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

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Abstract

We test for state-dependent bias in the European Central Bank's inflation projections. We show that the ECB tends to underpredict when the observed inflation rate at the time of forecasting is higher than an estimated threshold of 1.8%. The bias is most pronounced at intermediate forecasting horizons. This suggests that inflation is projected to revert towards the target too quickly. These results cannot be fully explained by the persistence embedded in the forecasting models nor by errors in the exogenous assumptions on interest rates, exchange rates or oil prices. The state-dependent bias may be consistent with the aim of managing inflation expectations, as published forecasts play a central role in the ECB's monetary policy communication strategy.

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

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

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1 Introduction

Forecasting is an essential part of monetary policy and published forecasts are at the core of central bank communication. In fact, central bank inflation forecasts affect private sector expectations (see e.g. Coibion et al. (2022), Granziera et al. (2024), Lyziak and Paloviita (2018), Hubert (2015a,b, 2017)) and therefore can serve as an additional policy tool. Published forecasts may be used by central banks that implement make-up rules such as average inflation targeting in order to create the expectation that inflation will over(under)shoot its target. In an environment of low interest rates and low inflation, policies directly impacting agents' inflation expectations can help to stabilize economic conditions (Coibion et al., 2020). Managing inflation expectations is crucial also in times of elevated inflation, when economic agents are more attentive to price developments (Weber et al., 2023) and expectations may become unanchored.

However, published inflation projections have come under scrutiny. The accuracy of central banks' forecasts decreased during the Great Financial Crisis (Alessi et al. (2014)), and monetary authorities overestimated the rate of inflation in the years that followed (Iversen et al. (2016), Kontogeorgos and Lambrias (2022)). Central banks made large forecasting errors during the COVID-19 pandemic and the subsequent reopening (Goodhart and Pradhan (2023), Levy (2023)). Repeated and systematic projection errors pose a challenge for central banks as they may increase the risk of de-anchoring of inflation expectations and deteriorate the credibility of monetary authorities (Mcmahon and Rholes, 2023).

Against this background, we analyze the bias in the Eurosystem/European Central Bank staff (hereafter ECB) projections for HICP inflation. As a first novel contribution, we test for state dependence in the bias. Specifically, we ask whether the ECB makes systematic forecast errors depending on the level of inflation observed when making its projections. To answer this question, we apply the newly developed state-dependent bias test by Odendahl et al. (2023). The test is based on a regression model where the forecast errors are allowed to depend on both a linear (an intercept, in our case) and a non-linear term. The latter is a function of some economic variables and an unknown parameter. We consider the threshold regression model specification of the test, where the bias depends on the level of inflation. Importantly, the test estimates the threshold level, which is *ex ante* unknown.

On average, we find no sign of bias in the ECB's inflation projections, consistent with previous studies. However, we document a significant difference in the properties of the forecasts conditional on the level of inflation at the time of forecasting. In particular, we detect a systematic, state-dependent bias, both statistically and economically significant for forecasts from one to four quarters ahead: when inflation is higher than the estimated threshold, the ECB tends to underpredict inflation. The estimated threshold value is 1.8% which is consistent with studies estimating the *de facto* target of the ECB (Hartmann and Smets (2018), Rostagno et al. (2019), Paloviita et al. (2021)). This suggests that there is a systematic bias towards the target, as the ECB projects inflation to revert to the estimated threshold value too quickly. Importantly, these results are not driven by large forecast errors observed in times of crisis, such as the Great Financial Crisis, the COVID pandemic, or the post-pandemic recovery period, as we exclude large outliers from our analysis. Thus, our finding implies that the bias is the result of systematic underprediction by the ECB even in times when inflation does not substantially overshoot the target.

As a second contribution, we investigate possible determinants of the state-dependent bias we documented. We consider two possible drivers: conditioning assumptions and forecasting models. The ECB projections are conditional forecasts, i.e., they are based on exogenous assumptions regarding the path of future values of relevant macroeconomic and financial variables. One could argue that systematic errors in inflation forecasts may reflect systematic errors in the exogenous assumptions. Indeed, recent literature finds that the accuracy of the ECB projections is negatively affected by the errors in the exogenous assumptions (Kontogeorgos and Lambrias, 2022). Using the ECB's confidential data on the conditioning assumptions for the short term interest rate, the Euro/US-Dollar exchange rate and oil prices, we test whether the errors in the exogenous assumptions can account for the state-dependent bias. We find that, while the inflation prediction errors are correlated with errors in the exogenous assumptions, the inflation forecasts exhibit a significant systematic bias even after controlling for errors in these assumptions.

Then, we turn to the forecasting models. We consider several reduced-form time series models which are widely used to obtain forecasts for inflation, such as a random walk model, an AR model, Autoregressive Distributed Lag (ADL) models and a small BVAR model (Stock and Watson (2007), Granziera and Sekhposyan (2019)). We construct a real time dataset and produce inflation forecasts for the same sample for which the ECB projections are available. We then apply the Odendahl et al. (2023) bias test to these real time forecasts. For all the models we find evidence of state-dependent bias, but of the opposite sign than the one observed for the ECB projections: the forecasting models tend to overpredict when inflation is higher than the estimated threshold, indicating that inflation is predicted to revert to its long term mean too slowly. This means that the persistence embedded in the models is higher than the persistence in the ECB forecasts. Thus, the forecasting models are not drivers of the state-dependent bias in the ECB projections.

Several papers rationalize the existence of bias in the published forecasts of central banks. Capistran (2008) ascribes the bias to an asymmetric loss function, with overprediction occurring when the monetary authority is more concerned about inflation above the target. However, this explanation predicts a bias opposite in sign to what we find and does not generate a state-dependent bias. Some recent studies have predictions in line with our findings. Herbert (2022) 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. Experimental evidence supports this prediction, finding that test subject central bankers make announcements that deviate from the "true" forecasts to manage agents' inflation expectations (Duffy and Heinemann (2021), Ahrens et al. (2023)). Gomez-Barrero and Parra-Polania (2014) prove the optimality of strategic forecasting in a theoretical model. Interestingly, they find that central banks have the strongest incentive to influence inflation expectations at intermediate forecast horizons. While we do not identify the source of the state-dependent bias, we note that it may be consistent with strategic behaviour of a central bank aiming at steering expectations towards the target.

This paper contributes to the literature on forecast evaluation of policy institutions. A large number of papers has analyzed the bias 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 Tealbook (earlier Greenbook) forecasts, and Romer and Romer (2008) and Arai (2016) for the FOMC. Evidence regarding the bias of the Fed forecasts is mixed and depends on the sample analyzed. Only a few papers investigate whether the properties of the forecasts are state-dependent, and they define the states at the time when inflation is *realized* (Sinclair et al. (2010), Messina et al. (2015)) rather than *at the time of forecasting*. Therefore, we relate the bias to the ECB's mandate and its forecasting process. Moreover, this is the first paper that applies the methodology by Odendahl et al. (2023) to testing for state-dependent bias with an unknown threshold value that determines the switch between states.

