Forecasting the Exchange Rate: A Comparison between Econometric and Neural Network Models

Gianna Boero[1] and Enrico Cavalli[2]

Abstract

In this paper the performance of four linear models of the exchange rate Spanish peseta/US dollar is compared with that of Artificial Neural Networks. The models are a random walk process and three different specifications based on the purchasing power parity (PPP) theory. The aim is to examine whether potentially highly nonlinear neural network models outperform traditional methods or give at least competitive results. The comparative exercise has been conducted both in-sample and out-of-sample. In general, the results confirm the difficulty in forecasting exchange rates, and reaffirm those obtained in previous literature which show that the performance of econometric models of the exchange rates is inferior to that of a random walk. A similar result is found for the neural networks. In the direct comparison between linear and nonlinear models, the experiment with quarterly data indicates that there is no advantage in the use of NNs for forecasting the exchange rate, while the performance of the NNs clearly improves when they are trained on monthly data.

Keywords

Exchange rate forecasting, purchasing power parity, econometric models, neural networks.

1) University of Cagliari and CRENoS, Viale Fra' Ignazio, 78, I - 09123 Cagliari (Italy); Tel: + 39-70-6753763, Fax: + 39-70-6753760, E-mail: boero@vaxcal.unica.it; G. Boero acknowledges financial support from CRENoS

2) University of Bergamo, Piazza Rosate, 2, I - 24129 Bergamo (Italy); Tel: + 39-35-277 518, Fax: + 39-35-277 535, E-mail: enrico@ibguniv.unibg.it; E. Cavalli acknowledges financial support from MURST 60% 1992.1993.1995

1. INTRODUCTION

This paper compares the forecasts from models of the exchange rates which derive from competing econometric and neural network (NN) specifications. The difficulty for econometric models to forecast exchange rates even in ex post simulations and the recent increasing interest in the use of neural networks for forecasting purposes have motivated this comparative exercise. Most econometric models assume a linear relationship among variables and this limitation can be one reason for the poor forecasting performance of these models. Several non linear time series models have recently been studied. Examples are the bilinear models, the threshold autoregressive models and the exponential autoregressive models. These are model-driven approaches (see Granger and Terasvirta, 1993) which are based on a specific type of relation among the variables. Neural networks, on the other hand, are data-driven models where the analysis depends on little a priori knowledge about the relation between variables (see Azoff, 1994 and Smith, 1993). Although several studies have compared NNs and traditional Box-Jenkins models (Tang et al., 1991, Wuertz and de Groot, 1992), surprisingly there are only a few comparative analyses between NNs and standard econometric techniques (see Church and Curram, 1994, for an application to consumer expenditures, Barucci, Gallo and Landi, 1995 for an application to the Italian Treasury Bill auction rates, and Verkooijen, Plasmans and Daniels, 1995 for an analysis of long-run exchange rate determination). In this paper, the performance of four linear models, a random walk process and three different specifications based on the purchasing power parity (PPP) theory, is compared with that of neural network models. The aim is to examine whether potentially highly nonlinear neural network models outperform traditional methods or yields at least competitive results.

The paper is organized as follows. In Section 2 we describe the theory behind the formulation of the models. In Section 3 we present the data and conduct some preliminary analysis to determine the forms in which each variable should enter the models. In Section 4 we present the empirical models: the econometric specifications and the neural networks. In Section 5 we assess the comparative forecasting properties of the linear and nonlinear approaches. In Section 6 we draw some conclusions.

2. THE PURCHASING POWER PARITY (PPP) RELATIONSHIP

The main idea of the PPP hypothesis is that nominal exchange rates and national price indices will adjust proportionally in order to maintain a given currency's purchasing power across countries. In its simplest form PPP states that the nominal exchange rate should equal the ratio of the domestic to the foreign price level. Using logarithms the relationship is as follows:

(1) $$s_t = p_t - p_t^* + d_t$$

where s_t is the logarithm of the spot exchange rate, i.e. the price of one unit of foreign currency in terms of domestic currency, p_t and p_t^* are the logarithms of the domestic and foreign price levels, respectively, and d_t represents the deviation from PPP in period t.

Relationship (1) is known as *absolute* PPP, as opposed to *relative* PPP. The latter is formulated in the first differences of the variables and states that the change in the nominal exchange rate is equal to the relative inflation rate, i.e.:

(2) $\Delta s_t = \Delta p_t - \Delta p_t^* + d_t$

where Δ denotes first difference.

