1998

Exchange rate forecasting: an application of radial basis function neural networks

Yih-Jiuan Wu
Iowa State University

Exchange rate forecasting:
An application of radial basis function neural networks

by

Yih-Jiuan Wu

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

Major Professor: Leigh Tesfatsion

Iowa State University

Ames, Iowa

1998

UMI Number: 9911659

Graduate College
Iowa State University

This is to certify that the Doctoral dissertation of

Yih-Jiuan Wu

has met the dissertation requirements of Iowa State University

Signature was redacted for privacy.

Major Professor

Signature was redacted for privacy.

For the Major Program

Signature was redacted for privacy.

For the Graduate College

DEDICATION

I would like to dedicate this dissertation to my parents, two sisters, and brother-in-law.

TABLE OF CONTENTS

CHAPTER 1. INTRODUCTION

The foreign exchange market is the largest financial market. According to the BIS (Bank for International Settlement) statistics, the daily global foreign exchange market turnover was around $1,490 billion in April 1998, up from $1,190 billion in 1995, and up from $820 billion in 1992. Participants in the foreign exchange market include central banks, multinational corporations, portfolio managers, banks, currency brokers, and private investors. Since future exchange rates are not certain, forecasts need to be made for hedge or speculation purposes that involve the spot and derivatives (forward, futures, and options) markets.

However, it is very difficult to forecast exchange rates accurately. In seminal work, Meese and Rogoff (1983) estimated three monetary models, 6 univariate time series models and unrestricted vector autoregressive (VAR) models, but they could not outperform the random walk model for out-of-sample forecasting. Many subsequent studies have focused on forecasting exchange rates using different methodologies,[1] but the results have been mixed.

Most exchange rate studies concentrate on linear models. Some researchers suggest that nonlinearity may offer an alternative way to improve forecasting performance. Some studies have estimated univariate nonlinear models. However, there are not many nonlinear multivariate studies. One reason may be that it is difficult to choose an appropriate nonlinear model among so many possible alternatives.[2]

---

[1] See chapter 2 for more discussion.
[2] Brock *et al.* (1991), Granger (1993), Granger and Terasvirta (1993), and Swanson and White (1997) have further discussions.

The *Artificial Neural Network (ANN)* model may prove to be a useful alternative for nonlinear analysis of exchange rates. The ANN model is a universal and highly flexible function approximator that is well suited for pattern recognition and classification [Hornik *et al.* (1989), and Cybenko (1989)]. An ANN model is analogous to a nonparametric and nonlinear regression model, which can automatically deal with nonlinear relationships between inputs and output(s). It can estimate the function from the training set (in-sample) data without much *a priori* information about the data generating process.

As discussed in more detail in chapter 2, the results of recent studies concerning ANN models in forecasting financial and economic series seem to be very promising. In particular, there are some studies applying ANN models for exchange rate forecasting. Most of them focus on high-frequency data. Furthermore, most of them use multilayer perceptron (MLP) network models, with little financial data forecasting work being done by adopting the radial basis function (RBF) network models. The RBF networks that have been successfully applied to problems such as the signal and pattern recognition and classification [Chen and Grant (1991), Kassam and Cha (1993), Musavi *et al.* (1992), and Renals and Rohwer (1989)] could be alternatives to the MLP network in financial data forecasting.

In view of the previous promising performance of ANN models, this dissertation will investigate the predictive power of RBF exchange rate models. The RBF network model is also chosen because it is a universal approximator for continuous functions [Girosi and Poggio (1990a), Hartman *et al.* (1990), and Park and Sandberg (1991,1993)] and can be generally trained faster than the MLP network. In addition, when the classification problem is extended to higher dimensions, the RBF model may linearly separate complex pattern classification tasks better than the MLP model [Broomhead and Lowe (1988)].

The intent of this research is to explore the potential usefulness of RBF models for the purpose of predicting one-month-ahead and one-quarter-ahead exchange rates using monthly and quarterly data, respectively. Three exchange rates are investigated in this research: the German mark / US$, the Japanese yen / US$, and the Italian lira / US$. The primary focus of the thesis is on the following research questions.

First, do the univariate and multivariate RBF models forecast monthly exchange rates better than standard linear autoregressive integrated moving average (ARIMA) or random walk models? Second, do the multivariate RBF models forecast quarterly exchange rates better than the random walk model or the forward rate forecast?

1. Univariate Analyses: Is there any nonlinear relationship that can be explored by using a RBF model in order to improve exchange rate forecasting? For example, we intend to determine whether there exists a nonlinear relationship between a single exchange rate and its own lagged values. The univariate RBF models are only estimated for monthly exchange rate forecasting.
2. Multivariate Analyses: We intend to explore whether a multivariate RBF model can be used to determine whether there exists a nonlinear relationship between an exchange rate and other economic variables. The multivariate RBF models are estimated for both monthly and quarterly exchange rate forecasting. As discussed in chapter 2, many conventional statistical analyses use economic variables derived from theoretical monetary exchange rate models. However, some of these economic data might not be available at

the time when forecasts are made. Therefore, for practical forecasting purposes, the primary economic variables used in the multivariate RBF models are interest rates. In addition, the revised seasonally adjusted money supply (M1) variable is included in the quarterly RBF models for reference.

All models are successively estimated over six sliding-window time periods. The ARIMA models which have fixed-model specifications are evolved by changing the parameters through re-estimation. All RBF models may change both model specifications and parameters through re-estimation.

Most previous studies only use descriptive statistics to evaluate out-of-sample forecasting performance, and very few of them conduct statistical hypothesis tests on those descriptive statistics. Therefore, in this research, in addition to using descriptive statistics to evaluate out-of-sample forecasts, three statistical hypothesis tests for these descriptive statistics are also provided to obtain more objective conclusions. The descriptive statistics used are the root mean squared error (RMSE) criterion, which measures the point forecast errors, and the "correct direction" and "speculative direction" criteria which measure the percentage of times that a model can correctly predict future directions relative to the current spot rate and the forward rate, respectively. The Modified Diebold and Mariano test [Harvey *et al.* (1997)] is employed to test the equality of mean squared errors of two models. The Pesaran-Timmerman (1992, 1994) non-parametric market timing test, and the χ^2 test of independence [see Swanson and White (1997)] are both applied to the "correct direction" and "speculative direction" criteria to test whether the model can predict the relevant direction with statistical significance.

The forecasting results indicate that a model which forecasts best based on the RMSE criterion is not necessary best based on the direction criteria. Some models are very competitive with one another based on the descriptive criteria; but the hypothesis tests may indicate that these models are statistically different. Overall, more RBF models can predict better in the direction of change than in the point forecasts. Therefore, different RBF models may be favored by different end-users of the forecasts.

Generally, the quarterly multivariate RBF models have better forecasting ability than the monthly RBF models for all three exchange rates. In particular, the RBF models using interest rates as economic variables do have some forecasting value for all three exchange rates in one-quarter-ahead forecasting. For one-month-ahead forecasting, except for the Japanese yen / US dollar, most of the univariate RBF models generally do not forecast better than the multivariate RBF models. Furthermore, the interest rates may help more in one-quarter-ahead forecasting than in one-month-ahead forecasting. In the presence of the interest rates, the M1 variable does not seem to help much in forecasting for any of the three exchange rates.

The results of point forecasts for all three exchange rates indicate that the random walk models are worse than all other models based on the descriptive average RMSE values. However, the Modified Diebold and Mariano hypothesis tests of equal mean squared errors indicate that only some models are statistically different from the random walk models. These models include the MA(1) model of the monthly German mark, the multivariate cubic RBF and square RBF models and one univariate cubic RBF model of the monthly Italian Lira, and all the RBF models using the short-term interest rates (with or without the M1) as inputs of the quarterly Japanese yen.

Models that can predict the correct direction of change with statistical significance include two univariate RBF models and some multivariate nonlocalized models of the monthly German mark, all multivariate RBF models, three univariate localized RBF models and the MA(1) model of the monthly Italian Lira, and some RBF models of three quarterly exchange rates. Some quarterly RBF models of the three exchange rates and the quarterly random walk model of the German mark can predict the "speculative direction of change" with statistical significance.

In addition, the results show that the localized RBF models are more flexible in model estimation. For all three quarterly exchange rates, the residuals of some higher dimensional nonlocalized RBF models are not white noise and their forecasting results are not good. However, if the residuals of the nonlocalized cubic and square RBF models are white noise, usually these two types of nonlocalized RBF models can forecast quite well, especially in predicting the direction.

This dissertation is organized as follows. Chapter 2 reviews some conventional statistical analyses of exchange rate forecasting and also some ANN applications in economic and financial series forecasting. Chapter 3 briefly describes the mathematical background of RBF models that we consider. Chapter 4 describes the basic approach of this study, including the time frame of research, the data description, empirical models, evaluation criteria, and statistical hypothesis tests. Chapter 5 and 6 present and discuss the empirical results for monthly and quarterly forecasting, respectively. Chapter 7 provides a summary of major findings and suggests further research areas for future study. Appendix A provides the detailed tables of literature review. Appendix B describes RBF formulas and figures. Appendix C illustrates data resources. Appendix D and E present the detailed forecasting tables for Chapters 5 and 6, respectively.

CHAPTER 2. LITERATURE REVIEW

This chapter briefly reviews what has been done in exchange rate forecasting by using conventional statistical models and ANN models. In order to show that the ANN models are promising in forecasting, some other studies forecasting financial and economic time series are also discussed. In Appendix A, there are detailed tables for each study for further reference.

2.1 Conventional Statistical Estimation / Forecasting of Exchange Rates

2.1.1 Linear multivariate analyses (See Appendix A. Table A.1.1)

Meese and Rogoff (1983) use structural monetary exchange rate models to test out-of-sample forecast performance, but they find that these models fail to outperform the random walk model. Many subsequent studies have tried different kinds of methodologies[1] to investigate whether the same or variants of monetary models can beat the random walk model, but the results are mixed.

Boothe and Glassman (1987b) point out that previous studies may be misspecified due to not considering the "nonstationary" property of variables. Subsequently, the cointegration (CI) studies of exchange rate monetary models have become a new trend. Some of them use the Engle-Granger (1987) two-step procedure to test for a CI relationship between exchange rate and fundamental variables derived from monetary models.[2]

---

[1] For example, see Woo (1985), Somanath (1986), Schinasi (1987), Wolff (1987), Boothe and Glassman (1987a) add lagged terms of exchange rate and / or of fundamental variables. Alexander and Thomas (1987), Wolff (1987) and Schinasi and Swamy (1987) try time-varying coefficients methods.

[2] See, for example, Meese (1986), Baillie and Selover (1987), McNown and Wallace (1989), Kearney and MacDonald (1990) and Pittis (1993).

Furthermore, MacDonald and Taylor (1991, 1993, 1994) use a procedure by Johansen (1988,1991) for CI with error correction model (ECM) analyses. They find that an unrestricted monetary model with short-run dynamics outperforms the random walk model for some exchange rates.

In addition, there are some recent studies using vector autoregression (VAR) models for forecasting: for example, Driskill *et al.* (1992) and Liu *et al.* (1994). They conclude that a monetary/asset model with a VAR representation does have forecasting value for some exchange rates.

Sarantis and Stewart (1995) use both Johansen CI / ECM and VAR (or Bayesian VAR) analyses. They find no CI for the three monetary models of Meese and Rogoff (1983). They use variables derived from a modified uncovered interest parity (MUIP) model and a portfolio balance model (PB) to estimate ECM, BVAR and VAR (both level and differenced forms) for three exchange rates. Out of sample forecasts indicate that MUIP models perform better than PB models. The MUIP (CI / ECM) models for DM/pound, and FF/pound perform better than a random walk model, but the model for yen /pound is worse than a random walk model.

2.1.2 Nonlinear multivariate analysis (See Appendix A. Table A.1.2)

Meese and Rose (1991) investigate the possible existence of a nonlinear relationship between exchange rates and economic variables by using the same monetary models as Meese and Rogoff (1983) and two other models. They use a nonparametric and nonlinear (locally weighted regression) model and find that only the Hooper-Morton model can outperform a random walk model using a mean square error standard.

2.1.3 Nonlinear univariate analyses (See Appendix A. Table A.1.3)

Diebold and Nason (1990) use a nonparametric nonlinear (locally weighted regression) model to analyze weekly data for 10 currencies. They find no improvement on the random walk model. Satchell and Timmermann (1995) use nonparametric nonlinear (nearest neighbor) algorithms for 15 daily exchange rates, and they also fail to beat a random walk model using mean absolute error and mean square of percentage error standards. However, they are able to predict the direction of change better than a random walk model. Nachane and Ray (1992) use monthly data for 10 currencies by estimating 8 different models and find that ARCH, GARCH and GARCH-M models[3] can generally forecast better than a random walk model. Lye and Martin (1994) use monthly data to forecast US $/Australian dollar and find that a generalized exponential non-linear time series model performs better than a self-exciting threshold autoregressive model.

2.2 Artificial Neural Networks Application in Financial and Economic Series Forecasting

It is impossible to discuss all studies due to the large amount of relevant research in the artificial neural networks area. In general, these studies show that the use of artificial neural networks (ANN) for forecasting is very promising. A few of these studies are reviewed below. In addition to the studies discussed here, Zhang *et al.* (1998) review many empirical applications of ANN models.

[3] ARCH : autoregressive conditional heteroscedasticity ; GARCH: generalized autoregressive conditional heteroscedasticity; ARCH-M : ARCH in mean.

2.2.1 Multivariate analyses for exchange rate forecasting (See Appendix A. Table A.2.1)

Weigend *et al.* (1992) use a multivariate model employing past currency price information up through Monday to forecast the Tuesday return of $/DM. They do not compare any other statistical model with their ANN model. Green and Pearson (1994) use a multivariate ANN model incorporating data on interest rates and five different currencies (including level, volatility, and technical indicators) to forecast daily $/pound. They find that their ANN model outperforms a univariate ARIMA model. Poddig and Rehkugler (1996) use US, German, and Japanese stocks, bonds, and exchange rate data to forecast (yen/$, DM/$) monthly returns. They find that an integrated ANN model using technical indicators as inputs performs best. They also compare with multiple regression and random walk models.

2.2.2 Univariate analysis for exchange rate forecasting (See Appendix A. Table A.2.2)

Refenes (1993) forecasts hourly $/DM using a univariate ANN model, and finds that the trading return based on this model is profitable. He also compares his findings with those of exponential smoothing and autoregression models.

2.2.3 Other multivariate analyses (See Appendix A. Tables A.2.3)

Most of these analyses forecast stock (indices) returns.

2.2.4 Other univariate analyses (See Appendix A. Table A.2.4)

These analyses investigate different kinds of time series with different time horizons. Most of them compare ANN models with ARIMA models.

2.2.5 General characteristics of these ANN studies

- Except Weigend *et al.* (1992), who use two output neurons, the researchers cited above use ANN models having only one output neuron.
- For out-of-sample testing, most of them only compare one-step ahead forecasts. Chakraborty *et al.* (1992) try to use an iterated way to achieve multi-step forecasting.
- Most of the other studies use variants of multiple regression or ARIMA models for comparison.
- Feedforward networks are often used. Most of those ANN models are multilayer perceptron type models. However, some researchers also fit recurrent models: e.g. Steiner and Wittkemper (1995), Poddig and Rohkugler (1996), and Blake *et al.* (1995).
- Usually input data are rescaled into a $[0,1]$ range, but Ankenbrand and Tomassini (1995) suggest rescaling the input into a $[-1,1]$ range, and Brownstone (1996) rescales his input data into a [0.000001,0.99999] range.
- Blake *et al.* (1995) also discuss nonstationarity and seasonality problems. They estimate models using both preprocessed (transformed to be stationary, deseasonalized) inputs and raw data inputs. They find that input preprocessing is helpful.

CHAPTER 3. RADIAL BASIS FUNCTION NEURAL NETWORK MODELS

This chapter provides a general overview of radial basis function (RBF) neural network models. The specific RBF network models used in this thesis will be detailed in section 4.2, below.

3.1 Overview of Neural Network Models[1]

A neural network model includes several layers of units that are generally connected by weights. A neural network model can learn to approximate a function by adjusting the values of the weights.

The training process of a neural network model is analogous to the estimation process of a conventional statistical model and includes both *supervised* and *unsupervised* training techniques [Haykin (1994)]. Figure 3.1 illustrates a simple supervised training process.

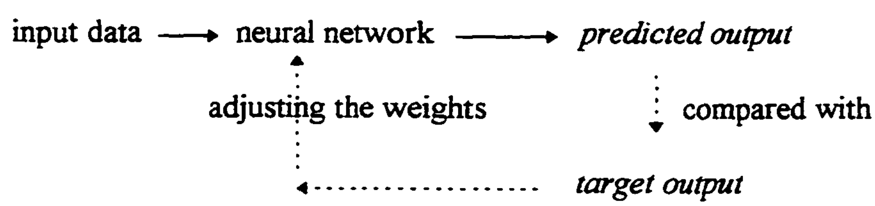


Figure 3.1 A simple supervised training process of a neural network model.

[1] Most of the following discussion is based on Broomhead and Lowe (1988), Demuth and Beale (1998), Mhaskar (1992,1995), Moody and Darken (1989) and Orr (1996).

During a supervised training process, several pairs of input-output training cases are presented to a neural network model to learn the input-output mapping function. That is, given the input data, the connecting weights of the neural network model are iteratively adjusted to match the predicted output with the target output.

There are different training (learning) algorithms to adjust the architecture and the weights of the neural network model.

3.2. RBF Neural Network Architecture

RBF neural network models can be applied to the problem of learning to perform a specific task from a set of training cases. Learning means to reconstruct a mapping surface in a high-dimension space that fits the training data best [Girosi (1992)]. To be more specific, the RBF neural network model is designed for interpolating data in a high dimensional space by linearly combining the activation values of the radial basis (kernel) functions. Figure 3.2 depicts a simple multi-input, one-output feedforward RBF neural network model.

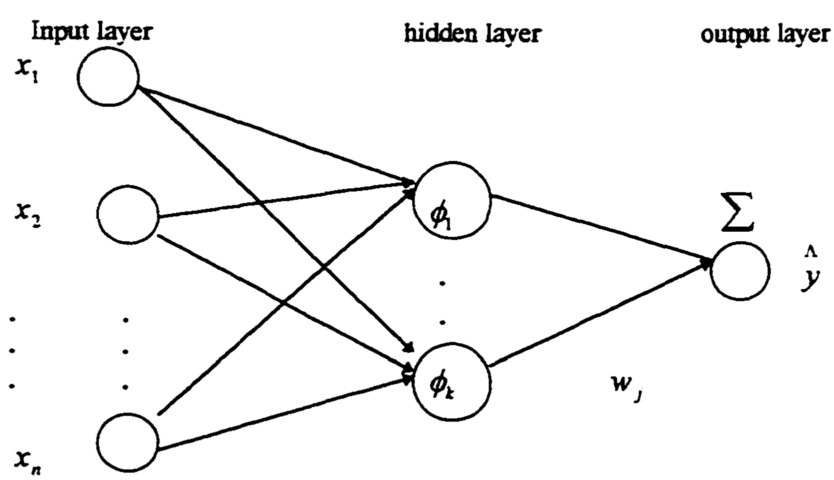


Figure 3.2 : A simple RBF neural network model

3.2.1 Layers of units (neurons)

A basic RBF neural network model consists of three layers: an input layer, a hidden layer, and an output layer. The input units x_i are the independent variables and the output unit $\hat{y}$ is the predicted dependent variable. The input and hidden layers are fully and directly connected, and the hidden and output layers are also fully and directly connected. The number of hidden units is often chosen by the training algorithm during the training process.

3.2.2 Radial basis function

Each unit j in the hidden layer has an associated transfer function ϕ_j. The radial basis function, which has a *radially symmetric* shape, is used as the transfer function for a RBF model. The radial basis function produces the same output for inputs with equal distance from its center. There are localized and nonlocalized radial basis functions. Micchelli (1986) and Powell (1987,1992) discussed some functions that can be used in the RBF models (see Appendix B.1 for some examples of the RBF formula and figures). The response of the localized function decreases with the distance away from the center. That is, the localized radial basis function generates a localized response to the input. Alternatively, the response of the nonlocalized function increases with the distance away from the center. Different radial basis functions perform better for different problems [Broomhead and Lowe (1988), and Brown and Harris (1994)]. For example, some nonlocalized radial basis functions provide better performance [Buhmann (1988), Franke (1982), and Hardy (1990)]; however, the localized radial basis functions may solve better for others.

The number of the radial basis functions is equal to the number of the hidden-layer units. An important decision in establishing the RBF architecture is to choose a sufficient number of radial basis functions and to position the centers of these basis functions to approximately cover the input space. By using ppropriate kinds of training algorithms, the decision of the placement and size of the RBF model can be made.

3.2.3 General RBF neural network model

A RBF network model builds a function space that depends on the positions of the known data points based on an arbitrary distance measure. By imposing Euclidean norms and employing radial basis functions, the interpolation function mapping from the input space to the output space can be expressed as in (3.1). Given a set of m pairs of input-output training examples, $\{X_i, y_i\}_{i=1}^{m}$, the training process of a RBF network model basically involves the solution of the following function approximation problem: Given a function $f: R^n \rightarrow R$, find a function $g: R^n \rightarrow R$ of the form

$$\hat{y} = g(X) = \sum_{j=1}^{k} w_j \phi_j (r\|X - C_j\|) \tag{3.1}$$

to approximate f on a compact subset K of R^n, where $\hat{y} \in R$ is the predicted output of the network given the input vector $X = \{x_1, x_2, ..., x_n\} \in R^n$, and $C_j = (c_1, c_2, ..., c_n) \in R^n$ is the center of the *jth* radial basis function $\phi_j: [0, \infty) \rightarrow R$. The || . || represents a norm on R^n, which is often taken to be Euclidean distance. Usually the same kind of radial basis function is employed for all the hidden-layer units. The r is the width (scaling factor) associated with the function ϕ_j, and the size of the *r* provides the flexibility of the localization for the localized radial basis functions.

In Figure 3.2, the *ith* component x_i of an input vector *X* is connected with the *jth* hidden unit by a scalar c_{ij}, which represents the *ith* component of the *jth* center vector C_j. By using Euclidean distance as the norm, the inputs to the *jth* hidden unit have the form of a *hypersphere*, i.e. $\sum_{i=1}^{n}(x_i - c_{ij})^2 = \|X - C_j\|^2$. The output of each *jth* hidden unit is generally a nonlinear function of $\|X - C_j\|^2$, that is, $\phi_j\left(r\|X - C_j\|\right)$. The values of the $\phi_j(.)$ functions are then linearly weighted by the associated weights $\{w_j\}_{j=1}^{k}$ to generate a predicted output $\hat{y}$.

In addition, a "bias" term (offset term), w_0, may be added to (3.1). The "bias" term is similar to the intercept term in a regression equation. In this case, equation (3.1) becomes

$$\hat{y} = g(X) = w_0 + \sum_{j=1}^{k} w_j \phi_j (r\|X - C_j\|) \tag{3.2}$$

3.3 Training (Learning) Procedure

To find an appropriate approximating function of the form shown in (3.1) involves the choices of the radial basis functions ϕ_j, the number *k* of hidden units, and values for the parameters *r*, C_j, and w_j. Different radial basis functions may be used; see Girosi (1994), Micchelli (1986), and Powell (1987, 1992) discusses some techniques to choose the parameters of a RBF model.

One practical supervised training procedure that uses the least squares algorithm is described by Chen and Grant (1991) and Orr (1996). Given a certain radial basis function ϕ, and the training data and a value for the width r, the remaining parameters c_j and w_j are decided automatically during the training process.

To be more specific, the training procedure consists of two steps. As detailed in section 3.3.2, below, the first step is to choose the centers of the hidden-layer radial basis functions. The number of hidden-layer units is equal to the number of radial basis functions. Therefore, once the centers are chosen during the training process, the number of the hidden-layer units is determined automatically. As detailed in section 3.3.3, below, the second step is then to obtain the weights w_j connecting the hidden units to the output units by using a pseudo-inverse least squares method [Broomhead and Lowe (1988)]. Thus, the learning procedure determines both the architecture of the RBF network and the weights.

3.3.1 Input-output data set

The data set is often divided into two subsets: the training (in-sample) set and the test (out-of-sample) set. The training set data are used for training only. After the model is trained, the test set data are used to test whether the model can generalize well or not.

- ***Rescaling the input data***

The activation value of the radial basis function of each hidden unit depends on the Euclidean distance between the input and the center. Therefore, all input variables had better have approximately the same range [Hrycej (1997)].

3.3.2 Center selection and model architecture selection criteria

As will now be explained, once a fixed value of the width r of the radial basis function is determined, the number of centers is decided automatically during the training process. In general, the value of the width is set to be larger than the distance between two adjacent input vectors. However, the width is set to be smaller than the distance between the two extreme input vectors [Demuth and Beale (1998)]. That is, the areas of significant response of the radial basis functions have to cover all the input space while overlapping in a way that not all radial basis functions are responding in the same wide area of input space.

The input vectors, $\{X_i\}_{i=1}^{m}$, of the training set are the candidate set for the centers of the radial basis functions. The centers may be selected from *all* of the input vectors or may be selected from only *a subset* of the input vectors. However, to position the centers of the radial basis functions using all input vectors of the training set may overfit the noise and result in an approximating function that does not generalize well for the test set.

Therefore, a subset of the input vectors of the training set is typically selected as the centers. In the supervised training case, by presenting several pairs of input-output training examples, the number of the hidden units is increased incrementally by picking those centers that sequentially reduce the value of a relevant cost function on the training set. That is, the input vector that can reduce the value of the cost function the most will be the first one that is selected as the center, and this center-selection process will be continued until some kind of stop-training criterion (i.e. model architecture selection criterion) is met.

Usually the cost function is the predicted neural network squared errors. Because there is no *a priori* information about the input-output interpolating relationship, in order not to overfit the data, the RBF model may be better designed to model the relationship as smoothly as possible [Bishop (1991,1993), Broomhead and Lowe (1988); Girosi et al. (1995); and Poggio and Girosi (1990a)]. That is, we want to find an interpolation function that are close to the data and also smooth. Smoothness means that similar outputs are obtained if given similar inputs. For example, a regularization term (stabilizer) that penalizes large weights may be considered in the cost function. This regularization term can help smooth the interpolation function. For example, the cost function might take the form

$$Cost = \sum_{i=1}^{m} \left[\hat{y}_i - y_i \right]^2 + \lambda \sum_{j=1}^{k} w_j^2 \ , \tag{3.3}$$

where $\hat{y}_i$ is the predicted output value, y_i is the actual output, m is the number of training cases, and k is the number of hidden units. The term $\sum_{i=1}^{m} \left[\hat{y}_i - y_i \right]^2$ known as the sum of squared prediction errors enforces closeness to data. The term $\lambda \sum_{j=1}^{k} w_j^2$ is the regularization term, where λ is a positive number that represents a regularization parameter.

In addition to using the regularization term, some early-stop training techniques can be used to terminate the training process, so that the number of the hidden centers selected will not be too large. One technique is to use an additional cross-validation data set [Demuth and Beale (1998)]. Usually, the prediction errors for the cross-validation set are used to monitor the training process. In general, when the RBF network model starts to overfit the training set data, the sum of prediction errors for the cross-validation set will start to increase. Therefore, the training process may need to be stopped after the sum of prediction errors for the cross-validation set reaches a minimum value and then starts to increase for some iterations.

However, in practice, the number of data points is often not large enough to be divided into an additional validation set. Therefore, an alternative way of minimizing some kind of model architecture selection criterion (e.g. *BIC*: Bayesian information criterion, *LOO*: leave-one-out , and *GCV*: generalized cross validation) in the training process might also be considered as an early-stop training technique. These criteria which consider both the training squared errors and model complexity are defined as the predicted errors of a model in predicting new observations. See Efron and Tibshirani (1993), Moody (1994), Nørgaard (1995), and Orr (1996) for further details.

3.3.3 Weights derivation method

After the centers are chosen, the weights connecting the hidden and output layers are calculated by using the *pseudo-inverse least squares* method. The general form of the weight vector is

$$\underset{k\times 1}{W} = (\underset{k\times m}{\Phi^T} \underset{m\times k}{\Phi} + \lambda \underset{k\times k}{I})^{-1} \Phi^T \underset{m\times 1}{Y} \quad . \tag{3.4}$$

If there is no regularization term in the cost function, the weight vector reduces to

$$W = (\Phi^T \Phi)^{-1} \Phi^T Y \, , \tag{3.5}$$

where $\Phi_{ij} \equiv \phi_j(X_i) \equiv \phi_j(r\|X_i - C_j\|)$ is the *jth* transfer function evaluated at the *ith* input vector X_i, *r* is the width, *k* denotes the number of hidden units, m denotes the number of training cases, and the transformation matrix Φ, output vector Y, and weight vector W take the following forms:

$$\underset{m \times k}{\Phi} = \left[\phi_j(X_i)\right] = \begin{bmatrix} \phi_1(X_1) & \phi_2(X_1) & \cdot & \cdot & \phi_k(X_1) \\ \phi_1(X_2) & \phi_2(X_2) & \cdot & \cdot & \phi_k(X_2) \\ \phi_1(X_3) & \phi_2(X_3) & \cdot & \cdot & \phi_k(X_3) \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \phi_1(X_m) & \phi_2(X_m) & \cdot & \cdot & \phi_k(X_m) \end{bmatrix}, \ Y = \begin{bmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_m \end{bmatrix}, \ \text{and } W = \begin{bmatrix} w_1 \\ w_2 \\ \cdot \\ \cdot \\ \cdot \\ w_k \end{bmatrix}.$$

If there is a bias term as described in equation (3.2), then there will be an additional component w_0 in the weight vector and an additional last column in the Φ matrix with all components equal to 1.

3.4 RBF Model versus MLP Model

An RBF neural network model will now be compared with a multilayer perceptron (MLP) model; see Rumelhart et al. (1986). Both types of models are fully connected feedforward models that can model arbitrary nonlinear interpolation functions mapping an input space to an output space. Like the RBF depicted in Fig. 3.2, a simple MLP model also consists of three layers with nonlinear transfer functions associated with the hidden units. Often sigmoid functions of the form $S(x) = \frac{1}{\left(1+e^{-x}\right)}$ are used as the transfer functions of the MLP model. Unlike the RBF model, the input-layer units and the hidden-layer units of the MLP are connected by weights. Figure 3.3 illustrates a simple three-layer MLP model. The mathematical formula of the MLP network model is described in equation (3.6).

$$\hat{y} = g(X) = \sum_{j=1}^{k} w_j S_j\left(\sum_{i=1}^{n} w_{ij} x_i\right) \tag{3.6}$$

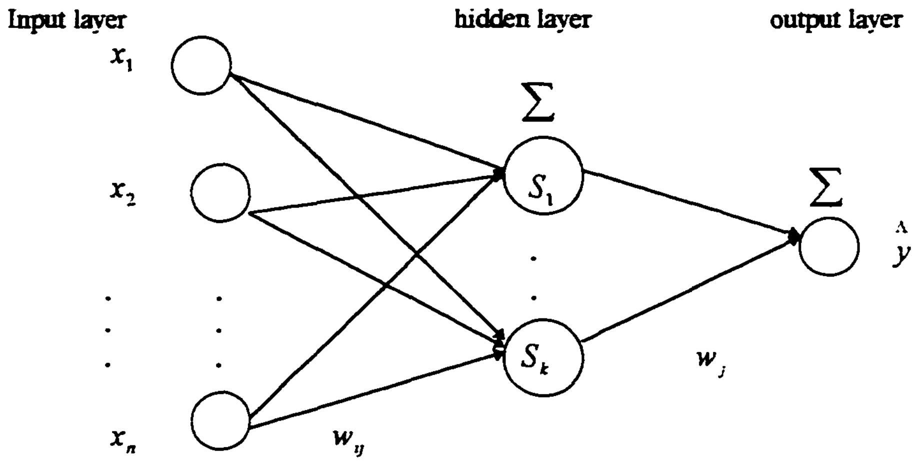


Figure 3.3 : A simple MLP neural network model.

For the RBF model, the input-layer units and the hidden-layer units are typically connected by the "*hypersphere*" form (i.e. Euclidean distance). In contrast, for the MLP model, the input-layer units and the hidden-layer units are typically connected by the "*hyperplane*" form (i.e. the input units are linearly weighted by the associated weights, w_{ij}, and then are fed into each hidden unit). A classification problem is more likely to be linearly separable if cast in a high-dimensional space than if cast in a low-dimensional space [Cover (1965)]. Therefore, the RBF model that expands input vectors into a higher-dimensional space is more likely to linearly separate classification problems than the MLP model [Broomhead and Lowe (1988); and Renals and Rohwer (1989)]

The learning procedure of the MLP model typically involves updating the weights by some iterative technique, generally taken to be an unconstrained nonlinear least squares optimization method. There is no global existence theorem regarding convergence to the correct minimum error solution for the latter method; it could end up at a local minimum. In contrast, by imposing a Euclidean norm and employing radial basis functions, a RBF model with one hidden layer can be designed to derive the hidden-output weights by using a linear least squares method, and there is a global existence theorem guaranteeing convergence to the correct minimum error solution for this method [Broomhead and Lowe (1988)]. Furthermore, the training speed of the RBF model is generally faster than that of the MLP model. For these reasons, only RBF neural network models are used in this thesis.

CHAPTER 4. EMPIRICAL METHODS

4.1 Time Periods of Research and Data Description

The time period under study extends from 1973:3 to 1996:6. This time period is divided into six sliding windows. This research investigates three exchange rates: the German mark / US$, the Japanese yen / US$, and the Italian lira / US$. One-month-ahead and one-quarter-ahead forecasts are made for each exchange rate by using monthly and quarterly data, respectively. The monthly data for the three exchange rate seriesare illustrated in Figure 4.1.

One-month-ahead exchange rate forecasting is investigated for each exchange rate by using both univariate and multivariate RBF models. As is clarified below, in addition to exchange rate data, the multivariate RBF model includes interest rates as economic variables. These RBF models are compared with two ARMA models and a random walk model. The one-quarter-ahead exchange rate forecasting only uses multivariate RBF models, and the economic variables used are interest rates and the money supply. These RBF models are compared with a random walk model and a forward rate forecast.

For the German mark and Japanese yen, both long-term and short-term interest rates are investigated. Different long-term and short-term interest rates are also compared. Because the short-term interest rate data for Italy are not complete for the relevant research period, only the effects of the long-term interest rates are investigated. The money supply data are used for the M1 measure of money. Appendix C.1 describes the relevant data and sources

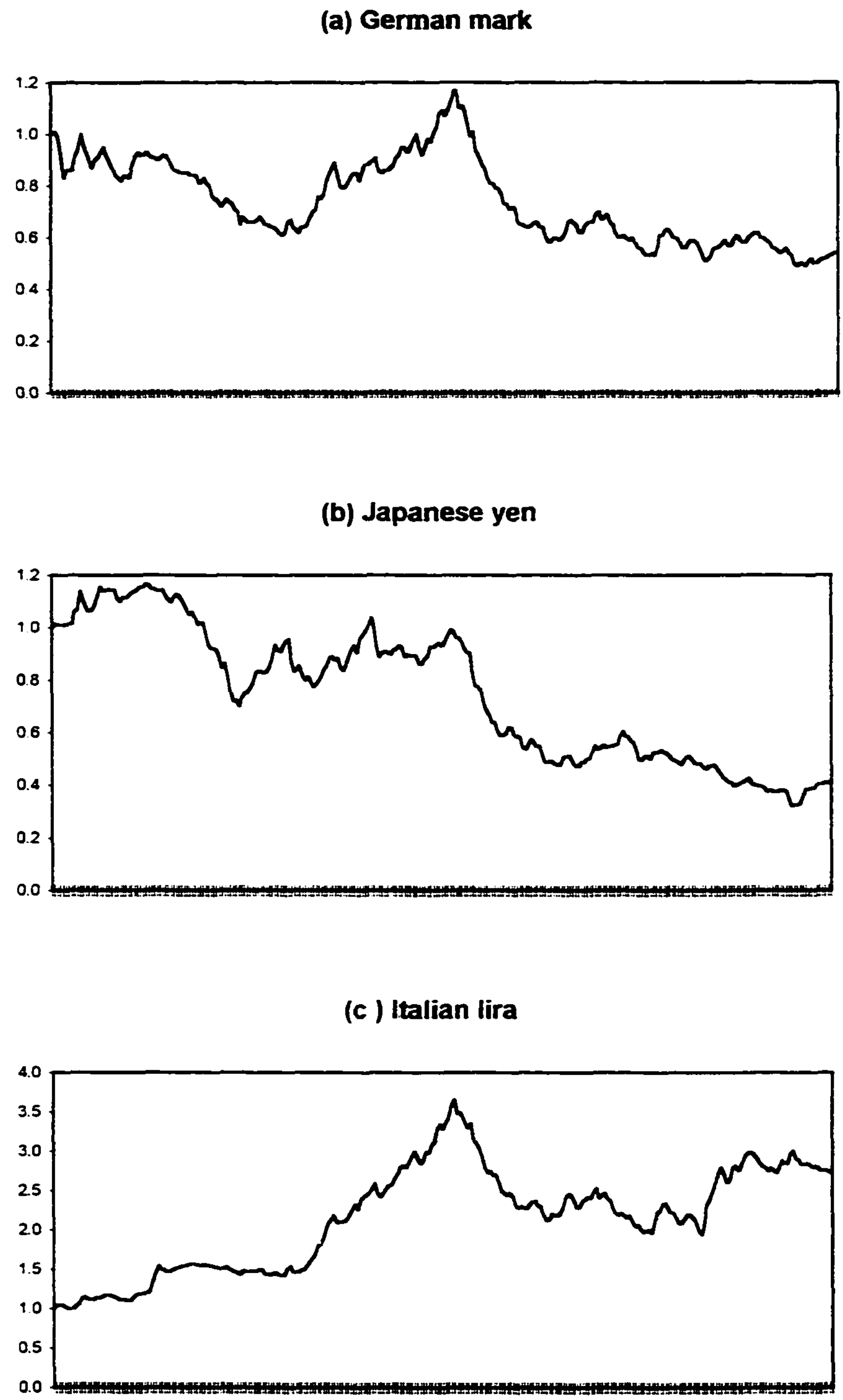


Figure 4.1. Three monthly exchange rates 1973:3-1996:6 (normalized to 1 for 1973:3)

for each country in more detail.

4.1.1 One-month-ahead exchange rates forecasting

The monthly exchange rates are expressed as "foreign currency units per US dollar ". They are the monthly averages of the noon buying rates in New York City certified by the Federal Reserve Bank of New York for customs purposes for cable transfers payable in foreign currencies.

To reserve sufficient lags for input variables, 1974:5 is chosen as the starting point for monthly model estimation. Each sliding window includes 224 monthly data as training set data and the following 12 months data are reserved for test set data. The purpose is to use the 224 training set data for estimation and then to forecast 12 one-step (one-month) ahead values. These forecast values will then be compared to the actual values reserved in the test set.

Starting from the second window, each sliding window deletes the first six oldest data from the previous window and then adds six following data to form a new window. The six sliding windows are shown in Table 4.1.

Table 4.1. Sliding windows (monthly data)

Sliding window	Size	Training set (estimation)	Test set (forecast)	Size
Period 1	224	1974:5 -1992:12	1993:1-1993:12	12
Period 2	224	1974:11-1993: 6	1993:7-1994:6	12
Period 3	224	1975:5 -1993:12	1994:1-1994:12	12
Period 4	224	1975:11-1994: 6	1994:7-1995:6	12
Period 5	224	1976:5 -1994:12	1995:1-1995:12	12
Period 6	224	1976:11-1995: 6	1995:7-1996:6	12

Tables 4.2 through 4.4 list descriptive statistics for the three exchange rates corresponding to the six sliding windows. The Ljung-Box Q statistic, skewness, kurtosis, and Jarque-Bera (JB) statistics are described in chapter 4.4.1. For each table, part (a) describes the training set data and part (b) describes the corresponding test set data. For the German mark and the Italian lira, the minimum and maximum values of the test set data are all within the range of the corresponding training set data, for all six sliding window periods. For the Japanese yen, the minimum values of the test set data are also all within those of the range of the corresponding training set data for all six sliding windows periods. However, for the 5th and 6th sliding window periods, the maximum values of the test set data are higher than those of the corresponding training set data.

The Jarque-Bera tests for the three exchange rates indicate that only the German mark does not reject the normality hypothesis. The Ljung-Box statistics Q(12) for the first twelve lags are significant at the 5% significance level for all six periods, indicating autocorrelation in each exchange rate series.

4.1.2 One-quarter-ahead exchange rate forecasting

To compare forecasting ability with the end-of-quarter forward rate, one-quarter-ahead (end-of-quarter) exchange rate forecasts are made. The end-of-quarter exchange rates are expressed as " foreign currency units per US dollar ".

For quarterly data, to reserve sufficient lags (that is, two years) for input variables, 1975:Q2 is chosen as the starting point for quarterly model estimation. Each sliding window includes 71 quarterly data as training set data and four subsequent quarterly data reserved as test set data. The purpose is to use the 71 training set data for estimation and then to

Table 4.2 Statistics for the German mark (monthly)

(a) Training set (first difference of natural logarithm of German mark)

Period	74:5-92:12	74:11-93:6	75:5-93:12	75:11-94:6	76:5-94:12	76:11-95:6
Mean	-0.0021	-0.0020	-0.0015	-0.0021	-0.0021	-0.0025
Std	0.0277	0.0277	0.0278	0.0275	0.0277	0.0280
Min	-0.0704	-0.0704	-0.0704	-0.0704	-0.0704	-0.0704
Max	0.0852	0.0852	0.0852	0.0852	0.0852	0.0852
Q(12)	31.1435*	31.1475*	29.5775*	28.6615*	28.7084*	28.6520*
Skewness	0.0588	0.0504	0.0125	0.0177	0.0187	-0.0009
Kurtosis	0.0802	0.0951	0.0717	0.1110	0.0581	0.0251
JB	0.1524	0.1344	0.0234	0.0741	0.0213	0.0000

(b) Test set

Period	93:1-93:12	93:7-94:6	94:1:94:12	94:7-95:6	95:1-95:12	95:7-96:6
Mean	0.0065	-0.0014	-0.0071	-0.0125	-0.0073	0.0072
Std	0.0250	0.0249	0.0188	0.0249	0.0280	0.0177
Min	-0.0437	-0.0437	-0.0374	-0.0661	-0.0661	-0.0319
Max	0.0362	0.0362	0.0206	0.0206	0.0402	0.0402

Note : Q(12) is the Ljung-Box Q statistic; reject the null hypothesis of no autocorrelation if the value Q(12) is greater than $\chi^2_{(0.05,12)} = 21$.

JB represents the Jarque-Bera test (Normality test); reject the null hypothesis that the series are independent normally distributed if the value of JB is greater than $\chi^2_{(0.05,2)} = 5.991$.

* Significant at 5 percent level.

forecast 4 one-step (one-quarter) ahead values. These forecast values are then compared to the actual values reserved in the test set.

Starting from the second window, each sliding window deletes the first two oldest quarterly data from the previous window, and then adds two subsequent quarterly data to form a new window. The six sliding windows are shown in Table 4.5.

The summary statistics of the end-of-quarter exchange rates are analyzed similarly to the monthly data. The results are shown in Appendix C.2. The Jarque-Bera tests indicate that all three quarterly exchange rates do not reject the normality hypothesis. In contrast to the

Table 4.3 Statistics for the Japanese yen (monthly)

(a) Training set (first difference of natural logarithm of Japanese yen)

Period	74:5-92:12	74:11-93:6	75:5-93:12	75:11-94:6	76:5-94:12	76:11-95:6
Mean	-0.0036	-0.0046	-0.0044	-0.0048	-0.0049	-0.0055
Std	0.0277	0.0277	0.0278	0.028	0.0282	0.0290
Min	-0.0969	-0.0969	-0.0969	-0.0969	-0.0969	-0.0969
Max	0.0610	0.0610	0.0610	0.0610	0.0610	0.0610
Q(12)	39.2975*	38.2285*	37.3923*	35.9805*	35.4305*	34.9760*
Skewness	- 0.5450*	-0.4833*	-0.4994*	-0.4592*	-0.4497*	-0.5010*
Kurtosis	0.7167*	0.6115	0.5712	0.4944	0.4222	0.3917
JB	15.1804*	11.6497*	11.8265*	9.7143*	8.8402*	10.4310*

(b) Test set

Period	93:1-93:12	93:7-94:6	94:1:94:12	94:7-95:6	95:1-95:12	95:7-96:6
Mean	-0.0101	-0.0039	-0.0077	-0.0160	0.0014	0.0210
Std	0.0233	0.0214	0.0207	0.0342	0.0473	0.0271
Min	-0.0402	-0.0472	-0.0472	-0.0818	-0.0818	-0.0081
Max	0.0186	0.0186	0.0216	0.0216	0.0806	0.0806

Note : same as in Table 4.2.

Table 4.4 Statistics for the Italian lira (monthly)

(a) Training set (first difference of natural logarithm of Italian lira)

Period	74:5-92:12	74:11-93:6	75:5-93:12	75:11-94:6	76:5-94:12	76:11-95:6
Mean	0.0036	0.0036	0.0044	0.0038	0.0028	0.0029
Std	0.0268	0.0274	0.0276	0.0276	0.0264	0.0266
Min	-0.0640	-0.0640	-0.0640	-0.0640	-0.0640	-0.0640
Max	0.1075	0.1075	0.1075	0.1075	0.1075	0.1075
Q(12)	49.6170*	50.2171*	51.6672*	52.3040*	48.2567*	46.1718*
Skewness	0.4839*	0.4536*	0.3980*	0.4404*	0.3350*	0.3205*
Kurtosis	1.0795*	0.8537*	0.7134*	0.7566*	0.6953*	0.6272
JB	8.5032*	13.6729*	10.0375*	11.8904*	8.1166*	6.9944*

(b) Test set

Period	93:1-93:12	93:7-94:6	94:1:94:12	94:7-95:6	95:1-95:12	95:7-96:6
Mean	0.0148	0.0047	-0.0027	0.0025	-0.0021	-0.0051
Std	0.0320	0.0243	0.0175	0.0224	0.0185	0.0061
Min	-0.0402	-0.0246	-0.0246	-0.0346	-0.0346	-0.0185
Max	0.0542	0.0524	0.0310	0.0413	0.0413	0.0039

Note : same as in Table 4.2.

