

Foreign Currency Prognostication: Diverse Tests for Germany

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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 models are in equations (3), (10), (17), and (18), although none 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: efficiency, exchange rate determination, exchange rate policy, forecasting, foreign exchange

1. Introduction

Most economic time series alternate periods of relative volatility and tranquility and thus do not display a constant mean. A brief examination of exchange rates, among other time series data, suggests that these rates do not have a constant mean and variance in its stochastic variable(s) either, and can therefore be classified as heteroscedastic. For such series exhibiting volatility, the unconditional variance may be constant while the variance is sometimes quite large in relative terms. The trends displayed by some variables may contain either stochastic or deterministic components, which makes a great deal of difference in our analysis as to how a time series is estimated and forecasted.

A graph drawn of the different exchange rates shows their fluctuation over time. Formal testing naturally follows in order to prove any initial impressions as correct. The first pattern shows that these series are not stationary because the sample means do not appear as constant and there is a strong appearance of heteroscedasticity. Overall, it is difficult to maintain the proposition that these series have a time-invariant mean, as they do not contain a clear trend and the dollar-to-deutsche mark exchange rate shows no particular tendency of either increasing or decreasing. The dollar seems to go through sustained periods of appreciation and then depreciation without a tendency of reversion to a long-run mean. In fact, this kind of "random walk" behavior is typical of non-stationary series.

Any shock to the series displays a high degree of persistence although 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 series in other currencies. For example, large shocks to the U.S. appear to be timed similarly to those in the U.K. and Canada. That said, the presence of such co-movements should not be too surprising, however, as we can reasonably expect that the underlying economic forces affecting the American economy would also affect the international economy.

The empirical data in our series demonstrate the aforementioned tranquil and volatile periods of a majority of time series, thereby making any assumption of a constant variance, i.e., homoscedasticity, inappropriate. Our situation is in contrast with those conventional econometric models that assume the existence of a constant variance in its disturbance term. As an asset holder denominated in one currency, one might want to forecast the exchange rate and

its conditional variance over the asset's holding period. The unconditional, or long-run forecast, variance would not be critical if one were planning to purchase it at time period t and then sell it at $t+1$. Taylor (1995) and Kallianiotis (1995) provide a recent literature review on exchange rate economics; Chinn and Meese (1995) examine the performance of four structural exchange rate models.

This paper is organized as follows. Different linear time series models and trends are presented in section 2. Multi-equation time series models are discussed in section 3. The tables of empirical results are given in section 4 and section 5 contains the summary of our findings.

2. Some Time-Series Models

In this section, we introduced stochastic processes and discussed the use of their properties in foreign exchange forecasting. Our objective is to develop models that explain the movement of the time series s_t using both its own previous values and a weighted sum of lagged and current random disturbances without recourse to the regression model's explanatory variables.

The Moving Average (MA) Model

In the moving average process of order q , each observation s_t is generated by a weighted average of random disturbances going back q periods. We denote this process as MA(q) and its equation is

$$s_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \dots - \theta_q\varepsilon_{t-q} \quad (1)$$

where the parameters $\theta_1, \dots, \theta_q$ could be either positive or negative.

The moving average process of order 1, MA(1) is:

$$s_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} \quad (2)$$

Mixed Autoregressive – Moving Average (ARMA) Model

Many stationary random processes cannot be modeled as merely autoregressive because they actually contain qualities of these two processes (autoregressive and moving average) simultaneously. The logical extension of the models presented in the last two sections is the mixed autoregressive-moving average process of order (p,q) and we represent it by

$$s_t = \phi_1s_{t-1} + \dots + \phi_p s_{t-p} + \delta + \varepsilon_t - \theta_1\varepsilon_{t-1} - \dots - \theta_q\varepsilon_{t-q} \quad (3)$$

and its mean is either

$$\mu = \phi_1\mu + \dots + \phi_p\mu + \delta \quad (4)$$

or

$$\mu = \delta / (1 - \phi_1 - \dots - \phi_p). \quad (5)$$

The ARMA (1,1) is:

$$s_t = \phi_1s_{t-1} + \delta + \varepsilon_t - \theta_1\varepsilon_{t-1} \quad (6)$$

Homogeneous Nonstationary Processes: ARIMA Model

The exchange rate time series are not stationary. Therefore, the characteristics of the underlying stochastic process change over time. We say that s_t is homogeneous nonstationary of order d if

$$w_t = \Delta^d s_t \quad (7)$$

is a stationary series. Here, Δ denotes differencing, i.e.,

$$\Delta s_t = s_t - s_{t-1}, \quad \Delta^2 s_t = \Delta s_t - \Delta s_{t-1} \quad (8)$$

and so forth.

