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ANALYSIS OF THE EUROPEAN COMMISSION'S FORECASTS OF GDP GROWTH AND INFLATION FOR CROATIA

ANALIZA PROGNOZE EUROPSKE KOMISIJE RASTA BDP-a I INFLACIJE ZA HRVATSKU

ABSTRACT: The paper analyses the quality of forecasts of Croatian GDP growth and inflation made by the European Commission in the period of 2005 – 2020. Forecast accuracy, bias and efficiency are examined. The findings show that forecast errors increase with the forecast horizon with little evidence of forecast bias. However, additional variables used for efficiency testing were all found to be significant at least on one of the analysed horizons for both GDP growth and inflation forecasts. The forecasters were not efficient in predicting GDP growth at any of the observed horizons. There is less evidence of inefficiency for inflation. It can be concluded that there is a potential for some general EU variables/indicators to be used for improving the country specific variable forecasts. The best improvement could be achieved using the window length for calculating the variables used as predictors similar to the forecast horizon.

KEYWORDS: macroeconomic variables, forecast accuracy, forecast bias, forecast efficiency

JEL: C53, E37

SAŽETAK: Rad analizira kvalitetu prognoze rasta BDP-a i inflacije za Hrvatsku, koju je izradila Europska komisija u razdoblju od 2005. do 2020. godine. Ispitane su točnost prognoza, pristranost i učinkovitost. Rezultati pokazuju da se pogreške prognoza poveća-

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vaju s duljinom vremenskog horizonta, uz malu prisutnost pristranosti prognoza. Međutim, dodatne varijable korištene za testiranje učinkovitosti pokazale su se značajnima barem na jednom od analiziranih horizonata za prognoze rasta BDP-a i inflacije. Prognozeri nisu bili učinkoviti u predviđanju rasta BDP-a na bilo kojem od promatranih horizonata. Za inflaciju je prisutno manje neefikasnosti. Može se zaključiti da postoji potencijal za korištenje nekih općih varijabli/indikatora Europske unije za poboljšanje prognoza specifičnih za zemlju. Najveće poboljšanje moglo bi se postići korištenjem duljine vremenskog okvira za izračunavanje varijabli koje se koriste kao prediktori, sličnog horizontu prognoze.

KLJUČNE RIJEČI: makroekonomske varijable, točnost prognoze, pristranost prognoze, učinkovitost prognoze

JEL: C53, E37

1. INTRODUCTION

The subject of this paper is the analysis of the quality of forecasts of gross domestic product (GDP) growth and inflation for Croatia. Forecasting key macroeconomic variables is extremely important for monitoring economic trends, which are very important not only for government institutions but also for investors in financial markets. These macroeconomic variables are regularly forecasted and monitored by the European Commission (EC) for Croatia since it was granted its European Union (EU) candidate country status in 2004. However, little research can be found in the literature addressing the assessment of the quality of the forecasts of GDP growth and inflation for Croatia made by any institution. Moreover, most of the papers only analyse forecast accuracy and do not address topics as bias and efficiency which provide insight into the rationality of forecasts.

Institute of Economics, Zagreb (EIZ, 2010) assessed their own projections for real GDP growth rate, current account balance and consumer price inflation for the period from year 2003 to 2009 by four accuracy measures: mean error, mean absolute error, mean percentage error and mean absolute percentage error. An article by PwC Croatia (2014) compared the GDP growth forecast performance from various institutions for the 5-year period, from 2009 to 2013 by calculating the average absolute difference between GDP projections and the real GDP outcome (the mean absolute error). Croatia was included in the research by Krkoska and Teksoz (2007) on the accuracy of GDP growth forecasts prepared by the European Bank for Reconstruction and Development (EBRD) for transition countries in central and eastern Europe and the Commonwealth of Independent States between 1994 and 2004. The analysis included unbiasedness and efficiency tests but all the results are reported only on aggregate level. Tica and Viljevac (2019) compared GDP growth projection accuracy of the International Monetary Fund (IMF), the Organisation for Economic Co-operation and Development (OECD) and a naïve projection for several horizons by calculating three measures of forecast accuracy (root mean squared error, mean absolute error and mean absolute percentage error). The sample included forecasts of GDP growth rates for 26 economies and the twenty-year period from 1998 until 2017. Croatia was not included in the analysis and no other aspects of forecast quality were assessed apart from accuracy.

