Forecasting economic growth using financial variables - Comparison of linear regression and neural network models

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Abstract: - According to both the theoretical and empirical literature, financial variables contain useful leading information regarding economic activity and thus can be used in forecasting GDP growth. However, empirical studies of the relationship between the financial development and the economic growth, as well as those of forecasting economic growth using financial variables are mainly based on linear econometric models. Since nonlinearities could exist in the relationship between the variables, in this paper we compare forecasting performance of the linear econometric models and the neural network model for panel data of European Union countries' economic growth. Our results show that at the 1-year forecasting horizon, according to three out of four valuation criteria, neural networks improve forecasting accuracy.

Key-Words: - Forecasting, economic growth, financial variables, linear models, neural networks, panel data

1 Introduction

Reliable forecasts of GDP growth are important in both the macroeconomic and microeconomic policy decision-making. In order to improve reliability, among other things, the choice of the variables and forecasting methodology has an important role.

In the last two decades there has been a huge increase in literature in the growth theory on the relationship between the financial development and the economic growth (for the survey see Levine [14], and Ang [1]). The literature combines the theory of financial intermediation and two views of the endogenous growth theory. In order to explain the arguments for existence of the financial intermediaries, the theory of financial intermediation adds specific frictions to models of resource allocation based on the perfect market. Namely, if there is the perfect market, all the traders are price takers, there is no private information, allocation of resources is Pareto optimal; and hence in a pure neoclassical framework there is no role of financial intermediation to add value. But, according to the theory of financial intermediation, the real-world market is characterized by frictions that include transaction costs (Gurley and Shaw [9]) and asymmetric information that could lead to adverse selection (Leland and Pyle, [13]) and moral hazard problems (Diamond, [3]). Performing numerous functions (payment, pooling of resources, resource allocation, provision of means of risk managing, providing price information and means to deal with asymmetric information problems) financial intermediaries are able to lower the frictions. Besides having the importance of financial intermediaries, financial markets have a role in providing financing, liquidity and risk diversification. Linking of the financial intermediation and markets and economic growth has been enabled by the development of endogenous growth theory. According to the new growth models financial development could affect economic growth through four channels: changing the marginal productivity of capital, proportion of saving funneled to investment, saving rate and rate of technological innovation. Using different measures of financial development (money supply, stock market capitalization, banks' credit to private sector, interest margin, etc.) a numerous empirical studies evidence that financial development plays a growth-supporting role (for the survey see Levine [14] and Ang [1]). Thus, financial variables contain useful leading information regarding economic activity and can be used in forecasting GDP growth. However, the empirical studies of the relationship between the financial development and the economic growth as well those of forecasting economic growth using financial variables, are mainly based on linear econometric models. But, since nonlinearities could exist in the relationship between the variables (Favara [4], Fok et al. [5]) the linear models could be less powerful in forecasting GDP growth rates. The objective of this paper is to forecast economic growth of European Union (EU) countries using both linear panel data models and neural network model and to compare their forecasting performance.

The paper is organized as follows. In section 2 the data are described. Section 3 presents linear panel regression models and neural network model. In section 4 the estimation results are presented and the forecasting performances of alternative models are evaluated. The paper finishes with concluding remarks outlined in section 5.

2 Data

In our estimation and forecasting we use a pooled (cross-country, time-series) dataset consisting of 27 EU member states over the period of 1991-2007. Using of the pooled dataset serves as the bride of the problem of no availability of the data for the part of the EU member countries (those of transition ones) for the longer period of time.

The main source of the data is World Bank (World development indicators and Financial structure dataset) while part of the data for transition EU member countries is obtained from European Bank for Reconstruction and Development (Transition Report).

The data contain four variables. The first one is GDP growth rate that measures economic growth. We use two financial variables. One of them is M2 as the measure of the money supply. M2 includes all the coins, notes and checkable deposits plus savings and other time deposits. The second financial variable is stock market capitalization as the sum of the products of the share prices and the number of the share outstanding of all the companies listed at the stock exchange. Finally, we use dummy variable in order to take into account the specific economic dynamics of the transition EU member countries.

In analyzing the data we apply procedure as follows. First, we estimate coefficients of the linear regression models using data for the first 15 years. The same data serve as data for training of neural networks. In the next stage the models are employed to obtain 1-year horizon forecasts in the period 2006-2007. Finally, we compute forecasting errors and compare forecasting performance of the models.

3 Methodology

In this section we describe the econometric models and neural network model we use for forecasting GDP growth.

