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The Bias and Efficiency of the ECB Inflation Projections: a State Dependent Analysis *

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Abstract

We test for bias and efficiency of the ECB inflation forecasts using a confidential dataset of ECB macroeconomic quarterly projections. We investigate whether the properties of the forecasts depend on the level of inflation, by distinguishing whether the inflation observed by the ECB at the time of forecasting is above or below the target. The forecasts are unbiased and efficient on average, however there is evidence of state dependence. In particular, the ECB tends to overpredict (underpredict) inflation at intermediate forecast horizons when inflation is below (above) target. The magnitude of the bias is larger when inflation is above the target. These results hold even after accounting for errors in the external assumptions. We also find evidence of inefficiency, in the form of underreaction to news, but only when inflation is above the target. Our findings bear important implications for the ECB forecasting process and ultimately for its communication strategy.

Keywords: Forecast Evaluation, Forecast Efficiency, Inflation Forecasts, Central Bank Communication

JEL classification: C12, C22, C53, E31, E52

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1 Introduction

Forecasting is an essential part of monetary policy making and published forecasts are at the core of central bank communication strategy, particularly for central banks targeting inflation. In fact, central bank inflation forecasts affect private sector expectations (see e.g. Fujiwara (2005), Hubert (2014, 2015, 2017) and Lyziak and Paloviita (2018)). Inflation projections published by monetary authorities are likely to gain further prominence in expectations management and serve as an additional policy tool. In the current environment of low interest rates and low inflation, as the maneuvering space of traditional tools is limited, policies directly impacting agents' inflation expectations can be used to stabilize economic conditions (Coibion et al., 2020). In addition, as central banks reconsider their strategies and assess make-up rules such as average inflation targeting, published forecasts might be used to create the expectation that inflation will overshoot its target.

However, published inflation projections have gone under scrutiny. The accuracy of central banks' forecasts decreased during the financial crisis (Potter (2011), Stockton (2012), Alessi et al. (2014), Fawcett et al. (2015)). Also, following the crisis many monetary authorities have consistently overestimated the rate of inflation (Iversen et al. (2016), Kontogeorgos and Lambrias (2019)), which has remained persistently below target. Repeated large and systematic projection errors pose a challenge for central banks as these errors may increase the risk of deanchoring of inflation expectations and deteriorate the credibility of monetary authorities.

Against this background we analyze the properties of the Eurosystem/European Central Bank staff (hereafter ECB) projections for inflation. First, we check whether the forecasts are biased by testing whether the forecast errors have mean zero (Holden and Peel, 1990). Second, we investigate whether projections are efficient by testing whether the ex-post forecast error is uncorrelated with the previous forecast revisions, following Nordhaus (1987) and Coibion and Gorodnichenko (2015).

As a novel contribution we relate bias and efficiency to the economic conditions at the time of forecasting. Specifically, we ask whether systematic forecast errors are related to the level of inflation, by distinguishing whether inflation is above or below target when the forecasts are made. We conjecture that, because of the ECB price stability mandate, the level of inflation observed at the time of forecasting might influence the way in which new information is incorporated in the forecasts.

We analyze the ECB projections for the Euro Area HICP inflation rate. We focus only on inflation because the mandate of the ECB is defined in terms of price stability. Our data include real time estimates of current-quarter values and real time projections until eight quarters ahead. Note that in every quarter the ECB publishes annual projections for full calendar years, while our dataset includes original confidential quarterly projections, which are unavailable to the public.[1]

On average, we find no sign of bias nor inefficiency in inflation forecasts. However, we document a significant difference in the properties of the forecasts depending on the level of inflation at the time of forecasting. In particular, we detect a systematic bias, both statistically and economically significant, for medium term forecasts when conditioning on the level of inflation. This suggests that when inflation is lower (higher) than the target, the ECB tends to overpredict (underpredict) inflation. Therefore, we conclude that there is a systematic bias towards the target. We also document that the magnitude of the bias is considerably larger in absolute value when inflation is above the target.

The ECB projections are conditional forecasts, i.e. they are based on assumptions regarding a path of future values of relevant macroeconomic and financial variables. One might argue that systematic errors in these external assumptions might result into systematic errors in inflation forecasts. However, we find that, while the prediction errors in inflation are correlated with errors in the external assumptions, the inflation forecasts exhibit a significant systematic bias even after controlling for errors in these assumptions.

Biased forecasts are not necessarily irrational. Capistran (2008) ascribes the bias to an asymmetric loss function of the central bank, and shows that overprediction occurres when the monetary authority is more concerned about inflation above than below target. Charemza and Ladley (2016) show that a bias towards the target can result from the voting system and dynamics within the monetary policy committee. Herbert (2020) shows that it is optimal for the monetary authority to systematically overpredict (underpredict) aggregate conditions in recessions (expansions) in order to bias agents' beliefs, if agents have heterogeneous priors about the state of the economy. In a laboratory experiment, Duffy and Heinemann (2021) find that their test subject central bankers act strategically and make announcements that deviate from the "true" forecasts in order to manage agents' inflation expectations. While we do not identify the source of the state dependent bias, we

[1]The ECB started to publish quarterly projections in 2017Q2.

note that it is consistent with a strategic behaviour of a central bank aiming at steering expectations towards the target.

Regarding efficiency, we find that forecast revisions do predict forecast errors, but only when the deviations of inflation from the target are positive. In particular, when inflation is above the target, the estimated coefficient associated with the revisions is positive. This means that, for example, when the revision is positive, i.e. the new forecast is higher than the forecast made in the previous period, the forecast error is positive, i.e. the ECB underpredicts, so the forecast was not revised "enough". These findings point to an "under-reaction" of the ECB to new information, and can be due to information rigidities (Coibion and Gorodnichenko, 2015) or smoothing (Tillman, 2011).[2]

A large number of papers has analyzed the bias and efficiency of the forecasts produced by the Federal Reserve: Clements et al. (2007), Capistran (2008), Sinclair et al. (2010), Messina et al. (2015) and El-Shagi et al. (2016) for Greenbook forecasts, and Romer and Romer (2008) and Arai (2016) for FOMC. We depart from these studies in two dimensions: first, we analyze bias and efficiency of the ECB projections, which have not been studied previously, with the exception of Kontogeorgos and Lambrias (2019).[3] Note that several institutional differences distinguish the ECB from the Federal Reserve. The ECB's mandate is defined in terms of price stability, while the Fed has a dual mandate. The Fed has an explicit target of 2% for inflation, while the ECB aims at keeping inflation below, but close to 2%. Finally, the Fed produces two sets of forecasts: the Tealbook (earlier Greenbook) forecasts, which represent staff forecasts and are kept confidential for five years, and the FOMC projections, which summarize the forecasts of the FOMC members and are available to the public in real time. In contrast, the ECB projections are staff forecasts, similarly to the Tealbook, but they are released to the public in the same quarter in which they are produced, like the FOMC forecasts. These differences might affect the properties of the forecasts and therefore the findings documented for the Fed's forecasts might not hold in the ECB context.

Second, only few papers investigate whether the properties of the forecasts are state dependent, and they define the states according to the phases of the business cycle, i.e. recessions or expansions,

[2]Some recent studies analyze forecast efficiency using survey-based expectations of households and professional forecasters and report conflicting results regarding under- or over-reaction to news (Fuhrer (2018), Angeletos et al. (2020), Bordalo et al. (2020), Kohlhas and Walther (2021)). These studies ignore strategic motives in monetary policy communication, which might be present in forecasts made by an inflation-targeting central bank.