The EC's forecasts have been assessed in Fioramanti et al. (2016) for the EU and the euro area but Croatia was not included in that study due to insufficient data. Recently, Cronin and McQuinn (2021) also analysed EC forecasts but Croatia was not included in this research either. A recent paper by Vlah et al. (2020) analysed the quality of GDP growth and inflation forecasts by multiple forecasters for the Croatian economy. The authors assessed forecast accuracy, directional accuracy, bias and efficiency for the ten-year period from 2006 until 2015. Evidence of bias was found for both analysed variables, although the bias regarding GDP growth was more pronounced. There was also some evidence of inefficiency, but only for certain horizons and again, it was more pronounced for GDP growth forecasts. However, only few variables known at the time the forecast was made were included in the information set regarding efficiency test. For GDP growth those included: the forecasters' most recent forecast, the latest available official final GDP growth value and the latest available official estimation of actual value for GDP growth. In the case of inflation forecasting the variables included: the forecasters' most recent forecast and the latest available actual value for inflation.

In this analysis we include additional accuracy measures in respect to Vlah et al. (2020) and more importantly, we extend the efficiency tests by including additional variables: the ones suspected to have the ability to improve the forecasts of GDP growth and inflation forecasts i.e. reduce the forecast error, which are specific to Croatia. Moreover, we analyse the impact of the time window length used for calculating the rate of change of the mentioned variables as well as their lag length on the ability to explain the forecast error i.e. efficiency estimation. To the best of our knowledge, this is the first attempt to test efficiency of Croatian GDP growth and inflation forecasts in this manner.

The remainder of the paper is organised as follows. Section 2 describes the methodology used to assess the quality of GDP growth and inflation forecasts for Croatia by the EC. Section 3 presents the data and summarizes the results of our empirical research. Finally, section 4 provides our conclusions.

2. METHODOLOGY

One of the objectives of the paper is to measure the accuracy of forecasts based on the size of the deviation of forecasted values from the realized values. There are many metrics known in the literature for measuring forecast accuracy. Hyndman and Koehler (2006) reviewed them and grouped them into four categories (scale-dependent measures, measures based on percentage errors, measures based on relative errors, relative measures). Furthermore, they propose a new measure named Mean Absolute Scaled Error (scaling the error based on the in-sample Mean Average Error from the naïve forecast method) which is also an idea related to relative measures. A more recent survey of measures i.e. an update of the review mentioned above was given by Chen et al. (2017) in which they grouped the accuracy measures into three categories: scale-dependent measures, percentage-based measures and relative-based measures. That way all measures related to the idea of relative errors or relative measures are merged into one category. Given that all accuracy measures have their advantages and disadvantages, we use some from each category. Hence, for EC GDP growth and inflation forecasts we calculate the Mean Average Error (MAE) and Root Mean Squared Error (RMSE) as scale-dependent measures, Mean Absolute Percentage Error (MAPE) as a percentage-based measure and Mean Absolute Scaled Error (MASE) as a Relative-based measure. It should be noted that the in-sample MAE for naïve method in this analysis is based on the last known final variable value at the time the forecast is made. This is either a one-step or multi-step naïve forecast depending on the variable and the forecasting horizon.

Another way of assessing forecast performance we use on EC GDP growth and inflation forecasts is directional accuracy i.e. if the increase or the decrease in GDP growth is forecasted correctly, as well as inflation versus deflation. Thus, to see if the forecasters anticipate the outcome's sign correctly, we use Pesaran and Timmermann's (1992) directional accuracy test as distribution-free procedure for testing the accuracy of forecasts that focuses on the prediction of the direction of change in the variable of interest.

