Foreign Currency Forecasts: A Combination Analysis

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Abstract

This paper uses a large variety of different models and examines the predictive performance of these exchange rate models by applying parametric and non-parametric techniques. For forecasting, we will choose that predictor with the smallest root mean square forecast error (RMSE). The results show that the better model is equation (34), but none of them gives a perfect forecast. At the end, error correction versions of the models will be fit so that plausible long-run elasticities can be imposed on the fundamental variables of each model.

Keywords: *Foreign Exchange, Forecasting, Efficiency, Exchange Rate Determination, Exchange Rate Policy*

1. Introduction

Many economic time series do not have a constant mean and most exhibit phases of relative tranquility followed by periods of high volatility. Casual inspection of exchange rates and many other economic time series data suggest that they do not have a constant mean and variance. (A stochastic variable with a constant variance is called homoscedastic, as opposed to heteroscedastic.) For series exhibiting volatility, the unconditional variance may be constant even though the variance during some periods is unusually large. The trends displayed by some variables may contain deterministic or stochastic components. In our analysis, it actually makes a great deal of difference if a series is estimated and forecasted under the hypothesis of a deterministic versus a stochastic trend.

By graphing the different exchange rates, we can illustrate their behavior just by looking at the fluctuation of these rates over time. Of course, formal testing is necessary to substantiate any first impressions. The first visual pattern is that these series are not stationary, in that the sample means do not appear to be constant and there is a strong appearance of heteroscedasticity. It is hard to maintain that these series do have a time-invariant mean. They do not contain a clear trend. The dollar/pound exchange rate shows no particular tendency to increase or decrease. The dollar seems to go through sustained periods of appreciation and then depreciation without a tendency of reversion to a long-run mean. This type of "random walk" behavior is typical of non-stationary series.

Any shock to the series displays a high degree of persistence. Notice that the $/£ exchange rate experienced a violently upward surge in 1980 and remained at this higher growth for nearly four years; it had almost returned to its previous level after nine years. The volatility of these series is not constant over time. (Such series are called conditionally heteroscedastic if the unconditional or long-run variance is constant but there are periods in which the variance is relatively high.) Some exchange rates series share co-movements with other series. Large shocks to the U.S. appear to be timed similarly to those in the U.K. and Canada. The presence of such co-movements should not be too surprising. We might expect that the underlying economic forces affecting the U.S. economy also affect the economy internationally.

In conventional econometric models, the variance of the disturbance term is assumed to be constant. However, the data demonstrate that our series in question exhibit periods of unusually large volatility followed by periods of relative tranquility. In such circumstances, the assumption of a constant variance (homoscedasticity) is inappropriate.

As an asset holder denominated in one currency, you might want to forecast the exchange rate and its conditional variance over the holding period of the asset. The unconditional variance (i.e., the long-run forecast of the variance) would be unimportant if you plan to buy the asset at t and sell it at t+1. Kallianiotis (1995) and Taylor (1995) provide a recent survey and review of the literature on exchange rate economics. Chinn and Meese (1995) examine the performance of four structural exchange rate models.

The paper is organized as follows. Different trend models are described in section 2. Other linear time series models are presented in section 3. Multi-equation time series models are discussed in section 4. The empirical results are given in section 5 and a summary of the findings appears in section 6.

2. Time-Series Trends

One approach to forecasting the variance is to explicitly introduce an independent variable that helps predict the volatility. Consider the simplest case, in which

$s_{t+1} = \varepsilon_{t+1} X_t$ (1)

wheres_{t+1} = thespotexchangerate(thevariableofinterest),ε_{t+1} = awhite-noisedisturbancetermwithvariance σ^2, andX_t=an independent variable that can be observed at periodt. (If X_t = X_{t-1}= X_{t-2} = ... = constant, then the $\{s_t\}$ sequence is the familiar white-noise process with a constant variance.)

If the realization of the $\{X_t\}$ sequence are not all equal, the variance of s_{t-1}conditional onthe observable value of$X_t$is

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

It is helpful to represent the general solution to a linear stochastic difference equation as consisting of the four distinct parts:

s_t=trend +cyclical +s easonal + irregular

The exchange rate series have no obvious tendency for mean reversion. A critical task for eco nometricians is to develop simple stochastic difference equation models that can mimic the behavior of trending variables, keeping in mind that the key feature of a trend is its permanent effect on a series. Since the irregular component is stationary, the effects of any irregular components will "die out" while the trending elements will remain in long-term forecasts.

