



# The Comparison of GDP Strategies Forecasting in Romania

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## ABSTRACT

The aggregates, like GDP, can be forecasted using two different strategies, the criterion of predictions' accuracy being used to select the best strategy. The aim of this paper is to find out what is the best strategy to be used in predicting GDP in Romania. In this study, for data series of GDP and its components for the Romanian economy in 1996-2011, we have come to the conclusion that the direct forecasting strategy is the most suitable one in making one-step-ahead predictions. Another possible strategy is based on the aggregation of GDP components using constant or variable weights, but in the case of Romania it is not recommended. The one-step-ahead forecasts are better than those on a horizon of 3 years. The selection of the best forecast has an important contribution in reducing the degree of uncertainty in forecasting.

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## 1. Introduction

One of the sources of forecast uncertainty less depth in the literature is the aggregation of variables that compose the indicator that will be forecasted. Interestingly, no author identifies this source together with other sources of uncertainty of forecasts that are based on models. In literature, there are studies where the forecasts accuracy is evaluated when the interest variable is modeled using its components. In these studies, the variables are also forecasted by aggregating the forecasts of their components.

The forecasts of macroeconomic aggregates are of interest not only for government, but also for private sector. The accuracy can be improved for forecasts obtained by forecasting the aggregate's components, followed by the aggregation of these predictions. The conclusion was stated in literature, but it remains valid only in the context of knowledge of data series used to draw up estimates of the models. Hubrich (2005) showed that the aggregation of forecasts components does not necessarily help in annual forecasting.

The proposed objective is to find out a strategy that improves the GDP forecasts accuracy for Romania. The direct forecasts strategy is more suitable than the predictions aggregation approach.

In this paper, after a brief introduction, the forecasting strategies used in literature (aggregation, disaggregation and direct forecasting) are presented, and the most important results of some researches are provided literature. The problem of forecasts accuracy evaluation was developed mentioning some important measures of accuracy. The case study refers to Romania's GDP predictions using the direct strategy and the components aggregation. The accuracy of the obtained forecasts was evaluated and the conclusion was that the direct strategy generated better one-step-forecasts for 1996-2011. The main contribution is related to the application of the methodology for Romania data set and the new way, never mentioned before in literature, used to calculate the variable weights, starting from ARIMA models.

## 2. Forecasting strategies

Hendry and Hubrich (2009) consider that one of the causes of forecast failure is the inconsistency of parameters generated by the use of disaggregated data in the absence of structural shocks. Therefore, the aggregation / disaggregation of variables can be considered as a source of forecast uncertainty.

In the last years, due to the aggregation of geographical areas, the problem of calculating and forecasting the aggregate indicators occurred for each region or member state in the case of the Euro zone.

Hendry DF and Hubrich K. (2006) propose instead of the forecasting of an aggregate's components, followed by the forecasts aggregation, to include in a model the variables that compose the aggregate, because the forecasts would be more accurate.

Hendry, DF and Hubrich, K. (2006) list authors such as Espasa, Senra and Albacete (2002), Hubrich (2005) and Benalal, Diaz del Hoyo, Land, Rome and Skudelny (2004) with important contributions to preview inflation in the euro area. Fair and Shiller (1990) performed an analysis similar but for the U.S. GDP. About aggregation

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and disaggregation in related activity forecasting few authors have important contributions, being recalled by Hendry, DF and Hubrich, K. (2006): Grunfeld and Griliches (1960), Kohn (1982), Lutkepohl (1984, 1987), Pesaran, Pierse and Kumar (1989), Van Garderen, Lee and Pesaran (2000). Granger (1990) puts forward the issue of aggregation from the time series variables and Lutkepohl (2005) takes into account aggregate forecasts based on VARMA models. The concept of predictability used by Hendry, DF and Hubrich, K. (2006) refers to the connection between variables analyzed and the appropriate data set and was previously used by Diebold and Kilian. Clements MP and DF Hendry (2010) and Hendry and DF and Hubrich, K. (2006, 2009) are concerned with the assessment obtained by aggregating indicators forecast accuracy of other variables. The data used by them refers to the rate of inflation in the euro area and U.S.

