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An Econometric Study of Forecasting French Foreign Exchange Rates

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Abstract:

Purpose: *The objective of this paper is to study possible diversity of exchange rate models, by applying both parametric and nonparametric techniques, and examines said models' collective predictive performance.*
Design/Methodology/Approach: *We shall choose the forecasting predictor with the smallest Root Mean Square Forecast Error (RMSE). The better type of exchange rate model is in the Autoregressive model's equation, according to the empirical evidence, although none of this data yields an optimal forecast.*
Findings: *In our conclusion, the error correction versions of these exchange rate models will be adjusted so that credible long-run elasticities can be imposed on each model's fundamental variables.*

Keywords: *Efficiency, exchange rate determination, exchange rate policy, forecasting, foreign exchange policy.*

JEL classification: *C13, C22, C53, F31, G11.*

Paper Type: *Research study.*

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1. Introduction

A large percentage of economic time series exhibit phases of relatively high volatility followed by periods of relative stability, and therefore avoid displaying any constant mean. Even a cursory examination of time-series data -- currency exchange rates chief among them -- imply that they are heteroscedastic because of the absence of this constant mean and variance (the presence of such a constant variance with a stochastic variable would define such time series as homoscedastic.) For any such series with that degree of volatility, the unconditional variance could be constant even while also being unusually large at times. The trends of some variables may contain deterministic or stochastic elements, with the analysis of these ingredients influencing the forecasted results of the time series under study.

We may graph different currency exchange rates in order to see their behavior, first noticing their fluctuations over time but then following up these initial impressions with more rigorous and formal testing. One observes, for example, that these series are not stationary, in the sense of the sample means not appearing to be constant while there is also a strong appearance of heteroscedasticity. This deficiency in any specific trend makes it difficult to prove the existence of a time-invariant mean for these time series. For example, the U.S. dollar-to-U.K. pound exchange rate does not show a tendency towards either increasing or decreasing, with the dollar going through long stretches of both appreciation and depreciation without a reversion to the long-run average. This instance of "random walk" behavior is quite characteristic for a nonstationary series.

A shock to any such series shows a tremendous amount of endurance, the dollar/pound exchange rate experienced great upward movement in 1980, remained at this level into 1984, and only returned near to its previous level in 1989. However, the volatility of these series is not constant and, in fact, some currency exchange rate series have at least a partial correlation with other series. Such series are named ‘conditionally heteroscedastic’ if the unconditional (long-run) variance is constant but also contains localized periods of relatively high variance. For instance, large shocks in the U.S. appear at about the same time as they appear in Canada and Great Britain, although these co-movements’ existence can be predicted or anticipated because of the underlying forces affecting the American economy and that of other nations.

The disturbance term’s variance is taken as constant in conventional econometric models, although our series changes between periods of unusual amounts of volatility and periods of relative tranquility. Therefore, our assumption of a constant variance or homoscedasticity in such cases is not warranted. As an investor in only one currency, however, one may want to forecast the exchange rate as well as its conditional variance over the life of the investment in such an asset. The unconditional variance, namely, the variance’s long-run forecast, would be unimportant if an investor plans to buy such an asset at time period t and then sell it at $t+1$. Kallianiotis (1985) and Taylor (1995) provide reviews of the literature on exchange rate economics and

Chinn and Meese (1995) examine four structural exchange rate models' performance. This paper is organized as follows. Different trend models are described in section 2. Other linear time-series models are presented in section 3 with multiequation time-series models discussed in section 4. The empirical results are given in section 5 with a summary of the findings presented at the end of section 6.

2. Time-Series Trends

One way to predict a time-series variance is to introduce an independent variable explicitly that helps forecast the volatility of this time series. Consider the simplest case, in which

$$s_{t+1} = \varepsilon_{t+1} X_t \tag{1}$$

where s_{t+1} = the spot exchange rate (the variable of interest), ε_{t+1} = a white-noise disturbance term with variance σ^2, and X_t = an independent variable that can be observed at time period *t*. If $X_t = X_{t-1} = X_{t-2} = \ldots$ = a constant, then the $\{s_t\}$ sequence is a standard white-noise process with a constant variance.