Deterministic Trends

One of the basic character is tics of s_t that can be described is its long-term growth pattern. Despite the short-run up-and-down movement, it is ossible that s_t might exhibit a clear-cut long-term trend. According to Pindyck and Rubinfeld (1981), Chatfield (1985), and Enders (1995), there are many models that describe this deterministic trend and can be used to forecast, i.e., extrapolate, s_t. They are the following:

Linear time trend:

$S_t = \alpha_0 + \alpha_1 t + \varepsilon_t$(3)

Exponential growth curve:

$S_t = Ae^{rt}$ (4)

or

$\ln S_t = \ln A + rt + \varepsilon_t$ (5)

or

$s_t = \beta_0 + \beta_1 t + \varepsilon_t$ (6)

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

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

Quadratic trend:

$s_t = \delta_0 + \delta_1\, t + \delta_2 t^2 + \varepsilon_t$ (8)

Polynomial time trend:

$s_t = \zeta_0 + \zeta_1 t + \zeta_2 t^2 + \ldots + \zeta_n t^n + \varepsilon_t$(9)

Logarithmic growth curve:

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

or a (stochastic) approximation:

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

Sales saturation pattern:

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

or

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

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

Models of Stochastic Trend

The deterministic trend models can be augmented with lagged values of the $\{s_t\}$sequenceand the $\{\varepsilon_t\}$ sequence. These equations now become models with stochastic trends. The models used here are:

(i) The Random Walk Model

The random walk model seems to approximate the behavior of the exchange rates shown below for the Federal Republic of Germany. The various exchange rate series have no particular tendency to increase or decrease overtime; neither do they exhibit any tendency to revert to a given mean value. The random walk model is a special case of the AR (l) process.

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

with α_0 = 0 and α_1 = 1 (where s_t - s_{t-1} = $\Delta s_t = \varepsilon_t$)

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

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

$E_t S_{t+\lambda} = S_t + E\sum_{i=1}^{\lambda} \varepsilon_{t+i} = s_t$ (16)

The variance is time-dependent.

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

Since the variance is not constant, the random walk process is nonstationary. As $t \to \infty$, $var(s_t) \to \infty$. (18)

The forecast function will be

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

(ii) **The Random Walk** plus Drift Model

The random walk plus drift model augments the random walk model by adding a constant term α_0. Then, s_t becomes partially deterministic and partly stochastic.

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

The general solution for s_t is:

$s_t = s_0 + \alpha_0 t + \sum_{i=1}^{t} \varepsilon_i$(21)

and

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

The forecast function by λ periods yields

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

(iii) The Random Walk plus Noise Model

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

$s_t = \mu_t + n_t$ (24)
and
$\mu_t = \mu_{t-1} + \varepsilon_t$ (25)

where $\{n_t\}$ is a white-noise process with variance σ_n^2 and ε_t and n_t are independently distributed for all t. [E($\varepsilon_t n_{t-\lambda}$) = 0]; the $\{\mu_t\}$ sequence represents the stochastic trend.

The solution for this model can be written as:
$s_t = s_0 - n_0 + \sum_{i=1}^{t} \varepsilon_i + n_t$ (26)
The forecast function is
$E_t S_{t+\lambda} = s_t - n_t$ (27)

(iv) The General Trend plus Irregular Model
We replace eq. (25) with the so-called "trend plus noise model,"
$\mu_t = \mu_{t-1} + \alpha_0 + \varepsilon_t$ (28)
where α_0 is a constant and $\{\varepsilon_t\}$ is a white-noise process.
The solution is
$s_t = s_0 - n_0 + \alpha_0 t + \sum_{i=1}^{t} \varepsilon_i + n_t$ (29)

Let A(L) be a polynomial in the lag operator L; it is possible to augment a random walk plus drift process with the stationary noise process A(L)n. Then, we have the "general trend plus irregular model":
$s_t = \mu_0 + \alpha_0 t + \sum_{i=1}^{t} \varepsilon_i + \text{A(L)} n_t$ (30)