If we have a series w_t , we can get back to s_t by summing w_t d times in total, written as:

$$s_t = \sum^d w_t \quad (9)$$

We can model w_t as an ARMA process after we have differenced the series s_t and produced the stationary series w_t .

If $w_t = \Delta^d s_t$ and is also an ARMA(p,q) process, then s_t is called an integrated autoregressive-moving average process of order (p,d,q), or ARIMA (p,d,q).

The equation for the ARIMA (p,d,q) process using the backward shift operator is:

$$\phi(B)\Delta^d s_t = \delta + \theta(B)\varepsilon_t \quad (10)$$

$$\text{with } \phi(B) = 1 - \Phi_1 B - \Phi_2 B^2 - \dots - \Phi_p B^p \quad (11)$$

$$\text{with } \theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q \quad (12)$$

where $\phi(B)$ is the autoregressive operator and $\theta(B)$ is the moving average operator.

The mean of $w_t = \Delta^d s_t$ is given by

$$\mu_w = \delta / (1 - \Phi_1 - \dots - \Phi_p) \quad (13)$$

The Monetary Model of Exchange Rate Determination

The monetary model presented here is a descendant of those by Bilson (1978) and Kallianiotis (1985, 1988). It starts with the conventional money demand functions of domestic and foreign economies and, through purchasing power parity (PPP), calculates the spot exchange rate as either

$$s = (\alpha - \alpha^*) + (m - m^*) - \beta(y - y^*) + \gamma(i - i^*) + \varepsilon \quad (14)$$

or

$$s_t = \beta_0 + \beta_1 m_t + \beta_2 m_t^* + \beta_3 y_t + \beta_4 y_t^* + \beta_5 f p_t + \varepsilon_t \quad (15)$$

where s is the spot exchange rate (the domestic currency per unit of foreign currency), m is the money supply, y is the country's real income proxied by its industrial production, i is the nominal (short-term) interest rate, fp is the forward premium, and an asterisk denotes a foreign variable.

Combining Regression Analysis with a Time-Series Model:

Transfer Function Models

Suppose that we would like to forecast the variable s_t using a regression model that we can presume to include all those independent variables which could explain s_t 's movements but which are collinear themselves. Let us suppose that the best regression model contains the following independent variables as an extended monetary model of the one discussed above:

$$s_t = f[(m_t - m_t^*), (y_t - y_t^*), (q_t - q_t^*), (i_t - i_t^*), \\ (\pi_t - \pi_t^*), (tb_t - tb_t^*), (bd_t - bd_t^*)] + \alpha_0 + \varepsilon_t \quad (16)$$

This equation has an implicit additive error term (ε_t) that accounts for any unexplained variances in s_t . In other words, this error term accounts for the portion of s_t 's variance that remains unexplained by the presence of any other independent variables. The equation can be estimated, and an $R^2 < 1$ will be the result; such equation can then be used to forecast s_t . One source of forecast error would come from the additive noise term whose future values cannot be predicted.

By subtracting the estimated values of s_t from its actual values, we can calculate a residual series u_t which represents unexplained movements in s_t , i.e., pure noise in the process. One useful application of time-series analysis is the construction of an ARIMA model for the regression's residual series u_t and the subsequent substitution of this model for the implicit error term in the original regression equation. When using the equation to forecast s_t , we could also forecast the error term ε_t using this ARIMA model which, in turn, provides some information as to what future values of ε_t could likely be and also helps explain the regression equation's previously unexplained variance. The combined regression-time series model is

$$s_t = \alpha_0 + AX_t + \Phi^{-1}(B)\theta(B)n_t \quad (17)$$

where X_t represents the independent variables and n_t is a normally distributed error term which may have a different variance from ε_t . This model is likely to provide a significantly better forecast compared to either regression equation (16) or a time-series model alone since it includes a structural/economic explanation of s_t 's variance parts that can be explained structurally and a time-series explanation for those parts of this variance that cannot be explained structurally.

Equation (17) is referred to as a MARMA (multivariate autoregressive-moving average) or transfer function model, which simply relates a dependent variable to lagged values of itself, current and lagged values of one or more independent variables, and an error term which is partially explained by a time-series model. The technique of transfer function modeling uses tests of partial and total autocorrelation functions for the independent variables X_t as well as the dependent variable s_t to try to specify the lag polynomials. The structural part of the model is derived through mixing the monetary approach theory with other econometric models while the model's time-series portion is calculated through the structural model's residuals. This combination of a time-series model of the error term with

regression analysis is particularly powerful in its forecasting ability such that in some cases it provides the best of both worlds.

3. Multiequation Time-Series Models

One of the most fertile areas of time-series research today concerns multiequation models. Many economic systems exhibit feedback from other variables but it is not always known if the time path of a series designated to be the independent variable has been unaffected by the time path of the dependent variable. However, there is a type of analysis that treats all variables symmetrically without making any reference to issues of dependence, and this is Vector Autoregression (VAR) analysis.

