NAÏVE, COSTANT OR RATIONAL EXPECTATIONS?

Course of Advanced Macroeconomics

UNIVERSITA' DEGLI STUDI DI MILANO

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RESEARCH QUESTION:

Which methodology should we use to make better forecasts on inflation? Naïve, constant, or rational expectations?

WHY IS IT IMPORTANT?

Anticipating inflation in a correct way and forming expectations that are as close as possible to the realisation of inflation is crucial, because it affects the effectiveness of monetary policies. The way in which expectations are formed change the monetary policy and affects the AS curve, so they have a crucial impact on the CB's ability to affect equilibrium.

DATA AND METODOLOGY:

I tried to find the answer to my research question looking at the real data and in particular I decided to analyse the quarterly HICP inflation rate in the euro area between 1999:Q4 and 2020:Q1.

I used four series:

- the ***quarterly realisation of HICP inflation rate*** for the euro area (between 1999:Q4 and 2020:Q1),
- ***ECB's HICP inflation forecast (one year ahead)*** of the professional forecasters (SPF[1]),
- ***naïve expectations*** (last observed variable),
- ***the constant expectations*** (2% ECB inflation target).

The aim of this analysis is to compare the three forecasts of interest (naïve, constant, and professional/rational expectations) with the realisations of inflation (*ex-post*) to understand which method return the best predictions. To do so I calculated the residuals (that represent the *forecast error*, since they are calculated as the difference between actual and forecasted inflation for the same period *t*) for all these series and thanks to the Diebold and Mariano test I was able to compare the predictive accuracy of the different forecast's methods.

To be able to compare realisations with forecasts, I set my sample of observations between 1999Q4 and 2014Q4, and I used as forecasted period the one between 2015Q1 and 2020Q1. So, I compared the actual results between 2015Q1 and 2020Q1 and the forecast for the same period, then I obtain the following results.

RESULTS:

To run this analysis, I used the software EViews, for this reason I do not have a script with the code, but I will try to explain the procedures I used to obtain the results. I will demonstrate my results including graphs and outputs[2] found from my investigation done with this software.

First, it is important to define:

- ***Naïve expectations***: $\pi^e_{t-1,t} = \pi_{t-1}$ → *AS curve:* $\pi_t = \pi_{t-1} + k(y_t - y^n_t)$
- ***Constant expectations***: $\pi^e_{t-1,t} = \bar{\pi}$ (where $\bar{\pi}$ is the inflation target) → *AS curve:* $\pi_t = \bar{\pi} + k(y_t - y^n_t)$
- ***Rational expectations***: $\pi^e_{t-1,t} = E_{t-1}(\pi_t)$ → *AS curve:* $\pi_t = E_{t-1}(\pi_t) + k(y_t - y^n_t)$

This are the three methods of forming expectation that I will analyse in this paper, which are the three main approaches studied during our course. It would be interesting to see how they work on real data.

I started my analysis looking at the graph of the of the realisations of the quarterly inflation between 1999:Q4 and 2020:Q1 in the euro area (*Figure 1)* and I could observe that, even after shocks (as it happened for

[1] The Survey of Professional Forecasters asks a panel of approximately 75 forecasters located in the European Union (EU) for their short- to longer-term expectations for macroeconomic variables such as euro area inflation, growth, and unemployment.

[2] **All graphs and outputs are at the end of the report**

example between 2008 and 2009), the values of quarterly inflation tend to revert to the mean and continue fluctuating around it. In this case the mean is around 2, since ECB, to maintain price stability, define annual HICP inflation rate of 2% over the medium term. So, from an economic point of view, there is always mean reverting in inflation since the Central Banks tend to keep it under control and stabilize it. It is also possible to notice that values between 1999 and 2007 present lower variance than the ones between 2007 and 2020 (even if always between certain boundaries).