Additional insight into the quality of forecasts can be obtained by checking whether the forecasts exhibit systematic error i.e. a bias. Most often checking for bias implies investigating whether the forecasts have a general tendency to be too high or too low, which would be an indication of mean bias. In this work, mean bias is analysed in one of the usual ways, by regressing forecast errors on a constant and testing whether the coefficient on the constant is significantly different from zero. Optimal forecasts are mean-unbiased under quadratic loss. Thus, the corresponding accuracy measure under this scenario would be MSE (or RMSE since it is a square root of MSE) since a rational analyst minimizes MSE of anticipated forecast errors. However, under linear loss, optimal forecasts are median-unbiased (Zellner, 1986). Therefore, in this case, a rational analyst minimizes MAE of anticipated forecast errors meaning that the corresponding accuracy measure is MAE. In this work, we complement regression looking for mean bias by a Wilcoxon signed rank test with a null hypothesis that the median of the forecast error is equal to zero. This test is also here to account for the small sample being used and it is quite useful in evaluating the properties of optimal forecast errors (Diebold and Lopez, 1996) despite not being used much in the literature on forecast evaluation. The difference between mean and median bias as well as the connection between accuracy measures and bias are well described e.g. in Clatworthy et al. (2012), where the authors also address the case of asymmetric loss function.

One last look into the quality of forecast will be obtained by analysing forecasts efficiency. The concept of forecasting efficiency shows the extent to which information is incorporated into the forecast. Forecasts are considered inefficient if forecast errors are correlated with information known at the time the forecast is made. In this paper the efficiency is tested by regressing the forecast errors on selected variables that were part of the set of information available at the time of forecasting. If the selected variable is statistically significant, it means that the forecaster did not take this information into account and could have improved the forecast by using it.

To explain the methodology behind the efficiency tests, it should be emphasized that the concept of rationality of forecasts encompasses unbiasedness and efficiency. Namely, rationality requires both unbiasedness and efficiency. To test rationality (or optimality as referred to by Diebold and Lopez, 1996), the relevant regression is (Nordhaus, 1987):

$$et = B'Xt + \nu t, \qquad (1)$$

where et is the forecast error, Xt is a column vector of variables observable at time forecast is made, B is row vector of coefficients and are regression residuals. If the information set

Xt consists of a constant and the forecast, this is identical to the unbiasedness test described before. When the information set *Xt* consists of a constant and current or lagged forecast, the test examines a weak version of rationality. Another possibility is that information set *Xt* contains other information, independent of both the constant and the forecast.

To test the efficiency of the Croatian GDP growth and inflation forecasts by the EC, we consider two usual variables that are likely members of the information set: the latest available outcome at the time the forecast was made and the most recent forecast by the EC (from longer horizons). As a proxy for the latest available official final GDP growth rate we most often take GDP growth rate lagged three years. For inflation forecasts, inflation lagged one year is considered to be the latest available actual value, at the time forecast is made.

Aside from those variables that are typically used, an additional effort is made in an attempt to find variables which could be correlated with the forecast error that stem from the specifics of Croatian economy. Namely, the choice of variables in assessing the effectiveness of forecasts of GDP growth and inflation is very important and specific for Croatian economy compared to other economies in Europe and the United States. In assessing the effectiveness of inflation forecasts for Germany by Behrens et al. (2018) some of the indicators used were the U.S. federal funds rate, the German money market rate, the year-on-year returns on the OECD share-price index for Germany, the year-on-year growth rate of U.S. industrial production, the year-on-year growth rate of German industrial production, the year-on-year returns of the oil price etc. Given the specifics of the Croatian economy, certain indicators used in the analysis of the German economy cannot be used or must be adjusted to the Croatian market. For example, in research by Ravnik (2014) several time-varying parameter vector autoregressive models for the short-term forecasting of Croatian GDP were proposed which include CROBEX annual rate of change, loans (as annual rate of change), the interest rate on short-term loans (in levels) and credit default swap for the Croatian sovereign bond (in levels) as domestic variables with the addition of European Union's GDP. In this work, in addition to the usual variables mentioned before i.e. the latest available outcome and the most recent forecast, to test efficiency of Croatian GDP and inflation forecasts as variables that are likely members of the information set, we also use share prices for EA19 (Euro Area with 19 countries), euro area loans (Central government, State government, Local Authorities, Social security Funds, Non-financial corporations and Households) and CROBEX returns at different horizons. We test different horizons i.e. time window length when calculating the rate of change in an attempt to check whether the shorter(longer) time windows for the rate of change of the variable used as predictor will be more useful when observing shorter(longer) horizon forecasts. The idea comes from a similar concept in forecasting stock price movements using technical indicators (Shynkevich et al. 2017) in which case the evidence suggested prediction performance to be the best when the input window length is approximately equal to the forecast horizon.