Given its central role in theories of exchange rate determination, PPP has been the focus of a vast number of empirical studies testing its consistency with the data. The findings are mixed, depending on the methodology used, the sample period considered, and the data frequency. In general there is some agreement that PPP does not hold in the short-run, while it may be a valid description of the long-run co-movement of nominal exchange rates and relative prices.
Because s_t, p_t and p_t^* are likely to be non stationary, the long-run validity of PPP has been recently tested by using cointegration analysis. Various statistical methods have been employed to detect cointegration. Some studies apply the Engle-Granger (1987) two-stage cointegration methodology which involves an arbitrary normalization by regressing one variable, say s_t, on the price variables and testing the cointegration hypothesis by applying unit root tests on the regression residuals (see Edison and Fisher, 1991). Other studies use Johansen's (1991) multivariate cointegration method (MacDonald and Taylor, 1991). The advantage of the Johansen technique is that it explicitly allows for possible interactions between the variables and it accounts for long-run equilibrium properties as well as short-run dynamics.

3. THE DATA AND PRELIMINARY ANALYSIS

The data are taken from the IMF's International Financial Statistics data tapes[1], and consist of both quarterly and monthly observations for the nominal exchange rate of Spanish currency units against the US dollar, and the consumer price indices for Spain and US, for the period 1973-1994. The nominal exchange rate observations correspond to the last trading day of the quarter, while the price indices are reported for the second month of the quarter (1990=100). The price indices are seasonally unadjusted. All the series are in natural logarithms. The choice of using both quarterly and monthly data is based on the consideration that quarterly data are more appropriate for the econometric models used in the following empirical analysis, since PPP is a long-run relation and the adjustment towards it may be very slow, while higher frequency data are more adequate for training NNs. Thus the econometric models are estimated with quarterly data, whereas, to avoid penalizing the performance of Neural Network models by using a relatively small number of observations, NNs are estimated both with quarterly and monthly data. This will enable us to assess the extent to which their performance improves with higher frequency data.

[1] The authors thank Emanuela Marrocu for providing the data.

Unit root tests and cointegration analysis

Nonstationarity invalidates many standard results in econometric models, and to avoid spurious regressions it is important to test the order of integration of the series. Therefore, in order to estimate the PPP cointegration relationship, each series was first checked for the presence of a unit root. In this paper we applied the Augmented Dickey-Fuller (Dickey and Fuller, 1979) (ADF) and Phillips-Perron (Phillips, 1987, and Phillips and Perron, 1988) (PP) tests. The ADF accounts for temporally dependent and heterogeneously distributed errors by including higher order autoregressive terms in the test regressions, Phillips and Perron, in contrast, allow for non-independent and potentially heteroscedastic disturbances using a non-parametric adjustment to the standard Dickey-Fuller procedure. Since in the presence of more than one unit root the application of the DF testing procedure can be incorrect we pretested the data for a second unit root (a unit root in the first difference), following the Dickey-Pantula (1987) strategy. Table 1 summarizes the trend properties of the series suggested by these tests, leaving out the individual numerical results. The series in log levels and first differences aredepicted in Figure 1.

Both tests suggest the presence of a single unit root in the nominal exchange rate variable without drift process, one unit root with drift for the relative price index, and there is evidence for a second unit root for both price indices.

Table 1
Trend properties of the variables

	LER	LSCP	LUSCP	LRCP
ADF tests	I(1) with no drift	I(2)	I(2)	I(1) with drift
Phillips and Perron tests	I(1) with no drift	I(2)	I(2)	I(1) with drift

LER= log of exchange rate; LSCP= log of Spanish consumer price index; LUSCP= log of US consumer price index; LRCP= log of relative price indices.

This last result is consistent with recent empirical evidence about the order of integration of prices and nominal variables and is confirmed by a visual inspection of Figure 1 which shows non-stationarity in mean and in variance of the log-differences of the series.