Vector Autoregression (VAR) Analysis

When a variable is not exogenous -- as happens with s_t here -- a natural extension of the transfer function analysis (see Enders, 1995, pp. 277-290) is the treatment of each variable symmetrically. In the two-variable case of the spot and forward exchange rate, we can let the time path of $\{s_t\}$ be affected by both current and past realizations of the $\{f_t\}$ sequence and also let the time path of the $\{f_t\}$ sequence be affected by current and past realizations of the $\{s_t\}$ sequence.

A Vector Autoregression is a system of equations that makes each endogenous variable a function of its own past and of the past of all other endogenous variables in the system. A VAR has proven successful in forecasting systems of interrelated time-series variables. We are actually using here a slight generalization of a simple VAR by admitting the possibility of exogenous variables that could help determine the endogenous variables: the simplest exogenous variables can be a time trend, for instance.

Our methodology involves estimating spot and forward exchange rates in a VAR framework with a time trend component as

$$\begin{aligned} s_t &= \alpha_{10} + A_{11}(L)s_{t-1} + A_{12}(L)f_{t-1} + A_{13}t + \varepsilon_{1t} \\ f_t &= \alpha_{20} + A_{21}(L)s_{t-1} + A_{22}(L)f_{t-1} + A_{23}t + \varepsilon_{2t} \end{aligned} \quad (18)$$

where α_{10} and α_{20} are constants, A_{ij} = the polynomials in the lag operator L , and t = time trend.

4. Empirical Evidence

We present an analysis of summarized empirical evidence of several different models of foreign currency forecasting. The data are monthly from March 1973 through and including December 1994 and come from Main Economic Indicators of the OECD and International Financial Statistics of the IMF for the Federal Republic of Germany. The exchange rate is defined as the U.S. dollar per German deutsche mark (with direct quotations for the U.S.), the lowercase letters denote the natural logarithm of the variables, and an asterisk denotes the corresponding variable for Germany.

The first model is a linear time-series, namely, the moving average (MA) model in equation (1), and its results are shown in Table 1. The ARMA (mixed autoregressive-moving average) model in equation 3 and the ARIMA (homogeneous nonstationary) process in equation 10 follow for Tables 2 and 3 respectively. All of these results are poor, however; we can deduce that time-series models cannot be used to forecast any exchange rates that follow such high volatility.

The monetary model of exchange rate determination follows in Table 4, using equations 14 and 15, but the estimated results do not inspire much confidence, either, chiefly because some of the explanatory variables are significant at the 10%+ threshold and most of the variables have the anticipated signs. Subject to certain econometric issues, the D-W (Durbin-Watson) display a serial correlation of the error term (i.e., small) while the sum of the squares of the residuals are large. These factors, combined with the low explanatory power associated with the R^2 , show that this monetary model of balance of payments theory is unsupported by our data.

We next use a transfer function model in equation 17 with Table 5, namely, a combining regression analysis along with a time-series model, and we received more encouraging results. This MARMA (multivariate autoregressive-moving average) model is particularly powerful in foreign exchange forecasting because it combines the time-series model with the fundamental approach of an economic theory's regression analysis.

The VAR (vector autoregression) model, a multiequation time-series model, follows in equation 18 / Table 6. The best models that can be used in foreign exchange forecasting based on these tables' empirical data are the ARMA, ARIMA, MARMA, and VAR models for equations 3, 10, 17, and 18, respectively.

Table 1. The Moving Average (MA) Model, eq. (1):

$s_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \dots - \theta_q\varepsilon_{t-q}$	
μ	3.873*** (.003)
θ_1	1.180*** (.059)
θ_2	1.229*** (.054)
θ_3	.947*** (.043)
θ_4	.797*** (.057)
θ_5	.521*** (.037)
θ_6	.358*** (.039)
θ_7	.245*** (.025)
θ_8	.163*** (.023)
θ_9	.093*** (.013)
θ_{10}	.048*** (.010)
θ_{11}	.019*** (.004)
θ_{12}	.005*** (.002)
R^2	.950
D-W	1.434
SSR	.519
F	386.98
RMSE	.0450

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 March 1973 through June 1994, *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level.

Table 2. Mixed Autoregressive-Moving Average (ARMA) Model, eq. (3):

$s_t = \phi_1s_{t-1} + \dots + \phi_p s_{t-p} + \delta + \varepsilon_t - \theta_1\varepsilon_{t-1} - \dots - \theta_q\varepsilon_{t-q}$	
δ	3.979*** (.099)
ϕ_1	.917 (.324)
ϕ_2	-.124 (.412)
ϕ_3	.182 (.164)

θ_1	.115 (.329)
θ_2	.272* (.150)
θ_3	.040 (.122)
R ²	.971
D-W	1.997
SSR	.306
F	1,376.48
RMSE	.0346

Notes: See the previous tables.

