9. SCENARIOS OF THE ROMANIAN GDP EVOLUTION WITH NEURAL MODELS[1]

Corina SAMAN[2]

Abstract

This paper aims to explore the nonlinear relation between investments and GDP. The method of neural network is used to construct two nonlinear models of GDP in relation to domestic investments, foreign direct investments and real interest rate. The results show that the two neural models present good performance measures on the dataset. The improved forecast accuracy may be capturing more fundamental non-linearities between investment and financial variables and the real output for a longer horizon.

Keywords: investment, simulation, GDP, neural networks

JEL Classification: E22, C22, C45

Introduction

In the last thirty years, a substantial literature deals with testing and modeling non-linearity in time series data and much of this interest was focused on neural network models. One of the reasons for the choice of these models is that they approximate any type of non-linearity in the data (Hornik, Stinchcombe and White, 1989) and that neural networks do not need any a priori knowledge of the distribution and the relation (functional form) they approximate.

Although still regarded as a novel methodology, neural networks are shown to have matured to the point of offering real practical benefits in many of their applications.

Applications of this technique in macroeconomics are not too many, due to the relative shortness of the series, but they proved the utility of this approach.

Swanson and White (1997a, 1997b) estimate forecasting neural models for the USA macroeconomic data (seasonally adjusted), with better long-term forecasting performance than the linear models.

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[2] *Institute for Economic Forecasting, Centre for Macroeconomic Modeling, NIER, Romanian Academy. E-mail: csaman@ines.ro.*

Also Moody, Levin and Rehfuss (1993) obtain better performance than with conventional linear models for estimating the aggregated industrial production (the USA).

Tkacz (2001) shows that models based on neural networks for the Canadian GDP growth rate present smaller errors than the constant coefficient linear models, especially in predicting the annual growth rate, but not for the quarterly rate.

In this paper, two multivariate neural models of the GDP are constructed using as determinants the domestic investments, the foreign direct investments and the real interest rate.

The models differ by the lag between the independent variable GDP and the non-financial independent variables. One of the models (NN_GDP) considers the short-term link (one month) between independent variables and the GDP and the other one the medium-term relation (one quarter).

The investment plays a role that has immediate impact on the economy and a role that needs a period of time for the investment to be implemented and to begin to affect the economy positively.

The short-term model has the disadvantage that data on investments are usually published with delay by the central institutions (NBR, NIS) and that the major investments usually have no immediate impact on the GDP due to the necessary period for implementing the investment projects.

The paper analyzes the performance measure on the data set used to construct the model and makes simulations considering two scenarios. The first one is based on the premise that the future evolution follows the trend of the historical data, while the second scenario is more pessimistic, considering a decrease in the rate of foreign direct investments and an identical rate of domestic investments.

The models show a rather similar GDP evolution for both scenarios, first a slight increase in GDP followed by a decrease that does not go below the value for the last month from the dataset, but a difference in the magnitude of the evolution – the medium-time model provides more optimistic predictions.

Data

The data frequency is monthly and encompasses the period January 2000-June 2010. The dataset (Figure 1) contains the variables: GDP (Gross Domestic Product), INV (domestic investments), FDI (foreign direct investment) and IR (real interest rate calculated as log((1+i)/(1+inf)), where i is the nominal interest rate for non-banking clients and inf is the inflation rate) as a proxy for the cost of capital. The data for GDP and investments are the logarithm of the values in constant prices, base year 2000.

The data are taken from the official monthly bulletins of the National Bank of Romania and the National Institute of Statistics, except for the GDP series, which was constructed by Stanica (2010) from the quarterly data by interpolation in relation with the monthly data on private demand (equates the sum of gross fixed capital formation and private consumption).

Because the seasonal adjustment is not a linear filter (Ghysels, Granger and Siklos, 1996) we used unadjusted data in order to avoid potential nonlinearities introduced or eliminated through the filtered data.

The data are preprocessed by normalization, in order to assure a better control on the training process of the neural network.

Neural Models of the GDP

The neural model of GDP is a nonlinear functional form and estimates the function and the parameter using feed-forward neural networks with one hidden layer.