(v) The Local Linear Trend Model
The local linear trend model is built by combining several random walk plus noise processes. Let $\{\varepsilon_t\}$, $\{n_t\}$, and $\{u_t\}$ be three mumtually uncorrelated white-noise processes. The local linear trend model can be represented by
$s_t = \mu_t + n_t$
$\mu_t = \mu_{t-1} + \alpha_t + \varepsilon_t$ (31)
$\alpha_t = \alpha_{t-1} + u_t$

From all the above models, this is the most detailed one. The other processes are special cases of the local linear trend model. The local linear trend model consists of the noise term n_t plus the stochastic trend term μ_t. What is interesting about the model is that the change in the trend is a random walk plus noise:
$\Delta\mu_t = \mu_t - \mu_{t-1} = \alpha_t + \varepsilon_t$ (32)

The forecast function of $s_{t+\lambda}$ is the current value of s_t less the transitory component n_t, plus λ multiplied by the slope of the trend term in t:
$E_t s_{t+\lambda} = (s_t - n_t) + \lambda(\alpha_0 + u_1 + u_2 + \ldots + u_t)$ (33)

As a future research, we will estimate all those models and we will conduct different testing for the series and the error terms. At the end, we will have specification and diagnostic tests in order to determine the adequacy of the statistical specifications and we will compare the forecasting results from the different models.

3. Some Linear Time-Series Models

In this section, we introduced stochastic processes and discussed some of their properties and their use in forecasting. Our objective is to develop models that "explain" the movement of the time series s_t. Unlike the regression model, however, a set of explanatory variables will not be used. Instead we explain s_t by relating it to its own past values and to a weighted sum of current and lagged random disturbances.

The Autoregressive (AR) Model
In the autoregressive process of order p, the current observation s_t is generated by a weighted average of past observations going back p periods, together with a random disturbance in the current period. We denote this process as AR(p) and write its equation as
$s_t = \phi_1 s_{t-1} + \phi_2 s_{t-2} + \ldots + \phi_p s_{t-p} + \delta + \varepsilon_t$ (34)
δ is a constant term which relates to the mean of the stochastic process.

The first-order process AR(1) is
$s_t = \phi_1 s_{t-1} + \delta + \varepsilon_t$ (35)
Its mean is: $\mu = \delta / (1 - \phi_1)$ (36)
and is stationary if $|\phi_1| < 1$.(The random walk with drift is a first-order autoregressive process that is not stationary, however.)

4. Empirical Evidence

We provide here a summary and analysis of empirical evidence regarding the different models of foreign currency forecasts. The data are monthly from 1973.03 to 1994.12 and are coming from Main Economic Indicators, (OECD) and International Financial Statistics, (IMF). The data have been applied for Germany. The exchange rate is defined as the U.S. dollar per unit of foreign currency (direct quotes for the U.S.). The lowercase letters denote the natural logarithm of the variables and an asterisk denotes the corresponding variable for the foreign country.

The first equations estimated are the deterministic models, eqs. (3), (6), (8), (9), (11), and (13). The results appear in Table 1 below and indicate that the exchange rate forecast cannot be supported by models of deterministic trends. The second group of equations used here is the stochastic trend model, eqs. (15) and (20). The results are given in Table 2 and show that this alternative model is much better to interpret the data and forecast the exchange rate. The next model is a linear time-series, namely, the autoregressive (AR) model, eq. (34), and the results are shown in Table 3. These results are also pretty poor, however; time-series models cannot then be used to forecast the exchange rates that follow such high volatility.

Table 1
Deterministic Trends
(i) Linear time trend, eq. (3):
$S_t = \alpha_0 + \alpha_1 t + \varepsilon_t$
α_0 35.249^{***} (1.043)
α_1 $.088^{***}$ (.006)

R^2 .449
D-W .060
SSR 13,299.37
F 206.770
RMSE 7.2077

(ii) Exponential Growth Curve, eq. (6):
$s_t = \beta_0 + \beta_1 t + \varepsilon_t$
$\beta_0 3.598^{***}$ (.022)
$\beta_1 .002^{***}$ (.0001)
R^2.409
D-W .051
SSR 6.168
F 176.06
RMSE .1552

Notes: 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 1973.03 to 1994.06, $***$ = significant at the 1% level, $**$ = significant at the 5% level, $*$ = significant at the 10% level.

