Structural models of exchange rate determination

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Abstract

This study compares the forecasting accuracy of state space techniques based on the monetary models of exchange rate with univariate and random walk models for four countries. It is found that these structural models outperform ARIMA and random walk models for all four countries. A state space vector that contains variables based on the monetary model easily outperforms random walk as well as ARIMA models for France, Germany, UK, and Japan during the sample period of this study. © 2000 Elsevier Science B.V. All rights reserved.

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JEL classification: F31; F47

1. Introduction

It is now recognized that exchange rates are difficult to track and exchange rate models are characterized by parameter instability and dismal forecast performance. Exchange rate models developed over the last two decades proved unreliable and unstable when presented with different data sets compared to naive models such as

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a random walk. For example, Meese and Rogoff (1983) show that a simple random walk forecasts as well as linear exchange rate models. It has also become increasingly apparent that our understanding of exactly what factors affect exchange rates are limited.

Recent research has focused on the importance of non-linearities in exchange rates. The univariate distribution of exchange rate changes is known to be leptokurtic (see, for example, Westerfield, 1977; Hsieh, 1988). Researchers have also shown the existence of conditional heteroskedasticity in the residuals of both time-series and structural models of spot exchange rates. The existence of residual conditional heteroskedasticity or leptokurtosis in exchange rates may not improve our ability to explain the levels of exchange rates. This point is demonstrated in a recent paper by Diebold and Nason (1990).

Multivariate models allow for the analysis of related time series. In such analysis, the task is twofold: (1) identifying the related or explanatory variables that would shed some light on the behavior of the variables of interest; and (2) selecting a suitable multivariate statistical procedure. Sarantis and Stewart (1995) argue that exchange rate modeling should begin with an investigation of equilibrium relationships.

One of the very few papers that attempts to test structural multivariate models of exchange rates with a non-linear technique is Schinasi and Swamy (1987). They show that non-linear random coefficient techniques sometimes lead to improved forecasting ability of exchange rate models. They show that when coefficients of the monetary model are allowed to change, the model can outperform forecasts of a random walk model. Sarantis and Stewart (1995) compare the out-of-sample forecasting accuracy of structural, BVAR, and VAR models and conclude that these structural models outperform other models in medium-term forecasting accuracy.

Wolff (1987) suggests the use of a state space model with the Kalman filtering technique to study exchange rate behavior. He argues that the advantage of this signal extraction approach is that we can empirically characterize the temporal behavior of exchange rates using only data on spot and forward exchange rates. Yin-Wong (1993) employs a state space model, which allows for the covariation of risk premiums and unexpected rates of depreciation to study exchange rate risk premiums.

MacDonald and Taylor (1994) use a multivariate cointegration technique to test for the existence of long-run relationships underpinning the monetary model. They find evidence of cointegration and report that their error correction model outperforms the random walk model. MacDonald and Marsh (1997) in a recent paper demonstrate that a purchasing-power-parity (PPP) based model can outperform the random walk and the vast majority of professional exchange rate forecasts over horizons as short as 3 months.

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See, for example, Cumby and Obstfeld (1984), Domowitz and Hakkio (1985), Hsieh (1989), and Engle et al. (1990).
The purpose of this paper is to test the forecasting power of state space techniques based on structural models. Similar to a recent study by Sarantis and Stewart (1995), we identify the related or explanatory variables that would shed some light on the behavior of the exchange rate and then forecast exchange rates using Kalman filtering in the state space framework. The forecasting capability of these models is then compared to ARIMA models as well as random walk models. Our preliminary results are very encouraging. We find that forecasts obtained by a state space technique based on the monetary models easily outperform the random walk and ARIMA models for all four countries used in this study. Our study is different from that of Sarantis and Stewart (1995) in the sense that we use a different technique (state space vs BVAR and VAR) and our data is monthly, whereas their data is quarterly.

2. Data and methodology

2.1. Data

Monthly exchange rates (vis-à-vis the US Dollar) and other macroeconomic variables are obtained from the *International Financial Statistics* for January 1978 through July 1996. The variables used are money aggregates (M1), industrial production, and short-term and long-term interest rates for France, Germany, Japan, and UK. The money supply and industrial production series are seasonally adjusted. Natural logarithms are taken for the exchange rates and money aggregates.