A supervised neural network is a nonlinear parameterized mapping from an input x to an output. The output is a continuous function of the input x and of the parameters w, the functional form of the mapping equivalent with the network architecture being N:

$$\hat{y} = y(x \; ; w, N) \quad (1)$$

The neural network architecture N (Figure 2) consist of a specification of the number of layers, the number of units in each layer, the type of activation function performed by each unit, and the available connections between units. Such networks can be trained to perform regression tasks.

In the case of regression problems, the networks used are feedforward networks with one hidden layer, which proved to have an universal approximation property.

Cybenko (1988) and Hornik (1989) demonstrated that one-hidden layer FNN can approximate with arbitrary precision most classes of linear and nonlinear continuous functions with bounded inputs and outputs.

The mapping for this kind of network has the form:

$$\hat{y} = f(x) = l\left(\sum_{j=1}^{n_h} w_{o[j,1]} h\left(w_{i[n+1,j]} + \sum_{i=1}^{n} w_{i[i,j]} x_i\right) + w_{o[n_h+1,1]}\right) \quad (2),$$

where: $h(.)$ is a smooth, monotonically increasing function such as a sigmoid function h(x)= $(1-e^{-x})/(1+e^{-x})$, $\vec{w}$ are coefficients and n_h is the number of hidden nodes and l(x)=x is the activation function for the output. The nonlinear function h(.) gives the computational flexibility to the model, which allows an adjusting process with minimal errors.

For a given set of inputs, $\{\vec{x}_t\}$, and outputs, $\{y_t\}$, finding a feed-forward neural network means estimation of n_h +1 parameters $\{w_{o[i,1]}\}_{i=1,..,}$ n_h and (n+1) n_h parameters $\{w_{i[j,i]}\}$, totally (n+2) n_h +1 parameters.

The non-linear sigmoid function h at the hidden layer gives a greater computational flexibility to the neural network than a linear regression model.

There is equivalence between the architecture of the network shown in Figure 1 and the functional form from equation (2), named N in the description of a supervised neural network in (1).

The training set for the network is a set of input-target pairs D={x^m, t^m}, where m is the label over the point in the problem space.

If a set of values **w** (consisting of all weights) is assigned to the network, it defines a mapping from the inputs to the target variable.

The distance of this mapping to the training set is measured by the error function:

$$E_D(D / w, N) = \sum_m \frac{1}{2} [y(x^m; w, N) - t^m]^2 \tag{3}$$

The network is trained using data set by adjusting w so as to minimize this error function.

The learning process is the searching of a set of connections, w, that gives a mapping that fits the training set well and, hopefully, generalizes well to new examples.

An important question for neural networks techniques concern the type and complexity of the model for the network to be used for a specific problem.

Girosi, Jones and Poggio (1993) showed a relation between the smoothness of the function to be approximated and different approximation schemes, but even if the type of architecture could be chosen from such prior information about the function there still was a problem of choosing the number of parameters.

Finally, the model comparison could embody the Occam's razor, the principle that declares preference for simple theories. If several models are good explanations of the set of data, the Occam's razor advices to chose the least complex one.

Considering this principle, we can perform a search from the simple network (that with one unit in the hidden layer) to the more complex one, adding a hidden unit until the network fails to improve the error function.

The models we consider in this paper estimate the GDP using the data set:

$$GDP_t = f(GDP_{t-1}, \mathrm{X}_t) + u_t \tag{4}$$

where: **X** represent the determinants of the GDP, u is a random variable representing the residues and f is a nonlinear function estimated with the neural network.

For the model with short-term link, the vector is **X** = {INV_{t-1}, $FDI_{t-1,}$ IR_t}, and for the model with medium-term link, the model is **X** = {INV_{t-1}, $FDI_{t-1,}$ INV_{t-4}, $FDI_{t-4,}$ IR_t}.

The short-term link model is a developed version of the model presented in Saman (2010) that adds the interest rate to the determinants and expands the data to June 2010.

In order to find the most appropriate neural model, the data are preprocessed by normalization – each resulting series will give mean 0 and standard deviation 1.

The chosen neural networks **NN_GDP** and **NN_GDP(-4)** has three hidden nodes (n_h=3) and four and six, respectively, input variables (n=4, n=6).

