CORRECTION OF EQUILIBRUM AND AUTOREGRESSIVE MODELS USED IN THE MACROECONOMIC FORECAST

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Abstract

Macroeconomic forecasting is an essential element in planning and considering evolutionary elements over a period of time. The macroeconomic forecast has developed and, over the last period of time, the use of macroeconomic forecasting or, in other words, the use of econometric models in the macroeconomic forecast has become increasingly useful. A series of dVAR and EqCM models have been developed that are often used in macroeconomic forecasts. These models are typically used to bring some corrections to the balance that must characterize macroeconomic developments, but also self-regression, which is an essential element in macroeconomic analyzes. Due to these developments, makers of macroeconomic models and forecasting specialists may have justification when considering modern EqCM models would achieve a better prognosis than when using models using differential data such as the dVAR model.

From the mathematical study it can be appreciated that the dVAR model can be considered a particular case of the EqCM model because it requires some additional unit root system restrictions. In this article, the authors emphasized the mathematical and econometric analysis of the two EqCM and dVAR models that are used in macroeconomic forecasting from the macroeconomic chronological series, considered to be integrated in the first order, considering that they often include deterministic terms that allow a Linear evolutionary trend. Mathematical computations are presented, concluding that both forecasting models EqCM and dVAR use the estimated parameters. We can not ignore some uncertainties of these parameters and therefore we have analyzed the probability limits of the parameter estimates to highlight that the results of the prognosis by using these two models yield results and become consistent in the context of the equilibrium correction and also the self-regression.

Keywords: *model, prognosis, macroeconomic balance, self-regression, econometric model*

JEL Classification: *C25, C53*

Introduction

The development of macroeconomic models during the 1980s and 1990s, with a focus on dynamic specification and model evaluation, meant that models became less exposed to criticism over previous generations of models, ie those models that largely ignore dynamic dynamics and properties Time data will necessarily produce suboptimal forecasts. At the same time, other model features have changed in response to developments in the real economy, for example, more detailed modeling of supply factors and the transmission mechanism between the real and financial sectors of the economy. Due to these developments makers of macroeconomic models and forecast makers can be justified when claiming that modern EqCM models would predict better than models using differentiated data, such as the dVAR model.

Michael Clements and David Hendry re-examined a few issues in macroeconomic forecasting, including the relative merits of the dVAR and EqCM models. Assuming the existence of constant parameters during the forecasting period, the dVAR model is wrong-specified in relation to a correctly-specified EqCM model, so the dVAR-type forecasts will be suboptimal. However, if the parameters change after the forecast is made, the EqCM model is also wrong-specified during the forecast. Clements and Hendry have shown that forecasts in a dVAR model are solid on some classes of parameter changes. So in practice EqCM-type forecasts may turn out to be less accurate than those from dVAR-type models. In other words, the „best model" on economic interpretation and econometrics may not be the best model for forecasts. At first sight, it is paradoxical, since any dVAR model can be considered as a special case of the EqCM model because it imposes additional unit root system restrictions. However, if the parameters of the level variables that are excluded from the dVAR model change over the forecast period, it instead makes the EqCM model erroneously-specified in relation to the generating mechanism that prevails over the period we are trying to predict.

Literature review

The study of Karlsson (2012) is focused on the application of Bayesian VAR in prognoses.Ait-Sahalia and Mancini (2008) have compared the forecasts of quadratic variation for the cases of realized volatility and the two scales realized volatility, for a dataset characterized by high frequency, their results show the prevalence of the second method in comparison with the first one. Rubio-Ramirez, Waggoner and Zha (2010) have developed useful algorithms for estimation in case of small samples and inference.

