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Temi di discussione

(Working Papers)

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Number 1270 - March 2020

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

ASYMMETRY IN THE CONDITIONAL DISTRIBUTION OF EURO-AREA INFLATION

by Alex Tagliabracci*

Abstract

Macroeconomic conditions are among the key determinants of the inflation outlook. This paper studies how business cycles affect the conditional distribution of euro-area inflation forecasts. Using a quantile regression approach, I estimate the conditional distribution of inflation to assess the impact of business cycle conditions over time and the possible asymmetries across quantiles of inflation. Interestingly, downside risks to inflation forecasts are related to the business cycle while upside risks are instead relatively stable over time and are not affected by the state of the economy.

JEL Classification: C32, E31, E32, E37.
Keywords: inflation, quantile regression, conditional distribution, asymmetry, downside risks.
DOI: 10.32057/0.TD.2020.1270

Contents

* Bank of Italy, DG Economics, Statistics and Research.

"If we look at the uncertainty dimension of inflation, we see two phenomena. The first is that tail risks have disappeared. [...] And we also see that the uncertainty about the path of inflation has also decreased."

Mario Draghi, 8 June 2017

1 Introduction[1]

Predicting inflation is of primary importance for several reasons, especially for the conduct of monetary policy. The literature on forecasting inflation has showed an increasing effort over the last years in better characterizing the level of uncertainty associated to point estimates, which is generally captured by means of the predictive density (e.g. Elliott and Timmermann [2008]). An accurate representation of the possible risks related to future inflation is undoubtedly relevant both for economic agents and policymakers. The importance of this point is clear in most of the economic surveys: indeed, professional forecasters, and more in general market operators participating in these questionnaires, are asked to provide not only their point estimates but also the probability distribution of their forecasts. Similarly, policymakers regularly evaluate the probability of different scenarios, such as deflation or high-inflation rate, to gauge possible risks associated to future inflation, which is a major threat to policy effectiveness.

Macroeconomic conditions are generally considered the major driver of inflation. Scholars have extensively investigated how the state of the economy propagates into the dynamics of future prices. This paper takes a step into this direction: indeed, it contributes to the literature on inflation forecasting by providing a comprehensive study on how macroeconomic conditions shape the conditional distribution of inflation forecasts in the euro area. To do so, first it uses a quantile-regression approach to characterize the effects of changes in the current state of the economy with respect to the entire distribution of inflation. Then, it adopts the quantile function to estimate the conditional distribution of inflation forecasts. This method follows Adrian, Boyarchenko, and Giannone [2019] who focus on the relation between US gross domestic product and financial conditions. Their approach fits with the purpose of this paper because it allows to investigate the properties of the conditional

[1]This paper previously circulated with the title "*The Vulnerability of Euro Area Inflation Forecasts*". I would like to thank Andrea Gazzani, Domenico Giannone, Alberto Musso, Stefano Neri, Andrea Nobili, Gabriel Pérez-Quirós and Roberta Zizza for their helpful comments. I also benefited from comments made by participants at seminars at Universitat Autonoma de Barcelona, ECB, IAEE 2019. All the possible errors remain mine.

distribution, focusing not only on the first two moments, as generally done in the literature, but rather on the entire shape of the distribution.

Existing studies have already investigated the distribution of inflation forecasts using a different perspective. Some examples are Tsong and Lee [2011] who show asymmetric inflation dynamics for twelve OECD countries and Manzan and Zerom [2013] who challenged the view that random-walk models are more accurate for forecasting inflation by exploring the power of leading indicators of economic activity as valuable predictors, especially at the tails of the distribution. Busetti et al. [2015] adopt a quantile phillips-curve approach for the euro area with the aim of improving the accuracy of standard linear forecasting models.

This paper takes a different direction with respect to the existing literature because it does not propose a standard "horse-race" forecasting exercise for competing models but rather it uses a quantile regression approach to estimate the conditional distribution of inflation forecasts in the euro area and analyze its evolution over time with respect to economic conditions. Loosely speaking, this allows to study how the current state of the economy shapes the (model-based) uncertainty and risks associated to future inflation. The idea is that macroeconomic conditions matter for future inflation but in an asymmetric way, i.e. more for lower quantiles of inflation whereas are not informative for the upper quantiles.