3.1 Linear models

We utilize panel data techniques for parameters estimation and panel data models for forecasting. According to Tample [17], using panel data techniques in empirical work on economic growth has several advantages. Panel data methods allow one to control for omitted variables that are persistent over time and to control for heterogeneity in the initial level. Moreover, they make it possible to alleviate problems of measurement error and endogeneity biases. But, what is more important for our work, are the advantages of panel models for economic growth forecasting that are confirmed by empirical studies. Here is a brief review of their results.

In forecasting of real gross national product growth rates of 9 OECD countries over the period 1951-1981 Garcia-Ferrer et al. [6] examine various model specifications – naive models, AR(3) and AR(3) with leading indicators (AR(3)LI) that include money supply, stock market index and world return (the median of countries' real stock return). They find that pooling techniques lead to an improvement in forecasting precision. Using the same sample and state-space methods and OLS estimator, Mittnik [16] shows that a more parsimonious fixed-parameter model, with no autoregressive element, leads to better forecasts than the fixed-parameter AR(3)LI. Hoogstrate et al. [10] investigate theoretically the improvement of forecasting performance using pooling techniques instead of single country forecasts for N fixed and T large. They apply a set of dynamic regression equations with contemporaneously correlated disturbances. According to their simulation results for small and moderate values of T, pooling results in reduction in the mean squared error, even under parameter heterogeneity. They apply these results to growth rates for 18 OECD countries over the period 1950-1991 using an AR(3) model and an AR(3)LI model. They find that the median mean squared error of OLS based pooled forecasts is smaller than that of OLS based individual forecasts for a fairly large sample size. Finally, their analysis shows that GLS-based pooled forecasts outperform GLS-based individual and OLS-based pooled and individual forecasts. Marcelino et al. [15], using an array of forecasting models to data on real GDP, industrial production, inflation and unemployment rate for 11 countries originally in the EMU, over the period 1982-1997, find that pooling of country-specific forecast outperform forecast constructed using the aggregate data. Gavin and Theodorou [7] use forecasting criteria to examine the macro-dynamic behavior of 15 OECD countries using quarterly data over the period 1980-1996. They find that forecasts from panel model are more accurate than the forecasts from the individual country models. Fok et al. [5] focusing on panels of nonlinear time series as many macroeconomic variables have nonlinear properties, find that forecasts of macroeconomic series such as total industrial production and unemployment can be improved by considering panel models for the disaggregate series covering 48 states. Forecasting of the annual GDP growth rates of the 16 German Länder over the period 1991-2006, Kholodilin et al. [11] show that panel models provide better forecasting performance than the individual autoregressive models estimated for each of the Länder separately. For the surveys how forecasts are used in panel data applications and their advantages see Baltagi [2].

The first model we use in our research is the pooled panel model for the next three model specifications that in part follow Garcia-Ferrer et al. [6], and Hoogstrate et al. [10]:

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 y_{it-2} + \beta_3 y_{it-3} + \beta_4 DT_{it} + \varepsilon_{it} \quad (1)$$

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 y_{it-2} + \beta_3 y_{it-3} + \beta_4 DT_{it} + \\ + \beta_5 M2_{it-1} + \varepsilon_{it} \quad (2)$$

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 y_{it-2} + \beta_3 y_{it-3} + \beta_4 DT_{it} + \\ + \beta_5 M2_{it-1} + \beta_6 SC_{it-1} + \varepsilon_{it} \quad (3)$$

with subscript i denoting country and t denoting time, y_{it} is the rate of GDP growth, $M2_{it}$ denotes the first difference of the money supply in relation to GDP, SC is the first difference of the stock market capitalization in relation to GDP, DT denotes transition country dummy and ε_{it} is disturbance term, ε_{it}~N.I.D.$(0,\sigma^2)$. The pooled panel model has constant coefficients, referring to both intercepts and slopes across all the countries.

The next model is the fixed-effects model for the same three model specifications. The fixed-effects model has constant slopes, but intercepts that differ according to the country (α_{it}).

The parameters of the models are estimated by using the OLS estimator, since, as pointed by Kholodilin et al. [11], in dynamic panels with small time dimension the GMM estimator is preferred to the OLS estimator from the theoretical point of view, but in the forecasting a more accurate forecasting performance may still be obtained by a biased but stable estimator more than by an unbiased but unstable one.