Bardsen, Nymagen and Jansen (2005) develop on the use of econometrics in macroeconomic modeling. Anghelache, Panait, Marinescu, and Niță (2017) have presented a set of models and indicators dedicated to forecasting at macroeconomic level. Benjamin, Herrard, Hanee-Bigot, Tavere (2010) develop on the use of econometric models in forecasting. Clements and Hendry (2002) discuss on the methodology of modelling and failure of forecast. Eitrheim, Jansen, Nymoen 2002) analyze a forecast failure case, influenced by financial de-regulation, update the model and subsequently the parameters are more reliable despite data variation across the interval studied. Müller and Watson (2015) is concerned with measuring the uncertainty in predictions made on the long-run, they have built prediction sets that asymptotically cover a wide array of processes that generate data and provide greater reliability over time. Anghelache and Anghel (2016), Mitruţ and Şerban (2007) describe the use of econometric instruments in economic analyses. Hendry (2002) discusses some good practices in econometric studies, he criticizes the, said, less appropriate approaches, and comments on the compromises that are sometimes made, the acceptation and the rejection of such decisions. Sun, Phillips and Jin (2008) study the selection of optimal bandwith in testing heteroskedasticity-autocorrelation characteristics. Baumeister and Hamilton (2015) have provided significant contributions on the use of Bayesian inference, VAR models, impulse-response functions. Carr and Wu (2009) introduce a reliable method useful for measuring variance risk premiums for financial assets. Schorfheide and Song (2015) develop on using VAR tools in real-time forecasts. Tudor (2008) approaches the application of symmetrical Garch models in the modelling of time series' volatility. Hendry (2003) discusses on the econometric metholodogy of the London Business School. Mertens and Ravn (2010) are preoccupied with measuring the impact of fiscal policies. Kilian and Lutkepohl (2016) were preoccupied with the application of VAR as structural analysis. Colander (2009) has described the application of CVAR in economic studies at the macro level. Villani (2009) has implemented some methods for VAR application, both stationary and cointegrated, and outlined some favorable conditions with impact on accuracy, Giannone, Lenza and Primiceri (2015) have developed on a close topic. Jarociski and Marcet (2010) have studied the case of autoregressive instruments used for small samples. Dew-Becker et.al. (2017) have studied the price associated with the variance risk. Egloff, Madrkus and Liuren have evaluated some characteristics of optimal variance swap investments. Forni and Gambetti (2014) were preoccupied with the lack of sufficient information for structural AR vectors. Conley, Hansen, and Rossi (2012) have studied some characteristics of endogenous explanatory variables.

Research methodology, data, results and discussions

The forecast errors of an EqCM model and its dVAR counterpart are affected differently by structural discontinuities. Practical forecasting models are open systems with exogenous variables. Although the model studied, its properties prove to be useful in interpreting the forecast errors of large systems.

• We start from the premise that the macroeconomic chronological series can be considered as integrated ones and that they often include deterministic terms that allow for a linear trend. The next simple two-dimensional system (VAR of first order) can serve as an example:

$$y_t = k + \lambda_1 y_{t-1} + \lambda_2 x_{t-1} + e_{y,t} \quad (1)$$

$$x_t = \varphi + x_{t-1} + e_{x,t} \quad (2)$$

where deviations $e_{y,t}$ and $e_{x,t}$ have a normal distribution. Their dispersions σ_y^2 and σ_x^2, respectively, the correlation coefficient is denoted by $\rho_{y,x}$. The opening of the practical prognostic models is expressed by xt which is exogenous (strong). x_t is the one-order integral, denoted |(1), and contains a linear deterministic trend if $\varphi \neq 0$. We assume that (1) and (2) constitute a small cointegrated system so y_t is also |(1), but cointegrated with x_t. This entails the inequalities $0 < \lambda_1 < 1$ and $\lambda_2 \neq 0$. With a change in scoring, DGP can be written as:

$$\Delta y_t = -\alpha[y_{t-1} - \beta x_{t-1} - \varsigma] + e_{y,t},\ 0 < \alpha < 1 \quad (3)$$

$$\Delta x_t = \varphi + e_{x,t} \quad (4)$$

where $\alpha = (1- \lambda_1)$, $\beta = \lambda_1/\alpha$ şi $\varsigma = k/\alpha$. In equation (3), α is the equilibrium correction coefficient and β is the derived coefficient of the cointegration relationship.

