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Random walk or bandwagon: some evidence from foreign exchanges in the 1980s

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The predictive performance of the bandwagon expectations model for weekly spot exchange rates over the 1980–6 period is evaluated. Empirical results generally indicate the presence of significant bandwagon effects in the exchange rate dynamics, as found in survey expectations data. Specifically, we find that the bandwagon forecasting scheme can improve the forecasting accuracy in terms of both mean squared errors and market timing upon the random walk and vector autoregressive models. The results illustrate that bandwagon expectations can be rational, and the exchange rate appears to follow a more general integrated process than a random walk.

I. INTRODUCTION

An interesting proposition regarding exchange rate expectations is the bandwagon expectations model, which has attracted much attention in recent literature (Dooley and Shafer, 1983; Frankel and Froot, 1986; 1987; Frankel and Meese, 1987). It suggests that a rise (fall) in the exchange rate will generate anticipations of a further rise (fall). Frankel and Froot (1986) examine survey expectations data for the yen/dollar exchange rate and find that the model is particularly relevant for short-term expectations.

Empirical research on exchange rate dynamics suggests, however, that the actual spot rate seems to behave differently from that conceived by survey respondents. For example, Meese and Singleton (1982) report that the random walk hypothesis is supported by the exchange rate data based on formal unit root tests. More direct evidence has been presented by Meese and Rogoff (1983) using out-of-sample forecasting experiments. Meese and Rogoff found that the random walk forecasts of exchange rates are generally more accurate than the forecasts of various monetary models and time series models where a unit root is not imposed.[1]

While the out-of-sample analysis conducted by Meese and Rogoff has provided significant evidence in favour of a null of a unit root, the analysis does not discriminate a random walk from a general integrated process. The distinction between the two processes can be important. The random walk model implies that successive exchange rate changes are independent. It follows that knowledge of the previous exchange rate change is of no value at all in predicting the following exchange rate change. If the exchange rate evolves as a random walk, bandwagon expectations will be suboptimal and suggest irrationality and destabilizing effects, as noted by Frankel and Meese (1987). In contrast, the exchange rate dynamics implied by the bandwagon expectations hypothesis involve significant positive correlations between successive exchange rate changes. This is true for autoregressive integrated processes, for example.

The behaviour of the observed exchange rate process and the rationality of the bandwagon expectations scheme are re-examined. Specifically, the relative predictive ability of the bandwagon expectations scheme and the random walk scheme is evaluated. If the former can actually predict better than the latter, bandwagon expectations will not be irrational, and it will indicate that the exchange rate does not follow strictly a random walk.

The bandwagon expectations model is discussed and the

[1]Wolff (1987) illustrates that allowing for time-varying parameters can enhance the forecasting performance. The results remain not impressive when compared with the simple random walk forecasts, nonetheless.

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forecasting experiments are described together with a nonparametric test of direction due to Henriksson and Merton (1981), and empirical results are presented.

II. BANDWAGON EXPECTATIONS AND DESTABILIZING EXPECTATIONS

Let S_t and E_tS_{t+1} denote respectively the (log of the) spot exchange rate and the next-period expected spot rate at time t. Frankel and Froot specify the bandwagon expectations model as follows:

$$E_tS_{t+1} - S_t = \phi(S_t - S_{t-1}) \tag{1}$$

where $\phi > 0$. When $\phi = 0$, we have a static or random walk expectations scheme

$$E_tS_{t+1} = S_t \tag{2}$$

When $\phi < 0$, we have a simple scheme of distributed lag expectations.

Frankel and Froot define that expectations are destabilizing if the expected future spot rate as a function of the current rate has an elasticity that exceeds unity. This definition is convenient, as Frankel and Meese (1987) remark, because it avoids the problem of correctly specifying the market fundamentals. For example, since $\phi > 0$, the evidence of bandwagon expectations presented by Frankel and Froot (1986) will suggest that the short-term yen/dollar expectations are destabilizing. As shown in Table 1, the result appears robust across different exchange rates. Table 1 contains the estimation results for the following regression:

$$E_tS_{t+1} - S_t = b_0 + b_1S_t + b_2S_{t-1} + \varepsilon \tag{3}$$

where ε is an error term and under the bandwagon expectations hypothesis, $b_1 > 0$, $b_2 < 0$ and $b_1 + b_2 = 0$. Results of unrestricted estimation indicate that all the estimates of both b_1 and b_2 are statistically significant and of the correct sign, and that the corresponding estimates of b_1 and b_2 are of similar magnitude. Except in the case of British pound forecasts, the hypothesis that $b_1 + b_2 = 0$ cannot be rejected at the 5% level of significance. Further, the estimates of ϕ, i.e. the estimates of the coefficient on $S_t - S_{t-1}$ from the restricted regressions, are all significantly greater than zero at the 1% level, indicating that expectations are destabilizing according to Frankel and Froot's definition.[2]