Bermingham C. and D'Agostino A. (2011) show that if the suitable econometric model is chosen the forecasts aggregation could improve the prediction performance.

Considering that the components are ARIMA models, Rose (1977) analyzes the DGP and predictions for an aggregate of these models. Tiao and Guttman (1980), Kohn (1982) and Luetkepohl (1984a, 1984b) use this method with the DGP or forecast performance of the aggregated process related to an assumed structure for the DGP of the components. Luetkepohl (1984a) considered that the superiority of the disaggregate prediction falls if the DGPs are not known, being necessary their estimation.

Duarte and Rua (2005), Bruneau et al (2007) and Moser et al (2007) conclude that forecast aggregation improved forecasts for inflation for Portugal, France and Austria.

Zellner and Tobias (2000) predict the aggregate growth rate of 18 industrial countries and showed the superiority of the disaggregate approach. Marcellino, Stock and Watson (2003) forecast prices for the euro area directly and by aggregating country models.

Clements MP and DF Hendry (2010) specify two forecasting strategies: aggregating forecasts for disaggregate components and direct forecasting of the aggregates.

First, we assess the modification effects of the information set by adding the aggregates of the analyzed macroeconomic indicator. Lack of predictability depends on available information. We consider the variable over which predictions are made having an evolution as follows:  $x_t = f_t(I_{t-1}) + u_t$ . In this case,  $u_t$  is a non-degenerate and unpredictable vector of random variables in relation to the information set from the past ( $I_{t-1}$ ).

By reducing the information set from  $I_{t-1}$  to  $J_{t-1}$  forecasts with a lower degree of accuracy will result, even if they remain unbiased, as Clements and Hendry (2005) showed. So, a larger set of information is preferred to be used in order to improve accuracy. If we start from the conditioned distribution ( $D_{x_{T+1}^a}(x_{T+1}^a / \cdot)$ ), the amount

of information from the original set increases by disaggregating the variable  $x_T^a$  in variables  $x_{i,T}^a$  and by adding the aggregates in the set of information. Practically, the new set of information, having a longer length, is  $J_{t-1}$ , including the old aggregates and disaggregates. It is considered a scalar  $x_T^a$  on which the forecasts are made and this will be split into the following form:  $x_{T+1}^a = x_{1,T+1} \cdot g_{1,T+1} + x_{2,T+1} \cdot g_{2,T+1}$  (a)

$g_{1,T+1}, g_{2,T+1}$  - Specific weights or ponders which can be fix or may change in time. We know that:

$g_{1,T+1} = 1 - g_{2,T+1}$  Assuming that GDP is the aggregated variable, then  $z_T$  is the set of variables that contains:

- Aggregate variable with lags;
- Disaggregated components;
- Other variables.

The aggregate variable and its components are represented by:

$$\begin{aligned} x_t^a &= z_{t-1}' \delta_t + v_t \\ x_{i,t} &= z_{t-1}' \gamma_{i,t} + e_{i,t} \end{aligned}$$

Conditional expectation of each component can vary over time and it is equal to the minimum value of square error of predictors:  $E_{T+1}[x_{i,T+1} / z_T] = z_T' \cdot \gamma_{i,T+1}$ . (b)

(b) Introducing the relation (a) in (b) it will result:

$$E_{T+1}[x_{T+1}^a / z_T] = \sum_{i=1}^2 g_{i,T+1} E_{T+1}[x_{i,T+1} / z_T] = \sum_{i=1}^2 g_{i,T+1} z_T' \gamma_{i,T+1} = \sum_{i=1}^2 z_T' \gamma_{i,T+1}^* = \lambda_{T+1}' x_T \quad (c)$$

$$x_{T+1}^a \text{ is predicted starting from } : z_T : E_{T+1}[x_{T+1}^a / z_T] = \delta_{T+1}' z_T \quad (d)$$

The above two relations, (c) and (d) are equivalent, fact that implies the same prediction error:  $\delta_{T+1}' z_T = \lambda_{T+1}' z_T, \forall z_T \Rightarrow x_{T+1} - E_{T+1}[x_{T+1}^a / z_T] = v_{T+1}$ .