The system can be written in the „model form" as a conditioned model of correction - yt balance and as a marginal model for x_t.

$$\Delta y_t = \gamma + \pi \Delta x_t - \alpha[y_{t-1} - \beta x_{t-1} - \varsigma] + \varepsilon_{y,t}, \quad (5)$$

$$\Delta x_t = \varphi + e_{x,t} \quad (6)$$

where

$$\pi = \rho_{y,x} \frac{\sigma_y}{\sigma_x}$$

$$\gamma = -\varphi\pi$$

$$\varepsilon_{y,t} = e_{y,t} - \pi e_{x,t}$$

properties of the two-dimensional normal distribution.

We define two parameters, μ and η, such that $E[y_t - \beta x_t] = \mu$ and $E[\Delta y_t] = \eta$. Considering the probabilities in (4), it follows that $E[\Delta xt] = \varphi$. Similarly, considering probabilities in (3) and notating $\eta = \beta\varphi$, we find the following relationship between these parameters:

$$\beta\varphi = \alpha(\varsigma - \mu) \quad (7)$$

Referring to μ, it results:

$$\mu = \varsigma - \frac{\beta\varphi}{\alpha} = \frac{k-\beta\varphi}{\alpha} \quad (8)$$

In the case of $\varphi \neq 0$, both series contain a deterministic trend that comes from the x_t process and, conversely, if $\varphi = 0$ there is no deterministic increase of a variable. In the second case we deduce from (8) that $\mu = \varsigma$.

The case of a linear deterministic trend is relevant to several variables of interest to those who make forecasts. Typical examples of exogenous variables associated with the positive trend are external demand indicators, external price indices and average labor productivity, while the zero trend assumption is most interesting for variables such as oil prices and monetary policy instruments, ie interest rates and exchange rates exchange.

• The goal is to trace the impact of parameter changes in DGP on the forecasts of the two DGP models. First, the equilibrium correction model, EqCM, coincides with DGP in the survey, that is, there is no mistaken initial specification and the second, dVAR.

The EqCM model is made up of equations (5) and (6). Equation (5) is the conditional model of y_t, which has many opponents in practical forecasting models, following the impact of econometric methodology and cointegration theory. Equation (6) is the marginal equation for the explicative variable x_t. The dVAR model of y_t and x_t requires a restriction, ie a = 0, so the dVAR model consists of:

$$\Delta y_t = \gamma + \pi\Delta x_t + \epsilon_{y,t} \quad (9)$$

$$\Delta x_t = \varphi + e_{x,t} \quad (10)$$

The error process in the dVAR model, $\epsilon_{y,t}$ $(= \varepsilon_{y,t} - \alpha[y_{t-1} - \beta x_{t-1} - \varsigma]$, will generally be autocorrelated provided that there is a certain autocorrelation in terms of omitted imbalance (for$0 < \alpha < 1$).

Next, we assume that:

– the parameters are known;

– in forecasts, $\Delta x_{T+j} = \varphi$ (j = 1, ..., h);

– the forecasts for T+1, T+1,...T+h periods are realized during T.

The first hypothesis is deduced from small sample interference in the EqCM model and estimated parameters (inconsistently) for dVAR. The second hypothesis negates one of the sources of prognostic failure that is probably important in practice, namely that un-modeled or exogenous variables are wrongly predicted. In our case, systemic predictive errors in Δx_{T+j} are equivalent to a change in φ.

Although all other coefficients may change during the forecast period, the most relevant coefficients in our context are α, β and ζ, ie those coefficients are present in the EqCM model, but not in the dVAR. Among them, we focus on α and ζ, since β represents the partial structure, being a cointegration parameter for an analysis of the importance and the possibility of detecting changes.

Next, we deduce interference for the EqCM and dVAR forecasts when both models are wrong-specified during the forecast period. We distinguish between the case where the change of the parameter takes place after the forecast and where the change takes place before the forecast period.