Then, I proceeded by creating the naïve (as *realised*$_{t-1}$) and constant (equal to 2% constant) expectations series, and I plotted them in a graph (*Figure 2*) with realised inflation and the forecast of professional forecasters (orange line). As we can see from this graph, the naïve series (green line) has the same shape of the realised inflation (red line) but slightly shifted to the right, because with this type of expectations agents take account of macroeconomic conditions with a one-period lag. Graphically we can also notice that the constant expectations (blue line) do not seem to predict well inflation since they are so far from the realisation of inflation. To better understand which method of forecast return results that are as close as possible to the realised one, I calculated the residuals/forecast errors (as the difference between the realised values and the values obtained from the forecasts) and I plotted them in *Figure 3*. From this last graph, we can observe that in this case the naïve forecast is the one that return the lowest residuals and calculating its residual sum of squares (RSS), we obtain that it is equal to 2.87; for the professional forecast the RSS is equal to 5.06, whereas for the constant expectations it is equal to 9.59. So, up to now the naïve forecast seems the one that return the best results in terms of forecast error.

At this point, I have all I need to run the Diebold and Mariano test. The DM test is a test to compare the predictive accuracy of two forecasts. Under the null hypothesis the two forecasts have the same accuracy (H_0: $E(d_t) = 0$), whereas under the alternative hypothesis is that the two forecasts have different levels of accuracy (H_1: $E(d_t) \neq 0$). Here, d_t is the loss differential between the two forecasts ($d_t = e_{1t}^2 - e_{2t}^2$). Moreover, e_{1t} and e_{2t} are the *forecast errors* obtained respectively from forecast 1 ($\widehat{Y_1}$) and forecast 2 ($\widehat{Y_2}$). More in detail, $e_{1t=} Y_1 - \widehat{Y_1}$ and $e_{2t=} Y_2 - \widehat{Y_2}$ (where Y_1 and Y_2 represent the realised values). If $E(d_t) > 0$ the second forecast is better (the first one has a higher MSE than the second forecast), whereas if $E(d_t) < 0$ the first forecast is better than the second one (the second one has a higher MSE than the first forecast).

I started by comparing the ***naïve forecasts and the professional forecasts*** obtaining the results stated in *Output 1*. In this case I could not reject the null hypothesis for every confidence interval (p-value = 0.1806). This means that the two models could have the *same predictive accuracy*. Also, the coefficient is close to zero, even if negative; this means that the naïve forecast is doing slightly better than the professional forecasts in terms of predictive accuracy.

Then I compared the ***professional forecasts with the constant expectations***, obtaining the results stated in *Output 2*. As it is possible to see from the output of this DM test, the two forecast could have *different predictive ability*, since the p-value (0.0079) suggest rejecting the null hypothesis at a 99% confidence interval. Looking at the estimated coefficient of C, we can observe that the professional forecasts produce more accurate results than the one obtained using constant expectations (since the sign of C is positive, so the RSS of constant expectations is higher than the one of professional forecasters).

Finally, I compared ***naïve and constant expectations***, obtaining the results stated in *Output 3*. As it is possible to see from the output of this DM test, the two forecast could have *different predictive ability*, since the p-value (0.0209) suggest rejecting the null hypothesis at a 95% confidence interval. Looking at the estimated coefficient of C, we can observe that the naïve forecasts produce more accurate results than the one obtained using constant expectations (since the coefficient is negative, so the RSS of constant expectations is higher than the one of naïve expectations).

CONCLUSIONS:

Thanks to the analysis ran on this sample, it is possible to conclude that the constant expectations method, that take as expectation for inflation its target value (2%), is not a good way for forming expectations on inflation since its accuracy is very low (or at least lower than the accuracy of the other two methods studied). This result was expected since the constant expectation method is a form of bounded rationality. There is no corrections of private agents expectational errors and this implies that the central bank can permanently raise output by tolerating persistently high inflation. For these reasons and for the results obtained by the analysis ran, this method is ill-advised when it comes to predict inflation or forming expectations on it.