Table 3. Homogenous Nonstationary Process

ARIMA Model, eq. (10): $\phi(B)\Delta^d s_t = \delta + \theta(B)\varepsilon_t$	
δ	.002 (.002)
ϕ_1	-.004 (.270)
ϕ_2	-.045 (.288)
ϕ_3	-.054 (.190)
ϕ_4	.315* (.167)
ϕ_5	.052 (.149)
ϕ_6	-.297** (.144)
θ_1	.042 (.279)
θ_2	.139 (.292)
θ_3	.080 (.205)
θ_4	-.346* (.187)
θ_5	-.073 (.196)
θ_6	.169 (.206)
R ²	.052
D-W	1.977
SSR	.296
F	1.118
RMSE	.0340

Notes: See the previous tables. German data = stationary, d = 1.

Table 4(i). The Monetary Model, eq. (14):

$s_t = (\alpha - \alpha^*) + \mu(m_t - m_t^*) - \beta(y - y_t^*) + \gamma(i - i_t^*) + \varepsilon_t$	
$\alpha - \alpha^*$	2.320*** (.290)
μ	1.055*** (.184)
β	.231 (.141)
γ	-.004 (.004)
R^2	.317
D-W	.083
SSR	7.132
F	38.990
RMSE	.1669

Notes: See the previous tables. s_t = ln of spot exchange rate, t = time, m_t = money supply, i_t = short-term interest rate, and asterisk denotes the foreign country.

Table 4(ii). The Monetary Model, eq. (15):

$s_t = \beta_0 + \beta_1 m_t + \beta_2 m_t^* + \beta_3 y_t + \beta_4 y_t^* + \beta_5 f p_t + \beta_6 f p_t^* + \varepsilon_t$	
β_0	-3.342*** (.558)
β_1	1.154*** (.159)
β_2	-1.629*** (.174)
β_3	1.539*** (.190)
β_4	.301*** (.119)
β_5	-.009* (.005)
β_6	.034*** (.004)
R^2	.630
D-W	.198
SSR	3.860
F	70.759
RMSE	.1228

Notes: See the previous tables. s_t = ln of spot exchange rate, t = time, m_t = money supply, $f p_t$ = the forward premium, y_t = the real income proxied by industrial production, and asterisk denotes the foreign country.

Table 5. The Combined Model, eq. (17):

$s_t = \alpha_0 + AX_t + \Phi^{-1}(B)\theta(B)n_t$	
c	.317 (.394)
m_t	.050 (.109)
m_t^*	-.047 (.061)
y_t	.037 (.074)
y_t^*	.049 (.034)
i_t	-.003 (.002)
i_t^*	-.0002 (.002)
π_t	.142 (.097)
π_t^*	-.250 (.214)
s_{t-1}	.929*** (.023)
θ_4	-.346* (.187)
ε_{t-2}	.090 (.068)
ε_{t-3}	.029 (.068)
R^2	.972
D-W	1.999
SSR	.292
F	703.931
RMSE	.1123

Notes: See the previous tables.

Table 6. The Vector Autoregression Model, eq. (18)

Dep. Var.	s_t	f_t
c	1.043** (.472)	.995** (.471)
s_{t-1}	.957 (.728)	.510 (.730)
s_{t-2}	-1.234** (.617)	-1.304** (.616)
f_{t-1}	.013 (.724)	.472 (.723)

f_{t-2}	1.221* (.618)	1.279** (.617)
t	.001** (.0007)	.001** (.0007)
m_t	-.094 (.077)	-.087 (.076)
i_t	-.006*** (.002)	-.005** (.002)
m_t^*	-.080 (.050)	-.077 (.050)
i_t^*	.003 (.001)	.002 (.001)
R ²	.973	.972
D-W	1.986	2.004
SSR	.286	.285
F	969.896	932.853
RMSE	.0334	.0034

Notes: See the previous tables. s_t = the natural logarithm of the spot exchange rate, f_t = the natural logarithm of the forward exchange rate, t = time, m_t = the money supply, i_t = the short-term interest rate, and the asterisk in the dependent variable denotes the foreign currency.

5. Summary

This paper utilizes several different time-series trends and linear time-series as well as the balance of payments approach, the transfer function, and the vector autoregression model to examine the predictive performance of several exchange rate forecast models. For every such model, we calculate the root mean square forecast error (RMSE) as $= \sqrt{((\sum_{t=1}^n (A_t - F_t)^2)/n)}$, where A = the actual value of the dependent variable, F = the forecast value, and n = the number of observations. The foreign exchange forecast model with the smallest RMSE is the best predictor that must be chosen to forecast the foreign exchange rate.

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

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