Table 4.5. Sliding windows (quarterly data)

Sliding window	Training set (estimation)	Size	Test set (forecast)	Size
Period 1	1975:Q2-1992:Q4	71	1993:Q1-1993:Q4	4
Period 2	1975:Q4-1993:Q2	71	1993:Q3-1994:Q2	4
Period 3	1976:Q2-1993:Q4	71	1994:Q1-1994:Q4	4
Period 4	1976:Q4-1994:Q2	71	1994:Q3-1995:Q2	4
Period 5	1977:Q2-1994:Q4	71	1995:Q1-1995:Q4	4
Period 6	1977:Q4-1995:Q2	71	1995:Q3-1996:Q2	4

monthly data, the Ljung-Box statistics Q(12) for the first twelve lags are not significant at the 5% significance level for any of the three exchange rates.

4.2 Empirical Design of RBF Neural Network Models

The design of an RBF network model for forecasting is an empirical art. There are several decisions that need to be made. For example, how should one decide on the lag length (i.e. the number of lagged values used as inputs)? What type of radial basis function is more appropriate? What size should be selected for the width r of the radial basis function? How many hidden units should be used? What cost function should be used for the training process? Finally, when should the training process be halted in order to appropriately fit the training set data but not to overfit the noise? The following sections describe the basic design of the RBF network models used in this empirical study.

The RBF neural network models are estimated by experimenting with the number of inputs. The exact number of the lagged values needed as inputs for the neural network model is not clear; this is the lag length selection decision. Initially, one lagged value of each variable is used as input to estimate a tentative model, and a residual diagnostic check is made to investigate whether there is autocorrelation in the residuals. The residuals are supposed to be white noise for a well-estimated model. The above model estimation and residuals diagnostic checking procedure is then repeated using higher-order lagged values as inputs.

In this research, for each model, the hidden-layer units all use the same kind of radial basis function as the transfer function. Seven different specifications for these radial basis functions are compared. These radial basis functions are as follows: Gaussian; Cauchy; inverse multiquadric; multiquadric; linear; square (quadratic); and cubic.[1] The first three functions are 'localized' functions and the last four functions are 'nonlocalized' functions. These functions are employed for models using different numbers of lagged values as inputs. In general, the models that use these seven radial basis functions are referred to as GRBF, CRBF, IRBF, MRBF, LRBF, QRBF, and CCRBF respectively. The shapes of the first three localized radial basis functions are similar. However, when the width of the radial basis functions is small, the results obtained by applying these functions to a given training data set can differ.

For models incorporating GRBF, CRBF, IRBF, and MRBF, the width r determines the localization of these radial basis functions. However, the optimal value of r is unknown. Different widths ranging from $r = 0.1$ to $r = 4$ were tried. A constant value was used as the width for all the radial basis functions in the same model.[2]

The number of centers of the radial basis functions is equal to the number of hidden-layer units. Centers of the hidden-layer radial basis function were chosen from a candidate set taken to be the set of all input vectors in the training set data. In particular, during the training process, the input vectors that reduced the cost function the most were chosen as the centers.

---

[1] The first four functions are discussed in Orr (1996), and the linear and cubic functions are discussed in Girosi (1994) and Powell (1987,1992).

[2] However, different values could be used for different radial basis functions; see Appendix B.3 for details.

This research adopts the Orr (1996) program of the least squares training algorithm and the stop-training criterion. Unless otherwise indicated, a cost function always includes a regularization term. In order not to overfit the training set data (i.e., not to fit the noise in the data), the center selection process was continued until some minimum value of the early-stop training criterion was reached. Specifically, an additional center was added until the value of the criterion reached a minimum value and then started to increase for another four[3] training iterations (see Figure 4.2).

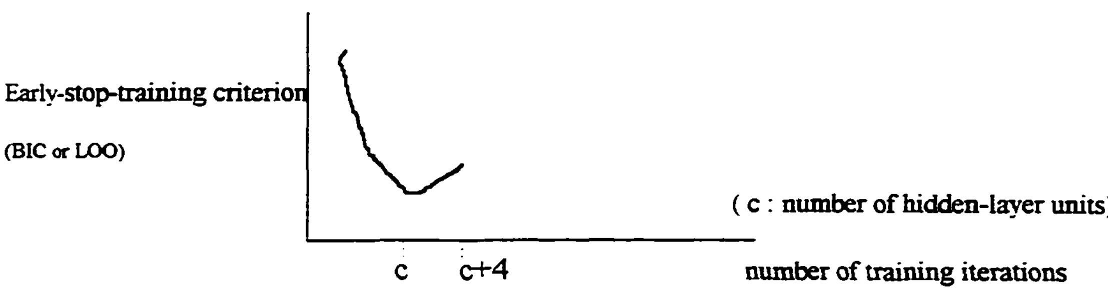


Figure 4.2. Early-stop-training criterion versus number of hidden-layer units

In this research, either the BIC (Bayesian information criterion) or the LOO (leave one out) criterion was used as the early-stop training criteria.

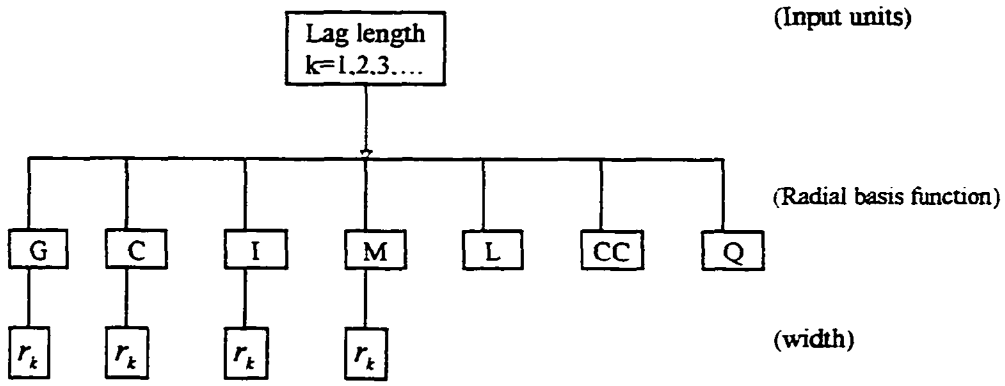
Unless otherwise indicated, there is also a regularization term λ in the cost function for the training process. The initial value for λ was arbitrarily chosen to be 0.1 for the monthly data analysis and 1.0 for the quarterly data analysis, and the value for λ was allowed to converge during the training process.

---

[3] The process by which an additional center is added to the hidden layer is called a 'training iteration'. If the number of additional training iterations is too small, the minimum value of the stop-training criterion (BIC or LOO) may be only a local minimum. After experimenting with different values, four additional training iterations were used.

To be more specific, two criteria were used for each training process: a λ selection criterion, and an early-stop training criterion. In this research, the BIC was used as both the λ selection and early-stop training process criterion for the monthly exchange rates RBF model training process. In addition, the GCV (generalized cross validation) criterion was used as the λ selection criterion and the LOO criterion was used as the early-stop training criterion for the quarterly exchange rates RBF model training process. The formula for the BIC, LOO, and GCV criteria are given in section B.2 of the Appendix.

In summary, the experimental design illustrated in Figure 4.3 was applied for each exchange rate.



Where the width r_k ranges from 0.1 to 4 and
G : represents Gaussian function
C : represents Cauchy function
I : represents inverse Multiquadric function
M : represents Multiquadric function
L : represents Linear function
CC : represents Cubic function
Q : represents Square function

Figure 4.3. Experimental design

4.3 Description of Empirical Models

For one-month-ahead forecasting, both univariate and multivariate RBF models were estimated and compared with two ARMA(p,q) models and a random walk model. For one-quarter-ahead forecasting, multivariate RBF models were compared with a random walk model and a forward rate forecast model. These models are as follows:

4.3.1 Random walk model

$$\hat{y}_t = y_{t-1}, \qquad t = 1,\ldots,T,$$

where y represents the natural logarithm of the exchange rate. The random walk forecast is the previous period realized value.

4.3.2 Forward rate forecast model

$$\hat{y}_t = f_t, \qquad t = 1,\ldots,T,$$

where f_t represents the natural logarithm of the forward rate for period t that is obtained in period t-1 .

4.3.3 ARMA(p,q) model

$$\Delta\hat{y}_t = \phi_1 \Delta y_{t-1} + \ldots + \phi_p \Delta y_{t-p} - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q}, \qquad t = 1,\ldots,T,$$

where Δ represents the difference operator, and p and q represent the lag lengths used for y and the error term ε, respectively.

4.3.4 RBF Models

- ***Rescaling the inputs***

If the inputs are rescaled, they are rescaled by using the following formula. Rescale the input series (z) into a series (s) having a *mid-range* equal to 0 and a *range* equal to 2.

$$midrange = \frac{\max(z) + \min(z)}{2};$$

$$range = \max(z) - \min(z);$$

$$s = \frac{z - (midrange)}{range/2}$$

- ***Univariate RBF model***

For univariate analysis, the general form of the forecasting function is as follows:

$$\hat{\Delta y_t} = f(\Delta y_{t-1}, \Delta y_{t-2}, \Delta y_{t-3}, \ldots, \Delta y_{t-k}),\ t = 1, \ldots, T, \tag{4.1}$$

where k represents the lag length. In this research, the RBF models that do not rescale the inputs are compared with those RBF models that rescale the inputs.

- ***Multivariate RBF model***

For multivariate analysis, the general form of the forecasting function is as follows:

$$\hat{\Delta y_t} = f(\Delta y_{t-1}, \Delta y_{t-2}, \ldots \Delta y_{t-k};\ \Delta x_{t-1}, \Delta x_{t-2}, \ldots, \Delta x_{t-k}),\ t = 1, \ldots, T, \tag{4.2}$$

where $x = x^F - x^{US}$ represents the differential of economic variables[4] between a foreign

[4] There is no need to take the natural logarithm of an interest rate. However, the money supply data are transformed by taking natural logarithms.

country and the United States, and k represents the lag length which is the same for both the exchange rate and the economic variables. In addition, all of the input variables $\Delta y_{t-1}, \ldots, \Delta x_{t-k}$ are rescaled as explained above.

4.4 Model Evaluation Criteria and Statistical Hypothesis Tests

4.4.1 In-sample (training set) evaluation criteria

- ***AIC (Akaike information criterion) and SBC (Schwartz Bayesian criterion)***

  The AIC and SBC criteria are used to select the ARIMA models.

$$\text{AIC} = \text{T}\ \ln(\text{residual sum of squares}) + 2\,p\ ,$$

where the residual sum of squares is $\sum_{t=1}^{m}\left(y_t - \hat{y}_t\right)$, T is the number of usable observations, and p is the number of estimated parameters.

$$\text{SBC} = \text{T}\ \ln(\text{residual sum of squares}) + p\ln(\text{T})\ .$$

- ***BIC (Bayesian information criterion), GCV (Generalized cross validation) criterion, and LOO (Leave-one-out) criterion [see appendix B.2 for details]***

  These criteria are used to select the RBF model architecture. See Efron and Tibshirani (1993), Moody (1994), Nørgaard (1995), and Orr (1996).

- ***Ljung-Box Q statistic***

  This statistic is used to test the null hypothesis of no autocorrelation of series.

$$Q(m) = T(T+2)\left[\sum_{j=1}^{M}\frac{r_j^2}{T-j}\right],$$

where r_j is the *jth* lag autocorrelation of the residuals, $M = \min(T/4, 3\sqrt{T})$ is the number of autocorrelations used in the summation, and T is the number of data points available after differencing the series.

- ***Skewness and Kurtosis (Kendall and Stuart 1958)***

These two statistics are applied to investigate the differenced log exchange rate data. Skewness measures the degree of asymmetry of a distribution around its mean. If a distribution is symmetric, skewness equals zero. A positive skewness value indicates a distribution with an asymmetric extended right tail, and a negative skewness value indicates a distribution with an asymmetric extended left tail. Skewness sk is measured by

$$\text{sk} = \frac{N^2}{(N-1)(N-2)} \cdot \frac{m_3}{s^3},$$

where N is the number of observations, $s = \left(\frac{1}{N-1} \sum_{i=1}^{N} (y_i - \bar{y})^2 \right)^{1/2}$, and

$$m_k = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^k .$$

The statistic to test whether $sk = 0$ is

$$z = sk\sqrt{\frac{(N-1)(N-2)}{6N}} .$$

Kurtosis measures the peakedness or flatness of a distribution relative to those of the normal distribution. A positive kurtosis value indicates a relatively peaked distribution, and a negative kurtosis value indicates a relatively flat distribution. Kurtosis ku is measured by

$$\text{ku} = \frac{N^2}{(N-1)(N-2)(N-3)}\left(\frac{(n+1)m_4 - 3(n-1)m_2^{\ 2}}{s^4}\right).$$

The statistic to test whether $ku = 0$ is

$$z = ku\sqrt{\frac{(N-1)(N-2)(N-3)}{24N(N+1)}}.$$

- ***Jarque-Bera normality test (see Diebold 1988)***

In addition to the skewness and kurtosis statistics, this test is applied to investigate the normality of the differenced log exchange rate data.

The Jarque-Bera (JB) test statistic is defined as

$$JB = \frac{N}{6}\left(\hat{S}^2 + \frac{1}{4}\left(\hat{K}-3\right)^2\right),$$

where N denotes the number of observations,

$$\hat{S} = \frac{\frac{1}{N}\sum_{t=1}^{N}(y_t - \bar{y})^3}{\hat{\sigma}^3},$$

$$\hat{\sigma} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \bar{y})^2} \quad , \quad \bar{y} = \frac{1}{N}\sum_{t=1}^{N} y_t$$

and $$\hat{K} = \frac{\frac{1}{N}\sum_{t=1}^{N}(y_t - \bar{y})^4}{\hat{\sigma}^4}.$$

The JB statistic is distributed as a χ^2 distribution with two degrees of freedom in large samples under the null hypothesis that the observations y are independent normally distributed.

4.4.2 Out-of-sample (test set) descriptive evaluation criteria

The RMSE (root mean squared error) criterion measures forecasting error, the "correct direction" criterion measures the ability to predict the direction of future spot rates relative to the current spot rates, and the "speculative direction" criterion measures the ability to predict the direction of future spot rates relative to forward rates.

- ***RMSE***

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n_2} (y_t - \hat{y}_t)^2}{n_2}},$$

where n_2 is the number of forecasts. This criterion penalizes any extreme forecast errors. Note that the square of RMSE is mean squared error (MSE). The RMSE is easier to interpret than the MSE. The RMSE has the same unit as those of the forecast errors. If the forecast errors are in dollars, the RMSE is also in dollars whereas the MSE is in dollars squared.

- ***Correct direction criterion***

This criterion is the percentage of times that the sign of the actual future direction of an exchange rate, $\Delta y_{t-1} = y_{t-1} - y_t$, is correctly predicted by the sign of the forecasted direction of change, $\Delta \hat{y}_{t-1} = \hat{y}_{t+1} - y_t$.

- ***Speculative direction criterion (Melvin 1992)***

This criterion is the percentage of times that a forecast is on the correct side of the forward rate. Define actual and predicted speculative direction of change as follows:

actual: $\Delta y^s_{t+1} = y_{t+1} - f_{t+1|t}$,

predicted: $\Delta \hat{y}^s_{t+1} = \hat{y}_{t+1} - f_{t+1|t}$,

where $f_{t+1|t}$ is the forward rate for period t+1 that is formulated at period t. Then the speculative direction criterion is the percentage of times that the sign of $\Delta \hat{y}^s_{t+1}$ is the same as the sign of Δy^s_{t+1}. Profits can potentially be made by participating in spot and forward markets. Some corporate treasurers or speculators may therefore favor a forecast procedure that generates accurate forecasts of speculative direction over other forecast procedures that have smaller forecast errors or that generate more accurate forecasts for the correct direction Δy_{t+1}.

4.4.3 Statistical hypothesis tests for out-of-sample evaluation criteria

- ***A Modified Diebold and Mariano (MDM) test (Harvey et al. 1997)***

The MDM test evaluates the equality of prediction mean squared errors for two given models. The MDM test is a modification of the Diebold and Mariano (1995) "loss differential" test. The modified test allows for contemporaneously correlated prediction errors, autocorrelated prediction errors, and heavy-tailed error distributions. In addition, the MDM test does not rely on the assumption of unbiased forecast errors and can be applied to more than one-step ahead forecasts. Furthermore, the loss function used in the MDM test is not limited to quadratic functions.

Assume that two competing forecasting models have generated a pair of *h*-step ahead prediction errors (e_{1t}, e_{2t}), $t=1,\ldots,n$. The null hypothesis to test the expected equality of mean squared errors (MSE) for the two models is

$$E(e_{1t}^2 - e_{2t}^2) = 0, \qquad t = 1, \ldots, n.$$

Define the loss difference sequence to be

$$d_t = e_{1t}^2 - e_{2t}^2, \quad t = 1, \ldots, n.$$

The sample mean of d_t is

$$\bar{d} = n^{-1} \sum_{t=1}^{n} d_t .$$

Assuming that d_t is a moving average process of order *(h-1)*, the approximate variance of $\bar{d}$ is

$$Var\left(\bar{d}\right) \approx n^{-1}\left[\gamma_0 + 2\sum_{k=1}^{h-1} \gamma_k\right],$$

where γ_k is the *k*th autocovariance of d_t. If γ_k is estimated as

$$\hat{\gamma}_k = n^{-1} \sum_{t=k-1}^{n} \left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right),$$

then the estimated variance of $\bar{d}$ is

$$\hat{Var}\left(\bar{d}\right) \approx n^{-1}\left[\hat{\gamma}_0 + 2\sum_{k=1}^{h-1} \hat{\gamma}_k\right].$$

The Diebold-Mariano (1995) loss difference test statistic is

$$S_1 = \left[\hat{Var}\left(\bar{d}\right)^{-1/2}\right]\bar{d}.$$

Harvey et al. (1997) instead use an approximately unbiased estimator for the variance of $\bar{d}$,

$$\hat{Var}_{*}(\bar{d}) = \left\{1 - n^{-1}\left[\ 1 + 2n^{-1}\sum_{k=1}^{h-1}(n-k)\ \right]\right\}\hat{Var}(\bar{d}).$$

In this case the *modified Diebold-Mariano test statistic* is

$$S_1^* = \left[\left(V\hat{a}r_*(\bar{d})^{-1/2} \right) \bar{d} \right]$$

$$= \left\{ 1 - n^{-1} \left[\ 1 + 2n^{-1} \sum_{k=1}^{h-1} (n-k) \ \right] \right\}^{-1/2} S_1 .$$

The value of S_1^* is compared with the critical value of the Student's t distribution with (n-1) degrees of freedom in order to test the null hypothesis that the mean squared errors (MSE) for the two given models are equal.

- ***The Pesaran-Timmerman non-parametric market timing test (1992, 1994): PT test***

This is a test of the null hypothesis that the signs of the predicted and actual future directions are independent. Rejecting the null hypothesis of independence suggests that the model is useful for predicting future directions. This test is applied to both the correct direction and the speculative direction criteria.

Define b_t and a_t to be the predicted and actual directions respectively. Let

$$A_t = 1 \quad \text{if } a_t > 0, \qquad = 0 \quad \text{otherwise,}$$

$$B_t = 1 \quad \text{if } b_t > 0, \qquad = 0 \quad \text{otherwise,}$$

and

$$Z_t = 1 \quad \text{if } z_t = a_t b_t > 0, \qquad = 0 \quad \text{otherwise.}$$

Let $P_b = \Pr(b_t > 0)$, $P_a = \Pr(a_t > 0)$, and $\hat{P}$ denotes the *realized* proportion of times that the sign of a_t is correctly predicted by the sign of b_t. That is, $\hat{P} = n^{-1} \sum_{t=1}^{n} Z_t = \bar{Z}$. Denote the *ex* *ante* probability that the sign will be predicted correctly under the null hypothesis as

$$
\begin{aligned}
P_{\bullet} = \Pr(Z_t = 1) = \Pr(a_t b_t > 0) \\
&= \Pr(a_t > 0, b_t > 0) + \Pr(a_t < 0, b_t < 0) \\
&= P_b P_a + (1 - P_b)(1 - P_a).
\end{aligned}
$$

The standardized test statistic

$$S_n = \left\{ \frac{P_{\bullet}(1 - P_{\bullet})}{n} \right\}^{-\frac{1}{2}} \left(\hat{P} - P_{\bullet} \right),$$

is asymptotically distributed as $N(0,1)$ under the null hypothesis. If the true probabilities of P_b and P_a are unknown, then use estimated values based on the null independence hypothesis, $\hat{P}_{\bullet} = \hat{P}_b \hat{P}_a + (1 - \hat{P}_b)(1 - \hat{P}_a)$. where $\hat{P}_a = \sum_{t=1}^{n} A_t / n = \bar{A}$ *and* $\hat{P}_b = \sum_{t=1}^{n} B_t / n = \bar{B}$, and the *standardized test statistic* is denoted as

$$S_n = \frac{\hat{P} - \hat{P}_{\bullet}}{\left\{ \hat{\text{var}}(\hat{P}) - \hat{\text{var}}(\hat{P}_{\bullet}) \right\}^{\frac{1}{2}}}, \quad \sim N(0,1)$$

where,

$$\hat{\text{var}}(\hat{P}) = n^{-1} \hat{P}_{\bullet}(1 - \hat{P}_{\bullet}) \text{ and}$$

$$
\begin{aligned}
\hat{\text{var}}(\hat{P}_{\bullet}) &= n^{-1}(2\hat{P}_a - 1)^2 \hat{P}_b(1 - \hat{P}_b) + n^{-1}(2\hat{P}_b - 1)^2 \hat{P}_a(1 - \hat{P}_a) \\
&\quad + 4n^{-2} \hat{P}_a \hat{P}_b (1 - \hat{P}_a \hat{P}_b).
\end{aligned}
$$

- χ^2 ***test of independence*** (see Swanson and White 1997)

This test is applied to both the correct direction and the speculative direction criteria. Rejecting the null hypothesis of independence suggests that a given model is useful for predicting the correct direction (or speculative direction).

The direction forecasts, of size n, can be classified into 2 classes (up and down) by the sign of the actual direction and into 2 classes (up and down) by the sign of the predicted direction. The frequencies of each cell of the 2 by 2 classes are shown in Table 4.6.

Table 4.6. Frequencies of sign of direction

	actual up	actual down	Total
predicted up	n_{11}	n_{21}	n_{p1}
predicted down	n_{12}	n_{22}	n_{p2}
Total	n_{a1}	n_{a2}	N

The χ^2 test statistic is calculated as

$$\chi^2 = \sum_{i=1}^{2}\sum_{j=1}^{2}\left\{\frac{(n_{ij} - n_{ai} \times n_{pj} / N)^2}{n_{ai} \times n_{pj} / N}\right\}$$

where,

n_{ij} : denotes the realized frequency when the predicted direction is up or down given the actual direction is up or down;

$(n_{ai} \times n_{pj} / N)$: denotes the expected frequency when the predicted direction is up or down given the actual direction is up or down.

The χ^2 test statistic is compared with the critical value of the χ^2 distribution with degree of freedom (r-1)(c-1) =1, where r = 2 is the two classes (up and down) of the prediction direction and c = 2 is the two classes (up and down) of the actual direction. If the χ^2 test statistic is greater than the critical value then the null hypothesis of independence is rejected.

CHAPTER 5. EMPIRICAL RESULTS USING MONTHLY DATA

5.1 Overview

This chapter discusses one-month-ahead forecasting results for three exchange rates: the German Mark, the Japanese Yen, and the Italian Lira relative to US$. Six sliding window time periods are studied. For each time period, two conventional statistical ARIMA models are estimated and are selected based on the AIC and SBC criteria. In addition, both univariate and multivariate RBF models are investigated for each exchange rate. The multivariate RBF models use monthly long-term or short-term interest rates as the economic variable. The estimated RBF models are compared with a random walk model and with two ARIMA models over each of the six time periods.

The following sections briefly describe the empirical univariate and multivariate analyses of RBF models for each exchange rate. There are three kinds of univariate analyses for each monthly exchange rate. Analysis 1 investigates univariate RBF models without rescaling their inputs and without a regularization term in the cost function. Analysis 2 investigates univariate RBF models without rescaling their inputs but with a regularization term included in the cost function. Analysis 3 investigates univariate RBF models with rescaled inputs and without a regularization term in the cost function. The purpose is to investigate whether adding a regularization term in the cost function helps to improve forecasting results, and whether rescaling the inputs helps to improve the forecasting results. Furthermore, in order to make an objective comparison, there are two parts to each univariate analysis. Part (a) compares univariate RBF models using the same number of lagged values for inputs as in the selected statistical autoregressive (AR) models, and part (b) compares univariate RBF models using different numbers of lagged values selected by choosing those resulting in the lowest BIC value. Note that the BIC is not a typical lag length selection criterion, because its calculation is not directly involved with the number of inputs. However, this research investigates whether the BIC provides some information that may help choose the lag length of inputs. Finally, seven different radial basis functions are examined in each part of each RBF analysis.

There are also two parts to each multivariate analysis. Part (a) describes multivariate RBF models using a specific number of lagged value(s) as inputs that generally have better forecasting ability than models using other numbers of lagged values as inputs. Part (b) describes multivariate RBF models with different lag lengths selected by minimizing the BIC value. The forecasting results for RBF models using more than three lagged values as inputs were generally found to be no better than those for RBF models using no more than three lagged values. Therefore, in part (b) of each multivariate analysis, only RBF models with lag lengths ranging from one to three selected by minimizing the BIC value are investigated. Seven different radial basis functions are also studied in each part of each RBF analysis. To investigate whether the interest rate has explanatory power for the exchange rate movement, each of the multivariate RBF models is compared with its corresponding univariate RBF model that uses the same radial basis function and has the same lag length.

The two descriptive criteria used to evaluate out-of-sample forecasting performance are 'RMSE' and 'correct direction'. The random walk model cannot predict the future direction of an exchange rate, because the forecast value from a random walk model always indicates 'no change' of the future value; hence no "correct direction" results are reported for the random walk models. The following analyses are based mostly on *average* forecasting results over six time periods. In addition to the summary table for each exchange rate appearing in the main text, detailed tables of model descriptions and forecasting results for individual sliding window time periods are provided in Appendix D for further reference.

Three statistical hypotheses are also conducted for each analysis. As discussed in chapter 4, the MDM test is used to check whether the difference of mean squared error (MSE) of two models is statistically significant. Each RBF model is compared pairwisely with the following benchmark models: a random walk model; an AR model; and an MA model. If the value of the MDM statistic is positive, this means that the MSE value of the benchmark model is bigger than the relevant model being tested. Also, two direction tests (PT test and χ^2 independence test) are used to test whether a given model can correctly predict the future direction with statistical significance.

The following discussion first compares the forecasting results of different models by using the two descriptive evaluation criteria, and then investigates the statistical significance of these descriptive criteria by conducting hypothesis tests. Some conclusions are then provided for each exchange rate.

As mentioned in chapter 4, different widths r are examined for the GRBF, CRBF, IRBF, and MRBF models. In the following sections, only RBF models using specific widths that perform well for each of the six sliding window time periods will be discussed. However, in order to make sure that the residuals of the models are white noise, the RBF models chosen for discussion may have different width values for each time period.

5.2 German Mark

Seven RBF models are compared with an MA(1) model, an AR(1) model, and a random walk model in each part of the following analysis. The forecasting results and the relevant statistical hypothesis tests for the univariate and multivariate analyses are summarized in Tables 5.1(a)-(b). In total, 105 (42 univariate and 63 multivariate) RBF models investigated.

5.2.1 Model comparisons using descriptive average RMSE and average correct direction criteria

Model comparison results will now be explained in detail. Briefly, it will be shown that, based on the average RMSE criterion, the random walk model is the worst. Most RBF models are no worse than the AR(1) model and some of them are similar to the MA(1) model. Based on the correct direction criterion, however, some nonlocalized multivariate RBF models are better than the AR(1) and MA(1) models.

5.2.1.1 Univariate analyses

Analysis 1(a): No rescaling of inputs / no regularization term / Lag length equal to one.

Based on the average RMSE criterion, the MA(1) model is best. Based on the average correct direction criterion, except for the CCRBF model, all other RBF models do not predict the direction as well as the MA(1) and AR(1) models.

Analysis 1(b): No rescaling of inputs / no regularization term / Lag length is selected from one to three lags by minimizing the BIC value.

Comparing the results with those of analysis 1(a), not every RBF model improves based on the RMSE criterion. However, almost all RBF models generally predict the direction

Table 5.1 Descriptive evaluation criteria and hypothesis tests (German mark)

(a) Descriptive evaluation criteria: one-month-ahead prediction (German Mark)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
				Average RMSE				
Random Walk	0.0235							
AR(1)	0.023							
MA(1)	0.0225							
Univariate								
Analysis 1(a)		0.0229	0.0230	0.0229	0.0229	0.0227	0.0229	0.0229
Analysis 1(b)		0.0230	0.0230	0.0228	0.0226	0.023	0.0226	0.0228
Analysis 2(a)		0.0228	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Analysis 2(b)		0.0229	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Analysis 3(a)		0.0228	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Analysis 3(b)		0.0228	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Multivariate (*i*)								
Analysis 4(a1)		0.0224	0.0222	0.0216	0.0224	0.0224	0.0225	0.0226
Analysis 4(a2)		0.0225	0.0224	0.0224	0.0224	0.0224	0.0225	0.0226
Analysis 4(b)		0.0229	0.0229	0.0226	0.023	0.0230	0.0226	0.0231
Analysis 4(c)		0.0224	0.0224	0.0224	0.0223	0.0224	0.0226	0.0225
Analysis 4(d)		0.0226	0.0228	0.0231	0.0228	0.0227	0.0225	0.0230
Analysis 5(a)		0.0228	0.0227	0.0229	0.0229	0.0228	0.0227	0.0227
Analysis 5(b)		0.0229	0.0229	0.023	0.0231	0.0232	0.0228	0.0227
Analysis 5(c)		0.0227	0.0228	0.0229	0.023	0.0229	0.0226	0.0227
Analysis 5(d)		0.0227	0.0228	0.0229	0.0229	0.0229	0.0226	0.0226
				Average Correct Direction (% of accuracy)				
AR(1)	0.61							
MA(1)	0.60							
Univariate								
Analysis 1(a)		0.58	0.58	0.58	0.56	0.56	0.60	0.56
Analysis 1(b)		0.57	0.60	0.63 *	0.60	0.60	0.61 *	0.57
Analysis 2(a)		0.56	0.57	0.58	0.60	0.57	0.61	0.60
Analysis 2(b)		0.54	0.57	0.58	0.60	0.57	0.61	0.60
Analysis 3(a)		0.57	0.57	0.58	0.58	0.56	0.60	0.60
Analysis 3(b)		0.57	0.56	0.58	0.58	0.56	0.60	0.60
Multivariate (*i*)								
Analysis 4(a1)		0.57	0.60	0.57	0.60	0.60	0.61	0.60
Analysis 4(a2)		0.61	0.58	0.58	0.60	0.60	0.61	0.60
Analysis 4(b)		0.54	0.56	0.60	0.54	0.57	0.64 *	0.56
Analysis 4(c)		0.60	0.58	0.60	0.58	0.60	0.63 *	0.61
Analysis 4(d)		0.53	0.56	0.56	0.56	0.56	0.67 *	0.61
Analysis 5(a)		0.60	0.58	0.58	0.61	0.56	0.60	0.65 *
Analysis 5(b)		0.60	0.56	0.56	0.58	0.54	0.60	0.60
Analysis 5(c)		0.61	0.54	0.56	0.56	0.54	0.65 *	0.63 *
Analysis 5(d)		0.61	0.56	0.56	0.57	0.58	0.65 *	0.60

Note: x indicates that the relevant model does not fit the data well in some time periods, hence the results for the model are not shown.

[a] Reject the null hypothesis of equal mean squared error if the test statistic value is greater than $t(71, 0.025) \approx 1.99$.

[b] Reject the null hypothesis of independence if the test statistic value is greater than $N(0,1) = 1.96$.

[c] Reject the null hypothesis of independence if the test statistic value is greater than $\chi^2_{(1, 0.05)} = 3.841$.

* Significant at 5% level.

Table 5.1 (continued)

(b) MDM, PT and χ^2 tests: One-month-ahead prediction (German Mark)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		MSE (MDM test)[a]						
		(1) Compared with Random Walk						
Random Walk								
AR(1)	0.80							
MA(1)	3.87 *							
Univariate								
Analysis 1(a)		0.57	0.57	0.58	0.63	0.56	0.78	0.65
Analysis 1(b)		0.55	0.67	0.98	1.02	0.39	1.37	0.75
Analysis 2(a)		0.82	0.83	0.83	0.81	1.00	0.96	0.93
Analysis 2(b)		0.74	0.83	0.83	0.81	1.00	0.96	0.93
Analysis 3(a)		0.84	0.86	0.86	0.82	0.95	0.99	0.91
Analysis 3(b)		1.24	0.94	0.86	0.82	0.95	0.99	0.91
Multivariate (*i*)								
Analysis 4(a1)		0.87	0.82	1.25	1.29	1.31	x	1.36
Analysis 4(a2)		1.23	1.29	1.36	1.33	1.31	x	1.36
Analysis 4(b)		0.49	0.42	0.61	0.57	0.59	1.47	-1.02
Analysis 4(c)		1.26	1.21	1.32	1.30	1.23	1.23	1.43
Analysis 4(d)		0.96	0.66	0.35	0.79	0.96	1.37	0.81
Analysis 5(a)		1.28	1.23	0.83	0.92	0.91	1.05	1.42
Analysis 5(b)		1.05	0.89	0.70	0.69	0.44	0.91	0.59
Analysis 5(c)		1.51	0.93	1.00	0.79	0.85	1.94	1.56
Analysis 5(d)		1.51	0.86	0.75	0.94	0.77	1.94	1.29
		(2) Compared with MA(1)						
AR(1)								
Univariate								
Analysis 1(a)		-0.71	-0.76	-0.76	-0.57	-0.27	-0.97	-0.56
Analysis 1(b)		-0.92	-0.89	-0.65	-0.22	-0.57	-0.10	-0.46
Analysis 2(a)		-0.60	-0.57	-0.63	0.72	-0.99	-1.01	-0.83
Analysis 2(b)		-0.75	-0.57	-0.63	0.72	-0.99	-1.01	-0.83
Analysis 3(a)		-0.56	-0.59	-0.59	-0.70	-1.04	-0.89	-0.82
Analysis 3(b)		-0.81	-0.53	-0.59	-0.70	-1.04	-0.89	-0.82
Multivariate (*i*)								
Analysis 4(a1)		0.08	0.22	0.57	0.09	0.15	x	-0.29
Analysis 4(a2)		-0.01	0.15	0.19	0.10	0.15	x	-0.29
Analysis 4(b)		-0.37	-0.43	-0.11	-0.68	-0.78	-0.13	-0.90
Analysis 4(c)		0.15	0.11	0.11	0.21	0.15	-0.15	-0.05
Analysis 4(d)		-0.16	-0.28	-0.72	-0.39	-0.37	-0.09	-0.62
Analysis 5(a)		-0.60	-0.5	-0.94	-0.76	-0.66	-0.53	-0.39
Analysis 5(b)		-0.84	-0.90	-1.04	-1.29	-1.27	-0.67	-0.47
Analysis 5(c)		-0.83	-0.54	-0.81	-0.91	-0.77	-0.30	-0.52
Analysis 5(d)		-0.83	-0.62	-0.68	-0.77	-0.98	-0.30	-0.38

Table 5.1(b) (continued)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
				MSE (MDM test)[a] (3) Compared with AR(1)				
Univariate								
Analysis 1(a)		0.21	0.22	0.23	0.40	0.45	0.42	0.38
Analysis 1(b)		-0.004	0.57	1.15	1.36	-0.07	0.10	0.67
Analysis 2(a)		0.76	0.86	0.82	0.76	0.59	0.45	0.78
Analysis 2(b)		0.38	0.86	0.82	0.76	0.59	0.45	0.78
Analysis 3(a)		0.73	0.83	0.84	0.86	0.51	0.77	0.85
Analysis 3(b)		0.98	0.89	0.84	0.86	0.51	0.77	0.85
Multivariate (*i*)								
Analysis 4(a1)		0.65	0.83	0.71	1.99 *	2.06 *	x	1.67
Analysis 4(a2)		1.59	1.51	1.68	1.74	2.06 *	x	1.67
Analysis 4(b)		0.15	0.06	0.43	-0.05	-0.02	1.56	-0.67
Analysis 4(c)		1.33	1.27	0.29	1.56	1.59	0.87	1.96
Analysis 4(d)		1.30	0.40	-0.20	0.31	0.69	0.86	0.05
Analysis 5(a)		1.04	1.27	0.22	0.31	0.79	0.72	0.65
Analysis 5(b)		0.57	1.04	0.16	-0.33	-0.77	0.55	0.17
Analysis 5(c)		1.12	0.96	0.32	-0.04	0.35	1.26	0.71
Analysis 5(d)		1.12	0.73	0.45	0.90	0.38	1.26	1.83
				Correct Direction (PT test) [b]				
AR(1)	1.90							
MA(1)	1.66							
Univariate								
Analysis 1(a)		1.43	1.43	1.43	0.99	0.99	1.69	0.99
Analysis 1(b)		1.20	1.67	2.14 *	1.74	1.69	2.12 *	1.21
Analysis 2(a)		0.99	1.23	1.46	1.69	1.23	1.93	1.69
Analysis 2(b)		0.73	1.23	1.46	1.69	1.23	1.93	1.69
Analysis 3(a)		1.23	1.23	1.46	1.46	0.99	1.72	1.69
Analysis 3(b)		1.23	0.97	1.46	1.46	0.99	1.72	1.69
Multivariate (*i*)								
Analysis 4(a1)		1.31	1.74	1.23	1.68	1.67	x	1.69
Analysis 4(a2)		1.93	1.46	1.46	1.68	1.67	x	1.69
Analysis 4(b)		0.73	0.96	1.68	0.73	1.21	2.58 *	0.97
Analysis 4(c)		1.67	1.44	1.67	1.43	1.67	2.52 *	1.91
Analysis 4(d)		0.49	0.95	0.96	0.96	0.95	3.02 *	1.94
Analysis 5(a)		1.72	1.46	1.48	1.93	0.97	1.69	2.64 *
Analysis 5(b)		1.72	0.97	0.96	1.44	0.72	1.69	1.78
Analysis 5(c)		1.95	0.73	1.06	0.97	0.74	2.64 *	2.18 *
Analysis 5(d)		1.95	0.97	0.99	1.21	1.43	2.64 *	1.74

Table 5.1(b) (continued)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		Correct Direction (χ^2 test) [c]						
AR(1)	3.56							
MA(1)	2.72							
Univariate								
Analysis 1(a)		2.03	2.03	2.03	0.96	0.96	2.83	1.68
Analysis 1(b)		1.42	2.74	4.50 *	3.00	2.83	4.43 *	1.44
Analysis 2(a)		0.96	1.48	2.10	2.83	1.48	3.66	2.83
Analysis 2(b)		0.52	1.48	2.10	2.83	1.48	3.66	2.83
Analysis 3(a)		1.48	1.48	2.10	2.10	0.96	2.90	2.83
Analysis 3(b)		1.48	0.94	2.10	2.10	0.96	2.90	2.83
Multivariate (*i*)								
Analysis 4(a1)		1.68	3.00	1.48	2.78	2.74	x	2.83
Analysis 4(a2)		3.66	2.10	2.10	2.78	2.74	x	2.83
Analysis 4(b)		0.52	0.90	2.78	0.52	1.44	6.55 *	0.94
Analysis 4(c)		2.74	2.06	2.74	2.01	2.74	6.24 *	3.60
Analysis 4(d)		0.24	0.89	0.90	0.91	0.89	9.00 *	3.74
Analysis 5(a)		2.90	2.10	2.17	3.66	0.94	2.83	6.85 *
Analysis 5(b)		2.90	0.94	0.91	2.06	0.51	2.83	3.13
Analysis 5(c)		3.74	0.52	1.11	0.94	0.53	6.85 *	4.68 *
Analysis 5(d)		3.74	0.94	0.96	1.44	2.03	6.85 *	3.00

better than their corresponding RBF models in analysis 1(a) and are similar to the MA(1) model. Now the IRBF model predicts the direction best. In general, based on the average RMSE and average correct direction criteria, the CCRBF and MRBF models are similar to the MA(1) model.

Analysis 2(a): No rescaling of inputs / regularization term / Lag length equal to one.

Comparing the results with those of analysis 1(a), some RBF models improve slightly based on the average RMSE and average correct direction criteria. However, the results are very similar to those of analysis 1(a).

Analysis 2(b): No rescaling of inputs / regularization term / Lag length is selected from one to three lags by minimizing the BIC value.

The results are similar to those of analysis 2(a). This is because except for the GRBF model, all other RBF models also choose one lagged value as input.

Analysis 3(a): Rescaling of inputs / regularization term / Lag length equal to one.

In general, the forecasting results do not improve on those of 2(a).

Analysis 3(b): Rescaling of inputs / regularization term / Lag length selected from one to three lags by minimizing the BIC value.

The results are similar to those of analysis 2(a). Again, most RBF models choose one lagged value as input.

5.2.1.2 Multivariate analyses

Analysis 4(a1): Long-term interest rate differential (LR1) / Lag length equal to one / width r = 0.1.

The long-term interest rate used for estimation for Germany is the yield on public sector bonds (7-15 years), and for the U.S. it is the yield on 10-year Treasury notes.

Based on the average RMSE criterion, almost all RBF models are no worse than the MA(1) model. Note that the IRBF model is best based on the average RMSE criterion but it is not as good at predicting the direction. Based on average correct direction, except for the GRBF and IRBF models, all other RBF models predict the direction similarly to the MA(1) and AR(1) models. Overall, most of these multivariate models seem to improve on their corresponding univariate models discussed in analysis 3(a).

Analysis 4(a2): Long-term interest rate differential (LR1) / Lag length equal to one / width r = 1.

The results of using a larger width r = 1 for the relevant RBF models are examined. Now, the IRBF (r = 1) model is not so impressive compared with the IRBF (r = 0.1) model based on the average RMSE criterion. However, it can predict the direction slightly better. The GRBF (r = 1) model also predicts the direction better than the GRBF (r = 0.1) model. For other RBF models the results are similar to their corresponding models in analysis 4(a1) and are similar to the MA(1) model.

Analysis 4(b): Long-term interest rate differential (LR1) / Lag length selected from one to three lags by minimizing the BIC value.

The same data is used as in analysis 4(a). In general, the forecasting results are worse than those of analysis 4(a) except that the CCRBF model can predict the direction well. Therefore, it seems that using more than one lagged value of long-term interest rates as inputs does not improve forecasting performance.

Analysis 4(c): Long-term interest rate differential (LR2) / Lag length equal to one / width r = 1.

The long-term interest rate used for estimation for Germany is the yield on public sector bonds (more than three years), and for the U.S. it is the yield on 10-year Treasury notes.

Based on average RMSE and average correct direction criteria, the forecasting results are similar to those of analysis 4(a2). However, the results are not so similar if the forecasts are compared by each individual time period. Also, the forecasting results are better than those of the univariate analysis 3(a).

Analysis 4(d): Long-term interest rate differential (LR2) / Lag length selected from one to three lags by minimizing the BIC value.

The same data is used as in analysis 4(c). In general, except that the CCRBF model improves in predicting the direction, other RBF models are worse than their corresponding models in analysis 4(c).

Analysis 5(a): Short-term interest rate differential (SR1) / Lag length equal to three.

The short-term interest rate used for estimation for Germany is the call money rate, and for the U.S. it is the Federal funds rate.

Based on average RMSE and average correct direction criteria, all RBF models are no worse than their corresponding univariate models. The reason for this is that the lag length is also equal to three. See Table D.9 in Appendix D for further reference. However, they are all worse than the MA(1) models based on the RMSE criterion. Based on the average correct direction criterion, the QRBF model predicts better than all other models.

Analysis 5(b): Short-term interest rate differential (SR1) / Lag length selected from one to three lags by minimizing the BIC value.

The same data is used as in analysis 5(a). Based on average RMSE and average correct direction criteria, most of the RBF models are worse than their corresponding RBF models in analysis 5(a).

Analysis 5(c): Short-term interest rate differential (SR2) / Lag length equal to three.

The short-term interest rate used for estimation for Germany is the call money rate, and for the U.S. it is the three-month Treasury bill rate.

Comparing analysis 5(a) with 5(c), both results are similar based on the average RMSE criterion. However, most of the RBF models are not as good in predicting the direction as their corresponding models in analysis 5(a). Only the CCRBF model improves, especially in predicting the direction. Furthermore, the results of these two analyses are different if compared by individual time period.

Overall, the CCRBF and QRBF models predict the direction fairly well.

Analysis 5(d): Short-term interest rate differential (SR2) / Lag length selected from one to three lags by minimizing the BIC value.

The same data is used as in analysis 5(c). The forecasting results of the RBF models are generally similar to those of analysis 5(c). The reason is that some RBF models also select the lag length equal to three.

5.2.2 Statistical hypothesis tests

All of the models discussed above are investigated together.

- ***MDM test***

(1) Only the MA(1) model is significantly different from the random walk model at the 5% level. The AR(1) model and all the univariate and multivariate RBF models are not significantly different from the random walk model at the 5% level.

(2) The AR(1) model and all the univariate and multivariate RBF models are not significantly different from the MA(1) model at the 5% level.

(3) Only some multivariate RBF models using long-term interest rates as economic variables, that is, MRBF in analysis 4(a1) and LRBF in analyses 4(a1) and 4(a2), are significantly different from the AR(1) model at the 5% level. All other univariate and multivariate RBF models are not significantly different from the AR(1) model at the 5% level.