On the sample studied in this analysis, the naïve expectations, and rational expectations (SPF) result to have more or less the same predictive ability, so they are both great methods when it comes to forecasting inflation. In this case the naive expectations results even better than the rational expectations, but we always must bear in mind that the naïve expectations present a persistent bias, both in forecast error and output gap, whereas under rational expectations they are unbiased. So, it is hard to definitely answer the research question stated at the beginning, because each method has its pros and cons, but in this case, it is possible to conclude that under both naïve and rational expectations we obtained reasonable results, so it is acceptable to use these two methods when it comes to making expectation about inflation.

GRAPHS and OUTPUTS:

Figure 1 – HICP Inflation rate (%) euro area between 1999Q4 and 2020Q1

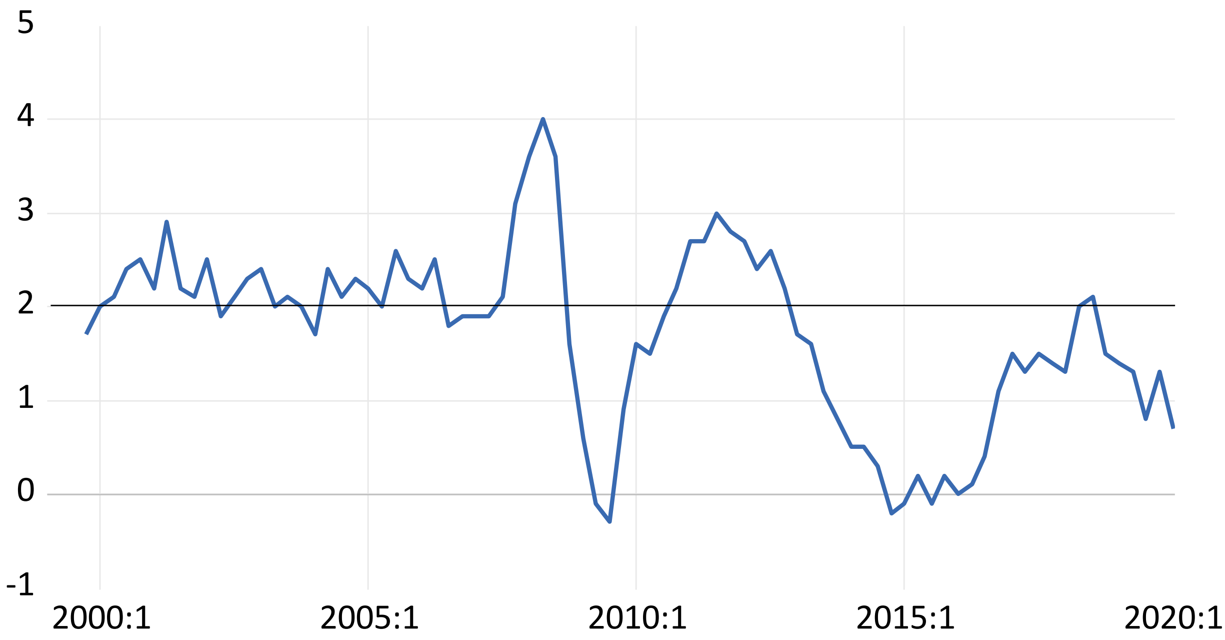


Figure 2 – Comparison between results obtained from the different forecast methods and realised values (2015Q1 - 2020Q1)