The estimates of GDP follow closely the data trend (see Figures 2 and 3).

Performance Measures and Statistical Tests

The selection criterion of the most appropriate model was the minimization of error function (3) which is the sum of squared residuals, but for analysis other measures of performance could be considered.

The performance measures for predictions are:

- The coefficient of variations ('CV', a sum squared error measure normalized by the data mean of dependent variable, GDP)
- Mean bias error ('MBE', the average residual normalized by the data mean of dependent variable, GDP).

Other global performance measures:

- Sum of squared residuals ('SSE')
- Root mean square residual ('RMS')

And robust measures:

- Root mean square of the smallest 90% of the residuals ('$RMS_{90\%}$')
- Robust coefficient of variations ('RCV' = $RMS_{90\%}$/ / (90% data range)).

The values of the global indicators are significant by themselves, but they can be used also for model comparison. All the indicators are measures of the size of forecast deviations from the actual values; the lower these statistics, the more accurate the forecasts.

MBE shows that, on average, the models present a deviation of order 10^{-4} from the observed values of dependent variable.

Statistically, the residuals can be analyzed using the descriptive statistics in Table 2, and the graphical representation in Figure 5. The residues are not normal, but the mean is approximately 0.

The performance accuracy proved good for both models.

The medium-term model is more robust than the short-time one, having better performance on robust indicators. The improved forecast accuracy may capture more fundamental non-linearities between investments and financial variables and the real output for the longer horizon.

Simulations

Prediction is an important application of the time series analysis. For a neural model in equation (4), suppose that we are at the time index t and interested in forecasting y_{t+l}, where $l \geq 1$. Let $\hat{y}_t(l)$ be the forecast of y_{t+l} and F_t be the information available at the forecast origin t:

$$\hat{y}_t(l) = E(y_{t+l} / F_t) = E(f(y_{t+l-1}, \mathrm{X}_t)) + E(u_t) = E(f(y_{t+l-1}, \mathrm{X}_t)) .$$

The set X_t has as elements the contemporary variable F_c={IR_t}, as well as the previously known values of the other determinants of GDP {GDP_{t-1}, INV_{t-p}, FDI_{t-p}}, which are part of F_t, the collection of information available at the forecast origin t. On could make predictions based on scenarios that make assumptions on the variables in set F_c.

After 2000, the foreign direct investments represent the most significant factor of economic growth. During the transition period, including the pre-accession period and the first years of post-accession, the foreign direct investments present a high rate in GDP. It is unlikely that such an inflow will continue, considering the increasing risk and the lack of capital in the actual crisis situation. Accordingly, we will encompass two scenarios in the simulation.

A possible scenario is S1:

- The foreign capital flow decreases, so that the rate of foreign investments in relation to GDP is worsening in the next period due to the international context;
- The available reserves and the support of International Monetary Fund and European Commission allow the National Bank to keep the inflation rate under control. One presumes that the real interest rate is almost constant.
- The domestic investment rate is kept constant.

The second scenario, S2:

- All the exogenous variables maintain the historical trend.

The neural models proved to be more robust for long-term predictions, so we try a prediction for the next two quarters.

The simulations according to the neural models and the scenarios are presented in Tables 3 and 4.

In the first scenario, the simulations conducted with the model with short-term link show a slight decrease in output and an increasing trend for the medium-term model.

In the second scenario, the investment and the real interest rate follow the historical trend. The simulations for *the model with short-term link* indicate an increase in GDP for the first quarter and a slight reduction in the last quarter of 2010. This is due to the increasing trend in real interest rate and the decrease in the foreign direct investments. For *the model with medium-term link,* the simulations present a small increasing trend of GDP for the next two quarters of 2010. The difference from the short-term link model is the beneficial influence of the effect of the past investments (domestic and foreign) on GDP. At the beginning, the investments determine a negative effect on production due to the increasing cost and in the next medium to long-term period the positive effect follows.

Conclusions

Based on our experiments and the literature, we believe that neural networks may be of use in the macroeconomic modeling.

The economic theory does not always yield a specific functional form that could be used for empirical verification of the theory. If linear models performed poorly in spite of well-developed economic theory, then non-linearities may exist in the data; so neural networks can be potentially useful.