3.2 Neural network model

Neural network is essentially a collection of interconnected neurons, grouped in layers. The simplest form of network has only two layers: an input layer and an output layer. Each connection between the input and the output is characterized by the weight a_i which expresses the relative importance of a particular input in the calculation of the output. Each output neuron has an activation function that is used for computation of the final output. In the simplest form of neural network, the activation function is identity, i.e. f(x)=x. To exploit the potential of neural networks completely, a nonlinear activation function must be used. The most frequently used activation functions in the neural network community are the logistic cumulative distribution function (4) and hyperbolic tangent (5).

$$f(x) = \frac{1}{1+e^{-x}} \quad (4)$$

$$f(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})} \quad (5)$$

In the real-world applications, network structure includes one or more hidden layers. Hidden units do not represent any real concept and have no parallel in econometrics. They are merely an intermediate result in the process of calculating the output value. Many authors demonstrate that a three-layer neural network with a logistic activation function in the hidden units is a universal approximator. This means that if a sufficient number of hidden units is included, the network can approximate almost any linear or nonlinear function to a desired level of precision. This suggests that neural networks could be used as a powerful tool in identifying and reproducing complex nonlinear relations between the data.

Two types of neural networks are commonly used for forecasting: the feedforward (Fig. 1) and the recurrent networks. In our work we use feedforward network. This type of network consists of the input layer, a number of hidden layers and the output layer. Information is processed from the input layer to the output layer via hidden layers.

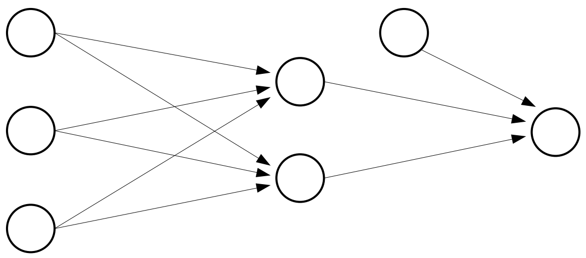

Fig.1 - Feedforward neural network with one hidden layer

If the network uses logistic function (4) in hidden layer and identity function (f(x)=x) in output layer, the output of the network is:

$$Y = b_0 + b_1 H_1 + b_2 H_2 \quad (5)$$

$$Y = b_0 + \frac{b_1}{1 + e^{-(a_{01} + a_{11} X_1 + a_{21} X_2)}} + \frac{b_2}{1 + e^{-(a_{02} + a_{12} X_1 + a_{22} X_2)}} \quad (6)$$

There is no theoretical basis to determine the optimal number of hidden units or layers in a network. In practice, it is a process of trial and error. It is necessary to estimate a large number of different networks and select the one that leads to the smallest forecasting error.

The most popular algorithm for estimation of network weights (training of the network) is backpropagation algorithm. Overfitting of the data in the training set is the main issue related to this process. The procedure called early stopping is developed to minimize this problem. It involves the division of the data set into three parts: a training set, a validation set and a test set. This method ensures that the network is not specialized in the data of the training set, but that it is also able to generalize out-of-sample data.

Due to the large number of parameters of neural networks that connect input, hidden and output neurons, neural networks require an appropriate size of the sample data in order to be well trained. There is no general rule that defines the optimal size of the sample data needed for neural network. The information about the minimum sample size for training of neural network could be found in the literature. Depending on the author, this number lies between 120 and 300 observations. This fact explains why in the literature it is possible to find only a small number of applications of neural networks on macroeconomic forecasting.

Despite these limitations, in the last decade the researchers have developed promising models with neural networks for forecasting of macroeconomic variables. Tkacz [18] compares linear models and neural networks on forecasting of Canada's output growth. The list of explanatory variables includes a long-short interest rate spread, real 90-day commercial paper and the real long-term bond rates, the growth rates of narrow (real M1) and broad (real M2) monetary aggregates, and the growth rate of the real TSE 300 index. Gonzalez [8] forecasts quarterly the growth of Canada's real GDP using linear regression and neural networks. Five explanatory variables are used: the quarterly growth rate of Finance Canada's index of leading indicators of economic activity, employment growth, the Conference Board's index of consumer confidence, the first difference of the real long term interest rate, the first difference of the federal government budgetary balance as a share of GDP. Kabundi et al. [12] compare neural networks and econometrics models on forecasting South African inflation.

General conclusion of these researches is that neural networks represent a very useful tool for macroeconomic forecasting, but they should not be treated as an alternative to econometric methods, but as their complement in order to achieve the best forecasting results.