[3]Kontogeorgos and Lambrias (2019) focus on forecasting accuracy, efficiency, rationality and optimality and conclude that the ECB projections for inflation are unbiased and efficient on average.

at the time when the outcome is realized. We differ because we investigate whether the properties of the forecasts are related to the *level of inflation* with respect to the target and we define the state based on the level of inflation *at the time of forecasting*. Therefore, we relate bias and efficiency to the ECB mandate and its forecasting process.

The rest of the paper is organized as follows: section 2 presents the data, section 3 summarizes the baseline econometric framework and empirical results, section 4 describes the state dependent analysis and results, section 5 concludes.

2 Data

We analyze the ECB projections for the year-over-year Euro Area Harmonized Index of Consumer Prices (HICP) inflation rate at the quarterly frequency. Our data include real time estimates of current-quarter values (nowcast estimates) and real time projections until eight quarters ahead. Note that in every quarter the ECB publishes *annual* projections for full calendar years, while our dataset includes original confidential *quarterly* projections, which are unavailable to the public. The sample runs from 1999Q4 to 2019Q4, resulting in 81 observations for forecast evaluation of the nowcast and 73 of the eight step-ahead forecasts.[4]

The macroeconomic projections are produced by the ECB staff in March and September, and by both ECB staff and experts in national central banks in June and December. However, in each quarter monthly inflation projections are provided by national central bank experts for forecasting horizon up to 11 months, through the Narrow Inflation Projection Exercise (NIPE). Finally, the projections are based on a series of assumptions and are produced combining models as well as expert knowledge and judgement.[5] The macroeconomic projections play a key role in monetary policy decision-making, as the forecasts are presented to the Governing Council ahead of its monetary policy deliberations.

Panel A of Figure (1) shows the year-over-year Euro Area HICP inflation from 1999Q4 to 2019Q4. Our sample period includes the relatively stable pre-crisis years, followed by the financial crisis, the sovereign debt crisis and more recently a period of persistently low inflation.

[4] We evaluate the forecasts against the vintage published by Eurostat in April 2020. We do not experiment with other vintages since both means and medians of data revisions of real-time observed inflation are close to zero.

[5] Alessi et al. (2014) and Kontogeorgos and Lambrias (2019) provide further details on the ECB forecasting process.

Panel B of Figure (1) summarizes the projections for different forecast horizons over the whole sample. For each forecast origin the figure shows selected quantiles of the projected path from nowcasting to two years ahead. The solid lines show the median projection for each horizon conditional on the rate of inflation in the quarter when the forecasts are produced. In particular, the blue (red) line shows the median inflation forecasts if inflation is above (below) 1.8% at the time of forecasting. The red (blue) shaded areas denote the 10th and 25th (75th and 90th) percentiles of the distribution conditional on inflation being below (above) target. Regardless of their initial level, the forecasts revert towards the target rather quickly, within the first 4 quarters, and flatten out at longer horizons. Also, when inflation is above target at the time of forecasting, there is evidence of undershooting (forecasting inflation to fall below target) from 4 to 10 quarters ahead.

3 Testing for Bias and Efficiency

In this section, we analyze the properties of the ECB inflation forecasts. First, we test for *bias* by testing whether the forecast errors have zero mean (Holden and Peel (1990), Capistran (2008), Kontogeorgos and Lambrias (2019)):

$$\epsilon_{t,h} = y_t - y_{t|t-h} = \alpha_{0,h} + u_{t,h} \qquad h = 0, ..8 \tag{1}$$

where $\epsilon_{t,h}$ is the h-step ahead forecast error, y_t is the realized value and $y_{t|t-h}$ is the forecast of y_t made at time $t-h$. Then, the null of unbiasedness is $\alpha_{0,h} = 0$.

Second, we investigate whether projections are *inefficient*, i.e. whether there was additional information readily available to the forecasters that could have been used to improve the accuracy of the projections. Specifically, we test whether the forecast error is uncorrelated with the previous forecast revision: if the forecast revision between $t-h-1$ and $t-h$ can predict the forecast error, then the information that became available at $t-h$ was not properly incorporated in the revised projections, i.e. the forecasts were overly or insufficiently adjusted.[6] This approach was originally suggested by Nordhaus (1987) and has been recently adopted by Lahiri and Sheng (2008), Coibion and Gorodnichenko (2015), Fuhrer (2018) and Bordalo et al. (2020). Forecast efficiency can be

[6]The validity of our results is confirmed using alternative tests of bias and efficiency, following Mincer and Zarnowitz (1969) and Loungani et al. (2013). Results for these exercises are available from the authors upon request.

tested through the following regression model:

$$\epsilon_{t,h} = \beta_{0,h} + \beta_{1,h} r_{t,h} + e_{t,h} \qquad h = 0, ..7 \tag{2}$$

where $r_{t,h} = y_{t|t-h} - y_{t|t-h-1}$ is the forecast revision between $t-h-1$ and $t-h$. Then, the null of efficiency is $\beta_{0,h} = \beta_{1,h} = 0$. A positive correlation between ex post forecast error and ex ante forecast revision implies that not all new information that became available in the prior period was properly utilized. In contrast, a negative correlation can be interpreted as overreaction to new information, i.e. forecasts are revised unnecessarily.

Coibion and Gorodnichenko (2015) motivate the regression model (2) as the empirical specification of two alternative theoretical rational expectations models of information frictions: a sticky-information model, in which agents update their information set infrequently due to fixed costs of acquiring information, and a noisy-information model. In the latter, agents can never observe the true state, so they update their beliefs about the fundamentals through a signal extraction problem by averaging their prior beliefs and a signal about the underlying fundamentals. Both models assume that expectations are rational and imply the same empirical relationship between ex ante forecast revisions and ex post forecast errors. Therefore, equation (2) can be used to test for full-information rational expectations (FIRE) and a rejection of the null points towards the presence of information rigidities. The coefficient $\beta_{1,h}$ determines the degree of information rigidities, either the probability of not acquiring new information in the sticky-information model or the weight assigned to prior beliefs in the noisy-information model.[7] Note that the FIRE hypothesis has been empirically tested mainly on survey data because the predictability in model (2) holds for the average forecasts error across agents. However, since the ECB inflation projections are the result of averaging across many forecasters and institutions (ECB and Euro Area national central banks), which employ thick modelling and expert judgement, we argue that the regression model (2) can be interpreted through the lens of the sticky information models described in Coibion and Gorodnichenko (2015).

Panel A of Table (1) shows the estimated coefficients for regressions (1) for each forecast horizon $h = 0, .., 8$ as well as the heteroskedasticity and autocorrelation corrected standard errors. Except

[7] Although we cannot empirically distinguish between the two models, we believe the noisy-information model is a better description of the information rigidities associated with the ECB macroeconomic forecasting process, given the amount of resources the Eurosystem allocates to the forecasting process each quarter.

for the nowcasting horizon, the constant is positive and largest for horizons 3 through 6. A positive coefficient implies that on average the outcome is larger than the forecasts, i.e. there is a tendency to underpredict. However, given that the coefficient associated with the constant is not statistically significantly different from zero at any forecast horizon, we find no systematic bias in the ECB inflation projections.

Results for efficiency are shown in the Panel A of Table (2). Including the forecast revision as regressor does not alter the estimate for the constant.[8] The coefficients associated with the revisions are positive (under-reaction) for horizons up to 3 quarters ahead and negative (over-reaction) at longer horizons. However, none of the coefficient is statistically significant, implying that forecast revisions have no predictive power for the forecast errors at any horizon. Therefore, we find no evidence of inefficiency nor of departure from FIRE.