The stationarity properties of the series detect the form in which the data should enter the model. The next step is to test for cointegration. The cointegration analysis allows us to discover whether long-run relationships exist among variables integrated of the same order. Since in both countries involved in this study the price levels have been found to be integrated of order two, the necessary condition for a long-run PPP equilibrium is that the nominal exchange rate is cointegrated with the relative price. The analysis of cointegration is done by using two procedures: the Engle-Granger two-step method and the Johansen's approach. If cointegration is detected, then the most appropriate specification is the Error Correction model, which takes into account both long-run and short-run dynamics. The results from these tests, not reported here, are mixed. The Engle-Granger method finds no cointegration, therefore suggesting a model in the first differences, while the Johansen's procedure finds one cointegrating vector, so that an ECM representation should be adopted. Giving these mixed results on the cointegration properties of the series, in the next section we estimate different econometric specifications of the PPP hypothesis, and Neural Networks based on equivalent specifications are then estimated to examine whether introducing nonlinearities improves the predictive performance of the econometric models.

4. THE EMPIRICAL MODELS

In section 2 we have illustrated two different representations of the PPP relation: *absolute* PPP and *relative* PPP. In the remainder of this paper we estimate four linear specifications including the two representations of the PPP hypothesis, an error correction model (ECM), and a simple random walk process. The random walk has often been found to perform better than more complicated models, and it is usually taken as a benchmark for forecast comparisons. The performance of these four linear specifications is then compared with that of Neural Network models, where the same explanatory variables included in the linear specifications are used as the input to the networks. The econometric specifications are estimated with quarterly data, while the NNs are fitted to both quarterly and monthly data.
The linear models are summarized in Table 2, the correspondent neural networks architectures are illustrated in Table 4.

Econometric models

The first three linear models are very simple. The random walk process is a naive representation of the exchange rate series in terms of its own lag value only. Models 2 and 3 are simple representations of the PPP hypothesis, whereby the exchange rate (or the variation in the exchange rate) depends on the relative price (or the relative inflation rate) between the two countries considered: the first is a long run static relationship, the second only considers short run adjustments. The error correction model (ECM) combines long run information with short run dynamics and is specified according to the cointegration analysis described previously and the general to specific methodology (Hendry, 1983).

Table 2
Linear-Econometric specifications

1. Random walk	$s_t = s_{t-1} + u_t$
2. Linear in the log-levels	$s_t = \alpha_0 + \alpha_1 (p_t/p_t*) + u_t$
3. Linear in log-differences	$Ds_t= \beta_0 + \beta_1 D(p_t/p_t*) + u_t$
4. ECM	$Ds_t=\gamma_0+\gamma_1 Ds_{t-1}+\gamma_2 Ds_{t-3}+\gamma_3 D(p/p*)_t+ \gamma_4 D(p/p*)_{t-2} + \gamma_5 D(p/p*)_{t-4} + \gamma_6 s_{t-1} + \gamma_7 (p/p*)_{t-1}+u_t$

D indicates first differences

For each econometric model we report in Table 3 the R^2 and four residual diagnostics for autocorrelation (AR), autoregressive conditional heteroscedasticity (ARCH), normality (NORM) and functional form misspecification (RESET).

Table 3 Econometric models R^2 and Residual diagnostics P-values Estimation period: 1973.1-1991.4					
	R^2	AR	ARCH	NORM	RESET
1. Random walk	n.a.	n.a.	n.a.	n.a.	n.a.
2. Linear in the log-levels	0.70	***	***	0.18	0.33
3. Linear in log-differences	0.06	**	0.43	0.37	**
4. ECM.	0.15	0.27	0.68	0.50	0.86

***, ** significant at the 1% and 5% level respectively

As we can see from Table 3, the overall fit of these econometric models is poor, specifically model 3 in first differences, which neglects an important long run component, and suffers from functional form misspecification, perhaps due to neglected nonlinearities. It is however important to emphasize that these models are based on a very simple economic theory of the exchange rate, and their specification could be further improved with the addition of a wider range of macroeconomic fundamentals suggested by different theoretical models. However, for the purpose of this paper, we have chosen to keep the structure of the models as simple as possible. Moreover, despite these problems of misspecification, recursive estimates of the coefficients showed stability in most parameters, which is an important requisite for proceeding to the next stage of the analysis, where we use the models for predictions.