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In our work, for all the three model specifications we test more than 10000 neural networks, varying the number of neurons in the hidden layer from 3 to 30. Each of these networks is initialized and trained 500 times. We use *tansig* (hyperbolic tangent) activation function in the hidden layer and *purelin* activation function in the output layer. In order to avoid overfitting of in-sample data, an early stopping procedure is used. The size of validation set is fixed to 50 observations for all the three models. The criterion for selection of the best network is minimal mean square error (MSE) on the out-of-sample data. Our best network for model 1 has 20 neurons in the hidden layer (4-20-1), model 2 has 11 neurons in the hidden layer (5-11-1) and model 3 has 13 neurons in the hidden layer (6-13-1).

4 Estimation results and forecasting performance

The estimates of the parameters of linear models are presented in Table 1 and Table 2.

Independent variables	Dependent variable: GDP growth		
	(1)	(2)	(3)
Constant	0.01542*** (0.003431)	0.014528*** (0.004070)	0.030322*** (0.010685)
GDP growth $_{-1}$	0.563381*** (0.061254)	0.569302*** (0.073083)	-0.111794 (0.119079)
GDP growth $_{-2}$	-0.038531 (0.054495)	-0.032646 (0.068554)	-0.048782 (0.103369)
GDP growth $_{-3}$	-0.006204 (0.047421)	-0.005350 (0.051774)	0.023952 (0.064066)
Transition dummy	0.007577* (0.004356)	0.007439** (0.003911)	0.030468** (0.015001)
Money supply		0.033642*** (0.011027)	0.013428* (0.008996)
Stock capitalization			0.017189** (0.007907)
Adjusted R-squared	0.377825	0.369021	0.531936
F-stat	50.49198***	35.50549***	38.66548***
Durbin-Watson stat	1.926282	1.908774	1.982439

Standard errors in parentheses. ***, **, * denote statistical significance at the 1, 5, 10 percent level

Table 1 Estimation results - pooled model

One period lagged value of GDP growth enters positively and at 1 percentage level significantly into the growth equation in all the specifications, but for the last one in pooled panel model. Financial variables have an expected positive sign and they are statistically significant, with the exception of the stock capitalization in fixed-effects model. Transition country dummy variable is statistically significant in all the model specifications for both the pooled and the fixed-effects models.

Independent	Dependent variable: GDP growth		
	(1)	(2)	(3)
Constant	0.013061*** (0.002081)	0.011862*** (0.002472)	0.010540*** (0.002068)
GDP growth $_{-1}$	0.629253*** (0.061752)	0.647931*** (0.060347)	0.628674*** (0.065376)
GDP growth $_{-2}$	-0.017145 (0.061294)	-0.025095 (0.095666)	-0.091099 (0.142450)
GDP growth $_{-3}$	-0.005642 (0.037357)	-0.002991 (0.050479)	0.104553** (0.060379)
Transition dummy	0.006981* (0.004254)	0.007190* (0.003846)	0.008664** (0.004144)
Money supply		0.032132*** (0.009267)	0.019630** (0.008711)
Stock capititalization			0.007163 (0.006837)
Adjusted R-squared	0.457699	0.459794	0.498314
F-stat	16.28565***	14.21517***	15.62327***
Durbin-Watson stat	2.017252	1.986901	1.713474

Standard errors in parentheses. ***, **, * denote statistical significance at the 1, 5, 10 percent level

Table 2 Estimation results - fixed-effects model

The forecasting performances of the models using testing data are shown in Table 3. Evaluating of forecasting performances of both linear and neural network models is based on the four criteria: root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil inequality coefficient (TIC).

		Pooled	FE	NN
Model 1	RMSE	0.018415	0.016768	0.015910
	MAE	0.013388	0.011994	0.011875
	MAPE	28.81848	26.73660	34.17703
	TIC	0.191295	0.170875	0.144025
Model 2	RMSE	0.017816	0.016314	0.015766
	MAE	0.012464	0.011286	0.011138
	MAPE	27.40471	25.68094	26.90782
	TIC	0.182749	0.164475	0.148088
Model 3	RMSE	0.016945	0.016485	0.014623
	MAE	0.012397	0.011464	0.011240
	MAPE	28.67506	26.32435	32.11426
	TIC	0.172729	0.166927	0.136526

Table 3 Forecasting results (out-of-sample data)

For the pooled panel model, including financial variables improves forecasting accuracy in terms of all the evaluation criteria. MAPE in the specification with two financial variables slightly grows in comparison to the specification with only one financial variable. Fixed-effects model with financial variables yields lower forecasting errors in comparison to specification with no financial variables. In the specification with both M2 and SC forecasting accuracy is lower in comparison to the specification only with M2. The forecasting errors in neural network model lower as financial variables are included.

