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INTEGRATING FORECASTING AND SIMULATION TECHNIQUES. AN ANALYSIS OF THE INFLATION RATE IN ROMANIA'S EMU ACCESSION PERSPECTIVE

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Abstract: *The paper discusses some aspects of integrating the forecasting and simulation techniques used in macroeconomic models. It proposes a method to evaluate Romania's EMU accession chances in 2015, by a forecasting and simulation model, using a main nominal convergence indicator of the Romanian economy for the period 2007-2015, namely the inflation rate. The analysis is based on the recent data of the updated convergence programme of Romania, 2009-2012.*

Key words: *forecasting, simulation, macroeconomic model, European Monetary Integration (EMU), nominal convergence indicator.*

1. Introduction

In an earlier paper (Bârsan and Tache, 2009) analyzing Romania's European Monetary integration evolution, we concluded that euro adoption has minimum chances to be realized at the beginning of 2014; it seems that 2015, with a much higher likelihood of meeting all the nominal convergence indicators, will be a more realistic time horizon for Romania's accession into the EMU.

In this paper, using an integrated forecasting simulation model, we try to see if, by the end of 2015, one of the main convergence indicators - the inflation rate - can be still considered as a realistic target for EMU accession.

First, we have drawn a comparison between the forecasting model and the simulation model.

2. Forecasting versus Simulation

We shall try to analyze here the main pros and cons about forecasting and simulation. Each of these methods has some strong and week points, and we underline some of them.

2.1 Pros and Cons of Forecasting

If we analyze the main characteristics of a forecasting model, we have the following:

– Inputs are single point estimates;

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– The model relates the inputs mathematically;
– Outputs are deterministic and represent a single scenario.

The forecasting model can answer questions such as “If things happen the way we hope, we can expect…”

In Fig. 1, one can see a generic forecasting model. Usually, the forecasting model is of a deterministic nature.

If $x_1, x_2, ..., x_n$ are the input variables, from the forecasting model we also obtain the deterministic output variable with the relation $y = f(x_1, x_2, ..., x_n)$.

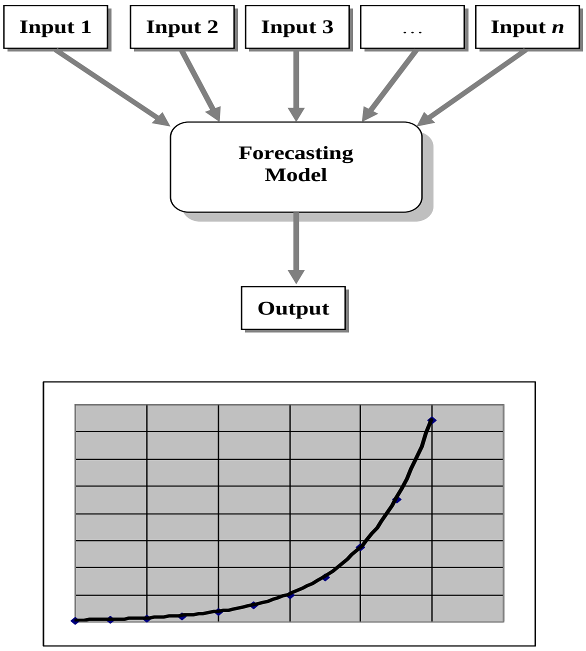

Fig. 1. *Generic forecasting model*

Let us discuss now the following sayings of Professor Sheldon M. Ross, from the Department of Industrial Engineering and Operations Research, University of California, Berkeley, USA.

“Any realistic model of a real-world phenomenon must take into account the possibility of randomness”

Taking into account this inherent randomness, we get the simulation models, and Professor Ross tells us:

"Computer simulations let us analyze complicated systems that can't be analyzed mathematically. With an accurate computer model, we can make changes and see how they will affect a system."

Let us see now some cons of the forecasting models. The main issue of the forecasting model is its “deterministic” dimension, as the amount of randomness incorporated in the model is relative low. Another weak characteristic can be represented by the mathematical complexity of some classes of forecasting models.

2.2 Pros and Cons of Simulation

The main characteristics of a simulation model are:
– Inputs are distributions of uncertainty;
– The model relates the inputs mathematically;

– Outputs are representative distributions of what is possible, with likelihoods able to be calculated for any value.