If the training period is sufficiently long to incorporate different episodes in the history of the data generation process, then the estimated parameters in the neural model can incorporate these differences. A structural break that appears in linear models is a special form of nonlinearity that the neural net can learn.

Neural networks, more than the linear models, need larger samples to be estimated properly. In order to construct nonlinear models based on neural networks for macroeconomic variables, one has to accept the fact that, due to the short data series, their precision is not automatically good. The precision could be affected because the examples available for the network to learn the intrinsic structure of data are in a smaller number than for applications in finance, physics and other domains.

Nevertheless, the neural models of this kind were created for datasets on industrial production, growth rate of GDP and other macroeconomic variables.

This paper seeks to determine whether more accurate models of output evolution based on investments and financial variables can be developed using neural networks. This approach is especially useful in modeling crisis situations, which are characterized by structural breaks in data.

Two neural models for the influence of domestic investments, foreign direct investments and real interest rate on monthly GDP are estimated and simulations are conducted for GDP evolution in the following months. The two models differ by the assessment of the impact time of investment on GDP.

The first one (NN_GDP) considers the short-term impact (one month) of the independent variables on GDP, and the second one (NN_GDP(-4)) evaluates the medium-term impact (one quarter). This different approach refers to the lag structure of the non-financial variables.

The models can be used for simulation; two scenario simulations are conducted using these models, taking into consideration the international crisis.

The first scenario assumes that the rate of foreign direct investments to GDP decreases and the domestic investments is maintained at the same level in a stable financial environment characterized by almost constant interest rate. The second scenario assumes the same trend for the model determinants of GDP.

In both scenarios, the results show a slight recovery of the economy in the next quarters if the model with medium-term link is considered. The difference from the short-term link model is the beneficial influence of the effect of the past investments (domestic and foreign) on GDP. At the beginning, the investments determine a negative effect on production due to the increasing cost and in the next medium to long-term period the positive effect follows.

If the actual investment has short impact on the economy, then the evolution is characterized by a short time (one quarter) increase followed by a decrease. This is the case if the investment does not recover from decreasing.

Both models reflect the effect of the financial crisis on the Romanian economy, which has reduced the funds for investment and the slow recovery from this situation.