In conclusion, the direct prediction of  $x_{T+1}^a$  components is equivalent to forecasts aggregation.

In practice, even if the coefficients of models components or the specific weights change, forecasting the aggregate directly on its components has a higher degree of accuracy than if we aggregate the forecasts components. The explanations of this situation can be related to the fact that certain components of the aggregate can be volatile or that the covariance between them provide stability to the aggregate indicator. Disaggregates can be easily predicted under an increased stability of the models coefficients or weights. Clements MP and DF Hendry (2010) conclude that the aggregation of forecasts through disaggregates is a better solution in terms of accuracy than forecasting the aggregate directly. For forecasting the aggregate, it is not indicated the forecasting, but the inclusion of the lags of disaggregates, which shows that the specific weights of predictions are not necessary in order to aggregate the components forecasts.

### 3. The evaluation of forecasts performance

Forecast accuracy is a large chapter in the literature aimed at assessing forecast uncertainty. There are two methods used to compare the quality of forecasts: vertical methods (for example, the mean square error of prediction) and horizontal methods (such as distance in time). A comprehensive coverage of the issue taking into account all the achievements of the literature is impossible, but we will outline some important conclusions.

To assess the forecast performance, as well as their ordering, statisticians have developed several measures of accuracy. For comparisons between the MSE indicators of forecasts, Granger and Newbold propose a statistic. Another statistic is presented by Diebold and Mariano for comparison of other quantitative measures of errors. Diebold and Mariano test proposed in 1995 a test to compare the accuracy of two forecasts under the null hypothesis that assumes no differences in accuracy. The test proposed by them was later improved by Ashley and Harvey, who developed a new statistic based on a bootstrap inference. Subsequently, Diebold and Christoffersen have developed a new way of measuring the accuracy while preserving the cointegrating relation between variables.

Armstrong and Fildes (1995) show that the purpose of measuring an error of prediction is to provide information about the distribution of errors form and they propose to assess the prediction error using a loss function. They show that it is not sufficient to use a single measure of accuracy.

Since the normal distribution is a poor approximation of the distribution of a low-volume data series, Harvey, Leybourne, and Newbold have improved the properties of small length data series, applying some corrections: the change of DM statistics to eliminate the bias and the comparison of this statistics not with normal distribution, but with the T-Student one. Clark evaluate the power of equality forecast accuracy tests, such as modified versions of the DM test or those used by or Newey and West, based on Bartlett core and a determined length of data series.

Clements and Hendry (2010) present the most used accuracy measures in literature, which are described below.

#### 1. The specific loss function

Diebold, Gunther and Tay (1998) started from a loss function  $L(a_t, x_{t+1})$ , where:

$a_t$  - specific action

$x_{t+1} \rightarrow f(x_{t+1})$  - the future value of a random variable whose distribution is known

$f(\cdot)$  - density forecast

The optimal condition involves minimizing the loss function when the density forecast is  $p_{t,1}(x_{t+1})$ :

$$a_{t,1}^* = \underset{a_{t,1} \in A}{\operatorname{argmin}} \int L(a_{t,1}, x_{t+1}) p_{t,1}(x_{t+1}) dx_{t+1}$$

The expected value of the loss function is:

$$E[L(a_{t,1}^*, x_{t+1})] = \int L(a_{t,1}^*, x_{t+1}) f(x_{t+1}) dx_{t+1}$$

The density forecast will be preferred above to any other density for a given loss function if the following condition is accomplished:

$$E[L(a_{t,1}^*(p_{t,1}(x_{t+1})), x_{t+1})] < E[L(a_{t,2}^*(p_{t,2}(x_{t+1})), x_{t+1})]$$

where  $a_{t,i}^*$  - the optimal action for the following forecast:  $p_{t,i}(x)$ .