Overall, our regressions indicate that the ECB inflation projections for all forecast horizons are unbiased and efficient on average. These findings confirm the results in Kontogeorgos and Lambrias (2019) who conclude that ECB inflation projections are optimal and rational using the same confidential dataset with sample ending in 2016Q3.

4 Testing for Bias and Efficiency: State Dependent Analysis

Next, we investigate whether the properties of the projection errors are related to economic conditions. Previous studies have documented the presence of systematic bias related to the state of the economy both in the projections of monetary authorities and in survey data (Herbert (2020), Sinclair et al. (2010), Messina et al. (2015), Charemza and Ladley (2016)). If those systematic errors are opposite in sign and cancel out, then we would fail to reject the null that the coefficient $\alpha_{0,h}$ in the regression model (1) is statistically different from zero. Therefore, we would conclude that the forecast errors are unbiased, because they are zero on average.

In order to test whether errors are systematic conditional on the state of the economy, we can simply add a dummy variable to equation (1):

$$\epsilon_{t,h} = \alpha_{0,h} + \alpha_{1,h} d_{t-h} + u_{t,h} \qquad h = 0, ..8 \tag{3}$$

[8] Table (3) in the Appendix reports some descriptive statistics for the forecast revisions.

where d_{t-h} is a dummy variable defined below. Then, the null of unbiasedness is $\alpha_{0,h} = \alpha_{1,h} = 0$.

The state of the economy might also influence how new information is incorporated into the forecasts. Then, similarly to (3) and following Messina et al. (2015) we can modify equation (2) to test whether forecast revisions help predict forecast errors only during specific periods:

$$\epsilon_{t,h} = \beta_{0,h} + \beta_{1,h}d_{t-h} + \beta_{2,h}r_{t,h} + \beta_{3,h}r_{t,h}d_{t-h} + e_{t,h} \qquad h = 0, ..7 \tag{4}$$

If the coefficients $\beta_{2,h}$ and $\beta_{3,h}$ are not statistically significantly different from zero, this indicates that the forecast errors cannot be explained by the forecast revisions. If instead the coefficients on the revision or on the interaction term are significantly different from zero, then the new information available at time $t-h$ is not correctly incorporated in the updated forecasts. Including the interaction term $r_{t,h}d_{t-h}$ allows for the possibility that the ECB revises forecasts differently in the different states of the economy defined by d_{t-h}. For example, it might weight information differently during high vs low inflation episodes.

4.1 Definition of States

We investigate whether systematic errors are related to particular states, classified according to the level of inflation when the forecasts are made. In particular, we consider whether the inflation rate observed by the ECB is *above* or *below* the target.

In defining the states (i.e. constructing the dummies in (3) and (4)), we carefully approximate the information set available to the ECB during the projection exercise. Therefore, consistent with the cutoff dates of the forecasting process, we assume that the ECB takes into account both the previous quarter year-over-year inflation rate $\left(\pi^{Q}_{t-1}\right)$ and the year-over-year inflation of the first month of the current quarter $\left(\pi^{M1}_{t}\right)$. Then, the observed inflation measure π^{I}_{t} is the simple average of the two: $\pi^{I}_{t} = \left(\pi^{Q}_{t-1} + \pi^{M1}_{t}\right)/2$.

Note that we use d_{t-h} rather than d_t in equations (3) and (4). Therefore, we test whether the level of inflation known when the forecasts were made, rather than realized, affects the characteristics of the forecasting process. This approach distinguishes our analysis from most of the studies available in the literature.

We test for state dependent bias by defining d_{t-h} to take the value of one if our constructed measure of observed inflation π_t^I is below the inflation target π^* in the quarter when the forecast is made:

$$d_{t-h} = \begin{cases} 1 & \text{if } \pi_{t-h}^I < \pi^* \\ 0 & \text{otherwise} \end{cases}$$

The ECB price stability definition is ambiguous with respect to the level of the target. In 2003 the ECB's Governing Council stated that 'in the pursuit of price stability it aims to maintain inflation rates below, but close to, 2% over the medium term'. Following Hartmann and Smets (2018) we choose 1.8% as the threshold value for the definition of the dummy variable d_{t-h}.[9] This results in 45% of observations taking the value of one, indicated as shaded areas in Figure (1). While most episodes occur during the latest portion of the sample (after 2013Q2), inflation has dropped below the target also after the financial crisis (2009Q1-2010Q3) and in a few instances in the earlier portion of the sample.

4.2 Results

Panel B of Table (1) shows the results for bias (equation 3). The coefficients for the constant up to $h = 5$ and for the dummy from $h = 2$ to $h = 4$ are highly significant. When the dummy takes the value of one (zero), the fitted values from the regression are negative (positive), which indicates that the forecast is higher (lower) than the realized value. This means that when inflation is below (above) 1.8%, the ECB tends to overpredict (underpredict) inflation.[10] Interestingly, the size of this bias, measured as the sum of the coefficients α_0 and α_1, increases with the forecast horizon up to $h = 4$, and it declines till $h = 8$. The bias is not only statistically but also economically significant: when inflation is above the target, it ranges from 0.09p.p. for one quarter ahead to 0.37p.p. for four quarters ahead. Overall, we document that the forecasts are biased towards the target at short and intermediate forecast horizons, between two and four quarters ahead. Note that the bias is asymmetric in its magnitude: it is larger in absolute value when inflation is above target than when

[9] Hartmann and Smets (2018) estimate the reaction functions of the ECB's Governing Council using the same dataset. They conclude that the ECB inflation aim is 1.8%. This number is in line with estimates by Paloviita et al. (2021) and Rostagno et al. (2019) based on the same data and alternative approaches.

[10] As mentioned in the Introduction, some papers define state dependence based on the phases of the business cycle, i.e. recessions or expansions. For completeness, we repeat our analysis according to this classification. Then, the dummy takes the value of one when output growth is below the 25th quantile of its distribution. As shown in Table (7) and (11) of the Appendix, in this case we find no state dependent bias nor inefficiency.

below (e.g. fivefold for $h = 3$).

The literature has suggested several explanations for systematic bias in central banks' forecasts. Capistran (2008) shows that if a central bank considers inflation above the target more (less) costly than inflation below the target, then it should systematically over(under)-predict inflation. In his model the parameter that determines the level of asymmetry in the loss function is constant. This explanation is difficult to reconcile with our findings because it does not allow for the bias to be state dependent.[11] Romer and Romer (2008) find that Greenbook forecasts are of higher quality than FOMC projections. The difference in accuracy can be explained by distinct objectives of these two sets of forecasts or by different loss functions of the FOMC members and the Fed's staff (Ellison and Sargent, 2012). The Greenbook forecasts are confidential staff forecasts which aim at being as accurate as possible, while the FOMC forecasts, which are available in real time, are used for communication purposes. The ECB produces only one set of forecasts, which serve as inputs for the Governing Council decisions and are released immediately. Therefore, if there is a strategic component in published inflation projections, there might be a tension between accuracy of forecasts and management of expectations, resulting in a systematic bias. Strategic communication motives are put forward as an explanation for bias also by Gomez-Barrero and Parra-Polania (2014), which argue that a central bank might use its published inflation projections to steer inflation expectations of private agents. In their stylized model the incentive to manage expectations is higher at intermediate horizons, because in the medium term the central bank has both relevant private information about future shocks hitting the economy and the possibility to affect future inflation through its influence on private agents' expectations. In a laboratory experiment, Duffy and Heinemann (2021) provide support to this theory and find that test subject central bankers make announcements that deviate from the "true" forecasts in order to manage agents' inflation expectations.