- ***PT and χ^2 independence tests***

The results of the PT and χ^2 independence tests are consistent. Only the IRBF and CCRBF models in analysis 1(b), CCRBF models in analysis 4(b)-(d) and 5(c)-(d), and the QRBF model in analyses 5(a) and 5(c) reject the null hypothesis that a given model is of no value in predicting the direction of exchange rate at the 5% level. That is, only these models can predict the direction with statistical significance. The AR(1), MA(1) and all other RBF models do not reject the null hypothesis.

5.2.3 Conclusions of univariate and multivariate analyses

The following conclusions are derived after considering the statistical hypothesis tests.

(1) Rescaling the input seems to be unnecessary for the univariate RBF analyses.

(2) Whether or not a regularization term is included in the cost function does not seem to make much difference in the forecasting of the univariate RBF models.

(3) According to the results of all three hypothesis tests, for all univariate RBF(1) models using the same number of inputs as the statistical AR(1) model, the resulting forecasts are not statistically different from those generated by the AR(1) model.

(4) The random walk model is worse than all other models according to the descriptive average RMSE criterion. Only the MA(1) model is significantly different from the random

walk model based on the MSE criterion, according to the MDM test. Even the AR(1) and all RBF models are not significantly different from the random walk model according to the MDM test. However, the AR(1) and all RBF models are not significantly different from the MA(1) model by using the MDM test, either. And only three out of the 105 investigated RBF models are significantly different from the AR(1) model according to the MDM test. Overall, forecasts from all of the investigated models are fairly similar based on the MDM test.

(5) Only nine out of the 105 investigated RBF models are significant in predicting the future direction. More precisely, only the univariate IRBF and CCRBF models using more than one-lagged inputs, the multivariate CCRBF models including long-term or short-term interest rates as inputs, and the multivariate QRBF models including short-term interest rates as inputs, can predict the correct direction with statistical significance. Overall, the CCRBF models generally forecast the correct direction better than most other RBF models.

(6) The MA(1), AR(1) and all investigated RBF models not mentioned in (5) are not statistically significant in predicting the correct direction.

(7) The multivariate RBF models including one lagged value of the long-term interest rate seem to improve forecasts relative to their corresponding univariate RBF models based on the descriptive RMSE criterion in some time periods, and are competitive with the MA(1) model based on the MDM test. However, these RBF models are not significantly different from the random walk model. Furthermore, among these RBF models, only the CCRBF

models using one lagged value of the long-term interest rate can predict the correct direction with statistical significance.

(8) The multivariate RBF models including three lagged values of the short-term interest rates do not seem to improve on point forecasts. However, the CCRBF models in analysis 5(c) and QRBF models estimated in analyses 5(a) and 5(c) predict the direction with statistical significance.

5.3 Japanese Yen

Seven RBF models are compared with an MA(1) model, an AR(3), and a random walk model in each part of the following analysis. The results are summarized in Tables 5.2(a)-(c) on the following pages. In total, 42 (21 univariate and 21 multivariate) RBF models are investigated.

5.3.1 Model comparison using descriptive average RMSE and average correct direction criteria

Summary of findings: Based on the average RMSE criterion, the random walk model is worst. Some localized RBF models are no worse than the MA(1) model, and most RBF models are better than the AR(3) model. Based on the correct direction criterion, almost all RBF models are better than the MA(1) and AR(3) model.

5.3.1.1 Univariate analyses

The following analyses compare the RBF models using the same three lagged values for inputs as in the statistical AR(3) model. This research also investigates the RBF models selecting from one to three lagged values as inputs by minimizing the BIC value. However, the RBF

Table 5.2 Descriptive evaluation criteria and hypothesis tests (Japanese yen)

(a) Descriptive evaluation criteria: one-month-ahead prediction (Japanese yen)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
				Average RMSE				
Random Walk	0.0303							
AR(3)	0.0293							
MA(1)	0.0289							
Univariate								
Analysis 1		0.0294	0.0292	0.0293	0.0292	0.0290	0.0293	0.0292
Analysis 2		0.0289	0.0288	0.0289	0.0291	0.0300	0.0293	0.0290
Analysis 3		0.0288	0.0289	0.0289	0.0291	0.0301	0.0295	0.0296
Multivariate (i)								
Analysis 4		0.0288	0.0292	0.0293	0.0292	0.0303	0.0298	0.0300
Analysis 5(a)		0.0288	0.0289	0.0288	0.0289	0.0293	0.0295	0.0295
Analysis 5(c)		0.0288	x	x	0.0289	0.0292	0.0294	0.0295
				Average Correct Direction (% of accuracy)				
AR(3)	0.44							
MA(1)	0.42							
Univariate								
Analysis 1		0.47	0.53	0.50	0.50	0.57	0.54	0.50
Analysis 2		0.51	0.54	0.54	0.47	0.51	0.43	0.53
Analysis 3		0.49	0.54	0.54	0.53	0.53	0.44	0.49
Multivariate (i)								
Analysis 4		0.56	0.54	0.57	0.51	0.46	0.50	0.44
Analysis 5(a)		0.51	0.57	0.54	0.56	0.53	0.44	0.46
Analysis 5(c)		0.53	x	x	0.56	0.54	0.46	0.47

Note: x indicates that the relevant model does not fit the data well in some time periods, hence the results for the model are not shown.

[a] Reject the null hypothesis of equal mean squared error if the test statistic value is greater than $t_{(71,0.025)} \approx 1.99$.

[b] Reject the null hypothesis of independence if the test statistic value is greater than $N_{(0,1)} = 1.96$.

[c] Reject the null hypothesis of independence if the test statistic value is greater than $\chi^2_{(1,0.05)} = 3.841$.

* Significant at 5% level.

Table 5.2 (continued)

(b) MDM test: one-month ahead prediction (Japanese Yen)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		MSE (MDM test) [a]						
		(1) Compared with Random Walk						
AR(3)	0.69							
MA(1)	0.79							
Univariate								
Analysis 1		0.66	0.78	0.74	0.68	0.80	0.51	0.62
Analysis 2		0.86	1.02	0.98	0.84	0.44	0.60	0.77
Analysis 3		0.92	0.97	0.98	0.83	0.44	0.64	0.70
Multivariate (*i*)								
Analysis 4		0.92	0.77	0.84	0.75	0.26	0.51	047
Analysis 5(a)		1.04	1.01	1.00	0.96	0.80	0.57	0.76
Analysis 5(c)		0.95	0.95	x	0.95	0.82	0.57	0.75
		(2) Compared with MA(1)						
AR(3)	-2.03 *							
Univariate								
Analysis 1		-0.96	-0.35	-0.62	-0.57	-0.50	-0.66	-0.67
Analysis 2		-0.23	-0.05	-0.18	-0.49	-1.35	-0.79	-0.47
Analysis 3		-0.16	-0.22	-0.12	-0.47	-1.39	-0.96	-0.88
Multivariate (*i*)								
Analysis 4		-0.18	-0.54	-0.62	-0.58	-1.60	-1.80	-1.12
Analysis 5(a)		-0.19	-0.25	-0.06	-0.38	-0.68	-0.83	-0.81
Analysis 5(c)		-0.23	-0.26	x	-0.32	-0.55	-0.80	-0.72
		(3) Compared with AR(3)						
Univariate								
Analysis 1		-0.19	0.27	0.07	0.15	0.51	-0.19	0.12
Analysis 2		0.33	0.40	0.29	0.02	-1.00	-0.37	0.07
Analysis 3		0.37	0.27	0.35	0.02	-1.04	-0.60	-0.58
Multivariate (*i*)								
Analysis 4		0.20	-0.19	-0.28	-0.19	-1.29	-0.72	-1.03
Analysis 5(a)		0.25	0.20	0.43	0.05	-0.18	-0.49	-0.50
Analysis 5(c)		0.20	0.19	x	0.12	-0.02	-0.53	-0.43

Table 5.2 (continued)

(c) PT and χ^2 tests: one-month ahead prediction (Japanese Yen)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		Correct Direction (PT test) [b]						
AR(3)	-0.95							
MA(1)	-1.43							
Univariate								
Analysis 1		-0.48	0.51	0.00	0.00	1.23	0.75	0.00
Analysis 2		0.25	0.76	0.76	-0.49	0.25	-1.20	0.52
Analysis 3		-0.25	0.76	0.76	0.50	0.49	-0.96	-0.24
Multivariate (*i*)								
Analysis 4		0.99	0.74	1.23	0.25	-0.72	0.00	-0.97
Analysis 5(a)		0.26	1.27	0.76	1.06	0.50	-0.75	-0.96
Analysis 5(c)		0.53	1.35	x	1.06	0.76	-0.52	-0.73
		Correct Direction (χ^2 test) [c]						
AR(3)	0.89							
MA(1)	2.01							
Univariate								
Analysis 1		0.23	0.25	0.00	0.00	1.48	0.55	0.00
Analysis 2		0.06	0.58	0.58	0.24	0.06	1.42	0.26
Analysis 3		0.06	0.58	0.58	0.25	0.24	0.90	0.06
Multivariate (*i*)								
Analysis 4		0.96	0.53	1.48	0.06	0.51	0.00	0.94
Analysis 5(a)		0.07	1.60	0.58	1.11	0.25	0.55	0.91
Analysis 5(c)		0.28	1.79	x	1.11	0.58	0.26	0.52

models using one or two lagged values as inputs generally show autocorrelation in the residuals for most of the six time periods. Therefore, only the results of the RBF models using three lagged values as inputs are discussed here.

Analysis 1: No rescaling of inputs / no regularization term / Lag length equal to three.

Based on the average RMSE criterion, the MA(1) model is best. Based on both the average RMSE and average correct direction criteria, the LRBF model is better than other RBF models, and is similar to the MA(1) model based on the average RMSE criterion.

Analysis 2: Rescaling inputs / regularization term / Lag length equal to three.

Comparing the results with those of analysis 1, only the GRBF, CRBF, IRBF and QRBF models show improved forecasting ability based on the average RMSE and average correct direction criteria, and they are no worse than the MA(1) model. These three localized RBF models also perform better than the MA(1) model in the first four time periods in terms of these criteria.

Analysis 3: Rescaling of inputs / regularization term / Lag length equal to three.

Comparing the results with those of analysis 2, the GRBF, CRBF, and IRBF models show no improvement in forecasting ability but still outperform the other RBF models.

5.3.1.2 Multivariate analyses

The multivariate RBF models using one or two lagged values of all variables as inputs have autocorrelated residuals. Therefore, the following multivariate analyses discuss only the RBF models that use three lagged values for each variable as inputs.

Analysis 4: Long-term interest rate differential (LR) / Lag length equal to three.

The long-term interest rate used for estimation for Japan is the yield on central government bonds, and for the U.S. it is the yield on10-year Treasury notes.

Based on the average RMSE criterion, except for the GRBF model, almost all other multivariate RBF models performed no better than the corresponding univariate RBF models. However, the GRBF, CRBF, and IRBF models performed slightly better based on the average correct direction criterion.

Analysis 5(a): Short-term interest rate differential (SR1) / Lag length equal to three.

The short-term interest rate used for estimation for Japan is the call money rate, and for the U.S. it is the Federal funds rate. Based on the average RMSE and average correct direction criteria, most of the RBF models do not show remarked improvement in forecasting ability compared with the corresponding univariate RBF models.

Analysis 5(c): Short-term interest rate (SR2) / Lag length equal to three.

The short-term interest rate used for estimation for Japan is the call money rate, and for the U.S. it is the 3-month Treasury bill rate.

The residuals of the CRBF and IRBF models indicate autocorrelation in some of the six time periods. Therefore, the results for these models are not discussed here. Also, most RBF models do not show remarked improvement in forecasting ability compared with the corresponding univariate RBF models.

5.3.2 Statistical hypothesis tests

All the models discussed above are investigated together.

- ***MDM test***

(1) None of the models is significantly different from the random walk model at the 5% level.

(2) None of the univariate and multivariate RBF models are significantly different from the MA(1) model at the 5% level. Only the AR(3) model is significantly different from the MA(1) model at the 5% level.

(3) None of the univariate and multivariate RBF models are significantly different from the AR(3) model at the 5% level.

- ***PT and χ^2 independence tests***

The results of the PT and χ^2 independence tests are consistent. None of the models rejects the null hypothesis that a given model is of no value in predicting the direction of change. That is, none of the model can predict the direction with statistical significance at the 5% level.

5.3.3 Conclusions of univariate and multivariate analyses

The following conclusions are derived after considering the statistical hypothesis tests.

(1) Rescaling the input values seems to be unnecessary for the univariate RBF models.

(2) For most univariate RBF models, adding a regularization term in the cost function seems to result in some improvement in forecasting ability based on the descriptive evaluation criteria. However, based on the statistical tests, the forecasting results are not very different from the results obtained for the corresponding RBF models without using a regularization term in the cost function.

(3) Most of the univariate RBF(3) models are no worse than the AR(3) model based on the descriptive RMSE criterion and can predict the correct direction better than the AR(3) model. However, according to the results of the three statistical hypotheses tests, none of the univariate RBF(3) models using the same number of inputs as the statistical AR(3) model seems to forecast with statistical difference from the AR(3) model.

(4) Based on the descriptive *average* RMSE value over all six time periods, the random walk model is worse than all other models. The nonlocalized LRBF model in analysis 1 and most of the three localized RBF models explored in analyses 2(a) through 5(c) are competitive with the MA(1) model. The MDM tests indicate that none of the RBF models is significantly different from the random walk model, the MA(1) model and the AR(3) model based on the MSE criterion. The MDM tests indicate that the AR(3) model is

significantly different from the MA(1) model based on the MSE criterion. In general, the forecasts from all of these models seem to be similar based on the MDM test.

(5) Almost all RBF models predict the correct direction better than the MA(1) and AR(3) models. However, according to the direction hypothesis tests, none of these predictions is statistically significant.

(6) Based on the average RMSE criterion, adding three lagged values of long-term or short-term interest rates as explanatory variables generally does not improve the point forecasting ability of most RBF models. Based on the average correct direction criterion, some localized RBF models may help predict the correct direction better. However, they cannot predict the correct direction with statistical significance.

(7) Overall, the localized RBF models seem to forecast better than the nonlocalized RBF models.

5.4 Italian Lira

Seven RBF models are compared with an MA(1) model, an AR(1) model and a random walk model in each part of the following analysis. The forecasting results of the univariate and multivariate analyses are summarized in Tables 5.3(a)-(c) on the following pages. In total, 56 (42 univariate and 14 multivariate) RBF models are investigated.

5.4.1 Model comparisons using descriptive average RMSE and average correct direction criteria

Summary of findings: Based on the average RMSE criterion, the random walk model is worst. Most RBF models are no worse than the AR(1) model. Only the CCRBF and QRBF

Table 5.3 Descriptive evaluation criteria and hypothesis tests (Italian lira)

(a) Descriptive evaluation criteria: one-month-ahead prediction (Italian lira)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
				Average RMSE				
Random Walk	0.0203							
AR(1)	0.0192							
MA(1)	0.0183							
Univariate								
Analysis 1(a)		0.0191	0.0191	0.0191	0.0194	0.0193	0.0195	x
Analysis 1(b)		0.0190	0.0191	0.0191	0.0190	0.0193	0.0185	x
Analysis 2(a)		0.0191	0.0191	0.0192	0.0193	0.0191	0.0191	0.0192
Analysis 2(b)		0.0191	0.0191	0.0192	0.0193	0.019	0.0192	0.0192
Analysis 3(a)		0.0191	0.0191	0.0192	0.0193	0.0191	0.0192	0.0194
Analysis 3(b)		0.0191	0.0191	0.0192	0.0193	0.0189	0.0185	0.0188
Multivariate (*i*)								
Analysis 4(a)		0.0194	0.0192	0.0189	0.0192	0.0187	0.0182	0.0183
Analysis 4(b)		0.0189	0.0189	0.0191	0.0192	0.0188	0.019	0.0191
				Average Correct Direction (% of accuracy)				
AR(1)	0.60							
MA(1)	0.63 *							
Univariate								
Analysis 1(a)		0.63 *	0.63 *	0.63 *	0.60	0.58	0.50	x
Analysis 1(b)		0.63 *	0.63 *	0.63 *	0.60	0.58	0.58	x
Analysis 2(a)		0.58	0.58	0.60	0.60	0.60	0.58	0.60
Analysis 2(b)		0.58	0.58	0.60	0.60	0.60	0.58	0.58
Analysis 3(a)		0.58	0.58	0.60	0.60	0.57	0.60	0.61
Analysis 3(b)		0.58	0.58	0.60	0.60	0.61	0.60	0.60
Multivariate (*i*)								
Analysis 4(a)		0.64 *	0.63 *	0.61 *	0.61 *	0.65 *	0.64 *	0.67 *
Analysis 4(b)		0.60	0.58	0.58	0.56	0.65 *	0.61	0.61

Note: x indicates that the relevant model does not fit the data well in some time periods, hence the results for the model are not shown.

[a] Reject the null hypothesis of equal mean squared error if the absolute value of the test statistic is greater than $t_{(71,0.025)} \approx 1.99$; " An underlined value indicates that the numerical test value is around the critical value".

[b] Reject the null hypothesis of independence if the test statistic value is greater than $N_{(0,1)} = 1.96$.

[c] Reject the null hypothesis of independence if the test statistic value is greater than $\chi^2_{(1,0.05)} = 3.841$.

* Significant at the 5% level.

Table 5.3 (continued)

(b) MDM test: one-month ahead prediction (Italian Lira)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		MSE (MDM test) [a]						
		(1) Compared with Random Walk						
AR(1)	1.13							
MA(1)	1.71							
Univariate								
Analysis 1(a)		1.39	1.39	1.39	1.07	1.12	0.92	x
Analysis 1(b)		1.46	1.39	1.39	1.72	1.12	0.96	x
Analysis 2(a)		1.30	1.26	1.32	1.27	1.39	1.31	1.26
Analysis 2(b)		1.30	1.26	1.32	1.27	1.65	1.28	1.25
Analysis 3(a)		1.48	1.36	1.18	1.10	1.44	1.36	1.43
Analysis 3(b)		1.48	1.36	1.18	1.10	1.82	1.99 *	1.87
Multivariate (*i*)								
Analysis 4(a)		1.06	1.30	1.59	1.39	1.60	2.18 *	1.98
Analysis 4(b)		1.59	1.65	1.40	1.38	1.39	1.89	1.52
		(2) Compared with MA(1)						
AR(1)	-2.10 *							
Univariate								
Analysis 1(a)		-1.98	-1.96	-1.98	-2.53 *	-3.51 *	-2.55 *	x
Analysis 1(b)		-1.95	-1.96	-1.98	-2.18 *	-3.51 *	-1.99 *	x
Analysis 2(a)		-2.07 *	-2.17 *	-3.34 *	-2.47 *	-1.52	-1.41	-1.62
Analysis 2(b)		-2.07 *	-2.17 *	-3.34 *	-2.47 *	-1.56	-1.46	-1.67
Analysis 3(a)		-1.36	-1.46	-1.92	-2.46 *	-1.44	-1.36	-1.58
Analysis 3(b)		-1.36	-1.46	-1.92	-2.46 *	-1.29	-0.36	-1.53
Multivariate (*i*)								
Analysis 4(a)		-1.71	-1.50	-1.18	-1.46	-0.60	0.42	-0.17
Analysis 4(b)		-1.01	-1.29	-1.54	-1.70	-1.54	-1.69	-1.70
		(3) Compared with AR(1)						
Univariate								
Analysis 1(a)		0.94	1.01	1.00	0.03	-0.03	-0.02	x
Analysis 1(b)		1.25	1.01	1.00	1.02	-0.03	0.16	x
Analysis 2(a)		1.47	1.33	0.97	0.49	1.43	0.49	1.10
Analysis 2(b)		1.47	1.33	0.97	0.49	1.02	0.39	0.92
Analysis 3(a)		2.22 *	1.75	0.87	0.52	0.70	0.42	-0.59
Analysis 3(b)		2.22 *	1.75	0.87	0.52	1.47	1.54	1.36
Multivariate (*i*)								
Analysis 4(a)		-0.37	0.50	1.44	0.38	1.34	2.22 *	2.12 *
Analysis 4(b)		1.30	0.88	0.97	0.46	1.83	0.74	0.31

Table 5.3 (continued)

(c) PT and χ^2 tests: one-month ahead prediction (Italian Lira)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		Correct Direction (PT test) [b]						
AR(1)	1.63							
MA(1)	2.14 *							
Univariate								
Analysis 1(a)		2.08 *	2.08 *	2.08 *	1.71	1.41	0.38	x
Analysis 1(b)		2.11 *	2.08 *	2.08 *	1.67	1.41	1.54	x
Analysis 2(a)		1.45	1.45	1.71	1.71	1.71	1.71	1.41
Analysis 2(b)		1.45	1.45	1.71	1.71	1.67	1.45	1.49
Analysis 3(a)		1.41	1.45	1.71	1.71	1.19	1.85	1.63
Analysis 3(b)		1.41	1.45	1.71	1.71	1.89	1.81	1.67
Multivariate (*i*)								
Analysis 4(a)		2.45 *	2.24 *	2.02 *	2.02 *	2.58 *	2.36 *	2.84*
Analysis 4(b)		1.71	1.49	1.54	1.06	2.56 *	1.93	1.93
		Correct Direction (χ^2 test) [c]						
AR(1)	2.62							
MA(1)	4.53 *							
Univariate								
Analysis 1(a)		4.25 *	4.25 *	4.25 *	2.88	1.96	0.14	x
Analysis 1(b)		4.38 *	4.25 *	4.25 *	2.74	1.96	2.35	x
Analysis 2(a)		2.07	2.07	2.88	2.88	2.88	1.96	2.88
Analysis 2(b)		2.07	2.07	2.88	2.88	2.74	2.07	2.20
Analysis 3(a)		1.96	2.07	2.88	2.88	1.40	3.38	2.62
Analysis 3(b)		1.96	2.07	2.88	2.88	3.51	3.24	2.74
Multivariate (*i*)								
Analysis 4(a)		5.92 *	4.93 *	4.04 *	4.04 *	6.59 *	5.51 *	7.95 *
Analysis 4(b)		2.88	2.01	2.35	1.11	6.44 *	3.66	3.66

models are no worse than the MA(1) model. Based on the correct direction criterion, some RBF models are no worse than the AR(1) or MA(1) model.

5.4.1.1 Univariate analyses

Analysis 1(a): No rescaling of inputs / no regularization term / Lag length equal to one.

The three localized RBF models that are better than other RBF models are worse than the MA(1) model based on the RMSE criterion, but are similar to the MA(1) model in predicting the correct direction.

Analysis 1(b): No rescaling of inputs / no regularization term / Lag length selected from one to three lags by minimizing the BIC value.

Comparing the results with those of analysis 1(a), based on the average RMSE criterion, only the MRBF and CCRBF models improve because only these models select more lagged values as inputs. Most of the other models still select one lagged value as an input. Even the CCRBF model predicts similarly to the MA(1) model. However, it does not predict the direction as well as most of the other models.

Analysis 2(a): No rescaling of inputs / regularization term / Lag length equal to one.

Comparing the results with those of analysis 1(a), based on the average RMSE and average correct direction criteria, only the LRBF, CCRBF, and QRBF models improve slightly. However, all RBF models are worse than the MA(1) model.

Analysis 2(b): No rescaling of inputs / regularization term / Lag length selected from one to three lags by minimizing the BIC value.

The results are similar to those of analysis 2(a). This is because, except for the LRBF model, all RBF models select one lagged value as input.

Analysis 3(a): Rescaling of inputs / regularization term / Lag length equal to one.

Comparing the results with those of analysis 2(a), based on the average RMSE and average correct direction criteria, most RBF models are similar to those of analysis 2(a).

Analysis 3(b): Rescaling of inputs / regularization term / lag length selected from one to three lags by minimizing the BIC value.

The LRBF, CCRBF, and QRBF models are better than those of analysis 3(a), based on the RMSE criterion. Other RBF models do not change because they still select one lagged value as input.

5.4.1.2 Multivariate analyses

Data for the Italian short-term interest rate are not available for some months of the relevant research period. Therefore, only results using long-term interest rates are discussed below.

Analysis 4(a): Long-term interest rate differential (LR1) / Lag length equal to three.

The long-term interest rate used for estimation for Italy is the yield on long-term government bonds and for the U.S. it is the yield on 10-year Treasury notes.

Based on both evaluation criteria, all the RBF models generally improve compared with their corresponding univariate RBF models using three lagged values as inputs (see Table D.32 in Appendix D for reference). Furthermore, most of the RBF models predict the correct direction better than the MA(1) model. The results also show that the CCRBF and QRBF models are competitive with the MA(1) model.

Analysis 4(b): Long-term interest rate differential (LR1) / Lag length selected from one to three lags by minimizing the BIC value.

The same data is used as in analysis 4(a). Based on the average RMSE criterion, except for the GRBF, CRBF, and MRBF models, the forecasting results of for RBF models are worse than those obtained in analysis 4(a). None of the RBF models is better than the MA(1) model.

Based on the average correct direction criterion, almost all RBF models are worse than those of their corresponding RBF models in analysis 4(a).

5.4.2 Statistical hypothesis tests

All the models discussed above are investigated together.

- ***MDM test***

(1) Only the CCRBF model in analyses 3(b) and 4(a) are significantly different from the random walk model at the 5% level. The QRBF model in analysis 4(a) may be significantly different from the random walk model at the 5% level (because the MDM statistic value is near the critical value threshold). The AR(1), MA(1), and all other univariate and multivariate RBF models are not significantly different from the random walk model at the 5% level.

(2) Only the GRBF, CRBF, IRBF models in analyses 3(a)-(b), the LRBF, CCRBF, QRBF models in analyses 2(a)-3(b), and all RBF models in the multivariate analyses 4(a)-(b) are *not* significantly different from the MA(1) model at the 5% level.

(3) Only the GRBF models in analysis 3(a)-(b), and the CCRBF and QRBF models in analysis 4(a) are significantly different from the AR(1) model at the 5% level. All other univariate and multivariate RBF models are not significantly different from the AR(1) model at the 5% level.

- ***PT and χ^2 independence tests***

The results of the PT and χ^2 independence tests are consistent. The GRBF, CRBF and IRBF models in analyses 1(a)-(b), all RBF models in analysis 4(a), the LRBF model in analysis 4(a)-(b), and the MA(1) model reject the null hypothesis that the given model is of no value in predicting the correct direction. That is, these models can predict the correct direction with statistical significance at the 5% level. The AR(1) and all other RBF models do not reject this null hypothesis.

5.4.3 Conclusions of univariate and multivariate analyses

The following conclusions are derived after considering the statistical hypothesis tests.

(1) Rescaling the input seems to be unnecessary for most of the univariate RBF models except for the CCRBF model in analysis 3(b), which is statistically different from the random walk model based on the MDM test.

(2) Adding a regularization term in the cost function does not seem to result in much improvement in predicting the correct direction when using univariate localized RBF models.

(3) In a comparison of the results of univariate RBF models using one lagged value as input with those of the AR(1) model, almost all RBF models are no worse than the AR(1) model based on the RMSE criterion. However, the GRBF model in analysis 3(a) is significantly different from the AR(1) model based on the MDM test. Based on the correct direction criterion, some RBF models are generally no worse than the AR(1) model. However, according to the direction tests, only the GRBF, CRBF and IRBF models in analysis 1(a) can predict the correct direction with statistical significance and are better than the AR(1) model.

(4) The random walk model is worse than all other models based on the descriptive average RMSE criterion. Only the CCRBF models in analyses 3(b) and 4(a) (and probably the QRBF model in analysis 4(a)) are significantly different from the random walk model at

the 5% level. However, these three models are not significantly different from the MA(1) model at the 5% level.

(5) Only the MA(1) model, the univariate localized RBF models using one lagged value as input, and the multivariate RBF models with lag length equal to three can predict the correct direction with statistical significance.

(6) The multivariate CCRBF and QRBF models that include three lagged values of the long-term interest rate as inputs are no worse than the MA(1) model based on descriptive average RMSE and average correct direction criteria. It seems that the long-term interest rate may have more explanatory power in predicting the correct direction than in predicting the point forecasts, because all multivariate RBF models using long-term interest rates as economic variables reject the null hypothesis that the given model is of no value in predicting the correct direction.

CHAPTER 6. EMPIRICAL RESULTS USING QUARTERLY DATA

This chapter discusses one-quarter-ahead forecasting results for three exchange rates: the German Mark, the Japanese Yen, and the Italian Lira related to US$. Only multivariate RBF models are estimated. For each time period, the results of the estimated multivariate RBF models are compared with those of a random walk model and a corresponding forward rate. The economic variables used are short-term and long-term interest rates, and the money supply.

For each exchange rate, two types of multivariate analysis are undertaken. Analysis I examines the RBF models with eight lagged values of own exchange rate and long-term or short-term interest rates as inputs. Analysis II investigates the RBF models with eight lagged values of the money supply as additional inputs. The results of using different input lag lengths are also investigated. Since quarterly data are used for estimation, a two year (eight quarter) period of input lagged values are usually investigated. After trying different lag lengths, it was found that RBF models using eight lagged values of each input variable generally have the best model explanatory power. For most of the empirical RBF models, the number of parameters which are the weights connecting hidden-layer and output-layer are fewer than the number of inputs. Therefore, unless otherwise indicated, the RBF models below use eight lagged values for each input variable.

In general, seven types of RBF models are compared in each analysis. However, if a RBF model does not fit the data well in some time period, then its results are not discussed. A regularization term is used in the cost function for all RBF models of the three exchange rates.

The three criteria used to evaluate out-of-sample forecasting performance are RMSE, correct direction, and speculative direction. All RBF models are compared with the random walk model based on the RMSE and speculative direction criteria. In addition, all RBF models are compared with the forward rate forecast based on the RMSE and correct direction criteria. These evaluations are based mostly on the *average* forecasting results obtained over six sliding window time periods. The model description and results for individual time periods are provided in Appendix E for further reference.

In addition, some statistical hypothesis tests of these three evaluation criteria are conducted. The MDM test is used to check whether the difference in mean squared error (MSE) for two models is statistically significant. Each RBF model is compared with a random walk model and with a forward rate forecast. Two direction tests (PT test and χ^2 independence test) are applied to the correct direction and speculative direction criteria to investigate whether the given model can predict the relevant direction of change with statistical significance.

The following discussion first compares the forecasting results obtained for different models making use of the three descriptive evaluation criteria, and then investigates the statistical significance of these descriptive criteria by conducting statistical hypothesis tests. At the end of this discussion, summary conclusions are provided for each exchange rate.

As mentioned in chapter 4, different widths r are examined for the GRBF, CRBF, IRBF, and MRBF models. In the following discussion, only RBF models using a specific width that generally perform well across the six sliding window time periods are chosen for discussion. However, in order to make sure that the residuals of the models are white noise, the RBF models chosen for discussion may have different width value for each time period.

6.1 German Mark

The results of the following analyses are summarized in the Table 6.1(a)-(c) on the following pages. In total 56 multivariate RBF models investigated.

6.1.1 Model comparisons using three descriptive criteria

In the following four analyses, the residuals of the MRBF, LRBF, CCRBF, and QRBF models are not white noise in some periods. However, their results are included in Table 6.1(a) for reference.

As detailed further below, based on the average correct direction criterion, all RBF models generate better forecasts than the forward rate. Based on the average speculative direction criterion, however, all RBF models generate worse forecasts than the random walk model.

Based on the average RMSE criterion, all localized RBF (GRBF, CRBF, and IRBF) models generate better forecasts than the random walk model and the forward rate. On the other hand, almost all nonlocalized RBF (MRBF, LRBF, CCRBF, and QRBF) models generate worse forecasts than the random walk model, and most of them also generate worse forcasts than the forward rate.

In general, localized RBF models perform better than the nonlocalized RBF models based on the three descriptive evaluation criteria.

Table 6.1 Descriptive evaluation criteria and hypothesis tests (Quarterly German mark)

(a) Descriptive evaluation criteria: one-quarter-ahead prediction (German mark)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		Average RMSE						
Random Walk	0.0441							
Forward	0.0451							
Multivariate I (i)								
Analysis 1(a)		0.0368	0.0389	0.0396	[0.0465]	[0.0433]	[0.0447]	[0.0445]
Analysis 1(b)		0.0398	0.0389	0.0383	[0.0482]	[0.0446]	[0.0477]	[0.0441]
Analysis 2(a)		0.0410	0.0427	0.0426	[0.0446]	[0.0482]	[0.0533]	[0.0460]
Analysis 2(b)		0.0406	0.0412	0.0420	[0.0458]	[0.0452]	[0.0502]	[0.0449]
Multivariate II ($i+M1$)								
Analysis 3(a)		0.0416	0.0388	0.0400	x	x	x	[0.0472]
Analysis 3(b)		0.0398	0.0377	0.0402	x	x	[0.0486]	[0.0479]
Analysis 4(a)		0.0428	0.0403	0.0415	x	x	x	[0.0500]
Analysis 4(b)		0.0419	0.0404	0.0419	x	x	x	[0.0524]
		Average Correct Direction (% of accuracy)						
Forward	0.25							
Multivariate I (i)								
Analysis 1(a)		0.71 *	0.67 *	0.67 *	[0.46]	[0.46]	[0.50]	[0.54]
Analysis 1(b)		0.63 *	0.63 *	0.71 *	[0.42]	[0.46]	[0.50]	[0.46]
Analysis 2(a)		0.67 *	0.67 *	0.63 *	[0.67] *	[0.38]	[0.58]	[0.54]
Analysis 2(b)		0.54	0.67 *	0.58	[0.42]	[0.50]	[0.50]	[0.67] *
Multivariate II ($i+M1$)								
Analysis 3(a)		0.63 *	0.67 *	0.58	x	x	x	[0.42]
Analysis 3(b)		0.63 *	0.67 *	0.58	x	x	[0.42]	[0.42]
Analysis 4(a)		0.58	0.67 *	0.63 *	x	x	x	[0.46]
Analysis 4(b)		0.54	0.67 *	0.63 *	x	x	x	[0.33]

Note: x indicates that the relevant model does not fit the data well in some time periods, hence the results for the model are not shown.

'[ ]' indicates that the residuals of MRBF, LRBF, CCRBF and QRBF are not white noise in some time periods.

[a] Reject the null hypothesis of equal mean squared error if the absolute value of the test statistic is greater than $t_{(23,0.025)} \approx 2.069$.

[b] Reject the null hypothesis of independence if the test statistic value is greater than $N(0,1)=1.96$;

[c] Reject the null hypothesis of independence if the test statistic value is greater than $\chi^2_{(1,0.05)} = 3.841$

* Significant at the 5% level.

Table 6.1(a) (continued)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		Average Speculative Direction (% of accuracy)						
Random walk	0.79 *							
Multivariate I (i)								
Analysis 1(a)		0.71 *	0.63	0.71 *	[0.50]	[0.54]	[0.46]	[0.54]
Analysis 1(b)		0.67	0.63	0.67 *	[0.42]	[0.42]	[0.46]	[0.54]
Analysis 2(a)		0.63 *	0.67 *	0.67 *	[0.63]	[0.42]	[0.63]	[0.58]
Analysis 2(b)		0.58	0.71 *	0.58	[0.54]	[0.50]	[0.50]	[0.58]
Multivariate II $(i+M1)$								
Analysis 3(a)		0.54	0.63	0.67 *	x	x	x	[0.50]
Analysis 3(b)		0.58	0.75 *	0.71 *	x	x	[0.54]	[0.42]
Analysis 4(a)		0.58	0.58	0.67 *	x	x	x	[0.42]
Analysis 4(b)		0.54	0.58	0.63 *	x	x	x	[0.33]

(b) MDM test: one-quarter-ahead prediction (German mark)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		MSE(MDM test) [a]						
		(1) compared with Random Walk						
Forward	-0.42							
Multivariate I (i)								
Analysis 1(a)		1.30	1.52	1.23	[-0.26]	[0.20]	[-0.20]	[0.05]
Analysis 1(b)		0.72	1.04	1.07	[-0.45]	[0.10]	[-0.87]	[0.18]
Analysis 2(a)		0.89	0.72	0.39	[-0.07]	[-0.54]	[-1.15]	[-0.50]
Analysis 2(b)		0.69	0.88	0.37	[-0.19]	[-0.03]	[-1.18]	[0.01]
Multivariate II $(i+M1)$								
Analysis 3(a)		0.48	1.68	1.03	x	x	x	[-0.41]
Analysis 3(b)		1.05	1.50	0.77	x	x	[-0.71]	[-0.86]
Analysis 4(a)		0.39	1.13	0.78	x	x	x	[-0.76]
Analysis 4(b)		0.51	1.13	0.73	x	x	x	[-0.94]
		(2) compared with Forward Rate						
Multivariate I (i)								
Analysis 1(a)		1.48	1.73	1.41	[-0.21]	[0.29]	[-0.12]	[0.17]
Analysis 1(b)		0.83	1.18	1.21	[-0.39]	[0.18]	[-0.74]	[0.32]
Analysis 2(a)		1.04	0.89	0.51	[0.00]	[-0.49]	[-1.11]	[-0.34]
Analysis 2(b)		1.01	0.48	-0.11	[0.04]	[0.15]	[-1.14]	[0.15]
Multivariate II $(i+M1)$								
Analysis 3(a)		0.58	1.82	1.15	x	x	x	[-0.34]
Analysis 3(b)		1.16	1.66	0.89	x	x	[-0.67]	[-0.74]
Analysis 4(a)		0.50	1.28	0.92	x	x	x	[-0.74]
Analysis 4(b)		0.62	1.28	0.86	x	x	x	[-0.92]

Table 6.1 (continued)

(c) PT and χ^2 tests: one-quarter-ahead prediction (German mark)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
				(1) Correct Direction (PT test)[b]				
Forward	-1.67							
Multivariate I(i)								
Analysis 1(a)		3.21 *	2.65 *	2.65 *	[0.43]	[0.46]	[0.85]	[1.26]
Analysis 1(b)		2.15 *	2.15 *	3.21 *	[0.00]	[0.00]	[0.83]	[0.42]
Analysis 2(a)		2.89 *	2.65 *	2.15 *	[2.54] *	[-0.42]	[1.69]	[1.29]
Analysis 2(b)		1.38	2.89 *	1.69	[0.00]	[0.85]	[0.85]	[2.54] *
Multivariate II $(i+M1)$								
Analysis 3(a)		2.57 *	2.65 *	1.77	x	x	x	[0.00]
Analysis 3(b)		2.29 *	2.65 *	1.69	x	x	[0.00]	[0.00]
Analysis 4(a)		1.77	2.89 *	2.29 *	x	x	x	[0.42]
Analysis 4(b)		1.38	2.89 *	2.57 *	x	x	x	[-0.85]
				(2) Correct Direction (χ^2 test)[c]				
Forward	2.67							
Multivariate I(i)								
Analysis 1(a)		9.88 *	6.75 *	6.75 *	[0.18]	[0.20]	[0.69]	[1.52]
Analysis 1(b)		4.44 *	4.44 *	9.88 *	[0.00]	[0.00]	[0.67]	[0.17]
Analysis 2(a)		8.00 *	6.75 *	4.44 *	[6.17] *	[0.17]	[2.74]	[1.60]
Analysis 2(b)		1.82	8.00 *	2.74	[0.00]	[0.69]	[0.69]	[6.17] *
Multivariate II $(i+M1)$								
Analysis 3(a)		6.32 *	6.75 *	3.00	x	x	x	[0.00]
Analysis 3(b)		5.04 *	6.75 *	2.74	x	x	[0.00]	[0.00]
Analysis 4(a)		3.00	8.00 *	5.04 *	x	x	x	[0.17]
Analysis 4(b)		1.82	8.00 *	6.32 *	x	x	x	[0.69]
				(1) Speculative Direction (PT test)[b]				
Random Walk	2.93 *							
Multivariate I(i)								
Analysis 1(a)		2.66 *	1.48	2.19 *	[0.11]	[0.50]	[-0.35]	[0.42]
Analysis 1(b)		1.71	1.34	2.03 *	[-0.73]	[-0.76]	[-0.35]	[0.42]
Analysis 2(a)		2.06 *	2.03 *	2.03 *	[1.34]	[-0.77]	[1.26]	[0.87]
Analysis 2(b)		1.11	2.66 *	0.97	[0.50]	[0.11]	[0.19]	[0.97]
Multivariate II $(i+M1)$								
Analysis 3(a)		1.39	1.69	2.03 *	x	x	x	[0.11]
Analysis 3(b)		1.74	2.95 *	2.19 *	x	x	[0.50]	[-0.80]
Analysis 4(a)		1.74	1.74	2.36 *	x	x	x	[-0.80]
Analysis 4(b)		1.39	1.74	2.06 *	x	x	x	[-1.64]
				(2) Speculative Direction (χ^2 test)[c]				
Random Walk	8.22 *							
Multivariate I(i)								
Analysis 1(a)		6.77*	2.10	4.61 *	[0.01]	[0.24]	[0.12]	[0.17]
Analysis 1(b)		2.82	1.73	3.96 *	[0.51]	[0.55]	[0.12]	[0.17]
Analysis 2(a)		4.06 *	3.96 *	3.96 *	[1.73]	[0.55]	[1.51]	[0.73]
Analysis 2(b)		1.19	6.77 *	0.91	[0.24]	[0.01]	[0.04]	[0.91]
Multivariate II $(i+M1)$								
Analysis 3(a)		1.85	2.74	3.96 *	x	x	x	[0.01]
Analysis 3(b)		2.90	8.36 *	4.61 *	x	x	[0.24]	[0.62]
Analysis 4(a)		2.90	2.90	5.34 *	x	x	x	[0.62]
Analysis 4(b)		1.85	2.90	4.06 *	x	x	x	[2.59]

6.1.1.1 ***Multivariate analysis I*** *: using an interest rate as the economic variable*

Analysis 1(a): Long-term interest rates differential (LR1). / Lag length equal to eight.

The long-term interest rate used for estimation for Germany is the yield on public sector bonds (7-15 years), and for the U.S. it is the yield on 10-year Treasury notes.

Overall, the GRBF model is better than most other models based on all three evaluation criteria.

Analysis 1(b): Long-term interest rate differential (LR2). / Lag length equal to eight.

The long-term interest rate used for estimation for Germany is the yield on the public sector bonds (more than three years), and for the U.S. it is the yield on the 10-year Treasury notes.

Based on the average RMSE criterion, most of the RBF models perform no better than the corresponding RBF models in analysis 1(a). The *average* forecasting results of the best three models (GRBF, CRBF, and IRBF) are competitive with those of the corresponding RBF models in analysis 1(a). Also, except for the IRBF model, the RBF models do not improve in terms of forecasting the correct direction and the speculative direction. Based on all three evaluation criteria, the IRBF model shows better overall performance than most of other RBF models.

Analysis 2(a): Short-term interest rate differential (SR1). / Lag length equal to eight.

The short-term interest rate used for estimation for Germany is the call money rate and for the U.S. it is the Federal funds rate.

The best three RBF models (GRBF, CRBF, and IRBF) are generally no better than the corresponding RBF models using long-term interest rates as inputs in analysis 1(a).

Analysis 2(b): Short-term interest rate differential (SR2). / Lag length equal to eight.

The short-term interest rate used for estimation for Germany is again the call money rate and for the U.S. it is now the 3-month Treasury bill rate.

The GRBF, CRBF, and IRBF models are slightly better than the corresponding RBF models in analysis 2(a). Based on the two direction criteria, the GRBF and IRBF models are worse than the corresponding RBF models in analysis 2(a).

6.1.1.2 Multivariate analysis II : using an interest rate and the money supply (M1) as economic variables.

Similar to the findings in analyses 1(a)-2(b), the residuals of the nonlocalized MRBF, LRBF, CCRBF, and QRBF models in some periods are not white noise. Furthermore, the MRBF, LRBF, CCRBF models forecast poorly in the first period because of overfitting the data. Therefore, the following results generally only compare the GRBF, CRBF, and IRBF models (with the QRBF model listed only for reference) with the corresponding RBF models in analyses 1(a)-2(b) to see whether the inclusion of the money supply as input variable can improve on forecasting. Moreover, these three models are also compared with the corresponding RBF models in analyses 1(a) and 1(b), which so far generally forecast best based on the descriptive RMSE and direction criteria.

Analysis 3(a) : Long-term interest rate differential (LR1) / M1 differential / Lag length equal to eight.

The same interest rates are used as in analysis 1(a). The GRBF and IRBF models are worse than the corresponding models in analysis 1(a) based on the average RMSE, correct direction and speculative direction criteria. The CRBF model is similar to its corresponding

CRBF model in analysis 1(a). Even the average forecasting results are similar. However, the results of each individual time period are different. Overall, it seems that the money supply does not help improve on forecasting.

Analysis 3(b) : Long-term interest rate differential (LR2) / M1 differential / Lag length equal to eight.

The same interest rates are used as in analysis 1(b). Compared with analysis 1(b), the GRBF and IRBF models generally do not improve. Nevertheless, the CRBF model improves ,especially based on the average RMSE and speculative direction criteria. Overall, this CRBF model is competitive with the GRBF model in analysis 1(a) and the IRBF model in analysis 1(b), which both only use long-term interest rates as the economic variable.

Analysis 4(a) : short-term interest rates differential (SR1) / M1 differential / Lag length equal to eight.

The same interest rates are used as in analysis 2(a). Compared with analysis 2(a), the three localized RBF models generally do not improve in forecasting, except that the CRBF and IRBF models improve based on the average RMSE criterion. Overall, the forecasting results are no better than those obtained for the models in analyses 3(a) and 3(b).

Analysis 4(b) : Short-term interest rate differential (SR2) / M1 differential / Lag length equal to eight.

The same interest rates are used as in analysis 2(b). Compared with analysis 2(b), the three localized RBF models generally do not improve in forecasting except that the CRBF model improved based on the RMSE criterion and the IRBF model improves based on the two direction criteria. Overall, the general forecasting results are no better than those obtained for the corresponding models in analyses 3(a) and 3(b).

6.1.2 Statistical hypothesis tests

All the models discussed above are investigated together.

- ***MDM test***

(1) The forward rate and all multivariate RBF models are not significantly different from the random walk model at the 5% level.

(2) No multivariate RBF model is significantly different from the forward rate model at the 5% level.

- ***PT and χ^2 independence tests***

The results of the PT and χ^2 independence tests are consistent.