Annexes

Figure 1. Data Set

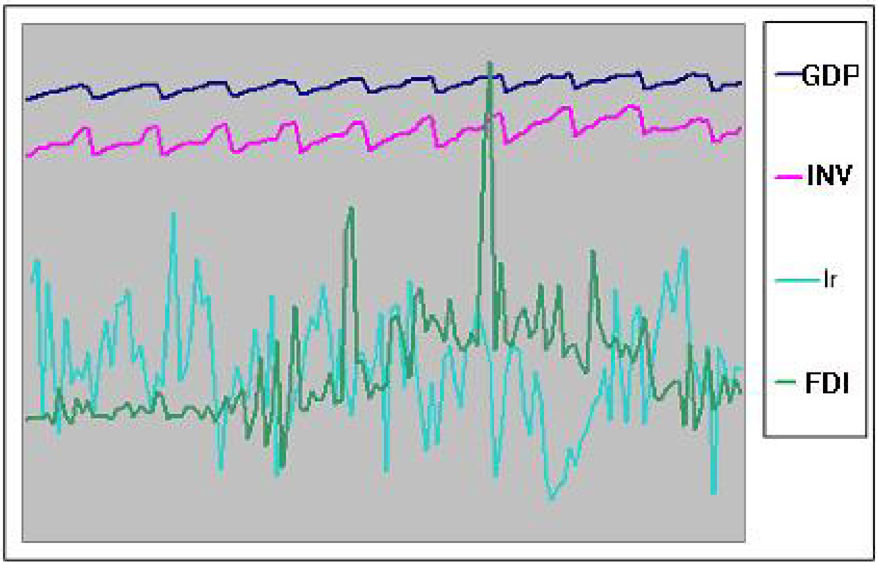

Figure 2

A Neural Net-based Function Estimator of a One Hidden-layer Network

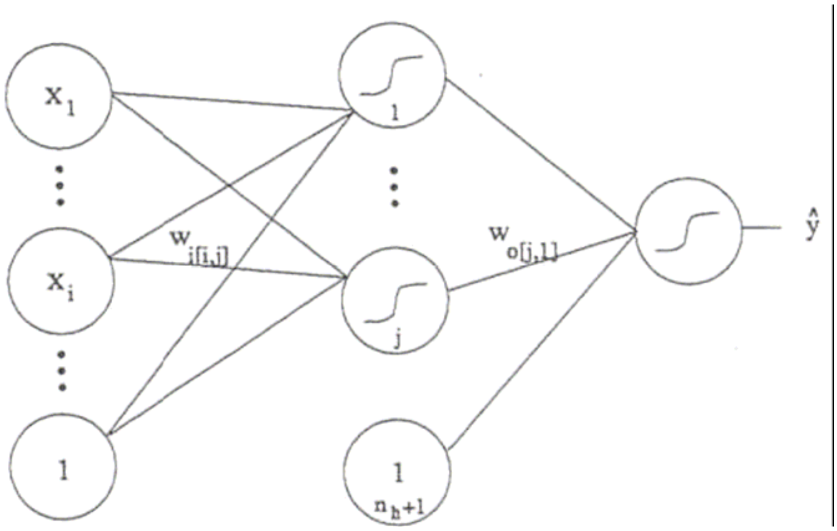

Figure 3

The Graph of GDP versus the Calculated Values by the NN_GDP Model

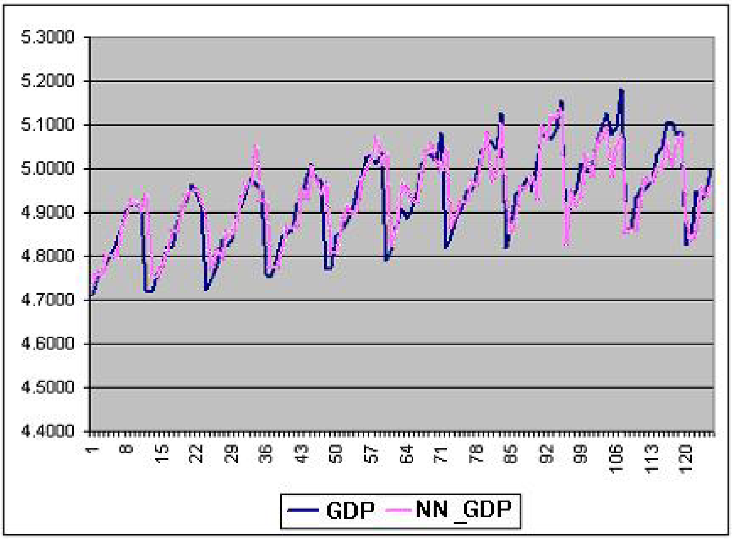

Figure 4

The Graph of GDP versus the Calculated Values by the NN_GDP(-4) Model

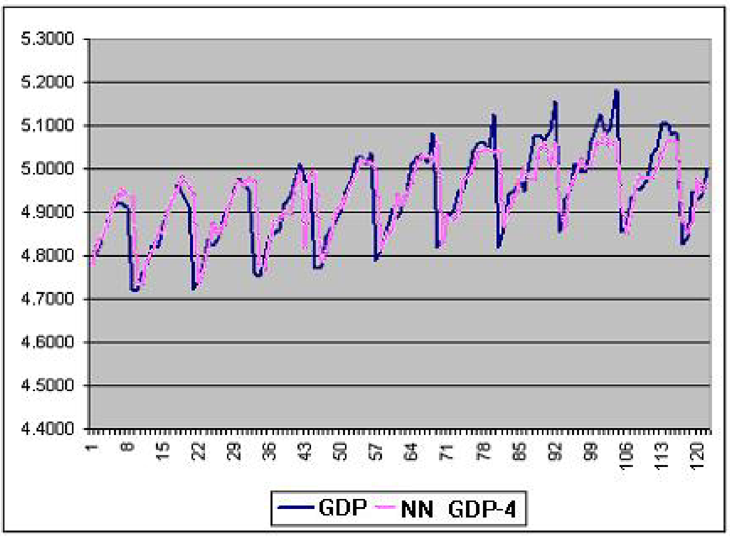

Table 1

Global performance measures

Model	RMS	SSE	CV	MBE	$RMS_{90\%}$	RCV
NN_GDP	0.0578	0.4199	0.0852	6.112E-04	0.1158	0.0261
NN_GDP(-4)	0.0646	0.5084	0.1032	2.15E-04	0.0320	0.0072

Source: Author calculations.