While we do not identify the specific reason for the systematic, state-dependent bias in the ECB projections, we believe it might be consistent with the management of inflation expectations. Also, the bias is present up to five quarters ahead, consistent with the medium-term orientation of the ECB policy making and the lags in the transmission mechanism of monetary policy.

[11] To be consistent with our results the model should be modified to allow for a state dependent asymmetry parameter in the loss function of the central bank. Moreover, the size of the asymmetry parameter should differ across the two states, to reflect our finding that the magnitude of the bias is larger when inflation is above the target.

Panel B of Table (2) shows the estimation results for the efficiency regression in (4). Similarly to the bias results, the constant is significant for all (but one) forecasting horizons up to $h = 5$. The dummy is also significant at intermediate horizons and retains the negative sign observed in Table (1). Moreover, for $h = 3$ we find evidence that the forecast revisions do predict the forecast errors. In particular, when inflation is above the target, the forecasts are not revised "enough" as the estimated coefficient for the revisions is positive. Although not significant, the coefficient associated with the interaction term between the dummy and the revisions is negative at $h = 3$. However, the sum of $\beta_{2,3}$ and $\beta_{3,3}$ is still positive but smaller than $\beta_{2,3}$. Then, the ECB adjusts its forecasts less in response to new information when inflation is above target.[12]

The underutilization of information documented in Panel B of Table (2) has been interpreted as evidence of smoothing or information rigidities. Central banks might be cautious about changing their projections, because such changes convey a message about future economic conditions. Alternatively, policymakers might be concerned for their reputation as forecasters and might prefer to avoid large and frequent revisions (Scotese (1994), Tillman (2011)). The coefficient associated with the revision is significant only in the state dependent regression, and the conservatism of the ECB projections is stronger when inflation is above the target. Therefore, when inflation is high, and possibly the economic environment is more volatile, the staff may only partially revise its previous forecast in order to avoid having to reverse the changes incorporated into the new forecast, if subsequent data reverse the earlier movements. As a second explanation, our findings can also be interpreted as a rejection of the FIRE hypothesis in favor of models of information rigidities. According to the noisy-information model, which we believe provides a better description of the ECB context than the sticky information model, and given the estimates of the parameters $\beta_{2,3}$ and $\beta_{3,3}$, the relative weight put on new information is 0.64 when inflation is above target and 0.77 when inflation is below target. This again reflects higher conservatism when inflation is high. Note that our results do not hold on average, but they are state dependent. Then, models that deviate from FIRE might need to accommodate an endogenous degree of information rigidities to replicate

[12]We check the robustness of our results for different values of the target. Results are stronger if we assume a lower target ($\pi^* = 1.7$), while the coefficients retain their sign but lose significance if we assume a higher target, ($\pi^* = 1.9$), see Table (5) and (9) of the Appendix. We further repeat our analysis using alternative assumptions regarding the information set available to the ECB at the time of forecasting. As shown in Table (6) and (10) of the Appendix, results are qualitatively unchanged if we assume the inflation rate observed by the ECB is the nowcast or actual inflation. Finally, we confirm that state dependent bias and inefficiency hold in the published yearly projections, see Table (8) and (12) in the Appendix.

this finding.

4.3 The Role of External Assumptions

The ECB projections are conditional on a number of external assumptions, i.e. technical assumptions regarding the future developments of the international economic environment.[13] Then, one could argue that *systematic* errors found in the inflation projections might be driven by *systematic* errors in external assumptions, which result in bias and inefficiency.

Given our access to the assumptions for the external variables, we are in a unique position to test this conjecture. We focus on three variables which are considered the main drivers of inflation: a short term interest rate (3M EURIBOR), the EURUSD exchange rate and the Brent Crude oil prices. The assumptions made by the ECB for the oil prices and interest rates are obtained from futures prices while the exchange rate is assumed to be constant through the forecast horizon, consistent with the prediction from a random walk model. Note that these conditioning assumptions are completely exogenous, therefore not affected by the ECB projections published in the same quarter.

In order to assess the role of external assumptions in inflation projections, we add the forecast errors in external assumptions as additional predictors in the bias regression models (1) and (3). Define the error in the external assumption i at time t for horizon h as:

$$\zeta^i_{t,h} = x^i_t - x^i_{t|t-h} \qquad i = 1, .., 3;\ h = 0, ..8 \tag{5}$$

where x^i_t is the realization and $x^i_{t|t-h}$ is the value assumed at $t-h$ for date t. The variable x^i_t is the level of interest rate or exchange rate, or the growth rate of oil prices. First, we test whether the errors in the external assumptions are biased in both the unconditional and state dependent cases:

$$\zeta^i_{t,h} = \alpha^i_0 + e^i_{t,h} \qquad i = 1, .., 3; h = 0, ..8 \tag{6}$$

$$\zeta^i_{t,h} = \alpha^i_0 + \alpha^i_{1,h} d_{t-h} + e^i_{t,h} \qquad i = 1, .., 3; h = 0, ..8 \tag{7}$$

[13] Kontogeorgos and Lambrias (2019) find that errors in these external assumptions decrease the accuracy of the ECB projections for inflation.

where d_{t-h} is the dummy constructed as in 4.1. If we were to find some systematic bias in the conditional model, one could argue that it explains the systematic bias observed in the inflation forecast errors. Then, we run the following regression, which includes the error $\zeta^i_{t,h}$ as an additional predictor:

$$\epsilon_{t,h} = \beta^i_{0,h} + \beta^i_{1,h} d_{t-h} + \beta^i_{2,h} \zeta^i_{t,h} + u^i_{t,h} \qquad i = 1, .., 3; \quad h = 0, ..8 \tag{8}$$

where, $\epsilon_{t,h}$ is the forecast error for predicting inflation at forecast origin t for horizon h. If the estimated parameters $\beta^i_{0,h}$ and $\beta^i_{1,h}$ were not significant in (8), while $\beta^i_{2,h}$ were significant, the bias in the inflation forecasts could be attributed to the bias in the external assumptions.

Ideally, to carry out our investigation, we would first construct a counterfactual series of *adjusted* errors for inflation by using internal ECB models conditioned on the true realization of the external variables, and then check whether the adjusted errors are biased. However, we are unable to construct such counterfactual series based on the forecasting models used in real time or to include the ECB expert judgement. We think that our simple approach is sensible because if systematic errors in the external assumptions were driving the forecast errors, then the dummy should not have additional explanatory power.

Results for regressions (6) and (7) are displayed in Table (4) of the Appendix. Panel A shows that intercept term in the regressions for the short term rate is negative, meaning that on average the short term rate is assumed to be larger than the realized value. This holds at every horizon, although the coefficients are significant only at longer horizons. In the state dependent regressions the constant is still negative and significant, while the dummy is positive but not statistically significantly different from zero, suggesting that there is systematic bias only when inflation is above target. The bias is large in absolute terms, up to 70 basis points, when inflation is above target.

The results for the exchange rate show no evidence of bias on average (Panel B). However, when inflation is above (below) the target the exchange rate versus the US dollar is assumed to be weaker (stronger) than realized. The coefficients associated with the constant and the dummy are significant for all horizons higher than two and the bias increases with the horizon.

Finally, the oil price assumptions are not biased on average. In contrast, the state dependent analysis shows that at very short horizons there is evidence of underprediction (overprediction) when inflation is higher (lower) than the target. This is consistent with the systematic bias observed for inflation. However, the size of the bias is small, amounting to 0.06p.p. at most.