(1) Correct direction: the CRBF models in all analyses, the GRBF models in analyses 1(a)-2(a), 3(a)-(b), the IRBF models in analyses 1(a)-2(a), 4(a)-(b), the MRBF model in analysis 2(a), and the QRBF model in analysis 2(b) all reject the null hypothesis that the given model is of no value in predicting the correct direction, implying that these models can predict the correct direction with statistical significance at the 5% level. The forward rate and all other RBF models do not reject the null hypothesis.

(2) Speculative direction: the random walk model, the IRBF models in all analyses except in analysis 2(b), the GRBF models in analyses 1(a) and 2(a), and the CRBF models in analyses 2(a)-(b) and 3(b) all reject the null hypothesis that a given model is of no value in predicting the speculative direction, implying that these models can predict the speculative

direction with statistical significance at the 5% level. All other RBF models do not reject the null hypothesis.

6.1.3 Conclusions of multivariate analyses I and II

The following conclusions are derived after considering the statistical hypothesis tests.

(1) Overall, based on all three descriptive evaluation criteria, and using only interest rates as economic variables, the localized GRBF, CRBF, and IRBF models are better than nonlocalized RBF models. Also, these localized RBF models are better than the random walk model and the forward rate based on the descriptive average RMSE or correct direction criteria. However, the MDM tests indicate that there is no significant difference of mean squared error between the RBF model and the random walk model or the forward rate. Also, the direction hypothesis tests indicate that almost all the localized GRBF, CRBF, IRBF models can predict the correct direction with statistical significance and confirm that the forward rate forecast cannot predict the correct direction with statistical significance. Furthermore, based on the average speculative direction criterion, all RBF models are worse than the random walk model. However, the direction hypothesis tests indicate that some of the localized RBF models can predict the speculative direction with statistical significance.

(2) The localized RBF models using a long-term interest rate as the economic variable seem to possess better explanatory power than the corresponding models using a short-term interest rate as the economic variable, especially based on the average RMSE criterion. The GRBF model in analysis 1(a) and the IRBF model in analysis 1(b), which use long-

term interest rates as economic variables, forecast better than most other models based on all three criteria.

(3) The RBF models using a short-term interest rate and M1 as the economic variables generally do not forecast better than the corresponding RBF models using a long-term interest rate and M1 as the economic variables.

(4) The CRBF model discussed in analysis 3(b), which uses a long-term interest rate and M1 as the economic variables, seems to be competitive with these RBF models that use only a long-term interest rate as an economic variable. Most of the other RBF models using the additional M1 variable do not seem to improve on forecasting, however, which casts doubt whether M1 helps to forecast the movement of the German Mark exchange rate. Moreover, based on the average speculative direction criterion, all of the multivariate RBF models perform worse than the random walk model.

(5) The forward rate is generally worse than the random walk and most of the multivariate RBF models based on either the average RMSE or the correct direction criteria. However, the MDM tests indicate that there is no significant difference of mean squared error between the forward rate and the RBF model or between the forward rate and the random walk model. The PT and χ^2 direction tests confirm that the forward rates cannot predict the speculative direction with statistical significance.

6.2 Japanese Yen

The results of the following analyses are summarized in Tables 6.2(a)-(c) on following pages. In total, 49 multivariate RBF models are investigated.

Table 6.2 Descriptive evaluation criteria and hypothesis tests (Quarterly Japanese yen)
(a) Descriptive evaluation criteria: one-quarter-ahead prediction (Japanese yen)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		Average RMSE						
Random walk 0.0680								
Forward	0.0673							
Multivariate I (i)								
Analysis 1(a)		0.0630	0.0618	0.0641	0.0617	[0.0625]	[0.0629]	[0.0634]
Analysis 1(b)		0.0624	0.0633	0.0624	[0.0604]	[0.0643]	[0.0646]	[0.0592]
Analysis 2(a)		0.0545	0.0536	0.0565	0.0536	0.0539	x	0.0491
Analysis 2(b)		0.0602	0.0568	0.0584	0.0556	0.0580	0.0547	0.0540
Multivariate II $(i+M1)$								
Analysis 3(a)		0.0618	0.0619	0.0607	0.0651	[0.0620]	0.0757	0.0624
Analysis 4(a)		0.0588	0.0590	x	0.0582	[0.0606]	0.0562	0.0548
Analysis 4(b)		0.0566	0.0605	0.0584	0.0575	[0.0574]	[0.0558]	[0.0572]
		Average Correct Direction (% of accuracy)						
Forward	0.58							
Multivariate I (i)								
Analysis 1(a)		0.58	0.58	0.58	0.58	[0.67]	[0.63]	[0.75] *
Analysis 1(b)		0.71 *	0.63	0.67	[0.71] *	[0.58]	[0.83] *	[0.75] *
Analysis 2(a)		0.67	0.75 *	0.63	0.71 *	0.71 *	x	0.67
Analysis 2(b)		0.63	0.67	0.67	0.67	0.67	0.75 *	0.63
Multivariate II $(i+M1)$								
Analysis 3(a)		0.67	0.63	0.71	0.58	[0.63]	0.67	0.75 *
Analysis 4(a)		0.54	0.63	x	0.67	[0.58]	0.75 *	0.71 *
Analysis 4(b)		0.63	0.67	0.63	0.67	[0.75] *	[0.67]	[0.67]
		Average Speculative Direction (% of accuracy)						
Forward 0.50								
Multivariate I (i)								
Analysis 1(a)		0.58	0.58	0.67	0.46	[0.63]	[0.67]	[0.58]
Analysis 1(b)		0.75 *	0.54	0.63	[0.58]	[0.54]	[0.71] *	[0.75] *
Analysis 2(a)		0.79 *	0.79 *	0.75 *	0.75 *	0.75 *	x	0.88 *
Analysis 2(b)		0.67	0.75 *	0.71 *	0.75 *	0.75 *	0.79 *	0.79 *
Multivariate II $(i+M1)$								
Analysis 3(a)		0.58	0.75 *	0.71 *	0.63	[0.67]	0.54	0.75 *
Analysis 4(a)		0.67	0.71 *	x	0.71 *	[0.67]	0.79 *	0.79 *
Analysis 4(b)		0.83 *	0.67	0.71 *	0.71 *	[0.71] *	[0.75] *	[0.71] *

Note: x indicates that the relevant model does not fit the data well in some time periods, hence the results for the model are not shown.
'[ ]' indicates that the residuals of its corresponding RBF model are not white noise in some time periods.
[a] Reject the null hypothesis of equal mean squared error if the absolute value of the test statistic is greater than $t(23, 0.025) \approx 2.069$.
[b] Reject the null hypothesis of independence if the test statistic value is greater than N(0,1)=1.96.
[c] Reject the null hypothesis of independence if the test statistic value is greater than $\chi_{(1,0.05)}^{2} = 3.841$.
* Significant at 5% level.
n.a. : Not available.

Table 6.2 (continued)

(b) MDM test: one-quarter-ahead prediction (Japanese yen)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
					MSE(MDM test)[a]			
					(1) compared with Random Walk			
Forward	-0.11							
Multivariate I (i)								
Analysis 1(a)		0.49	1.11	0.32	0.64	[0.67]	[1.29]	[0.56]
Analysis 1(b)		1.91	1.18	1.25	[0.99]	[0.93]	[1.09]	[1.74]
Analysis 2(a)		2.69 *	2.58 *	2.09 *	2.40 *	2.53 *	x	2.82 *
Analysis 2(b)		1.27	2.10 *	1.59	2.16 *	2.20 *	2.39 *	2.52 *
Multivariate II ($i+M1$)								
Analysis 3(a)		1.19	1.53	2.24	0.24	[1.56]	-1.08	1.32
Analysis 4(a)		1.49	2.12 *	x	4.91 *	[1.46]	1.55	2.70 *
Analysis 4(b)		2.04 *	1.46	2.37 *	2.55 *	[2.62] *	[1.86]	[2.37] *
					(2) compared with Forward Rate			
Multivariate I (i)								
Analysis 1(a)		0.82	1.71	0.54	0.95	[1.02]	[1.40]	[0.91]
Analysis 1(b)		1.68	1.86	1.80	[1.36]	[1.72]	[1.13]	[2.41] *
Analysis 2(a)		2.99 *	2.77 *	2.29 *	1.88	2.64 *	x	3.16 *
Analysis 2(b)		1.61	1.57	1.71	2.57 *	2.57 *	2.19 *	3.02 *
Multivariate II ($i+M1$)								
Analysis 3(a)		1.56	2.24 *	2.40 *	0.31	[1.98]	-3.28 *	1.17
Analysis 4(a)		1.49	2.04 *	x	4.50 *	[1.57]	1.70	2.75 *
Analysis 4(b)		3.38 *	4.21 *	2.38 *	2.72 *	[2.16] *	[1.77]	[2.72] *

Table 6.2 (continued)

(c) PT and χ^2 tests: one-quarter-ahead prediction (Japanese yen)

	Random Walk	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
			(1) Correct Direction (PT test) [b]						
Forward		0.00							
Multivariate I (i)									
Analysis 1(a)			0.26	0.26	0.26	0.26	[1.51]	[1.01]	[2.44]*
Analysis 1(b)			2.24*	0.96	1.50	[2.00]*	[0.38]	[3.29]*	[2.44]*
Analysis 2(a)			1.50	2.43*	1.01	1.97*	1.97*	x	1.50
Analysis 2(b)			0.95	1.57	1.50	1.50	1.50	2.72*	1.01
Multivariate II ($i+M1$)									
Analysis 3(a)			1.79	1.23	2.00	0.49	[0.95]	1.50	2.39*
Analysis 4(a)			0.08	1.01	x	1.50	[0.60]	2.39*	2.05*
Analysis 4(b)			1.01	1.47	1.01	1.09	[2.44]*	[1.57]	[1.47]
			(2) Correct Direction (χ^2 test) [c]						
Forward		n.a.							
Multivariate I (i)									
Analysis 1(a)			0.06	0.06	0.06	0.06	[2.19]	[0.97]	[5.71]*
Analysis 1(b)			4.80*	0.88	2.14	3.82*	0.14	[10.36]*	[5.71]*
Analysis 2(a)			2.14	5.66*	0.97	3.70*	3.70*	x	2.14
Analysis 2(b)			0.87	2.37	2.14	2.14	2.14	7.07*	0.97
Multivariate II ($i+M1$)									
Analysis 3(a)			3.05	1.46	3.82	0.23	0.87	[2.14]	5.49*
Analysis 4(a)			0.06	0.97	x	2.14	0.34	[5.49]*	4.03*
Analysis 4(b)			0.97	2.06	0.97	1.14	[5.71]*	[2.37]	[2.06]
			(1) Speculative Direction (PT test) [b]						
Random Walk	n.a.								
Multivariate I (i)									
Analysis 1(a)			0.88	0.88	1.93	-0.51	[1.38]	[1.69]	[0.88]
Analysis 1(b)			2.65*	0.46	1.26	[0.96]	[0.42]	[2.09]*	[2.54]*
Analysis 2(a)			2.93*	2.93*	2.54*	2.50*	2.54*	x	3.38*
Analysis 2(b)			1.93	2.50*	2.09*	2.65*	2.65*	3.38*	3.01*
Multivariate II ($i+M1$)									
Analysis 3(a)			0.96	2.54*	2.15*	1.29	[1.77]	0.43	2.54*
Analysis 4(a)			1.77	2.15*	x	2.09*	[1.77]	2.93*	2.93*
Analysis 4(b)			3.34*	1.77	2.15*	2.15*	[2.15]*	[2.54]*	[2.15]*
			Speculative Direction (χ^2 test) [c]						
Random Walk	n.a.								
Multivariate I (i)									
Analysis 1(a)			0.75	0.75	3.56	0.25	[1.82]	[2.74]	[0.75]
Analysis 1(b)			6.75*	0.20	1.51	[0.89]	[0.17]	[4.20]*	[6.17]*
Analysis 2(a)			8.22*	8.22*	6.17*	6.00*	6.17*	x	10.97*
Analysis 2(b)			3.56	6.00*	4.20*	6.75*	6.75*	10.97*	8.71*
Multivariate II ($i+M1$)									
Analysis 3(a)			0.89	6.17*	4.44*	1.60	[3.00]	0.18	6.17*
Analysis 4(a)			3.00	4.44*	x	4.20*	[3.00]	8.22*	8.22*
Analysis 4(b)			10.67*	3.00	4.44*	4.44*	[4.44]*	[6.17]*	[4.44]*

6.2.1 Model comparison using three descriptive criteria

The residuals of some of the nonlocalized RBF models in some time periods are not white noise. However, their results are included in Tables 6.2(a)-(c) for reference.As will now be described in detail, based on the three descriptive criteria: average RMSE, correct direction, speculative direction, almost all RBF models are no worse than the random walk model or the forward rate.

*6.2.1.1 **Multivariate analysis I:** Using interest rate as the economic variable.*

Analysis 1(a): Long-term interest rate differential (LR) / Lag length equal to eight.

The long-term interest rate used for estimation for Japan is the yield on central government bonds, and for the U.S. it is the yield on 10-year Treasury notes.

The MRBF model is worse than the random walk model in predicting the speculative direction. All other RBF models are no worse than the random walk model or the forward rate based on the three descriptive evaluation criteria,.

The LRBF, CCRBF, and QRBF models perform markedly better than most of the other RBF models based on the two direction criteria. However, the residuals of these models are not white noise.

Analysis 1(b): Long-term interest rate differential (LR) / Lag length equal to seven.

The same data is used as in analysis 1(a), but with seven lagged values of each input variable instead of eight.

Compare the forecasting results with those of analysis 1(a) based on the average RMSE criterion, except all RBF models except the GRBF, IRBF, MRBF, and QRBF models, perform worse than the corresponding models in analysis 1(a). In contrast, most of the RBF models improve on predicting the correct direction. Based on the average correct direction criterion, the CCRBF model performs best. The QRBF model is best based on the average RMSE and speculative direction criteria and is also good at predicting the correct direction. However, since the residuals of nonlocalized RBF models are not white noise in some time periods, the forecasting results of these models need to be interpreted with caution. Therefore, attention is focused on comparing the localized GRBF, CRBF, and IRBF models. The three localized RBF models generally perform better than the corresponding RBF models in analysis 1(a), especially in predicting the correct direction. The GRBF model performs well based on all three criteria.

Analysis 2(a): Short-term interest rate differential (SR1) / Lag length equal to eight.

The short-term interest rates used for estimation for Japan is the call money rate, and for the U.S. it is the Federal funds rate.

Compared with analysis 1(a), the results of almost all RBF models are generally better based on all three evaluation criteria. Compared with analysis 1(b), the results of almost all RBF models are especially better based on the RMSE and speculative direction criteria. The QRBF model is best based on the RMSE and correct direction criteria. Note that, in the 6^{th} time period, except for the IRBF and QRBF models, all RBF models are now better than the random walk model based on the RMSE criterion. Therefore, inclusion of a short-term interest rate as an input variable seems to improve on models using a long-term interest rate as input variable as in analyses 1(a) and 1(b).

Analysis 2(b): Short-term interest rate differential (SR2) / Lag length equal to eight.

The short-term interest rate used for estimation for Japan is the call money rate, and for the U.S. it is the three-month Treasury bill rate.

Compared with analysis 2(a), the results are slightly worse. However, the results are generally no worse than the results obtained with models using a long-term interest rate as input variable in analysis 1(a).

*6.2.1.2 **Multivariate analysis II** :Using interest rates and the money supply (M1) as economic variables*

<u>*Analysis 3(a)*</u> : Long-term interest rate differential (LR) / M1 differential / Lag length equal to eight.

The long-term interest rates are the same as in analysis 1(a). Compared with analysis 1(a), some models seem to improve in forecasting, especially in predicting the correct and speculative directions. The IRBF and QRBF models improve in forecasting based on all three criteria. The QRBF model is best in predicting the correct and speculative directions. However, when compared with models that only use short-term interest rates as inputs (i.e. those discussed in analysis 2(a)), the M1 variable does not appear to help much to improve on forecasting, especially based on the RMSE and speculative direction criteria.

<u>*Analysis 4(a)*</u> : Short-term interest rate differential (SR1) / M1 differential / Lag length equal to eight.

The interest rates are used are the same as in analysis 2(a). Except for some nonlocalized RBF models that improve on predicting the correct direction, the RBF models for this case perform worse than the corresponding models in analysis 2(a) based on all three descriptive criteria. Thus, except for helping some non-localized RBF models to predict the correct direction, the M1 variable does not appear to help in forecasting the Yen/US$ exchange rate, especially based on the RMSE and speculative direction criteria.

Analysis 4(b) : Short-term interest rate difference (SR2) / M1 differential / Lag length equal to eight

The interest rates used are the same as in analysis 2(b). The GRBF model ahows improved forecasting ability based on the RMSE and speculative direction criteria, and the LRBF and QRBF models shows improved ability to predict the correct direction. However, the other RBF models generally do not do no show any improvement in forecasting ability based on these three criteria. Furthermore, almost all RBF models perform worse than the corresponding models in analysis 2(b), which only use short-term interest rates as economic variables.

6.2.2 Statistical hypothesis tests

The models discussed above are investigated together.

- *MDM test*

(1) Most RBF models that include short-term interest rates as economic variables (analyses 2(a), 2(b) and 4(b)), together with the CRBF, MRBF and QRBF models in analysis 4(a), are significantly different from the random walk model at the 5% level. The forward rate and all multivariate RBF models that include long-term interest rates as economic variables (analyses 1(a)-(b) and 3(a)) are not significantly different from the random walk model at the 5% level.

(2) All RBF models that only use long-term interest rates as economic variables are not significantly different from the forward rate model at the 5% level. Most RBF models in

analyses 2(a) and 4(b), all nonlocalized RBF models in analysis 2(b), the CRBF, IRBF, LRBF, CCRBF models in analysis 3(a), and the CRBF, MRBF and QRBF models in analysis 4(a) are significantly different from the forward rate model at the 5% level.

- ***PT and χ^2 independence tests***

Except for the correct direction test of the IRBF model in analysis 3(a), the results of the PT and χ^2 independence tests are consistent.

(1) Correct direction: The forward rate and most of the RBF models in analyses 1(a), 2(b), and 3(a)-4(b) do not reject the null hypothesis that the given model is of no value in predicting the direction of exchange rate at the 5% level. Other RBF models such as GRBF, MRBF, CCRBF, and QRBF models in analysis 1(b) and the CRBF, MRBF and LRBF models in analysis 2(a) reject the null hypothesis that the given model is of no value in predicting the correct direction at the 5% level.

(2) Speculative direction: Almost all the RBF models in analyses 2(a), 2(b), 4(a) and 4(b), the GRBF, CCRBF, QRBF models in analysis 1(b), and the CRBF, IRBF and QRBF models in analysis 3(a) reject the null hypothesis that the given model is of no value in predicting the speculative direction at the 5% level. All other RBF models do not reject this null hypothesis.

6.2.3 Conclusions of Multivariate analysis I and II

The following conclusions are derived after considering the statistical hypothesis tests.

(1) Overall, almost all RBF models that include interest rates as economic variables are better than the random walk model, based on the average RMSE and speculative direction

criteria. The inclusion of interest rates thus seems to help explain exchange rate movements. Moreover, the short-term interest rate seems to help more in forecasting than the long-term interest rate.

(2) Comparing analyses 2(a) and 2(b) with analysis 1(a), the RBF models that use short-term interest rates as economic variables seem to have better forecasting ability than the corresponding RBF models that use long-term interest rates, especially when measured by the RMSE, correct direction, and the speculative direction criteria. Most of the RBF models discussed in analysis 2(a) perform better than the random walk model for all six sliding window periods based on the RMSE criterion.

(3) The hypothesis tests confirm that the best RBF models are those that use only short-term interest rates as economic variables, especially for Japan using the call money rate and the U.S. using the Federal funds rate. Overall, the inclusion of M1 does not seem to help explain the movement of the Yen/US$ exchange rate.

(4) All RBF models perform no worse than the forward rate based on the average RMSE and correct direction criteria.

6.3 Italian Lira

The results of the following analyses are summarized in Table 6.3(a)-(b) on the following pages. The short-term interest rate data for Italy are not complete for the early periods of this research time frame. Therefore, only long-term interest rates are investigated for the Italian Lira. In total, 14 multivariate RBF models are investigated.

Table 6.3 Descriptive evaluation criteria and hypothesis tests (Quarterly Italian lira)

(a) Descriptive evaluation criteria: one-quarter-ahead prediction (Italian lira)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
				Average RMSE				
Random walk	0.0414							
Forward	0.0445							
Multivariate I (i)								
Analysis 1		0.0383	0.04	0.0383	0.0454	[0.041	[0.0397	0.0386
Multivariate II $(i+M1)$								
Analysis 2		0.0409	0.039	0.0396	x	x	x	x
				Average Correct Direction (% of accuracy)				
Forward	0.41							
Multivariate I (i)								
Analysis 1		0.58	0.49	0.54	0.40	[0.40]	[0.58]	0.68 *
Multivariate II $(i+M1)$								
Analysis 2		0.54	0.60	0.63 *	x	x	x	x
				Average Speculative Direction (% of accuracy)				
Random walk	0.58							
Multivariate I (i)								
Analysis 1		0.68	0.68	0.68	0.53	[0.61]	[0.69]	0.82 *
Multivariate II $(i+M1)$								
Analysis 2		0.64	0.82 *	0.78 *	x	x	x	x

Note: x indicates that the relevant model does not fit the data well in some time periods, hence the results for the model are not shown.

'[ ]' indicates that the residuals of its corresponding RBF model are not white noise in some time periods.

[a] Reject the null hypothesis of equal mean squared error if the absolute value of the test statistic is greater than $t_{(21,0.025)} \approx 2.08$.

[b] Reject the null hypothesis of independence if the test statistic value is greater than N(0,1)=1.96.

[c] Reject the null hypothesis of independence if the test statistic value is greater than $\chi_{(1,0.05)}^2 = 3.841$.

* Significant at the 5% level.

n.a. Not available.

Table 6.3 (continued)

(b) MDM, PT and χ^2 tests: one-quarter-ahead prediction (Italian Lira)

		GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
		MSE (MDM test)[a]						
		(1) Compared with Random Walk						
Forward	-0.47							
Multivariate I (i)								
Analysis 1		1.18	0.73	0.82	-0.57	[0.18]	[0.64]	0.92
Multivariate II ($i+M1$)								
Analysis 2		0.70	0.85	0.79	x	x	x	x
		(2) Compared with Forward rate						
Multivariate I								
Analysis 1		2.33 *	1.85	1.90	-0.38	[0.91]	[1.67]	2.84 *
Multivariate II ($i+M1$)								
Analysis 2		1.45	4.22 *	3.59 *	x	x	x	x
		Correct Direction (PT test) [b]						
Forward	n.a.							
Multivariate I (i)								
Analysis 1		0.97	0.45	-0.54	0.82	[-0.42]	[1.45]	2.45 *
Multivariate II ($i+M1$)								
Analysis 2		0.82	1.88	2.17 *	x	x	x	x
		Correct Direction (χ^2 test) [c]						
Forward	n.a.							
Multivariate I (i)								
Analysis 1		0.90	0.20	0.28	0.65	[0.17]	[2.01]	5.71 *
Multivariate II ($i+M1$)								
Analysis 2		0.65	3.38	4.48 *	x	x	x	x
		Speculative Direction (PT test)[b]						
Random walk	0.00							
Multivariate I (i)								
Analysis 1		1.54	1.54	0.44	1.70	[1.19]	[1.70]	3.33 *
Multivariate II ($i+M1$)								
Analysis 2		1.08	3.11 *	2.52 *	x	x	x	x
		Speculative Direction (χ^2 test) [c]						
Random walk	n.a.							
Multivariate I (i)								
Analysis 1		2.26	2.26	0.19	2.76	[1.35]	[2.76]	10.54 *
Multivariate II ($i+M1$)								
Analysis 2		1.12	9.21 *	6.05 *	x	x	x	x

6.3.1 Model comparisons using three descriptive criteria

As explained in detail below, based on the three descriptive evaluation criteria, the RBF models generally perform no worse than the random walk model and the forward rate.

6.3.1.1 Multivariate analysis I: Using interest rates as economic variables.

Analysis 1: Long-term interest rates differential (LR) / Lag length equal to eight.

The long-term interest rate used for estimation for Italy is the yield on long-term government bonds and for the U.S. it is the yield on the 10-year Treasury notes.

Except for the MRBF and LRBF models, all RBF models perform better than the random walk model and the forward rate based on the three descriptive evaluation criteria. The forward rate is worse than the random walk model based on the RMSE criterion. Overall, the QRBF model performs best based on the correct and speculative direction criteria and second best based on the RMSE criterion.

6.3.1.2 Multivariate analysis II : Using interest rates and the money supply (M1) as economic variables.

Analysis 2 : Long-term interest rate differential (LR) / M1 differential / Lag length equal to eight.

The interest rates used are the same as in analysis 1. The MRBF, LRBF, CCRBF, and QRBF models do not fit the first sliding window time period data well. Therefore, the forecasting results are not shown here.

Compared with analysis 1, the GRBF model does not show improved forecasting ability based on any of the three descriptive evaluation criteria. However, the CRBF model does show improved forecasting ability based on all of these criteria. The IRBF model does not improve based on the RMSE criterion, but does improve based on the two direction criteria, especially the speculative direction criterion. It appears that the inclusion of M1 as an input variable may help in predicting the correct direction of the Lira/US$ exchange rate when using the localized RBF models. However, the QRBF model that only uses the long-term interest rate as an economic variable outperforms the localized RBF models that add M1 as an additional economic variable.

6.3.2 Statistical Hypothesis tests

The models discussed above are investigated together.

- ***MDM test***

(1) The forward rate and all RBF models are not significantly different from the random walk model at the 5% level.

(2) Only the GRBF and QRBF models in analysis 1 and the CRBF and IRBF models in analysis 2 are significantly different from the forward rate model at the 5% level.

- ***PT and χ^2 independence tests***

The results of the PT and χ^2 independence tests are consistent.

(1) Only the QRBF model in analysis 1 and the IRBF model in analysis 2 reject the null hypothesis that the given model is of no value in predicting the correct direction at the 5% level.

(2) Only the QRBF model in analysis 1 and the CRBF and IRBF models in analysis 2 reject the null hypothesis that the given model is of no value in predicting the speculative

direction at the 5% level.

6.3.3 Conclusions of Multivariate analysis I and II

The following conclusions are derived after considering the statistical hypothesis tests.

(1) Most RBF models that use long-term interest rates as economic variables forecast better than the random walk model and forward rate, based on each of the three descriptive evaluation criteria. However, the MDM tests indicate that the forecasts obtained using the RBF models are not significantly different from the forecasts obtained using the random walk model, although the forecasts from some of RBF models are significantly different from the forward rate forecasts.

(2) The forward rate forecasts are worse than the forecasts obtained using the random walk model, based on the RMSE criterion. However, the MDM tests indicate that the forward rate forecasts are not significantly different from the forecasts obtained using the random walk model.

(3) Overall, the QRBF model that use long-term interest rates as economic variables perform best based on the correct and speculative direction criteria, and second best based on the RMSE criterion. The direction tests show that this QRBF predict both correct and speculative directions with statistical significance.

(4) The CRBF and IRBF models that use long-term interest rates and M1 as economic variables perform similarly to the QRBF model using only long-term interest rates as economic variables, according to all hypothesis tests. Therefore, even though the inclusion of M1 helps some RBF models to forecast better, the effect appears to be small.

CHAPTER 7. SUMMARY OF FINDINGS

7.1 Findings for One-month-ahead Forecasting for All Three Exchange Rates

(1) Whether the input is rescaled or a regularization term is incorporated into the cost function does not seem to make much difference in forecasting for most of the univariate RBF models.

(2) For the German mark and Japanese yen: According to the results of all three hypothesis tests, all univariate RBF(k) models using the same number of inputs as the statistical AR(k) model forecast similarly to the AR(k) model. For the Italian lira, some univariate localized RBF(k) models are better than the AR(k) model based on the results of hypothesis tests.

(3) The univariate RBF analyses indicate that, except for the German mark RBF models in analysis 1(a),[1] most of the other RBF models using the BIC as the lag length selection criterion often choose the same lag length as the AR(k) model selected by using the AIC and SBC criteria. In addition, multivariate RBF models using a fixed number of lagged inputs of own exchange rate and interest rate as inputs generally have better forecasting results than their corresponding multivariate RBF models that may select different lag lengths by using the BIC criterion over six sliding-window time periods.

(4) For all three exchange rates, when forecast accuracy is measured by the descriptive average RMSE criterion, some of the RBF models are competitive with the MA(1) model and are better than the AR model. The random walk model is worse than all other

[1] These RBF models do not rescale the input and do not include a regularization term in the cost function.

models. For the German mark, only the MA(1) model is significantly different from the random walk model based on the MDM test. However, all RBF models and the AR(1) model are not significantly different from the MA(1) model based on the MDM test. Most of the RBF models are not significantly different from the AR(1) model by using the MDM test. For the Japanese yen, the MDM tests indicate that all RBF models are not significantly different from the random walk, MA(1), and AR(3) models. For the Italian lira, a few nonlocalized RBF models in some analyses are significantly different from the random walk model or the AR(1) model. However, these RBF models are not significantly different from the MA(1) model. See Table 7.1 for details.

Table 7.1 Summary of MDM tests based on the mean squared error

		Random walk	MA	AR
German mark	RBF	no	no	yes (LRBF, MRBF using one-lagged long-term interest rate as input)
	MA	yes	---	no
	AR	no	no	---
Japanese yen	RBF	no	no	no
	MA	no	---	yes
	AR	no	yes	---
Italian lira	RBF	yes (one univariate CCRBF model; and two multivariate CCRBF and QRBF models using three-lagged long-term interest rates as inputs)	1) yes (some univariate RBF models); 2) no (other models including the two multivariate CCRBF and QRBF models using three-lagged long-term interest rates as inputs)	yes (the two multivariate CCRBF and QRBF models using three-lagged long-term interest rates as inputs, and one univariate GRBF model)
	MA	no	---	yes
	AR	no	yes	---

Note: yes (no) indicates there is (there is not) a statistical difference in the mean squared error of the two models based on the MDM test.

(5) For the German mark, only a few RBF models investigated are significant in predicting the future direction. For the Japanese yen, no RBF models are significant in predicting the future direction. For the Italian lira, all multivariate RBF models and some univariate localized RBF models investigated are significant in predicting the correct direction. For all three exchange rates, the AR models are not significant in predicting the correct direction based on the direction tests. Except for the MA(1) model of the Italian lira, the MA(1) models of other exchange rates are not significant in predicting the correct direction based on the direction tests. See Table 7.2 for details.

Table 7.2 Summary of direction tests based on the "correct direction" criterion

	German mark	Japanese yen	Italian lira
RBF	yes (univariate IRBF, CCRBF and multivariate CCRBF using long-term and three-lagged short-term interest rates, and QRBF using three-lagged short-term interest rates as economic variables)	no	yes (all multivariate RBF models using three lagged long-term interest rates as economic variables; and three univariate localized RBF models)
MA	no	no	yes
AR	no	no	no

Note: yes (no) indicates that the model can (cannot) predict the correct direction with statistical significance based on two direction hypothesis tests

(6) For the German mark, the multivariate RBF models using one lagged value of the long-term interest rate are competitive with the MA(1) model based on the MDM test. However, they are not significantly different from the random walk model. Among all multivariate RBF models that use one lagged value of the long-term interest rate as economic input, only the CCRBF model can predict the direction with statistical significance. For the Japanese yen, adding three lagged values of the long-term interest

rates as explanatory variables generally does not appear to help predict point forecasts for most of the RBF models. They seem to help predict the direction better by using the localized RBF models, but this result is not statistically significant. For the Italian Lira, the CCRBF and QRBF models including three-lagged values of the long-term interest rate are no worse than the MA(1) model based on the average RMSE and average correct direction criteria. It seems that the long-term interest rate may have more explanatory power in predicting the correct direction of Italian lira, because all multivariate RBF models using three lagged values of long-term interest rates as economic variables can predict the direction with statistical significance.

(7) For the German mark, the multivariate RBF models including three lagged values of the short-term interest rates do not seem to improve on point forecasts. However, the CCRBF models[2] in analysis 5(c) and the QRBF models estimated in analyses 5(a) and 5(c) predict the direction with statistical significance. For the Japanese Yen, adding the short-term interest rate as an explanatory variables does not seem to improve forecasting performance beyond that of the univariate RBF models.

7.2 Findings for One-quarter-ahead Forecasting for All Three Exchange Rates

(1) For the German mark, forecasts from the localized GRBF, CRBF, and IRBF models using interest rates as economic variables are better than those from the random walk model or the forward rate based on the descriptive average RMSE or correct direction criteria. The localized RBF models using long-term interest rates as economic variables seem to have

[2] These RBF models all use three-lagged values of short-term interest rate.

better explanatory ability than the corresponding RBF models using short-term interest rates as economic variables, especially based on the average RMSE criterion.

However, the MDM tests indicate that there is no significant difference of mean squared error between the RBF model and the random walk model or forward rate. The direction hypothesis tests indicate that most of the localized RBF models can predict the correct direction with statistical significance. Furthermore, based on the descriptive average speculative direction criterion, all RBF models are worse than the random walk model. However, the hypothesis tests indicate that some of these localized RBF models can also predict the speculative direction with statistical significance.

(2) For the Japanese yen, almost all forecasts generated from the RBF models using interest rates as economic variables are better than those from the random walk model or forward rate based on three descriptive criteria. The short-term interest rate seems to help more in forecasting than the long-term interest rate. The three statistical hypothesis tests confirm that the best RBF models are those using only short-term interest rates, especially for Japan using the call money rate and the U.S. using the Federal funds rate as economic variables.

(3) For the Italian lira, most forecasts from the RBF models using long-term interest rates as economic variables are better than those from the random walk model or forward rate based on three descriptive criteria. However, the MDM tests indicate that all RBF models are not significantly different from the random walk model, and only some RBF models are significantly different from the forward rate forecast based on the mean squared error. Only the QRBF using the long-term interest rate, and the IRBF using the long-term

interest rate (with or without M1) can predict both the correct direction and the speculative direction with statistical significance.

(4) Table 7.3 summarizes (1), (2) and (3).

(5) The forward rate is generally worse than forecasts from the random walk model or RBF models based on the descriptive criteria. However, the MDM tests indicate that the forward rate forecast is not significantly different from the forecasts of the random walk model for all three exchange rates, and is significantly different from the forecasts of some RBF models of the Japanese yen and Italian lira only.

Table 7.3 Summaries of hypothesis tests

(a) Summary of MDM test based on the mean squared error[a]

		Random walk	Forward
German mark	RBF	no	no
	Forward	no	—
Japanese yen	RBF	yes [for most of multivariate RBF models including short-term interest rates (with or without M1) as inputs]	yes (for most of multivariate RBF models including short-term interest rates (with or without M1) as inputs; also few RBF models including both long-term interest rates and M1 as inputs)
	Forward	no	—
Italian lira	RBF	no	yes (GRBF and QRBF including long-term interest rates as inputs; CRBF and IRBF including long-term interest rates and M1 as inputs)
	Forward	no	—

[a] yes (no) indicates there is (there is not) a statistical difference in the mean squared error of the two models based on the MDM test.

[b] Note: yes (no) indicates that the model can (cannot) predict the correct direction with statistical significance based on two direction hypothesis tests.

[c] Note: yes (no) indicates that the model can (cannot) predict the speculative direction with statistical significance based on two direction hypothesis tests.

[d] The nonlocalized CCRBF and QRBF models only using long-term interest rates as economic variables also can predict the speculative direction with statistical significance, however, the residuals of these RBF models are not white noise.

Table 7.3 (continued)

(b) Summary of direction tests based on the 'correct direction' [b]

	German mark	Japanese yen	Italian lira
RBF	yes [most of localized RBF models using long-term and short-term interest rates (with or without M1) as economic variables; especially for the CRBF models in all analyses]	yes [some nonlocalized RBF models using short-term interest rates (with or without M1) as economic variables; one QRBF model using both long-term interest and M1 as economic variables; and one GRBF model using the long-term interest rate and one CRBF model using the short-term interest rate as economic variable]	yes (QRBF using long-term interest rates as economic variables; and IRBF using both long-term interest rates and M1 as economic variables)
Forward	no	no	no

(c) Summary of direction tests based on the 'speculative direction' [c]

	German mark	Japanese yen	Italian lira
RBF	yes [some localized RBF models using long-term or short-term interest rates (with or without M1) as economic variables; especially for the IRBF models in almost all analyses]	yes [most RBF models using short - term interest rates (with or without M1) as economic variables; and GRBF using long-term interest rates, and CRBF, IRBF, and QRBF using both long-term interest rates and M1 as economic variables) [d]	yes (QRBF using long-term interest rates as economic variables; and CRBF and IRBF using both long-term interest rates and M1 as economic variables)
RW	yes	no	no

The direction tests indicate that all forward rates for all three exchange rates cannot predict the direction with statistical significance.

(6) For all three exchange rates, most of the RBF models using the additional M1 variable do not seem to improve forecasting performance.

(7) The results show that the localized RBF models may be more flexible in model estimation because the residuals of some higher dimensional nonlocalized RBF models are not white noise and their forecasting results are not good.

CHAPTER 8. CONCLUSIONS AND FUTURE WORK

8.1 Conclusions

In general, statistical hypothesis tests provide a more objective way to compare forecasting performance among different models than descriptive evaluation criteria. All tested models for all three exchange rates perform better than a random walk model based on the descriptive average RMSE criterion. However, the MDM hypothesis tests for equal mean squared errors indicate that only some of these models are statistically different from the random walk model. Moreover, although some models appear to be very competitive with one another based on the descriptive evaluation criteria, hypothesis tests indicate that these models are statistically different. Furthermore, models that forecast best based on one evaluation criterion is not necessary best based on the other evaluation criteria. Overall, RBF models are better at predicting the correct direction and the speculative direction than at predicting point forecasts. Therefore, different RBF models may be favored by different end-users of the forecasts.

For one-month-ahead forecasting of the three exchange rates, only a few nonlocalized RBF (CCRBF and QRBF) models for the Italian lira and the MA(1) model for the German mark are statistically different from the random walk model based on the MDM test of equal mean squared error. Furthermore, when compared pairwise with the random walk, MA(1), and AR(k) models using the MDM test, no RBF model dominates all of these three benchmark models across all three exchange rates. Based on the correct direction test, some German mark RBF models (one univariate localized IRBF, the nonlocalized univariate and multivariate CCRBF, and the multivariate QRBF), some Italian RBF models (all multivariate RBF, and three localized univariate RBF), and the MA(1) model can predict the correct direction with statistical significance. The RBF models of the monthly Japanese yen are similar to the random walk, MA(1) and AR(3) models based on all hypothesis tests. Finally, some multivariate CCRBF and QRBF models can predict correct direction reasonably well for the monthly German mark, and can also predict both point forecasts and correct direction well for the monthly Italian lira.

Regarding one-quarter-ahead forecasting for the three exchange rates, only the Japanese yen RBF models using short-term interest rates (with or without the M1) as inputs are statistically different from a random walk model based on the MDM test of equal mean squared error. Quarterly models that can predict the correct direction with statistical significance include some localized German mark RBF models, some nonlocalized and two localized Japanese yen RBF models, and one nonlocalized QRBF model and one localized IRBF model of the Italian lira. Some quarterly RBF models can predict the speculative direction with statistical significance. These include a few localized RBF models and a random walk model of the German mark, almost all Japanese yen RBF models using short-term interest rates as economic inputs, and one QRBF model and two localized RBF models of the Italian lira.

In general, forward rates are worse than the forecasts obtained from most of the tested models; they failed to predict the correct direction with statistical significance for any of the three exchange rates using quarterly data.

For one-quarter-ahead forecasting, the multivariate RBF models using interest rates as economic variables do have some forecasting value for all three exchange rates. For one-month-ahead forecasting, except for the Japanese yen, most of the univariate RBF exchange rate models generally do not forecast better than the corresponding multivariate RBF models using interest rates as economic variables. Furthermore, the inclusion of interest rates generally helps more in one-quarter-ahead forecasting than in one-month-ahead forecasting. In the presence of the interest rates, the inclusion of the M1 variable as an additional economic variable does not seem to help much in forecasting for any of the three exchange rates.

The results show that the localized RBF (GRBF, CRBF, and IRBF) models are more flexible in model estimation. The reason for this appears to be that the width of the localized radial basis functions can be selected to make the areas of significant activation values of these radial basis functions cover the input space better, and to ensure the residuals of the localized RBF models are white noise. For all three quarterly exchange rates, the residuals of some higher dimensional nonlocalized RBF models are not white noise and their forecasting results are not good. However, when the residuals of the nonlocalized CCRBF and QRBF models are white noise, these two types of RBF models usually forecast quite well, especially with regard to the direction of change.

Overall, the estimation results show that the RBF model specifications evolve over the six sliding window periods, especially when quarterly RBF data are used. In contrast, the monthly AR and MA model specifications are fixed over the six sliding window periods and are only evolved through changing parameters. Therefore, the more flexible RBF model specifications evolved through training procedures may improve out-of-sample forecasting.

8.2 Future Work

Many issues may be investigated further concerning the application of neural network models for time series forecasting. The following discussion only addresses a few issues among the many possible areas.

The research may be extended to other exchange rates. Furthermore, the results obtained from the multivariate RBF models need to be compared with linear multivariate models.

Tests exist for choosing the appropriate lag length for input variables for statistical parametric models. To apply the neural network model for time series forecasting, the lag length selection problem needs to be investigated further.

Most economic time series data are nonstationary. There may be some nonlinear cointegration relationships between exchange rates and economic variables. Therefore, instead of using just differenced form data, level form data may also be estimated for comparison [Swanson and White (1997)].

In this research, some statistical hypothesis tests were conducted to evaluate out-of-sample forecasting performance among competing models. Alternatively, error bars for the forecasts of competing models could be compared. A forecast that has a smaller error bar is preferred to a model that has a larger error bar. The derivation of the error bars for RBF models needs to be researched more [Weigend (1996)].

Better performance might be achieved by allowing the width (scale factor) *r* for the localized and multiquadric radial basis functions to be different at different locations [Girosi

(1992) , and Hardy (1990)] instead of using a constant width r for all the radial basis functions in the same RBF model. That is, instead of having

$$\phi_j(X) = \exp(-\frac{\|(X - C_j\|}{r^2}), \qquad j = 1,\dots,k \quad ,$$

a different width r_j may be implemented for each Gaussian radial basis function, so that

$$\phi_j(X) = \exp(-\frac{\|(X - C_j\|}{r_j^2}).$$

The latter method has been investigated in this research. However, the forecasting results were no better than those of RBF models that implemented a constant value of r at different locations and hence are not reported in this thesis. Further investigation could be made by using a simulated annealing algorithm to search for an appropriate width (scale factor) r_j for the localized and multiquadric radial basis functions during the training process to determine better location positions for these functions.

The RBF models evaluated in this research are the approximation of real-valued functions $R^n \to R$. If the forecasting purpose focuses only on the prediction of the future direction of a variable, then the RBF models could be designed to solve the classification problems $R^n \to B$, where R are the real values and B is $\{0,1\}$.

APPENDIX A. TABLES OF LITERATURE REVIEW

A1. Conventional Statistical Estimation/Forecasting of Exchange Rates

Table A1.1 Linear Multivariate Analyses

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
1) Meese and Rogoff (1983) ---------- hereafter called M-R (1983)	1) flexible price (FLMA): F-B model 2) sticky price (SPMA): D-F model 3) Hooper- Morton :H-M model 4) six univariate time series models 5) unrestricted VAR model 6) forward rate 7) random walk (r.w.) with drift model 8) r.w. model	1) $/DM 2) $/yen 3) $/pound 4) traded weighted $	1973/3-1981/6 (total) --------- 1973/3-1976/11 (estimate)	1976/12-1981/6 --------- forecast 1,3,6,12 months ahead	yes	1) fails to improve on the r.w. model.	1)ME 2)MAE 3)RMSE
2) Woo (1985)	1) monetary model (use m, y as explanatory variables). 2) (add lagged term of exchange rate), fit both VAR(endogenous) model and other exogenous model.	1) DM/$	1974/3-1981/10	1980/3-1981/10 --------- forecast 2 ,3,4,6,12 months ahead	yes	1) structural model outperforms the r.w. model and its own constrained equivalent (a pure time series model) 2) reason of (1), might due to "lagged term".	1)MAE 2)RMSE
3) Somanath (1986)	1) use same models as M-R (1983), Bilson wealth (Frankel (1979)) and Branson et al.(1977) model. 2) add one lagged term of exchange rate.	1) DM/$	1975-1978/1	1978/12- forecast 1, 3, 6, 12, month ahead	yes	1) Bilson model: FLMA (use m, y as explanatory variables) performs best.	1)ME 2)MAE 3)RMSE
4) Alexander and Thomas (1987)	1) use M-R(1983) model, and also AR(1) and AR (2) models. 2) Kalman Filter (time-varying parameters).	1) $/pound 2) $/DM 3) $/yen	1974/1-1985/10 (142#)	1980/1-1985/10 forecast 1,3 , 6, 12 24, 36 months ahead	yes	1) structural model still performs unimpressively out of sample after considering structural instability by using Kalman Filter.	1) ME 2) MAE 3) RMSE 4) U

Table A1.1 (continued)

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
5) Wolff, C.C.P. (1987)	1) use FLMA and SPMA as in M-R 1983 models, with /or without an augmented term of real exchange term (Balassa type changes in real exchange rate). 2) also include lagged one terms of all dependent and independent variables. 3) Kalman Filter (time-varying parameters).	1) $/pound 2) $/DM 3) $/yen	1973/3-1984/4 (total) --------- 1973/3-1981/6 and 1973/3-1976/11 (estimate)	forecast 1,3,6,12,24 months ahead	yes	1) ex-post forecasts for $/D compare favorably with those of r.w. model (with or without augmented real exchange rate).	1) ME 2) MAE 3) RMSE
6) Wolff, C.C.P. (1988)	1) use VAR for exogenous variables only. 2) use one constant term and 11 seasonal dummy variables in VAR. 3) also investigate cross exchange rate. 4) explanatory variables (m, y, i, Π,q),where q is real exchange term, using relative prices of traded and non traded goods.	1) $/pound 2) $/DM 3) $/yen 4) pound/mark 5) pound/yen 6) mark/yen	1973/3-1984/4	1977/11-1984/4 forecast period k=1, 3, 6, 12, 24 ahead	yes	1) the results are mixed. 2) 4 (cross rates and $/DM) out of 6 exchange rates do not outperform the r.w. model.	1) ME 2) MAE 3) RMSE
7) Schinasi and Swamy (1989)	1) use M-R (1983) models. 2) compare fixed and stochastic coefficients with or without a lagged exchange rate.	1) $/pound 2) $/DM 3) $/yen	1973/3-1981/6 -------- 1973/3-1980/3	1980/4-1981/6 forecast multi-step	no	1) multi-step forecast, stochastic coefficient method is better than those of fixed coefficient models and r.w. model. 2) SPMA (D-F) model is most accurate for $/pound, $/DM. 3) H-M model is the best for $/yen.	1) ME 2) MAE 3) RMSE

Table A1.1 (continued)

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
8) Boothe and Glassman (1987a)	1) Frankel (1979) real interest difference (RID) model, using (m, i : short term rate, y, Π,) as explanatory variables. 2) compare constrained with unconstrained model. 3) add lagged terms of all variables. 4) compare with AR(1), forward rate, r.w. model.	1) CD/$ 2) DM/$	1974/3-1976/11 (estimate)	1976/12-1984/9	yes	1) r.w. performs best in forecast accuracy. 2) r.w. is best in profitability for DM/$. 3) CD/$ profitability rank is different from forecast accuracy.	1) RMSE 2) profitability in forward market speculation
9) Boothe and Glassman (1987b)	1) RID 2) FLMA 3) SPMA	1) DM/$	1) 1974/7-1978/2 ------- 2) 1974/7-1980/4 ------- 3) 1979/10-1984/3	x	x	1) discuss the "nonstationary " property of variables and point out the mistakes of previous studies using RID model without considering the "nonstationarity" of variables.	x
10) Meese (1986)	1) examine CI between exchange rate and (m, y) variables.	1) $/pound 2) $/DM 3) $/yen	1973-1982	x	x	1) reject the joint hypothesis of no bubble and stable autoregressive process for relative money supply and real income for $/DM, $/pound. 2) No CI between exchange and economic variables.	x
11) Baillie and Selover (1987)	1) use Keynesian view of monetary model and Dornbush (1976) monetary model (m,y,i,p) as explanatory variables. 2) use Engle-Granger CI test.	1) $/pound 2) $/DM 3) $/yen 4) $/CD 5) $/FF	1973/3-1983/12 (130 #)	x	x	1) use Engle-Granger CI procedure found no CI between exchange rate and fundamental variables. 2) PPP CI test, only $/FF seems to satisfy, other currencies show no CI for PPP relationship.	x

Note: x indicates "no analysis".