It should be noted that although the CROBEX index is not a flawless representation of the Croatian capital market, it is still a valuable tool for testing efficiency. The CROBEX includes the most liquid and traded shares on the market, which are influential in reflecting the overall performance and trends within Croatia's capital sector. While the Croatian capital market is not highly developed, the CROBEX index captures significant movements that can serve as reliable indicators in efficiency tests. Similar studies have shown that indices from less developed markets can still provide insightful data for efficiency analysis, especially when paired with other variables, such as macroeconomic factors. For instance, Ravnik (2014) utilizes the CROBEX annual rate of change in vector autoregressive models to forecast Croatian GDP, demonstrating its relevance despite the limitations of the capital market and justify the inclusion of the Zagreb Stock Exchange Index as a relevant high-frequency measure for forecasting real economic developments, as confirmed and explained in Barro (1990). Furthermore, Kvainickas and Stankevičienė (2019) provide a comprehensive overview of studies on the relationship between macroeconomic variables and stock returns, giving insights into the regional limitations, particularly in emerging and transition economies. While they acknowledge that the explanatory power of these models can be influenced by regional factors, this highlights the importance of carefully selecting appropriate models and variables. Despite these challenges, stock indices like CROBEX continue to be valuable tools for forecasting and analysing economic trends, as they capture significant movements in less developed markets.

3. DATA AND EMPIRICAL RESULTS

The data were collected from several sources for the period from 2005 to 2020. Croatian Bureau of Statistics (www.dzs.hr) publishes the data for GDP and inflation (the actual values and the estimates). GDP and inflation forecasts were collected from the European Commission webpage (https://ec.europa.eu/). The European Commission's publications are published at least twice a year, in spring and autumn, while in the last four years the European Commission has published for all four quarters, i.e. for spring, summer, autumn and winter. For the GDP growth rate and inflation, EC forecasts are given for horizons of 3, 6, 12, 18, 24 and 30 months, but in this the paper only the forecasts for 6, 12 and 18 months ahead are analysed since for those horizons the highest number of observations are available.

Figure 1 and figure 2 show the actual values as well as the forecasts at different horizons for the GDP growth and inflation respectively. As expected, it can be observed that the forecasts tend to be more distant from the actual values as the forecasting horizon increases. This is especially prominent in times of crisis (for inflation in 2008, for GDP growth in 2009 and for both in the pandemic 2020). Given the shocks, forecasts had even less information at the time of forecasting for e.g. 18 months ahead values than in other years. It should be noted that the 6 months ahead inflation forecast for year 2015 as well as 18 months ahead inflation forecast for 2016 are missing values.

Additional data required for efficiency tests are retrieved from CROBEX website (https://zse.hr/) for CROBEX index values, OECD data web (https://data.oecd.org/) for OECD share prices for EA19 and European Central Bank Statistical Data Warehouse (https://sdw.ecb.europa.eu/) for the euro area loans.

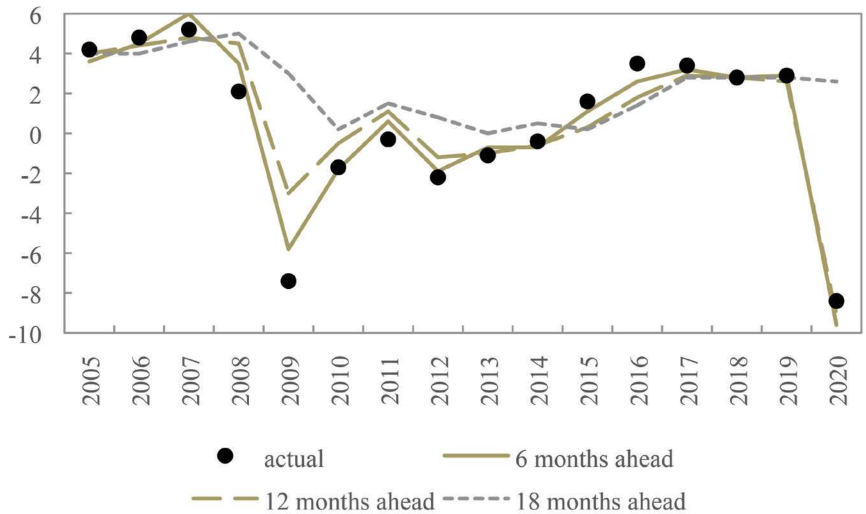

Fig. 1 The actual real GDP growth rate values and forecasts at different horizons