• Suppose that the segment ζ changes from its initial level to a new level, ie, $\zeta \rightarrow \zeta^*$ after the forecast is made during the period T. Since we maintain a constant α, the modification ζ is fundamentally the product of a change in k, the segment Of equation (1). In the right form of balance, DGP over the forecasting period is therefore:

$$\Delta y_{T+h} = \gamma + \pi \Delta \mathrm{x}_{\mathrm{T+h}} - \alpha[y_{T+h-1} - \beta x_{T+h-1} - \varsigma^*] + \varepsilon_{y,T+h} \Delta$$
$$\mathrm{x}_{\mathrm{T+h}} = \varphi + e_{x,T+h}$$

where h = 1, ..., H. Forecasting errors for period 1 for EqCM and dVAR models can be written:

$$y_{T+1} - \hat{y}_{T+1,EqCM} = -\alpha[\varsigma - \varsigma^*] + e_{y,T+1} \tag{11}$$
$$y_{T+1} - \hat{y}_{T+1,dVAR} = -\alpha[y_T - \beta x_T - \varsigma^*] + e_{y,T+1} \tag{12}$$

In the following, we focus on the interference of forecast errors. Stage 1 interferences are defined by conditional probability (IT) of forecast errors, and the biasT + 1, EqCM and interference interference $\mathrm{bias}_{\mathrm{T+1,dVAR}}$:

$$bias_{T+1,EqCM} = -\alpha[\varsigma - \varsigma^*] \tag{13}$$
$$bias_{T+1,dVAR} = -\alpha[y_T - \beta x_T - \varsigma^*] \tag{14}$$

We consider x_t^o the notation for stable state values of the x_t process. The corresponding steady state values of the y_t process, denoted y_t^o, are given by:

$$y_t^o = \mu + \beta x_t^o \tag{15}$$

Using this definition and (13), the dVAR prognostic error (14) can be rewritten as:

$$bias_{T+1,dVAR} = -\alpha\left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha} + (\varsigma - \varsigma^*)\right]$$
$$= -\alpha\left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha}\right] + bias_{T+1,EqCM} \tag{16}$$

Note that both EqCM and dVAR forecasts are affected by changing the parameter from ζ to ζ*. Assuming that the deviations of the initial values from the stable state are negligible, ie, $x_T \approx x_T^o$ şi $y_T \approx y_T^o$, we can simplify the expression in:

$$bias_{T+1,dVAR} = \beta\varphi + bias_{T+1,EqCM} \tag{17}$$

The one-stage prognostic error interferences of the two models are identical if y_T is equal to its long-term average $\bar{y}_T$. An example of such a case would be the unrestricted dVAR model of the Smallest Single Square (OLS) method.

For comparison, interferences of forecast errors for period 2 (maintaining stable condition hypothesis):

$$bias_{T+2,EqCM} = -\alpha\delta_{(1)}[\varsigma - \varsigma^*] \tag{18}$$

$$\begin{aligned} bias_{T+2,dVAR} &= \beta\varphi\alpha - \alpha\delta_{(1)}\left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha} + (\varsigma - \varsigma^*)\right] \\ &\approx \beta\varphi\big(\alpha + \delta_{(1)}\big) + bias_{T+2,EqCM} = 2\beta\varphi + bias_{T+2,EqCM} \end{aligned} \tag{19}$$

where:

$\delta_{(1)} = 1 + (1 - \alpha)$.

Generalizing, for the h period forecasts, we get the following expressions:

$$bias_{T+h,EqCM} = -\alpha\delta_{(h-1)}[\varsigma - \varsigma^*] \tag{20}$$

$$bias_{T+h,dVAR} = \beta\varphi\big(\alpha\psi_{(h-2)} - \delta_{(h-1)}\big) - \alpha\delta_{(h-1)}[(y_T - y_T^o) - \beta(x_T - x_T^o) + (\varsigma - \varsigma^*)] \tag{21}$$

For forecast horizons h = 2, 3, ..., where δ_{h-1} and ψ_{h-2} are given by:

$$\begin{aligned} \delta_{(h-1)} &= 1 + \sum_{j=1}^{h-1}(1-\alpha)^j \\ &= 1 + (1-\alpha)\delta_{(h-2)} = 1 + (1-\alpha)\delta_{(h-2)},\ \delta_{(0)} = 1 \end{aligned} \tag{22}$$

$$\begin{aligned} \psi_{(h-2)} &= 1 + \sum_{j=1}^{h-2}\delta_{(j)} \\ &= (h-1) + (1-\alpha)\psi_{(h-3)},\ \psi_{(0)} = 1,\ \psi_{(-1)} = 0 \end{aligned} \tag{23}$$

and we used it again (15). As the prognostic horizon h increases to infinity, $\delta_{h-1} \rightarrow 1/\alpha$, so the interference EqCM addresses asymptomatically the magnitude of the change itself, that is, $bias_{T+h,EqCM} \rightarrow \varsigma - \varsigma^*$.