(iii) Quadratic Trend, eq. (8):
$s_t = \delta_0 + \delta_1 t + \delta_2 t^2 + \varepsilon_t$

$\delta_0 3.770^{***}$ (.041)
$\delta_1 -.001^{*}$ (.0006)
δ_2 1.0-05*** (2.0-06)
R^2.462
D-W .056
SSR 5.616
F 108.73
RMSE .1481
Notes: See the previous table.

(iv) Polynomial time trend, eq. (9):
$s_t = \zeta_0 + \zeta_1 t + \zeta_2 t^2 + \ldots + \zeta_n t^n + \varepsilon_t$
$\zeta_0 4.778^{***}$ (.526)
$\zeta_1 -.065^{*}$ (.038)
ζ_2 .001 (.001)
$\zeta_3$1.6-06 (1.5-05)
ζ_4-1.4-07 (1.2-07)
ζ_5 1.1-09** (5.1-10)
ζ_6 -3.4-12*** (1.2-12)
ζ_7 3.9-15*** (1.1-15)
R^2.793
D-W .144
SSR 2.160
F 135.84
RMSE .0919
Notes: See the previous table.

(v) Stochastic approximation, eq. (11):
$(\Delta s_t / s_{t-1}) = k_0 - k_1 s_{t-1} + \varepsilon_t$

k_0 .063 (.042)
k_1-.016 (.011)
R^2.008
D-W 1.893
SSR .310
F 2.150
RMSE .0348

(vi) Sales Saturation Pattern, eq. (13):
$s_t = \lambda_0 - (\lambda_1 / t) + \varepsilon_t$
$\lambda_0 3.997^{***}$ (.018)
$\lambda_1 -13.884^{***}$ (1.540)

R^2.242
D-W .039
SSR 7.911
F 81.27
RMSE .1758
Notes: See the previous tables.
Δ = change of the variable.

Table 2
Stochastic Trends
(i) The Random Walk Model, eq. (15):
$s_t = s_{t-1} + \varepsilon_t$
$s_{t-1} 1.000^{***}$ (.0006)
R^2 .970
D-W 1.906
SSR .312
L (.) 495.48
RMSE .0349

(ii) The Random Walk plus Drift Model, eq. (20):
$s_t = \alpha_1 s_{t-1} + \alpha_0 + \varepsilon_t$
α_0 .063 (.042)
$\alpha_1 .984^{***}$ (.011)
R^2 .970
D-W 1.893
SSR .310
F 8,315.19
RMSE .0348
Notes: See the previous tables.
L (.) = log of likelihood function

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 -3.580 (6.591)
$\phi_1 1.030^{***}$ (.062)
ϕ_2 .018 (.088)
ϕ_3 -.011 (.088)
ϕ_4 .024 (.088)
ϕ_5 -.015 (.089)
$\phi_6 -.157^{*}$ (.088)
ϕ_7 .132 (.088)
ϕ_8 -.007 (.089)
ϕ_9 .013 (.089)
ϕ_{10} -.060 (.089)
$\phi_{11} .153^{*}$ (.090)
ϕ_{12}-$.120^{*}$ (.063)
R^2 .991
D-W 2.019
SSR .266
F 2,385.36
RMSE .0319
Notes: See the previous tables.

5. Summary

This paper uses a large variety of different time-series trends, linear time-series, the balance of payments approach, the transfer function, and the vector autoregression model to examine the predictive performance of these exchange rate forecast models. At every model, we report the root mean square forecast error (RMSE), which is given by the formula:

RMSE = the square root of $((\sum_{t=1}^{n}(A_t - F_t)^2) / n)$

where A = the actual value of the dependent variable, F = the forecast value, and n = the number of observations. The model with the smallest RMSE is the best predictor that must be chosen for forecasting the exchange rate.

The exchange rate is the relative price of two countries' currencies. The fundamental factors most likely to determine the value of a country's currency are significantly related to the relative money supplies, relative real incomes, the interest rate differentials, relative prices (TOT), differences in inflation, trade balance differentials, budget deficit differentials, and many other factors. Overall, the empirical evidence regarding this approach is not very satisfactory. The combination analysis (the MARMA model) is more relatively satisfactory and shows that this model has a better specification, but there is still room for improvement in the existing modeling of foreign currency forecasts. Exchange rate movements may result from a parametric change in the above determinants or from an artificial intervention by governments.

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