If the realization of this $\{X_t\}$ sequence is not all equal, then the variance of s_{t-1} that is conditional on the observable value of X_t is

$$Var\ (s_{t+1} / X_t) = X_t^2 \sigma^2 \tag{2}$$

We may formulate the general solution to a linear stochastic difference equation with these four components in the following equation:

$$s_t = trend + cyclical + seasonal + irregular$$

Exchange rate series do not have an evident tendency of reverting to any mean. One important function of econometricians is the formation of understandable stochastic difference equation models that can simulate trending variables' behavior, with the distinctive feature of a trend being its permanent effect on a time series. Because the irregular component is stationary, its effects will diminish over time while the trending elements and their effects will persist in long-term forecasts.

2.1 Deterministic Trends

One of s_t's basic characteristics is its long-term growth persisting despite its short-term volatility. In fact, s_t may have a long-term trend that is quite apparent and clear-cut. According to Pindyck and Rubinfeld (1981), Chatfield (1985), and Enders (1995), there are eight models that describe this deterministic trend and can be used in forecasting s_t. They are the following:

Linear time trend:

$$S_t = \alpha_0 + \alpha_1 t + \varepsilon_t \tag{3}$$

Exponential growth curve:

$$S_t = \mathrm{A}e^{rt} \tag{4}$$

or

$$\mathrm{ln}S_t = \mathrm{lnA} + \mathrm{rt} + \varepsilon_t \tag{5}$$

or

$$s_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{6}$$

Logarithmic / stochastic autoregressive trend (the only function that can be applied for exchange rates):

$$s_t = \gamma_0 + \gamma_1 s_{t-1} + \varepsilon_t \tag{7}$$

Quadratic trend:

$$s_t = \delta_0 + \delta_1\, t + \delta_2 t^2 + \varepsilon_t \tag{8}$$

Polynomial time trend:

$$s_t = \zeta_0 + \zeta_1 t + \zeta_2 t^2 + \ldots + \zeta_n t^n + \varepsilon_t \tag{9}$$

Logarithmic growth curve:

$$s_t = 1 / (\theta_0 + \theta_1 \theta_2^t);\ \theta_2 > 0 \tag{10}$$

or a stochastic approximation:

$$(\Delta s_t / s_{t-1}) = k_0 - k_1\, s_{t-1} + \varepsilon_t \tag{11}$$

Sales saturation pattern:

$$S_t = e^{\lambda_0 - (\frac{\lambda_1}{t})} \tag{12}$$

or

$$s_t = \lambda_0 - (\lambda_1 / t) + \varepsilon_t \tag{13}$$

where S_t = the spot exchange rate, *t* = time trend, and the lowercase letters are the natural logarithms of their uppercase counterparts.

2.2 Models of Stochastic Trend

We can add the deterministic trend models to the lagged values of the $\{s_t\}$ and $\{\varepsilon_t\}$sequences; these equations become models with their own stochastic trends and are used here as the following:

(i) The Random Walk Model

The random walk model (itself a special case of the AR(1) process) appears to imitate the exchange rates' behavior as given below. These series neither revert to a given mean nor fluctuate over time.

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \varepsilon_t \tag{14}$$

with α_0 = 0 and α_1 = 1, where s_t - s_{t-1} = Δs_t = ε_t, becomes

$$s_t = s_{t-1} + \varepsilon_t \tag{15}$$

The conditional mean of $s_{t+\lambda}$ for any $\lambda > 0$ is

$$E_t S_{t+\lambda} = S_t + \mathrm{E}\textstyle\sum_{i=1}^{\lambda} \varepsilon_{t+i} = s_t \tag{16}$$

The variance is time-dependent:

$$\text{var}\ (s_t) = \text{var}\ (\varepsilon_t + \ \varepsilon_{t-1} + \ldots + \varepsilon_1) = \text{t}\sigma^2 \tag{17}$$

