Run Dynamics and How To Beat the Random Walk," *Journal of International Money and Finance*, 1994, pp. 276-290.

[19] Meese, R., and K. Rogoff, "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics*, 1983a, pp. 3-24.

[20] Meese, R., and K. Rogoff, "The Out-of-Sample Failure of Empirical Exchange Rate Models: Sampling Error or Misspecification?" in: J. Frenkel, ed., *Exchange Rates and International Macroeconomics*, (University of Chicago Press, Chicago, IL), 1983b.

[21] Meese, R., and K. Rogoff, "Was It Real? The Exchange Rate-Interest Differential Relation Over The Modern Floating Rate Period," *Journal of Finance*, 1988, pp. 933-948.

[22] McCurdy, T., and I. Morgan, "Testing the Martingale Hypothesis in Deutsche Mark Futures with Models Specifying the Form of the Heteroscedasticity," *Journal of Applied Econometrics* 3, 1988, pp. 187-202.

[23] Nelson, D., "Conditional Heteroscedasticity in Asset Returns: A New Approach," *Econometrica*, 1991, pp. 347 -370.

[24] Nelson, M., "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability," *American Economic Review*, 1995, pp. 201-218.

[25] Schinasi, G., and P. Swamy, "The Out-of-Sample Forecasting Performance of Exchange Rate Models When Coefficients are Allowed to Change," *Journal of International Economics*, 1989, pp. 375-390.

[26] Sheen, J., "Modelling the Floating Australian Dollar: Can the Random Walk be Encompassed by a Model Using a Permanent Decomposition of Money and Output?" *Journal of International Money and Finance*, 1989, pp. 253-276.

[27] Taylor, S., "Modeling Financial Time Series," Wiley,New York, NY, 1986.

[28] Tucker, A., and L. Pond, "The Probability Distribution of Foreign Exchange Price Changes: Tests of Candidate Processes," *Review of Economics and Statistics*, November 1988, pp. 638-647.

[29] Woo, W., "The Monetary Approach to Exchange Rate Determination Under Rational Expectations:The Dollar-Deutschemark Rate," *Journal of International Economics*, 1985, pp. 1-16.