We depart from these earlier studies also because we analyze the ECB projections, which have received little attention so far. 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, until July 2021, the ECB aimed at keeping inflation below, but close to 2%. Finally, the Fed produces two sets of forecasts: the Tealbook forecasts, which represent staff forecasts and are kept confidential for five years, and the Summary of Economic Projections (SEP), which summarize the views of the FOMC members and are published 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 may affect the properties of the forecasts, and therefore the findings documented for the Fed's forecasts may not hold in the ECB context.

A very recent set of papers analyzes the ECB inflation projections. Kontogeorgos and Lambrias (2022), Goodhart and Pradhan (2023) and Argiri et al. (2024) attribute the bias in the ECB projections to periods of crises. We exclude the largest forecast errors in our sample, which coincide with quarters during the Great Financial Crisis, the COVID pandemic, and the war in Ukraine, and find that the underprediction during times of high inflation is statistically significant even outside of these crisis periods. Glas and Heinisch (2023) and Kontogeorgos and Lambrias (2022) find a strong association between inflation forecast errors and errors in the conditioning assumptions for oil prices. We confirm the finding in those studies but show that the errors in external assumptions cannot fully account for the state-dependent bias.

The rest of the paper is organized as follows: section 2 describes the testing framework, section 3 presents the data and the implementation details, section 4 summarizes the baseline results and the robustness checks, and section 5 explores the role of the external assumptions and the forecasting models in explaining the bias. Section 6 concludes.

2 Testing for Bias

In this section, we describe our methodological approach. First, we outline how to test for bias in a linear framework. Then, we present the novel forecast evaluation testing methodology proposed by Odendahl et al. (2023) and we show how it can be applied to testing for bias in a state-dependent setting. Finally, we describe the simplified approach to test for state-dependent bias used in previous studies.

Linear Model. Denote as $y_{t+h|t}$ the prediction of the target variable y_{t+h} made at time t for the forecast horizon h and as $\mathfrak{L}_{t+h|t}$ the loss function. In our framework, the loss is simply the difference between the realization of the target variable and its forecast, i.e., the forecast error: $\mathfrak{L}_{t+h|t} = \varepsilon_{t+h|t} = y_{t+h} - y_{t+h|t}$. A positive (negative) forecast error indicates under(over)prediction.

In a linear framework, testing for bias is equivalent to testing whether the forecast errors have zero mean (Holden and Peel (1990), Capistran (2008)) and to run the regression model:

$$\varepsilon_{t+h|t} = \mu_h + u_{t+h|t} \tag{1}$$

where μ_h is the intercept and $u_{t+h|t}$ is an error term. The null of unbiasedness is $\mu_h = 0$.

Then, this test answers the question: are the ECB inflation forecasts for horizon h systematically biased? Or equivalently: on average, is the ECB systematically overpredicting (or underpredicting) inflation?

State-Dependent Model with Unknown Threshold. We further investigate whether (and how) 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 (Goodhart and Pradhan (2023), Herbert (2022), Messina et al. (2015), Sinclair et al. (2010)). If those systematic errors are opposite in sign and offset each other, then we would fail to reject the null that the coefficient μ_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.

We test for state-dependent bias using the approach in Odendahl et al. (2023). They propose a moment-based forecast evaluation test that has power against the alternative of state dependence in the forecasting performance. The state dependence is modelled parametrically, as a threshold model. Then, the forecast error loss is a non-linear function of an observable variable and an unknown threshold value. In particular, it is assumed to evolve according to the following non-linear model:

$$\mathfrak{L}_{t+h|t} = X_t' \mu_h + X_t' \theta_h G(S_t; \gamma_h) + u_{t+h|t} \tag{2}$$

where X_t is a $(k_1 \times 1)$ vector of explanatory variables, S_t is the observable variable that introduces the state dependence, γ is an unknown parameter, $G(\cdot)$ is a nonlinear function and $u_{t+h|t}$ an error term. Both the parameters μ_h and θ_h are of interest. Odendahl et al. (2023) propose several functional forms for $G(\cdot)$. Given the research question of this paper, we assume $G(S_t; \gamma_h)$ is a threshold regression model:

$$G(S_t; \gamma_h) = \mathbb{1}(S_t \geq \gamma_h). \tag{3}$$

so that we allow the effect of X_t on $\mathfrak{L}_{t+h|t}$ to differ according to whether S_t is above or below the unknown threshold γ_h. It is straightforward to apply the model in equation (2), combined with the functional form (3), to test for state-dependent bias. The unbiasedness test can be formulated as follows:

$$\varepsilon_{t+h|t} = \mu_h + \theta_h G(S_t; \gamma_h) + u_{t+h|t} \tag{4}$$

Given the functional form assumed for $G(\cdot)$, the state-dependent model can also be written as:

$$\varepsilon_{t+h|t} = \begin{cases} \mu_h + u_{t+h|t} & \text{if } S_t < \gamma_h \\ \mu_h + \theta_h + u_{t+h|t} & \text{if } S_t \geq \gamma_h \end{cases} \tag{5}$$

In our approach there are no additional explanatory variables X_t, S_t is the inflation rate observed by the ECB when the projections are made, and γ_h is the level of inflation that determines a switch in the behavior of the forecast errors, which is allowed to differ across forecast horizons. Note that we use S_t rather than S_{t+h} in equations (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 previous studies.

Then, this test answers the question: are the ECB inflation forecasts for horizon h systematically biased conditional on inflation being above (below) the estimated threshold value? Or equivalently: is the ECB systematically overpredicting or underpredicting inflation when inflation is lower (higher) than the estimated threshold value?

State-Dependent Model with Known Threshold. The approach by Odendahl et al. (2023) described above tests for potential state dependence without having to fix the threshold value that determines the change in the state. In contrast, previous studies test for state-dependent bias by exogenously defining the state of the economy (Herbert (2022), Messina et al. (2015)). This amounts to picking a value for the threshold parameter, say γ^*, and constructing a dummy variable such that:

$$d_t = \begin{cases} 0 & \text{if } S_t < \gamma^* \\ 1 & \text{otherwise} \end{cases}$$

Then, to test whether errors are systematic conditional on the state of the economy, it is sufficient to include the dummy variable in equation (1):

$$\varepsilon_{t+h|t} = \mu_h + \theta_h d_t + u_{t+h|t}. \tag{6}$$

The null of unbiasedness is $\mu_h = \theta_h = 0$. While using a known threshold value may be appropriate in some applications, for example when testing for bias during recessions versus expansions, allowing for an unknown threshold is paramount in our setting, where the value of inflation that determines the change in the state cannot be set *a priori*. We will show the results from applying the test with a known threshold in the robustness section.