Table A1.1 (continued)

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
12) McNown and Wallace (1989)	1) use monetary model (Johnson 1972), use variables (m, y, i). 2) also use Engle and Granger CI procedure.	1) $ 2) DM 3) FF 4) yen 5) CD 6) pound ---------------- use $, pound, DM as 3 different bases	1973/4- ---- 1970/7- ----- 1972/6-	x	x	1) among 24 cases studied, only FF/$ with common parameter restriction show CI.	x
13) Kearney and MacDonald (1990)	1) FLMA and RID using Engle-Granger CI procedure to examine the role of fundamental economic variables in explaining movements in the A$/$. 2) they mentioned that many studies for FLMA model using short run rate as approximator for expected inflation, they thought that long-term interest rate might be better.	1) Australian$/$ (A$/$)	1984/1-1986/12 (small sample size)	x	x	1) CIs existed for most equations which indicated that those economic variables in the FLMA and RID models were capable of explaining long-term movement in the Australian$/$. However some coefficients are not so significant, thus, the support for monetary model is limited. 2) show no overshooting or speculative bubbles. 3) tests shows consistence with rational expectation and coefficient restriction suggested by the monetary model.	x
14) Pittis (1993)	1) use Engle-Granger CI procedure. 2) test exchange rate between (y, m) and (y, m, real exchange rate) CI relationship.	1) $/pound 2) $/DM 3) $/FF	1973/3-1989/5	x	x	1) CI results support the fundamental determination for the $/pound, $/DM but not for $/FF(possible bubble).	x
15) MacDonald and Taylor (1991)	1) use Johansen procedure to test CI between exchange rate and fundamental variables. 2) FLMA(m, y and long term interest rate i).	1) $/pound 2) $/DM 3) $/yen	1976/1-1990/12	x	x	1) only in-sample analysis. 2) $/pound and $/yen :at least 2 CI's relationship. 3) $/DM : one CI relationship. 4) monetary model does provide a valid explanation of the long run nominal exchange rates for 3 key currencies. 5) especially for $/DM, a number of popular monetary restrictions all can not be rejected, may reconsider the monetary model at least as long run model for nominal exchange rate.	x

Table A1.1 (continued)

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
16) MacDonald and Taylor (1993)	1) forward looking rational expectation monetary model. 2) Johansen CI test on exchange rate and (m, y, i2) and (m, y), where i2 is short term interest rate.	$/DM	1976/1-1990/12 (total) ------- 1976/1-1988/12 (estimate)	1989/1-1990/12	yes	1) 3 CI's for exchange rate with (m, m' ,y, y' i, i'); fit VAR 12 lags. 2) one CI for exchange rate between (m, m', y, y'), fit VAR using 8 lags. 3) CI test supports flexible price monetary model as long run equilibrium model, and use exchange rate and(y, m, i) to fit ECM model. And found a restricted ECM outperformed r.w. model. 4) reject rational expectation conditions and speculative bubble.	compare RSE of model vs RSE of r.w.
17) MacDonald and Taylor (1994)	1) FLMA monetary approach; (m, y, i1) 2) RID:(m,y,i1, i2) i1: long -term rate i2: short run rate	$/pound	1974/1-1990 (total) ----- 1976/1-1988/12 (estimate)	1989/1-1990/12	yes	1) use Johnsen procedure found 3 CI's, but use Engle and Granger procedure found no CI. 2) unrestricted monetary model is valid for analyzing long-run ER. 3) fit ECM and found unrestricted monetary model with short run dynamics outperform r.w.	RSE
18) Driskill *et al.* (1992)	1) develop and test a monetary rational expectations model. for Swiss franc/$ by considering "imperfect capital substitutability , current account effect, and PPP does not have to hold" concepts.	Swiss franc/$	1976/III-1987/IV (total) ------- 1)1976/III-1984/IV (estimate)	k=1,2,3,4 quarters ahead --- 1)1985/I-1986:IV	yes	1) treat m, y, p , as exogenous variables. 2) fit VAR differenced form. 3) did not use trade balance or capital account data due to well known errors in the data. 4) outperformed the r.w. with drift model. 5) reject joint hypothesis of structural model and rational expectations.	RMSE
19) Hoque and Latif (1993)	1) unrestricted level formed VAR,BVAR and structural CI/ECM model. 2) using 5 variables: log of exchange rate index; 3-month forward rate; CA/GDP, log of relative price. 3) BVAR parameters, λ= 0.1, 0.25,0.3, w=0.1,0.15 d=1,2	A$/$	1976:I-1990:I	1990:II-1991: I		1) BVAR is better than VAR. 2) use Engle-Granger CI procedure and found structural model better than multivariate time series models.	RMSE

Table A1.1 (continued)

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
20) Liu *et al.* (1994)	1) use Driskill *et al.* 1992 model. 2) use (e, m, p, y, i2, tr,), where tr: trade balance. 3) compare FVAR (unstricted), MVAR(mixed), BVAR (Baynesian) with parameters (λ, d w) = (0.2,1,0.5). 4) did not use CI procedure.	1) $/yen 2) $/CD 3) $/DM	1973/3-1989/12 (total) ------- 1973/3-1982/12 (estimate)	1983/1-1989/12 k=1,3,6,12		1) MVAR an BVAR are better than FVAR. 2) monetaaary/asset model in a VAR representation does have forecasting value for some exchange rates. 3) FVAR: biased and exhibited no significant information content or market timing ability. 4) MVAR, BVAR: less biased and show in information content and/or market timing ability. 5) MVAR: most significant information content 6) BVAR: least bias. 7) MVAR and VAR: equal in market timing. 8) MVAR,BVAR most successful in forecasting $/CD, less successful in predicting $/yen, but no value in predicting $/DM.	1) bias test 2) informational content test 3) market timing test (directional test) 4) ME 5) RMSE
21) Sarantis and Stewart (1995)	1) compare both Johansen and Engle -Granger CI procedures. 2) fit selective ECM. 3) fit both level and differenced forms of VAR,BVAR(with parameters (λ=0.1,0.2) ,(w=0.3,0.5,0.8), 8 combination. 4) use M-R (1983) three models and develop MUIP (modefied uncovered interest parity),and PB (portfolio balance model. 5) for BP model, some data are not available, thus they only use part of those variables.	1)$/pound 2)DM/pound 3)yen/pound 4)FF/pound	1973:I-1990:III quarterly data (total) ---- 1973:Q2-1990:Q2 (estimate)	1987:I-1990:III k=1,2,3,...,10 quarters ahead	yes	1) No CI for 3 M-R(1983) monetary models. 2) CI in MUIP,PB models for DM/pound, FF/pound, yen/pound, but no CI for $/pound, thus fit ECM model for those 3 CI exchange rates using both MUIP and PB variables. 3) MUIP is better than PB models. 4) MUIP for DM/pound , FF/pound is better than r.w. model , but for yen/pound is worse than r.w. 5) MUIP is better than BVAR in longer term, BVAR is better in shorter term (up to 3-4 quarters). 6) level forms of VAR,BVAR are better than differenced forms. 7) BVAR is better than VAR.	1)RMSE, 2)U

Table A1.2. Nonlinear Multivariate Analysis

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
22) Meese and Rose (1991)	1) use M-R (1983) 3 structural models and 2 additional variants of monetary models. 2) use parametric and nonparametric techniques to examine nonlinearity. 3) use nonparametric (locally weighted regression) analysis try to fit nonlinear structural model.	1) $/CD 2) $/DM 3) $/yen 4) $/pound	1974-1987 monthly	1984/1-1987/12	yes	1) nonlinear approach seems not promising. 2) H-M (sticky price model incorporate trade balance term outperforms r.w. model by RMSE criteria, But other fails to outperforms r.w. model. 3) they claimed that poor structural model performance can not be attributed to nonlinearity arising from time-deformation or improper functional form.	1)ME 2)MAE 3)RMSE

Table A1.3. Univariate Analysis

Author	Model	Currency	Time Period	Out-of-Sample Forecast	Rolling Regression	Estimation and / or Forecast Performance	Evaluation Criteria
1) Diebold and Nason (1990)	1) nonparametric, nonlinear (locally weighted regression). 2) univariate analysis to forecast : Δln e (difference of log exchange rate).	10 currencies	1973/1/3-1987/9/23 weekly data ----- 6-701#	702-768# one step ahead and also k=4, 8, 12	yes	1) nonlinear did not improve on r.w. 2) they suggested extend to multivariate model.	MSPE
2) Nachane and Ray (1992)	1) r.w. 2) ARMA 3) bilinear 4) state dependent model 5) dynamic linear model 6) ARCH 7) GARCH 8) GARCH-M ----------------------------- also test stationarity, linearity, Gaussian assumption.	10 currencies	1973-1-1990/3 monthly	1990/3- k= 1-12	yes	1) linear ARMA poor forecast. 2) ARCH,GARCH,ARCH-M in general is better than r.w. 3) other models except dynamic linear model do not have impressive performance. 4) use Hsieh (1989) and other methods to test nonlinearity, 10 currencies except DM reject linearity.	U(h)
3) Lye and Martin (1994)	1) GENTS(generalized exponential non-linear time series) vs SETAR(self-exciting threshold autoregressive models)--- parametric model.	$/A$	1977/1-1990/10 monthly	1989/11-1990/10 k=1	no	1) GENTS model is better than SETAR. 2) did not compare with linear model.	RMSE
4) Satchell and Timmermann (1995)	1) compare nonlinear, nonparametric, nearest neighbor forecasting algorithm with r.w. model and AR(1). 3) use 1000 moving window recursively to reestimate the model.	15 currencies	1980/1/1-1992/12/31 daily	k=1	yes	1) nonlinear model's MAE and MSPE are higher than r.w., AR(1). 2) But nonlinear model correctly forecast the sign of the change in a statistically proportion of this time period for about half of the investigated currencies. 3) probability of correctly predicted the sign of daily exchange rate change use nonlinear is higher than that of r.w. 4) and the payoff from a trading model based on the nonlinear model is higher than that of basing on buy and hold strategy from a r.w. model. 5) test nonlinearity, showed that nonlinearity existed in these exchange rates.	1)MAE 2)MSPE 3)market-timing-test

A2. Artificial Neural Networks Application in Financial and Economic Series Forecasting

Table A2.1 Multivariate Analyses of Exchange Rates Forecasting

Author	ANN model	Learning Algorithm	Other Model	Target Output	Time Period	Out-of-Sample Forecast	Estimation and / or Forecast Performance	Evaluation Criteria
1) Weigend *et al.* (1992)	1) feedforward fully connected ANN with several inputs and 5 hidden neurons and 2 output neurons. 2) inputs include DM, yen, Swiss franc, pound, CD vs $ rates's Monday returns and DM's 45 past daily returns, and 11 trends, volatility of $/DM and Monday prices of $/DM and average of other rates to forecast Tuesday return (Δln et) and sign of return of $/DM. all input data are rescaled to [0,1] range. 3) hidden neurons use tanh function and linear for the return output and sigmoid function for the sign output. 4) learning algorithm minimizes the cost function which includes both error term and weight elimination term.	BP with weight decay	x (no analysis)	Tuesday 1) return of $/DM 2) sign of return	1975/5/5-1984/12/3 weekly data (estimation period)	1)1973/5/5-1984/12/3 2)1984/12/10-1987/5/8	1) out of sample correlation of forecast and target values are 0.2. *** the model did not use any fundamental input , e.g. interest rate.	minimum quadratic error; min cross entropy error.
2) Green and Pearson (1994)	1) choose 5 inputs from 26 selection (including FF, DM, yen, Swiss ff, pound level and volatility; interest rate, and other technical indicators, etc.)	hybrid BP and Cauchy algorithm	univariate ARMA	$/pound daily rate	1988/1-(4 and 1/2 years)	1992/4-1993/3 ------ one day ahead	1) ANN is better than univariate ARMA. ***they claimed that ARMA model needs to be retrained when new data are available. ANN does not have to be retrained so often because short term decay is not so strong.	
3) Poddig and Rehkugler (1996)	1) fit both multilayer feedforward and recurrent networks. 2) fit separate individual country models and also integrated world (3 countries) models for bond, stock and exchange rates (yen/$, DM/$), use fundamental and technical variables. 3) use ANN as nonlinear analysis of integrated financial markets combine 3 countries and 3 assets (bond, stock, exchange rates) use recurrent networks to forecast each asset. 4) forecast 6 month ahead of 3 assets. (lnPt - lnPt-6)	BP weight pruning (Finnoff/ Zimmer-mann in multilayer feed-forward networks)	1) stepwise multivariate regression (feedforward and backward) 2) r.w. and martingale model	3 countries stock, bond and exchange rates 6 month ahead return	1980/1-1991/11 monthly Jackknife procedure cross-validation	1991/12-1993/11	1) traditional regression model can not outperform the r.w. model. 2) integrated ANN using technical indicators as inputs performs best. 3) even use cross validation procedure to choose ANN models, however, the out of sample forecast results are still not satisfactory. 4) they suggest choose inputs carefully in stead of relying on the ANN to optimize the inputs selection.	1) MSE 2) U 3) % of correct sign 4) average and standard deviation of trading return 5) Sharpe ratio 6) Profit index

Table A2.2 Univariate Analysis of Exchange Rates Forecasting

Author	ANN model	Learning Algorithm	Other Model	Target Output	Time Period	Out-of-Sample Forecast	Estimation and / or Forecast Performance	Evaluation Criteria
1) Refenes (1993)	1) feedforward multilayer. 2) use CLS+ algorithm to constructively add neurons of hidden layer during training. 3) multi-step ahead forecast using one step ahead forecast fed back as input.	CLS+ algorithm	1) Exponential smoothing 2) Autoregression 3)BP NN	US/DM hourly ahead rate	1988-1989 hourly data ----- first 200 days' hourly data for training	k=1 and multi-step ---- use 60 days's hourly data for forecast	1) In general CLS+ NN perform better. 2) trading results based on multi-step forecast make favorable profits.	

Table A2.3 Multivariate Analyses of Other Financial and Economic Series

Author	ANN model	Learning Algorithm	Other Model	Target Output	Time Period	Out-of-Sample Forecast	Estimation and / or Forecast Performance	Evaluation Criteria
1) Chakraborty *et al.* (1992).	1) multivariate (trivariate) time series analysis. 2) use normalized inputs from 3 flour price series with lag terms for each indevidual flour price. 3) fully connected feeforward ANN, try 6x6x1, and 8x8x1 ANN, etc.(use one output neuron) 4) one-lag ahead forecast for next 10 months using actual past values, for multi-lag forecast for next 10 months using iterated way with predicted values as input data. 5) also compare with univariate ANNs.	BP	VARMA Tiao and Tsay (1989) model	log of indices of monthly flour prices of 3 cities	1972/8-1980/1 (estimation) ------- 90#	1980/2-1980/11	1) RMSE for trivariate ANN is better than Tiao and Tsay (1989) VARMA model. 2) 8x8x1 ANN is best.	RMSE
2) Kimoto *et al.* (1993)	1) multilayer fully connected feedforward ANNs. 2) inputs include economic indexes , technical indicators and previous stock index value, input data are transformed by logarithm or other ways. 3) input and output values are normalized into [0,1] range. 4) use signoid in output neuron. 5) use moving window to estimate and forecast. 6) 2/3 data for learning set, and 1/3 data set for test set. 7) also use the predicted out as signal for a trading system.	variant of BP	multiple regression	weekly return of Topix stock index (AlnPt)	1985/1-1989/9 ----- 33# ----- use moving window size =6,12,18,24 to forecast one month returns	1987/1-1989/9	1) use correlation valuation of predicted and target values, ANN is better than the multiple regression.	correlation coefficient

Table A2.3 (continued)

Author	ANN model	Learning Algorithm	Other Model	Target Output	Time Period	Out-of-Sample Forecast	Estimation and / or Forecast Performance	Evaluation Criteria
3) Grudnitski and Osburn (1993)	1) 24 x 8 x 2 x1 (2 hidden layers) 2) 24 inputs include change and volatility of gold, S&P index futures; M1 and commitments of market participants. 3) entirely data set covers 90 months, they adaptively train 41 ANNs with different 15-month training set to test over 75 months.	BP	x	monthly price change of S&P and gold futures.	1983/1-1990/9		1) predicting change of price and trading return based on the prediction of the 41 simulated NNs seems to be promising.	
4) Baestanes and Van den (1995)	1) use 17 variables (level, logarithms, %, seasonally adjusted), also include one lag term of stock index level. 2) one hidden layer and input layer also directly connected to the output layer. 3) output range [0,1]. 4) they also do variable contribution analysis.	BP	OLS regression	monthly return of Amesterdan stock market return	1979/11-1991/3	1990/4-1991/3 --- 10#	1) ANN outperforms OLS regression.	
5) Yang (1995)	1) BP model with dual NNs to catch long term and short term trend, and the result was used as a trading signal in a trading system. 2) sliding window. 3) use technical indicators and stock market volume as input. 4) use genetic algorithm(GA) with conjugate gradient algorithm to derive the weights within the input and hidden layer, then use regression methods to get the weights associated with the hidden layer and output layer.	BP with GA with conjugate (Masters 1993)	x	Hong Kong, Taiwan , Japan stock index 3-day ahead trend of stock movement	1987-1991	1992-1993	1) the trading result based on the ANN was favorable.	
6) Steiner and Wittkemper (1995)	1) Feedforward and recurrent ANN forecast return of a single stock. (5 ANNs). 2) inputs include daily prices and turnovers of stock prices and other stock indexes. 3) linearly rescale inputs and output into [0,1] range. 4) use 1983 data to estimate model to forecast 1984, then use 1984 data to reestimate model to forecast 1985 return, etc.	BP	linear regression	stock return (daily)	1983-1986	1984-1986	1) In general ANNs perform better than regression. 2) recurrent model performs better.	MAE
7) Kaastra and Boyd (1995)	1) variables feedforward net.(also include lag term), all variables are preprocessed by 3-period moving average and then use mean standard /deviation to rescale into [0,1] range.($\mu\pm2\sigma$), to approach more uniform distribution and surpass outlier effect. 2) for 6 commodities forecast 1-9 months ahead, fit total 54 nets.(fit one ANN for each forecast period).	BP	ARIMA	monthly futures trading volume	1977-1993	1-9 months ahead	1) in general ANN outperformed r.w. model and ARIMA in longer period. 2) is best in first period(because inputs are 3-period MA).	RMSE MAPE U

Table A2.3 (continued)

Author	ANN model	Learning Algorithm	Other Model	Target Output	Time Period	Out-of-Sample Forecast	Estimation and / or Forecast Performance	Evaluation Criteria
8) Ankenbrand and Tomassini (1995)	1) 3x2x1 with sigmoid function. 2) only use fundamental data as inputs, which are rescaled into [-1,-1] range. Take log on 2 stock indices, due to outliers. Lag terms are not included. 3) output is Δln Pt. monthly log difference, output is rescaled into [0.2, 0.8] range.	BP	univariate Box-Jenkin	Swiss stock index (end of month closing price)	1987/1-1994/12 ------- 84#	10# (use every 9th data)	1) results for ANN are favorable.	normalize MSE
9) Refenes and Bolland (1996)	1) 10x4x1 (run 30 times). 2) do input variables sensitive analysis. 3) inputs are rescaled into (0,1). 4) use reduced window size to test the model stability until last window size is 4 years.	BP	stepwise linear regression	FTSE all share index quarterly return	1975-1990 ----- 80#	1991/1-1994/2 ----- 40#	1) ANN is better than stepwise linear regression.	
10) Brownstone (1996)	1) feedforward, and add number of neurons gradually. 2) 49x8x1. 3) use Neuroshell program. 4) inputs normallized into (0.000001,0.99999).	BP	4 multiple linear regression (MLR)	FTSE 100 share index, 5 day ahead and 25 day ahead	1985/2/6- ------ 1700#	1991/8/13 ---- 200#	1) ANN is accurate in 5 day ahead prediction 2) MLR can predict total accuracy better 3) ANN results show that prediction based on least MSE bears little relationship to that of measured by overall percentage accuracy.	1) RMSE 2) MSE 3) total accuracy

Table A2. 4 Univariate Analyses of Other Financial and Economic Series Forecasting

Author	ANN model	Learning Algorithm	Other Model	Target Output	Time Period	Out-of -Sample Forecast	Estimation and / or Forecast Performance	Evaluation Criteria
1) Tang *et al.* (1991)	1) feedforward ANN univariate time series. 2) 1x6x1 ; 6x6x1 ; 12x12x1 ; 24x24x1	BP	Box-Jenkin time series model	1) international airline passenger 2) domestic car sale 3) foreign car sale		k =1, 6, 12, 24 ahead	1) for time series with long memory (more lag inputs), ANN and Box-Jenkin model are comparable. 2) for short memory series (with fewer lag inputs) ANN outperform Box-Jenkin model. 3) ANNs are good at forecast longer period ahead.	forecast error
2) Sharda and Patil (1993)	1) feedforward, one hidden layer ANN. 2) use 13 annual data, 20 quarterly data and 68 monthly series. 3) normalize input and output data with [01] range.	BP	Box-Jenkin time series	individual output for those series	different time horizon	annually data k=6; quarterly data k=8; monthly data, k=18	1) for long memory series both ANN and Box-Jenkin series both perform well. 2) with Box-Jenkin slightly better for short term forecast. 3) for short run memory, ANN is better .	1)MAPE 2)APE
3) Blake *et al.* (1995)	1) compare BP , jump connection and recurrent ANNs. 2) discuss variables nonstationary and seasonal problems and compare several NNs with stationarized and deseasonalized inputs. 3) fit NNs with variables both transformed and raw data respectively. 4) fit models for 7 different time horizon series. 5) use internal cross validation set , choose randomly 12% from training data for feedforwad NNs (but for recurrent NNs, not choose randomly).		Box-Jenkin model	7 series short run and long run ahead	different horizon	short run and long run ahead	1) NNs in general are better than Box-Jenkin model. 2) preprocess the input data(take logarithm, difference, deseasonalized) will be helpful, but seems not so important as choosing the right NN structure 3) increase the number of inputs and neurons do not necessarily improve the forecasting.	1) MSE 2) average relative variance
4) Kohzadi *et al.* (1996)	1) 6x5x1 feedforward ANN, which repeats times for successive 3 years walkforward or sliding windows. 2) chaos view nonlinearity. 3) cross validation set and training set contain 75-90% data and out of sample set use 10%. 4) N-Train NN software.	BP	ARIMA	monthly cattle and wheat price	1950-1969 ----- 1952-1972 sliding window	1970/-1990/ 12	1) by MSE criteria, ANN is better than ARIMA model. 2) ANN can capture turning point of both wheat and cattle prices. 3) ARIMA can only capture the turning point of wheat price.	1)MSE, 2)MAE 3)MAPE 4)Henrikson and Merton turning point

APPENDIX B. RBF FORMULA AND FIGURES, MODEL SELECTION CRITERIA, AND Φ^p MATRIX

B.1 Radial Basis Functions

Seven radial basis functions are used for this research. Figure B.1 depicts the relevant functions. The first four functions are described in Orr (1996), and the linear and cubic functions are discussed in Girosi (1994) and Powell (1987, 1992).

(1) Gaussian function : (GRBF)

$$\phi_j(X) = \exp\left(-\frac{\|(X - C_j\|}{r_j^2}\right),$$

where X denotes the input vector, C_j is the center vector and r_j is the radius (or width) of the radial basis function of the jth hidden-layer unit.

(2) Cauchy function: (CRBF)

$$\phi_j(X) = \frac{r_j^2}{\|X - C_j\| + r_j^2},$$

(3) Inverse Multiquadric function: (IRBF)

$$\phi_j(X) = \frac{r_j}{\sqrt{\|X - C_j\| + r_j^2}},$$

(4) Multiquadric function: (MRBF)

$$\phi_j(X) = \frac{\sqrt{\|X - C_j\| + r_j^2}}{r_j}.$$

(5) Linear function: (LRBF)

$$\phi_j(X) = \|X - C_j\|,$$

(6) Square (Quadratic) function :(QRBF)

$$\phi_j(X) = \|X - C_j\|^2, \quad ,$$

(7) Cubic function : (CCRBF)

$$\phi_j(X) = \|X - C_j\|^3,$$

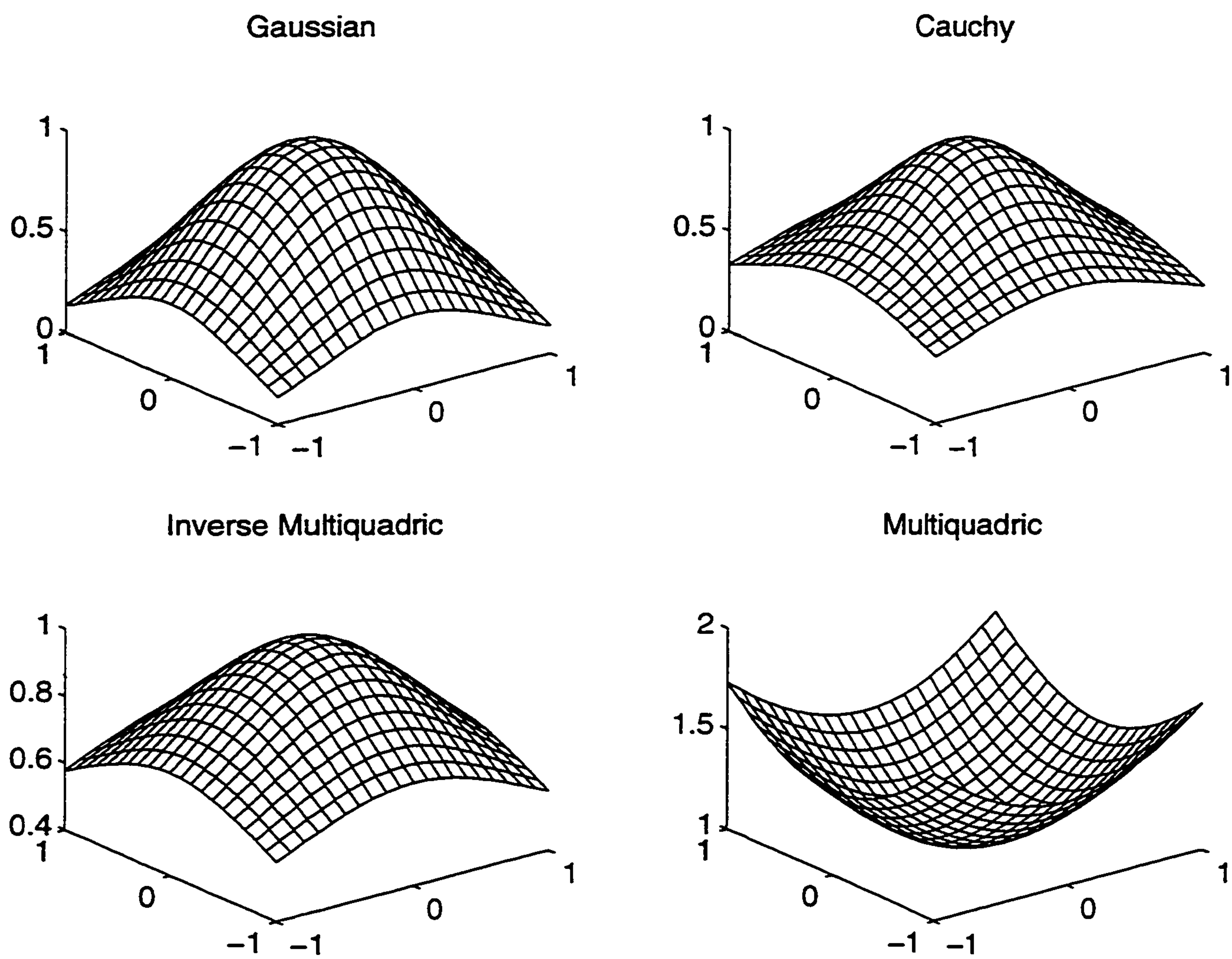


Figure B.1. Seven radial basis functions.

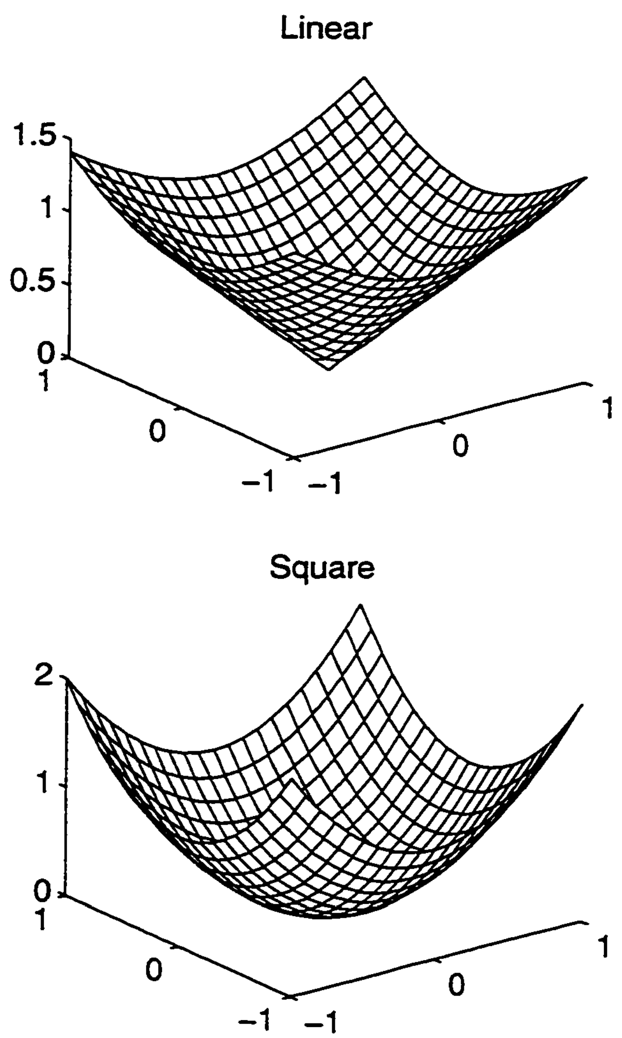


Figure B.1. (continued)

B2. BIC, GCV and LOO

1. ***BIC***

$$\text{BIC} = \frac{m + (\ln(m) - 1)\delta}{m - \delta} \cdot \frac{Y^T P^2 Y}{m},$$

where: $Y = [y_1, y_2, \ldots, y_m]$ is the actual output of the m training cases; Y^T is the transpose of Y;

$$P = I_m - \Phi(\Phi^T \Phi + \lambda I_m)^{-1} \Phi^T,$$

where Φ and λ are defined as in chapter 3; I_m is the identity matrix; and $\delta = m - trace(P)$. If there is no regularization term in the cost function, then $trace(P) = m - k$ and $\delta = k$, where k is the number of hidden units.

2. **LOO**

$$\text{LOO} = \frac{Y^T P(diag(P))^{-2} PY}{m},$$

3. **GCV**

$$\text{GCV} = \frac{mY^T P^2 Y}{(m - \delta)^2}$$

B.3 Φ^p : candidate Φ matrix

During the training process, if three radial basis functions with three different widths (r = a, b, or c) are centered on top of each input point of the training data, the candidate Φ matrix (Φ^p) for selection will be expressed as follows.

$$
\underset{m x 3m}{\Phi^p} = \left[\begin{array}{cccc|cccc|cccc}
\phi_1(X_1)_a & \phi_2(X_1)_a & \cdot\cdot & \phi_m(X_1)_a & \phi_1(X_1)_b & \phi_2(X_1)_b & \cdot\cdot & \phi_m(X_1)_b & \phi_1(X_1)_c & \phi_2(X_1)_c & \cdot\cdot & \phi_m(X_1)_c \\
\phi_1(X_2)_a & \phi_2(X_1)_a & \cdot\cdot & \phi_m(X_2)_a & \phi_1(X_2)_b & \phi_2(X_1)_b & \cdot\cdot & \phi_m(X_2)_b & \phi_1(X_2)_c & \phi_2(X_1)_c & \cdot\cdot & \phi_m(X_2)_c \\
\phi_1(X_3)_a & \phi_2(X_3)_a & \cdot\cdot & \phi_m(X_3)_a & \phi_1(X_3)_b & \phi_2(X_3)_b & \cdot\cdot & \phi_m(X_3)_b & \phi_1(X_3)_c & \phi_2(X_3)_c & \cdot\cdot & \phi_m(X_3)_c \\
\cdot & \cdot & \cdot\cdot & \cdot & \cdot & \cdot & \cdot\cdot & \cdot & \cdot & \cdot & \cdot\cdot & \cdot \\
\cdot & \cdot & \cdot\cdot & \cdot & \cdot & \cdot & \cdot\cdot & \cdot & \cdot & \cdot & \cdot\cdot & \cdot \\
\phi_1(X_m)_a & \phi_2(X_m)_a & \cdot\cdot & \phi_m(X_m)_a & \phi_1(X_m)_b & \phi_2(X_m)_b & \cdot\cdot & \phi_m(X_m)_b & \phi_1(X_m)_c & \phi_2(X_m)_c & \cdot\cdot & \phi_m(X_m)_c
\end{array}\right],
$$

(with the width "a") (with the width "b") (with the width "c")

where $\Phi^p{}_{ij} = \phi^p{}_j(X_i)_r$ is the value of the jth transfer function (with width r) evaluated at the ith input vector X_i, and there are m n-dimensional input vectors, $X_i = (x_{i1}, x_{i2}, \ldots, x_{in})$, $i = 1, 2, \ldots, m$.

If an additional bias term is adopted, then the Φ^p matrix will have an additional last column with components equal to 1. The final Φ matrix chosen after the training process is the subset of the candidate Φ^p matrix.

APPENDIX C. DATA

C.1 Data Resources

The data sets include monthly series from March 1973 to June 1996, and quarterly data from 1973:Q1 to 1996:Q2.

Bilateral exchange Rates

1. average monthly data: [Source: Federal Reserve Board data base: Federal Reserve Statistical Release 5]
2. end-of-quarter data (both spot and forward rates): [Source: International Financial Statistics]

Money supply (end of period, seasonal M1): [Source: OECD Main Economic Indicators]

C.1.1 Specific data for each country

- ***Germany***

Long-term interest rate (LR)---Bond yields (public sector bonds)

1. LR1 (more than 3 years): [Source: OECD Main Economic Indicators]
2. LR2 (7-15 years): this data series combine two data series, before January 1987 the data series use bonds (more than three years) yields, start from January 1987, the data series use bonds (7-15 years) yields.

[Source: OECD Main Economic Indicators; OECD monthly Financial Statistics]

Short-term interest rates (SR)---Call money rate (money market rate)

[Source: International Financial Statistics]

- ***Japan***

*Long-term interest rate* (LR)---Yields on the central government bonds

[Source: OECD Main Economic Indicators]

*Short-term interest rates* (SR)---Call money rate (money market rate)

[Source: International Financial Statistics]

- ***Italy***

*Long-term interest rate* (LR)---Yield on the long-term government bonds

[Source: OECD Main Economic Indicators]

- ***Unites States*** [Source: Federal Reserve Board data base]

*Long-term interest rate* (LR)---yield on the ten year Treasury notes

*Short-term interest rates* (SR)

1. SR1--- three-month Treasury bill rate
2. SR2--- Federal funds rate

C.2 Descriptive Statistics Of Three Exchange Rates

Table C.2.1 German mark (quarterly)

(a) Training set (first difference of natural logarithm of German mark)

Period	75:2-92:4	75:4-93:2	76:2-93: 4	76:41-94:2	77:2-94:4	77:4-95:2
Mean	-0.0053	-0.0064	-0.0054	-0.0060	-0.0061	-0.0072
Std	0.0663	0.0647	0.0653	0.0653	0.0652	0.0664
Min	-0.1505	-0.1505	-0.1505	-0.1505	-0.1505	-0.1505
Max	0.1391	0.1391	0.1391	0.1391	0.1391	0.1391
Q(12)	14.6493	13.8491	15.4741	15.8583	15.5740	16.0664
Skewness	0.2475	0.2142	0.1789	0.2059	0.2125	0.1919
Kurtosis	-0.4446	-0.3987	-0.4863	-0.4729	-0.4673	-0.5394
JB	1.4258	1.1311	1.2130	1.2954	1.3070	1.4314

Note : Q(12) is the Ljung-Box Q statistic; reject the null hypothesis of no autocorrelation if the value of Q(12) is greater than $\chi^2_{(0.05,12)} = 21$.

JB represents the Jarque-Bera test (Normality test); reject the null hypothesis that the series are independent normally distributed if the value of JB is greater than $\chi^2_{(0.05,2)} = 5.991$.

* Significant at the 5 % level.

(b) Test set

Period	93:1-93:4	93:3-94:2	94:1:94:4	94:3-95:2	95:1-95:4	95:3-96:2
Mean	0.0168	-0.0141	-0.0271	-0.0356	-0.0193	0.0238
Std	0.0470	0.0522	0.0198	0.0533	0.0631	0.0093
Min	-0.0413	-0.0469	-0.0469	-0.1127	-0.1127	0.0103
Max	0.0636	0.0636	0.0003	0.0003	0.0251	0.0308

Table C.2.2 Japanese yen (quarterly)

(a) Training set (first difference of natural logarithm of Japanese yen)

Period	75:2-92:4	75:4-93:2	76:2-93: 4	76:41-94:2	77:2-94:4	77:4-95:2
Mean	-0.0121	-0.0147	-0.0139	-0.01501	-0.0144	-0.0161
Std	0.0613	0.0620	0.0627	0.0632	0.0630	0.0641
Min	-0.1698	-0.1698	-0.1698	-0.1698	-0.1698	-0.1698
Max	0.1142	0.1142	0.1142	0.1142	0.1142	0.1142
Q(12)	9.3022	9.9323	10.6770	11.9390	12.8749	15.3350
Skewness	-0.3984	-0.2928	-0.2978	-0.2536	-0.2826	-0.2382
Kurtosis	-0.3068	-0.4695	-0.5215	-0.6093	-0.5690	-0.6971
JB	2.2298	1.7733	1.9621	1.9811	2.0175	2.2017

Note : same as in Table C.2.1.

(b) Test set

Period	93:1-93:4	93:3-94:2	94:1:94:4	94:3-95:2	95:1-95:4	95:3-96:2
Mean	-0.0273	-0.0187	-0.0286	-0.0394	0.0076	0.0643
Std	0.0667	0.0601	0.0413	0.0550	0.1146	0.0576
Min	-0.0861	-0.8097	-0.8097	-0.1100	-0.1100	0.0291
Max	0.0618	0.0618	0.0130	0.0130	0.1501	0.1501

Table C.2.3 Italian lira (quarterly)

(a) Training set (first difference of natural logarithm of Italian lira)

Period	75:2-92:4	75:4-93:2	76:2-93: 4	76:41-94:2	77:2-94:4	77:4-95:2
Mean	0.0119	0.0114	0.0100	0.0086	0.0086	0.0087
Std	0.0641	0.0642	0.0603	0.0608	0.0611	0.0615
Min	-0.1259	-0.1259	-0.1259	-0.1259	-0.1259	-0.1259
Max	0.2064	0.2064	0.1764	0.1764	0.1764	0.1764
Q(12)	7.5558	9.7920	15.3067	14.8220	14.4382	14.0087
Skewness	0.5496	0.5611	0.2717	0.3121	0.3137	0.2943
Kurtosis	0.4606	0.4419	-0.1895	-0.2461	-0.2865	-0.3633
JB	3.7766	3.8867	1.0364	1.3931	1.4781	1.5075

Note : same as in Table C.2.1.

(b) Test set

Period	93:1-93:4	93:3-94:2	94:1:94:4	94:3-95:2	95:1-95:4	95:3-96:2
Mean	0.0368	0.0068	-0.0111	0.0083	-0.0070	-0.0166
Std	0.0542	0.0557	0.0422	0.0459	0.0388	0.0050
Min	-0.0348	-0.0559	-0.0559	-0.0422	-0.0422	-0.0222
Max	0.0830	0.0742	0.0459	0.0484	0.0484	-0.0100

APPENDIX D DETAILED TABLES FOR CHAPTER 5

German Mark

Univariate analyses (monthly data)

Table D.1. German Mark analysis 1(a)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0247	0.0247	0.0247	0.0247	0.0241	0.0248	0.0244
	2	0.0239	0.0233	0.0224	0.0231	0.0232	0.0232	0.023	0.0222	0.0233	0.0234
	3	0.0193	0.0184	0.0189	0.018	0.0182	0.018	0.0177	0.017	0.0179	0.0177
	4	0.0269	0.0254	0.0256	0.0249	0.0249	0.0249	0.0247	0.0245	0.0252	0.0247
	5	0.0278	0.0277	0.0269	0.0276	0.0275	0.0275	0.0275	0.0282	0.0273	0.0247
	6	0.0184	0.0186	0.0176	0.0193	0.0193	0.0193	0.0196	0.0202	0.0189	0.0193
	Average	0.0235	0.0230	0.0225	0.0229	0.0230	0.0229	0.0229	0.0227	0.0229	0.0229
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.6667	0.5833	0.5833	0.6667	0.5833
	2		0.5833	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.6667	0.5
	3		0.6667	0.5	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.5	0.5	0.5	0.4167	0.4167	0.5	0.5
	Average		0.6111	0.5972	0.5833	0.5833	0.5833	0.5556	0.5556	0.5972	0.5556
No. of centers	1				2	2	2	2	2	2	4
	2				2	2	2	2	2	2	4
	3				2	2	2	2	2	2	5
	4				2	2	2	2	2	2	4
	5				2	2	2	2	2	2	4
	6				2	2	2	2	2	2	7

Notes : Lag length is equal to 1.
GRBF,CRBF,IRBF,MRBF use width (r) = 0.1

Table D.2. German Mark analysis 1(b)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0245	0.0246	0.0246	0.0243	0.0245	0.0245	0.0244
	2	0.0239	0.0234	0.0224	0.0233	0.0233	0.0234	0.023	0.0229	0.0233	0.0228
	3	0.0193	0.0184	0.0189	0.0184	0.0182	0.0181	0.0179	0.0178	0.0181	0.0177
	4	0.0269	0.0254	0.0256	0.0252	0.0253	0.0252	0.0246	0.0245	0.0244	0.0247
	5	0.0278	0.0277	0.0269	0.0274	0.0271	0.0271	0.0268	0.0282	0.0263	0.0277
	6	0.0184	0.0186	0.0176	0.0192	0.0192	0.0183	0.0191	0.0202	0.0188	0.0193
	Average	0.0235	0.0230	0.0225	0.0230	0.0229	0.0228	0.0226	0.0230	0.0226	0.0228
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.5833
	2		0.5833	0.5	0.5833	0.5833	0.5833	0.5833	0.6667	0.6667	0.5833
	3		0.6667	0.5	0.5833	0.6667	0.6667	0.6667	0.75	0.5833	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.5	0.5	0.5	0.4167	0.6667	0.4167
	6		0.6667	0.6667	0.5	0.5	0.6667	0.5	0.4167	0.4167	0.5
	Average		0.6111	0.5972	0.5694	0.5972	0.6250	0.5972	0.5972	0.6111	0.5694
No. of centers	1				2	2	2	2	2	2	4
	2				2	2	2	2	2	2	11
	3				2	2	2	2	2	2	5
	4				2	2	2	2	2	2	4
	5				2	2	2	2	2	2	4
	6				2	2	2	2	2	2	7
No. of lag	1				2	2	2	3	3	3	1
	2				3	3	3	3	3	3	2
	3				3	3	3	3	3	3	1
	4				3	3	3	3	1	3	1
	5				2	3	3	3	1	3	1
	6				2	2	3	3	1	3	1

Notes : Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF,IRBF,MRBF use width (r) = 0.1

Table D.3. German Mark analysis 2(a)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0246	0.0245	0.0246	0.0246	0.0246	0.0247	0.0245
	2	0.0239	0.0234	0.0224	0.0229	0.0229	0.023	0.0231	0.0229	0.0233	0.0231
	3	0.0193	0.0184	0.0189	0.0179	0.0179	0.0179	0.018	0.0179	0.0183	0.0181
	4	0.0269	0.0254	0.0256	0.0249	0.0249	0.0249	0.0249	0.0255	0.0252	0.0251
	5	0.0278	0.0277	0.0269	0.0273	0.0273	0.0273	0.0273	0.0274	0.0272	0.0272
	6	0.0184	0.0186	0.0176	0.0193	0.0193	0.0192	0.0191	0.0188	0.0188	0.019
	Average	0.0235	0.0230	0.0225	0.0228	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Correct Direction	1		0.5833	0.5833	0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667
	2		0.5833	0.5	0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667
	3		0.6667	0.5	0.6667	0.75	0.6667	0.75	0.6667	0.75	0.75
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.4167	0.4167	0.4167	0.4167	0.5	0.5	0.4167
	Average		0.6111	0.5972	0.5556	0.5694	0.5833	0.5972	0.5694	0.6111	0.5972
No. of centers	1				9	9	9	8	6	7	6
	2				5	9	10	8	8	7	6
	3				5	17	7	7	4	10	5
	4				8	14	7	6	3	7	7
	5				8	7	7	7	3	7	6
	6				8	7	7	7	3	7	5

Notes : Lag length is equal to 1.
Except that IRBF,MRBF in periods 3,4 use width (r) = 0.05, all others use r=0.1.