The random walk process is nonstationary because the variance is not constant. Therefore, as

$$t \to \infty,\ \text{var}(s_t) \to \infty. \tag{18}$$

Therefore, the forecast function is:

$$E_t s_{t+\lambda} = s_t \tag{19}$$

(ii) The Random Walk plus Drift Model

The random walk plus drift model adds a constant term α_0 to the random walk model above such that s_t becomes partially deterministic and partially stochastic at the same time.

$$s_t = s_{t-1} + \alpha_0 + \ \varepsilon_t \tag{20}$$

The general solution for s_t is:

$$s_t = s_0 + \alpha_0 \text{t} + \textstyle\sum_{i=1}^{t} \varepsilon_i \tag{21}$$

and

$$E_t s_{t+\lambda} = \ s_0 + \alpha_0\ (\text{t} + \lambda) \tag{22}$$

The forecast function by λ periods yields

$$E_t s_{t+\lambda} = s_t + \alpha_0 \lambda \tag{23}$$

(iii) The Random Walk plus Noise Model

The s_t here is the sum of a stochastic trend and a white-noise component

$$s_t = \mu_t + n_t \tag{24}$$

and

$$\mu_t = \mu_{t-1} + \varepsilon_t \tag{25}$$

where $\{n_t\}$ is a white-noise process with variance σ_n^2 and ε_t and n_t are both independently distributed for all *t*.

$\mathrm{E}(\varepsilon_t\, n_{t-\lambda}) = 0$; the $\{\mu_t\}$ sequence represents the stochastic trend, and this model's solution is:

$$s_t = s_0 - n_0 + \textstyle\sum_{i=1}^{t} \varepsilon_i + n_t \tag{26}$$

The forecast function is

$$E_t S_{t+\lambda} = s_t - n_t \tag{27}$$

(iv) The General Trend plus Irregular Model

We replace equation (25) above with the so-called "trend plus noise model,"

$$\mu_t = \mu_{t-1} + \alpha_0 + \varepsilon_t \tag{28}$$

where α_0 is a constant and $\{\varepsilon_t\}$ is a white-noise process.

The solution is this equation:

$$s_t = s_0 - n_0 + \alpha_0 \text{t} + \sum_{i=1}^{t} \varepsilon_i + n_t \tag{29}$$

Let A(L) be a polynomial in the lag operator L. We may augment a random walk plus drift process with the stationary noise process A(L) n_t and thus obtain the "general trend plus irregular model":

$$s_t = \mu_0 + \alpha_0 \text{t} + \sum_{i=1}^{t} \varepsilon_i + \text{A(L)}\, n_t \tag{30}$$

(v) The Local Linear Trend Model

We construct this model by combining several random walk plus noise processes. Let $\{\epsilon_t\}$, $\{n_t\}$, and $\{u_t\}$ be three mutually uncorrelated white-noise processes. The local linear trend model's equations can be written:

$$s_t = \mu_t + n_t$$
$$\mu_t = \mu_{t-1} + \alpha_t + \varepsilon_t \tag{31}$$
$$\alpha_t = \alpha_{t-1} + u_t$$

This is the most detailed out of all the above models because the other processes are special cases of the local linear trend model consisting of the noise term n_t and the stochastic trend term μ_t. What is key for us now about this model is that the change in its trend yields a random walk plus noise:

$$\Delta\mu_t = \mu_t - \mu_{t-1} = \alpha_t + \varepsilon_t \tag{32}$$

The forecast function of $s_{t+\lambda}$ equals the current value of s_t minus the transitory component n_t, added to λ multiplied by the slope of the trend term in *t*:

$$E_t s_{t+\lambda} = (s_t - n_t\ ) + \lambda\ (\alpha_0 + u_1 + u_2 + \ldots + u_t\ ) \tag{33}$$

For future projects, we will estimate all of these models and run different tests on both the series and the error terms, ending up with specification and diagnostic tests as a way of gauging the statistical specifications' adequacy and accuracy. We shall then compare the forecasting results from the different models.