3 Data

We analyze the ECB projections for the year-on-year rate of change of the euro area Harmonized Index of Consumer Prices (HICP) at the quarterly frequency. We focus on this measure of inflation because it is the one targeted by the ECB and used to define its price stability mandate. Our data include real time estimates of current-quarter values (nowcasts) and real time projections until eight quarters ahead. The sample runs from 1999Q1 to 2023Q4, resulting in 100 observations for forecast evaluation of the nowcast and 92 of the eight step-ahead forecasts.[1]

The macroeconomic projections play a key role in monetary policy decision-making, as the forecasts are presented to the ECB Governing Council ahead of its monetary policy deliberations. They are produced by the ECB staff in March and September, and by both the 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 horizons up to 11 months, through the Narrow Inflation Projection Exercise (NIPE). Finally, the projections are based on a set of exogenous assumptions and are produced combining models as well as expert knowledge and judgement.[2]

Panel A of Figure (1) shows the year-on-year euro area HICP inflation for the full sample. Our sample period includes the relatively stable pre-crisis years, followed by the financial crisis, the sovereign debt crisis and a period of persistently low inflation. The COVID-19 pandemic triggered

[1]We evaluate the forecasts against the vintage published by Eurostat in January 2024. We do not experiment with other vintages since both means and medians of data revisions of real-time observed inflation are close to zero.

[2]Alessi et al. (2014) and Kontogeorgos and Lambrias (2022) provide further details on the ECB forecasting process.

a further drop in inflation, while the recovery has been characterized by an unprecedented surge, with inflation reaching a peak of almost 10%. The shaded areas in the figure mark the quarters in which the inflation observed by the ECB, as defined below, lies above 1.8%, which turns out to be the estimated value of the threshold parameter γ_h for most forecasting horizons. This coincides with the estimated value for the *de facto* ECB inflation target before the explicit target was announced in the new ECB monetary policy strategy in July 2021 (Hartmann and Smets, 2018). With this estimated threshold value, $G(S_t;\gamma_h)$ takes the value of one in 58% of the observations. While the latest portion of the sample sees the highest surge, inflation was above the estimated threshold also shortly after the financial crisis and in the early 2000s.

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 up to two years ahead. We distinguish whether the inflation rate observed at the time the forecasts are made is above or below 1.8%. The blue (red) line shows the median inflation forecasts if the inflation observed by the ECB during the projection exercise is above (below) 1.8%. The red (blue) shaded areas denote the 10th and 25th (75th and 90th) percentiles of the distribution conditional on inflation being below (above) 1.8%.

This figure highlights three properties of the forecasts. First, regardless of their initial level, the forecasts revert towards 1.8% by the end of the projection horizon. Second, the convergence happens rather quickly, within the first four quarters, and forecasts flatten out at longer horizons. If the forecasts are reverting to the target quicker than actual inflation, i.e., the ECB is underestimating the persistence of inflation, then we will observe positive (negative) forecast errors when inflation during the projection exercise is high (low). Third, when inflation is high at the time of forecasting, inflation projections fall below 1.8% from three quarters ahead onwards, suggestive of undershooting. However, we do not see evidence of overshooting when inflation is low. If inflation is eventually reverting to the target, then we will observe a larger bias, in absolute terms, for projections made when inflation is high.

We investigate whether systematic errors are related to particular states, classified according to the level of inflation observed by the ECB when the forecasts are made. In defining the observed level of inflation at the time of forecasting, we carefully approximate the information set available to the ECB during the projection exercise. Because of volatile economic conditions, such as sharp changes in food and energy prices, it is reasonable to assume that the ECB observes price developments in recent months rather than only the latest available inflation figure. Therefore, consistent with the cutoff dates of the forecasting process, we assume that the ECB takes into account both the previous quarter year-on-year inflation rate $\left(\pi_{t-1}^{Q}\right)$ and the year-on-year inflation of the first month of the current quarter $\left(\pi_t^{M1}\right)$. Then, the observed inflation measure S_t is the simple average of the two: $S_t = \left(\pi_{t-1}^{Q} + \pi_t^{M1}\right)/2$.

The ECB conditions its projections on a future path of a set of exogenous variables. We include in our analysis three exogenous variables which are considered the most important in driving HICP inflation: the three-month EURIBOR rate, the Euro/US-Dollar exchange rate, and oil prices, measured by the global price of Brent Crude in USD.[3] These assumptions are mainly based on financial market expectations. With regard to the short-term interest rates, initially they were assumed to stay constant at the level prevailing during the two weeks preceding the cut-off date. Since June 2006, market expectations are derived from forward rates, reflecting the term structure of interest rates at the cut-off date. The technical assumptions for oil prices are based on the path implied by futures markets, taking the average of the two-week period ending on the cut-off date. For the bilateral exchange rate, the assumption is that it remains unchanged over the projection horizon at the average levels prevailing during the two-week period ending on the cut-off date. While the technical assumptions for the exogenous variables are published together with the macroeconomic projections for full calendar years, assumptions for fixed forecasting horizons of each quarter remain confidential.

The latest four years in our sample have been ridden by extraordinary economic events. The pandemic represented an unprecedented shock to the economy and generated an extremely high level of uncertainty about future economic developments, such that the Fed did not publish the SEP

[3]Technical assumptions regarding oil prices are available starting in 2001Q3.

projections in March 2020 while the ECB published two alternative scenarios, in addition to the baseline scenario. The surge in commodity prices that followed the reopening of the economy and the war in Ukraine brought inflation to levels unseen since the late 1980s. These shocks resulted in particularly large forecast errors, which may drive results. For this reason, we exclude outliers from our analysis. In particular, we disregard forecast errors larger than 1% for the one and two quarters ahead horizons, 1.5% for the three to five and 1.75% for the six to eight.[4]

4 Results

First, we report the results for the linear model in (1). We then comment on the results for the state-dependent model (4). Finally, we present some robustness checks.

4.1 Bias in the ECB Projections

We replicate the exercise done in previous studies by showing the results for the linear regression model in (1). Panel A of Table (1) shows the estimated coefficients for each forecast horizon from nowcasting until five quarters ahead, $h = 0, .., 5$, and for the pooled horizons 0 through 5, and 0 through 8, as well as the heteroskedasticity and autocorrelation corrected standard errors. Except for the nowcasting horizon, the constant is positive and largest for horizons 3 through 5. 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. Therefore, overall our regressions indicate that the ECB inflation projections for all forecast horizons are unbiased on average. These findings for the single horizon forecasts confirm the results in Kontogeorgos and Lambrias (2022) who conclude that ECB inflation projections are optimal and rational using a sample ending in 2018Q4 and analyzing one, four and eight steps ahead projections. Note that, when pooling forecasting horizons, we find some statistically

[4] Using this criterion, we also exclude from the analysis two vintages of forecasts made during the Great Financial Crisis.

significant, positive bias, and therefore evidence of overall underprediction. Pooling allows us to increase the number of observations and therefore improve on statistical significance.