2.2. The monetary model of exchange rate determination

Over the last two decades, a number of exchange rate determination models have been put forth as alternatives to the traditional flow market models. Those alternative models, known as asset market models, differ from the flow models in that the exchange rate adjusts to international demand for stocks of national assets. One set of asset market models, known as the monetary model, assumes perfect substitutability between domestic and foreign bonds. For the monetary model, the exchange rate is determined by the relative demand for and supply of money. A standard flexible-price monetary approach can be written as\(^3\):

\[
s_t = \beta_1 m_t + \beta_2 m_t^* + \beta_3 y_t + \beta_4 y_t^* + \beta_5 i_t + \beta_6 i_t^* + \eta_t
\]

where \(s_t\) is the spot exchange rate (home currency price of the foreign currency), \(m_t\) denotes the domestic money supply, \(y_t\) denotes domestic income, and \(i_t\) denotes the long-term domestic interest rates. Corresponding foreign variables are denoted by an asterisk and \(\eta_t\) is a disturbance term.

\(^3\) See Bilson (1978), Hodrick (1978) and Frankel (1989) for further discussion.
The expected signs for the above monetary model are as follows: $\beta_1$ and $\beta_2$ should be positive and negative, respectively, $\beta_3$ and $\beta_4$ should be negative and positive, respectively, and $\beta_5$ and $\beta_6$ should, respectively, be positive and negative. The domestic interest rate has a positive influence on the exchange rate because interest rates reflect the inflation premium in this model. An increase in the domestic expected inflation rate causes investors to switch from the domestic currency to foreign bonds resulting in the home currency depreciation.

Numerous researchers have estimated Eq. (1) and other versions of the monetary model. Early tests of Eq. (1) for the period prior to 1978 tended to be supportive of the model. However, for the period after 1978 the models have not performed well. Estimated coefficients sometimes were found to have wrong signs or be insignificant. Possibly, the worst blow to the class of monetary models is the finding by Meese and Rogoff (1983) that these models fail to outperform a simple random walk in an out-of-sample forecasting competition.

Recently a number of researchers\(^4\) have attempted to test for the validity of the monetary model using the two-step cointegration methodology. The sweeping conclusion to emerge from this body of research is that exchange rates are not cointegrated with the standard vector of monetary variables. However, MacDonald and Taylor (1994) argue that the standard two-step cointegration methodology is not appropriate for testing the monetary model. They propose a multivariate cointegration technique and find support for the monetary model.

The purpose of this paper is to employ an appropriate multivariate approach to forecasting exchange rates and then compare the results to other models. The technique we use is state space modeling. Since this approach is relatively new, we discuss this methodology in a later section of the paper. Initially, we test Eq. (1) to find out what variables are significant in the monetary model and should, therefore, be included in the state vector.

Table 1 reports OLS estimates of the monetary model (Eq. (1)) for different countries. The coefficients for France are close to the predicted signs by the monetary model. All the coefficients have the expected signs and are statistically significant except for foreign income (US industrial production) which has the correct sign but is statistically insignificant. The coefficients for Germany also have the expected signs and are statistically significant with the exception of foreign income, which has the wrong sign and is statistically significant.

Japan’s results are not quite as good. The coefficient for the domestic money supply has the correct sign but is statistically insignificant. The coefficient for foreign income has the wrong sign and is statistically significant. The coefficient for domestic long-term interest rates has the wrong sign but is statistically insignificant. The results look much better for the UK. All the coefficients have the expected signs and are statistically significant except for the long-term domestic interest rate, which has the wrong sign but is statistically insignificant. The results confirm the finding of other researchers who test the monetary model (see, for example,\(^4\) See, for example, Meese (1986), Boothe and Glassman (1987), McNown and Wallace (1989).
Table 1
Regression results of the monetary model
\[ s_t = \beta_0 + \beta_1 m_t + \beta_2 m_t^* + \beta_3 y_t + \beta_4 y_t^* + \beta_5 i_t + \beta_6 i_t^* + \eta_t, \]