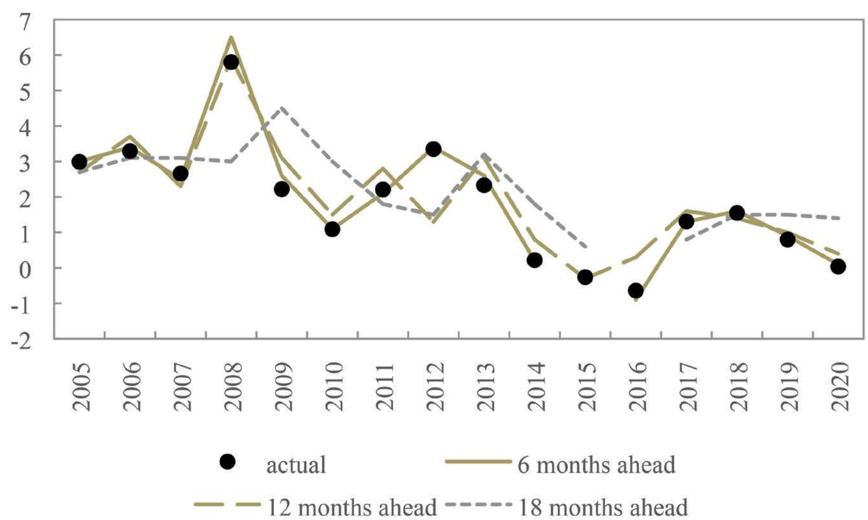

Fig. 2 The actual inflation values and forecast at different horizons

3.1 Forecast accuracy and unbiasedness

Table 1 summarizes the results on accuracy measured by different metrics, directional accuracy, as well as mean and median bias for GDP growth forecasts. Here again, it can be observed that accuracy decreases as the forecasting horizon increases, for all metrics employed, as expected. Looking at MAPE, the results show that the average difference between the forecasted value and the actual value is 39.51% for 6 months ahead GDP forecasts, while for 18 months ahead forecasts it grows to 111.52%. MASE values are all smaller than 1 and indicate that the EC forecasts are better, on average, than naïve forecasts. The direction of change in GDP was predicted successfully by EC at horizons of 6 and 12 months (94% of cases). However, the 18 months ahead forecasts are not directionally accurate.

According to Table 1, EC forecasts do not show many sings of bias for GDP. The mean forecasts errors are negative for all horizons suggesting that there is a tendency to over-predict GDP growth. Nevertheless, only at 18 months horizon it is significantly different than zero (at 10 percent level). Interestingly, median forecast error is only negative at 18 months horizon, meaning there are more cases where the forecasted value is less than the actual although the mean is negative suggesting over-prediction. Figure 1 indicates that the reason for this might lie mostly in the year 2009 when the GDP growth was severely over-predicted. However, median forecast error is not significantly different from zero at any of the usual levels and any horizon.

Table 1. Accuracy, directional accuracy and bias for GDP growth forecasts

Horizon	MAE	RMSE	MAPE	MASE	Directional accuracy	Mean bias	Median bias	
18	2.42	4.05	111.52	0.67	0.56	-1.70*	-0.45	
12	1.01	1.49	62.47	0.29	0.94***	-0.30	0.20	
6	0.59	0.77	39.51	0.17	0.94***	-0.08	0.05	

Significance at the 10%, 5% and 1% levels is indicated by single, double and triple asterisks, respectively.

Table 2 presents the results on accuracy measured by different metrics, directional accuracy, as well as mean and median bias for inflation forecasts. Again, as expected, all accuracy metrics values decrease as the forecasting horizon increases. MAPE results show that the average difference between the forecasted value and the actual value is 18.27% for 6 months ahead inflation forecasts, while for 18 months ahead forecasts it grows to 336.53%. It seems shockingly a lot, but when having in mind how MAPE is measured, it makes sense. For example, inflation in year 2020 was 0.04% and the 18 months ahead forecast was 1.40%, which leads to a percentage error of 3400% (100 x 1.36/0.04). Thus, when measuring this way, as percentage of actual value, error for 2020 is huge and much larger than the percentage error for e.g. year 2008 in which case we would consider 18 months ahead inflation forecast as bad by observing Figure 1.