Panel B of Table (1) shows the results for the state-dependent bias regression model in equation (4). The coefficient associated with the intercept term is negative for all horizons but the nowcast, albeit not statistically significant. The coefficient for the non-linear term instead is positive for all horizons except for the nowcast and is significant for $h = 1$ up to $h = 4$ and for the pooled horizons $h = 0-5$ and $h = 0-8$. When inflation is below the estimated threshold, the bias is given by the intercept term and is therefore negative. Instead, when inflation is above the estimated threshold level, the fitted values from the regression are positive, as the sum of μ_h and θ_h is positive. Given that the forecast errors are defined as the difference between the realization and the forecast, a positive (negative) bias indicates that the forecast is lower (higher) than the realized value. This means that when inflation is above (below) the threshold, the ECB tends to underpredict (overpredict) inflation. Interestingly, the size of this bias when inflation is high, measured as the sum of the coefficients μ_h and θ_h, increases with the forecast horizon up to $h = 4$, and it declines until $h = 8$. The bias is not only statistically but also economically significant: when inflation is above the threshold, it ranges from 0.10p.p. for one quarter ahead to 0.37p.p. for four quarters ahead. Note that the bias is asymmetric in its magnitude: it is larger in absolute value when inflation is above the threshold than when below (e.g., fourfold for $h = 3$). Because we exclude from the sample the large forecast errors made during the Great Financial Crisis and the post-COVID period, our results speak of the properties of the projections during "normal" times, when inflation does not deviate substantially from the target. In this respect, the magnitude of the bias is quite substantial. Interestingly, we find no evidence of bias for the nowcasting horizon. This may be due to the fact that current quarter inflation is easier to forecast. Also, at this horizon forecasting accuracy may be more important than other objectives, like managing expectations, for the credibility and reputation of the central bank, as the public may be more aware of errors made for the current level of inflation than for longer horizons.

Note that the estimated threshold parameter is 1.8% for all the forecasting horizons except for the nowcast. This number is consistent with the value of the *de facto* target estimated for the ECB. Until the new monetary policy mandate was announced in July 2021, the ECB's price stability definition was 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'. Hartmann and Smets (2018) estimate the reaction functions of the ECB's Governing Council and conclude that the ECB's inflation aim is 1.8%. This number is in line with estimates by Paloviita et al. (2021) and Rostagno et al. (2019) which are based on alternative approaches. As stressed in section (2), we do not impose the value of the indicator variable that determines the switch in the state, so it is quite remarkable that the estimates for γ_h are equal to the *de facto* target. Also, note that we allow for γ_h to change with the forecast horizon, so it is interesting that the estimated threshold is virtually the same for all h. Overall, we document that the forecasts are biased towards the target at short and intermediate forecast horizons, between one and four quarters ahead, and for pooled forecast horizons $h = 0-5$ and $h = 0-8$. In section (5) we will explore some possible explanations for the bias and we will discuss our results in relation to the literature.

4.2 Robustness

We perform several exercises to check the robustness of our results.

First, we repeat our analysis using alternative assumptions regarding the information set available to the ECB at the time of forecasting. Table (4) reports the estimated coefficients from these regressions. Results are qualitatively and quantitatively unchanged if we assume the inflation rate observed by the ECB at the time of forecasting is either the nowcast published by the ECB, or realized inflation for the target quarter, or the simple average of the year-on-year inflation on the first month of the quarter when the forecasts are made and the previous two months. In all these cases, and for all forecast horizons, the estimated threshold is around 1.8%, the estimated coefficient for the intercept is negative while the estimated coefficient associated with the non-linear term is positive, significant and similar in magnitude to our baseline estimation.

Second, we check the robustness of our results for different values of the threshold that determines the change between states. For this exercise, we fix the threshold level to either $\pi^* = 1.7$, $\pi^* = 1.75$, $\pi^* = 1.85$ or $\pi^* = 1.9$ and define the dummy variable d_t to equal one if observed inflation is higher than the threshold. Then, we run the regression model (6). Results are unchanged if we assume a lower target ($\pi^* = 1.7$ or $\pi^* = 1.75$), see Table (5). Interestingly, both coefficients turn positive if we assume a higher target, ($\pi^* = 1.85$ or $\pi^* = 1.9$), although they lose their significance, suggesting overall underprediction. This robustness exercise highlights that it is crucial to estimate the threshold that determines the state-dependent bias, as a predetermined value can greatly affect the results.

Finally, we replicate the approach in previous papers and condition the state on the value of inflation observed when inflation is realized, i.e., we define the state based on S_{t+h} rather than on S_t. Table (6) shows that, for this exercise, the bias is qualitatively the same as in our baseline results, but quantitatively much stronger. In particular, when inflation is above the threshold, it ranges from 0.14p.p. for one quarter ahead to 0.75p.p. for four quarters ahead.

5 Potential Drivers of Bias

In this section we analyze several potential drivers of state-dependent bias and discuss our results with respect to the existing literature. The ECB projections are the result of the combination of three main ingredients: (i) the conditioning assumptions on the future path of exogenous variables, (ii) a set of forecasting models, and (iii) expert judgement. We will analyze the role of the first two ingredients in explaining the bias documented above and provide some alternative explanations related to the loss function of the central bank and its strategic behavior.

5.1 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. One could argue that *systematic* errors found in the inflation projections may be driven by *systematic* errors in external assumptions. In fact, Kontogeorgos and Lambrias (2022) find that errors in the external assumptions decrease the accuracy of the ECB inflation projections. Glas and Heinisch (2023) show that higher forecast errors in oil prices are associated with higher forecast errors for inflation. Those studies are based on linear models. Still, the results may hold in our non-linear framework and lead to a state-dependent bias. Given our access to the ECB assumptions for the conditioning variables, we are in a unique position to test this conjecture.

We focus on three variables which are considered to be among the main drivers of inflation: the short term interest rate (3M EURIBOR), Euro/US-Dollar exchange rate (EURUSD),[5] and 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. Importantly, these conditioning assumptions are completely exogenous, i.e., not affected by the ECB projections published in the same quarter.

In order to assess the role of the conditioning assumptions in inflation projections, we include the forecast errors in external assumptions as additional predictors in the bias regression models (6), where we fix the threshold values to the ones estimated in model (4) and reported in Table (1). Define the error in the external assumption i at time t for horizon h as:

$$\zeta^i_{t+h|t} = x^i_{t+h} - x^i_{t+h|t} \qquad i = 1,..,3;\ h = 0,..8 \tag{7}$$

where x^i_{t+h} is the realization and $x^i_{t+h|t}$ is the value assumed at t for date $t+h$. The variable x^i_{t+h} is the level of interest rate or exchange rate, or the growth rate of oil prices.

Then, we apply the bias test with a known threshold,[6] including the error $\zeta^i_{t,h}$ as an additional predictor:

$$\varepsilon_{t+h|t} = \beta^i_{0,h} + \beta^i_{1,h}\zeta^i_{t+h|t} + \beta^i_{2,h}d_t + u^i_{t+h|t} \qquad i = 1,..,3;\ \ h = 0,..8 \tag{8}$$

[5]The exchange rate is defined as the amount dollars traded for one euro, so that when the exchange rate increases, the euro appreciates.