We observe that whether exchange rate expectations are stabilizing or not cannot be determined appropriately without information about the actual process governing the exchange rate. It is plausible that forecasts based on the bandwagon expectations scheme are indeed justified by the

Table 1. *OLS regressions of the bandwagon expectations model*

Currency	b_0	b_1	b_2	Restrict $b_1+b_2=0$	DF	DW	R^2	F
BP	−0.0118	0.1433	−0.1059		60	2.136	0.275	
	(0.0028)[a]	(0.0401)[a]	(0.0400)[a]					
	−0.0026			0.1236	60	1.785	0.119	12.6[a]
	(0.0011)[b]			(0.0489)[b]				
DM	0.0131	0.2025	−0.1902		60	1.527	0.367	
	(0.0082)	(0.0363)[a]	(0.0373)[a]					
	−0.0001			0.2038	60	1.458	0.338	2.63
	(0.0007)			(0.0362)[a]				
SF	0.0156	0.2263	−0.2101		59	1.799	0.367	
	(0.0083)	(0.0430)[a]	(0.0439)[a]					
	0.0011			0.2253	59	1.713	0.310	3.06
	(0.0009)			(0.0533)[a]				
JY	0.0849	0.2256	−0.2083		60	1.725	0.329	
	(0.0474)	(0.0483)[a]	(0.0502)[a]					
	0.0001			0.2391	60	1.626	0.284	4.00
	(0.0007)			(0.0607)[a]				

The data are one-week-ahead exchange rate forecasts from surveys carried out by the Money Market Services from October 1984 to February 1986 for the British pound (BP), Deutschemark (DM), Swiss franc (SF), and Japanese yen (JY) against the US dollar. Standard errors are given in parentheses. Significance levels are indicated by [b] for 5% and [a] for 1%.

[2]The survey evidence should be interpreted with caution. Tests based on survey data employ a joint hypothesis, namely traders' expectations follow a specified model and the survey data accurately describe the market expectations. When there is little or no cost in making errors, individual respondents may have little incentive to give revealing answers. Indeed, it can be in the interest of a market trader to misrepresent his belief, since his response possibly constitutes information that can be profitably exploited by another trader. Since survey forecasts can be prone to such a problem, additional evidence purged of the problem appears desirable.

actual changes in the exchange rate. The extrapolative forecasts may correctly anticipate and reflect systematic changes affecting the market fundamentals. If follows that bandwagon expectations do not necessarily imply destabilizing effects. If rises (falls) in exchange rates are often followed by further rises (falls) in exchange rates, bandwagon expectations will be rational and stabilizing. If the exchange rate follows a random walk, however, bandwagon expectations will be irrational and destabilizing. The behaviour of the actual exchange rate process is therefore crucial to the assessment. To provide that information, the rolling regression methodology is employed to study the exchange rate behaviour, as in Meese and Rogoff (1983).

III. EVIDENCE FROM OUT-OF-SAMPLE FORECASTING

In this section the predictive performance of the bandwagon forecasting scheme relative to the random walk scheme is investigated. We examine weekly spot rates from the first week of January 1980 to the last week of December 1986 for five bilateral exchange rates – the British pound (BP), Deutschemark (DM), French franc (FF), Swiss franc (SF), and Japanese yen (JY). The entire sample consists of 366 point-in-time observations for each series of spot rates, drawn from the *International Monetary Market Yearbook*. The data are interbank closing spot prices (bid side) on Wednesdays. When a data point fell on a holiday, the observation of the next business day was used.

As noted earlier, bandwagon expectations are rational when rises (falls) in exchange rates tend to be followed by further rises (falls). Suppose, specifically, the exchange rate follows a simple process as

$$S_t - S_{t-1} = \phi(S_{t-1} - S_{t-2}) + e_t \tag{4}$$

where $\{e_t\}$ is a white noise process with mean zero and finite variance. The rational forecasts for S_t, given by least squares predictors, will then be characterized by bandwagon effects, as modelled by Equation 1. For forecasting in real time, the value of ϕ can be estimated using the rolling regression technique so that the forecasts will reflect the most up-to-date information available at the time of the forecasts.