<table>
<thead>
<tr>
<th>Country</th>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>-1.972 (-5.30)</td>
<td>1.368 (16.79)</td>
<td>-0.467 (-4.91)</td>
<td>-0.030 (-10.11)</td>
<td>0.003 (1.12)</td>
<td>0.045 (4.91)</td>
<td>-0.074 (6.42)</td>
</tr>
<tr>
<td>Germany</td>
<td>0.063 (0.24)</td>
<td>0.276 (2.63)</td>
<td>-0.476 (-5.23)</td>
<td>-0.007 (-2.28)</td>
<td>-0.005 (-1.97)</td>
<td>0.034 (2.63)</td>
<td>-0.065 (-6.74)</td>
</tr>
<tr>
<td>Japan</td>
<td>7.47 (24.73)</td>
<td>0.001 (0.06)</td>
<td>-0.268 (-2.62)</td>
<td>-0.003 (-2.38)</td>
<td>-0.014 (-5.75)</td>
<td>-0.004 (-1.35)</td>
<td>-0.049 (-8.24)</td>
</tr>
<tr>
<td>UK</td>
<td>-2.445 (-1.86)</td>
<td>0.210 (2.49)</td>
<td>-0.326 (-2.42)</td>
<td>-0.011 (-3.08)</td>
<td>-0.011 (-1.09)</td>
<td>-0.017 (-1.17)</td>
<td>-0.026 (-2.44)</td>
</tr>
</tbody>
</table>

*a* $s_t$, natural logarithm of exchange rate (vis-à-vis US dollar); $m_t$, money supply for home country; $m_t^*$, money supply for US; $y_t$, industrial production for home country; $y_t^*$, industrial production for US; $i_t$, long-term interest rate for home country; $i_t^*$, long-term interest rate for US; t-statistics are in parentheses.
MacDonald and Taylor, 1994) and find that the coefficients may have the wrong signs. Overall, we have found some support for the monetary model in the sense that most coefficients have the expected signs as suggested by the model. What is important is that the analysis here establishes the variables that are consequential in determining the exchange rates in order to include them in the state vector.

2.3. State space modeling and the Kalman filter

The state space model is an enormously powerful tool that opens the way to handling a wide range of time series models. The general state space model applies to a multivariate time series, \( y_t \), containing \( N \) elements. These observable elements are related to a \( mx1 \) vector, \( \Omega_t \), known as the state vector, via a measurement equation

\[
y_t = F_t \Omega_t + I_t \xi_t,
\]

(2)

where \( F_t \) is an \( Nxm \) matrix, \( I_t \) is an \( Nxm \) matrix (innovation matrix), and \( \xi_t \) is an \( mx1 \) vector of serially uncorrelated disturbances with mean zero and covariance matrix \( H_t \), that is

\[
E(\xi_t) = 0 \quad \text{and} \quad \text{Var}(\xi_t) = H_t
\]

(3)

In general the elements of \( \xi_t \) are not observable. However, they are known to be by first-order Markov process,

\[
\Omega_t = G_t \Omega_{t-1} + \omega_t
\]

(4)

where \( G_t \) is an \( mxm \) matrix and \( \omega_t \) is a \( gx1 \) vector of serially uncorrelated disturbances with mean zero and covariance matrix \( Q_t \). Eq. (4) is the \textit{transition matrix}. The definition of \( \Omega_t \) for any particular statistical model is determined by construction. The aim of the state space formulation is to set up \( \Omega_t \) in such a way that it contains all the relevant information on the system at time \( t \).

2.3.1. The Kalman filter

Once a model has been put in a state space form, the Kalman filter can be applied. The Kalman filter is a recursive procedure for computing the optimal estimator of the state vector at time \( t \), based on the information available at time \( t \). This information consists of the observation up to and including \( y_t \). The current value of the state vector is of prime interest and the Kalman filter enables the estimate of the state vector to be continually updated as new observations become available. The Kalman filter also facilitates the estimation of the likelihood function via what is known as the prediction error decomposition. This opens the way for the estimation of any unknown parameters in the model. It also provides the basis for statistical testing and model specification.