Table D.4. German Mark analysis 2(b)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0248	0.0245	0.0246	0.0246	0.0246	0.0247	0.0245
	2	0.0239	0.0234	0.0224	0.0229	0.0229	0.023	0.0231	0.0229	0.0233	0.0231
	3	0.0193	0.0184	0.0189	0.0182	0.0179	0.0179	0.018	0.0179	0.0183	0.0181
	4	0.0269	0.0254	0.0256	0.0249	0.0249	0.0249	0.0249	0.0255	0.0252	0.0251
	5	0.0278	0.0277	0.0269	0.0273	0.0273	0.0273	0.0273	0.0274	0.0272	0.0272
	6	0.0184	0.0186	0.0176	0.0193	0.0193	0.0192	0.0191	0.0188	0.0188	0.019
	Average	0.0235	0.0230	0.0225	0.0229	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Correct Direction	1		0.5833	0.5833	0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667
	2		0.5833	0.5	0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667
	3		0.6667	0.5	0.5833	0.75	0.6667	0.75	0.6667	0.75	0.75
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.4167	0.4167	0.4167	0.4167	0.5	0.5	0.4167
	Average		0.6111	0.5972	0.5417	0.5694	0.5833	0.5972	0.5694	0.6111	0.5972
No. of centers	1				2	9	9	8	6	7	6
	2				5	9	10	8	8	7	6
	3				2	17	7	7	4	10	5
	4				8	14	7	6	3	7	7
	5				8	7	7	7	3	7	6
	6				8	7	7	7	3	7	5
no. of lag	1				2	1	1	1	1	1	1
	2				1	1	1	1	1	1	1
	3				3	1	1	1	1	1	1
	4				1	1	1	1	1	1	1
	5				1	1	1	1	1	1	1
	6				1	1	1	1	1	1	1

Notes: Except that IRBF,MRBF in periods 3,4 use width (r) = 0.05, all others use r=0.1.
Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.

Table D.5. German Mark analysis 3(a)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0245	0.0245	0.0245	0.0246	0.0246	0.0247	0.0246
	2	0.0239	0.0234	0.0224	0.0229	0.0228	0.0229	0.0231	0.023	0.0233	0.0231
	3	0.0193	0.0184	0.0189	0.0179	0.0179	0.0179	0.018	0.0179	0.0181	0.0182
	4	0.0269	0.0254	0.0256	0.0249	0.0249	0.0249	0.025	0.0255	0.0252	0.025
	5	0.0278	0.0277	0.0269	0.0273	0.0273	0.0273	0.0273	0.0275	0.0272	0.0271
	6	0.0184	0.0186	0.0176	0.0193	0.0193	0.0192	0.0191	0.019	0.0188	0.0192
	Average	0.0236	0.0230	0.0225	0.0228	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Correct Direction	1		0.5833	0.5833	0.5833	0.6667	0.6667	0.6667	0.5833	0.6667	0.6667
	2		0.5833	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.6667	0.6667
	3		0.6667	0.5	0.75	0.6667	0.75	0.75	0.6667	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.4167	0.4167	0.4167	0.4167	0.4167	0.5	0.5
	Average		0.6111	0.5972	0.5694	0.5694	0.5833	0.58[illegible]	0.5556	0.5972	5972
No. of centers	1				5	8	10	8	7	7	4
	2				5	10	10	7	4	7	3
	3				10	4	10	7	4	2	3
	4				8	6	6	7	3	8	3
	5				8	6	6	7	3	7	3
	6				7	16	6	7	2	8	3

Notes : Lag length is equal to 1.
GRBF,CRBF,IRBF,MRBF use width (r) = 1.

Table D.6. German Mark analysis 3(b)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0244	0.0245	0.0245	0.0246	0.0246	0.0247	0.0246
	2	0.0239	0.0234	0.0224	0.0229	0.0227	0.0229	0.0231	0.023	0.0233	0.0231
	3	0.0193	0.0184	0.0189	0.0181	0.0179	0.0179	0.018	0.0179	0.0181	0.0182
	4	0.0269	0.0254	0.0256	0.0252	0.0249	0.0249	0.025	0.0255	0.0252	0.025
	5	0.0278	0.0277	0.0269	0.0272	0.0273	0.0273	0.0273	0.0275	0.0272	0.0271
	6	0.0184	0.0186	0.0176	0.0188	0.0193	0.0192	0.0191	0.019	0.0188	0.0192
	Average	0.0236	0.0230	0.0225	0.0228	0.0228	0.0228	0.0228	0.0229	0.0229	0.0229
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.6667	0.6667	0.5833	0.6667	0.6667
	2		0.5833	0.5	0.5833	0.5	0.5833	0.5833	0.5833	0.6667	0.6667
	3		0.6667	0.5	0.5833	0.6667	0.75	0.75	0.6667	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.5	0.4167	0.4167	0.4167	0.4167	0.5	0.5
	Average		0.6111	0.5972	0.5694	0.5556	0.5833	0.5833	0.5556	0.5972	0.5972
No. of centers	1				3	8	10	8	7	7	4
	2				3	3	10	7	4	7	3
	3				3	4	10	7	4	2	3
	4				3	6	6	7	8	3	3
	5				3	6	6	7	3	7	3
	6				3	16	6	1	2	8	3
No. of lag	1				3	1	1	1	1	1	1
	2				3	3	1	1	1	1	1
	3				3	1	1	1	1	1	1
	4				3	1	1	1	1	1	1
	5				3	1	1	1	1	1	1
	6				3	1	1	1	1	1	1

Notes : G,C,IRBF choose from lag1(r=1), lag2(r=1), lag (r=1); MRBF choose from lag1(r=1), lag2(r=1), lag3(r=0.5)
Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.

Table D.7. German Mark analysis 4(a2)---LR1

Criteria	period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0248	0.0249	0.0248	0.0249	0.0247	0.0245	0.0248
	2	0.0239	0.0234	0.0224	0.0231	0.0229	0.023	0.0231	0.0228	0.0234	0.0232
	3	0.0193	0.0184	0.0189	0.0175	0.0172	0.0172	0.0172	0.0172	0.0178	0.0176
	4	0.0269	0.0254	0.0256	0.0243	0.0239	0.0239	0.024	0.0241	0.0245	0.0244
	5	0.0278	0.0277	0.0269	0.0266	0.0266	0.0265	0.0266	0.0269	0.0267	0.0269
	6	0.0184	0.0186	0.0176	0.0187	0.0187	0.0187	0.0185	0.0185	0.018	0.0185
	Average	0.0235	0.0230	0.0225	0.0225	0.0224	0.0224	0.0224	0.0224	0.0225	0.0226
Correct Direction	1		0.5833	0.5833	0.6667	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	2		0.5833	0.5	0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5833
	3		0.6667	0.5	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.5	0.5	0.5	0.5833	0.5	0.5833	0.5
	6		0.6667	0.6667	0.5833	0.5833	0.5833	0.5	0.5833	0.5833	0.5833
	Average		0.6111	0.5972	0.6111	0.5833	0.5833	0.5972	0.5972	0.6111	0.5972
No. of centers	1				2	3	4	5	3	2	3
	2				2	3	4	5	3	2	3
	3				2	3	5	7	3	2	2
	4				2	3	5	5	3	2	3
	5				3	3	5	5	3	2	3
	6				3	3	4	4	3	2	3

Notes : Lag length is equal to 1.
Width: GRB, CRBF, IRBF,MRBF(r=1)

Table D.8. German Mark Univariate analysis [this is used to compare with multivariate analysis in analysis 4(a)]

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0242	0.0244	0.0242	0.0246	0.0246	0.0247	0.0246
	2	0.0239	0.0234	0.0224	0.0227	0.0227	0.0226	0.0229	0.023	0.0233	0.0232
	3	0.0193	0.0184	0.0189	0.0177	0.0176	0.0176	0.018	0.0179	0.0181	0.0181
	4	0.0269	0.0254	0.0256	0.0251	0.0251	0.0251	0.0255	0.0255	0.0252	0.025
	5	0.0278	0.0277	0.0269	0.0281	0.0276	0.028	0.0274	0.0275	0.0272	0.0271
	6	0.0184	0.0186	0.0176	0.0195	0.0192	0.0198	0.0187	0.019	0.0188	0.0192
	Average	0.0235	0.0230	0.0225	0.0229	0.0228	0.0229	0.0229	0.0229	0.0229	0.0229
Correct Direction	1		0.5833	0.5833	0.6667	0.5	0.5	0.5833	0.5833	0.6667	0.6667
	2		0.5833	0.5	0.6667	0.5	0.5	0.5833	0.5833	0.6667	0.5833
	3		0.6667	0.5	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.4167	0.4167	0.5	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.4167	0.4167	0.5	0.5	0.4167	0.5	0.5
	Average		0.6111	0.5972	0.5834	0.5278	0.5556	0.5695	0.5556	0.5973	0.5834
No. of centers	1				3	4	4	6	7	7	4
	2				3	4	4	8	4	7	3
	3				3	4	5	4	4	2	3
	4				3	4	4	3	3	8	3
	5				3	3	4	3	3	7	3
	6				3	3	4	3	2	8	3

Notes : Lag length is equal to 1.
Width: GRB, CRBF (r=0.2); IRBF,MRBF(r=0.1)

Table D.9. German Mark Univariate analysis [this is used to compare with multivariate analysis in analysis 5(a) and 5(c)]

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0244	0.0242	0.0251	0.0251	0.0247	0.0243	0.025
	2	0.0239	0.0234	0.0224	0.0229	0.0227	0.0234	0.0237	0.0233	0.024	0.0238
	3	0.0193	0.0184	0.0189	0.0181	0.0182	0.018	0.0182	0.0182	0.0186	0.0183
	4	0.0269	0.0254	0.0256	0.0252	0.0252	0.0251	0.0253	0.0254	0.0256	0.0257
	5	0.0278	0.0277	0.0269	0.0272	0.0272	0.0274	0.0271	0.0273	0.0274	0.0273
	6	0.0184	0.0186	0.0176	0.0188	0.019	0.0189	0.0181	0.0181	0.0181	0.0178
	Average	0.0235	0.0230	0.0225	0.0228	0.0228	0.0230	0.0229	0.0228	0.0230	0.0230
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.5	0.4167	0.5833	0.5833	0.6667
	2		0.5833	0.5	0.5833	0.5	0.5833	0.5833	0.5833	0.4167	0.6667
	3		0.6667	0.5	0.5833	0.5833	0.75	0.5833	0.5833	0.5833	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.75	0.6667	0.75	0.75
	5		0.5	0.6667	0.4167	0.4167	0.4167	0.5	0.4167	0.4167	0.5
	6		0.6667	0.6667	0.5	0.4167	0.4167	0.6667	0.6667	0.6667	0.75
	Average		0.6111	0.5972	0.5695	0.5417	0.5556	0.5833	0.5833	0.5695	0.6667
No. of centers	1				3	3	4	3	3	2	2
	2				3	3	4	3	3	2	2
	3				3	3	7	4	3	2	2
	4				3	3	5	3	3	4	2
	5				3	3	5	3	3	3	2
	6				3	3	4	3	3	3	2

Notes : Lag length is equal to 3.
Width: GRB, CRBF, IRBF (r=1); MRBF (r=0.5), if MRBF(r=1), r-square is not good.

Multivariate analyses (monthly data)

Table D.10. German Mark analysis 4(a1)—LR1

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0239	0.0241	0.0238	0.0247	0.0247	0.0245	0.0246
	2	0.0239	0.0234	0.0224	0.0212	0.0218	0.0213	0.0229	0.0228	0.0234	0.0232
	3	0.0193	0.0184	0.0189	0.0174	0.0177	0.0173	0.0174	0.0172	0.0178	0.0176
	4	0.0269	0.0254	0.0256	0.0244	0.0223	0.0223	0.0242	0.0241	0.0245	0.0248
	5	0.0278	0.0277	0.0269	0.0274	0.0281	0.0259	0.0269	0.0269	0.0267	0.0268
	6	0.0184	0.0186	0.0176	0.02	0.0194	0.0192	0.0186	0.0185	0.018	0.0185
	Average	0.0235	0.0230	0.0225	0.0224	0.0222	0.0216	0.0224	0.0224	0.0225	0.0226
Correct Direction	1		0.5833	0.5833	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	2		0.5833	0.5	0.5	0.5833	0.5	0.5833	0.5833	0.5833	0.5833
	3		0.6667	0.5	0.6667	0.6667	0.5833	0.6667	0.6667	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	5		0.5	0.6667	0.5	0.5	0.5	0.5	0.5	0.5833	0.5
	6		0.6667	0.6667	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	Average		0.6111	0.5972	0.5694	0.5972	0.5694	0.5972	0.5972	0.6111	0.5972
No. of centers	1				5	4	6	3	3	2	3
	2				5	4	6	3	3	2	3
	3				5	4	6	3	3	2	2
	4				5	4	4	3	3	2	3
	5				8	4	4	3	3	2	3
	6				4	4	4	3	3	2	3

Notes : Lag length is equal to 1.
Width: GRB, CRBF (r=0.2); IRBF,MRBF(r=0.1)

Table D.11. German Mark analysis 4(b)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0244	0.0242	0.0252	0.0249	0.0247	0.0248	0.0254
	2	0.0239	0.0234	0.0224	0.0222	0.0233	0.0234	0.0234	0.0232	0.0234	0.0236
	3	0.0193	0.0184	0.0189	0.0173	0.0171	0.0176	0.0174	0.0176	0.0178	0.0176
	4	0.0269	0.0254	0.0256	0.0243	0.0233	0.0223	0.0242	0.0245	0.0245	0.0246
	5	0.0278	0.0277	0.0269	0.0282	0.0285	0.0279	0.028	0.0278	0.0267	0.0278
	6	0.0184	0.0186	0.0176	0.0208	0.0211	0.0192	0.0202	0.0202	0.0182	0.0198
	Average	0.0235	0.0230	0.0225	0.0229	0.0229	0.0226	0.0230	0.0230	0.0226	0.0231
Correct Direction	1		0.5833	0.5833	0.5833	0.5833	0.6667	0.5833	0.5833	0.6667	0.5
	2		0.5833	0.5	0.5	0.5833	0.5833	0.5	0.5833	0.5833	0.5
	3		0.6667	0.5	0.5833	0.6667	0.6667	0.6667	0.6667	0.6667	0.5833
	4		0.6667	0.6667	0.6667	0.5833	0.6667	0.6667	0.75	0.6667	0.75
	5		0.5	0.6667	0.5	0.4167	0.4167	0.4167	0.4167	0.5833	0.4167
	6		0.6667	0.6667	0.4167	0.5	0.5833	0.4167	0.4167	0.6667	0.5833
	Average		0.6111	0.5972	0.5417	0.5556	0.5972	0.5417	0.5694	0.6389	0.5556
No. of centers	1				3	3	4	3	4	2	2
	2				4	4	4	3	4	2	2
	3				4	3	4	3	4	2	2
	4				3	5	4	3	4	2	3
	5				4	4	5	3	3	2	3
	6				3	5	4	3	3	3	3
No. of lag	1				2	2	2	2	2	2	3
	2				2	3	2	2	2	1	2
	3				2	2	2	1	3	1	1
	4				3	2	1	1	3	1	3
	5				2	2	2	2	2	1	2
	6				2	2	1	2	2	3	2

Notes: Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF select from lag1(r=0.2), lag2(r=0.5);lag3(r=1); IRBF,MRBF select from lag1(r=0.1), lag2(r=0.5);lag3(r=1)

Table D.12. German Mark analysis 4(c)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0236	0.0251	0.0251	0.0251	0.0251	0.0251	0.0254	0.0245
	2	0.0239	0.0234	0.0224	0.0231	0.0232	0.0232	0.0234	0.023	0.0234	0.0235
	3	0.0193	0.0184	0.0189	0.0172	0.0172	0.0172	0.0171	0.0169	0.0175	0.0175
	4	0.0269	0.0254	0.0256	0.0235	0.0234	0.0235	0.0232	0.0236	0.0239	0.0244
	5	0.0278	0.0277	0.0269	0.0264	0.0265	0.0265	0.0265	0.0267	0.0265	0.0266
	6	0.0184	0.0186	0.0176	0.0190	0.0191	0.0189	0.0189	0.019	0.0188	0.0185
	Average	0.0235	0.0230	0.0225	0.0224	0.0224	0.0224	0.0223	0.0224	0.0226	0.0225
Correct Direction	1		0.5833	0.5833	0.5	0.5	0.5	0.5	0.5833	0.4167	0.5833
	2		0.5833	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	3		0.6667	0.5	0.6667	0.6667	0.6667	0.6667	0.6667	0.75	0.75
	4		0.6667	0.6667	0.6667	0.75	0.75	0.6667	0.6667	0.8333	0.6667
	5		0.5	0.6667	0.5833	0.5	0.5	0.5	0.5	0.6667	0.5
	6		0.6667	0.6667	0.5833	0.5	0.5833	0.5833	0.5833	0.5	0.5833
	Average		0.6111	0.5972	0.5972	0.5833	0.5972	0.5833	0.5972	0.6250	0.6111
No. of centers	1				3	3	5	4	4	2	3
	2				3	3	5	5	3	2	3
	3				3	3	5	10	4	2	2
	4				3	3	5	5	3	2	3
	5				3	3	5	5	3	2	3
	6				3	3	5	4	3	3	3

Notes : Lag length is equal to 1.
GRB, CRBF, IRBF,MRBF use width (r) = 1.

Table D.13. German Mark analysis 4(d)

Criteria	period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0236	0.0233	0.0247	0.026	0.0249	0.0252	0.0249	0.0251
	2	0.0239	0.0234	0.0224	0.0230	0.0236	0.024	0.0233	0.023	0.024	0.0236
	3	0.0193	0.0184	0.0189	0.0178	0.0176	0.0178	0.0171	0.0174	0.0175	0.0175
	4	0.0269	0.0254	0.0256	0.0241	0.0239	0.0233	0.0238	0.0241	0.0239	0.0245
	5	0.0278	0.0277	0.0269	0.0274	0.0268	0.0273	0.0276	0.0271	0.0265	0.0273
	6	0.0184	0.0186	0.0176	0.0201	0.0202	0.0205	0.0203	0.0194	0.0185	0.0199
	Average	0.0235	0.0230	0.0225	0.0226	0.0228	0.0231	0.0228	0.0227	0.0225	0.0230
Correct Direction	1		0.5833	0.5833	0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5833
	2		0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	3		0.6667	0.5	0.5833	0.5833	0.6667	0.6667	0.5833	0.75	0.75
	4		0.6667	0.6667	0.5833	0.6667	0.6667	0.6667	0.6667	0.8333	0.75
	5		0.5	0.6667	0.5	0.5	0.4167	0.4167	0.4167	0.6667	0.5
	6		0.6667	0.6667	0.4167	0.5	0.5	0.4167	0.5	0.5833	0.5
	Average		0.6111	0.5972	0.5278	0.5556	0.5556	0.5556	0.5556	0.6667	0.6111
No. of centers	1				5	2	3	4	4	2	2
	2				3	2	4	4	4	2	3
	3				4	4	6	10	4	2	2
	4				5	4	5	4	3	2	3
	5				4	3	5	3	3	2	2
	6				3	4	5	3	3	2	3
No. of lag	1				2	2	2	2	2	2	3
	2				3	2	2	2	2	3	3
	3				2	2	2	1	3	1	1
	4				2	3	2	2	2	1	3
	5				3	2	2	2	3	1	3
	6				2	2	2	2	3	3	2

Notes: Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF, IRBF, MRBF select from lag1(r=1), lag2(r=0.5), lag3(r=1).

Table D.14. German Mark analysis 5(a)

Criteria	period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0243	0.0238	0.0249	0.0247	0.0243	0.0242	0.0249
	2	0.0239	0.0234	0.0224	0.0230	0.0227	0.0232	0.0238	0.0231	0.0241	0.0236
	3	0.0193	0.0184	0.0189	0.0184	0.0184	0.0184	0.0181	0.0183	0.018	0.0179
	4	0.0269	0.0254	0.0256	0.0252	0.0253	0.0252	0.0252	0.025	0.0251	0.0252
	5	0.0278	0.0277	0.0269	0.0269	0.027	0.027	0.027	0.0271	0.0273	0.0266
	6	0.0184	0.0186	0.0176	0.0188	0.0191	0.0189	0.0185	0.0191	0.0177	0.018
	Average	0.0235	0.0230	0.0225	0.0228	0.0227	0.0229	0.0229	0.0228	0.0227	0.0227
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667	0.5833	0.6667
	2		0.5833	0.5	0.5833	0.5	0.5	0.6667	0.5833	0.5833	0.6667
	3		0.6667	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.75	0.75	0.6667	0.5833	0.6667
	5		0.5	0.6667	0.5833	0.5833	0.5833	0.4167	0.4167	0.4167	0.5833
	6		0.6667	0.6667	0.5	0.5	0.5	0.5833	0.4167	0.75	0.6667
	Average		0.6111	0.5972	0.5972	0.5833	0.5833	0.6111	0.5556	0.5972	0.6528
No. of centers	1				3	3	5	5	4	2	2
	2				4	3	5	5	4	2	4
	3				3	5	7	5	5	2	2
	4				4	4	6	5	6	2	3
	5				4	4	6	4	4	2	3
	6				4	4	4	4	4	2	3

Notes : Lag length is equal to 3.
Width: GRB, CRBF, IRBF (r=1); MRBF(r=0.5)

Table D.15. German Mark analysis 5(b)

Criteria	period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0243	0.0244	0.0246	0.0246	0.0245	0.0247	0.0244
	2	0.0239	0.0234	0.0224	0.023	0.0227	0.0232	0.0233	0.0233	0.0241	0.0235
	3	0.0193	0.0184	0.0189	0.0184	0.0184	0.0182	0.0184	0.0183	0.018	0.0179
	4	0.0269	0.0254	0.0256	0.0252	0.0253	0.0252	0.0252	0.0253	0.0251	0.0252
	5	0.0278	0.0277	0.0269	0.0269	0.0275	0.0274	0.0275	0.028	0.0273	0.0274
	6	0.0184	0.0186	0.0176	0.0197	0.0191	0.0194	0.0193	0.0195	0.0177	0.018
	Average	0.0235	0.0230	0.0225	0.0229	0.0229	0.0230	0.0231	0.0232	0.0228	0.0227
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.6667	0.6667	0.5833	0.5833	0.5833
	2		0.5833	0.5	0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5833
	3		0.6667	0.5	0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667
	4		0.6667	0.6667	0.6667	0.6667	0.6667	0.75	0.6667	0.5833	0.6667
	5		0.5	0.6667	0.5833	0.4167	0.4167	0.4167	0.4167	0.4167	0.4167
	6		0.6667	0.6667	0.5	0.5	0.4167	0.4167	0.4167	0.75	0.6667
	Average		0.6111	0.5972	0.5972	0.5556	0.5556	0.5833	0.5417	0.5972	0.5972
No. of centers	1				3	3	4	3	4	3	2
	2				4	3	5	3	4	2	3
	3				3	5	7	7	5	2	2
	4				4	4	5	5	4	2	3
	5				4	3	5	5	4	2	3
	6				3	4	5	5	4	2	3
No. of lag	1				3	2	1	1	1	1	1
	2				3	3	2	1	1	3	1
	3				3	3	1	1	3	3	3
	4				3	3	1	3	1	3	3
	5				3	1	1	1	1	3	1
	6				2	3	1	1	1	3	3

Notes: Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
Width: GRBF,CRBF, IRBF (r=1), MRBF (r=0.5).

Table D.16. German Mark analysis 5(c)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0244	0.0243	0.0249	0.0252	0.0248	0.0242	0.0249
	2	0.0239	0.0234	0.0224	0.0228	0.0228	0.0236	0.0236	0.0235	0.0233	0.0235
	3	0.0193	0.0184	0.0189	0.0181	0.0181	0.0181	0.018	0.0181	0.0182	0.018
	4	0.0269	0.0254	0.0256	0.0255	0.0249	0.0251	0.0250	0.0249	0.0251	0.0254
	5	0.0278	0.0277	0.0269	0.0271	0.0272	0.0269	0.0272	0.0271	0.0268	0.0267
	6	0.0184	0.0186	0.0176	0.0184	0.0193	0.0188	0.019	0.0192	0.0178	0.0178
	Average	0.0235	0.0230	0.0225	0.0227	0.0228	0.0229	0.0230	0.0229	0.0226	0.0227
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.4167	0.5	0.5	0.5833	0.6667
	2		0.5833	0.5	0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.6667
	3		0.6667	0.5	0.5833	0.5833	0.6667	0.75	0.6667	0.6667	0.5833
	4		0.6667	0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.75	0.6667
	5		0.5	0.6667	0.5833	0.4167	0.5833	0.4167	0.4167	0.5833	0.5
	6		0.6667	0.6667	0.5833	0.4167	0.4167	0.4167	0.4167	0.75	0.6667
	Average		0.6111	0.5972	0.6111	0.5417	0.5556	0.5556	0.5417	0.6528	0.6250
No. of centers	1				3	4	4	4	3	2	2
	2				2	3	5	4	4	2	3
	3				3	3	7	5	4	2	2
	4				2	3	6	4	4	2	2
	5				2	3	5	4	4	2	4
	6				2	3	4	4	4	2	2

Notes : Lag length is equal to 3.
Width: GRB, CRBF, IRBF, MRBF (r=1).

Table D.17. German Mark analysis 5(d)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0248	0.0245	0.0235	0.0244	0.0243	0.0244	0.0246	0.0245	0.0242	0.0248
	2	0.0239	0.0234	0.0224	0.0228	0.0228	0.0229	0.0231	0.0232	0.0233	0.0232
	3	0.0193	0.0184	0.0189	0.0181	0.0181	0.0179	0.0182	0.0182	0.0182	0.018
	4	0.0269	0.0254	0.0256	0.0255	0.0249	0.025	0.0250	0.0252	0.0251	0.025
	5	0.0278	0.0277	0.0269	0.0271	0.0272	0.0276	0.0272	0.0276	0.0268	0.027
	6	0.0184	0.0186	0.0176	0.0184	0.0196	0.0194	0.019	0.0191	0.0178	0.0178
	Average	0.0235	0.0230	0.0225	0.0227	0.0228	0.0229	0.0229	0.0229	0.0226	0.0226
Correct Direction	1		0.5833	0.5833	0.6667	0.6667	0.5833	0.6667	0.6667	0.5833	0.5833
	2		0.5833	0.5	0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.5833
	3		0.6667	0.5	0.5833	0.5833	0.5833	0.6667	0.6667	0.6667	0.5833
	4		0.6667	0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.75	0.6667
	5		0.5	0.6667	0.5833	0.4167	0.4167	0.4167	0.4167	0.5833	0.5
	6		0.6667	0.6667	0.5833	0.5	0.5	0.4167	0.5	0.75	0.6667
	Average		0.6111	0.5972	0.6111	0.5556	0.5556	0.5695	0.5833	0.6528	0.5972
No. of centers	1				3	4	3	3	4	2	3
	2				2	3	3	3	4	2	3
	3				3	3	4	4	3	2	2
	4				2	3	4	4	3	2	3
	5				2	3	4	3	3	2	3
	6				2	4	4	3	3	2	2
No. of lag	1				3	3	1	1	1	3	1
	2				3	3	1	1	1	3	1
	3				3	3	1	1	1	3	3
	4				3	3	1	3	1	3	1
	5				3	3	1	1	1	3	1
	6				3	1	1	1	1	3	3

Notes: Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF, IRBF select from lag=1(r=0.5), lag2(r=1) and lag3(r=1); MRBF select from lag1(r=0.5), lag2(r=1), lag3(r=0.5)

Japanese Yen

Univariate analyses (monthly data)

Table D.18. Japanese Yen analysis 1

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0248	0.0248	0.0259	0.0248	0.0245	0.0235	0.0245
	2	0.0208	0.0245	0.0242	0.0243	0.0247	0.0239	0.0248	0.0239	0.0237	0.024
	3	0.0213	0.0235	0.0234	0.023	0.0232	0.0231	0.0224	0.0228	0.0224	0.0228
	4	0.0364	0.0336	0.0334	0.0326	0.0319	0.0322	0.0325	0.0329	0.033	0.0333
	5	0.0453	0.0393	0.0384	0.0394	0.0387	0.0389	0.0388	0.039	0.0399	0.0394
	6	0.0334	0.0301	0.0293	0.0322	0.0318	0.0317	0.0319	0.031	0.0334	0.0316
	Average	0.0303	0.0293	0.0289	0.0294	0.0292	0.0293	0.0292	0.0290	0.0293	0.0292
Correct Direction	1		0.5	0.5	0.5	0.5833	0.5	0.5	0.5	0.5	0.5
	2		0.3333	0.3333	0.4167	0.5	0.4167	0.5	0.5833	0.5	0.5
	3		0.3333	0.3333	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.5
	4		0.4167	0.4167	0.5	0.5833	0.5833	0.5	0.5833	0.5	0.4167
	5		0.5833	0.5	0.5	0.5833	0.5833	0.5	0.6667	0.5833	0.5833
	6		0.5	0.4167	0.4167	0.3333	0.3333	0.4167	0.5	0.5833	0.5
	Average		0.4444	0.4167	0.4722	0.5278	0.5000	0.5000	0.5694	0.5417	0.5
No. of centers	1				2	2	2	2	3	2	7
	2				2	2	2	2	2	2	2
	3				2	2	2	2	2	2	2
	4				2	2	2	2	2	2	2
	5				2	2	2	2	2	2	7
	6				2	2	2	2	2	2	6

Notes : Lag length is equal to 3.
Width: GRB (r=1);CRBF, IRBF MRBF (r=0.1)

Table D.19. Japanese Yen analysis 2

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0233	0.0229	0.0232	0.0236	0.0252	0.0235	0.0233
	2	0.0208	0.0245	0.0242	0.0231	0.0235	0.0232	0.0231	0.0251	0.0223	0.0227
	3	0.0213	0.0235	0.0234	0.0222	0.0225	0.0223	0.022	0.023	0.0218	0.0219
	4	0.0364	0.0336	0.0334	0.0325	0.0315	0.0319	0.0326	0.0328	0.0338	0.0331
	5	0.0453	0.0393	0.0384	0.0398	0.0395	0.0399	0.0403	0.0409	0.0418	0.0404
	6	0.0334	0.0301	0.0293	0.0324	0.0327	0.0327	0.0329	0.0332	0.0325	0.0326
	Average	0.0303	0.0293	0.0289	0.0289	0.0288	0.0289	0.0291	0.0300	0.0293	0.0290
Correct Direction	1		0.5	0.5	0.5833	0.5833	0.5833	0.5	0.5	0.5	0.5
	2		0.3333	0.3333	0.5	0.5833	0.5833	0.4167	0.5	0.3333	0.5
	3		0.3333	0.3333	0.5833	0.5833	0.5833	0.5833	0.5	0.4167	0.5833
	4		0.4167	0.4167	0.5	0.5833	0.5833	0.5	0.5833	0.5	0.5833
	5		0.5833	0.5	0.5	0.5833	0.5833	0.5	0.5833	0.5	0.5833
	6		0.5	0.4167	0.4167	0.3333	0.3333	0.3333	0.4167	0.3333	0.4167
	Average		0.4444	0.4167	0.5139	0.5417	0.5417	0.4722	0.5139	0.4306	0.5278
No. of centers	1				4	3	4	4	4	14	3
	2				3	3	4	3	3	11	4
	3				3	3	4	5	3	13	3
	4				2	3	3	3	3	11	3
	5				3	3	3	2	3	11	3
	6				3	3	3	3	3	11	3

Notes : Lag length is equal to 3.
Width: GRB (r=0.2);CRBF, IRBF MRBF (r=0.1)

Table D.20. Japanese Yen analysis 3

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0232	0.0233	0.0233	0.0233	0.0251	0.0238	0.0237
	2	0.0208	0.0245	0.0242	0.0231	0.0232	0.0234	0.0232	0.0251	0.0229	0.0232
	3	0.0213	0.0235	0.0234	0.0222	0.0224	0.0227	0.0224	0.0232	0.0221	0.0222
	4	0.0364	0.0336	0.0334	0.0324	0.032	0.0315	0.0324	0.0328	0.0338	0.0334
	5	0.0453	0.0393	0.0384	0.0399	0.0399	0.0396	0.0403	0.0409	0.042	0.0419
	6	0.0334	0.0301	0.0293	0.0321	0.0326	0.0327	0.0333	0.0332	0.0326	0.0332
	Average	0.0303	0.0293	0.0289	0.0288	0.0289	0.0289	0.0291	0.0301	0.0295	0.0296
Correct Direction	1		0.5	0.5	0.5	0.5833	0.5833	0.5	0.5	0.5	0.5
	2		0.3333	0.3333	0.5	0.5833	0.5833	0.5833	0.5	0.3333	0.5
	3		0.3333	0.3333	0.5833	0.5833	0.5833	0.5833	0.5833	0.3333	0.4167
	4		0.4167	0.4167	0.5	0.5833	0.5833	0.5833	0.5833	0.5	0.5
	5		0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	6		0.5	0.4167	0.3333	0.3333	0.3333	0.3333	0.4167	0.4167	0.4167
	Average		0.4444	0.4167	0.4861	0.5417	0.5417	0.5279	0.5278	0.4444	0.4861
No. of centers	1				3	5	3	3	3	2	2
	2				3	3	3	3	3	2	2
	3				3	3	3	3	3	2	2
	4				3	3	3	3	3	2	2
	5				3	?	3	3	3	2	2
	6				2	3	3	3	3	2	2

Notes : Lag length is equal to 3.
Width: GRB, CRBF(r=2); IRBF MRBF (r= 1)

Table D.21. Japanese Yen univariate analysis [this is used to compare with multivariate analysis in analysis 4(a)]

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0233	0.0235	0.0233	0.0236	0.0251	0.0238	0.0237
	2	0.0208	0.0245	0.0242	0.0231	0.0233	0.0234	0.023	0.0251	0.0229	0.0232
	3	0.0213	0.0235	0.0234	0.0222	0.0222	0.0227	0.022	0.0232	0.0221	0.0222
	4	0.0364	0.0336	0.0334	0.0325	0.0323	0.0315	0.0327	0.0328	0.0338	0.0334
	5	0.0453	0.0393	0.0384	0.0398	0.0401	0.0396	0.0406	0.0409	0.042	0.0418
	6	0.0334	0.0301	0.0293	0.0324	0.0327	0.0327	0.0328	0.0332	0.0326	0.0332
	Average	0.0303	0.0293	0.0289	0.0289	0.0290	0.0289	0.0291	0.0301	0.0295	0.0296
Correct Direction	1		0.5	0.5	0.5833	0.5833	0.5833	0.5	0.5	0.5	0.5
	2		0.3333	0.3333	0.5	0.5833	0.5833	0.5833	0.5	0.3333	0.5
	3		0.3333	0.3333	0.5833	0.5833	0.5833	0.5833	0.5833	0.3333	0.4167
	4		0.4167	0.4167	0.5	0.5833	0.5833	0.5833	0.5833	0.5	0.5
	5		0.5833	0.5	0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.5833
	6		0.5	0.4167	0.4167	0.4167	0.3333	0.3333	0.4167	0.4167	0.4167
	Average		0.4444	0.4167	0.5139	0.5417	0.5416	0.5278	0.5278	0.4444	0.4861
No. of centers	1				4	5	3	5	3	2	2
	2				3	5	3	5	3	2	2
	3				3	5	3	5	3	2	2
	4				3	5	3	5	3	2	2
	5				3	4	3	5	3	2	2
	6				3	4	3	4	3	2	2

Notes : Lag length is equal to 3.
Width: GRB, CRBF(r=2.5); IRBF MRBF (r= 1)

Table D.22. Japanese Yen univariate analysis [this is used to compare with multivariate analysis in analysis 5(c)]

Criteria	Period	R.W.	AR(1)	MA(1)	GRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0237	0.0236	0.0251	0.0238	0.0237
	2	0.0208	0.0245	0.0242	0.0232	0.023	0.0251	0.0229	0.0232
	3	0.0213	0.0235	0.0234	0.0222	0.022	0.0232	0.0221	0.0222
	4	0.0364	0.0336	0.0334	0.0326	0.0327	0.0328	0.0338	0.0334
	5	0.0453	0.0393	0.0384	0.0403	0.0406	0.0409	0.042	0.0418
	6	0.0334	0.0301	0.0293	0.0325	0.0328	0.0332	0.0326	0.0332
	Average	0.0303	0.0293	0.0289	0.0291	0.0291	0.0301	0.0295	0.0296
Correct Direction	1		0.5	0.5	0.5833	0.5	0.5	0.5	0.5
	2		0.3333	0.3333	0.4167	0.5833	0.5	0.3333	0.5
	3		0.3333	0.3333	0.5833	0.5833	0.5833	0.3333	0.4167
	4		0.4167	0.4167	0.5	0.5833	0.5833	0.5	0.5
	5		0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5833
	6		0.5	0.4167	0.4167	0.3333	0.4167	0.4167	0.4167
	Average		0.4444	0.4167	0.5000	0.5278	0.5278	0.4444	0.4861
No. of centers	1				7	5	3	2	2
	2				5	6	3	2	2
	3				7	6	3	2	2
	4				9	6	3	2	2
	5				4	6	3	2	2
	6				4	4	3	2	2

Notes : Lag length is equal to 3.
Width: GRB (r=3); MRBF (r= 1)

Multivariate analyses (monthly data)

Table D.23. Japanese Yen analysis 4

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0222	0.0225	0.0237	0.0226	0.0258	0.0235	0.0244
	2	0.0208	0.0245	0.0242	0.0222	0.0226	0.0228	0.0227	0.0259	0.0224	0.0232
	3	0.0213	0.0235	0.0234	0.0227	0.0226	0.0221	0.0222	0.0223	0.0225	0.0226
	4	0.0364	0.0336	0.0334	0.0326	0.0329	0.0332	0.0333	0.0334	0.034	0.0336
	5	0.0453	0.0393	0.0384	0.0402	0.0417	0.0411	0.0413	0.0409	0.0429	0.0422
	6	0.0334	0.0301	0.0293	0.0328	0.0331	0.0332	0.0331	0.0337	0.0332	0.0342
	Average	0.0303	0.0293	0.0289	0.0288	0.0292	0.0293	0.0292	0.0303	0.0298	0.0300
Correct Direction	1		0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.5	0.5	0.5
	2		0.3333	0.3333	0.5833	0.5	0.5833	0.5	0.3333	0.4167	0.4167
	3		0.3333	0.3333	0.5	0.5	0.5	0.5	0.4167	0.4167	0.4167
	4		0.4167	0.4167	0.5	0.5	0.5833	0.5	0.5	0.5	0.5
	5		0.5833	0.5	0.6667	0.6667	0.6667	0.5833	0.5833	0.6667	0.5833
	6		0.5	0.4167	0.5	0.5	0.5	0.4167	0.4167	0.5	0.25
	Average		0.4444	0.4167	0.5556	0.5417	0.5694	0.5139	0.4583	0.5000	0.4445
No. of centers	1				4	5	5	4	4	3	2
	2				4	4	4	4	3	3	2
	3				4	4	4	4	4	3	2
	4				4	4	5	4	3	2	2
	5				4	4	6	4	4	2	3
	6				4	4	4	4	3	3	2

Notes : Lag length is equal to 3.
Width: GRB, CRBF(r=2.5); IRBF MRBF (r= 1)

Table D.24. Japanese Yen analysis 5(a)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.0232	0.0228	0.0237	0.023	0.0237	0.0237	0.0239
	2	0.0208	0.0245	0.0242	0.0224	0.0231	0.023	0.0223	0.0241	0.0228	0.0224
	3	0.0213	0.0235	0.0234	0.0218	0.0219	0.0225	0.0217	0.0223	0.0221	0.0218
	4	0.0364	0.0336	0.0334	0.0323	0.0324	0.0315	0.0328	0.0327	0.0336	0.0332
	5	0.0453	0.0393	0.0384	0.0402	0.0405	0.0395	0.041	0.0403	0.0414	0.0423
	6	0.0334	0.0301	0.0293	0.0329	0.0325	0.0325	0.0328	0.0327	0.0334	0.0335
	Average	0.0303	0.0293	0.0289	0.0288	0.0289	0.0288	0.0289	0.0293	0.0295	0.0295
Correct Direction	1		0.5	0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.5	0.5
	2		0.3333	0.3333	0.5833	0.5833	0.5833	0.5833	0.5833	0.3333	0.4167
	3		0.3333	0.3333	0.5833	0.5833	0.5833	0.5833	0.5833	0.3333	0.5833
	4		0.4167	0.4167	0.5	0.6667	0.5833	0.5833	0.5	0.5	0.5
	5		0.5833	0.5	0.5	0.6667	0.5833	0.5833	0.5833	0.5833	0.4167
	6		0.5	0.4167	0.4167	0.3333	0.3333	0.4167	0.3333	0.4167	0.3333
	Average		0.4444	0.4167	0.51	0.5694	0.5417	0.5556	0.5278	0.4444	0.4583
No. of centers	1				3	5	4	5	3	2	2
	2				3	3	3	4	3	2	3
	3				3	5	3	5	3	2	3
	4				3	5	3	4	3	2	3
	5				3	5	3	4	3	2	3
	6				3	3	3	4	3	2	3

Notes : Lag length is equal to 3.
Width: GRB, CRBF(r=2); IRBF(r=1); MRBF (r= 1.5)

Table D.25. Japanese Yen analysis 5(c)

Criteria	Period	Model							
		R.W.	AR(1)	MA(1)	GRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0245	0.025	0.0246	0.023	0.0232	0.024	0.0238	0.0239
	2	0.0208	0.0245	0.0242	0.0224	0.0227	0.0242	0.0226	0.0222
	3	0.0213	0.0235	0.0234	0.0214	0.0218	0.0224	0.0218	0.0215
	4	0.0364	0.0336	0.0334	0.0325	0.0324	0.031	0.0335	0.0334
	5	0.0453	0.0393	0.0384	0.0404	0.0403	0.0407	0.0416	0.0427
	6	0.0334	0.0301	0.0293	0.033	0.0333	0.0322	0.0329	0.0336
	Average	0.0303	0.0293	0.0289	0.0288	0.0289	0.0292	0.0294	0.0295
Correct Direction	1		0.5	0.5	0.5	0.5833	0.5833	0.5	0.5
	2		0.3333	0.3333	0.5833	0.5	0.5833	0.4167	0.5
	3		0.3333	0.3333	0.6667	0.5833	0.5833	0.4167	0.5833
	4		0.4167	0.4167	0.5	0.5833	0.5833	0.5	0.5
	5		0.5833	0.5	0.5	0.5833	0.5833	0.5833	0.5
	6		0.5	0.4167	0.4167	0.5	0.3333	0.3333	0.25
	Average		0.4444	0.4167	0.5278	0.55556	0.5417	0.4583	0.4722
No. of centers	1				5	4	3	2	2
	2				4	3	3	2	3
	3				6	3	3	2	2
	4				5	3	3	2	2
	5				5	3	3	2	2
	6				4	3	3	2	2

Notes : Lag length is equal to 3.
Width: GRB (r=3); MRBF (r= 1)

Italian Lira

Univariate analyses (monthly data)

Table D.26. Italian Lira analysis 1(a)

Criteria	Period	Model								
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF
RMSE	1	0.034	0.0299	0.0279	0.0292	0.0291	0.0292	0.0294	0.0293	0.0294
	2	0.0237	0.0211	0.0191	0.0213	0.0213	0.0213	0.0210	0.0212	0.0216
	3	0.017	0.0158	0.016	0.0156	0.0156	0.0156	0.0160	0.0158	0.0164
	4	0.0216	0.0229	0.0212	0.0229	0.0229	0.0229	0.0228	0.0233	0.0221
	5	0.0178	0.0188	0.0176	0.0191	0.0191	0.0191	0.0191	0.0192	0.0188
	6	0.0077	0.007	0.008	0.0066	0.0065	0.0066	0.0079	0.007	0.0087
	Average	0.0203	0.0192	0.0183	0.0191	0.0191	0.0191	0.0194	0.0193	0.0195
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.75	0.6667
	3		0.6667	0.5833	0.6667	0.6667	0.6667	0.5833	0.5833	0.4167
	4		0.5	0.5	0.5	0.5	0.5	0.4167	0.5	0.4167
	5		0.5	0.5833	0.5	0.5	0.5	0.5833	0.5	0.5
	6		0.5	0.5	0.6667	0.6667	0.6667	0.5833	0.5	0.3333
	Average		0.5972	0.6250	0.6250	0.6250	0.6250	0.5972	0.5833	0.5000
No. of centers	1				2	2	2	2	2	2
	2				2	2	2	2	2	2
	3				2	2	2	2	2	2
	4				2	2	2	2	2	2
	5				2	2	2	2	2	2
	6				2	2	2	2	4	2