Results for regressions (8) are reported in Panel C1 through C3 of Table (1). Regardless of the external assumption considered, adding the forecast errors to the bias regression does not alter the sign, the magnitude nor the significance of the coefficients observed in Panel B of Table (1). The interest rate forecast errors are significant only at horizons one and two and enter positively, so that a larger forecast error for interest rates predicts a larger forecast error for inflation. Similarly, in the bias regression augmented by the exchange rate forecast errors, these errors are not significant. Finally, the oil price forecast errors are highly significant at short term horizons and exhibit a positive coefficient, implying that a higher forecast error for oil prices translates into a higher forecast error for inflation. While the magnitude of the coefficient is again unchanged, the constant and the dummy are significant only for three quarters ahead forecasts.

In sum, we find evidence of systematic over(under)prediction for medium term projections when inflation is lower (higher) than the target even when controlling for the errors in external assumptions.

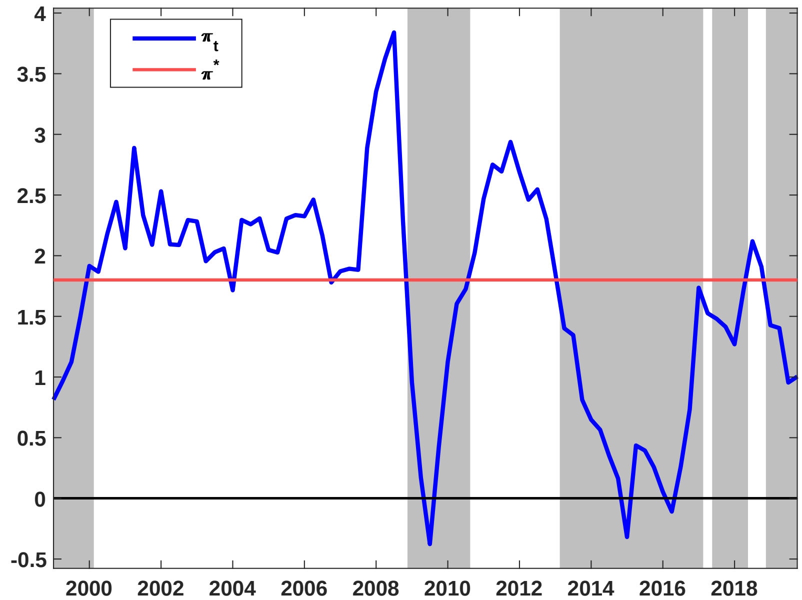
5 Conclusion

Using a confidential dataset of ECB macroeconomic quarterly projections we document three novel findings that relate the bias and efficiency of the ECB inflation forecasts to the level of inflation at the time of forecasting: (i) a systematic bias towards the target at medium horizons, which implies over (under) prediction when inflation is low (high); (ii) a larger bias when inflation is above the target; (iii) inefficiency, resulting in underutilization of new information at medium horizons when inflation is above target.

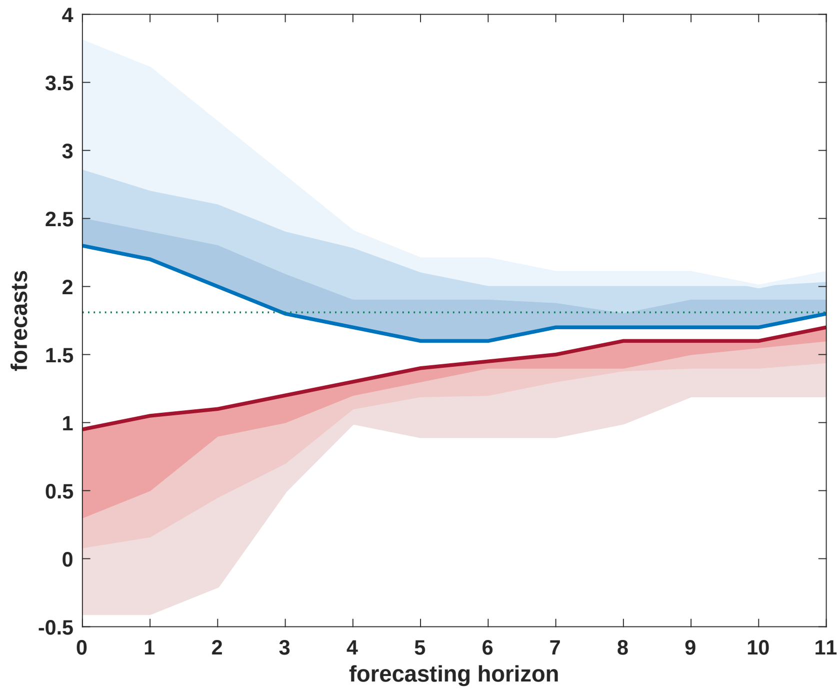
Our results suggest that looking at state dependence is crucial. We argue that theoretical models are unable to replicate the observed state dependence in bias and efficiency and hence, they might need to be reformulated in order to match these features of the forecasts. Given the lack of theoretical models that can simultaneously account for state dependent bias and inefficiency in central banks' forecasts, this paper has the potential to start a line of theoretical research that rationalizes these findings.

Our investigation of the properties of the published projections is relevant also from a policy perspective, in particular for the ongoing ECB strategy review: the forecasts form the basis for the monetary policy decisions of the ECB Governing Council and represent an important communication tool. While the reasons behind our findings are beyond the scope of this paper, we conjecture that the evidence of state dependent bias and inefficiency might be related to strategic motives in monetary policy communication. These are particularly strong at the intermediate horizons, reflecting the medium-term orientation of monetary policy making.

Figure 1: HICP Inflation and Inflation Projections



(a) Panel A: HICP Inflation and Distribution of States Across Time



(b) Panel B: ECB Projections for HICP Inflation: Paths

Panel A. The figure shows the year-over-year HICP inflation for the Euro Area and the periods in which inflation is below the target, i.e. 1.8% (shaded areas). Panel B. The figure shows for each forecasting horizon the maximum and minimum inflation projections, the 10^{th} and 25^{th} (75^{th} and 90^{th}) percentiles and the medians conditional on whether inflation was above or below the target (1.8%, green dashed line) during each projection exercise.