MASE values for inflation forecasts shown in Table 2 are all smaller than 1 and indicate that the EC inflation forecasts are better, on average, than naïve forecasts. Interestingly, the values seem similar to those of GDP forecasts. The direction of change in inflation was predicted successfully by EC at horizons of 6 and 12 months (94% of cases). However, the 18 months ahead forecasts are not directionally accurate. EC forecasts do not show many sings of bias for inflation either. The mean forecasts errors are negative for all horizons suggesting that there is a tendency to over-predict inflation growth. Nevertheless, mean forecast error is not significantly different from zero at any of the usual levels and any horizon. Median forecast errors are also negative at all horizons, meaning there are more cases where the forecasted value is greater than the actual again suggesting over-prediction. However, median forecast error is significantly different than zero only at 12 months horizon (at 10 percent level).

Table 2. Accuracy, directional accuracy and bias for inflation forecasts

Horizon	MAE	RMSE	MAPE	MASE	Directional accuracy		Mean bias		Median bias	
18	1.07	1.35	336.53	0.62	0.87		-0.26		-0.44	
12	0.53	0.71	101.15	0.34	0.94	***	-0.16		-0.32	*
6	0.15	0.24	18.27	0.10	0.94	***	-0.08		-0.05	

Significance at the 10%, 5% and 1% levels is indicated by single, double and triple asterisks, respectively.

3.2 Forecast efficiency

The results of testing efficiency of GDP growth forecasts based on CROBEX values and EA19 share price returns (logs) are summarized in Table 3. An interesting pattern is indicated by looking at the values which seem to be significant on secondary diagonal of the CROBEX as well as EA19 share price results. Namely, monthly CROBEX returns are significant for 6 months ahead GDP forecast error, quarterly returns are significant for 12 months ahead error, while year on year returns are significant for 18 months ahead error. The situation is similar with EA19 share price returns. Thus, it seems that shorter time windows for calculating returns are more successful in improving shorter horizon forecasts. Other than that, year on year returns are also significant for 12 months ahead errors. Based on these results, it can be concluded that forecasts were not efficient at any of the observed horizons.

Table 3. Efficiency of GDP forecasts based on CROBEX and EA19 share price returns

h	coef.	crobex.m.ret	cbex.q.ret	cbex.y.ret	EA19.m.ret	EA19.q.ret	EA19.y.ret
18		-1.36	-1.70	**-1.78 ***	-1.19	-1.69	**-1.94 ***
		(0.92)	(0.99)	**(0.97)**	(1.04)	(0.98)	**(0.93)**
		28.94	0.51	2.51	35.52	-2.73	7.10
		(17.22)	(10.10)	(3.36)	(31.09)	(13.01)	(4.81)
12		-0.26	-0.11	-0.37	-0.35	-0.38	-0.45
		(0.41)	(0.31)	(0.33)	(0.40)	(0.29)	(0.30)
		-1.88	**6.34 *****	**2.18 ****	6.48	**10.08 *****	**4.58 *****
		(7.40)	**(2.06)**	**(0.95)**	(14.45)	**(3.09)**	**(1.40)**
6		0.04	-0.07	-0.10	0.01	-0.06	-0.11
		(0.16)	(0.20)	(0.19)	(0.18)	(0.20)	(0.19)
		9.57 ***	-1.34	0.80	**9.56 ***	-1.49	1.44
		(2.96)	(2.01)	(0.67)	**(4.47)**	(2.43)	(1.00)

Significance at the 10%, 5% and 1% levels is indicated by single, double and triple asterisks, respectively.