Notes : Lag length is equal to 1.
GRBF,CRBF,IRBF,MRBF use width (r) = 0.1

Table D.27. Italian Lira analysis 1(b)

Criteria	Period	Model								
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF
RMSE	1	0.034	0.0299	0.0279	0.0292	0.0291	0.0292	0.0294	0.0292	0.0268
	2	0.0237	0.0211	0.0191	0.0213	0.0213	0.0213	0.0210	0.0201	0.0197
	3	0.017	0.0158	0.016	0.0156	0.0156	0.0156	0.0163	0.0163	0.0162
	4	0.0216	0.0229	0.0212	0.0229	0.0229	0.0229	0.0216	0.024	0.0214
	5	0.0178	0.0188	0.0176	0.0187	0.0191	0.0191	0.0183	0.0188	0.0181
	6	0.0077	0.007	0.008	0.0066	0.0065	0.0066	0.0076	0.0075	0.0086
	Average	0.0203	0.0193	0.0183	0.0190	0.0191	0.0191	0.0190	0.0193	0.0185
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.6667	0.5833	0.6667	0.6667	0.6667	0.5833	0.5833	0.5833
	4		0.5	0.5	0.5	0.5	0.5	0.4167	0.4167	0.4167
	5		0.5	0.5833	0.5	0.5	0.5	0.5	0.5	0.5
	6		0.5	0.5	0.6667	0.6667	0.6667	0.6667	0.5833	0.5833
	Average		0.5972	0.6250	0.6250	0.6250	0.6250	0.5972	0.5833	0.5833
No. of centers	1				2	2	2	2	2	2
	2				2	2	2	2	2	2
	3				2	2	2	2	2	2
	4				2	2	2	3	2	2
	5				4	2	2	2	2	2
	6				2	2	2	2	2	2
No. of lag	1				1	1	1	1	2	3
	2				1	1	1	1	2	3
	3				1	1	1	3	3	3
	4				1	1	1	3	2	3
	5				2	1	1	3	3	3
	6				1	1	1	3	3	3

Notes : Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF,IRBF,MRBF use width (r) = 0.1

Table D.28. Italian Lira analysis 2(a)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0293	0.0293	0.0292	0.0293	0.0297	0.0299	0.0296
	2	0.0237	0.0211	0.0191	0.0212	0.0211	0.021	0.0211	0.0212	0.0215	0.0212
	3	0.017	0.0158	0.016	0.0159	0.0159	0.016	0.016	0.016	0.016	0.0161
	4	0.0216	0.0229	0.0212	0.0224	0.0224	0.0226	0.0226	0.022	0.022	0.0223
	5	0.0178	0.0188	0.0176	0.0185	0.0186	0.0188	0.0188	0.0182	0.0182	0.0185
	6	0.0077	0.007	0.008	0.0072	0.0072	0.0074	0.0078	0.0075	0.0072	0.0075
	Average	0.0203	0.0193	0.0183	0.0191	0.0191	0.0192	0.0193	0.0191	0.0191	0.0192
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.6667	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	4		0.5	0.5	0.4167	0.4167	0.4167	0.4167	0.4167	0.5	0.4167
	5		0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5	0.5833
	6		0.5	0.5	0.5	0.5	0.5833	0.5833	0.5833	0.5	0.5833
	Average		0.5972	0.6250	0.5833	0.5833	0.5972	0.5972	0.5972	0.5833	0.5972
No. of centers	1				2	2	6	8	2	6	2
	2				2	2	6	8	2	5	2
	3				2	2	4	7	2	5	2
	4				2	2	5	7	2	5	2
	5				2	2	5	5	2	7	12
	6				2	2	5	5	2	7	3

Notes : Lag length is equal to 1.
GRBF,CRBF,IRBF,MRBF use width (r) = 0.1

Table D.29. Italian Lira analysis 2(b)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0293	0.0293	0.0292	0.0293	0.0297	0.0299	0.0296
	2	0.0237	0.0211	0.0191	0.0212	0.0211	0.021	0.0211	0.0187	0.0215	0.0212
	3	0.017	0.0158	0.016	0.0159	0.0159	0.016	0.016	0.0163	0.016	0.0161
	4	0.0216	0.0229	0.0212	0.0224	0.0224	0.0226	0.0226	0.0225	0.022	0.0223
	5	0.0178	0.0188	0.0176	0.0185	0.0186	0.0188	0.0188	0.0193	0.0182	0.0186
	6	0.0077	0.007	0.008	0.0072	0.0072	0.0074	0.0078	0.0077	0.0077	0.0077
	Average	0.0203	0.0193	0.0183	0.0191	0.0191	0.0192	0.0193	0.0190	0.0192	0.0192
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.8333	0.75	0.75
	3		0.6667	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	4		0.5	0.5	0.4167	0.4167	0.4167	0.4167	0.4167	0.5	0.4167
	5		0.5	0.5833	0.5833	0.5833	0.5833	0.5833	0.4167	0.5	0.5833
	6		0.5	0.5	0.5	0.5	0.5833	0.5833	0.6667	0.5	0.5
	Average		0.5972	0.6250	0.5833	0.5833	0.5972	0.5972	0.5972	0.5833	0.5833
No. of centers	1				2	2	6	8	2	6	2
	2				2	2	6	8	2	5	2
	3				2	2	4	7	2	5	2
	4				2	2	5	7	2	5	2
	5				2	2	5	5	2	7	12
	6				2	2	5	5	3	8	3
No. of lag	1				1	1	1	1	2	1	1
	2				1	1	1	1	3	1	1
	3				1	1	1	1	3	1	1
	4				1	1	1	1	3	1	1
	5				1	1	1	1	2	1	1
	6				1	1	1	1	3	3	3

Notes : Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF,IRBF,MRBF use width (r) = 0.1

Table D.30. Italian Lira analysis 3(a)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0295	0.0294	0.0294	0.0293	0.0299	0.03	0.0312
	2	0.0237	0.0211	0.0191	0.0213	0.0212	0.0211	0.0211	0.0212	0.0216	0.0218
	3	0.017	0.0158	0.016	0.0163	0.0159	0.0161	0.016	0.016	0.016	0.0163
	4	0.0216	0.0229	0.0212	0.0221	0.0223	0.0224	0.0226	0.0221	0.022	0.022
	5	0.0178	0.0188	0.0176	0.0184	0.0185	0.0187	0.0188	0.0182	0.0182	0.018
	6	0.0077	0.007	0.008	0.0071	0.0072	0.0074	0.0077	0.0072	0.0071	0.0071
	Average	0.0203	0.0193	0.0183	0.0191	0.0191	0.0192	0.0193	0.0191	0.0192	0.0194
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.6667	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833
	4		0.5	0.5	0.5	0.4167	0.4167	0.4167	0.4167	0.5	0.5
	5		0.5	0.5833	0.5	0.5833	0.5833	0.5833	0.5	0.5	0.5
	6		0.5	0.5	0.5	0.5	0.5833	0.5833	0.5	0.5833	0.6667
	Average		0.5972	0.6250	0.5833	0.5833	0.5972	0.5972	0.5694	0.5972	0.6111
No. of centers	1				2	2	3	8	2	2	2
	2				2	2	3	8	2	2	2
	3				2	2	3	7	2	2	2
	4				2	2	3	7	2	2	2
	5				2	2	4	5	2	2	2
	6				2	2	8	5	2	2	2

Notes : Lag length is equal to 1.
GRBF,CRBF,IRBF,MRBF use width (r) = 1

Table D.31. Italian Lira analysis 3(b)

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0295	0.0294	0.0294	0.0293	0.0297	0.0278	0.0287
	2	0.0237	0.0211	0.0191	0.0213	0.0212	0.0211	0.0211	0.0186	0.0205	0.0208
	3	0.017	0.0158	0.016	0.0163	0.0159	0.0161	0.016	0.0163	0.0164	0.0162
	4	0.0216	0.0229	0.0212	0.0221	0.0223	0.0224	0.0226	0.0224	0.0211	0.0217
	5	0.0178	0.0188	0.0176	0.0184	0.0185	0.0187	0.0188	0.0185	0.0175	0.0182
	6	0.0077	0.007	0.008	0.0071	0.0072	0.0074	0.0077	0.0077	0.0081	0.0072
	Average	0.0203	0.0193	0.0183	0.0191	0.0191	0.0192	0.0193	0.0189	0.0185	0.0188
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.8333	0.75	0.75
	3		0.6667	0.5833	0.5833	0.5833	0.5833	0.5833	0.5833	0.6667	0.5833
	4		0.5	0.5	0.5	0.4167	0.4167	0.4167	0.5	0.5	0.4167
	5		0.5	0.5833	0.5	0.5833	0.5833	0.5833	0.4167	0.5	0.5
	6		0.5	0.5	0.5	0.5	0.5833	0.5833	0.6667	0.5	0.6667
	Average		0.5972	0.6250	0.5833	0.5833	0.5972	0.5972	0.6111	0.5972	0.5972
No. of centers	1				2	2	3	8	2	2	2
	2				2	2	3	8	3	2	2
	3				2	2	3	7	3	3	2
	4				2	2	3	7	3	3	2
	5				2	2	4	5	2	4	2
	6				2	2	8	5	3	2	2
No. of centers	1				1	1	1	1	2	3	2
	2				1	1	1	1	3	3	2
	3				1	1	1	1	3	3	2
	4				1	1	1	1	3	3	2
	5				1	1	1	1	3	3	2
	6				1	1	1	1	3	3	3

Notes : Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF,IRBF,MRBF use width (r) = 1

Table D.32. Italian Lira univariate analysis [this is used to compare with multivariate analysis in analysis 4(a)]

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0321	0.0305	0.0303	0.0299	0.0298	0.0278	0.0288
	2	0.0237	0.0211	0.0191	0.0218	0.0207	0.0207	0.0212	0.0186	0.0205	0.021
	3	0.017	0.0158	0.016	0.016	0.0161	0.0159	0.0161	0.0163	0.0164	0.016
	4	0.0216	0.0229	0.0212	0.0227	0.0223	0.0227	0.0224	0.0224	0.0211	0.0223
	5	0.0178	0.0188	0.0176	0.0187	0.0195	0.0186	0.0186	0.0185	0.0175	0.0173
	6	0.0077	0.007	0.008	0.0083	0.0075	0.0076	0.0076	0.0077	0.0081	0.0072
	Average	0.0203	0.0193	0.0183	0.0199	0.0194	0.0193	0.0193	0.0189	0.0186	0.0188
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.8333	0.75	0.75
	3		0.6667	0.5833	0.5833	0.5833	0.6667	0.5833	0.5833	0.6667	0.5833
	4		0.5	0.5	0.4167	0.5	0.4167	0.4167	0.5	0.5	0.5
	5		0.5	0.5833	0.5	0.5833	0.5	0.5	0.4167	0.5	0.5
	6		0.5	0.5	0.5	0.5	0.5	0.5	0.6667	0.5	0.6667
	Average		0.5972	0.6250	0.5695	0.5972	0.5834	0.5695	0.6111	0.5972	0.6111
No. of centers	1						5	8	3	2	2
	2						6	7	3	2	2
	3						3	4	3	3	2
	4						5	7	3	3	2
	5						6	4	2	4	2
	6						6	6	3	2	2

Notes : Lag length is equal to 3.
Width: GRB ,CRBF(r=1.5); IRBF,MRBF (r= 1)

Multivariate analyses

Table D.33. Italian Lira analysis 4(a)---LR

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0308	0.0302	0.0297	0.0296	0.0281	0.0268	0.0276
	2	0.0237	0.0211	0.0191	0.0215	0.0203	0.0203	0.021	0.02	0.0204	0.0202
	3	0.017	0.0158	0.016	0.0153	0.0154	0.0149	0.0155	0.0161	0.016	0.0159
	4	0.0216	0.0229	0.0212	0.0222	0.0227	0.0221	0.0225	0.0222	0.0208	0.0217
	5	0.0178	0.0188	0.0176	0.0186	0.0184	0.0184	0.0187	0.0179	0.0174	0.0175
	6	0.0077	0.007	0.008	0.0078	0.0083	0.0082	0.0081	0.0079	0.0078	0.0071
	Average	0.0203	0.0193	0.0183	0.0194	0.0192	0.0189	0.0192	0.0187	0.0182	0.0183
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.6667	0.5833	0.75	0.75	0.75	0.75	0.6667	0.6667	0.6667
	4		0.5	0.5	0.5833	0.5833	0.5833	0.5833	0.4167	0.5	0.5
	5		0.5	0.5833	0.5	0.5	0.4167	0.5	0.6667	0.5833	0.6667
	6		0.5	0.5	0.5833	0.5	0.5	0.4167	0.75	0.6667	0.75
	Average		0.5972	0.6250	0.6389	0.6250	0.6111	0.6111	0.6528	0.6389	0.6667
No. of centers	1				3	3	4	3	4	2	2
	2				3	5	4	4	3	2	3
	3				4	5	4	4	3	2	2
	4				4	5	4	4	2	2	2
	5				5	5	6	4	2	3	2
	6				6	6	5	4	3	3	3

Notes : Lag length is equal to 3.
Width: GRB ,CRBF(r=1.5); IRBF,MRBF (r= 1)

Table D.34. Italian Lira analysis 4(b)—LR

Criteria	Period	Model									
		R.W.	AR(1)	MA(1)	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.034	0.0299	0.0279	0.0295	0.0302	0.0297	0.0293	0.0281	0.029	0.0306
	2	0.0237	0.0211	0.0191	0.0212	0.0203	0.0202	0.0211	0.0195	0.0218	0.0211
	3	0.017	0.0158	0.016	0.0155	0.0156	0.0163	0.016	0.0161	0.0163	0.0163
	4	0.0216	0.0229	0.0212	0.0218	0.0219	0.0221	0.0222	0.0233	0.0218	0.0216
	5	0.0178	0.0188	0.0176	0.0183	0.0184	0.0184	0.0187	0.0179	0.0174	0.0179
	6	0.0077	0.007	0.008	0.0072	0.0072	0.0082	0.0081	0.0079	0.0078	0.0071
	Average	0.0203	0.0193	0.0183	0.0189	0.0189	0.0191	0.0192	0.0188	0.0190	0.0191
Correct Direction	1		0.6667	0.75	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667	0.6667
	2		0.75	0.8333	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.6667	0.5833	0.6667	0.6667	0.5833	0.5833	0.6667	0.5833	0.5833
	4		0.5	0.5	0.5	0.5	0.5833	0.4167	0.4167	0.4167	0.4167
	5		0.5	0.5833	0.5833	0.5	0.4167	0.5	0.6667	0.5833	0.5
	6		0.5	0.5	0.4167	0.4167	0.5	0.4167	0.75	0.6667	0.75
	Average		0.5972	0.6250	0.5972	0.5833	0.5833	0.5556	0.6528	0.6111	0.6111
No. of centers	1				2	4	4	3	4	2	2
	2				2	4	4	3	4	2	2
	3				2	2	4	3	3	2	2
	4				2	2	4	3	4	2	2
	5				2	6	6	4	2	3	2
	6				2	2	5	4	3	3	3
No. of centers	1				1	3	3	1	3	2	1
	2				1	3	2	1	2	1	2
	3				1	1	2	1	3	1	2
	4				1	1	3	1	2	1	2
	5				1	3	3	3	3	3	2
	6				1	1	3	3	3	3	3

Notes: Lag length is selected from lag 1 to lag 3 by minimizing the BIC value.
GRBF,CRBF select from lag1(r=1), lag2(r=1);lag3(r=1.5); IRBF, MRBF select from lag1(r=1), lag2(r=1);lag3(r=1)

APPENDIX E DETAILED TABLES FOR CHAPTER 6

German Mark

Multivariate analysis (quarterly data)

Table E.1. German Mark Analysis 1(a): quarterly data (LR1)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.044	0.0418	0.0404	0.0429	0.0445	0.0579	0.054	0.0606	0.056
	2	0.0474	0.0498	0.0295	0.0281	0.0301	0.0365	0.0382	0.0314	0.0382
	3	0.0321	0.0356	0.0171	0.0274	0.0258	0.0287	0.0234	0.0342	0.0283
	4	0.0583	0.0569	0.0419	0.0482	0.0487	0.0584	0.0457	0.0599	0.0536
	5	0.068	0.0572	0.0437	0.0488	0.049	0.0434	0.0475	0.0553	0.0527
	6	0.0251	0.0294	0.0481	0.0377	0.0393	0.054	0.0511	0.0267	0.0378
	Average	0.0441	0.0451	0.0368	0.0389	0.0396	0.0465	0.0433	0.0447	0.0445
Correct Direction	1		0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	2		0.25	1	1	1	0.75	0.5	0.75	0.75
	3		0	1	0.75	0.75	0.25	0.5	0.25	0.5
	4		0.25	0.75	0.75	0.75	0.25	0.75	0.25	0.5
	5		0.25	0.5	0.5	0.5	0.5	0.25	0.5	0.5
	6		0	0.25	0.25	0.25	0.25	0	0.5	0.25
	Average		0.25	0.71	0.67	0.67	0.46	0.46	0.50	0.54
Speculative Direction	1	0.50		0.75	0.50	0.50	0.50	0.50	0.50	0.50
	2	0.75		1.00	1.00	1.00	0.75	0.50	0.75	0.75
	3	1.00		1.00	0.75	0.75	0.75	0.50	0.25	0.50
	4	0.75		0.75	0.75	0.75	0.25	0.75	0.25	0.50
	5	0.75		0.50	0.50	0.75	0.50	0.50	0.50	0.50
	6	1.00		0.25	0.25	0.50	0.25	0.50	0.50	0.50
	Average	0.79		0.71	0.63	0.71	0.50	0.54	0.46	0.54
No. of centers	1			14	16	14	14	16	13	4
	2			14	10	10	11	18	5	4
	3			5	10	10	14	12	5	4
	4			5	8	12	20	13	5	4
	5			5	8	8	19	12	4	4
	6			7	8	10	22	20	4	4
Width(r)	1			1.4	1.2	0.9	0.5			
	2			1.5	1.2	0.7	0.5			
	3			1.3	1.1	0.6	0.5			
	4			1.3	0.9	0.8	0.5			
	5			1.3	0.9	0.6	0.5			
	6			1.2	0.9	0.6	0.5			

Table E.2. German Mark Analysis 1(b): quarterly data (LR2)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.044	0.0418	0.0406	0.0416	0.0424	0.0639	0.0555	0.0597	0.0538
	2	0.0474	0.0498	0.026	0.0293	0.0314	0.0467	0.0352	0.0452	0.0416
	3	0.0321	0.0356	0.0294	0.0267	0.0204	0.0366	0.0358	0.0279	0.029
	4	0.0583	0.0569	0.0481	0.0512	0.0458	0.0482	0.0481	0.0643	0.053
	5	0.058	0.0572	0.0487	0.0416	0.0465	0.0469	0.047	0.0553	0.0529
	6	0.0251	0.0294	0.046	0.0433	0.0431	0.0471	0.046	0.0336	0.0343
	Average	0.0442	0.0451	0.0398	0.0389	0.0383	0.0482	0.0446	0.0477	0.0441
Correct Direction	1		0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.5
	2		0.25	1	1	1	0.75	0.75	0.75	0.5
	3		0	0.75	0.75	1	0.25	0.25	0.5	0.5
	4		0.25	0.5	0.5	0.75	0.25	0.25	0.25	0.5
	5		0.25	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	6		0	0.25	0.25	0.25	0.25	0.5	0.5	0.25
	Average		0.25	0.63	0.63	0.71	0.42	0.46	0.50	0.46
Speculative Direction	1	0.50		0.50	0.50	0.50	0.50	0.50	0.50	0.50
	2	0.75		1.00	1.00	1.00	0.75	0.75	0.50	0.75
	3	1.00		0.75	0.75	1.00	0.25	0.25	0.50	0.50
	4	0.75		0.50	0.50	0.75	0.25	0.25	0.25	0.50
	5	0.75		0.75	0.75	0.50	0.50	0.50	0.50	0.50
	6	1.00		0.50	0.25	0.25	0.25	0.25	0.50	0.50
	Average	0.79		0.67	0.63	0.67	0.42	0.42	0.46	0.54
No. of centers	1			18	11	11	20	12	6	5
	2			18	10	10	24	26	3	5
	3			12	10	8	13	13	6	4
	4			15	16	12	15	15	6	4
	5			9	15	9	14	14	6	5
	6			9	8	9	14	14	6	4
Width(r)	1			1.6	1.2	0.8	0.1			
	2			1.6	1.2	0.7	0.1			
	3			1.5	1.1	0.8	0.1			
	4			1.6	0.9	1.2	0.1			
	5			1.6	1.7	1.2	0.1			
	6			1.6	1.1	1.2	0.1			

Table E.3. German Mark Analysis 2(a): quarterly data (SR1)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.044	0.0418	0.042	0.0443	0.0493	0.0613	0.0604	0.0972	0.0482
	2	0.0474	0.0498	0.0334	0.0355	0.0337	0.0306	0.0334	0.0448	0.0499
	3	0.0321	0.0366	0.0264	0.0296	0.0211	0.0279	0.0326	0.0325	0.0263
	4	0.0583	0.0569	0.0484	0.0512	0.0515	0.0529	0.0522	0.0568	0.0569
	5	0.058	0.0572	0.0493	0.0521	0.05	0.054	0.0555	0.0567	0.0568
	6	0.0251	0.0294	0.0466	0.0434	0.0499	0.0407	0.0548	0.0316	0.0379
	Average	0.0442	0.0451	0.0410	0.0427	0.0426	0.0446	0.0482	0.0533	0.0460
Correct Direction	1		0.75	0.75	0.75	0.75	0.75	0.5	0.5	0.75
	2		0.25	1	1	0.5	0.75	0.5	0.75	0.5
	3		0	1	0.75	1	0.75	0.25	0.75	0.5
	4		0.25	0.75	0.75	0.75	0.75	0.25	0.75	0.75
	5		0.25	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	6		0	0	0.25	0.25	0.5	0.25	0.25	0.25
	Average		0.25	0.67	0.67	0.63	0.67	0.38	0.58	0.54
Speculative Direction	1	0.50		0.50	0.50	0.25	0.50	0.50	0.25	0.50
	2	0.75		0.75	1.00	1.00	0.75	0.75	0.50	0.50
	3	1.00		1.00	0.75	1.00	0.75	0.25	0.75	0.50
	4	0.75		0.75	0.75	0.75	0.75	0.25	0.75	0.75
	5	0.75		0.50	0.50	0.50	0.50	0.50	0.75	0.75
	6	1.00		0.25	0.50	0.50	0.50	0.25	0.75	0.50
	Average	0.79		0.63	0.67	0.67	0.63	0.42	0.63	0.58
No. of centers	1			5	2	8	22	24	7	3
	2			18	17	17	26	20	3	7
	3			6	2	8	21	20	3	6
	4			6	14	14	9	19	3	3
	5			7	13	11	9	34	3	3
	6			7	15	10	9	19	3	6
Width(r)	1			0.8	0.5	0.5	0.7			
	2			1.6	0.9	1.0	0.8			
	3			1.0	0.5	0.5	0.8			
	4			1.0	0.8	0.5	0.8			
	5			1.0	0.9	0.5	0.8			
	6			1.5	0.7	0.9	1.0			

Table E.4. German Mark Analysis 2(b): quarterly data (SR2)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.044	0.0418	0.0395	0.0456	0.0412	0.0558	0.0552	0.054	0.0501
	2	0.0474	0.0498	0.0258	0.0354	0.0299	0.0327	0.0304	0.0448	0.0472
	3	0.0321	0.0356	0.0249	0.0217	0.0212	0.031	0.0376	0.026	0.032
	4	0.0583	0.0569	0.0517	0.0499	0.051	0.0519	0.0493	0.0496	0.0543
	5	0.058	0.0572	0.0507	0.0503	0.0521	0.0533	0.0485	0.0609	0.0525
	6	0.0251	0.0294	0.0507	0.044	0.0562	0.05	0.0505	0.066	0.0333
	Average	0.0442	0.0451	0.0406	0.0412	0.0420	0.0458	0.0452	0.0502	0.0449
Correct Direction	1		0.75	0.75	0.75	0.75	0.5	0.5	0.75	0.75
	2		0.25	0.75	1	0.75	0.75	0.75	0.5	0.75
	3		0	0.5	0.75	0.75	0.25	0.25	0.25	0.75
	4		0.25	0.5	0.75	0.5	0.25	0.75	0.75	0.75
	5		0.25	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	6		0	0.25	0.25	0.25	0.25	0.25	0.25	0.5
	Average		0.25	0.54	0.67	0.58	0.42	0.50	0.50	0.67
Speculative Direction	1	0.50		0.75	0.75	0.50	0.50	0.50	0.25	0.50
	2	0.75		0.75	1.00	1.00	1.00	0.75	0.75	0.50
	3	1.00		0.75	0.75	0.75	0.25	0.25	0.50	0.75
	4	0.75		0.50	0.75	0.50	0.50	0.75	0.75	0.75
	5	0.75		0.50	0.50	0.50	0.50	0.50	0.50	0.50
	6	1.00		0.25	0.50	0.25	0.50	0.25	0.25	0.50
	Average	0.79		0.58	0.71	0.58	0.54	0.50	0.50	0.58
No. of centers	1			6	10	9	14	14	2	3
	2			20	11	20	13	19	2	3
	3			18	11	10	17	21	14	4
	4			12	17	20	13	16	4	4
	5			12	14	18	18	11	21	5
	6			10	7	19	20	17	21	4
Width(r)	1			1.3	0.8	0.8	0.1			
	2			1.3	0.8	0.8	0.2			
	3			1.4	0.7	0.8	0.2			
	4			1.0	0.8	0.8	0.3			
	5			1.0	0.8	0.8	0.3			
	6			1.0	0.8	0.8	0.2			

Table E.5. German Mark Analysis 3(a): quarterly data (LR1 / M1)

Criteria	Period	Model					
		R.W.	Forward	GRBF	CRBF	IRBF	QRBF
RMSE	1	0.044	0.0418	0.0464	0.0455	0.0472	0.0661
	2	0.0474	0.0498	0.0369	0.0352	0.0387	0.0434
	3	0.0321	0.0356	0.0173	0.0203	0.0229	0.034
	4	0.0583	0.0569	0.0476	0.0491	0.0463	0.0531
	5	0.058	0.0572	0.048	0.0489	0.0454	0.0462
	6	0.0251	0.0294	0.0535	0.0336	0.0395	0.0404
	Average	0.0442	0.0451	0.0416	0.0388	0.0400	0.0472
Correct Direction	1		0.75	0.75	0.75	0.75	0.75
	2		0.25	1	1	0.75	0.5
	3		0	0.75	0.75	0.5	0.25
	4		0.25	0.5	0.75	0.75	0.25
	5		0.25	0.5	0.5	0.5	0.5
	6		0	0.25	0.25	0.25	0.25
	Average		0.25	0.63	0.67	0.58	0.42
Speculative Direction	1	0.50		0.50	0.50	0.50	0.50
	2	0.75		0.75	0.75	0.75	0.75
	3	1.00		0.75	1.00	0.75	0.50
	4	0.75		0.50	0.75	0.75	0.25
	5	0.75		0.50	0.50	0.75	0.50
	6	1.00		0.25	0.25	0.50	0.50
	Average	0.79		0.54	0.63	0.67	0.50
No. of centers	1			11	11	16	7
	2			8	11	10	5
	3			8	11	10	5
	4			8	6	10	9
	5			8	4	10	6
	6			22	6	10	5
Width(r)	1			1.5	1.5	1.0	
	2			1.4	1.5	1.0	
	3			1.4	1.4	1.0	
	4			1.4	1.5	1.0	
	5			1.4	1.5	1.0	
	6			1.6	1.2	0.9	

Table E.6. German mark Analysis 3(b): quarterly data (LR2 / M1)

Criteria	Period	Model						
		R.W.	Forward	GRBF	CRBF	IRBF	CCRBF	QRBF
RMSE	1	0.044	0.0418	0.0455	0.0457	0.0523	0.0816	0.0608
	2	0.0474	0.0498	0.0375	0.035	0.0418	0.0429	0.0456
	3	0.0321	0.0356	0.0182	0.0226	0.0217	0.0315	0.031
	4	0.0583	0.0569	0.0479	0.0442	0.0442	0.0466	0.055
	5	0.058	0.0572	0.0476	0.0449	0.0419	0.0562	0.0542
	6	0.0251	0.0294	0.0421	0.0339	0.0395	0.033	0.041
	Average	0.0442	0.0451	0.0398	0.0377	0.0402	0.0486	0.0479
Correct Direction	1		0.75	0.75	0.75	0.75	0.5	0.5
	2		0.25	0.75	1	0.5	0.5	0.5
	3		0	0.75	0.75	0.75	0.25	0.25
	4		0.25	0.5	0.75	0.75	0.25	0.5
	5		0.25	0.5	0.5	0.5	0.5	0.5
	6		0	0.5	0.25	0.25	0.5	0.25
	Average		0.25	0.63	0.67	0.58	0.42	0.42
Speculative Direction	1	0.50		0.50	0.75	0.50	0.50	0.50
	2	0.75		0.75	1.00	0.75	0.75	0.50
	3	1.00		0.75	1.00	1.00	0.50	0.25
	4	0.75		0.50	0.75	0.75	0.25	0.50
	5	0.75		0.50	0.75	0.75	0.75	0.50
	6	1.00		0.50	0.25	0.50	0.50	0.25
	Average	0.79		0.58	0.75	0.71	0.54	0.42
No. of centers	1			11	16	13	6	7
	2			16	13	19	4	9
	3			8	4	11	6	6
	4			8	14	10	20	5
	5			8	10	10	3	5
	6			5	6	10	6	6
Width(r)	1			1.5	1.4	1.3		
	2			1.4	1.5	1.3		
	3			1.4	1.3	1.1		
	4			1.4	1.4	1.4		
	5			1.4	1.4	1.5		
	6			1.3	1.2	0.9		

Table E.7. German mark Analysis 4(a): quarterly data (SR1 / M1)

Criteria	Period	Model					
		R.W.	Forward	GRBF	CRBF	IRBF	QRBF
RMSE	1	0.044	0.0418	0.0436	0.0451	0.0461	0.0875
	2	0.0474	0.0498	0.0427	0.0405	0.0349	0.0499
	3	0.0321	0.0356	0.0243	0.0202	0.022	0.0328
	4	0.0583	0.0569	0.0482	0.0467	0.0485	0.0454
	5	0.058	0.0572	0.0502	0.0473	0.051	0.0432
	6	0.0251	0.0294	0.0475	0.0419	0.0465	0.0411
	Average	0.0442	0.0451	0.0428	0.0403	0.0415	0.0500
Correct Direction	1		0.75	0.75	0.75	0.75	0.5
	2		0.25	0.75	1	1	0.5
	3		0	0.5	0.75	0.5	0.25
	4		0.25	0.5	0.75	0.75	0.5
	5		0.25	0.5	0.5	0.5	0.5
	6		0	0.5	0.25	0.25	0.5
	Average		0.25	0.58	0.67	0.63	0.46
Speculative Direction	1	0.50		0.50	0.50	0.50	0.25
	2	0.75		0.75	0.75	1.00	0.50
	3	1.00		0.75	0.75	1.00	0.25
	4	0.75		0.50	0.75	0.78	0.50
	5	0.75		0.50	0.50	0.50	0.50
	6	1.00		0.50	0.25	0.25	0.50
	Average	0.79		0.58	0.58	0.67	0.42
No. of centers	1			2	10	10	12
	2			2	8	12	11
	3			23	7	14	9
	4			23	32	14	9
	5			17	14	13	11
	6			15	8	34	8
Width(r)	1			1.0	0.8	0.6	
	2			1.0	0.8	0.6	
	3			1.3	0.8	0.6	
	4			1.3	0.8	0.6	
	5			1.4	0.8	0.8	
	6			1.3	0.8	0.6	

Table E.8. German mark Analysis 4(b): quarterly data (SR2 / M1)

Criteria	Period	Model					
		R.W.	Forward	GRBF	CRBF	IRBF	QRBF
RMSE	1	0.044	0.0418	0.0436	0.0448	0.0459	0.0949
	2	0.0474	0.0498	0.0428	0.0405	0.0376	0.0458
	3	0.0321	0.0356	0.0229	0.0203	0.0228	0.0347
	4	0.0583	0.0569	0.0429	0.0471	0.0499	0.0481
	5	0.058	0.0572	0.0503	0.0479	0.05	0.0464
	6	0.0251	0.0294	0.0488	0.0416	0.045	0.0442
	Average	0.0442	0.0451	0.0419	0.0404	0.0419	0.0524
Correct Direction	1		0.75	0.75	0.75	0.75	0.5
	2		0.25	0.75	1	1	0.5
	3		0	0.5	0.75	0.75	0.25
	4		0.25	0.5	0.75	0.5	0.25
	5		0.25	0.5	0.5	0.5	0.5
	6		0	0.25	0.25	0.25	0
	Average		0.25	0.54	0.67	0.63	0.33
Speculative Direction	1	0.50		0.50	0.5	0.50	0.00
	2	0.75		0.75	0.75	0.75	0.50
	3	1.00		0.75	0.75	0.75	0.25
	4	0.75		0.50	0.75	0.75	0.25
	5	0.75		0.50	0.5	0.50	0.50
	6	1.00		0.25	0.25	0.50	0.50
	Average	0.79		0.54	0.58	0.63	0.33
No. of centers	1			2	10	10	6
	2			2	8	12	9
	3			12	7	10	11
	4			18	18	13	7
	5			21	18	13	10
	6			16	8	7	11
Width(r)	1			1.0	0.8	0.7	
	2			1.0	0.8	0.7	
	3			1.2	0.8	0.7	
	4			1.6	0.8	0.8	
	5			1.5	0.8	0.8	
	6			1.2	0.8	0.8	

Table E.9. Japanese Yen Analysis 1(a): quarterly data (LR-lag8)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0639	0.0617	0.0573	0.0581	0.0598	0.0591	0.0601	0.0623	0.0646
	2	0.0553	0.0536	0.0519	0.0508	0.0535	0.0485	0.0503	0.0548	0.0527
	3	0.0458	0.0435	0.0313	0.0316	0.0358	0.0334	0.0339	0.0397	0.0337
	4	0.0618	0.0538	0.0435	0.0452	0.0422	0.0369	0.0413	0.0504	0.0404
	5	0.0996	0.1007	0.0995	0.0932	0.0952	0.0959	0.0928	0.0857	0.0955
	6	0.0814	0.0908	0.0945	0.0917	0.0982	0.0963	0.0963	0.0846	0.0938
	Average	0.0680	0.0674	0.0630	0.0618	0.0641	0.0617	0.0625	0.0629	0.0634
Correct Direction	1		0.75	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	2		0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.75	0.75	0.75	0.75	0.75	1	0.5	1
	4		0.75	0.75	0.75	0.75	0.75	1	0.75	1
	5		0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.75
	6		0	0.25	0.25	0.25	0.25	0.25	0.5	0.5
	Average		0.58	0.58	0.58	0.58	0.58	0.67	0.63	0.75
Speculative Direction	1	0.25		0.50	0.50	0.50	0.50	0.50	0.50	0.50
	2	0.25		0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3	0.50		0.75	0.50	0.75	0.50	0.75	1.00	0.75
	4	0.50		0.50	0.75	0.75	0.25	0.50	0.50	0.50
	5	0.50		0.50	0.50	0.75	0.25	0.75	0.75	0.50
	6	1.00		0.50	0.50	0.50	0.50	0.50	0.50	0.50
	Average	0.50		0.58	0.58	0.67	0.46	0.63	0.67	0.58
No. of centers	1			10	10	11	6	11	11	8
	2			10	12	9	6	19	19	5
	3			9	12	10	14	6	35	7
	4			9	10	14	9	13	9	4
	5			9	11	6	9	7	4	8
	6			11	7	6	24	7	9	6
Width(r)	1			1.5	1.0	1.0	1.0			
	2			1.5	1.8	1.0	1.5			
	3			1.5	2.0	1.0	1.0			
	4			1.5	1.8	1.5	1.0			
	5			1.5	1.8	1.5	1.0			
	6			1.5	1.3	1.5	2.0			

Table E.10. Japanese Yen Analysis 1(b): quarterly data (LR-lag7)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0639	0.0617	0.0581	0.0575	0.0605	0.0598	0.0585	0.0639	0.0609
	2	0.0553	0.0536	0.0531	0.0491	0.052	0.0553	0.0537	0.0525	0.0449
	3	0.0458	0.0435	0.0412	0.0381	0.0399	0.0303	0.0433	0.0405	0.0306
	4	0.0618	0.0538	0.0492	0.0496	0.0444	0.0337	0.05	0.0532	0.0376
	5	0.0996	0.1007	0.0881	0.0981	0.0934	0.0867	0.0927	0.0937	0.095
	6	0.0814	0.0908	0.0849	0.0872	0.0841	0.0965	0.0876	0.0836	0.0865
	Average	0.0680	0.0674	0.0624	0.0633	0.0624	0.0604	0.0643	0.0646	0.0592
Correct Direction	1		0.75	0.75	0.5	0.75	0.5	0.75	0.75	0.75
	2		0.75	0.75	0.75	1	0.75	0.75	0.75	1
	3		0.75	0.75	0.75	0.5	1	0.5	0.75	1
	4		0.75	1	0.75	0.5	1	0.75	1	1
	5		0.5	0.75	0.5	0.75	0.75	0.5	1	0.5
	6		0	0.25	0.5	0.5	0.25	0.25	0.75	0.25
	Average		0.58	0.71	0.63	0.67	0.71	0.58	0.83	0.75
Speculative Direction	1	0.25		0.75	0.50	0.75	0.50	0.75	0.75	0.75
	2	0.25		0.75	0.75	0.75	0.75	0.50	0.75	1.00
	3	0.50		0.75	0.50	0.75	0.75	0.50	0.50	0.75
	4	0.50		0.75	0.25	0.50	0.75	0.50	0.75	0.75
	5	0.50		0.75	0.75	0.50	0.50	0.50	0.75	0.75
	6	1.00		0.75	0.50	0.50	0.25	0.50	0.75	0.50
	Average	0.50		0.75	0.54	0.63	0.58	0.54	0.71	0.75
No. of centers	1			6	8	13	7	10	6	5
	2			7	8	19	5	10	2	6
	3			10	8	13	4	7	8	4
	4			15	8	16	4	7	3	4
	5			20	13	9	11	19	3	7
	6			15	9	12	9	25	4	4
Width(r)	1			1	0.8	1	1			
	2			1	0.8	1.8	1			
	3			1.5	0.8	1.5	1			
	4			2	1	1.5	1			
	5			1.5	0.5	1.5	1			
	6			1.5	1.4	1.6	1			

Table E.11. Japanese Yen Analysis 2(a): quarterly data (SR1-lag8)

Criteria	Period	Model							
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	QRBF
RMSE	1	0.0639	0.0617	0.0554	0.0508	0.0527	0.0508	0.0558	0.0519
	2	0.0553	0.0536	0.0418	0.0359	0.0429	0.0443	0.0438	0.028
	3	0.0458	0.0435	0.0348	0.0359	0.0412	0.0362	0.0308	0.023
	4	0.0618	0.0538	0.0379	0.046	0.0431	0.0413	0.0433	0.0327
	5	0.0996	0.1007	0.0775	0.0735	0.0777	0.071	0.0753	0.0748
	6	0.0814	0.0908	0.0793	0.0788	0.0816	0.0783	0.0744	0.0841
	Average	0.0680	0.0674	0.0545	0.0535	0.0565	0.0536	0.0539	0.0491
Correct Direction	1		0.75	0.5	0.75	0.75	0.75	0.75	0.75
	2		0.75	0.75	1	0.75	0.75	0.75	1
	3		0.75	0.5	0.5	0.5	0.5	0.5	0.5
	4		0.75	0.5	0.5	0.5	0.5	0.5	0.5
	5		0.5	1	1	0.75	1	1	1
	6		0	0.75	0.75	0.5	0.75	0.75	0.25
	Average		0.58	0.67	0.75	0.63	0.71	0.71	0.67
Speculative Direction	1	0.25		0.75	0.75	0.75	0.75	0.75	0.75
	2	0.25		1.00	1.00	0.75	1.00	0.75	1.00
	3	0.50		0.75	0.75	0.75	0.75	0.75	0.75
	4	0.50		0.50	0.50	0.50	0.50	0.50	0.75
	5	0.50		1.00	1.00	1.00	0.75	1.00	1.00
	6	1.00		0.75	0.75	0.75	0.75	0.75	1.00
	Average	0.50		0.79	0.79	0.75	0.75	0.75	0.88
No. of centers	1			4	14	9	10	16	11
	2			4	10	10	14	16	8
	3			11	13	12	19	14	8
	4			14	9	9	11	10	6
	5			14	9	9	15	13	10
	6			14	11	14	8	15	8
Width(r)	1			3.5	3.5	1.5	1.0		
	2			3.5	3.5	1.5	1.0		
	3			3.5	3.0	1.5	1.0		
	4			3.5	3.5	1.5	1.0		
	5			3.5	3.5	1.5	1.0		
	6			3.5	3.5	1.5	1.0		

Table E.12. Japanese Yen Analysis 2(b): quarterly data (SR2-lag8)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0639	0.0617	0.0454	0.0487	0.0517	0.0538	0.0584	0.0559	0.055
	2	0.0553	0.0536	0.0474	0.0455	0.0514	0.0468	0.0464	0.0413	0.0416
	3	0.0458	0.0435	0.0429	0.05	0.0498	0.0279	0.0389	0.0307	0.0257
	4	0.0618	0.0538	0.0471	0.0537	0.0389	0.037	0.0397	0.0535	0.035
	5	0.0996	0.1007	0.0878	0.0708	0.0726	0.0826	0.087	0.0769	0.0822
	6	0.0814	0.0908	0.0907	0.0718	0.0864	0.0852	0.0775	0.0698	0.0848
	Average	0.0680	0.0674	0.0602	0.0568	0.0584	0.0556	0.0580	0.0547	0.0540
Correct Direction	1		0.75	0.75	0.75	0.5	0.5	0.5	0.75	0.75
	2		0.75	0.75	0.75	0.75	0.75	0.75	1	0.75
	3		0.75	0.5	0.5	0.5	0.5	0.5	0.75	0.5
	4		0.75	0.5	0.25	0.5	0.5	0.5	0.25	0.5
	5		0.5	0.75	1	1	1	1	0.75	0.75
	6		0	0.5	0.75	0.75	0.75	0.75	1	0.5
	Average		0.58	0.63	0.67	0.67	0.67	0.67	0.75	0.63
Speculative Direction	1	0.25		0.75	0.75	0.75	0.50	0.50	0.75	0.75
	2	0.25		0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3	0.50		0.75	0.75	0.75	0.75	0.75	1.00	0.75
	4	0.50		0.75	0.50	0.50	0.75	0.75	0.50	0.75
	5	0.50		0.50	0.75	0.75	1.00	1.00	0.75	1.00
	6	1.00		0.50	1.00	0.75	0.75	0.75	1.00	0.75
	Average	0.50		0.67	0.75	0.71	0.75	0.75	0.79	0.79
No. of centers	1			7	9	7	11	17	12	4
	2			9	21	6	10	14	19	5
	3			7	15	16	6	15	12	6
	4			7	21	19	5	5	20	6
	5			4	14	16	5	5	28	6
	6			4	15	5	5	10	22	6
Width(r)	1			1.5	2.5	2.0	1.0			
	2			1.5	2.5	2.0	1.0			
	3			1.5	2.5	2.0	1.0			
	4			1.5	2.5	2.0	1.0			
	5			1.5	2.5	2.0	1.0			
	6			1.5	2.5	2.0	1.0			

Table E.13. Japanese Yen Analysis 3(a): quarterly data (LR1+M1-lag8)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0639	0.0617	0.0532	0.053	0.0574	0.0432	0.05	0.0602	0.0569
	2	0.0553	0.0536	0.053	0.0536	0.0462	0.055	0.049	0.0824	0.0639
	3	0.0458	0.0435	0.034	0.0364	0.0389	0.0374	0.0389	0.0624	0.0352
	4	0.0618	0.0538	0.0472	0.0504	0.0498	0.0634	0.0548	0.0578	0.0585
	5	0.0996	0.1007	0.0937	0.0901	0.089	0.0989	0.0946	0.0909	0.0791
	6	0.0814	0.0908	0.0897	0.0881	0.0826	0.0907	0.0847	0.1007	0.081
	Average	0.0680	0.0674	0.0618	0.0619	0.0607	0.0648	0.062	0.0757	0.0624
Correct Direction	1		0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	2		0.75	0.75	0.75	0.75	0.5	0.75	0.5	0.75
	3		0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	4		0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.75
	5		0.50	0.75	0.50	0.75	0.5	0.5	0.75	0.75
	6		0.00	0.25	0.25	0.5	0.25	0.5	0.75	0.75
	Average		0.58	0.67	0.63	0.71	0.54	0.63	0.67	0.75
Speculative Direction	1	0.25		0.75	0.75	0.75	1.00	0.75	0.75	0.75
	2	0.25		0.75	0.75	0.75	0.50	0.75	0.5	0.75
	3	0.50		0.75	0.75	0.75	0.50	0.75	0.5	0.5
	4	0.50		0.25	0.75	0.5	0.25	0.25	0.25	0.75
	5	0.50		0.50	0.75	0.75	0.50	0.75	0.5	0.75
	6	1.00		0.50	0.75	0.75	0.50	0.75	0.75	1.00
	Average	0.50		0.58	0.75	0.71	0.54	0.67	0.54	0.75
No. of centers	1			13	13	11	12	11	15	11
	2			14	15	9	14	7	12	11
	3			19	19	18	16	21	30	8
	4			13	17	15	18	19	11	6
	5			11	9	17	15	7	31	6
	6			10	9	15	13	15	32	9
Width (r)	1			2.0	1.5	0.8	3.0			
	2			2.0	1.5	0.9	3.5			
	3			1.5	1.1	0.8	4.0			
	4			1.6	1.5	1.5	3.5			
	5			2.5	1.5	1.5	3			
	6			2.5	1.5	1.5	3			