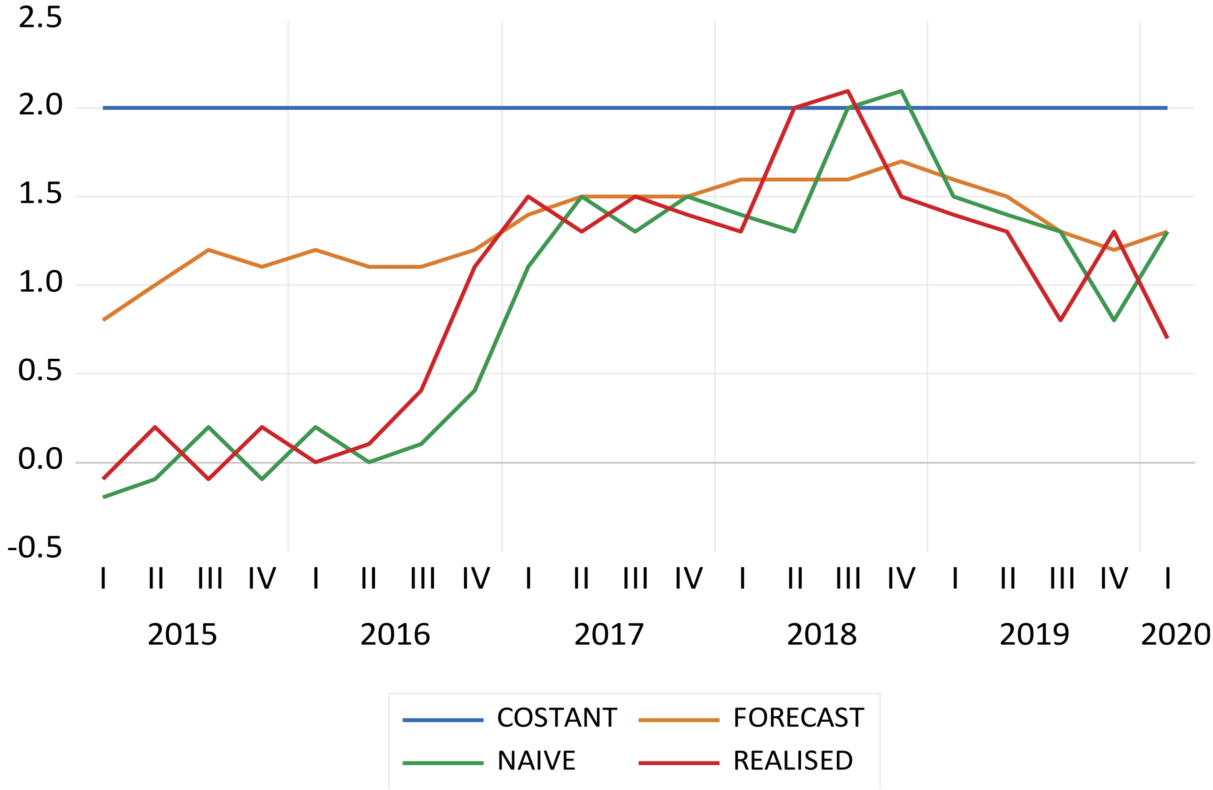
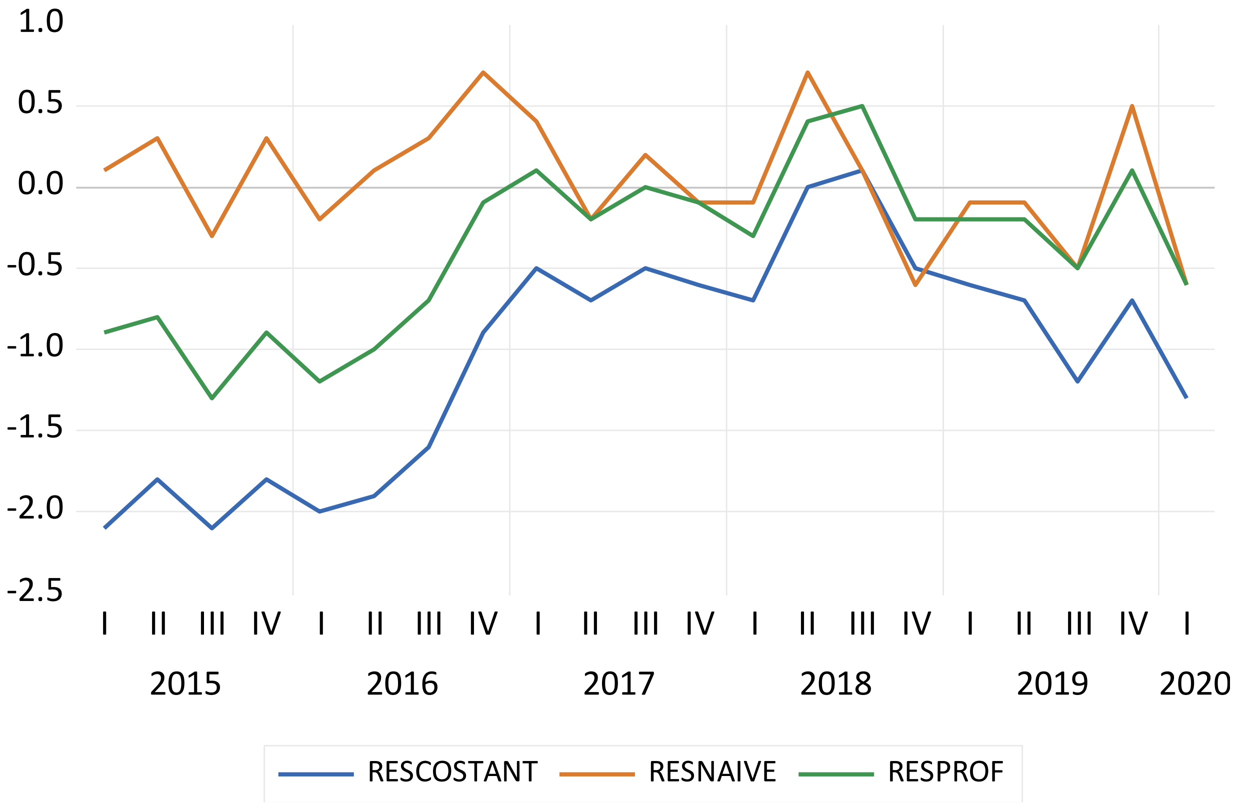