Making decisions based on forecast accuracy evaluation is important in macroeconomics, but few studies have focused on this. Notable achievements on forecasts performance evaluation were made in practical applications in finance and in metrology. Recent improvements refer to the inclusion of disutility that is presented in actions in the future states and take into account the entire distribution of forecast. Since an objective assessment of prediction errors cost can not be made, only general absolute loss functions loss or loss of error squares can be used.

## 2. Mean square forecast error (MSFE) and the second error of the generalized forecast (GFESM)

The most used measure to assess the forecasts accuracy is the mean square forecast error (MSFE). In the case of a vector of variables, a MSFE matrix will be built:  $V_h \equiv E[e_{T+h} e_{T+h}'] = V[e_{T+h}] + E[e_{T+h}]E[e_{T+h}]'$ , where  $e_{T+h}$  – vector of errors with h steps – ahead – forecast

The trace and the determinant of the mean square errors matrix are classical measures of forecast accuracy.

Generalized forecast error second moment (GFESM) is calculated according to Clements and Hendry (1993) as a determinant of the expected value of the forecast errors vector for future moments up to the horizon of interest. If forecasts up to a horizon of h quarters present interest, this indicator is calculated as:

$$GFESM = E \left[ \begin{pmatrix} e_{t+1} \\ e_{t+2} \\ \dots \\ e_{t+h} \end{pmatrix} \begin{pmatrix} e_{t+1} \\ e_{t+2} \\ \dots \\ e_{t+h} \end{pmatrix}' \right]$$

$e_{t+h}$  -n-dimensional forecast error of n variables model on horizon h

It is considered that GFESM is a better measure of accuracy, because it is invariant to elementary operations with variables, unlike the MSFE trace and it is also a measure that is invariant to basic operations of the same variables on different horizons of prediction, in contrast with MSFE matrix trace and determinant.

Clements and Hendry (1993) show that the MSFE disadvantages related to invariance models are determined by the lack of invariance indicator of non singular linear transformations, that preserves the scale. MSFE comparisons determined inconsistent ranks of forecast performance of different models with several steps along the variables transformations.

## 3. Measures of relative accuracy

Relative measures for assessing forecast accuracy suppose the comparison between forecast and the reference, forecast called in literature „benchmark forecast” or “naïve forecast”. However, it remains a subjective approach the choice of forecast used for comparison. Problems that may arise in this case are related to: the existence of outliers or inappropriate choice of models on which forecasts are developed, and the emergence of shocks. A first measure of relative accuracy is Theil's U statistic, for which the reference forecast is the last observed value recorded in the data series. Collopy and Armstrong proposed a new indicator instead of U statistics similar (RAE). Thompson has improved the MSE indicator, proposing a statistically determined MSE (mean squared error log ratio).

Relative accuracy can also be measured by comparing predicted values with those based on a model built using data from the past. The tests of forecast accuracy compare an estimate of forecast error variance derived from the past residue and the current MSFE.

To check whether the differences between mean square errors corresponding to the two alternative forecasts are statistically significant, the tests proposed by Diebold and Mariano, West, Clark and McCracken, Corradi and Swanson, Giacomini and White are used.

Starting from a general loss function based on predictive ability tests, the accuracy of two alternative forecasts for the same variable is compared. The first results obtained by Diebold and Mariano were formalized, as showed R. Giacomini and H. White (2006), by West, McCracken, Clark and McCracken, Corradi, Swanson and Olivetti, Chao, Corradi and Swanson. Other researchers started from the particular loss function (Granger and Newbold, Leitch and Tanner, West, Edison and Cho, Harvey, Leybourne and Newbold).