Equation 4 is simply a first-differenced autoregressive process, which includes the random walk model as a special case where $\phi = 0$. The rationality of bandwagon expectations then hinges on whether the actual exchange rate follows a more general integrated process than a random walk. In a related context Hakkio (1986) also observes that it is important to discriminate statistically a random walk from other interesting alternatives, in particular, from a more general process with a unit root, since the two processes can have rather different analytical implications. We face a similar problem here.

A preliminary in-sample analysis based on unit root tests is performed. The simple Dickey–Fuller (DF) and augmented Dickey–Fuller (ADF) tests (Dickey and Fuller, 1979; Fuller, 1976) and the Phillips–Perron test (Phillips, 1987; Phillips and Perron, 1988) are employed. Denote by L the lag operator. For a series $\{X_t,\ t=0,\ 1,\ldots,T\}$ the DF statistic is given by the t-statistic for c in

$$(1-L)X_t = c_0 + cX_{t-1} + e_t \tag{5}$$

and the ADF statistic is given by the corresponding t-statistic in

$$(1-L)X_t = c_0 + cX_{t-1} + c_1(1-L)X_{t-1} + \ldots + c_p(1-L)X_{t-p} + u_t \tag{6}$$

The Phillips–Perron test, which is a modified DF test, is robust to a wide variety of serial autocorrelation and time-dependent heteroskedasticity. The Phillips–Perron test statistic is given by

$$Z(t_c) = (s_0/s_{Tq})t_c - (s_{Tq}^2 - s_0^2)/2\left[T^{-1}s_{Tq}\left(\sum_{t=1}^{T} X_{t-1}^2\right)^{1/2}\right]^{-1} \tag{7}$$

where t_c is the usual t-statistic for c in Equation 5; s_0^2 is the sample variance of the estimated residuals; and s_{Tq}^2 is a consistent variance estimator given by

$$s_{Tq}^2 = T^{-1}\sum_{t=1}^{T} e_t^2 + 2T^{-1}\sum_{k=1}^{q}\sum_{t=k+1}^{T} w_{kq}e_t e_{t-k} \tag{8}$$

with q being a truncation lag and $w_{kq} = 1 - k/(q+1)$, the weighting scheme of Newey and West (1987) that ensures a positive variance estimate. The limiting distribution of $Z(t_c)$ can be shown to be the same as that of the DF statistic.

Table 2 contains the results of the unit root tests. The test results uniformly suggest the presence of a unit root in the exchange rate series. Unit root tests with time trend were also conducted, and they were found to give qualitatively the same results. These results underline the need to properly account for nonstationarities in exchange rate series in empirical analyses or forecasting.

The following autoregression is estimated next for each exchange rate series in first differences:

$$(1-L)S_t = a_0 + a_1(1-L)S_{t-1} + \ldots + a_k(1-L)S_{t-k} + \text{error} \tag{9}$$

Under the hypothesis of bandwagon effects, $a_0 = a_2 = \ldots = a_k = 0$ and $a_1 > 0$. Table 3 reports the estimation results for Equation 9 with $k = 1$, 2, 3, and 4. For all five currencies the coefficient estimates of a_0 and a_k ($k \geqslant 2$) are not significantly different from zero at the usual levels of significance. Except for the case of BP, the coefficient estimate of a_1 is statistically significant at the 5% level and is of the correct sign,

Table 2. *Statistics for unit root tests*

Series	Currency	Dickey–Fuller DF	ADF ($p=1$)	ADF ($p=4$)	Phillips–Perron Z (t_c; $q=1$)	Z (t_c; $q=4$)
S_t	BP	−1.421	−1.462	−1.481	−1.421	−1.419
	DM	−1.600	−1.613	−1.547	−1.620	−1.626
	FF	−2.250	−2.140	−2.108	−2.198	−2.181
	SF	−1.350	−1.479	−1.351	−1.418	−1.433
	JY	0.468	0.150	−0.052	0.305	0.101
$(1-L)S_t$	BP	−18.75[a]	−14.29[a]	−8.042[a]	−18.75[a]	−18.56[a]
	DM	−16.95[a]	−12.92[a]	−8.163[a]	−16.95[a]	−16.85[a]
	FF	−16.80[a]	−12.71[a]	−8.390[a]	−16.81[a]	−16.75[a]
	SF	−16.77[a]	−13.55[a]	−7.857[a]	−16.79[a]	−16.62[a]
	JY	−16.49[a]	−11.60[a]	−7.373[a]	−16.47[a]	−16.67[a]