Figure 3 – Residuals of constant, naïve, and professional forecasts



Output 1 – Diebold and Mariano test to compare naïve forecasts and the professional forecasts

Dependent Variable: RESNAIVE^2-RESPROF^2
Method: Least Squares
Date: 04/02/22 Time: 15:31
Sample: 2015Q1 2020Q1
Included observations: 21
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COSTANT	-0.125714	0.090618	-1.387300	0.1806

R-squared	0.000000	Mean dependent var	-0.251429
Adjusted R-squared	0.000000	S.D. dependent var	0.564918
S.E. of regression	0.564918	Akaike info criterion	1.742177
Sum squared resid	6.382657	Schwarz criterion	1.791916
Log likelihood	-17.29286	Hannan-Quinn criter.	1.752972
Durbin-Watson stat	0.764353		

Output 2 – Diebold and Mariano test to compare constant expectations forecasts and the professional forecasts

Dependent Variable: RESCOSTANT^2-RESPROF^2
Method: Least Squares
Date: 04/02/22 Time: 15:57
Sample: 2015Q1 2020Q1
Included observations: 21
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.174286	0.398096	2.949754	0.0079

R-squared	0.000000	Mean dependent var	1.174286
Adjusted R-squared	0.000000	S.D. dependent var	1.157772
S.E. of regression	1.157772	Akaike info criterion	3.177320
Sum squared resid	26.80871	Schwarz criterion	3.227059
Log likelihood	-32.36186	Hannan-Quinn criter.	3.188114
Durbin-Watson stat	0.214792		

Output 3 – Diebold and Mariano test to compare constant expectations forecasts and naïve forecasts

Dependent Variable: RESNAIVE^2-RESCOSTANT^2
Method: Least Squares
Date: 04/02/22 Time: 15:53
Sample: 2015Q1 2020Q1
Included observations: 21
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.425714	0.568627	-2.507294	0.0209

R-squared	0.000000	Mean dependent var	-1.425714
Adjusted R-squared	0.000000	S.D. dependent var	1.650480
S.E. of regression	1.650480	Akaike info criterion	3.886458
Sum squared resid	54.48171	Schwarz criterion	3.936197
Log likelihood	-39.80781	Hannan-Quinn criter.	3.897253
Durbin-Watson stat	0.280430		