## 4. The assessment of Romania's GDP forecasts accuracy using the two forecasting strategies

From the database of the National Institute of Statistics I downloaded data for Romanian economy for variables such as GDP, final consumption, gross capital formation, stocks' variation, and net exports.

The indicators are expressed in constant prices (million lei, 100 = 2005) and the period of registration is 1996-2011. The linear regression models were developed using dataset until 2008, 2009, respectively 2010 and they were used to make forecasts. There are two types of forecasts:

- One year ahead forecasts;
- Forecasts on a 3 year horizon.

Each of forecasts was developed in two specific versions, regarding the specific weights used to aggregate the forecasts of GDP components:

- With constant weights;
- With variable weights.

In the version with constant weights, structures of the year chosen as forecast origin, the last year in data series, are used as weights. These weights show the share of consumption, investment and government spending, net exports respectively in GDP of that year.

The evolution of components weights in GDP is described using the autoregressive moving average processes.

Forecasts of weights based on these models are presented in **Appendix A**. The models used to make one-step-ahead forecasts were built using EViews and these are presented in **Table 1**. Using data from the period 1995-2009, models for GDP and its components were obtained and used to predict the value of indicator in 2010. Using data from 1995-2010 series models used to forecast GDP in 2010 were developed.

**Table 1. Models used for one-year-ahead forecasts**

Year for which the forecast is made	The model used for direct forecasting
2009	$PIB_t = 10,458 \cdot PIB_{t-1} - 9,496 \cdot cf_{t-1} - 7,896 \cdot fbcf_{t-2} - 11,759 \cdot vs_{t-1} - 4,893 \cdot exn_{t-1} + e_t$
2010	$PIB_t = 6,954 \cdot PIB_{t-1} - 5,409 \cdot cf_{t-1} - 8,366 \cdot fbcf_{t-2} - 6,86 \cdot vs_{t-1} - 4,654 \cdot exn_{t-1} + e_t$
2011	$PIB_t = -1,782 \cdot PIB_{t-3} + 2,131 \cdot cf_{t-1} + 1,964 \cdot fbcf_{t-2} + 2,331 \cdot vs_{t-1} - 0,638 \cdot exn_{t-1} + e_t$