[6]We condition the threshold parameter γ_h to the value estimated in Table (1).

where, $\varepsilon_{t+h|t}$ is the forecast error for predicting inflation at the forecast origin t for horizon h. If the estimated parameters $\beta^i_{0,h}$ and $\beta^i_{2,h}$ were not significant in (8), while $\beta^i_{1,h}$ were significant, the bias in the inflation forecasts could be attributed to the bias in the external assumptions. We investigate the role of each technical assumption separately, as the relatively small number of observations does not allow us to increase further the number of predictors.

Ideally, to carry out our investigation, we would first construct a counterfactual series of *adjusted* forecasts for inflation by using internal ECB models conditioned on the true realization of the external variables, and then check whether the errors in the adjusted projections are biased. However, we are unable to construct such counterfactual series based on the forecasting models used in real time by the ECB and the national central banks or to include 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. Also, a similar specification has been used by Glas and Heinisch (2023), applied to forecast revisions.

Results for regressions (8) are reported in Panel A through C of Table (2). 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 for the pooled horizon regressions and enter positively, so that a larger forecast error for interest rates predicts a larger forecast error for inflation. In other words, underprediction of the short term rate coincides with underprediction of inflation. Similarly, the forecast errors for the exchange rate are not significant. The estimated coefficient is negative at short horizons and positive at longer horizons. A negative coefficient means that if the euro appreciates more than expected, inflation is lower than predicted. 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. As suggested by economic intuition, underprediction of oil prices results in underprediction of inflation. This result is consistent with previous findings in Kontogeorgos and Lambrias (2022) and Glas and Heinisch (2023). While oil prices seem to be the most relevant exogenous assumption in explaining the inflation forecast errors, as suggested by the higher adjusted R-squared for the regressions in Table (2), they do not fully account for the state-dependent bias documented in Table (1).

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

5.2 The Role of Forecasting Models

Another potential source of bias is given by the forecasting models used to obtain the forecasts. If there is little persistence embedded in the models, then inflation may be projected to return to target too quickly and this could explain the underprediction we documented when inflation is high and the overprediction when inflation is low. We test this hypothesis in this section.

The ECB staff and experts in national central banks make use of several forecasting models to produce their forecasts. While we do not know all the details of the reduced form time series models in use, we know their general structure (Ciccarelli et al., 2024). We consider simple univariate models, such as the random walk, an Autoregressive (AR) model, and the ADL as they have been shown to be very accurate models for predicting inflation (Stock and Watson (2007), Granziera and Sekhposyan (2019)). We include a small BVAR in our analysis because it is widely used in central banks for forecasting macro variables, as it jointly models the evolution of the output, inflation and interest rates. Finally, we want to study the property of the bias in the case where the central bank predicts inflation will be at the target value for all forecasting horizons. The random walk model assumes that inflation will remain at the realized value observed in the latest quarter. For example, when producing the forecasts in 2023Q1 it projects inflation to stay at the value observed in 2022Q4. In the baseline specification, the lag length of the AR model is fixed to one. The ADL model includes one lag of inflation and two lags of each exogenous assumption. The BVAR model includes the year-on-year growth rate of output, the EURIBOR rate and HICP inflation. We run an out-of-sample exercise with real time data, making sure to use only information available at the time when the ECB produced its forecasts. The models are estimated on data starting in 1970Q1 and forecasts are obtained with the expanding window approach starting in 1999Q1.

After we obtain the forecasts, we test for state-dependent bias with a known threshold, using the regression model (6), and conditioning the value of the threshold parameter γ_h to the one estimated for the ECB inflation projections shown in Table (1).[7] The results of this analysis are reported in Table (3). For the random walk, the AR and the ADL model the coefficient associated with the intercept term is positive but not statistically significant. The coefficient associated with the non-linear term is instead highly significant and negative and the sum of μ_h and θ_h is negative. Although there is evidence of bias, these results are opposite in sign to the ones obtained when analyzing the forecast errors from the ECB projections, as they point to overprediction when inflation is low and underprediction when inflation is low. This suggests that the persistence embedded in the forecasting models is quite high and is not consistent with the forecasts reverting quickly to 1.8%.[8] For the BVAR model the estimated coefficients are generally positive, which indicates overprediction, and the overprediction is stronger when inflation is above the threshold. Once again, this bias is inconsistent with the one documented in Table (1). Instead, the forecasting strategy of assuming a constant inflation rate equal to the *de facto* target generates a bias similar in magnitude and sign to the one documented for the ECB projections. One difference is that in the 1.8% forecast model the bias is highest for nowcasting and decreases with the forecast horizon, while in the ECB projections it is highest at four quarters ahead.

Our findings suggest that the forecasting models typically used to forecast inflation cannot generate the bias found in the ECB projections.

5.3 Alternative Explanations

So far, we provided evidence of ECB underprediction when inflation is high and overprediction when inflation is low. In the previous two subsections we ruled out two possible explanations

[7] In Table (7) we report results for state-dependent bias test with an unknown threshold, using the regression model (4). The qualitative results for this alternative exercise are very similar to the baseline results.

[8] Different lag lengths did not change the results in Table (3).

for this systematic bias: errors in the conditioning assumptions and the persistence embedded in economic models. What else can generate bias in inflation forecasts of a central bank? The literature has suggested several explanations. 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. Intuitively, the central bank forecasts an inflation rate higher than the forecast from a symmetric loss function in order to justify a tighter monetary policy stance. This explanation is difficult to reconcile with our findings for two reasons: first, because it predicts a bias opposite in sign to what we find, and second, it does not allow for the bias to be state-dependent. Other papers attribute the bias in published forecasts to strategic forecasting. 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 publicly 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 may be 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 may 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) 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. Similarly, in a laboratory experiment, Ahrens et al. (2023) document that strategic inflation projections stabilize the economy by bringing inflation faster towards the inflation target. Herbert (2022) 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.

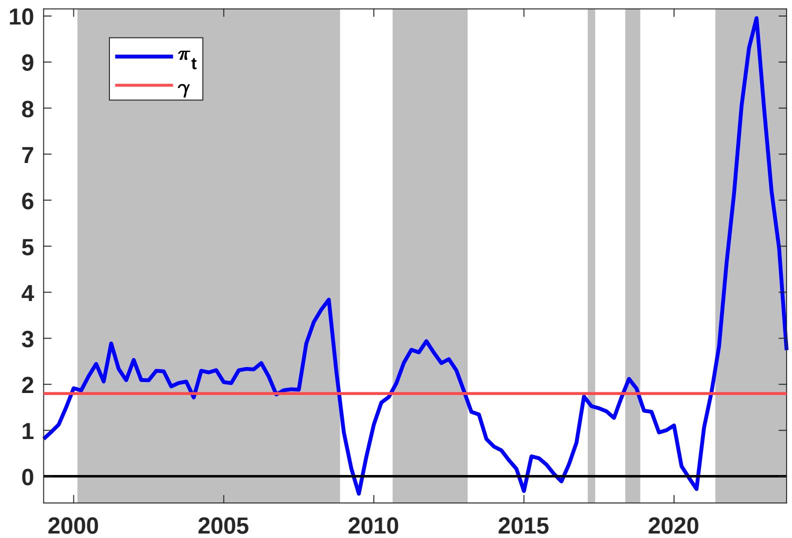
While we do not identify the specific reasons for the systematic, state-dependent bias in the ECB projections at intermediate horizons, we believe it may be consistent with the inflation expectations management motives outlined in the studies mentioned above.