The state space procedure is a relatively new econometric approach to examining causal relationships. The procedure has two important attributes found lacking in similar methodologies. One advantage is that the state space procedure makes no a priori assumptions about variable relationships, but relies on the data to identify
causal relationships. Stated differently, the procedure allows us to test hypothesized relationships without imposing a structural model on the data prior to estimation. In contrast, autoregressive moving average (ARMA) and vector autoregressive moving average (VARMA) models developed by Tiao and Box (1981) require the researcher to tentatively specify the model before estimation. As compared to the state space procedure, VARMA is unnecessarily restrictive when the direction of causal relationship is uncertain.

A second advantage of the procedure is that it can be used to obtain the minimum number of parameters necessary to span the state space of the time invariant linear relationship which best describes a given set of observations. In other words, the state space models are parsimonious.

Before proceeding, it should be noted that state space estimates seem to fare well against those generated by other econometric procedures. For example, Mittnik (1990) considered the forecasting performance of several models used in forecasting real economic activity in the US, including the St Louis Model, ARIMA, and the state space. He found that the state space procedure compares favorably with other widely used models.

3. Results

3.1. Results from state space

In this section we compare the forecast capability of the random walk, ARIMA, and state space models. To conserve space, the results of ARIMA models are not reported here. Both Schwartz and Akaike criterion indicate that ARIMA(1,1,1) models fit very well for all currencies.

In order to obtain our state space estimates, we include significant variables as suggested by the monetary model in the state space vector. We report the state space analysis for Germany in this section5. These variables are spot rates and differential interest rates between the US and the home country (Germany). Differential interest rates are important variables in the determination of exchange rates (for a detailed discussion, see Frankel, 1979). According to interest rate parity, under perfect capital mobility, the bonds of different countries are perfect substitutes. In the absence of capital controls and transaction costs, interest rate parity must hold since its collapse would imply unexploited profit opportunities. The foundation of the monetary model is a domestic and foreign money demand function. Each country’s demand for money depends on domestic income and the domestic nominal interest rate. An increase in the domestic nominal money supply relative to the foreign money supply results in an increase in domestic prices relative to foreign prices, which, in turn causes a depreciation in the domestic currency.

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5 The state space analyses for other countries are not reported here to conserve space but are available from the authors.
We begin by analyzing each time series separately and checking for non-stationarity. The series for money supplies, interest rates, and industrial productions did not appear to be stationary. In each case, stationarity was achieved by taking the first differences of the series observations.

The methodology for constructing state space models consists of three steps. The first step requires that a multivariate autoregressive (AR) model with $k$ lags (AR($k$)) be fitted. We use the Akaike Information Criterion (AIC) with $k = 1, \ldots, 10$ to find a definite starting point for the Yule–Walker equations\(^6\). Table 2 reports the resulting AIC values. Because the smallest AIC ($-4268.54$) occurs at lag 1, we opt for an initial autoregressive model approximation with $k = 1$.

In the second step, we employ canonical correlation analysis in developing a general Markovian or state space representation of our AR(1) model\(^7\). Our initial measurement equation relates an $m \times 1$ state space vector, $\mathbf{\Omega}_t$, to the multivariate time series $\mathbf{y}_t$ (see Eq. (2))\(^8\).

The following state space vector appears to span our multivariate time series: $\mathbf{V}_t = [s_t, m_t, m_t^*, y_t, i_t, i_t^*]$. The vector $\mathbf{V}_t$ is unique and should contain all of the information from the system that is required to predict its future behavior.

Table 2
Akaike’s information criterion (AIC) for autoregressive models

<table>
<thead>
<tr>
<th>Lag</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$-2753.44$</td>
</tr>
<tr>
<td>1</td>
<td>$-4268.54^*$</td>
</tr>
<tr>
<td>2</td>
<td>$-4652.72$</td>
</tr>
<tr>
<td>3</td>
<td>$-4600.95$</td>
</tr>
<tr>
<td>4</td>
<td>$-4532.05$</td>
</tr>
<tr>
<td>5</td>
<td>$-4488.30$</td>
</tr>
<tr>
<td>6</td>
<td>$-4438.70$</td>
</tr>
<tr>
<td>7</td>
<td>$-4412.14$</td>
</tr>
<tr>
<td>8</td>
<td>$-4357.39$</td>
</tr>
<tr>
<td>9</td>
<td>$-4315.55$</td>
</tr>
<tr>
<td>10</td>
<td>$-4309.51$</td>
</tr>
</tbody>
</table>

* Lag of 1 for Yule–Walker equations.