Neural Network models

The type of Neural Network used in this paper is the "multilayer perceptron" developed by Rumelhart *et al.* (1986). The models are trained using the same explanatory variables and data set as each econometric model. These models allow highly non-linear relationships to be fitted, if they exists, therefore they are expected to perform better than standard econometric models, at least in sample.
The networks have been developed using ExploreNet 3000, a neurosoftware tool licensed by HNC Inc. ExploreNet is a unified set of software tools for the creation and application of Neural Networks. The product is an icon-based, graphically oriented, point-and-click interface which operates under Microsoft 3.0. It supports the creation of various type of Neural Networks and it provides the data transformation, display and analysis tools necessary in most applications. The product embodies HNC Neurosoft Library with a set of packages for the rapid prototyping of the most useful N.N. architectures, including the back-propagation network family which is the most widely used type of neural network. The N.N. developed are feed-forward network in which the input flows through the connections and Processing Element (PE) until it reaches its final form at the output PEs. The N.N. chosen in our experiment are Multilayer Back-Propagation Networks: the HNC implementation supports up to 3 hidden layers (or slab) for MBPN. The (up to) 5 layers

are referred to as the input layer, the hidden layer(s) and the output layer. Each layer is fully connected to the next layer. The direct connections between input and output layers can be enabled or disabled optionally. The training slab, connected to the output layer in a one to one manner, inputs the correct desired output corresponding to the input vectors presented via the input layer.

Table 4
Neural Networks architectures

	Quarterly data	Monthly data
1. Random walk	(1,2,1)	(1,2,1)
2. Linear in the log-levels	(1,2,1) and (1,3,1)	(1,10,1)
3. Linear in log-differences	(1,2,1)	(1,3,2,1)
4. ECM	(1,3,1)	n.a.
training set	52 obs. (1973.1-1991.4)	174 obs. (1973.1-1993.10)
validation set	23 obs.	75 obs.
test set	12 obs. (1992.1-1994.4)	12 obs. (1993.11-1994.10)

The learning algorithm is based on feed-forward back-propagation: the errors between output and target values are propagated back through the network and the weights are altered using the steepest descent method to reduce the Mean Square Error. The architecture of the networks consist of three or four layers: one input, one or two hidden layers and one output. The number of neurons in the hidden layers varies between 2 and 3 for quarterly data and between 2 and 10 for monthly data, and it has been chosen through extensive tests in order to have a good generalization capability. In the case of the log-difference model we have chosen 2 hidden layers with 3 or 2 neurons respectively.
The training set consist of 53 observations for quarterly data (1973.1-1991.4) and 174 for monthly data (1973.1-1993.10). An independent validation set is used to test the ability of the network to generalize to data which have not been seen during the training process. For this the training process is stopped when the sum of the errors (MAE) computed from training data set and the validation data set reaches its minimum. The validation data are extracted from the training set and comprise 30% of the available observations. In our experiment the validation set consists of 23 observations for quarterly data, and 75 for monthly data. The test set consists of 12 observations used to evaluate the out-of-sample forecasting performance. For quarterly data we have produced predictions for the period 1992.1-1994.4, for monthly data over the period 1993.11-1994.10.

5. THE COMPARATIVE FORECASTING PERFORMANCE

We compare the performance of the linear models and of the Neural Networks on two levels: in-sample simulations (estimation and simulation period are the same), and out-of-sample forecasting (estimation period different from simulation period).
This comparative analysis is based on quarterly data. However, in order to assess whether the performance of the NNs can improve significantly with higher frequency data, we have repeated the analysis with the NN models by using monthly data.

In each case we computed the mean absolute error (MAE) and the root mean square error (RMSE) as overall measures of forecast accuracy, but as the rankings are very similar between each measure, we only report RMSEs.
The forecasts of the specifications in first differences are not reintegrated into levels, so they are not comparable with the log-level models. However, this does not affect our analysis as our main objective is the direct comparison between corresponding linear and non linear models.

5.1 In-sample predictions

For this exercise we have estimated the models over the whole sample period, and produced predictions within sample. The results of this exercise are shown in Table 5. Within the log-linear models the random walk specification dominates that based on the absolute PPP (log-levels), while the ECM model is marginally better than the relative PPP model (log-differences). A direct comparison between quarterly linear and neural network models shows that their performance within sample is similar, and, if anything, the linear specifications do slightly better than the nonlinear competitors. The only exception to this result is the NN (1,2,1) fitted to the log-level model which has a superior in-sample performance (RMSE 0.0628) than the linear competitor (RMSE 0.1885). However, as we will see later, this model did not have a good out-of-sample performance (perhaps due to an overfitting problem) and so we have chosen a different architecture with 3 rather than 2 hidden neurons. Although this model has a poorer performance in sample, it showed some improvement in the out of sample experiment.