Table E.14. Japanese Yen Analysis 4(a): quarterly data (SR1+M1-lag8)

Criteria	Period	Model							
		R.W.	Forward	GRBF	CRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0639	0.0617	0.043	0.0493	0.0499	0.0496	0.0445	0.0385
	2	0.0553	0.0536	0.0444	0.0491	0.05	0.051	0.0446	0.0424
	3	0.0458	0.0435	0.0387	0.0361	0.0351	0.0402	0.0353	0.0291
	4	0.0618	0.0538	0.0537	0.0492	0.057	0.0536	0.0393	0.0527
	5	0.0996	0.1007	0.089	0.0914	0.0884	0.0812	0.0791	0.0815
	6	0.0814	0.0908	0.0839	0.0788	0.0689	0.0884	0.0944	0.0843
	Average	0.0680	0.0674	0.0588	0.0590	0.0582	0.0606	0.0562	0.0548
Correct Direction	1		0.75	0.75	0.75	0.75	0.75	1.00	1.00
	2		0.75	0.75	0.75	0.75	0.75	0.75	1.00
	3		0.75	0.50	0.75	0.75	0.50	0.50	0.50
	4		0.75	0.25	0.25	0.25	0.25	0.75	0.25
	5		0.50	0.50	0.75	0.75	0.75	0.75	0.75
	6		0.00	0.50	0.50	0.75	0.50	0.75	0.75
	Average		0.58	0.54	0.63	0.67	0.58	0.75	0.71
Speculative Direction	1	0.25		1.00	0.75	0.75	0.75	1	1.00
	2	0.25		0.75	0.75	0.75	0.75	0.75	1.00
	3	0.50		0.75	0.75	0.50	0.75	0.75	0.75
	4	0.50		0.50	0.75	0.50	0.50	0.5	0.50
	5	0.50		0.50	0.75	0.75	0.75	0.75	0.75
	6	1.00		0.50	0.50	1.00	0.50	1	0.75
	Average	0.50		0.67	0.71	0.71	0.67	0.79	0.79
No. of centers	1			5	10	9	24	9	8
	2			9	6	11	10	10	8
	3			11	12	8	18	21	9
	4			11	9	18	25	21	7
	5			18	11	11	30	19	10
	6			10	18	20	9	15	6
Width (r)	1			3.5	3.0	1.0			
	2			5.0	4.0	1.0			
	3			3.5	4.0	1.0			
	4			3.5	4.0	1.0			
	5			3.5	4.0	1.5			
	6			3.5	3.0	1.0			

Table E.15. Japanese Yen Analysis 4(b): quarterly data (SR2+M1-lag8)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0639	0.0617	0.0426	0.0491	0.0493	0.045	0.049	0.0423	0.0462
	2	0.0553	0.0536	0.0416	0.0537	0.0498	0.0487	0.0498	0.0465	0.0441
	3	0.0458	0.0435	0.028	0.0351	0.0354	0.0356	0.0355	0.035	0.0315
	4	0.0618	0.0538	0.0494	0.0541	0.0488	0.0501	0.0482	0.0509	0.0487
	5	0.0996	0.1007	0.0914	0.0891	0.0879	0.0852	0.0845	0.0817	0.0847
	6	0.0814	0.0908	0.0866	0.082	0.0793	0.0803	0.0773	0.0782	0.0882
	Average	0.0680	0.0674	0.0566	0.0605	0.0584	0.0575	0.0574	0.0558	0.0572
Correct Direction	1		0.75	1	0.75	0.75	0.75	0.75	0.75	0.75
	2		0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	3		0.75	0.5	0.75	0.5	0.5	0.5	0.5	0.5
	4		0.75	0.5	0.25	0.5	0.25	0.75	0.25	0.5
	5		0.5	0.5	0.75	0.75	0.75	1	0.75	1
	6		0	0.5	0.75	0.5	0.75	0.75	1	0.5
	Average		0.58	0.63	0.67	0.63	0.67	0.75	0.67	0.67
Speculative Direction	1	0.25		1.00	0.75	0.75	0.75	0.75	0.75	0.75
	2	0.25		1.00	0.75	0.75	0.75	0.75	0.75	0.75
	3	0.50		1.00	0.50	0.75	0.75	0.75	0.75	0.75
	4	0.50		0.50	0.50	0.50	0.50	0.50	0.50	0.50
	5	0.50		0.75	0.75	0.75	0.75	0.75	0.75	0.75
	6	1.00		0.75	0.75	0.75	0.75	0.75	1.00	0.75
	Average	0.50		0.83	0.67	0.71	0.71	0.71	0.75	0.71
No. of centers	1			5	10	11	8	7	12	9
	2			4	9	9	8	8	16	8
	3			4	6	9	9	9	13	9
	4			7	14	11	11	8	12	8
	5			8	10	11	9	16	7	8
	6			4	6	9	9	6	9	9
Width (r)	1			4	3	2	1			
	2			4	3	3	1			
	3			4	3	3	1			
	4			3	3	2	1			
	5			3	3.5	2	1			
	6			4	3.5	3	1			

Table E.16. Italian Lira Analysis 1: quarterly data (LR)

Criteria	Period	Model								
		R.W.	Forward	GRBF	CRBF	IRBF	MRBF	LRBF	CCRBF	QRBF
RMSE	1	0.0596	0.0501	0.0430	0.0420	0.0355	0.0454	0.0425	0.0376	0.0420
	2	0.0487	0.0498	0.0459	0.0414	0.0446	0.0452	0.0491	0.0404	0.0440
	3	0.0427	0.0510	0.04448	0.0446	0.0426	0.0505	0.0508	0.0450	0.0514
	4	0.0456	0.0468	0.0438	0.0523	0.0528	0.0693	0.0537	0.0461	0.0367
	5	0.0343	0.0401	0.0344	0.0413	0.0432	0.0335	0.0369	0.0414	0.0353
	6	0.0171	0.0289	0.0180	0.0182	0.0129	0.0287	0.0159	0.0275	0.0221
	Average	0.0414	0.0445	0.0383	0.04	0.0383	0.0454	0.0415	0.0397	0.0386
Correct Direction	1		0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
	2		0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.75
	3		0.33	0.33	0.33	0.33	0.67	0.33	0.67	0.33
	4		0.67	0.67	0.33	0.67	0	0.33	0.33	1
	5		0.25	0.5	0.25	0.25	0.5	0	0.5	0.75
	6		0	0.75	0.75	0.75	0	0.5	0.5	0.5
	Average		0.41	0.58	0.49	0.54	0.40	0.40	0.58	0.68
Speculative Direction	1	0.25		0.75	0.50	0.75	0.75	0.75	0.50	1.00
	2	0.50		0.50	0.75	0.75	0.50	0.50	0.75	0.75
	3	0.66		0.67	1.00	1.00	0.67	0.67	1.00	0.67
	4	0.33		0.67	0.33	0.33	0	0.00	0.67	1.00
	5	0.75		0.75	0.75	0.25	0.50	0.75	0.75	0.75
	6	1.00		0.75	0.75	1.00	0.75	1.00	0.50	0.75
	Average	0.58		0.68	0.68	0.68	0.53	0.61	0.69	0.82
No. of centers	1			4	4	8	4	7	3	4
	2			6	4	6	5	4	3	4
	3			14	5	5	5	4	3	5
	4			5	6	4	14	8	5	3
	5			5	6	8	4	4	2	3
	6			3	5	6	3	6	3	4
Width(r)	1			2.5	1.5	1.5	1.0			
	2			3.0	1.5	1.5	1.0			
	3			1.0	1.0	1.0	1.0			
	4			2.5	1.0	0.9	1.0			
	5			3.0	3.0	1.5	1.0			
	6			2.0	2.5	1.5	1.0			

Table E.17. Italian Lira Analysis 2: quarterly data (LR / M1)

Criteria	Period	Model				
		R.W.	Forward	GRBF	CRBF	IRBF
RMSE	1	0.0596	0.0501	0.0510	0.0460	0.0519
	2	0.0487	0.0498	0.0450	0.0484	0.0470
	3	0.0427	0.0510	0.0411	0.0483	0.0447
	4	0.0456	0.0468	0.0497	0.0432	0.0439
	5	0.0343	0.0401	0.0381	0.0351	0.0349
	6	0.0171	0.0289	0.0205	0.0149	0.0154
	Average	0.0414	0.0445	0.0409	0.0393	0.0396
Correct Direction	1		0.75	0.5	0.75	0.75
	2		0.5	0.75	0.5	0.75
	3		0.33	0.67	0.67	0.33
	4		0.67	0.33	0.67	0.67
	5		0.25	0.5	0.25	0.5
	6		0	0.5	0.75	0.75
	Average		0.41	0.54	0.60	0.63
Speculative Direction	1	0.25		0.50	1.00	0.50
	2	0.50		0.75	0.50	0.50
	3	0.66		1.00	1.00	1.00
	4	0.33		0.33	0.67	0.67
	5	0.75		0.50	1.00	1.00
	6	1.00		0.75	0.75	1.00
	Average	0.58		0.64	0.82	0.78
No. of centers	1			14	10	7
	2			7	7	16
	3			14	16	10
	4			13	13	16
	5			14	12	16
	6			5	15	8
Width(r)	1			2.5	2.5	1.5
	2			2.5	2.0	1.0
	3			2.0	1.5	1.0
	4			2.0	1.5	1.0
	5			1.5	1.0	1.0
	6			3.0	1.5	1.0

REFERENCES

Alexander, D., and Thomas, L. R. (1987). "Monetary/Asset Models of Exchange Rate Determination: How Well have They Performed in the 1980's?" *International Journal of Forecasting*, Vol. 3, pp. 53-64.

Ankenbrand, T., and Tomassini, M. (1995). "Multivariate Time Series Modeling of Financial Markets with Artificial Neural Networks," in D.W. Pearson, N.C. Steele, and R.F. Albrecht (Eds). *Artificial Neural Nets and Genetic Algorithms.* Proceedings of the International Conference in Ales, France, pp. 257-260.

Azoff, M.E. (1994). *Neural Network Time Series Forecasting of Financial Markets*, New York: John Wiley & Sons, Inc.

Baillie, R.T., and Bollerslev, T. (March 1988). "Common Stochastic Trends in a System of Exchange Rates," *The Journal of Finance*, Vol. 44, No. 1, pp. 167-181.

Baillie, R.T., and Selover, D. D. (1987) ."Cointegration and Models of Exchange Rate Determination," *International Journal of Forecasting*, Vol. 3, pp. 43-51.

Bharath, R. and Drosen, J. (1994). *Neural Network Computing*. New York: Winderest / McGraw-Hill.

Bishop, C. M. (1991). "Improving the Generalization Properties of Radial Basis Function Neural Networks, " *Neural Computation*, Vol. 3, pp. 579-588.

Bishop, C. M. (1993). "Curvature-Driven Smoothing: A Learning Algorithm for Feeddorward Networks, " *IEEE Trans. Neural Networks.*

Bishop, C. M. (1995). *Neural Network for Pattern Recognition*, Oxford: Oxford University Press.

Blake, J., Francino, P., Catot, J. M., and Solé, I. (1995). "A Comparative Study for Forecasting Using Neural Networks vs Genetically Identified Box-Jenkins Models, " *Neural Computing & Applications*, Vol. 3, pp. 139-148.

Bollerslev, T. (1986). "Generalized Autoregressive Conditional Heteroscedasticity, "*Journal of Econometrics*, Vol. 31, pp. 307-327.

Boothe, P., and Glassman, D. (1987a). "Comparing Exchange Rate Forecasting Models: Accuracy versus Profitability," *International Journal of Forecasting*, Vol. 3, pp. 65-79.

Boothe, P., and Glassman, D. (1987b). "Off the Mark: Lessons for Exchange Rate Modeling," *Oxford Economic Papers*, Vol. 39, pp. 437-457.

Brock, W.A., Hsieh, D.A., and LeBaron, B. (1991). *Nonlinear Dynamics, Chaos and Instability*. Cambridge, MA: MIT Press.

Brooks, C. (1997),"Linear and Nonlinear (Non-) Forecastability of High-frequency Exchange Rates", *Journal of Forecasting*, Vol. 16, pp.125-145.

Broomhead, D.S. and Lowe, D. (1988). "Multivariable Functional Interpolation and Adaptive Networks," *Complex Systems* Vol. 2, pp. 321-355.

Brown, M., and Harris, C. (1994). *Neurofuzzy Adaptive Modelling and Control*, , Hemel-Hempstead, UK: Prentice Hall.

Brownstone, D. (1996). "Using Percentage Accuracy to Measure Neural Network Predictions in Stock Market Movements," *Neurocomputing*, Vol. 10, pp. 237-250.

Buhmann, M. D. (1993). "New Developments in the Theory of Radial Basis Function Interpolation," in K. Jetter and F.I. Utreras (Eds), *Multivariate Approximation and Waveletes*, Singapore: World Sci. Publ., pp. 35-75.

Buhmann, M. D. (1988). "Convergence of Univariate Quasi-Interpolation using Multiquadrics," *IMA Journal of Numerical Analysis*, Vol.8, pp.365-383.

Chakraborty, K., Mehrotra, K., Mohan, C.K., and Ranka, S. (1992). "Forecasting the Behavior of Multivariate Time Series Using Neural Networks," *Neural Networks*, Vol. 5, No. 6, pp. 961-970.

Chatfield,C. (1993). "Neural Networks: Forecasting Break-Through or Passing Fad ?" *International Journal of Forecasting*, Vol. 9, pp. 1-3.

Chen, S., Cowan C.F.N. and Grant P.M. (1991). "Orthogonal Least Squares Learning Algorithm for Radial Basis Functions Networks", *IEEE Transactions on Neural Networks* ,Vol. 2, No. 2, pp. 302-309.

Chen, S., Mulgrew, B. and Grant P.M. (1993). "A Clustering Technique for digital Communications Channel Equalization Using Radial Basis Function Networks," *IEEE Transactions on Neural Networks*, Vol. 4, No. 4, pp. 570-579.

Copeland, L.S., and Wang, P. (1994). "Estimating Daily Seasonality in Foreign Exchange Rate Changes," *Journal of Forecasting*, Vol. 13, pp. 519-528.

Cover, T. M. (1965), "Geometric and Statistical Properties of Systems of Linear Inequalities with Applications in Pattern Recognition, " *IEEE Transactions on Electronic Computers*, EC-14, pp.326-334.

Cybenko, G. (1989). "Approximation by Superposition of a Sigmoidal Function," *Mathematical Control Systems Signals*, Vol. 2, pp. 303-314.

Cybenko, G. (1988). *Continuous Valued Neural Networks with Two Hidden Layers are Sufficient* ,Technical Report, Department of Computer Science, Tufts University.

Deboeck, G.J.(Ed.) (1994). *Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic and Financial Markets.* New York: John Wiley & Sons, Inc.

Deco, G., Schuermann, B. and Trippi, R. R., "Neural Learning of Chaotic Time Series Invariants," in R.R. Trippi (Ed.), *Chaos & Nonlinear Dynamics in the Financial Markets: Theory, Evidence and Applications,* Chicago: Irwin Professional Publishing (1995) pp. 467-488.

Demuth, H. ,and Beale M. (1998). *Neural Network Toolbox User's Guide, version 3,* Natick, Massachusetts: The Mathworks Inc.

Diebold, F.X., Gardeazabal, J., and Yilmaz, K. (1994). "On Cointegration and Exchange Rate Dynamics," *The Journal of Finance*, Vol .49, No. 2, pp. 727-735.

Diebold, F.X., and Mariano, R.S. (1995). "Comparing Predictive Accuracy," *Journal of Business and Economic Statistics.* Vol. 13, No.3, pp.253-263.

Diebold, F.X., and Nason, J.A. (1990). "Nonparametric Exchange Rate Prediction?" *Journal of International Economics*, Vol. 28, pp. 315-332.

Diebold, F.X. (1998). *Elements of Forecasting.* Cincinnati, Ohio: South-Western College Publishing.

Baestaens D. E. and van den W. M. (1995). "Tracking the Amsterdam Stock Index Using Neural Networks," in A-P. Refenes (Ed.), *Neural Networks in the Capital Markets.* New York: John Wiley, pp. 149-161.

Driskill, R. A., Mark, N. C., and Sheffrin, S. M. (Feb 1992). "Some Evidence in Favor of a Monetary Rational Expectations Exchange Rate Model with Imperfect Capital Substitutability," *International Economic Review*, Vol. 33, No. 1, pp. 223-237.

Efron and R. J. Tibshirani (1993). *An Introduction to the Bootstrap*, Chapman and Hall.

Enders, W. (1995). *Applied Econometric Time Series.* New York: John Wiley & Sons, Inc.

Enders, W. (1996). Rats *Handbook for Econometrics Time Series*. New York: John Wiley & Sons, Inc.

Engle, R. F. and Granger, C. W. J. (1987). "Cointegration and Error-Correction: Representation, Estimation and Testing," *Econometrica*, Vol. 55, pp. 251-276.

Engle, R. F. and Yoo, B. S. (1987). " Forecasting and Testing in Cointegrated Systems," *Journal of Econometrics*, Vol. 35, pp. 143-159.

Engle, R. F., Lilien, D., and Robins, R. (1987). "Estimating Time-Varying Risk Premia in the Term Structure: The ARCH-M Model," *Econometrica*, Vol. 55, pp. 391-407.

Engle, R. F. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, Vol. 50, pp. 987-1007.

Fair, R. C. (1980). "Estimating the Expected Predictive Accuracy of Econometric Models," *International Economic Review*, Vol. 21, pp. 355-378.

Fair, R. C. and Shiller, R. J. (1990). "Comparing Information in Forecasts from Econometric Models", *The American Economic Review*, Vol. 80, No. 3, pp. 375-389.

Franke, R. (1982). "Scattered Data Interpolation: Tests of Some Methods," *Math. Comput.*, Vol. 38, pp.181-199.

Frankel, J. (1979). "On the Mark: A Theory of Floating Exchange Rates Based on Real Interest rate differentials," *American Economic Review*, Vol. 69, pp.610-622.

Fu L. (1994). *Neural Networks in Computer Intelligence*. New York: McGrow-Hill, Inc.

Gibbons J. D. (1993). *Nonparametric Statistics: An Introduction*. Newbury Park, CA: sage publications, Inc.

Girosi, F. (1994). "Regularization Theory, Radial Basis Functions and Networks," in V. Cherkassky, J. H. Friedman, and H. Wechsler (Eds.) *From Statistics to Neural Networks: Theory and Pattern Recognition Applications*, Springer-Verlag: New York, pp. 166-187.

Girosi, F. (1992). "Some Extensions of Radial Basis Functions and Their Applications in Artificial Intelligence," *Computers Math. Applic.*, Vol. 24, No. 12, pp.61-80.

Girosi, F., and Poggio, T. (1990). "Networks and Best Approximation Property," *Biological Cybernetics*, Vol. 2, pp. 169-176.

Girosi, F., Jones, M., and Poggio, T. (1995). "Regularization Theory and Neural Networks Architectures," *Neural Computation*, Vol. 7, pp. 219-269.

Gomm, J. B., Puge, G. F. and Williams, D. (1993). *Introduction to Neural Networks*. New York: Chapman and Hall.

Gorr, W. L. (1994). "Neural Networks in Forecasting: Special Section(Editorial), Research Prospective on Neural Network Forecasting," *International Journal of Forecasting*, Vol. 10, pp. 1-4.

Gorr, W. L., Nagin, D. and Szczypula, J. (1994). "Comparative Study of Artificial Neural Network and Statistical Models for Predicting Student Grade Point Average," *International Journal of Forecasting*, Vol. 10, pp. 17-34.Granger, C.W. J. (1986). "Developments in the Study of Cointegrated Economic Variables," *Oxford Bulletin of Economics and Statistics*, Vol. 48, pp. 213-227.

Green, H., and Pearson, M. (1994) "Neural Nets for Foreign Exchange Trading", In G.J. Deboeck, (Ed.), *Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic and Financial Markets*. New York: John Wiley & Sons, Inc., pp. 123-129.

Granger, C. W. J. (1993). Strategies for modelling nonlinear time series relationships. *The Economic Record*, Vol. 69, pp. 233-238.

Granger, C. W. J. (1993) and Terasvirta, T. 1993. *Modelling Nonlinear Economic Relationships*. New York: Oxford.

Grudnitski,G. (1993). "Forecasting S&P and Gold Futures Prices: An Application of Neural Networks," *The Journal of Futures Markets*, Vol. 13, No. 6, pp. 631-643.

Hardy, R. L. (1990). "Theory and Applications of the Multiquadric-Biharmonic Method," *Computers Math. Applic.* , Vol. 19, No.8/9, pp.163-208.

Hartman, E. J., Keeler, J. D., and Kowalski, J.M. (1990). "Layered Neural Networks with Gaussian Hidden Units as Universal Approximators," *Neural Computing*, Vol. 2, pp.210-215.

Harvey D., Leybourne, S., and Newbold, P. (1997), "Testing the Equality of Prediction Mean Squared Errors", *International Journal of Forecasting*, Vol. 13, pp.281-291.

Harvey, A., and Toulson, S. (1994). "Review of 4Thought," *International Journal of Forecasting*, Vol. 10, pp. 35-41.

Haykin, S., *Neural Networks. A Comprehensive Foundation* (1994), Englewood Cliffs, New Jersey: Prentice Hall.

Hecht-Nielson, R. (1990). *Neurocomputing*, Reading, MA: Addison-Wesley.

Hertz , J., Krogh, A., and Palmer, R. (1991). *Introduction to the Theory of Neural Computation*. Addison-Wesley Publishing Company, Menlo Park, California.

Hill, T., Marquez, L., O'conner, M., and Remus, W. (1994). "Artificial Neural Network Models for Forecasting and Decision Making," *International Journal of Forecasting*, Vol. 10, pp. 5-15.

Hoque,A., and Latif, A. (1993). "Forecasting Exchange Rate for the Australian Dollar via-á-vis the US Dollar Using Multivariate Time series Models," *Applied Economics*, Vol. 25, pp. 403-407.

Hornik, K., Stinchcombe. M., and White, H. (1989). "Multilayer Feedforward Networks are Universal Approximators," *Neural Networks*, Vol. 2, pp. 359-366.

Hsieh, D. A. (1989). "Testing for Nonlinear Dependence in Foreign Exchange Rates: 1974-1983," *Journal of Business*, Vol. 62, pp. 339-368.

Hrycej, T. (1997). *Neurocontrol : Toward an Industrial Control Methodology*. NY: John-Wiley and Sons, Inc.

Jenkins, G. M. (1982). "Some Practical aspects of Forecasting in Organizations," *Journal of Forecasting*, Vol. 1, pp. 3-21.

Johansen, S. (1988). "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control*, Vol. 12, pp. 231-254.

Johansen, S. (1991). "Estimation and Hypothesis Testing of Cointegrating Vectors in Gaussian Vector Autoregressive Models," *Econometrica*, Vol. 59, pp. 1551-1580.

Jones, R. D., et. al. (1990). "Function Approximation and Time Series Prediction with Neural Networks," *Proc. IEEE International Joint Conf. On Neural Network*, pp. 1649-1666.

Kaastra, I. and Boyd, M. S. (1996). "Designing a Neural Network for Forecasting Financial and Economic Time Series," *Neurocomputing*, Vol. 10, pp. 215-236.

Kaastra, I., and Boyd, M. S. (1995). "Forecasting Futures Trading Volume Using Neural Networks," *The Journal of Futures Markets*, Vol. 15, No. 8, pp. 953-970.

Kassam, S. A., and Cha, I. (1993). "Radial Basis Function Networks in Nonlinear Signal Processing," *Proc. 27th Annual Asilomar Conf. On Signals, Systems, and Computers*, pp. 1022-1025.

Kearney, C., and MacDonald, R. (June1990). "Rational Expectations, Bubbles and Monetary Models of the Exchange Rate: The Australian / US Dollar Rate During the Recent Float", *Australian Economic Papers*, pp. 1-20.

Kendall, M. G. and Stuart A. (1958), *The Advanced Theory of Statistics*, Vol. 2, New York: Hafner.

Kimoto, T., Asakawa, K., Yoda, M., and Takeoka, M., "Stock Market Prediction System with Modular Neural Networks," in R. R. Trippi and E. Turban (Eds.), *Neural Networks in Finance and Investing*. Chicago: Probus Publishing (1993).

Kohzadi, N., Boyd M. S., Kermanshahi, B. and Kaastra, I. (1996). "A Comparison of Artificial Neural Network and Time Series Models for Forecasting Commodity Prices," *Neurocomputing*, Vol. 10, pp. 169-181.

Kräger, H., and Kugler, P. (1993). "Nonlinear in Foreign Exchange Markets: A Difference Perspective," *Journal of International Money and Finance*, Vol. 12, pp. 195-208.

Kuan, C. M. and Lin, Y. (1995), "Forecasting Exchange Rates Using Feedforward and Recurrent Neural Networks, " *Journal of Applied Econometrics*, Vol. 10, pp. 347-364.

Leitch, G., and Tanner, J.E. (1991) "Economic Forecast Evaluation: Profits versus the Conventional Error Measures," *American Economic Review*, Vol. 81, pp.580-590.

Leonard, J. A., Kramer, M. A., and Ungar, L. H. (1992). "Using Radial Basis Functions to Approximate a Function and its Error Bounds," *IEEE Transactions on Neural Networks* Vol. 3, 4, pp. 624-627.

Lisi, F. and Medio, A. (1997) "Is a Random Walk the Best Exchange Rate Predictor?", *International Journal Forecasting*, Vol. 13, pp. 255-267.

Litterman, R. B. (1986). "Forecasting with Bayesian Vector Autoregressions-Five Years of Experience," *Journal of Business & Economic Statistics*, Vol. 4, No. 1, pp. 25-38.

Liu, T-R., Gerlow, M. E., and Irwin , S.H. (1994). "The Performance of Alternative VAR Models in Forecasting Exchange Rates," *International Journal of Forecasting*, Vol. 10, pp. 419-433.

Lowe D. (1989). "Adaptive Radial Basis Function Nonlinearityes, and the Problem of Generlization," *IEE International Conference on Artificial Neural Networks*, Nov. pp. 171-175.

Lye, J. N., and Martin, V. L. (1994). "Nonlinear Time Series Modeling and Distributional Flexibility," *Journal of Time Series Analysis*, Vol. 15, No. 1, pp. 65-84.

MacDonald, R., and Taylor, M.P. (1991). "The Monetary Approach to the Exchange Rate: Long-Run Relationships and Coefficients Restrictions," *Economics Letters*, Vol.37, pp.179-85.

MacDonald, R., and Taylor, M. P. (March 1993). "The Monetary Approach to the Exchange Rate: Rational Expectations, Long-Run Equilibrium, and Forecasting," *IMF Staff Papers*, Vol. 40, No. 1, pp. 89-107.

MacDonald, R., and Taylor, M. P. (1994). "The Monetary Model of Exchange Rate: Long-Run Relationships, Short-Run Dynamics and How to Beat a Random Walk," *Journal of International Money and Finance*, Vol.13, No.3, pp.276-290.

Makridakis, S. (1983). "Empirical Evidence versus Personal Experience," *Journal of Forecasting*, Vol. 2, pp. 295-306.

Marrinan, J. (1989). "Exchange Rate Determinaion: Sorting Out the Theory and Evidence," *New England Economic Review*, Nov-Dec.

Marquez, L., Hill, T., Remus, W. and Worthley, R. (1993). "Neural Network Models as an Alternative to Regression," in R. R. Trippi and E. Turban (Eds.), *Neural Network Applications in Finance and Investing*. Chicago: Probus Publishing, pp. 435-450.

Masters, T. (1993). *Practical Neural Network Recipes in C++*, New York: Academic Press.

Masters, T. (1994). *Signal and Image Processing with Neural Networks: a C++ Source Book*. New York: John Wiley.

McNown, R. and Wallace, M. (1989). "Co-Integration Tests for Long Run Equilibrium in the Monetary Exchange Rate Model," *Economic Letters*, pp.263-267.

Meese, R. A. (1986). " Testing for Bubbles in Exchange Markets: A Case of Sparkling Rates,"*Journal of Political Economy*, Vol. 94, No. 21, pp. 345-373.

Meese, R. A. and Rogoff, K. (1988). "Was it Real? The Exchange Rate-Interest Rate Differential Relation over the Modern Floating-Rate Period," *Journal of Finance*, Vol. 43, pp. 933-948.

Meese, R. A., and Rose, A. K. (1991). "An Empirical Assessment of Non-Linearities in Models of Exchange Rate Determination," *Review of Economic Studies*, Vol. 58, pp. 603-619.

Meese, R. A. and Singleton, K. J. (1982). "On Unit Roots and the Empirical Modeling of Exchange Rates," *Journal of Finance*, Vol. 37, pp. 1029-1035.

Melvin, M. (1992). *International Money and Finance*, 3rd ed. New York: HarperCollins Publishers Inc.

Mendelsohn, L., "Global Trading Utilizing Neural Networks: A Synergistic Approach," in R. S. Freedman, R. A. Klein and J. Lederman (Eds.), *Artificial Intelligence in the Capital Markets.* Chicago: Probus Publishing Company (1995), pp. 79-135.

Mhaskar, H. N. (1996). "Neural Networks for optimal approximation of smooth and analytic functions," *Neural Computation*, Vol. 8, pp. 164-177.

Mhaskar, H. N., and Micchelli, C. A. (1992). "Approximation by superposition of a sigmoidal function and radial basis functions, *Advances in Applied Mathematics*, Vol. 13, pp.350-373.

Mhaskar, H. N., and Micchelli, C. A., "How to choose an activation function," in J. D. Cowan, G. Tesauro, and J. Alspector (Eds.) *Advances in Neural Information Processing Systems*, Vol. 6 (1993), San Francisco: Morgan Kaufman Publishers, pp. 319-326.

Mhaskar , H. N., and Micchelli, C. A. (1995). "Degree of Approximation by Neural and Translation Networks with a Single Hidden Layer," *Advances in Applied Mathematics*, Vol. 16. pp. 151-183.

Micchelli, C. A. (1986). "Interpolation of Scattered Data: Distance Matrices and Conditionally Positive Definite Functions," *Constructive Approximation*, Vol. 2, pp. 11-22.

Moody, J. (1989) "Fast Learning in Multi-Resolution Hierarchies," *Advances in Neural Information Processing Systems*, Vol. 1, pp. 29-39.

Moody, J. and Darken, C. J. (1989). "Fast Learning in Networks of Locally-tuned processing elements," *Neural Computation*, Vol. 1 No. 2, pp. 281-294.

Moody, J. (1994). "Prediction Risk and Architecture Selection for Neural Networks," in V. Cherkassky, J. H. Friedman, and H. Wechsler (Eds) *From Statistics to Neural Networks: Theory and Pattern Applications*, Springer-Verlag: Berlin Heidelberg, pp. 147-165.

Musavi M. T., Ahmed, W., Chan, K. H., Faris, K. B., and Hummels, D. M. (1992). "On the Training of Radial Basis Function Classifiers," *Neural Networks* Vol. 5, pp. 595-603.

Nachane, D. M., and Ray, D. (1993). "Modeling Exchange Rate Dynamics: New Perspectives from the Frequency Domain," *Journal of Forecasting*, Vol. 12, pp. 379-394.

Newey, W. K. and West, K. D. (1987), "A Simple, Positive, Semi-definite Heteroscedasticity and Autocorrelation Consistent Covariance Matrix" *Econometrica*, Vol. 55, pp.703-708.

Nørgaard, M. (1995). *Neural Network Based System Identification Toolbox*. Tech. Report 95-E-773. Institute of Automation, Technical University of Denmark.

Oh, H-K (1992). *The Relaxation Method for Learning In Artificial Neural networks*, Ph.D. Dissertation, Iowa State University, Ames, Iowa.

Orr, M. J. L. (1996). *Introduction to Radial Basis Function Networks*. Center for Cognitive Science, Edinburgh University, Scotland, UK.

Orr, M. J. L. (1996). *Matlab Routines for Subset Selection and Ridge Regression in Linear Neural Networks*. Center for Cognitive Science, Edinburgh University, Scotland, UK.

Park, J. and Sandberg, I. W. (1991). "Universal Approximation Using Radial-Basis-Function Networks, " *Neural Computation*, Vol. 3, pp.246-257.

Park, J. and Sandberg, I. W. (1993). "Approximation and Radial-Basis-Function Networks," *Neural Computation*, Vol. 5, pp.305-316.

Pesaran, M. H. (1992), " A Simple Nonparametric Test of Predictive Performance", *Journal of Business & Economic Statistics*, Vol. 10, No.4, pp. 461-465.

Pesaran M. H. (1994), " A Generalization of Non-parametric Henriksson-Merton Test of Market Timing", *Economic Letters*, Vol. 44, pp. 1-7.

Pham, D. T. and Liu, X. (1995). *Neural Networks for Identification, Prediction and Control*. Spring-Verlag London Limited.

Pittis, N. (June 1993). "On the Exchange Rate of the Dollar: Market Fundamentals versus Speculative Bubbles," *The Manchester School*, Vol. 61, No. 2, pp. 167-184.

Poggio, T. and Girosi, F. (1990a). "Networks for Approximation and Learning,", *Proceedings of the IEEE*, Vol. 78, pp.1481-1497.

Poggio, T. and Girosi, F. (1990). "Regularization Algorithms for Learning that are Equivalent to Multilayer Networks," *Science*, Vol. 247, pp. 4-17.

Poddig, T. and Rehkugler, H. (1996). "A 'World' Model of Integrated Financial Markets Using Artificial Neural Networks," *Neurocomputing*, Vol. 10, pp. 251-273.

Powell, M. J. D. (1987) . "Radial Basis Functions for Multivariable Interpolation: A Review," in J.C. Mason and M.G. Cox (Eds.), *Algorithms for Approximation*, Oxford: Clarendon Press, pp. 143-167.

Powell, M. J. D. (1992). "The Theory of Radial Basis Function Approximation," in W.A. Light (Ed.), *Advances in Numerical Analysis*, Vol. 2, Oxford: Clarendon Press, pp. 105-210.

Ramsey, J. B. (1996). "Is Nonlinear Models Cannot Forecast, What Good are They?" *Studies in Nonlinear Dynamics and Economics*, Vol.1, pp.65-86.

Reeves,C. R., "Bias Estimation for Neural Network Predictions," in D.W. Pearson, N.C. Steele, and R.F. Albrecht (Eds.). *Artificial Neural Nets and Genetic Algorithms*. Proceedings of the International Conference in Ales, France (1995), pp. 242-244.

Refenes, A. N. and Bolland, P., "Modeling Quarterly Returns on the FTSE : A Comparative Study with Regression and Neural Networks," in C.H. Chen (Ed.). *Fuzzy Logic and Neural Network Handbook*. New York: MacGraw-Hill (1996), chapter 19.

Refenes, A. N., "Constructive Learning and its Application to Currency Exchange Rate Forecasting", in R.R. Trippi and E. Turban (Eds.), *Neural Networks in Finance and Investing*. Chicago: Probus Publishing (1993).

Renals, S, and Rohwer, R., (1989). "Phoneme Classification Experiments Using Radial Basis Functions," *Proc. Of the IEEE/INNS Int. Joint Conf. On Neural Networks, Sheraton Washington Hotel*, pp, I-461-I-467.

Ripley, B. D. (1996), *Pattern Recognition and Neural Networks*. Oxford: Oxford University Press.

Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986). "Learning international representations by error propagation," In D.E., Rmuelhart and J.L.,McClelland (Eds.), *Parallel Distributed Processing*, Vol. 1. MIT Press, Cambridge, MA, ch.8.

Saha, A., and Keeler, J. D. (1990). "Algorithms for Better Representation and Faster Learning in Radial Basis Function Networks," *Advances in Neural Information Processing Systems*, Vol. 2, pp. 482-489.

Saha, A., Christian J., Tang, D. S. , and Wu C-L. (1991). "Oriented Non-Radial Basis Functions for Image Coding and Analysis," *Advances in Neural Information Processing Systems*, Vol. 3, pp. 728-734.

Sarantis, N. and Stewart, C. (1995). "Structural, VAR and BVAR Models of Exchange Rate Determination: A Comparison of their Forecasting Performance," *Journal of Forecasting*, Vol. 14, pp. 201-215.

Satchell, S., and Timmermann, A. (1995). "An Assessment of the Economic Value of Non-Linear Foreign Exchange Rate Forecasts," *Journal of Forecasting*, Vol. 14, pp. 477-497.

Schinasi, G.J., and Swamy, P.A.V.B. (1989). "The Out-of-Sample Forecasting Performance of Exchange Rate Models When Coefficients Are Allowed to Change," *Journal of International Money and Finance*, Vol. 8, pp. 375-390.

Sharda, R., and Patil, R. B., "A Connectionist Approach to Time Series Prediction: An Empirical Test," in R.R. Trippi and E. Turban (Eds.), *Neural Networks in Finance and Investing*. Chicago: Probus Publishing (1993), pp. 451-464.

Shoesmith, G. L. (1995)."Multiple Cointegrating Vectors, Error Correction, and Forecasting with Litterman's Model," *International Journal of Forecasting*, Vol. 11, pp. 557-567.

Somanath, V. S., "Efficient Exchange Rate Forecasts: Lagged Models Better than the Random Walk," *Journal of International Money and Finance*, Vol. 5 (1986), pp. 195-220.

Steiner, M. and Wittkemper, H-G, "Neural Networks as an Alternative Stock Market Model," in A-P. Refenes (Ed.), *Neural Networks in the Capital Markets*. New York: John Wiley (1995) pp. 137-147.

Stekler H. O. (1991). "Macroeconomic Forecasts Evaluation Techniques," *International Journal of Forecasting*, Vol. 7, pp. 375-384.

Stekler H. O. (1994). "Are Economic Forecasts Valuable," *Journal of Forecasting*, Vol 13, pp. 495-505.

Swanson, N. R. and White H. (1995). "A Model Selection Approach to Assessing the Information in the Term Structure Using Linear Models and Artificial Neural Networks," *Journal of Business and Economic Statistics*, Vol. 13, No. 3, pp. 265-75.

Swanson, N. R. and White H. (1997). "Forecasting Economic Time Series Using Flexible versus Fixed Specification and Linear versus Nonlinear Econometric Models," *International Journal of Forecasting*, Vol. 13, pp.439-461.

Tang, Z., de Almerda, C. and Fishwick, P. (1991). "Time Series Forecasting Using Neural Networks vs. Box-Jenkins Methodology," *Simulation*, Vol. 57, pp. 307-310.

Trippi, R.R and Turban, E. (Eds.), *Neural Networks in Finance and Investing*, Chicago: Probus Publishing Company (1993).

Trippi, R. R., and Harriff, R. (1993)."Trading Equity Index Futures with a Neural Network," *Journal of Portfolio Management*, Vol. 19, pp. 27-33.

Ungar, L. H., Johanson, T., and De Veaux, R. D. (1994). " Radial Basis Function for Process Control," *Neural Networks for Process Control, CIMPRO Proc.*, pp. 357-364.

Vemuri, V. R. and Rogers, R. D. (Eds). *Artificial Neural Networks: Forecasting Time Series.* Los Alamitos, LA: IEEE Computer Society Press (1994).

Wahba, G. (1990). "Splines Models for Observational data," *SIAM Series in Applied Mathematics*, Vol. 59, SIAM. Philadelphia.

Weigend, A. S. "Time Series Analysis and Prediction," in P. Smolensky, M.C. Mozer, and D.E. Rumelhart. (Eds.) *Mathematical Perspectives on Neural Networks*. pp.395-449.

Weigend, A. S., Huberman, B.A. and Rumelhart, D.E., "Predicting Sunspots and the Exchange Rates with Connectionist Networks," in M. Casdagli and S. Eubank (Eds.). *Nonlinear Modeling and Forecasting*. New York: Addison-Wesley Publishing Company (1992), pp. 395-432.

White, H. (1988). "Economic Prediction Using Neural Networks: The Case of IBM Daily Stock Returns," *Proceedings of IEEE International Conference on Neural Networks.* San Diego, CA. (New York: IEEE), Vol. 2, pp. 451-459.

White, H. (1992). *Artificial Neural Networks: Approximation and Learning Theory.* New York: Blackwell Publishers.

White, H., "Learning in Neural Networks: A Statistical Perspective," *Neural Computation*, Vol. 4 (1989), pp. 425-464.

Wolff, C. C. P. (1988). "Exchange Rates, Innovations and Forecasting," *Journal of International Money and Finance*, Vol. 7, pp. 49-61.

Wolff, C. C. P. (January 1987). "Time-Varying Parameters and the Out of Sample Forecasting Performance of Structural Exchange Rate Models," *Journal of Business and Economic Statistics*, Vol. 5, No. 1, pp. 87-97.

Wong, Y-F., (1991). "How Gaussian Radial Basis Functions Work," *Proc. of the IEEE/INNS Int. Joint Conf. On Neural Networks, Seattle*, pp.II-133-II-138.

Woo, W. T. (1985) "The Monetary Approach to Exchange Rate Determination under Rational Expectations," *Journal of International Economics*, Vol. 18, pp. 1-16.

Yang, C-C., Chou, S-C, T., Chu, W-H, and Lai, F, "Using AI in Developing Market Predictions: A Study of the Pacific Basin Capital Markets," in R. S. Freedman, R. A. Klein and J. Lederman (Eds.), *Artificial Intelligence in the Capital Markets*. Chicago: Probus Publishing Company (1995), pp. 157-175.

Yoda, M. (1994). "Predicting the Tokyo Stock Market," in G. J. Deboeck (Ed.), *Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic and Financial Markets*. New York: John Wiley & Sons, Inc., pp. 67-79.

Yoon, Y. and Swales, G. (1993). "Predicting Stock Price Performance : A Neural Network Approach," in R.R. Trippi and E. Turban (Eds.), *Neural Networks in Finance and Investing*. Probus Publishing: Chicago, pp. 329-339.

Zell, A., Mache N., Sommer T., and Korb, T. (1991). "The SNNS Neural Network Simulator," *Proc. Applications of Neural Networks Conf., SPIE*, Orlando Florida: Aerospace Sensing Intl. Symposium, Vol. 1469, pp. 708-719.

Zhang, G., Patuwo, B. E., and Hu, M. Y. (1998), "Forecasting with Artificial Neural Networks: the State of the Art", *International Journal of Forecasting*, Vol. 14, pp. 35-62.

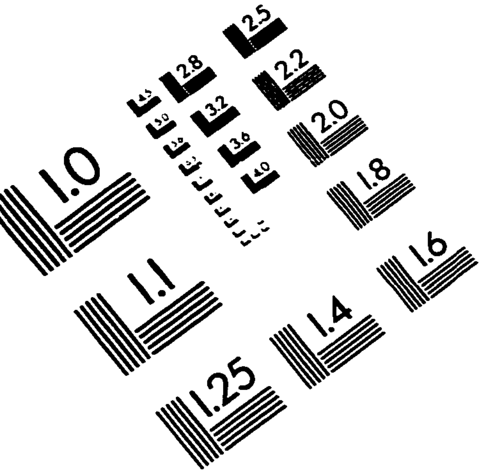
ACKNOWLEDGEMENTS

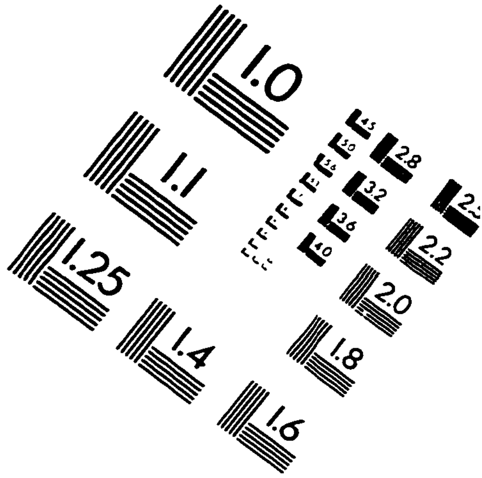
I would like to express my deepest appreciation for my major professor, Dr. Leigh Tesfatsion, for her guidance, support, and encouragement throughout this research. I appreciate her invaluable assistance in every aspect.

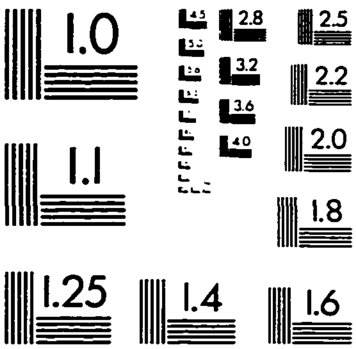
I would also like to thank Dr. Jennifer Davidson, Dr. Barry Falk, Dr. Walter Enders, and Dr. Sergio Lence for serving on my graduate committee and for their very helpful comments and suggestions for my dissertation.

I sincerely thank my friends, Shin-Miin Tzuoo and George Warren, for their support and encouragement.

IMAGE EVALUATION TEST TARGET (QA-3)

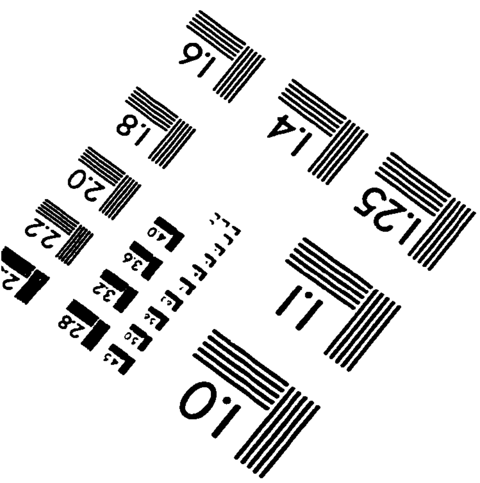






150mm

6″



APPLIED IMAGE . Inc
1653 East Main Street
Rochester, NY 14609 USA
Phone: 716/482-0300
Fax: 716/288-5989