Assuming $x_T \approx x_T^o$ şi $y_T \approx y_T^o$, we can simplify expression and forecast errors dVAR may contain a term x_t interference due to xt increase and not present in the EqCM predictive interference, according to the term $\beta\varphi\big(\alpha\psi_{(h-2)} - \delta_{(h-1)}\big)$ in (19). We can simplify this expression since the term in the square brackets containing the recurring formulas $\delta_{(h-1)}$ and $\psi_{(h-2)}$ can be rewritten as $[\alpha\psi_{(h-2)} + \delta_{(h-1)}] = h$,and a simple linear trend of the future dVAR error interference for step h in case where $\varphi \neq 0$, thus generalizing the results of stage 1 and step 2:

$$bias_{T+h,dVAR} = \beta\varphi h - \alpha\delta_{(h-1)}[(y_T - y_T^o) - \beta(x_T - x_T^o)] + bias_{T+h,EqCM} \tag{24}$$

At the same time, the interferences of the forecast errors of the two models are identical if there is no autonomous increase of x_t ($\varphi = 0$) and y_T and x_T are equal to their stable state values. In the case of a positive deterministic increase of x_t ($\varphi > 0$), while maintaining the stable hypothesis, the dVAR interference will dominate the long-term EqCM due to the trend in the dVAR interference.

• Next, we consider the situation in which the adjustment coefficient α changes to a new value, α^*, after the forecast for T + 1, T + 2, ..., T + h has been prepared. Provided the IT, the stage-1 interferences for the two models are:

$$bias_{T+1,EqCM} = -(\alpha^* - \alpha)[y_T - \beta x_T - \varsigma] \quad (25)$$

$$bias_{T+1,dVAR} = -\alpha^*[y_T - \beta x_T - \varsigma] \quad (26)$$

Using stable expression (15), we obtain:

$$bias_{T+1,EqCM} = -(\alpha^* - \alpha)\left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha}\right] \quad (27)$$

$$bias_{T+1,dVAR} = -\alpha^*\left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha}\right] \quad (28)$$

In general, the interference of the EqCM model is proportional to the magnitude of the change, while the dVAR interference is proportional to the magnitude of the new equilibrium correction coefficient. Assuming$x_T \approx x_T^o$ and $y_T \approx y_T^o$, we can simplify the expression in:

$$bias_{T+1,dVAR} = \beta\varphi + bias_{T+1,EqCM} \quad (29)$$

As a result, the difference between the forecast error interferences is identical to (17). For multi-period forecasts, the predictive error interferences of the EqCM and dVAR models are:

$$bias_{T+h,EqCM} = \beta\varphi\left(\alpha^*\psi^*_{(h-2)} - \alpha\psi_{(h-2)}\right) - \left(\alpha^*\delta^*_{(h-1)} - \alpha\delta_{(h-1)}\right) \times \quad (30)$$
$$\times\left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha}\right]$$

$$bias_{T+h,dVAR} = \beta\varphi\alpha^*\psi^*_{(h-2)} - \alpha^*\delta^*_{(h-1)} \times \left[(y_T - y_T^o) - \beta(x_T - x_T^o) - \frac{\beta\varphi}{\alpha}\right] \quad (31)$$

h = 2, 3, ..., where y_T^o is defined in (15), $\delta_{(h-1)}$ in (22), $\psi_{(h-2)}$ in (23). $\delta^*_{(h-1)}$and $\psi^*_{(h-2)}$ are given by:

$$\delta^*_{(h-1)} = 1 + \sum_{j=1}^{h-1}(1-\alpha^*)^j$$

$$\delta^*_{(0)} = 1$$

$$\psi^*_{(h-2)} = 1 + \sum_{j=1}^{h-2}\delta^*_{(j)}$$

$$\psi^*_{(0)} = 1, \qquad \psi^*_{(-1)} = 0$$

To facilitate comparison, assume again that $x_T \approx x_T^o$ and $y_T \approx y_T^o$ and insert (33) into (30). Proceeding as when deduced (24), we arrive at the following expression $bias_{T+h,dVAR}$:

$$bias_{T+h,dVAR} = \beta\varphi h + bias_{T+h,EqCM}$$

In the simplistic stable hypothesis, the difference between the intervals of the prognostic errors of stage h between the EqCM and the dVAR models is the same as (24). So there will be a linear trend in the difference between forecast error interferences between the EqCM and dVAR models due to the unsuccessful representation of the x_t value increase in the dVAR model.