The main finding of this paper is that the distribution of euro area inflation forecasts conditional on the current state of the economy evolves asymmetrically. Specifically, the left part of the distribution is sensitive to the deterioration of economic conditions while the right part remains relatively stable over time, regardless if the economy is experiencing an expansion phase. In other words, downside risks to inflation vary considerably with the business cycle whereas upside risks are less sensitive to economic fluctuations. This finding appears robust to a large and heterogeneous set of business cycle indicators commonly used to study the relation of between prices and output. This asymmetric relation appears important also for forecasting purpose: the performance of the model in an out-of-sample setting is higher for lower quantiles and the accuracy gain decreases nearly monotonically across quantiles.

Interestingly, other previous works investigated possible determinants of inflation risks: for instance Andrade et al. [2014] look at how financial market data affect survey-based inflation risk indicators in the euro area and Lopez-Salido and Loria [2019] document that financial conditions can carry substantial and persistent low-inflation risks both in the US and in the euro area. This paper differs from them because it focuses explicitly on the role of business cycle indicators rather than financial variables on the inflation outlook.

The rest of the paper is structured as follows. Section 2 illustrates the steps to estimate the conditional distribution of inflation forecasts which is then used in section 3 for further analyses. Section 4 performs perform an out-of-sample exercise while and 5 presents some robustness checks. Section 6 briefly concludes.

2 Estimating the conditional distribution

Characterizing the relation between inflation and the business cycle belongs to the long-lasting debate on the validity of the Phillips curve. To study this relation, I first consider the data for the euro area by looking at the year-on-year inflation rate and a business cycle variable. Specifically, I use the €-*coin* (Eurocoin) indicator, which is a measure introduced by Altissimo et al. [2010] and can be considered as a real-time "thermometer" of the euro area economy[2]. The choice of using the €-*coin* rather than other business cycle indicators as real GDP or unemployment rate is motivated by the fact that the €-*coin* is obtained as a smooth estimate that summarizes the current economic condition for the euro area in one index[3]. Together with the year-on-year inflation rate, data are taken at a quarterly frequency and spanned over the period 1999Q1-2019Q3 as illustrated in figure 11.

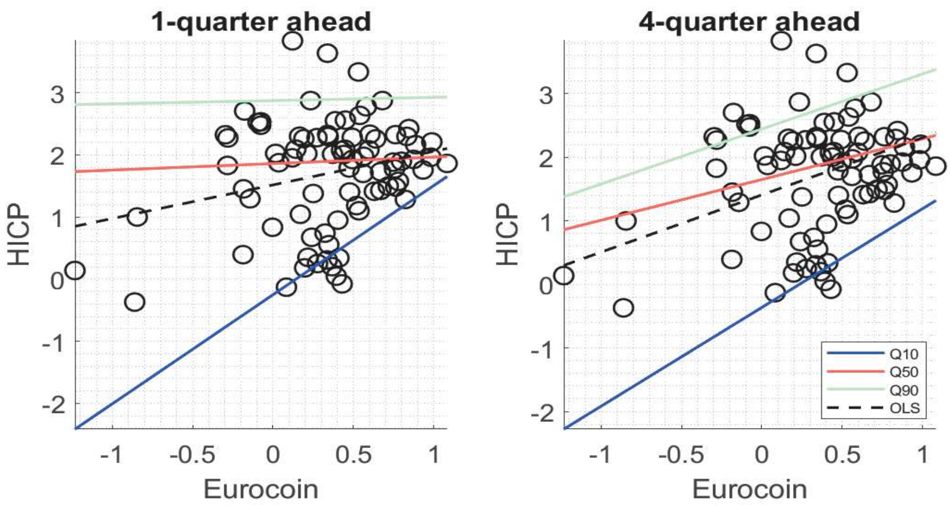
Figure 1 shows the scatter plots of the data together with the slope of 10th, 50th and 90th percentiles and the ordinary least squares (OLS) estimates (black-dashed line) for two different horizons, i.e. one and four quarters ahead. These charts are informative about the ability/inability of the OLS in fitting the data at all quantiles: for instance, if the OLS line is parallel to the ones characterizing the other quantiles, then it indicates that a linear regression model also does a good job in capturing the relation between inflation and €-*coin* in the tails.

The evidence suggests that the OLS performs poorly at both tails, especially at lower quantiles. In particular, the 10th percentile slope (blue line) behaves remarkably different from the other lines and this holds at both horizons. This represents a motivating point for the adoption of the quantile regression for the remaining of this paper.

[2]In practice, this index is constructed from a dynamic factor model which uses a large set of macroeconomic variables (industrial production, business surveys, financial and demand indicators and others) to extract the information that is relevant to forecast GDP.