6 Conclusion

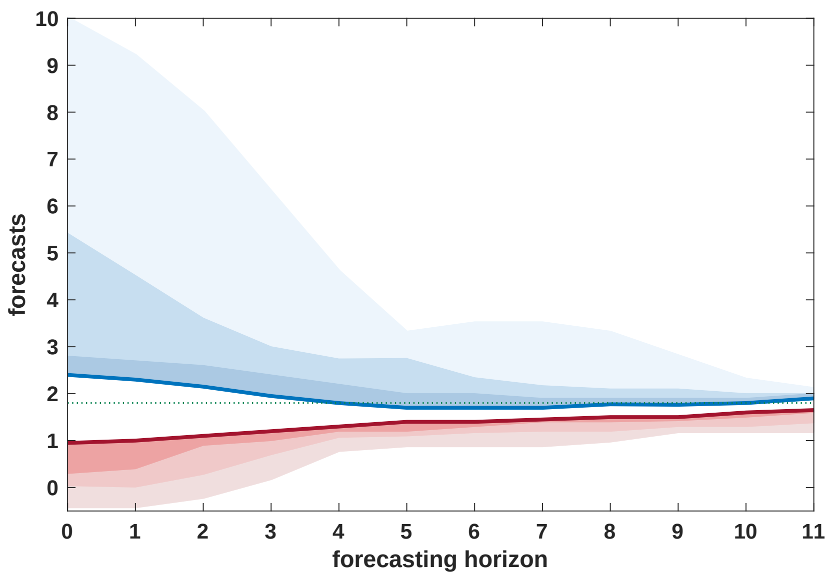
Using a novel testing approach, we document a systematic bias in the ECB inflation projections. The ECB systematically underpredicts inflation when inflation is high, which results in projections converging to the target too quickly. These findings are not driven by the large forecast errors made during the Great Financial Crisis or the pandemic period. Our result suggests that looking at state dependence is crucial, as previous studies which do not account for state dependence find no evidence of bias. We further show that the bias cannot be explained by the errors in the conditioning assumptions of short term interest rates, exchange rates or oil prices, contrary to the view that forecast errors for inflation arise because of errors in these conditioning assumptions. Moreover, forecasting models show a stronger inertia than what is implied in the ECB forecasts. Although the reasons behind our findings are beyond the scope of this paper, we conjecture that the evidence of state-dependent bias may be related to strategic motives in monetary policy communication.

Our investigation of the properties of the published projections is relevant also from a policy perspective: the projections form the basis for the monetary policy decisions of the ECB Governing Council and represent an important communication tool. Systematic bias in the projections may undermine the credibility of the central bank. Because the credibility of a monetary authority may be related to the forecast accuracy of its forecasts, further analysis about the determinants of the bias is needed.

Figure 1: HICP Inflation and Inflation Projections



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



(b) Panel B: ECB Projections for HICP Inflation

Panel A. Year-on-year HICP inflation for the Euro Area (solid line) and periods in which inflation is above the threshold, 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 threshold (1.8%, green dashed line) during each projection exercise from 1999Q1 till 2023Q4.

Table 1: Bias in ECB Inflation Forecasts

	Forecast Horizon							
	Single						**Pooled**	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
				Panel A: Linear Model				
μ_h	-0.01	0.04	0.09	0.13	0.17	0.19	0.10**	0.10**
	(0.01)	(0.04)	(0.07)	(0.13)	(0.14)	(0.15)	(0.05)	(0.05)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
				Panel B: State-Dependent Model				
μ_h	0.00	-0.03	-0.07	-0.07	-0.09	-0.05	-0.03	-0.01
	(0.04)	(0.05)	(0.09)	(0.13)	(0.17)	(0.16)	(0.05)	(0.05)
θ_h	-0.05	0.13*	0.28**	0.36*	0.46*	0.43	0.24***	0.19***
	(0.04)	(0.08)	(0.14)	(0.20)	(0.26)	(0.28)	(0.08)	(0.08)
γ_h	2.27	1.80	1.80	1.80	1.80	1.81	1.81	1.81
R^2	0.03	0.02	0.06	0.05	0.06	0.04	0.04	0.02

Note: Estimated coefficients from regressions (1) and (4) over the sample 1999Q1-2023Q4. R^2 is the adjusted R^2. Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

Table 2: Bias in ECB Inflation Forecasts: Exogenous Assumptions

	Forecast Horizon							
	Single						Pooled	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
				Panel A: Interest Rates				
$\beta^i_{0,h}$	-0.00	-0.03	-0.06	-0.07	-0.08	-0.04	-0.04	-0.02
	(0.02)	(0.05)	(0.10)	(0.14)	(0.19)	(0.20)	(0.06)	(0.06)
$\beta^i_{1,h}$	-0.00	0.22	0.25	0.18	0.21	0.15	0.17***	0.18***
	(0.27)	(0.16)	(0.16)	(0.17)	(0.15)	(0.14)	(0.08)	(0.05)
$\beta^i_{2,h}$	0.01	0.13*	0.28**	0.37*	0.48*	0.44	0.29***	0.29***
	(0.04)	(0.07)	(0.13)	(0.19)	(0.25)	(0.27)	(0.09)	(0.09)
R^2	0.00	0.02	0.08	0.06	0.08	0.05	0.07	0.08
				Panel B: Exchange Rate				
$\beta^i_{0,h}$	-0.00	-0.03	-0.06	-0.08	-0.08	-0.03	-0.04	-0.02
	(0.02)	(0.06)	(0.10)	(0.15)	(0.19)	(0.20)	(0.06)	(0.06)
$\beta^i_{1,h}$	-0.74	-0.78	0.16	0.01	0.58	1.36	0.69	1.68***
	(1.29)	(0.72)	(0.83)	(1.03)	(1.15)	(1.16)	(0.49)	(0.41)
$\beta^i_{2,h}$	0.02	0.12*	0.25*	0.35*	0.40	0.31	0.24***	0.17**
	(0.04)	(0.07)	(0.14)	(0.20)	(0.26)	(0.28)	(0.08)	(0.09)
R^2	0.00	0.01	0.03	0.04	0.05	0.06	0.06	0.10
				Panel C: Oil Prices				
$\beta^i_{0,h}$	-0.00	-0.03	-0.10	-0.14	-0.20	-0.16	-0.09*	-0.10
	(0.02)	(0.04)	(0.09)	(0.14)	(0.19)	(0.20)	(0.05)	(0.06)
$\beta^i_{1,h}$	0.01***	0.01***	0.01***	0.01*	0.01	0.01	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
$\beta^i_{2,h}$	0.05	0.07	0.25**	0.37**	0.49**	0.49	0.28***	0.28***
	(0.04)	(0.06)	(0.12)	(0.19)	(0.25)	(0.27)	(0.08)	(0.09)
R^2	0.09	0.42	0.21	0.12	0.12	0.10	0.15	0.10

Note: Estimated coefficients from regression (4) over the sample 1999Q4-2023Q4. R^2 is the adjusted R^2. 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. External assumptions for oil prices are available from 2001Q3.