Table 4 presents the results of efficiency tests for GDP forecasts based on loans, the latest own forecast and naïve forecast. The loans are included in different variants: quarterly rate of change lagged one quarter, year on year rate of change lagged one year, two years and three years, in logs. It is expected that the loans are not able to make any improvements in the forecast immediately, but could make contributions in the longer run i.e. with a lag. Evidence on the lag between monetary policy actions and the response of inflation was provided long time ago by Friedman (1972) and the results have been reaffirmed multiple times. For example, Batini and Nelson (2001) confirm that that it takes over a year before monetary policy actions have their peak effect on inflation based on UK and US data on money growth rates, inflation, and interest rates. For GDP growth, Table 4 shows that loans are significant for forecast error also with a lag of at least one year. However, latest own forecast and naïve forecast were not significant at any horizon. It can be concluded that GDP growth forecasts are not efficient at shorter forecasting horizons i.e. 6 and 12 months.

The results of efficiency tests based on CROBEX values and EA19 share price returns (logs) for inflation forecasts are presented in Table 5. There seems to be less evidence of inefficiency for inflation than for GDP growth forecast. Monthly CROBEX returns are significant for 6 months ahead GDP forecast error, while year on year returns are significant for 18 months ahead error. However, there is no evidence of inefficiency for 12 months ahead inflation forecasts. EA19 year on year share price returns are significant for both 6 and 18 month ahead forecast errors, while CROBEX year on year returns are also significant for 6 months ahead forecast errors.

Table 4. Efficiency of GDP forecasts based on loans, latest forecast and naïve forecast

h	coef.	loans.q. lagq	loans.y. lagy	loans.y. lag2y	loans.y. lag3y	latest. forecast	naive
18		-0.72	-0.61	-0.44	-0.89	-1.17	-1.34
		(1.24)	(1.17)	(1.17)	(1.30)	(1.93)	(1.06)
		-138.46	-38.75	-42.46	-23.87	-0.20	-0.22
		(115.62)	(25.87)	(25.50)	(25.81)	(0.64)	(0.28)
12		-0.03	0.42	**0.62 ***	0.61	0.06	-0.12
		(0.41)	(0.38)	**(0.32)**	(0.37)	(0.66)	(0.42)
		-60.74	**-26.25 *****	**-32.10 *****	**-28.76 *****	-0.16	-0.11
		(42.97)	**(8.54)**	**(6.97)**	**(7.71)**	(0.24)	(0.11)
6		-0.06	0.24	0.30	0.35 *	-0.04	-0.01
		(0.27)	(0.22)	(0.20)	(0.19)	(0.20)	(0.22)
		-3.10	**-11.72 ****	**-13.60 *****	**-14.61 *****	-0.05	-0.04
		(24.18)	**(4.81)**	**(4.44)**	**(4.22)**	(0.06)	(0.06)

Significance at the 10%, 5% and 1% levels is indicated by single, double and triple asterisks, respectively.

Table 5. Efficiency of inflation forecasts based on CROBEX and OECD share price returns

h	coef.	crobex.m.ret	cbex.q.ret	cbex.y.ret	EA19.m.ret	EA19.q.ret	EA19.y.ret
18		-0.19	-0.26	-0.36	-0.10	-0.26	-0.37
		(0.37)	(0.37)	(0.27)	(0.38)	(0.37)	(0.31)
		5.05	0.15	**3.04 *****	11.47	-1.17	**3.55 ****
		(6.68)	(3.64)	**(0.91)**	(11.33)	(4.71)	**(1.59)**
12		-0.18	-0.14	-0.18	-0.19	-0.18	-0.16
		(0.19)	(0.18)	(0.18)	(0.19)	(0.18)	(0.18)
		0.60	0.81	0.30	3.92	1.91	-0.28
		(3.49)	(1.24)	(0.52)	(6.78)	(1.86)	(0.87)
6		-0.05	-0.08	-0.09	-0.06	-0.07	-0.09
		(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
		2.14 *	-0.06	**0.40 ****	1.89	-0.42	**0.54 ***
		(1.00)	(0.60)	**(0.17)**	(1.44)	(0.73)	**(0.28)**

Significance at the 10%, 5% and 1% levels is indicated by single, double and triple asterisks, respectively.

Table 6 presents the results of efficiency tests for inflation forecasts based on loans, latest own forecast and naïve forecast. Again, the forecasts look better for inflation than for GDP growth here. Only 6 months ahead forecasts are not efficient according to the results, since the forecasts can be improved by including year on year rate of change in loans lagged two years and the latest own forecast.