Comparing forecasting performances of linear and neural network model we can conclude that neural network model outperform linear models in terms of RMSE, MAE and TIC. The same is not true only for MAPE.

5 Conclusion

For the pooled data on the rate of economic growth for 27 EU member countries using linear regression models and neural network model and forecasting techniques, forecasts were obtained for 1-year forecasting horizon, with the results as follow. Adding financial variables in models improves forecasting performances. Thus, financial variables contain leading information regarding economic activity. Neural networks model outperform linear regression models in forecasting accuracy. This could be explained by nonlinearity in the relationship between the financial variables and the economic growth. Hence, in forecasting macroeconomic variable such as GDP growth, in order to achieve better forecasting performances, one could combine both the linear regression and the neural networks models.

In the future work more variables, such as inflation, interest rates, exchange rates and government expenditures could be added to the models. Additionally, future work could apply panel models that explicitly account for spatial correlation due to the neighboring countries. Moreover, the comparison between the forecasting performances of the linear regression and neural network models could be extended to various forecasting horizons.

References:

[1] Ang, J. B., A survey of recent developments in the literature of finance and growth, *Journal of Economic Surveys*, Vol. 22, No. 3, 2008, pp. 536-576.

[2] Baltagi, B. H., Forecasting with panel data, *Journal of Forecasting*, Vol. 27, No. 2, 2008, pp. 153-173.

[3] Diamond, D. W., Financial Intermediation and Delegated Monitoring, *Review of Economic Studies*, Vol. 51, No. 3, 1984, pp. 393-414.

[4] Favara, G., An Empirical Reassessment of the Relationship Between Finance and Growth, *IMF Working Paper*, No. 03/123, 2003.

[5] Fok, D., van Dijk, D. and Franses, P. H., Forecasting aggregates using panels of nonlinear time series, *International Journal of Forecasting*, Vol. 21, No. 4, 2005, pp. 785-794.

[6] Garcia-Ferrer, A., Highfield, R. A., Palm, F. and Zellner, A., Macroeconomic Forecasting Using Pooled International Data, *Journal of Business & Statistics*, Vol. 5, No. 1, 1987, pp. 53-67.

[7] Gavin, W. T. and Theodorou, A. T., A common model approach to macroeconomics: using panel data to reduce sampling error, *Journal of Forecasting*, Vol. 24, No. 3, 2005, pp. 203-219.

[8] Gonzalez, S. (2000). Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models, *Bank of Canada Working Paper*, No. 2000-07, 2000.

[9] Gurley, J. G. and Shaw, E. S., *Money in a Theory of Finance*, The Brookings Institution, 1960.

[10] Hoogstrate, A. J., Palm, F. C. and Pfann, G. A., Pooling in Dynamic Panel-Data Models: An Application to Forecasting GDP Growth Rates, *Journal of Business & Economic Statistics*, Vol. 18, No. 3, 2000, pp. 274-283.

[11] Kholodilin, K. A., Siliverstovs, B. and Kooths, S., A Dynamic Panel Data Approach to the Forecasting of the GDP of German Länder, *Spatial Economic Analysis, Taylor and Francis Journal*, Vol. 3, No. 2, 2008, pp. 195-207.

[12] Kabundi, A., Marais D., Greyling, L., Forecasting South African Inflation: Neural Networks Versus Econometric Models, *Research Department of Economics RAU Working Paper*, No. 0303, 2003.

[13] Leland, H. E. and Pyle, D. H., Informational Asymmetries, Financial Structure, and Financial Intermediation, *The Journal of Finance*, Vol. 32, No. 2, 1977, pp. 371-387.

[14] Levine, R., Financial Development and Economic Growth: Views and Agenda, *Journal of Economic Literature*, Vol. 35, No. 2, 1997, pp. 688-726.

[15] Marcelino, M., Stock, J. H. and Watson, M., Macroeconomic forecasting in the EURO area: country specific versus area-wide information, *European Economic Review*, Vol. 47, No. 1, 2003, pp. 1-18.

[16] Mittnik, S., Macroeconomic Forecasting Using Pooled International Data, *Journal of Business & Economic Statistics*, Vol. 8, No. 2, 1990, pp. 205-208.

[17] Tample, J., The new growth evidence, *Journal of Economic Literature*, Vol. 37, No. 1, 1999, pp. 112-156.

[18] Tkacz, G., Neural network forecasting of Canadian GDP growth, *International Journal of Forecasting*, Vol. 17, No. 1, 2001, pp. 57–69.