3. Some Linear Time-Series Models

In this portion of the paper, we define stochastic processes and some of their properties and discuss their use in forecasting, all done with an eye on developing models that "explain" the movement of the time series s_t. However, this will not be done using a set of explanatory variables as was used in the regression model but by relating it to both a weighted sum of current and lagged random disturbances and its own past values.

The Autoregressive (AR) Model

In order p's autoregressive process, the current observation s_t is generated by a weighted average of past observations going back p periods, along with the current period's random disturbance. We define this process as AR(p) and write its equation as:

$$s_t = \phi_1 s_{t-1} + \phi_2 s_{t-2} + ... + \phi_p s_{t-p} + \delta + \varepsilon_t \tag{34}$$

δ is a constant term which relates to the mean of the stochastic process.

The first-order process AR(1) is:

$$s_t = \phi_1 s_{t-1} + \delta + \varepsilon_t \tag{35}$$

Its mean is:

$$\mu = \delta / (1 - \phi_1) \tag{36}$$

and is stationary if $|\phi_1| < 1$, although the random walk with drift is a first-order autoregressive process that is not stationary.

4. Empirical Evidence

We provide a summary and analysis of the empirical evidence of different models of foreign currency exchange forecasting. The data given are monthly from March 1973 through and including December 1994, are coming from Main Economic Indicators of the OECD (the Organization for Economic Cooperation and Development) and International Financial Statistics of the IMF (the International Monetary Fund), and have been applied for France. The exchange rate is defined as the U.S. dollar per unit of the French franc, with direct quotes for the dollar. The lowercase letters denote the natural logarithm of the variables and an asterisk denotes the corresponding variable for France.

The first equations estimated are the deterministic trend models in equations (3), (6), (8), (9), (11), and (13). The results appear in Table 1 and indicate that the exchange rate forecast cannot be supported by these types of models. The second group of equations is the stochastic trend model, from equations (15) and (20); these results, in Table 2, show that this alternative model is much better at interpreting the data and forecasting the currency exchange rate. The final model is of a linear time-series, namely, the autoregressive (AR) model of equation (34) shown in Table 3, but its results are also fairly poor. One may infer that time-series models cannot be used to forecast foreign exchange rates with a great degree of accuracy or confidence for models possessing such relatively high volatility.

Table 1. *Deterministic trends*

(i) Linear time trend, eq. (3): $S_t = \alpha_0 + \alpha_1 t + \varepsilon_t$		(ii) Exponential Growth Curve, eq. (6): $s_t = \beta_0 + \beta_1 t + \varepsilon_t$	
α_0	23.146^{***}	ß$_0$	3.091^{***}
	(.551)		(.029)
α_1	$-.034^{***}$	ß$_1$	$-.001^{***}$
	(.003)		(.0002)
R^2	.306	R^2	.208
D-W	.110	D-W	.029
SSR	3,915.37	SSR	9.970
F	114.620	F	66.63
RMSE	3.8658	RMSE	.1973
(iii) Quadratic Trend, eq. (8): $s_t = \delta_0 + \delta_1 t + \delta_2 t^2 + \varepsilon_t$		(iv) Polynomial time trend, eq. (9): $s_t = \zeta_0 + \zeta_1 t + \zeta_2 t^2 + ... + \zeta_n t^n + \varepsilon_t$	
δ_0	3.491^{***}	ζ_0	9.803
	(.045)		(12.389)
δ_1	$-.008^{***}$	ζ_1	-.300
	(.0007)		(.599)
δ_2	$2.0\text{-}05^{***}$	ζ_2	.005
	(2.0-06)		(.012)
		ζ_3	-3.8-05
			(.0001)
		ζ_4	9.0-08
			(9.2-07)
		ζ_5	3.2-10
			(3.5-09)
		ζ_6	-2.0-12
			(7.1-12)
		ζ_7	2.7-15
			(6.0-15)
R^2	.445	R^2	.811
D-W	.041	D-W	.118
SSR	6.983	SSR	2.382
F	101.47	F	151.77
RMSE	.1652	RMSE	.0965
(v) Stochastic approximation, eq. (11): $(\Delta s_t / s_{t-1}) = k_0 - k_1 s_{t-1} + \varepsilon_t$		(vi) Sales Saturation Pattern, eq. (13): $s_t = \lambda_0 - (\lambda_1 / t) + \varepsilon_t$	
k_0	.037	λ_0	2.732^{***}
	(.027)		(.020)
k_1	-.013	λ_1	15.899^{***}
	(.009)		(1.667)
R^2	.008	R^2	.264
D-W	1.946	D-W	.032
SSR	.286	SSR	9.265
F	1.950	F	91.01
RMSE	.0334	RMSE	.1902