Table 5
In-sample predictions RMSEs
Spanish peseta/US $ exchange rate.
Estimation and simulation period:
1973.1-1994.4 quarterly data;1973.1-1994.10 monthly data

	Linear models	**Neural Networks**	
data frequency	quarterly	quarterly	monthly
1. Random Walk	0.0575	0.0664 (1,2,1)	0.0480 (1,2,1)
2. Log-levels	0.1885	0.0628 (1,2,1)	0.0660 (1,10,1)
		0.1800 (1,3,1)	
3. Log-Differences	0.0568	0.0574 (1,2,1)	0.0347 (1,3,2,1)
4. ECM	0.0528	0.0557 (1,3,1)	n.a.

Given the superior flexibility of the neural networks, this result is not what we would expect to find, at least in a comparison within sample. There are two possible explanations for this: either there are no neglected nonlinearities in the data which NNs can exploit, and therefore their performance is similar to that of linear models, or, in order to achieve a satisfactory performance, NNs require a larger number of observations. This second explanation is partially confirmed by the results presented in the last column of Table 5 and by the plots of actual versus fitted values depicted in Figure 4, which show some improvement in the performance of the NNs, when these are trained on monthly data. As already mentioned, these results are based on a very simple economic theory of

the exchange rate, and both econometric specifications and NN architectures could be further improved with the addition of fundamentals, including interest rate differentials, relative money supply, relative GNP and trade balances, suggested by different theoretical models.
A more interesting exercise is to compare the out-of-sample forecast performance of the two approaches, to which we will turn in the next section.

5.2 Out-of-sample forecasts

The out-of-sample forecasts are obtained by estimating the models from 1973.1 to 1991.4 and forecasting one- to twelve-steps ahead from 1992.1 to 1994.4. This was done without re-estimating the models, i.e. assuming a constancy of the model coefficients during the forecasting horizon. The RMSEs are reported in Table 6.

Table 6
Out-of-sample forecasts RMSEs
Spanish peseta/US $ exchange rate.
Estimation and forecast period:
quarterly data: 1973.1-1991.4; 1992.1-1994.4
monthly data: 1973.1-1993.10, 1993.11-1994.10

	Linear models	**Neural Networks**	
data frequency	quarterly	quarterly	monthly
1.Random Walk	0.0671	0.0644 (1,2,1)	0.0261 (1,2,1)
2.Log-levels	0.1825	0.3163 (1,2,1)	0.0403 (1,10,1)
		0.1158 (1,3,1)	
3.Log-Differences	0.0686	0.0676 (1,2,1)	0.0218 (1,3,2,1)
4. ECM	0.0669	0.0897 (1,3,1)	n.a.

The ranking between the linear models is the same as that seen in the in-sample experiment: the random walk performs much better than the log-level specification, and the ECM is slightly better than the regression in first differences. With respect to the neural networks, their performance improves remarkably with monthly data (see also Figure 4), while the capability of quarterly NNs to predict out-of-sample is no better than that of the correspondent linear models, with only one significant exception, the log-level NN(1,3,1) which has a clear advantage with respect to the linear model. With regard to this model it is interesting to note that the performance of the alternative architecture reported in Table 6 (NN (1,2,1)), which seemed to have a better fitting capability in sample, is particularly poor out of sample. This problem was overcome by the NN (1,3,1).
To conclude, three main results can be extracted from this analysis. First, NNs do perform better with a larger number of observations. Second, with a relatively small number of observations NNs do not outperform the linear models, although their forecasts are no worse than those obtained using linear models: probably, the degree of non-linearity in the data is too small to be satisfactorily extracted from the networks. Finally, if anything, the results of this paper reinforce the importance of using a cross-

validation set in NN applications, as it has been shown that the ability of the networks to fit the data in-sample does not necessarily imply a good out-of-sample performance.

6. CONCLUSIONS

The econometric and neural network models used in this comparison are based on the hypothesis of the purchasing power parity and are estimated with quarterly data for the peseta/dollar exchange rate. The models represent two versions of PPP, absolute and relative PPP, the first requiring estimation in the log levels, the second in first differences. In addition we estimated a random walk process and an error correction model. All four models have been estimated with linear techniques (OLS) and the same variables which appeared in the linear models were then used as input of the NNs to see whether they could catch potential nonlinearities. The exercise has been repeated for the NNs also with monthly data.