The critical values for the unit root tests are tabulated in Fuller (1976, p. 373). Significance levels are indicated by [c] for 10%, [b] for 5% and [a] for 1%.

consistent with the bandwagon expectations proposition.[3] In general, the in-sample results suggest that Equation 4 can describe the observed exchange rate dynamics better than a random walk.

Statistical tests based on in-sample estimation are sometimes found to be misleading, however, as indicated in Meese and Rogoff (1983). It is thus desirable to evaluate the bandwagon forecasting rule by out-of-sample predictions. An initial estimate for ϕ is obtained by first estimating Equation 4 for each exchange rate using data over the period from the first week of January 1980 through the last week of December 1980. Using the estimate of ϕ thus obtained, a one-step-ahead forecast can be generated according to the bandwagon expectations model.[4] The observation for the first week of January 1981 is then added to the sample. The parameter ϕ is re-estimated, and a new forecast is generated for each exchange rate. The recursive process continues by updating the sample period by one additional observation at a time until we reach the end of the sample period.

Table 4 contains some descriptive statistics of the successive estimates of ϕ from rolling regressions. While the estimates of ϕ can vary due to sample variations, the estimates are all positive for every currency. In terms of standard deviation and the distribution of the ϕ estimates, the BP series displays the highest variability in the ϕ estimates among the five currencies. In general, the estimates of ϕ appear reasonably stable for all currencies, with about 90% of the estimates being within the ± 0.04 interval around the mean estimate of ϕ.

The seemingly unrelated regression (SUR) method was also used to estimate jointly the equations for different exchange rates to obtain estimates for ϕ. This method utilizes the information contained in the cross-equation error structure and provides more efficient coefficient estimates than the single equation estimation method. The SUR estimation can improve potentially the forecasting accuracy. The results obtained from joint rolling regressions (not reported) did not confirm this supposition, however. The iterated SUR technique failed to yield any improvement in the forecasting performance.

To provide further information regarding the exchange rate behaviour over time, the forecasts generated by the bandwagon forecasting scheme are also compared with those generated by relatively elaborate time series models. We estimate, specifically, VAR systems in levels or first differences of S_t. The uniform lag length p across all (five) equations is estimated using the standard Akaike information criterion (AIC) and Schwarz's Bayesian information criterion (BIC). Both the AIC and BIC criteria suggest a first-order VAR model for both levels and first differences of S_t. Since forecasts can be sensitive to the choice of the lag, we have experimented with different orders. The first-order VAR model is found to yield better forecasts than models of other orders, so this is the model we report below.

[3]The presence of significant correlations between successive changes in the exchange rate does not necessarily suggest market inefficiency. As Levich (1985) notes, the correlations between successive changes can be consistent with market efficiency, with equilibrium expected returns wandering over time.

[4]In this paper we focus the analysis on the one-step-ahead forecasts. This follows naturally from the specification of the bandwagon expectations model and its presumable relevance for short-term forecasts (Frankel and Froot, 1986). Conditional multi-step forecasts are sometimes examined to see how well forecasting models perform over longer horizons. Saidi (1983), for example, notes that the error statistics for multi-step forecasts may not be very informative. The point is that k-step-ahead forecast errors will in general follow a moving average process of order $k-1$.