- This situation is illustrated by considering how the forecasts for T+2, T+3,..., T+h+1 are updated subject to T+1 results. Changing $\zeta \rightarrow \zeta^*$ primarily affects T+1, results, information about parameter inconsistencies will be reflected accordingly in the y_{T+1} start value.
- Given that ζ changes to ζ^* during T+1, the (updated) forecast for y_{T+2}, provided that y_{T+1}, produces the following predictive error interferences for EqCM and dVAR:

$$bias_{T+2,EqCM}|I_{T+1} = -\alpha[(\varsigma - \varsigma^*)] \quad (32)$$

$$bias_{T+2,dVAR}|I_{T+1} = -\alpha[y_{T+1} - \beta x_{T+1} - \varsigma^*] \quad (33)$$

Equation (34) shows that the predictive error of the EqCM model is affected by the parameter change to exactly the same extent as in previous situations, according to (13), despite the fact that in this case the effect of the change is incorporated into the initial value y_{T+1}. Evidently, EqCM models' forecasts do not correct events that occurred before preparing the forecast. Indeed, unless forecasts detect the parameter change and take appropriate measures by segment correction (manual), the effect of the parameter change before the forecasting period will influence the „forever" forecasts. The situation is different for dVAR.

Using the fact that:

$$y_{T+1}^o = \mu^* + \beta x_{T+1}^o \quad (34)$$

where

$$\mu^* = \varsigma^* + \frac{\beta\varphi}{\alpha}$$

equation (33) can be expressed as:

$$bias_{T+2,dVAR}|I_{T+1} = -\alpha\left[(y_{T+1} - y_{T+1}^o) - \beta(x_{T+1} - x_{T+1}^o) - \frac{\beta\varphi}{\alpha}\right]$$

$$\approx \beta\varphi \approx \beta\varphi \quad (35)$$

under the stable assumption. If there is no deterministic increase in DGP, ie, $\varphi = 0$, the dVAR model will be immune to the parameter change. In this respect, there is an inherent segment correction element applied to the dVAR forecasts, while the parameter change that occurred before the start of the forecasting period will have an impact on the dVAR step 1 prognosis. A non-zero trend in the xt process will nonetheless produce an influence on the dVAR step 1 prognosis and the relative accuracy of the forecast between the dVAR and EqCM will depend on the magnitude of the trend related to the magnitude of change.

The expression for forecasting interferences over h, provided I_{T+1}, takes the form:

$$bias_{T+(h+1),EqCM}|I_{T+1} = -\alpha\delta_{(h-1)}[\varsigma - \varsigma^*] \quad (36)$$

$$bias_{T+(h+1),dVAR}|I_{T+1} = \beta\varphi h - \alpha\delta_{(h-1)}[(y_{T+1} - y^o_{T+1}) - \beta(x_{T+1} - x^o_{T+1})] \quad (37)$$

for h = 1, 2,.... This shows that the EqCM type forecast remains influenced for broad forecast horizons. Prognosis does the „correction of balance”, but in the direction of the „old” (irrelevant) balance. For broad horizons forecasts, the EqCM interference deals with the magnitude of the change $[(\zeta^* \rightarrow \zeta)]$ so that if the parameter changed before the forecast was prepared and therefore could not be detected.

For the dVAR forecast there is once again an interference trend due to x_t increase. If there is no deterministic increase in DGP, dVAR-type forecasts are not influenced for all h values.