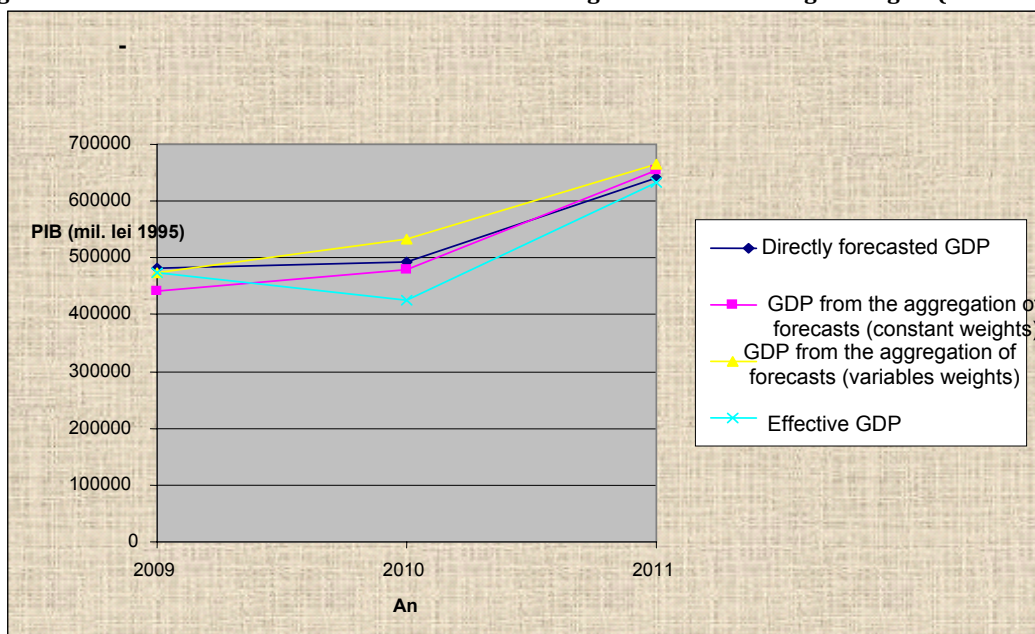
  

Year for which the forecast is made	The models used to develop forecasts that will be aggregated
2009	$PIB_t = 1,391 \cdot cf_{t-1} + e_{1,t}$ $PIB_t = 89,51 \cdot vs_{t-1} + e_{2,t}$ $PIB_t = 4,509 \cdot fbcf_{t-1} + e_{3,t}$ $PIB_t = -7,356 \cdot exn_{t-1} + e_{4,t}$
2010	$PIB_t = 1,357 \cdot cf_{t-1} + e_{1,t}$ $PIB_t = -12,22 \cdot vs_{t-1} + e_{2,t}$ $PIB_t = 3,99 \cdot fbcf_{t-1} + e_{3,t}$ $PIB_t = -7,47 \cdot exn_{t-1} + e_{4,t}$
2011	$PIB_t = 1,333 \cdot cf_{t-1} + e_{1,t}$ $PIB_t = 115,59 \cdot vs_{t-3} + e_{2,t}$ $PIB_t = 4,037 \cdot fbcf_{t-1} + e_{3,t}$ $PIB_t = -8,03 \cdot exn_{t-1} + e_{4,t}$

Source: own calculations using EViews.

In **Figure 1** there can be observed larger deviations of directly forecasted GDP values compared to those actually recorded or forecasted by aggregation. The directly forecasted GDP has the closest values of the registered ones. A tendency of overestimation of the indicator can be observed while applying the strategy of aggregation with constant weights. The direct strategy and the one based on variable weights generated underestimated predictions according to the real GDP values.

**Figure 1. The effective GDP and the forecasted GDP using the two forecasting strategies (2009-2011)**



Accuracy is assessed by a relative error used in making comparisons between predictions, the percentage error:

$$e_r = \frac{GDP_{\text{effectiv}} - GDP_{\text{forecasted}}}{GDP_{\text{effectiv}}} \cdot 100$$

RJ Hyndman and AB Koehler (2005) show that the percentage error can be used to calculate several indicators, including mean absolute percentage error-MAPS. For a one-step-ahead forecasts made on the horizon 2009-2011, the smallest mean absolute square error registers the directly forecasted GDP using the econometric model. For forecasts on 3 years, the ones with constant weights have the highest degree of accuracy, achieving a value of 9,1% for MAPE, unlike a value around 17% for the other forecasts.

Hyndman și Koehler (2005) propose for comparisons the use of a relative measure of accuracy which is independent of the measurement scale of the indicator, the relative RMSE, that is calculated as:

$$\text{rel\_RMSE} = \frac{\text{RMSE}}{\text{RMSE}_b}, \text{ unde } \text{RMSE}_b$$

root mean squared error of the „benchmark model”.

A value less than 1 of the indicator shows that the forecast to compare is better than the reference one, because of the higher degree of accuracy. The one-step-ahead forecasts and those on 3 years are compared using this indicator.

For one-step-ahead forecasts, the value of GDP obtained by aggregation with constant weights is higher than in the other two cases. The smallest value of RMSE is registered for the directly predicted GDP in both variants (one-step-ahead forecasts and those on 3 years). The relative RMSE is used to compare the one-step-ahead predictions with those on 3 years for each strategy. The values less than 1 for the relative RMSE show that one-step-ahead predictions are better than those on 3 years.