Table 3. *In-sample estimation results*

Currency	Constant	$(1-L)S_{t-1}$	$(1-L)S_{t-2}$	$(1-L)S_{t-3}$	$(1-L)S_{t-4}$	DW	R^2
BP	−0.0011	0.0139				1.996	0.006
	(−1.299)	(0.264)					
	−0.0012	0.0145	−0.0735			2.004	0.006
	(−1.403)	(0.275)	(−1.393)				
	−0.0013	0.0108	−0.0735	−0.0476		1.989	0.008
	(−1.487)	(0.205)	(−1.391)	(−0.898)			
	−0.0012	0.0108	−0.0735	−0.0478	0.0813	1.989	0.010
	(−1.340)	(0.282)	(−1.274)	(−0.902)	(1.535)		
DM	0.0003	0.1127				1.990	0.013
	(0.312)	(2.153)[b]					
	0.0003	0.1156	−0.0282			1.998	0.013
	(0.312)	(2.189)[b]	(−0.533)				
	0.0003	0.1146	−0.0250	−0.0309		1.994	0.014
	(0.310)	(2.164)[b]	(−0.468)	(−0.582)			
	0.0003	0.1154	−0.0244	−0.0351	0.0371	1.996	0.016
	(0.283)	(2.175)[b]	(−0.455)	(−0.656)	(0.696)		
FF	0.0011	0.1221				1.994	0.015
	(1.283)	(2.337)[b]					
	0.0011	0.1239	−0.0153			1.998	0.015
	(1.288)	(2.348)[b]	(−0.289)				
	0.0011	0.1233	−0.0108	−0.0376		1.993	0.016
	(1.323)	(2.331)[b]	(−0.202)	(−0.709)			
	0.0011	0.1254	−0.0104	−0.0452	0.0637	1.992	0.020
	(1.223)	(2.368)[b]	(−0.195)	(−0.846)	(1.198)		
SF	0.0000	0.1242				1.978	0.015
	(0.049)	(2.379)[b]					
	0.0000	0.1339	−0.0819			1.994	0.022
	(0.053)	(2.546)[b]	(−1.549)				
	0.0000	0.1345	−0.0844	0.0171		2.002	0.022
	(0.001)	(2.547)[b]	(−1.581)	(0.322)			
	0.0000	0.1325	−0.0801	0.0092	0.0587	1.997	0.025
	(0.024)	(2.503)[b]	(−1.495)	(0.172)	(1.102)		
JY	−0.0009	0.1401				2.001	0.019
	(−1.225)	(2.686)[a]					
	−0.0009	0.1325	0.0651			1.993	0.024
	(−1.193)	(2.518)[b]	(1.236)				
	−0.0009	0.1335	0.0637	0.0041		1.992	0.024
	(−1.158)	(2.521)[b]	(1.196)	(0.077)			
	−0.0009	0.1334	0.0612	0.0046	0.0065	1.998	0.024
	(−1.184)	(2.533)[b]	(1.142)	(0.086)	(0.122)		

Dependent variable: $(1-L)S_t$. The t-statistics are given in parentheses. Significance levels are indicated by [b] for 5% and [a] for 1%.

Table 4. *Descriptive statistics of rolling-regression estimates of ϕ*

Currency	Mean ($\bar{\phi}$)	Standard deviation	% of $\phi>0$	Distribution of the estimates $\bar{\phi}\pm0.02$	$\bar{\phi}\pm0.04$	$\bar{\phi}\pm0.06$	$\bar{\phi}\pm0.08$
BP	0.0518	0.0457	100%	51.4%	87.2%	87.9%	90.1%
DM	0.1093	0.0208	100%	85.3%	94.2%	97.8%	98.4%
FF	0.1481	0.0216	100%	70.9%	94.9%	98.4%	99.0%
SF	0.1381	0.0272	100%	64.5%	93.0%	96.2%	97.1%
JY	0.0960	0.0342	100%	55.3%	87.1%	92.7%	100.0%

Forecasting accuracy is measured by three statistics: the mean error (ME), the mean absolute error (MAE), and the root mean squared error ($RMSE$). They are defined in general as follows:

$$ME = \sum_{j=0}^{N-1} (A_{t+j+k} - F_{t+j+k})/N \tag{10a}$$

$$MAE = \sum_{j=0}^{N-1} |A_{t+j+k} - F_{t+j+k}|/N \tag{10b}$$

$$RMSE = \left\{ \sum_{j=0}^{N-1} (A_{t+j+k} - F_{t+j+k})^2/N \right\}^{1/2} \tag{10c}$$

where k denotes the forecast step; N the total number of forecasts in the projection for which the actual value, A_{t+j+k}, is known; F_{t+j+k} the forecast value; and t the starting period for forecasting. Since logarithms of spot exchange rates are considered, the statistics are unit-free (they are approximately in percentage terms) and comparable across currencies.

Following Meese and Rogoff, $RMSE$ is our principal criterion for comparing models' forecasts. An advantage of the $RMSE$ measure is that it penalizes more the relatively large forecast errors and thus identifies forecasts that are especially 'off the mark'. The $RMSE$ criterion is inappropriate if, for example, the exchange rate follows a non-normal stable Paretian process with infinite variance, as suggested by Westerfield (1977). In that case MAE, which is robust to fat-tailed distributions, will be a useful criterion.