The comparative exercise has been conducted both in-sample and out-of-sample. In general, the results confirm the difficulty in forecasting exchange rates, and reaffirm those obtained in previous literature (Meese and Rogoff, 1983, 1988) which show that the performance of econometric models of the exchange rates is inferior to that of a random walk.

With quarterly data the neural networks produce no better forecasts than the econometric models. There is only one exception to this results: one of the two neural network models in log-levels shows a much higher capability to represent the exchange rate behaviour in sample than the correspondent econometric model. However, this is not necessarily good news for the NN, given that in the out of sample performance that same log-level model is outperformed by the corresponding econometric model. This result reinforces the importance of using a cross-validation set in NN applications, as the ability of the networks to fit the data in-sample does not necessarily imply a good out-of-sample performance.

Overall, the experiment with quarterly data indicates either that there is not a great deal of non linearity to be extracted from the data, or that NNs require a larger number of observations so as to achieve a satisfactory performance. This second explanation is confirmed by the results obtained when the NNs are trained on monthly data, which show a clear improvement in their performance.

To conclude, there are several ways to extend this research. First of all it is possible to improve the econometric specification beyond the simple PPP theory used here. Although this is the most widely used theory, it has often been contradicted by empirical tests. The model can be extended in various ways, for example by including a larger number of fundamentals such as money, GNP, interest rates, inflation rates and wealth (see Chinn, 1991 and Parikh, 1992). Also further improvement of the NNs may be possible through experimentation with other variables and network architectures. Finally the exercise can be extended to other currencies.

REFERENCES

Azoff, E.M. (1994). Neural Network Time Series Forecasting of Financial Markets. Chichester: Wiley.

Barucci, E., Gallo G. M. and Landi L. (1995). Linear versus Nonlinear Information processing: a Look at Neural Networks. Mimeo, University of Florence.

Chinn, M.D. (1991). Some linear and nonlinear thoughts on exchange rates. *Journal of International Money and Finance*, 10, 214-230.

Church, K. and S. Curram (1994). Forecasting consumers' expenditure: a comparison between econometric and neural network models. *ESRC Macroeconomic Modelling Bureau* Discussion Paper No. 37.

Dickey, D.A and W.A. Fuller, (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74, 427-431.

Dickey, D.A. and S.G. Pantula (1987). Determining the Order of Differencing in Autoregressive Processes. *Journal of Business and Economic Statistics*, 5, 455-461.

Edison, H.J. and E. Fisher (1991). A Long-Run View of the European Monetary System. *Journal of International Money and Finance*, 10, 53-70.

Engle, R.F. and C.W.J. Granger (1987). Cointegration and Error Correction: Representation, Estimation and Testing. *Econometrica*, 55, 251-276.

Hendry, D.F. (1983). Econometric modelling: the "consumption function" in retrospect. *Scottish Journal of Political Economy* 30, 193-220.

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica*, 59, 1551-1580.

Kim, B.J.C. and Mo, S. (1995). Cointegration and the long-run forecast of exchange rates. *Economics Letters*, 48, 353-359.

MacDonald, R. and M.P. Taylor (1991). Exchange Rates, Policy Convergence, and the European Monetary System. *Review of Economics and Statistics*, 73, 553-558

Meese R. A. and K. Rogoff (1983). Empirical exchange rate models for the seventies: do they fit out of sample? *Journal of International Economics*, 14, 3-24.

Meese R. A. and K. Rogoff (1988). Was it real? The Exchange Rate-Interest Differential Relation over the Modern Floating-Rate Period. *Journal of Finance*, 43, 933-947.

Parikh, A. (1992). Nominal exchange rate, cointegration and uncovered interest parity. *The Journal of International Trade & Economic Development*, pp. 167-193.

Phillips, P.C.B. (1987). Time Series Regression with a Unit Root. *Econometrica*, 55, 277-301

Phillips, P.C.B. and P. Perron (1988). Testing for a Unit Root in Time Series regression. *Biometrika*, 75, 335-346.

Rumelhart, D.E., Hinton, G.E. and Williams, R.S. (1986). Learning internal representations by error propagation. In *Parallel Distributed Processing*, Vol. I, D.E. Rumelhart and J.L. (eds.), Cambridge, MA, MIT Press, pp.318-362

Smith, M. (1993). Neural Networks for Statistical Modeling. New York: Van Nostrand Reinhold.