As for the one-step-ahead forecasts and those on 3 years, the value of directly forecasted GDP is higher than the one of forecasts obtained from aggregating the GDP components. However, the higher mean square error for one-step-ahead forecasts is registered for directly predicted GDP and the lower for forecasted GDP using variable weights. The GDP forecasted values resulted applying the two strategies for one step ahead forecasts and those on 3 years, and the values of RMSE and MAPS are presented in **Table 2** and **Table 3**.

**Table 2. One-step-ahead forecasts of Romania GDP in 2009-2011**

Year	Directly forecasted GDP (mil. lei 2005)	Forecasted GDP by aggregating the components' forecasts (constant weights)	Forecasted GDP by aggregating the components' forecasts (variable weights)
2008	441273,1	473047	473047
2009	478756,6	532170,3	426021,6
2010	655436,8	665920,8	632348,9
RMSM	25703,40311	27320,33	39160,98
MAPE	4,4632 %	4,5087 %	5,4989 %
rel_RMSE	0,373738	0,199447	0,311913

*Source: own calculations using EViews.*

**Table 3. The forecasts on 3 years of Romania GDP (2009-2011)**

Year	Directly forecasted GDP (mil. lei 2005)	Forecasted GDP by aggregating the components' forecasts (constant weights)	Forecasted GDP by aggregating the components' forecasts (variable weights)
2008	441273,1	473047	473047
2009	485119,3	407638,7	420496,9
2010	528654,2	419458,1	435824,4
RMSM	68773,88	136980,6	125551
MAPE	9,0993 %	17,8175 %	16,0964 %

*Source: own calculations using EViews.*

For forecasted GDP by aggregating its components with variable weights there is a tendency of overestimation, while the directly forecasted GDP is underestimated. For forecasts developed on a three years horizon, the directly forecasted GDP has the highest accuracy, because the RMSM is the lowest.

Percentage error values are presented in **Table 4** and **Table 5**. The calculated relative errors are small for direct forecasts of GDP and higher in other cases. The lowest relative error was registered in 2011 for predicted GDP by aggregating the forecasts of GDP components (variable weights) and the largest one for the forecasted GDP using the aggregation strategy with constant weights in 2010.

**Table 4. Relative errors (errors percentages) of one-step-ahead forecasts (%)**

	2009	2010	2011
Directly forecasted GDP (mil. lei 2005)	-8,23%	-1,62%	-1,62%
Forecasted GDP by aggregating the components' forecasts ( constant weights)	-2,86%	7,97%	-13,56%
Forecasted GDP by aggregating the components' forecasts ( variable weights)	2,29%	3,93%	-1,31%

Source: own calculations using the data from **Table 2**

**Table 5. Relative errors (errors percentages) of 3-years horizon forecasts (%)**

	2009	2010	2011
Directly forecasted GDP (billions dollars 2005)	-8,23%	-1,62%	-1,62%
Forecasted GDP by aggregating the components' forecasts (constant weights)	-1,57%	-17,29%	-14,68%
Forecasted GDP by aggregating the components' forecasts (variable weights)	-17,49%	-34,54%	-31,98%

Source: own calculations using the data from **Table 3**

The relative errors in absolute value of directly one-step-ahead forecasted GDP became increasingly smaller. All the relative errors values are negative for the predictions on 3 years, showing a tendency of overestimation of forecasted values from those actually registered.