Table 6. Efficiency of inflation forecasts based on loans, latest forecast and naïve forecast

h	coef.	loans.q.lagq	loans.y.lagy	loans.y.lag2y	loans.y.lag3y	latest.forecast	Naive
18		-0.59	-0.31	-0.14	-0.40	-0.65	-0.38
		(0.47)	(0.50)	(0.52)	(0.51)	(1.14)	(0.61)
		45.43	1.51	-3.48	3.87	0.15	0.06
		(42.13)	(10.69)	(11.01)	(9.84)	(0.47)	(0.23)
12		-0.22	-0.20	-0.05	-0.24	0.34	-0.03
		(0.20)	(0.23)	(0.23)	(0.24)	(0.42)	(0.31)
		11.80	1.30	-4.12	2.21	-0.20	-0.07
		(21.43)	(5.20)	(5.10)	(5.10)	(0.17)	(0.12)
6		-0.05	0.01	0.04	-0.00	**0.17 ****	-0.01
		(0.08)	(0.08)	(0.07)	(0.08)	**(0.07)**	(0.10)
		-3.71	-2.79	**-3.85 ****	-2.39	**-0.12 *****	-0.03
		(7.14)	(1.64)	**(1.52)**	(1.62)	**(0.03)**	(0.04)

Significance at the 10%, 5% and 1% levels is indicated by single, double and triple asterisks, respectively.

All in all, the efficiency tests showed that none of the forecasts of GDP and inflation other than 12 months ahead inflation were efficient. However, the 12 months ahead inflation forecasts exhibited a median bias (only at 10% significance).

The findings are not surprising bearing in mind the relation between the tested variables and the GDP growth and inflation forecasts. Namely, it makes sense to include the CROBEX returns in the analysis in order to take into consideration the correlation between the domestic financial market and real economic activity, while including stock prices of EA19 reflects economic conditions in the euro area countries which are Croatian major trend partners. Similarly, changes in lending activity in the euro area (represented by the euro area loans variable) affect their economic growth and consequently the output of Croatian small and open economy. Increased lending activity in major trade partners can also increase demand affecting the domestic inflation trends, whereas changes in expected inflation in financial markets affect market returns represented here by CROBEX and EA19 stock prices and can therefore be used to improve inflation forecasts as suggested by the research results.

4. CONCLUSIONS

This article provides the first detailed analysis of the Croatian GDP growth and inflation forecasts obtained by EC, considering accuracy, directional accuracy, mean and median bias and efficiency.

Regarding accuracy and directional accuracy, the forecasts tend to be worsening as the forecasting horizon increases, which corroborates the results already known in the literature. Not much evidence of bias is shown in the obtained results. However, only 15 years of data were analysed so the results should be taken with caution. Thus, further research could include more forecasters and analyse the data within a panel setting. Also, an idea of forecasters minimizing symmetric linear loss function could be explored since some recent research suggest that optimistically biased forecasts are attributable to such setting. An alternative explanation of asymmetric loss function could also be tested regarding bias.

Aside from the variables which are typically used for efficiency tests such as the latest available outcome at the time the forecast was made and the most recent forecast by the same forecaster, the novelty of this research are the additional variables which could be correlated with the forecast error. To that purpose the following variables were included: EA19 share prices (Euro Area with 19 countries), euro area loans and CROBEX returns. The selected additional variables were all found to be significant at some horizon for explaining the forecast error for both GDP forecasts and inflation. However, there seems to be less evidence of inefficiency for inflation than for GDP growth forecast. It should be noted that these results show the potential for some general EU variables/indicators which could be used for improving the forecasts error for country specific variable forecasts. Thus, future work should possibly include expanding this efficiency related analysis to other EU countries as well.

Another contribution of this work is the analysis of the impact of the time window for calculating the rate of change of the variables used as a predictor within the efficiency tests.

The results indicate that the highest prediction performance is observed when the input window length is closer in length to the forecast horizon i.e. the shorter(longer) time windows for the rate of change of the variable used as predictor are more useful when observing shorter(longer) horizon forecasts. We believe that this idea deserves more investigation and tests on other time frames, countries and related variables and indicators.

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