Table 1: Bias in ECB Inflation Forecasts

	Forecast Horizon								
$h =$	0	1	2	3	4	5	6	7	8
				Panel A: Overall Sample					
c	-0.02	0.03	0.07	0.11	0.13	0.14	0.11	0.07	0.02
	(0.01)	(0.04)	(0.08)	(0.11)	(0.14)	(0.15)	(0.15)	(0.16)	(0.16)
				Panel B: Asymmetry					
c	-0.03*	0.09*	0.19**	0.32***	0.37**	0.35*	0.31	0.22	0.14
	(0.02)	(0.05)	(0.09)	(0.13)	(0.16)	(0.18)	(0.19)	(0.20)	(0.20)
d_t	0.03	-0.11	-0.25*	-0.38*	-0.44*	-0.38	-0.34	-0.25	-0.16
	(0.03)	(0.08)	(0.15)	(0.20)	(0.27)	(0.29)	(0.30)	(0.32)	(0.33)
				Panel C1: Short Term Interest Rate					
c	-0.03*	0.11**	0.23**	0.37***	0.44**	0.46**	0.42**	0.33	0.26
	(0.02)	(0.05)	(0.09)	(0.13)	(0.17)	(0.19)	(0.20)	(0.21)	(0.22)
ζ_t	-0.12	0.36**	0.37**	0.27	0.24	0.25	0.21	0.17	0.17
	(0.20)	(0.13)	(0.14)	(0.13)	(0.12)	(0.09)	(0.08)	(0.07)	(0.07)
d_t	0.03	-0.14*	-0.28**	-0.41**	-0.48*	-0.44	-0.39	-0.28	-0.18
	(0.03)	(0.08)	(0.14)	(0.20)	(0.26)	(0.28)	(0.30)	(0.31)	(0.32)
				Panel C2: Exchange Rate					
c	-0.03	0.10**	0.19**	0.32**	0.34**	0.26	0.15	0.02	-0.10
	(0.02)	(0.05)	(0.09)	(0.13)	(0.17)	(0.19)	(0.19)	(0.19)	(0.18)
ζ_t	-0.72	-0.94	0.16	0.11	0.65	1.62	2.49	2.93	3.18
	(1.00)	(0.73)	(0.88)	(1.04)	(1.17)	(1.21)	(1.16)	(1.03)	(0.93)
d_t	0.03	-0.13*	-0.24	-0.37*	-0.38	-0.21	-0.03	0.14	0.28
	(0.03)	(0.08)	(0.15)	(0.22)	(0.28)	(0.31)	(0.31)	(0.30)	(0.30)
				Panel C3: Oil Prices					
c	-0.02	0.02	0.12	0.25**	0.29*	0.30*	0.27	0.19	0.10
	(0.02)	(0.04)	(0.09)	(0.13)	(0.17)	(0.17)	(0.18)	(0.18)	(0.18)
ζ_t	0.78***	1.66***	1.24***	1.18*	1.39	1.19	1.01	1.41	1.51
	(0.30)	(0.26)	(0.45)	(0.64)	(0.85)	(0.84)	(0.86)	(0.91)	(0.93)
d_t	0.01	-0.05	-0.18	-0.35*	-0.41	-0.40	-0.37	-0.25	-0.15
	(0.03)	(0.07)	(0.14)	(0.20)	(0.26)	(0.26)	(0.28)	(0.29)	(0.29)

Note: Estimated coefficients from regressions (1), (3) and (8). Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level. For regressions involving the short term interest rates, note that before 2006 an assumption of constant short term interest rates was used.

Table 2: Efficiency in ECB Inflation Forecasts

	Forecast Horizon							
$h =$	0	1	2	3	4	5	6	7
				Panel A: Overall Sample				
c	-0.02	0.02	0.05	0.09	0.12	0.12	0.09	0.04
	(0.01)	(0.04)	(0.08)	(0.12)	(0.16)	(0.16)	(0.17)	(0.17)
$r_{t,h}$	0.03	0.11	0.20	0.36	-0.09	-0.59	-0.26	-0.32
	(0.05)	(0.10)	(0.21)	(0.30)	(0.78)	(0.95)	(0.87)	(0.91)
				Panel B: Asymmetry				
c	-0.04*	0.06	0.16*	0.28**	0.37**	0.35**	0.30	0.20
	(0.02)	(0.05)	(0.09)	(0.12)	(0.16)	(0.18)	(0.19)	(0.20)
$r_{t,h}$	0.04	0.17	0.22	0.56*	0.11	-0.50	-0.18	-0.70
	(0.06)	(0.13)	(0.24)	(0.31)	(0.78)	(1.14)	(1.09)	(1.28)
d_t	0.03	-0.09	-0.22	-0.34*	-0.48*	-0.40	-0.38	-0.27
	(0.03)	(0.08)	(0.14)	(0.19)	(0.27)	(0.30)	(0.31)	(0.33)
$r_{t,h} \times d_t$	0.00	-0.18	-0.06	-0.26	0.10	0.65	0.26	0.29
	(0.09)	(0.19)	(0.36)	(0.49)	(1.37)	(1.69)	(1.55)	(1.69)

Note: Estimated coefficients from regressions (2) and (4). Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

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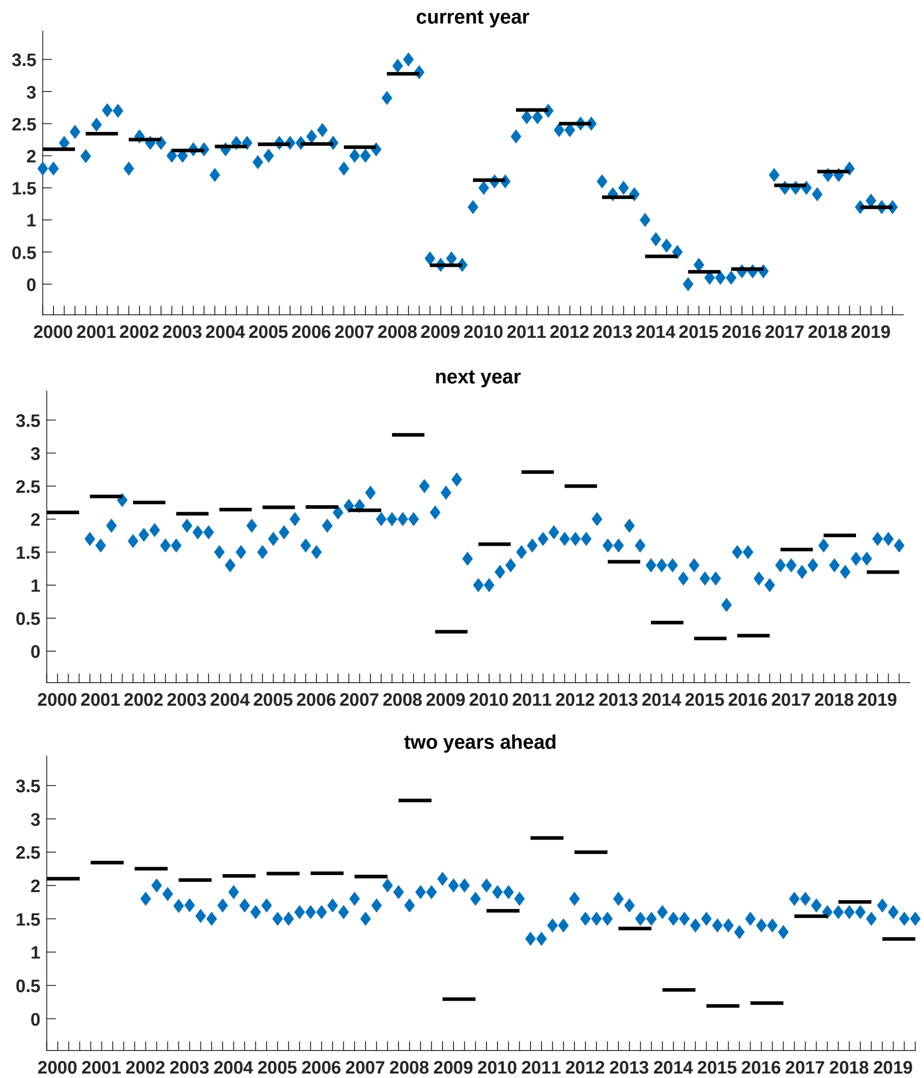
Appendix

Figure (2) reports the actual realization of inflation and the *published* ECB inflation projections for the full calendar years 2000-2019 distinguishing among three forecasting horizons: the current year (top panel), one year ahead (middle) and two years ahead (bottom). Solid lines indicate the actual data, while diamonds denote the projections made in each quarter. Unsurprisingly, the forecasts tend to be closer to the actual values towards the end of the year, when approaching the release date. As expected, nowcasts seem more accurate than longer horizons forecasts. Also, for one year forecasting horizons, it is apparent that the forecast errors (actual minus forecast) were the largest for 2009 while for two year forecasting horizons they were the largest for 2015-2016. Also, as the forecast horizon increases, the forecasts tend to be closer to the target.