Tang, Z., Almeida, C. and Fishwick, P.A. (1991). Time series forecasting using neural networks vs. Box-Jenkins methodology. *Simulations*, Simulations Councils, Inc., November, pp. 303-310.

Verkooijen, W., J. Plasmans and H. Daniels, 1995. Long-run exchange rate determination: a neural nertwork study. *CentER for Economic Research*, Tilburg University, Discussion Paper No. 95109.

Wuertz, D. and C. de Groot (1992). Neural Networks for Economic Applications: Connectionist Modelling for Time Series Analysis. Paper presented at the Workshop on "L'analisi e la previsione delle serie storiche", Torino, June 8-10, 1992.

FIGURE 1

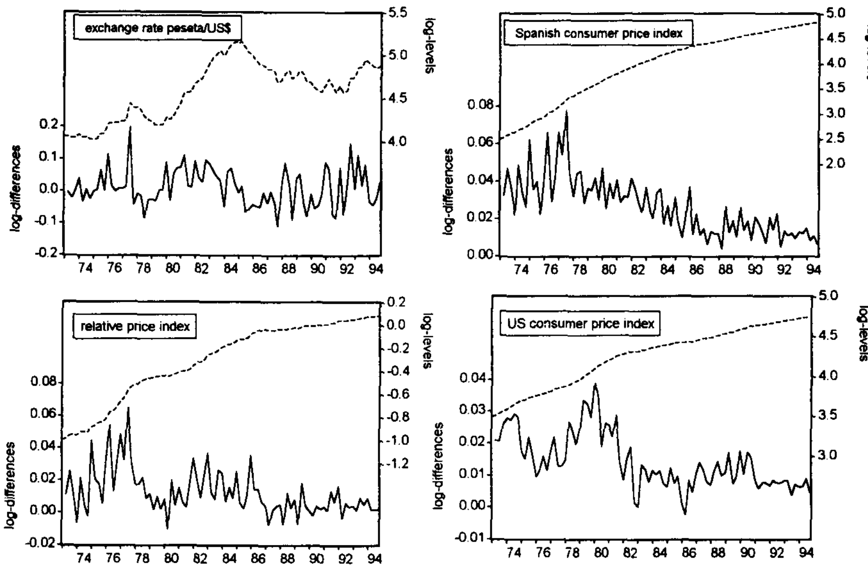

exchange rate peseta/US$
Spanish consumer price index
relative price index
US consumer price index
log-differences
log-levels
74 76 78 80 82 84 86 88 90 92 94

FIGURE 2

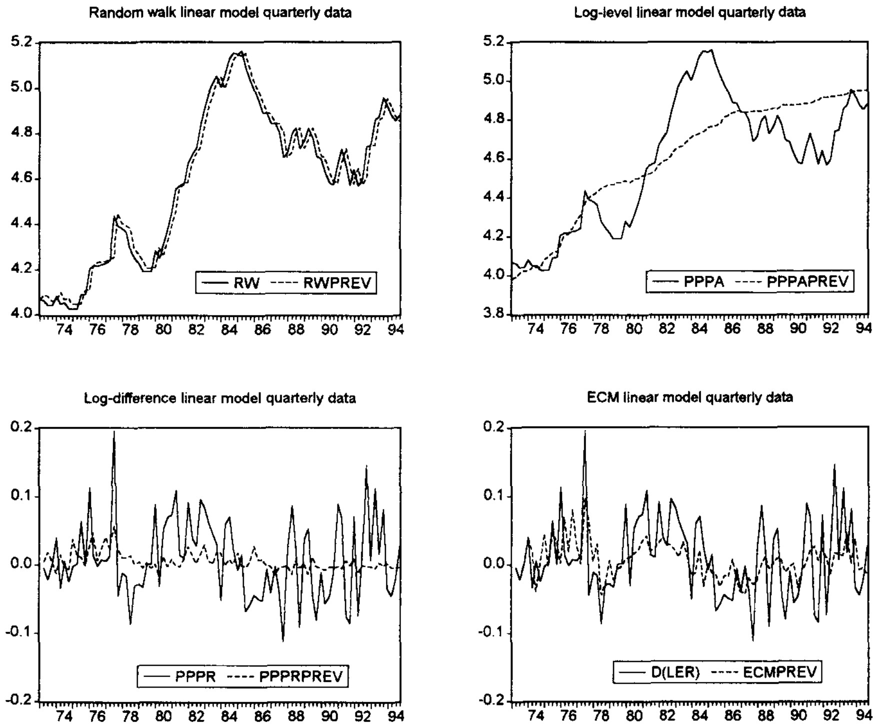
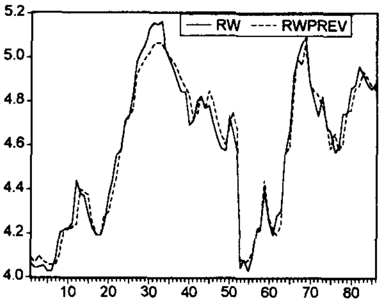
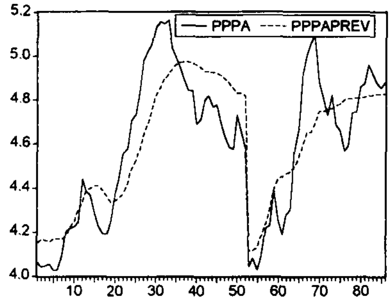