[3]The results of this paper are robust to the choice of using other business cycle indicators as shown by some evidence are presented in Section 5.

Figure 1: Scatter plot



2.1 Quantile regression approach

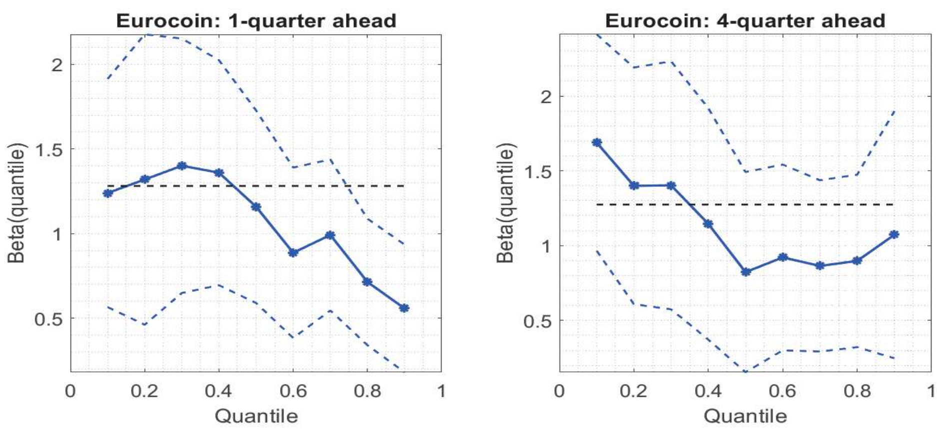
The quantile regression and the simple linear regression model (OLS) mainly differs in two ways: the minimization problem is based on the sum of *absolute* errors and not on the sum of squared errors and in addition the error terms are weighted differently according to the relative quantile (and not equally as in the OLS framework). Concretely, as shown by Adrian et al. [2019], the use of the quantile regression approach presents two main advantages. First, it allows to study the impact of the explanatory variables on different quantiles of the inflation distribution and not only on the mean as in the case of OLS. This feature is extremely important since recent periods have been characterized by two recessions and simple linear regression models might fail to capture the effects of large shocks on inflation. Second, estimation and inference in a quantile-regression framework are distribution-free and therefore no strong assumptions are needed on the distribution of the inflation rate.

Given this background, I estimate a quantile regression (see Koenker and Bassett [1978]) of y_t (euro area headline inflation) on x_t (the €-*coin* plus a constant). This allows the estimation of the conditional distribution in a second step as described in the next session. Equation 1 shows a standard quantile regression formula in which the coefficients $\beta_{\tau,h}$ are chosen to minimize the quantile weighted absolute errors as follows

$$\beta_{\tau,h} = \underset{\beta_h \in R^k}{\operatorname{argmin}} \sum_{t=1}^{T} (\tau \cdot \mathbb{1}(y_t \geq x_{t-h}\beta_h)|y_t - x_{t-h}\beta_{\tau,h}| + (1-\tau) \cdot \mathbb{1}(y_t < x_{t-h}\beta_h)|y_t - x_{t-h}\beta_{\tau,h}|) \tag{1}$$

where τ represents the different quantiles, h the forecast horizon and $\mathbb{1}(\cdot)$ denotes the indicator function. In what follows, the baseline model, i.e. the one that is used to construct the *conditional* distribution, uses as regressors the average inflation rate over the last four quarters and €-*coin* indicator. The first term aims at capturing the persistence of inflation (see Atkeson and Ohanian [2001]) while the second term describes the relation with the business cycle. Similarly, Lopez-Salido and Loria [2019] use the average inflation rate rather than the lag of inflation in conjunction with some financial indicators to study inflation dynamics in the euro area and in the US. The estimated coefficients of equation 1 for the conditional model are then analyzed to characterize their variation across quantiles. The forecast horizon is arbitrarily selected equal to one and four to provide a short and a medium-term view of this relation. Figures 2 illustrates the coefficient estimates across all quantiles, considering a grid from 0.1 to 0.9 with a 0.05-interval. First, the blue lines show that the coefficients are generally statistically significant (with the exception of the right tail at one-quarter ahead)[4]. Second, both graphs point out significant differences across quantiles, especially comparing the lower quantiles with the upper quantiles. Clearly, this reinforces the idea that OLS estimates (black dashed line) do not properly capture tails relations and therefore are less informative about tail behaviours which are better described in a quantile-regression approach.