Table (3) shows some descriptive statistics of the revisions of the confidential quarterly projections computed for each forecast horizon over the sample 1999Q4-2019Q4. Forecast revisions ($r_{t,h}$) are defined as the difference between two successive forecasts for the same target quarter t, i.e. $r_{t,h} = y_{t|t-h} - y_{t|t-h-1}$ where $y_{t|t-h}$ is the forecast of y_t produced with the information set available at $t-h$. The table reveals that revisions are relatively more sizable for $h = 1, .., 3$ as these horizons show the largest (in absolute value) minimum and maximum revisions, as well as the largest medians. At these horizons the variance of the revisions is also larger. For horizon $h = 4, .., 7$ instead, the revisions are more concentrated around zero. In absolute value the largest revisions occurred right after the financial crisis, when the ECB revised downwards its inflation forecasts substantially. In fact, the largest revisions, ranging from -0.8 to -1.4, were all negative meaning that the new forecast was lower than the forecast made the previous quarter for the same target date. For horizons up to 3 quarters ahead they were made for the target dates 2008Q4 to 2009Q3, while for horizons 4 to 8 for the target dates 2010Q1-2010Q4.

Figure 2: ECB Inflation Projections: 2000-2019



Note: The figure reports the actual HICP (solid horizonthal lines) and the published ECB projections (diamonds) for Euro Area annual year-on-year HICP for the 2000-2019 sample. For each target year four forecasts are published, one each quarter. The forecast horizons are the current year (top panel), the next year (middle panel) and two years ahead (bottom panel).

Table 3: Forecast Revisions

	Forecast Horizon							
$h =$	0	1	2	3	4	5	6	7
min	-0.80	-1.40	-1.40	-1.40	-0.60	-0.80	-0.90	-0.90
max	0.70	0.70	0.70	0.60	0.50	0.40	0.30	0.30
25% pc	-0.20	-0.13	-0.10	-0.20	-0.10	-0.10	-0.10	-0.10
median	0.10	0.10	0.10	0.10	0.00	0.00	0.00	0.00
75% pc	0.20	0.30	0.30	0.30	0.20	0.10	0.10	0.10
mean	0.05	0.04	0.05	0.03	0.02	-0.01	-0.02	-0.03
st dev	0.33	0.39	0.39	0.39	0.20	0.17	0.19	0.19

Descriptive statistics for the forecast revisions of the quarterly inflation projections computed for each forecast horizon over the sample 1999Q4-2019Q4. Forecast revisions are defined as $r_h = y_{t|t-h} - y_{t|t-h-1}$, where $y_{t|t-h}$ is the forecast of y_t based on the information set available at $t - h$.

Table 4: Bias in External Assumptions

	Forecast Horizon								
$h =$	0	1	2	3	4	5	6	7	8
	Panel A: Short Term Interest Rate								
c	-0.01	-0.04	-0.07	-0.11	-0.20	-0.32*	-0.43**	-0.54**	-0.66***
	(0.01)	(0.04)	(0.07)	(0.10)	(0.13)	(0.16)	(0.19)	(0.22)	(0.25)
c	-0.02	-0.08	-0.11	-0.16	-0.27*	-0.42**	-0.53**	-0.62**	-0.71**
	(0.01)	(0.05)	(0.09)	(0.12)	(0.16)	(0.21)	(0.25)	(0.28)	(0.32)
d_t	0.03	0.08	0.10	0.12	0.18	0.25	0.26	0.20	0.12
	(0.02)	(0.08)	(0.14)	(0.20)	(0.26)	(0.34)	(0.40)	(0.46)	(0.52)
	Panel B: Exchange Rate								
c	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.02	0.02
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
c	0.00	0.01	0.02	0.04**	0.05**	0.06**	0.06**	0.07**	0.08***
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
d_t	-0.01	-0.03**	-0.04*	-0.07**	-0.09**	-0.11***	-0.12***	-0.13***	-0.14***
	(0.00)	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
	Panel C: Oil Prices								
c	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
c	0.01	0.04*	0.04*	0.04	0.03	0.02	0.02	0.01	0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
d_t	0.00	-0.04	-0.06*	-0.05	-0.04	-0.04	-0.03	0.00	0.00
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)

Coefficient estimates from regression (6). Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level. For regressions involving the short term interest rates, note that before 2006 an assumption of constant short term interest rates was used.

Table 5: Robustness for Bias: Alternative Values for Target

	Forecast Horizon								
$h =$	0	1	2	3	4	5	6	7	8
				Panel A: $\pi^* = 1.7$					
c	-0.03*	0.08*	0.19**	0.31***	0.36***	0.36**	0.32*	0.24	0.17
	(0.02)	(0.05)	(0.09)	(0.13)	(0.16)	(0.18)	(0.19)	(0.20)	(0.20)
d_t	0.03	-0.10	-0.23	-0.36*	-0.43	-0.42	-0.38	-0.31	-0.24
	(0.03)	(0.08)	(0.15)	(0.21)	(0.27)	(0.29)	(0.31)	(0.32)	(0.33)
				Panel B: $\pi^* = 1.9$					
c	-0.04**	0.04	0.12	0.24	0.20	0.18	0.21	0.14	0.12
	(0.02)	(0.06)	(0.11)	(0.15)	(0.20)	(0.21)	(0.22)	(0.22)	(0.22)
d_t	0.05	0.00	-0.04	-0.12	0.01	0.03	-0.07	-0.03	-0.08
	(0.03)	(0.08)	(0.15)	(0.21)	(0.28)	(0.30)	(0.31)	(0.31)	(0.32)

Coefficient estimates from regression (3).

Table 6: Robustness for Bias: Information Set

	Forecast Horizon								
$h =$	0	1	2	3	4	5	6	7	8
				Panel A: $\pi^I_{t-h} = \pi_{t-h\|t-h}$					
c	-0.04**	0.07	0.19***	0.33***	0.37***	0.38***	0.32*	0.23	0.14
	(0.02)	(0.05)	(0.09)	(0.12)	(0.16)	(0.17)	(0.19)	(0.19)	(0.20)
d_t	0.04	-0.08	-0.25*	-0.41**	-0.45*	-0.47	-0.39	-0.28	-0.16
	(0.03)	(0.08)	(0.14)	(0.20)	(0.26)	(0.28)	(0.30)	(0.32)	(0.33)
				Panel B: $\pi^I_{t-h} = \pi_{t-h}$					
c	-0.04*	0.09*	0.20***	0.33***	0.36***	0.34*	0.26	0.17	0.13
	(0.02)	(0.05)	(0.09)	(0.13)	(0.17)	(0.19)	(0.20)	(0.21)	(0.21)
d_t	0.04	-0.10	-0.24*	-0.38*	-0.39	-0.32	-0.22	-0.11	-0.11
	(0.03)	(0.08)	(0.14)	(0.20)	(0.26)	(0.29)	(0.31)	(0.32)	(0.33)

Coefficient estimates from regression (3).

Table 7: Robustness for Bias: Technical Recessions

	Forecast Horizon								
$h =$	0	1	2	3	4	5	6	7	8
				Panel A: Overall Sample					
c	-0.02	0.03	0.07	0.11	0.13	0.14	0.11	0.07	0.02
	(0.01)	(0.04)	(0.08)	(0.11)	(0.14)	(0.15)	(0.15)	(0.16)	(0.16)
				Panel B: Asymmetry					
c	-0.02	0.07	0.14	0.25**	0.29*	0.32*	0.27	0.21	0.14
	(0.02)	(0.05)	(0.09)	(0.12)	(0.16)	(0.17)	(0.18)	(0.18)	(0.19)
d_t	0.01	-0.11	-0.18	-0.28	-0.34	-0.45	-0.35	-0.30	-0.21
	(0.03)	(0.09)	(0.18)	(0.24)	(0.31)	(0.32)	(0.34)	(0.35)	(0.36)

Coefficient estimates from regression (3). We define the state according to the phases of the business cycle. Then, the dummy takes the value of one during technical recessions, when output growth is below the 25th quantile of its distribution.