• Exactly as in the case of the long-term average, the EqCM forecast does not automatically adjust when the change $\alpha \rightarrow \alpha^*$ takes place prior to preparing the forecasts (for the T + 1 period). Interferences for the T + 2 period, provided I_{T+1}, take shape:

$$bias_{T+2,EqCM}|I_{T+1} == -(\alpha^* - \alpha)\left[(y_{T+1} - y^o_{T+1}) - \beta(x_{T+1} - x^o_{T+1}) - \frac{\beta\varphi}{\alpha}\right] \quad (38)$$

$$bias_{T+2,dVAR}|I_{T+1} = -\alpha^*\left[(y_{T+1} - y^o_{T+1}) - \beta(x_{T+1} - x^o_{T+1}) - \frac{\beta\varphi}{\alpha}\right] \quad (39)$$

where we used (15).

Thus, neither of these two forecasts automatically produces „segment correction” to parameter changes that occurred prior to preparing the forecast. For this reason, the Stage 1 interferences are functionally similar to the formulas in case a is changed to α^* after the forecast has been prepared. The generalization of multi - stage forecast error interferences is similar to previous derivations.

• In practice, both forecasting models EqCM and dVAR use estimated parameters. Since the dVAR model is wrongly specified by DGP (and EqCM), estimates of equation parameters (9) will generally be heterogeneous. Ignoring the uncertainty of the estimated parameter, the dVAR will be:

$$\Delta y_t = \gamma^* + \pi^*\Delta x_t + \epsilon^*_{y,t} \quad (40)$$

$$\Delta x_t = \varphi + e_{x,t} \quad (41)$$

where γ^* and π^* are probability limits of the parameter estimates. In the forecasting period $\gamma^* + \pi^* \Delta x_{T+h} = g \neq 0$, the dVAR forecast of y_{T+h} will include an additional deterministic trend (due to estimation interference) that will not necessarily correspond to the trend in DGP (of process x_t).

The influence of the parameter may be numerically small (for example, if the differential terms are near orthogonal to the omitted equilibrium correction) but can still accumulate a dominant linear trend in the interference of the dVAR forecast error.

One of the dVAR-type models, denoted dRIM, is opposite to (40). The empirical section shows examples of how dVAR models can be successfully strengthened against misconceptions of the trend.

Although we have analyzed the simplest forecasting systems, the results have some characteristics that one might recover from the forecast macroeconomic forecasting errors.

The analysis shows that neither EqCM nor dVAR provides protection against post-prognostic discontinuities. In the case where we have focused, where the dVAR model excludes growth when present in DGP, the dVAR forecast error interferences contain a trend component. Even in this case, depending on the initial conditions, the dVAR model can compete favorably with the EqCM on average forecast horizons.

The dVAR model does not offer protection against pre-forecasting long-term average, which reiterates an important opinion. While the dVAR model corrects the automated segment to pre-forecast discontinuity, the EqCM will deliver lower predictions unless model users are able to detect discontinuity and correct segment forecasting. Experience tells us that this is not always the case: in a large model, a structural discontinuity in one or more equations may go unnoticed or could be interpreted as „temporary" or just like a fall because the data available to evaluate Model are preliminary and susceptible to future revisions.

One suggestion is that the relative merits of EqCM and dVAR models for forecasting depend on:

- „mix" of pre- and post-prognosis parameters;
- the forecast horizon length.

This perspective is used to interpret the forecast results from a large-scale model..

Conclusion

The study underlying this article is based on the fact that the macroeconomic forecast is important for establishing macroeconomic developments. A number of models are used but in this article we have focused on the dVAR and EqCM models which from the mathematical and econometric point of view can provide the calculation of some coefficients on which to make a correct estimation. From this article we can draw a series of theoretical conclusions that these two models used in the macroeconomic forecast give results in the context in which the forecasting errors are identified and eliminated, the balance is provided or in more demanding terms the macrostabilization is hypothesized On the basis of which the main parameters of economic evolution in the country can be established. These models have been analyzed in the context in which they provide broad forecast horizons and combined with the interpretation of other estimated indicators can lead to a correct macroeconomic forecast. In this article we have emphasized the presentation of mathematical relations to highlight developments and trends in the evolution of a country's economy. It follows from the above that the two models can be used in the macroeconomic forecasting and consequently can be developed in the use of other econometric models.

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