The simulation model can answer questions such as "What is the likelihood of achieving…"

As one can see from Fig. 2, the inputs in the simulation model are random variables from different probability distributions. The result of such a mix of random inputs is an output probability distribution, used for statistical inference and decision-making about the analysed process.

There are also some cons relative to simulation models, mainly regarding their static or dynamic structure.

2.3 Integrating Forecasting and Simulation

Let us argue now for an integrated forecasting and simulation model.

Incorporating uncertainty in the forecasting model, we obtain a *simulation forecasting model*, with some pros:

– Many of the variables of interest for the model represent uncertain future events;
– Someone, whether implicitly or explicitly, will make assumptions and decisions based on these uncertain quantities;
– Simulation forecast models can incorporate a significant amount of complexity.

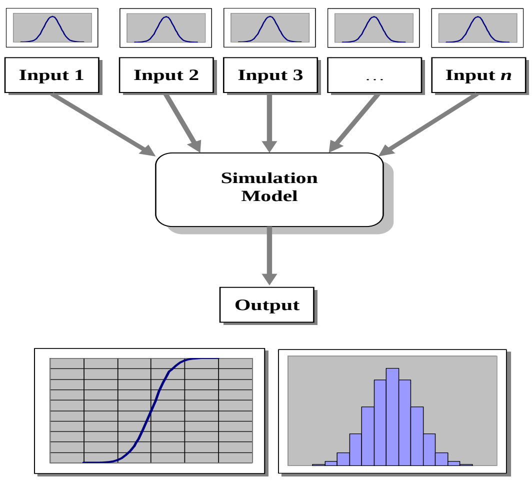

Fig. 2. *Generic simulation model*

3. An Integrated Forecasting and Simulation Model for the Nominal Convergence Indicators

We shall use an empirical flexible forecasting and simulation model, which could be rapidly updated, let us say quarterly, as new data become available concerning the evolution of the respective indicators.

The model was tested in an earlier paper [1] for the analysis of Romania's convergence programme, beginning with the year 2009. Later, we shall use some updated values for the year 2010.

The forecasting and simulation integrated model uses the following sources of information:

a) For the current period, it builds on the statistical data supplied by the websites of national agencies (the National Bank of Romania, the National Institute of Statistics) or international agencies (EU, ECB, IMF);

b) For the forecast data, the Holt–Winters method was applied – the case of time series with no seasonal effects (*non seasonal series*), as follows:

If $x_1, x_2, \ldots, x_n$ represent the time series values, the forecast method Holt–Winters is applied in several sequences:

(1) The estimated values $\hat{x}_t$ and the tendency values are obtained with the relations:

$$\hat{x}_2 = x_2$$
$$T_2 = x_2 - x_1$$
$$\hat{x}_t = \alpha \cdot (\hat{x}_{t-1} - T_{t-1}) + (1-\alpha) \cdot x_t \quad (0 < \alpha < 1;\ t = 3, 4, \ldots, n) \qquad (1)$$
$$T_t = \beta \cdot T_{t-1} + (1-\beta) \cdot (\hat{x}_t - \hat{x}_{t-1}) \quad (0 < \beta < 1;\ t = 3, 4, \ldots, n)$$

where α and β are *smoothing constants*, their values belonging to the interval (0,1).

(2) Starting from the period *n*, we obtain the forecast values x_{n+h} with the relation:

$$\hat{x}_{n+h} = \hat{x}_n + hT_n, \qquad (2)$$

where *h* is the number of periods in the future.

The simulation model uses the *triangular distribution* for which three values are supplied (minimum, the most likely and maximum), considering three types of scenarios:

- An "*optimistic*" scenario, which supplies the most convenient values of the observed variable;
- A "*realistic*" scenario, which supplies the most likely values of the observed variable and
- A "*pessimistic*" scenario, which supplies the less convenient values of the observed variable.

Our integrated model of forecasting and simulation was applied starting with the first quarter of 2007 (denoted by 2007Q1) and finishes with the last quarter of 2015 (denoted by 2015Q4). The current data are for the quarters 2007Q1–2010Q2, considered as constant; starting with the period 2010Q3, the three above mentioned scenarios were applied. The "trident" model for each indicator was obtained from the α and β constants value.

4. The Forecasting Model for HIPC Inflation

The forecasting scenarios for the inflation criterion are represented in Fig. 3. The target for this indicator was considered 3.5% until 2011 and 3.0% beginning with 2012.