Table 3: Bias in Forecasting Models

	Forecast Horizon							
	Single						**Pooled**	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
				Panel A: Random Walk				
μ_h	0.03	-0.06	0.13	0.10	0.01	0.37	0.09	0.17**
	(0.15)	(0.09)	(0.13)	(0.19)	(0.19)	(0.20)	(0.08)	(0.07)
θ_h	-0.03	0.03	-0.20	-0.25	-0.14	-0.55*	-0.18*	-0.27***
	(0.19)	(0.12)	(0.18)	(0.25)	(0.25)	(0.25)	(0.10)	(0.09)
R^2	0.00	0.00	0.00	0.00	0.00	0.24	0.01	0.03
				Panel B: AR				
μ_h	-0.00	-0.06	-0.06	0.04	0.27	0.27	0.08	0.13*
	(0.03)	(0.11)	(0.13)	(0.20)	(0.20)	(0.18)	(0.07)	(0.07)
θ_h	0.00	0.01	0.00	-0.14	-0.46*	-0.45**	-0.17*	-0.30***
	(0.04)	(0.14)	(0.17)	(0.27)	(0.25)	(0.24)	(0.09)	(0.09)
R^2	0.00	0.00	0.00	0.00	0.07	0.06	0.02	0.04
				Panel B: AR with exogenous assumptions				
μ_h	-0.01	0.08	0.05	0.02	0.14	0.01	0.04	0.00
	(0.03)	(0.11)	(0.13)	(0.18)	(0.17)	(0.17)	(0.06)	(0.07)
θ_h	0.00	-0.14	-0.21	-0.24	-0.47**	-0.42*	-0.23***	-0.35***
	(0.04)	(0.13)	(0.16)	(0.23)	(0.22)	(0.22)	(0.08)	(0.09)
R^2	0.00	0.00	0.00	0.00	0.08	0.05	0.03	0.06
				Panel C: Small BVAR				
μ_h	-0.01	-0.08	-0.00	0.13	0.13	0.12	0.04	0.15*
	(0.03)	(0.08)	(0.12)	(0.17)	(0.18)	(0.21)	(0.07)	(0.08)
θ_h	0.00	0.22**	0.17	0.28	0.26*	0.23	0.18**	0.02
	(0.04)	(0.10)	(0.15)	(0.22)	(0.23)	(0.26)	(0.09)	(0.11)
R^2	0.00	0.05	0.00	0.00	0.00	0.00	0.02	0.00
				Panel D: 1.8% Forecast				
μ_h	-0.96***	-0.25***	-0.23**	-0.31*	-0.18	-0.07	-0.39***	-0.30***
	(0.36)	(0.08)	(0.11)	(0.16)	(0.18)	(0.19)	(0.13)	(0.11)
θ_h	2.15***	0.56***	0.53***	0.60***	0.39*	0.20	0.84***	0.60***
	(0.48)	(0.10)	(0.14)	(0.20)	(0.23)	(0.25)	(0.17)	(0.14)
R^2	0.33	0.42	0.25	0.18	0.06	0.00	0.16	0.10

Note: Estimated coefficients from regression (6) with value of the threshold as in Table (1). The forecasts are obtained from the forecasting models described in section 5.2 over the sample 1999Q1-2023Q4. R^2 is the adjusted R^2. Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

Table 4: Bias: Alternative Information Set

	Forecast Horizon							
	Single						**Pooled**	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
				Panel A: Nowcast				
μ_h	-0.01	-0.02	-0.07	-0.09	-0.09	-0.11	-0.06	-0.04
	(0.07)	(0.05)	(0.10)	(0.14)	(0.17)	(0.17)	(0.05)	(0.05)
θ_h	0.04	0.10	0.28**	0.39**	0.46*	0.53**	0.28***	0.24***
	(0.07)	(0.07)	(0.13)	(0.18)	(0.24)	(0.28)	(0.08)	(0.08)
γ_h	2.50	1.80	1.80	1.80	1.80	1.80	1.80	1.80
R^2	0.00	0.00	0.06	0.07	0.06	0.08	0.05	0.03
				Panel B: Realized Inflation				
μ_h	-0.02	-0.03	-0.06	-0.07	-0.07	-0.05	-0.05	0.00
	(0.06)	(0.05)	(0.09)	(0.14)	(0.17)	(0.16)	(0.05)	(0.05)
θ_h	0.07	0.13*	0.29**	0.39**	0.46*	0.45*	0.27***	0.20***
	(0.05)	(0.08)	(0.13)	(0.18)	(0.24)	(0.25)	(0.07)	(0.08)
γ_h	2.33	1.87	1.87	1.87	1.87	1.87	1.87	1.92
R^2	0.00	0.02	0.06	0.05	0.06	0.04	0.05	0.02
				Panel C: Average of latest three months				
μ_h	-0.01	-0.03	-0.07	-0.07	-0.09	-0.05	-0.04	-0.02
	(0.06)	(0.05)	(0.09)	(0.13)	(0.17)	(0.17)	(0.05)	(0.05)
θ_h	0.03	0.13*	0.28**	0.36*	0.46*	0.43	0.26***	0.21***
	(0.05)	(0.07)	(0.13)	(0.19)	(0.25)	(0.29)	(0.08)	(0.08)
γ_h	2.30	1.78	1.78	1.78	1.78	1.78	1.78	1.78
R^2	0.00	0.02	0.06	0.05	0.06	0.04	0.05	0.02

Coefficients' estimates from regression model ((4)) when observed inflation π^I is assumed to be: the nowcast value (panel A), realized inflation (panel B) or the average of the current and last two months (panel C).