Table 2

Descriptive Statistics of the Residuals u_t

Model	*NN_GDP*	*NN_GDP(-4)*		*NN_GDP*	*NN_GDP(-4)*
Mean	0.0030	0.0011	Standard Deviation	0.05811	0.0650
Standard Error	0.0052	0.0059	Sample Variance	0.0034	0.0042
Median	-0.0032	-0.0065	Kurtosis	5.659	5.4769
Range	0.3572		Skewness	1.8334	1.9171
Minimum	-0.1116	-0.154	Count	125	121
Maximum	0.2456	0.2409	Largest (2)	0.2271	0.2254
Confidence Level (95.0%)	0.0103	0.0117	Smallest(2)	-0.1022	-0.1189

Source: Author's calculations.

Figure 5

The Residuals NN_GDP

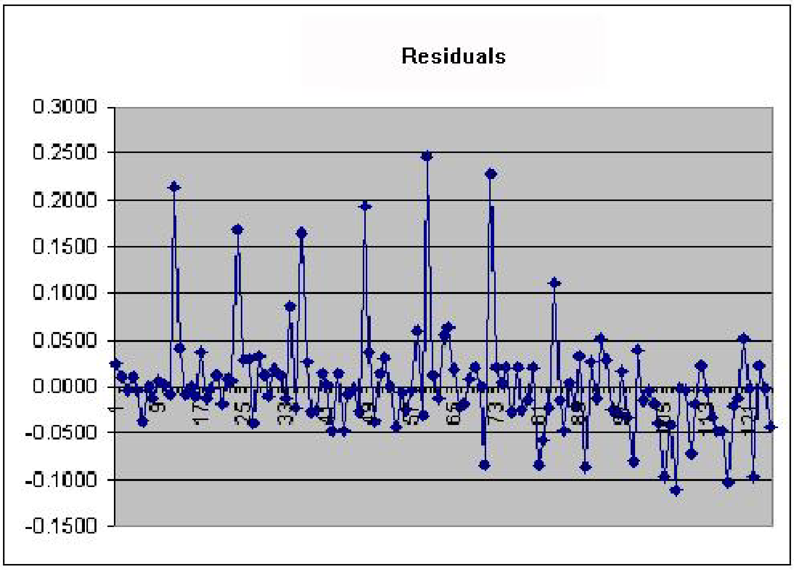

Table 3

Simulations for Scenario S1

$\hat{y}_t(l)$		GDP in constant prices, base 2000		
NN_GDP	NN_GDP(-4)	NN_GDP	NN_GDP(-4)	
5.0062	5.0041	9932.0	10095.0	July 2010
4.9954	5.0057	9907.1	10131.2	August 2010
4.9937	5.0095	9855.1	10220.7	September 2010
		29694.2	30446.9	Quarter 3 2010
4.9904	5.0101	9780.6	10236.1	October 2010
4.9862	5.0099	9687.1	10230.2	November 2010
4.9813	5.0092	9577.9	10213.0	December 2010
		29045.6	30679.4	Quarter 4 2010

Table 4

Simulations for Scenario S2

$\hat{y}_t(l)$		GDP in constant prices, base 2000		
NN_GDP	NN_GDP(-4)	NN_GDP	NN_GDP(-4)	
5.0062	5.0043	10161.34	10098.8	July 2010
4.995	5.0058	10111.09	10134.0	August 2010
5.0038	5.0096	10087.98	10222.8	September 2010
		30360.4	30455.6	Quarter 3 2010
4.9909	5.0102	9793.1	10236.8	October 2010
4.9765	5.0098	9473.4	10229.3	November2010
4.9411	5.0085	8732.3	10198.5	December 2010
		27998.8	30664.7	Quarter 4 2010

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