A generalization of Diebold-Mariano test (DM) is used to determine whether the MSFE matrix trace of the model with aggregation variables is significantly lower than the one of the model in which the aggregation of forecasts is done. If the MSFE determinant is used, the DM test can not be used in this version, because the difference between the two models MSFE determinants can not be written as an average. In this case, a test that uses a bootstrap method is recommended. The DM statistic is calculated as:

$$DM_t = \frac{\sqrt{T} \cdot [\text{tr}(\text{MSFE}_{\text{aggregated\_model}})_h - \text{tr}(\text{MSFE}_{\text{aggregated\_forecasts\_model}})_h]}{s} = \frac{1}{s} \cdot \sqrt{T} \cdot \left[ \frac{1}{T} \sum_{t=1}^T (\text{em}_{1,h,t}^2 - \text{er}_{1,h,t}^2 - \text{er}_{2,h,t}^2 - \text{er}_{3,h,t}^2) \right]$$

T – the number of years for which forecasts are developed;

$\text{em}_{i,h,t}$  – the h-steps-ahead forecast error of variable i at time t for the aggregated model;

$\text{er}_{i,h,t}$  – the h-steps-ahead forecast error of variable i at time t for the model with aggregated forecasts;

s – the square root of a consistent estimator of the limiting variance of the numerator.

The null hypothesis of the test refers to the same accuracy of forecasts. Under this assumption and taking into account the usual conditions of central limit theorem for weakly correlated processes, DM statistic follows a standard normal asymptotic distribution. For the variance the Newey-West estimator with the corresponding lag-truncation parameter set to  $h - 1$  is used.

The DM test was applied both for the version with constant specific weights of GDP components and for the one with variable weights for one-step-ahead forecasts. In the first case, the value of DM statistic (34,06) is higher than the critical one, so if we use constant weights in the forecasts aggregation model we get the same accuracy as if we directly forecast the GDP. If we use variable weights, the DM statistic value (27.057) is greater than the critical value, so the accuracy of direct forecasts differs significantly from the one obtained by aggregating the forecasts with variable weights. The forecasts based on aggregated model have a higher degree of accuracy than those obtained by aggregating the forecast with variable specific weights.

Another possibility is to apply the CPA test in MatLab, which leads to the same result. DM test statistic is modified so that another measure of forecasts accuracy is used instead of MSFE, namely GFESM. The results are the same.

## 5. Conclusions and other future research directions

The methodology used in this paper consists of two parts: predicting GDP directly and using the aggregation of components forecasts and the evaluation of these forecasts accuracy. As a novelty, the forecasting strategies were applied for Romania's GDP. Moreover, the methodology of aggregation was improved, because the variable weights were built using MA models.

After the empirical study of GDP forecasts, the following conclusions resulted:

- The directly forecasted GDP using an econometric model has the highest degree of accuracy.
- Moreover, one-step-ahead directly obtained forecasts are better than the 3-year horizon forecasts.
- For forecasts of indicators resulted from aggregation the evaluation of aggregation as a source of uncertainty and the choice of most accurate forecasting strategy are recommended.

In future, we can improve this research by developing the forecasting strategies. The GDP can be predicted by using an econometric model that uses as explanatory variables other indicators than the GDP components.

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## APPENDIX A

### Models used to predict variable weights

Period	Variable weights
1995-2009	$g_{FBCF_t} = 0,9202 \cdot e_{t2-1} + e_{t2}$ $g_{exp\_net_t} = 0,9333 \cdot e_{t3-1} + e_{t3}$ $g_{VS_t} = -0,0494 \cdot e_{t4-1} + e_{t4}$
1995-2010	$g_{C_t} = 0,937 \cdot e_{t1-1} + e_{t1}$ $g_{FBCF_t} = 0,924 \cdot e_{t2-1} + e_{t2}$ $g_{exp\_net_t} = 0,959 \cdot e_{t3-1} + e_{t3}$ $g_{VS_t} = -0,018 \cdot e_{t4-1} + e_{t4}$

Source: own calculations using EViews.

Period	Constant weights
1995-2008	$g_{C_t} = 0,9328 \cdot e_{t1-1} + e_{t1}$ $g_{FBCF_t} = 0,9166 \cdot e_{t2-1} + e_{t2}$ $g_{exp\_net_t} = 0,9552 \cdot e_{t3-1} + e_{t3}$ $g_{VS_t} = 0,9328 \cdot e_{t4-1} + e_{t4}$