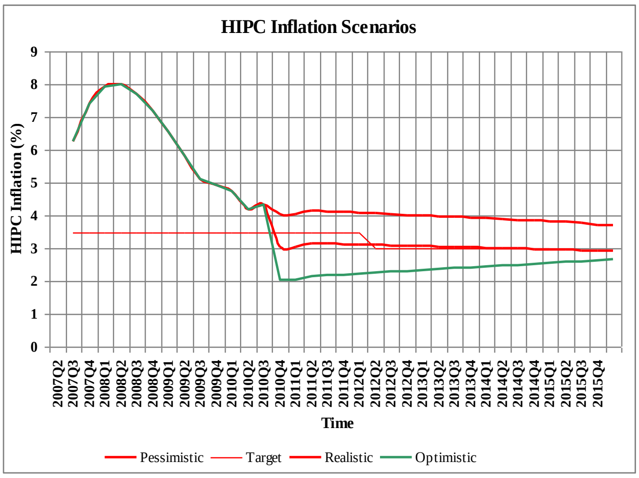

Fig. 3. *HIPC Inflation Scenarios*

5. The Simulation Model for HIPC Inflation

Applying the simulation model, we have determined the values of the relative cumulative frequency distribution for this indicator in the period 2015Q4, as one can see in Fig. 4.

The estimated probability that the inflation rate is lower than the 3,5% target at the end of 2015 is:

$Prob\{\ HIPC\ Inflation \leq 3.5\} \approx 0{,}94$,

which means that the inflation target of 3,5% has high chances to be obtained in 2015Q4.

But the National Bank of Romania set a target of 3.0%, beginning with 2010. It results that the estimated probability that the inflation rate is lower than the 3% target at the end of 2015 is:

$Prob\{\ HIPC\ Inflation \leq 3.0\} \approx 0{,}40$,

which means that the inflation target of 3% has relative low chances to be realized in 2015Q4.

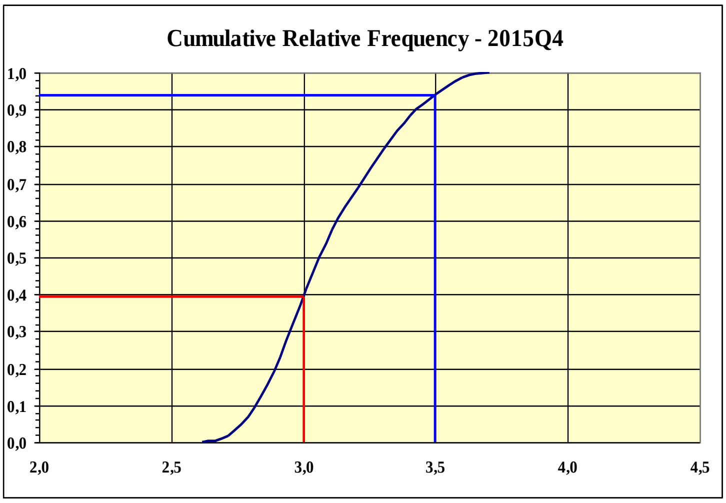

Fig. 4. *HIPC Inflation distribution in 2015Q4*

6. Conclusions

The same procedure of forecasting and simulation can be applied also to the other convergence indicators such as:

– General government balance
– Government gross debt
– Exchange rate
– Long term interest rate

After forecasting and simulating the degree of fulfilment of each nominal convergence criterion for the period 2015Q4, we can evaluate the degree to which all indicators will be met at the end of 2015. We can thus synthesize our forecasting and simulation results taking into account the proposed scenarios for these indicators' dynamics.

Undoubtedly, as any empirical model, the model used in this paper could have weaknesses and subjective elements derived especially from the way of defining the different scenarios in the forecasting approach.

References

1. Bârsan-Pipu, N., Tache, I.: *Some Considerations about Romania's European Monetary Integration.* In: Metalurgia International, Special Issue, No. 3, 2010, pp. 171-176.

2. European Commission. *Recommendation for Council Opinion on the Updated Convergence Programme of Romania, 2009-2012*, April 2010.
3. National Bank of Romania. *Report on inflation*, May 2010.
4. Ros, Sheldon M. *Simulation*, Fourth Edition. Elsevier, 2006.
5. Applied Quantitative Sciences, Inc. *Simulation Forecast Models Using @Risk*, 2007.