\(^6\) The Akaike Information Criterion considers the relationship between $k$-lags in the initial Yule–Walker equations, where $k = 1, \ldots, n$ and the resulting autocovariances in selecting an optimal starting point. The optimal $k$-lag structure is that which minimizes the equations’ prediction error relative to the number of parameters used. The AIC’s analogue in regression analysis is the adjusted $R$-square.

\(^7\) A Markovian representation of the multivariate stochastic system is developed by: (1) producing a revised Yule-Walker equation by adding a moving average term to the initial equation and (2) examining the canonical correlation between the revised equation and its Markovian representation to determine whether the moving average term adds to the state vector’s explanatory power. This process continues until the incremental value of the canonical correlate is zero, indicating that the added moving average term contributes no additional explanatory ability to the model.

\(^8\) Canonical correlates are not reported here but are available from the authors.
Table 3
State space estimates of structural exchange rate model for Germany (1978–1996)*

<table>
<thead>
<tr>
<th></th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[ s_t = -0.014s_{t-1} + 0.018m_{t-1} - 0.016m^*<em>t - 0.002y</em>{t-1} - 0.027l_{t-1} + 0.026i_{t-1} + \epsilon_t ]</td>
</tr>
<tr>
<td>2</td>
<td>[ m_t = 0.243m_{t-1} + 0.686m^*<em>{t-1} + 0.948s</em>{t-1} + \epsilon_t ]</td>
</tr>
<tr>
<td>3</td>
<td>[ y_t = -0.776m_{t-1} + 0.730m^*<em>{t-1} - 0.425y</em>{t-1} - 0.607s_{t-1} + \epsilon_t ]</td>
</tr>
<tr>
<td>4</td>
<td>[ i_t = 0.124l_{t-1} + 0.273i^*<em>{t-1} + 1.028s</em>{t-1} + \epsilon_t ]</td>
</tr>
</tbody>
</table>

* \( s_t \) natural logarithm of exchange rate (vis-à-vis US dollar); \( m_t \), money supply for home country; \( m^*_t \), money supply for US; \( y_t \), industrial production for home country; \( i_t \), long-term interest rate for home country; \( i^*_t \), long-term interest rate for US. All coefficients in the table are statistically significant at least at the 10% level.

While the state vector \( \Omega_t \) spans the time series, the distributional properties of \( y_t \) are largely unknown, making parameter estimation difficult. Some such properties may, however, be ascertained by decomposing the state vector’s prediction error. In the third step of the methodology, we use the Kalman filter (i.e. forward recursion algorithms) to compute the one-step-ahead prediction error, \( \xi_t \), and its corresponding covariance matrix. This information is used in constructing an appropriate likelihood function. Maximum likelihood estimation (MLE) is then used to derive final parameter estimates for the state space model. We converted the state space estimates to ARMA form to facilitate interpretation of the results. The ARMA form results are shown in Table 3.