Note: *S_t = the spot exchange rate, s_t = ln(S_t), t = time, D-W = the Durbin-Watson statistic, SSR = sum of squares residuals, RMSE = root mean square error, Data from 03/1973 through 06/1994 inclusive, $***$ = significant at the 1% level, $**$ = significant at the 5% level, $*$ = significant at the 10% level, and Δ = change of the variable.*

Source: *Own study.*

Table 2. *Stochastic trends*

(i) The Random Walk Model, eq. (15): $s_t = s_{t-1} + \varepsilon_t$		(ii) The Random Walk plus Drift Model, eq. (20): $s_t = \alpha_1 s_{t-1} + \alpha_0 + \varepsilon_t$	
s_{t-1}	1.000^{***}	α_0	.037
	(.0007)		(.027)
		α_1	$.987^{***}$
			(.009)
R^2	.977	R^2	.977
D-W	1.957	D-W	1.946
SSR	.288	SSR	.286
L(.)	505.92	F	10,931.59
RMSE	.0335	RMSE	.0334

Note: *See the previous Table. L(.) = log of likelihood function.*
Source: *Own study.*

Table 3. *Linear time-series models*

The Autoregressive (AR) Model, eq. (34): $s_t = \phi_1 s_{t-1} + \phi_2 s_{t-2} + \ldots + \phi_p s_{t-p} + \delta + \varepsilon_t$	
δ	2.850^{***}
	(.117)
ϕ_1	$.998^{***}$
	(.063)
ϕ_2	.054
	(.089)
ϕ_3	.017
	(.089)
ϕ_4	.005
	(.089)
ϕ_5	-.066
	(.089)
ϕ_6	-.134
	(.089)
ϕ_7	.139
	(.089)
ϕ_8	-.010
	(.089)
ϕ_9	-.030
	(.089)
ϕ_{10}	-.040
	(.089)
ϕ_{11}	.037
	(.089)
ϕ_{12}	-.047
	(.063)
R^2	.978
$D-W$	1.995
SSR	.274
F	908.59
$RMSE$	.0327

Note: *See the previous Tables.*
Source: *Own study.*

5. Conclusions

This paper compares the predictive performance of several foreign currency exchange rate forecast models such as linear time-series, the balance of payments approach, the transfer function, the vector autoregression model, and various time-series trends.

For every such model, we calculate its Root Mean Square Forecast Error (RMSE) as follows:

$$\sqrt{\left(\sum_{t=1}^{n} (A_t - F_t)^2\right) / n}$$

where n = the number of observations, A = the actual value of the dependent variable, and F = the forecast value. The forecast model with the smallest RMSE is the best predictor we must choose as part of exchange rate forecasting process.

An exchange rate can be defined as the relative price of two countries' currencies. The most important factors that determine the value of one country's currency relative to another are differences in inflation, the relative money supplies, real incomes, and prices, and interest rate, trade balance, and budget deficit differentials. However, the empirical evidence for this approach is not satisfactory in general. Exchange rate movements may result from either a parametric change in the above determinants or an artificial intervention by governments.

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