Table 8: Bias in Published Projections

	Forecast Horizon		
	current year	*next year*	*year after next*
		Panel A: Overall Sample	
c	0.02	0.14	0.12
	(0.02)	(0.12)	(0.15)
		Panel B: Asymmetry	
c	0.04	0.28**	0.18
	(0.03)	(0.14)	(0.19)
d_t	-0.05	-0.35	-0.17
	(0.05)	(0.23)	(0.30)

Coefficient estimates from regression (3).

Table 9: Efficiency of ECB Inflation Forecasts: Alternative Values for Target

	Forecast Horizon							
$h =$	0	1	2	3	4	5	6	7
				Panel A: $\pi^* = 1.7$				
c	-0.04*	0.07	0.16*	0.28***	0.36**	0.35**	0.30*	0.21
	(0.02)	(0.05)	(0.09)	(0.12)	(0.16)	(0.17)	(0.18)	(0.20)
$r_{t,h}$	0.04	0.15	0.23	0.56**	0.21	-0.48	-0.33	-0.84
	(0.06)	(0.11)	(0.21)	(0.29)	(0.71)	(0.89)	(0.84)	(0.95)
d_t	0.03	-0.10	-0.22	-0.34*	-0.47*	-0.38	-0.42	-0.29
	(0.03)	(0.08)	(0.14)	(0.19)	(0.27)	(0.29)	(0.30)	(0.32)
$r_{t,h} \times d_t$	0.01	-0.17	-0.05	-0.24	0.16	2.54	2.04	1.43
	(0.09)	(0.20)	(0.38)	(0.51)	(1.59)	(2.17)	(1.85)	(1.79)
				Panel B: $\pi^* = 1.9$				
c	-0.06*	0.01	0.06	0.16	0.19	0.19	0.21	0.15
	(0.02)	(0.06)	(0.11)	(0.14)	(0.20)	(0.21)	(0.22)	(0.22)
$r_{t,h}$	0.10	0.23	0.33	0.72**	0.18	-0.45	-0.16	-1.03
	(0.07)	(0.14)	(0.27)	(0.37)	(0.90)	(1.26)	(1.23)	(1.41)
d_t	0.06	0.03	0.02	-0.03	-0.01	0.04	-0.10	-0.08
	(0.03)	(0.08)	(0.15)	(0.20)	(0.27)	(0.30)	(0.31)	(0.33)
$r_{t,h} \times d_t$	-0.06	-0.18	-0.10	-0.36	0.32	0.85	0.21	0.83
	(0.10)	(0.20)	(0.37)	(0.51)	(1.39)	(1.77)	(1.62)	(1.77)

Note: Estimated coefficients from regressions (4). Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

Table 10: Efficiency of ECB Inflation Forecasts: Information Set

	Forecast Horizon							
$h =$	0	1	2	3	4	5	6	7
				Panel A: $\pi^I_{t-h} = \pi_{t-h\vert t-h}$				
c	-0.04**	0.06	0.16*	0.27**	0.36**	0.38**	0.32*	0.22
	(0.02)	(0.05)	(0.09)	(0.12)	(0.16)	(0.18)	(0.19)	(0.20)
$r_{t,h}$	0.05	0.16	0.22	0.60**	0.13	-0.36	-0.04	-0.66
	(0.06)	(0.13)	(0.24)	(0.32)	(0.80)	(1.15)	(1.08)	(1.27)
d_t	0.05	-0.06	-0.22	-0.36*	-0.51*	-0.53*	-0.46	-0.35
	(0.03)	(0.08)	(0.15)	(0.20)	(0.27)	(0.30)	(0.31)	(0.34)
$r_{t,h} \times d_t$	0.03	-0.17	-0.13	-0.47	-0.45	-0.06	-0.25	0.02
	(0.10)	(0.20)	(0.37)	(0.50)	(1.38)	(1.70)	(1.55)	(1.70)
				Panel B: $\pi^I_{t-h} = \pi_{t-h}$				
c	-0.05**	0.06	0.16	0.26**	0.36**	0.34*	0.26	0.16
	(0.02)	(0.05)	(0.10)	(0.13)	(0.17)	(0.19)	(0.20)	(0.21)
$r_{t,h}$	0.06	0.16	0.25	0.65**	0.16	-0.42	-0.19	-0.82
	(0.07)	(0.14)	(0.25)	(0.34)	(0.83)	(1.19)	(1.12)	(1.30)
d_t	0.05	-0.08	-0.20	-0.32	-0.43	-0.35	-0.26	-0.14
	(0.03)	(0.08)	(0.15)	(0.20)	(0.27)	(0.30)	(0.31)	(0.33)
$r_{t,h} \times d_t$	-0.01	-0.16	-0.16	-0.52	-0.16	0.42	0.23	0.51
	(0.10)	(0.20)	(0.37)	(0.50)	(1.36)	(1.73)	(1.58)	(1.72)

Note: Estimated coefficients from regressions (4). Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

Table 11: Efficiency of ECB Inflation Forecasts: Technical Recession

	Forecast Horizon							
$h =$	0	1	2	3	4	5	6	7
				Panel A: Overall Sample				
c	-0.02	0.02	0.05	0.09	0.12	0.12	0.09	0.04
	(0.01)	(0.04)	(0.08)	(0.12)	(0.16)	(0.16)	(0.17)	(0.17)
$r_{t,h}$	0.03	0.11	0.20	0.36	-0.09	-0.59	-0.26	-0.32
	(0.05)	(0.10)	(0.21)	(0.30)	(0.78)	(0.95)	(0.87)	(0.91)
$h =$	0	1	2	3	4	5	6	7
				Panel B: Asymmetry				
c	-0.03	0.06	0.13	0.22**	0.28*	0.31*	0.26	0.18
	(0.02)	(0.04)	(0.08)	(0.11)	(0.15)	(0.17)	(0.18)	(0.19)
$r_{t,h}$	0.01	0.00	0.07	0.37	-0.23	-0.04	0.39	-0.29
	(0.05)	(0.12)	(0.23)	(0.32)	(0.84)	(1.27)	(1.07)	(1.12)
d_t	0.01	-0.09	-0.13	-0.21	-0.32	-0.44	-0.36	-0.31
	(0.03)	(0.09)	(0.16)	(0.22)	(0.30)	(0.32)	(0.34)	(0.36)
$r_{t,h} \times d_t$	0.09	0.31	0.48	0.35	1.33	0.04	-0.95	-0.47
	(0.10)	(0.20)	(0.37)	(0.51)	(1.37)	(1.71)	(1.56)	(1.67)

Note: Estimated coefficients from regression (4). We define the state according to the phases of the business cycle. Then, the dummy takes the value of one during technical recessions, when output growth is below the 25th quantile of its distribution. Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

Table 12: Efficiency of Published Projections

	Forecast Horizon	
	current year	*next year*
	Panel A: Overall Sample	
c	0.02	0.12
	(0.02)	(0.09)
$r_{t,h}$	0.00	1.39***
	(0.03)	(0.24)
	Panel B: Asymmetry	
c	0.10***	0.46***
	(0.05)	(0.09)
$r_{t,h}$	-0.14**	0.30
	(0.07)	(0.28)
d_t	-0.10	-0.57***
	(0.06)	(0.16)
$r_{t,h} \times d_t$	0.17*	1.04***
	(0.09)	(0.45)

Note: Estimated coefficients from regression (4). Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.