The results of the forecasting experiments are summarized in Table 5. The bandwagon forecasting scheme consistently outperforms the VAR schemes in both $RMSE$ and MAE. In addition, the bandwagon forecasting scheme yields lower $RMSE$ than the random walk in four out of five cases and lower MAE in three out of five cases. Although the improvements are quite marginal, the results are suggestive that the bandwagon forecasting scheme is at the least no less rational than the random walk or VAR models.

The forecast error statistics such as MAE and $RMSE$ may not be a good basis for judging the value of the forecasts, nonetheless. We consider them, as typically done in the literature. In this paper we are interested in another criterion, namely the ability to forecast the direction of future exchange rate changes. As Boothe and Glassman (1987) observe, a successful forecast should be on the correct side of the exchange rate change. This is because a trader can still experience significant losses even with reasonable forecast error statistics if the forecasts are not often on the correct side of the exchange rate changes. Hence, a formal test of direction is called for.

Henriksson and Merton (1981) develop a non-parametric test for superior predictive ability in market timing. The test has been employed by Havenner and Modjtahedi (1988) to evaluate exchange rate forecasts in out-of-sample forecasting analysis. The test focuses on the direction, not the magnitude, of the forecasts. The test requires no specific distributional assumption on the prices and permits non-stationary conditional probabilities through time, yet the test statistic has a well-defined finite sample distribution.

Let us define the conditional probabilities of a correct forecast by $p_1(t) = \text{Prob}\{\text{a correct forecast} \mid \text{the price fell at}$

Table 5. *Summary statistics on the forecasting performance*

Forecasting scheme	Currency	ME	MAE	RMSE	Theil U	N
Random walk	BP	−0.00152	0.01298	0.01759	1.0000	313
	DM	−0.00009	0.01344	0.01697	1.0000	313
	FF	0.00109	0.01312	0.01702	1.0000	313
	SF	−0.00033	0.01438	0.01847	1.0000	313
	JY	−0.00079	0.01077	0.01488	1.0000	313
VAR in levels	BP	0.00082	0.01330	0.01809	1.0286	313
	DM	−0.00127	0.01375	0.01757	1.0355	313
	FF	−0.00100	0.01328	0.01755	1.0312	313
	SF	−0.00050	0.01484	0.01938	1.0489	313
	JY	−0.00107	0.01117	0.01548	1.0403	313
VAR in differences	BP	0.00051	0.01329	0.01803	1.0251	313
	DM	−0.00207	0.01349	0.01743	1.0271	313
	FF	−0.00178	0.01300	0.01722	1.0120	313
	SF	−0.00178	0.01444	0.01886	1.0212	313
	JY	−0.00035	0.01119	0.01509	1.0143	313
Bandwagon	BP	−0.00137	0.01308	0.01769	1.0059	313
	DM	−0.00010	0.01340	0.01693	0.9976	313
	FF	0.00086	0.01308	0.01694	0.9955	313
	SF	−0.00030	0.01433	0.01844	0.9981	313
	JY	−0.00064	0.01086	0.01477	0.9930	313

N is the number of forecasts on which the statistics are based. In the estimation of the VAR forecasting systems intercepts have been included.

time $t\}$ and $p_2(t) = \text{Prob}\{\text{a correct forecast} \mid \text{the price did not fall at time } t\}$. Merton (1981) shows that a necessary and sufficient condition for the forecast to be rational or to have a positive value is that $p_1(t)+p_2(t)$ is greater than unity. The larger is the value of $p_1(t)+p_2(t)$, the more valuable will be the forecast information. These results provide the basis for Henriksson and Merton's test of direction, which examines the null hypothesis of no market-timing ability, i.e. the hypothesis of $p_1(t)+p_2(t) \leqslant 1$.