Random walk linear model quarterly data
RW ---- RWPREV
Log-level linear model quarterly data
PPPA ---- PPPAPREV
Log-difference linear model quarterly data
PPPR ---- PPPRPREV
ECM linear model quarterly data
D(LER) ---- ECMPREV
74 76 78 80 82 84 86 88 90 92 94

FIGURE 3

Random walk NN (1,2,1) quarterly data



Log-level NN(1,3,1) quarterly data



Log-difference NN(1,2,1) quarterly data

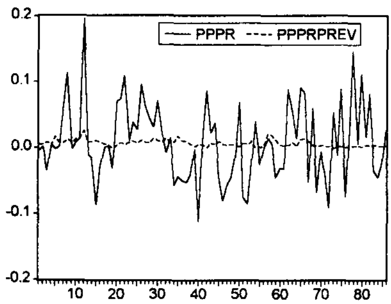
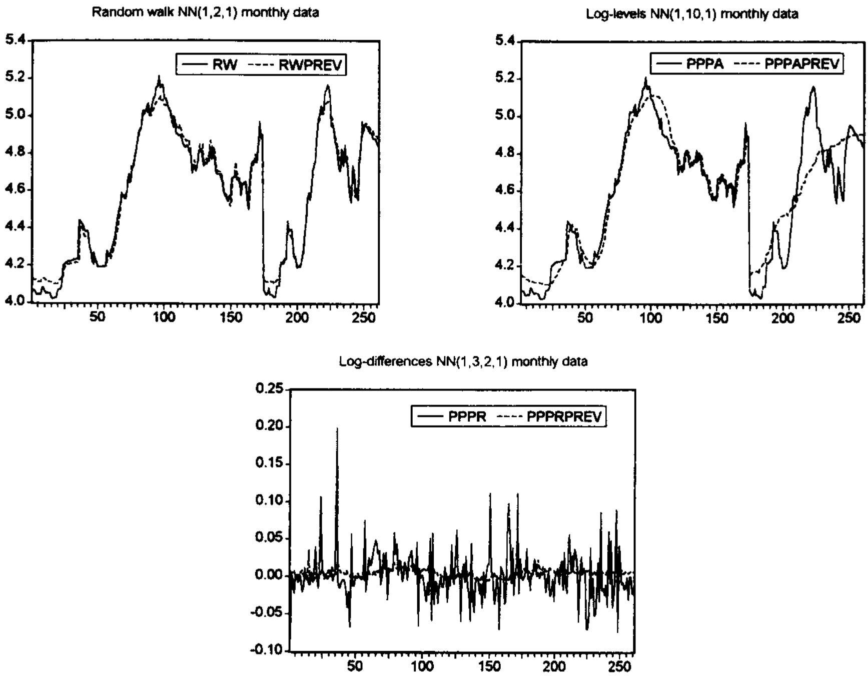


FIGURE 4


Random walk NN(1,2,1) monthly data
RW
RWPREV
Log-levels NN(1,10,1) monthly data
PPPA
PPPAPREV
Log-differences NN(1,3,2,1) monthly data
PPPR
PPPRPREV