Table 5: Bias: Alternative Values for Threshold

	Forecast Horizon							
	Single						**Pooled**	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
				Panel A: $\pi^* = 1.7$				
μ_h	0.00	-0.03	-0.06	-0.06	-0.09	-0.09	-0.05	-0.04
	(0.03)	(0.05)	(0.10)	(0.14)	(0.19)	(0.22)	(0.06)	(0.07)
θ_h	-0.00	0.13*	0.27**	0.34*	0.45*	0.48*	0.27***	0.23***
	(0.04)	(0.07)	(0.13)	(0.19)	(0.25)	(0.27)	(0.08)	(0.09)
R^2	0.00	0.01	0.05	0.05	0.06	0.01	0.05	0.02
				Panel C: $\pi^* = 1.75$				
μ_h	-0.00	-0.03	-0.07	-0.07	-0.09	-0.07	-0.05	-0.03
	(0.03)	(0.05)	(0.10)	(0.14)	(0.18)	(0.20)	(0.06)	(0.07)
θ_h	0.00	0.13*	0.28**	0.36*	0.46*	0.46*	0.27***	0.22***
	(0.04)	(0.07)	(0.13)	(0.19)	(0.25)	(0.27)	(0.08)	(0.09)
R^2	0.00	0.01	0.05	0.05	0.06	0.01	0.05	0.02
				Panel D: $\pi^* = 1.85$				
μ_h	0.00	0.01	0.02	0.04	0.09	0.09	0.04	0.04
	(0.03)	(0.05)	(0.09)	(0.14)	(0.18)	(0.19)	(0.06)	(0.06)
θ_h	-0.01	0.07	0.15	0.19	0.17	0.22	0.12	0.11
	(0.04)	(0.07)	(0.13)	(0.20)	(0.26)	(0.28)	(0.09)	(0.09)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
				Panel B: $\pi^* = 1.9$				
μ_h	0.00	0.02	0.04	0.07	0.14	0.15	0.07	0.07
	(0.03)	(0.05)	(0.09)	(0.14)	(0.18)	(0.19)	(0.06)	(0.06)
θ_h	-0.01	0.04	0.11	0.13	0.07	0.09	0.07	0.06
	(0.04)	(0.07)	(0.14)	(0.20)	(0.26)	(0.28)	(0.09)	(0.09)
R^2	0.00	0.02	0.06	0.05	0.06	0.04	0.05	0.02

Coefficient estimates from regression (6) where the threshold used to define the dummy is either 1.7 (panel A) or 1.9 (panel B).

Table 6: Bias in ECB Inflation Forecasts

	Forecast Horizon							
	Single						**Pooled**	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
	Panel B: State-Dependent Model							
μ_h	0.01	-0.06	-0.16	-0.24	-0.35	-0.40	-0.22***	-0.34***
	(0.04)	(0.06)	(0.11)	(0.18)	(0.25)	(0.26)	(0.07)	(0.07)
θ_h	-0.05	0.20***	0.47***	0.75***	1.10***	1.21***	0.60***	0.85***
	(0.04)	(0.07)	(0.10)	(0.16)	(0.18)	(0.18)	(0.07)	(0.07)
γ_h	2.27	1.87	1.84	1.89	1.94	1.94	1.84	1.87
R^2	0.03	0.08	0.22	0.32	0.47	0.52	0.26	0.36

Note: Estimated coefficients from regressions (4) over the sample 1999Q1-2023Q4 where the state indicator variable is S_{t+h} instead of S_t. R^2 is the adjusted R^2. Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

Table 7: Bias in Forecasting Models

	Forecast Horizon							
	Single						**Pooled**	
$h =$	0	1	2	3	4	5	$0-5$	$0-8$
	Panel A: Random Walk							
μ_h	0.06	0.01	0.13	0.16	0.08	0.31	0.13	0.16
	(0.26)	(0.09)	(0.14)	(0.20)	(0.24)	(0.26)	(0.08)	(0.07)
θ_h	-0.15	-0.15	-0.35***	-0.63***	-0.56**	-0.82**	-0.41***	-0.45***
	(0.25)	(0.10)	(0.13)	(0.21)	(0.24)	(0.23)	(0.08)	(0.08)
γ_h	2.29	2.18	2.18	2.18	2.29	2.18	2.18	2.18
R^2	0.00	0.01	0.07	0.14	0.09	0.24	0.08	0.08
	Panel B: AR							
μ_h	-0.00	-0.00	0.01	0.13	0.21	0.36*	0.10	0.16***
	(0.06)	(0.16)	(0.10)	(0.21)	(0.29)	(0.19)	(0.06)	(0.06)
θ_h	0.02	-0.20	-0.18*	-0.50**	-0.80***	-0.73***	-0.34***	-0.43***
	(0.05)	(0.16)	(0.10)	(0.22)	(0.24)	(0.22)	(0.05)	(0.08)
γ_h	2.39	2.36	2.18	2.18	2.34	1.89	2.18	1.94
R^2	0.00	0.01	0.00	0.07	0.21	0.21	0.07	0.09
	Panel B: AR with exogenous assumptions							
μ_h	-0.01	0.07	0.02	0.05	0.09	0.07	0.06	-0.00
	(0.06)	(0.08)	(0.12)	(0.18)	(0.20)	(0.20)	(0.06)	(0.07)
θ_h	-0.19	-0.31*	-0.50***	-0.69***	-0.66***	-0.70***	-0.34***	-0.40***
	(0.10)	(0.12)	(0.19)	(0.19)	(0.19)	(0.19)	(0.06)	(0.07)
γ_h	2.03	2.18	2.18	2.18	1.89	1.87	2.03	1.89
R^2	0.00	0.02	0.04	0.07	0.20	0.19	0.20	0.09
	Panel C: Small BVAR							
μ_h	-0.01	-0.06	0.01	0.20	0.41*	0.19	0.09	0.25**
	(0.06)	(0.10)	(0.12)	(0.18)	(0.23)	(0.25)	(0.07)	(0.10)
θ_h	0.02	0.22*	0.17	0.21	-0.44*	0.13	0.11	-0.33***
	(0.05)	(0.11)	(0.15)	(0.21)	(0.25)	(0.31)	(0.08)	(0.10)
γ_h	2.39	1.89	1.96	1.87	2.35	1.97	1.87	2.39
R^2	0.00	0.05	0.00	0.00	0.05	0.00	0.01	0.04
	Panel D: 1.8% Forecast							
μ_h	-0.04	-0.00	-0.11	-0.21	-0.07	0.00	-0.13**	-0.13**
	(0.17)	(0.14)	(0.14)	(0.16)	(0.15)	(0.16)	(0.06)	(0.06)
θ_h	0.55***	0.42***	0.43***	0.49*	0.24***	0.09	0.38***	0.29***
	(0.11)	(0.11)	(0.12)	(0.18)	(0.19)	(0.21)	(0.07)	(0.08)
γ_h	2.20	2.26	1.97	1.87	1.96	1.84	1.87	1.87
R^2	0.37	0.20	0.17	0.12	0.01	0.00	0.11	0.04

Note: Estimated coefficients from regression (4) applied to the forecasting models described in section (5.2) over the sample 1999Q1-2023Q4. R^2 is the adjusted R^2. Newey-West standard errors are in parenthesis. Stars denote the 10% (*), 5% (**) and 1% (***) significance level.

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