To apply the test we define for each exchange rate series the following sample statistics: n_1 is the number of observations where the exchange rate actually fell; n_2 is the number of observations where the exchange rate did not fall; $N = n_1 + n_2$; m_1 is the number of correct forecasts, given that the exchange rate fell; m_2 is the number of incorrect forecasts, given that the exchange rate did not fall; and $M = m_1 + m_2$. An average estimate of $p_1 + p_2$ is given by

$$\hat{p}_1 + \hat{p}_2 = m_1/n_1 + (n_2 - m_2)/n_2 \tag{11}$$

Under the null hypothesis that the forecasts are of no value, Henriksson and Merton show that the distribution of m_1 conditional on n_1, N and M is given by

$$\text{Prob}(m_1 = x \mid n_1, N, M) = \binom{n_1}{x}\binom{N-n_1}{M-x}\bigg/\binom{N}{M} \tag{12}$$

where $\underline{m}_1 = \max\{0, M - n_2\} \leqslant m_1 \leqslant \min\{n_1, M\} = \bar{m}_1$. From Equation 12 the observed significance level (p-value) for a one-tailed test for successful market timing is given by

$$p\text{-value} = \sum_{x=m_1}^{\bar{m}_1} \binom{n_1}{x}\binom{N-n_1}{M-x}\bigg/\binom{N}{M} \tag{13}$$

At a confidence level of c, the null hypothesis will be rejected if the observed significance value is less than or equal to $1-c$.

We note that the forecasts from the random walk model are of no value in market-timing forecasting. This follows from the fact that the random walk model always predicts that the exchange rate does not fall (or rise). By definition, $p_1(t)$ is always equal to zero and $p_2(t)$ is always equal to unity; the sum of $p_1(t)$ and $p_2(t)$ for the random walk model is always one, therefore. It then follows that the Henriksson–Merton test of forecasting ability has included the random walk model as part of the null hypothesis, and to that effect rejection of the null will imply a significantly better forecasting ability of the forecasting model than the random walk model.

The results of the non-parametric test are reported in Table 6. The bandwagon forecasting scheme consistently has a higher estimate of $p_1 + p_2$ and lower observed significance value than the VAR schemes. For all the exchange rates under consideration, the bandwagon forecasting schemes have positive estimates of market-timing ability, i.e. the estimates of $p_1 + p_2$ are greater than one. Indeed, the estimates are significantly greater than one at the 5% significance level for three out of five currencies. These results follow a similar pattern to that based on the forecast error statistics in Table 5.

It should be remarked that, as in many other studies, the above analysis has been abstracted from transactions costs and risk. Since these factors would affect different forecasting schemes equally, they should not affect their relative ranking. Moreover, to the extent that the factors presumably affect the magnitude but not the direction of an investor's response, the results of the non-parametric test are robust with respect to them.

Table 6. *Results of the Henriksson–Merton test*

Forecasting scheme	Currency	N	n_1	M	m_1	$\hat{p}_1+\hat{p}_2$	Observed significance level
VAR in levels	BP	313	130	79	35	1.0288	32.69%
	DM	313	143	130	65	1.0722	11.98%
	FF	313	138	90	43	1.0430	23.88%
	SF	313	147	152	74	1.0335	31.60%
	JY	313	141	131	56	0.9611	77.06%
VAR in differences	BP	313	130	52	14	0.9000	99.45%
	DM	313	143	63	32	1.0414	22.07%
	FF	313	138	59	28	1.0258	33.16%
	SF	313	147	82	38	0.9934	60.22%
	JY	313	141	153	72	1.0397	27.91%
Bandwagon	BP	313	130	133	60	1.0626	16.14%
	DM	313	143	145	77	1.1385	0.98%[a]
	FF	313	138	139	69	1.1000	4.91%[b]
	SF	313	147	147	80	1.1406	0.87%[a]
	JY	313	141	141	67	1.0449	24.79%

Significance levels are indicated by [b] for 5% and [a] for 1%.

IV. CONCLUSION

In this paper, out-of-sample forecasting experiments have been reported which evaluated the predictive ability of the bandwagon expectations model for weekly spot exchange rates over the 1980–6 period. The empirical results based on five major currencies generally suggest the presence of significant bandwagon effects in the actual exchange rate dynamics, as found in survey expectations data. Specifically, we find that the bandwagon forecasting scheme can improve the forecasting accuracy (at least for the sample period considered) in terms of both mean squared errors and market timing upon the random walk and VAR models. To the extent that the bandwagon forecasting scheme can be well consistent with the actual exchange rate dynamics, bandwagon expectations are not necessarily irrational.

The statistical results based on in-sample and out-of-sample fits also provide information concerning the time series properties of the exchange rate. The results suggest that the exchange rate does not generally follow a random walk, although the exchange rate process does appear to contain a unit root.

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