The results in Table 3 (Eq. (1)) indicate that the monthly German exchange rate \( s_t \) is dependent upon the exchange rate in the previous month \( s_{t-1} \), money supplies for Germany in previous month \( m_{t-1} \), the money supply for US \( m^*_{t-1} \), industrial production for Germany in the previous month \( y_{t-1} \), and long-term interest rates for Germany and US in the previous month \( i_{t-1}, i^*_{t-1} \), respectively. The results are very supportive of the monetary model. For instance, a rise in the differential interest rate in period \( t \) signals a forthcoming appreciation of the home currency relative to the foreign currency. Our results are consistent with prediction of the ‘monetary’ or ‘asset’ theory of exchange rate determination. Under this view, the exchange rate moves to equilibrate the international demand for assets rather than international demand for flow of goods (Frankel, 1979). According to this theory, changes in the nominal interest rate reflect changes in the tightness on monetary policy. A rise in the domestic interest rate relative to the foreign interest rate signals a contraction in the domestic money supply and causes the exchange rate to rise. The lower interest rate at home than abroad causes a capital outflow, which causes the domestic currency to depreciate. Therefore, we find a negative relationship between the exchange rate and home interest rates. Boothe and Glassman (1987) also find profitable trading rules based on an interest rate differential model for the Canadian dollar and Deutschmark. Eq. (1) also indicates that a fall in industrial production at home causes the exchange rate to depreciate.

Eq. (2) in Table 3 indicates that the money supply in Germany is a function of the money supply at home and the US money supply as well as the exchange rate in the previous month. A rise in the exchange rate (depreciation of home currency)
signals a forthcoming increase in the money supply. Eq. (3) indicates that Germany’s industrial production is a function of the money supplies both at home and abroad and the exchange rate. An appreciation of the home currency predicts a forthcoming increase in industrial production. Eq. (4) indicates that long-term interest rates at home are dependent on interest rates at home and abroad as well as the exchange rate for the previous month. A depreciation of the home currency causes the monetary authorities to respond by tightening the money supply and therefore causing the interest rates to rise. The system (state space) also provides the relationships between US variables and German variables but those are not reported here so as to keep our focus on the exchange rate and the monetary model. In Fig. 1, the actual and fitted values of the exchange rate for the period 1978:1 to 1996:8 are reported. The model is able to get most of the turning points correct.

Our state space models for other countries are very similar to the German results and therefore are not reported here.

3.2. Comparison of out-of-sample forecasting models

Out-of-sample accuracy of all the competing models is measured by root mean square error (RMSE). We generate forecasts over the last 12, 24, and 36 months of our sample period by using the above three models. Since we are using the
logarithm of the exchange rate, RMSE is unit free and comparable across currencies (Meese and Rogoff, 1983). The forecasting results are reported in Table 4.

In the case of France, a striking result is that none of the models achieve lower RMSE than the state space model at any of the three forecasting horizons. The state space outperforms random walk model by reducing the RMSE by 25, 66, and 68% for the three forecasting periods respectively.

In the case of Germany, the random walk outperforms the state space model by reducing RMSE by 40% for the 12-month forecasting horizon. However, the state space outperforms the random walk for the longer forecasting periods.

In the case of Japan, none of the models achieve a lower RMSE than the state space model. In fact, the reduction in the RMSE relative to the random walk is very large (95% for the 12-month horizon). This is true for all the forecasting periods.

The results for the UK are very similar to the results for Germany. The random walk model outperforms state space and ARIMA models for the 12-month forecasting horizon. However, the state space outperforms random walk and ARIMA for other periods.

With regard to comparison of ARIMA and state space models, we find that the state space model outperforms ARIMA in all four currencies and in all forecasting periods based on RMSE. The improvements in forecast errors obtained by state space are even larger than the random walk models. Our results are consistent with MacDonald and Taylor (1994) and MacDonald and Marsh (1997) and indicate the
importance of economic variables and other fundamentals in exchange rate determination.

4. Conclusion

This study compares the out-of-sample forecasting accuracy of random walk, autoregressive, and state space (based on the monetary) models for four countries using monthly data.

We find that a state space vector that contains the exchange rate, both domestic and foreign money supplies, industrial outputs, and long-term interest rates is significant in determining exchange rates. The state space model is fitted to the data, which is shown to perform well in terms of both in-sample and out-of-sample criteria. It is also shown that the state space model with variables suggested by the monetary model outperforms random walk forecasting and ARIMA techniques judged by root mean square error (RMSE) as the measure of performance for most forecasting horizons for all four countries.

State space models are also capable of detecting causal relations. We find that differential interest rates from the previous month are significant in the determination of exchange rates for the current month. The importance of the differential interest rate in explaining the movements in exchange rates is consistent with the ‘monetary’ theory of exchange rate determination.

References