Figure 2: Estimated coefficients over quantiles



[4]The confidence bands are obtained by estimating the variance-covariance matrix as described in Greene [2008].

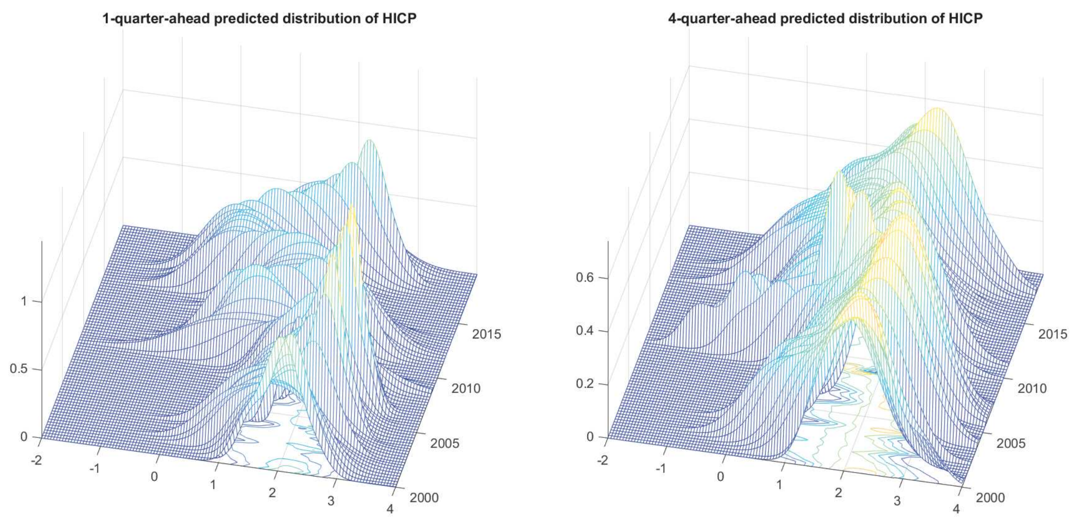
2.2 The conditional distribution

Using the estimated coefficients $\beta_{\tau,h}$ from equation 1, the predicted distribution of inflation $\hat{Q}_{y_{t+h}|x_t}$ can be directly computed as

$$\hat{Q}_{y_{t+h}|x_t}(\tau) = x_t \beta_{\tau,h} \quad (2)$$

where the forecast horizon is $h = 1, 4$. As described before, the conditional distribution model is obtained by including in x_t the average of the last four lags of inflation and the €-*coin*. Note that equation 2 produces a prediction for each quantile τ at each t which are then used to obtain the predicted distribution by means of a *non-parametric* approach as the normal kernel function (e.g. D'Agostino, Giannone, and Gambetti [2013])[5]. Figure 3 presents the estimated conditional distributions with respect to one- (left) and four-quarter (right) ahead forecasts.

Figure 3: Estimated distribution of inflation forecasts



The main finding is that there is a considerable time-variation in the shape of the conditional distribution which is mainly driven by the different behaviour of the tails. Indeed, for both horizons, the distribution shows asymmetric moves with the left tail more sensitive to business cycle developments while the right tail remains relatively stable over time. Loosely speaking, the conditional distribution of inflation forecasts points out that the left tail moves following business cycle conditions

[5]The empirical results are robust to different approaches for estimating the conditional distribution. In practice, several specifications for the kernel function or a simple linear interpolation as in Busetti et al. [2015] produce differences across methods that are negligible.

while the right one is more stable over time, not increasing even when the economy goes through an expansion phase. As a consequence, this also implies that changes in inflation uncertainty are entirely driven by the left tail of the conditional distribution, therefore when an increase in the uncertainty is not generated by symmetric moves of both tails.

2.3 In-sample fit

One way to look at the importance of business cycle indicators to explain the left part of the distribution is to consider their contribution in terms of goodness of fit for the tails of the distribution. To validate the (quantile regression) model, one can use the pseudo-R^2 measure suggested by Koenker and Machado [1999] which assesses the fit at each quantile by comparing the sum of weighted deviations for the model of interest with the same sum from a model in which only the intercept appears, i.e.:

$$R^2(\tau) = 1 - \frac{\sum_{y_i \geq \hat{y}_i} \tau \cdot |y_i - \hat{y}_i| + \sum_{y_i < \hat{y}_i} (1-\tau) \cdot |y_i - \hat{y}_i|}{\sum_{y_i \geq \overline{y}_i} \tau \cdot |y_i - \overline{y}| + \sum_{y_i < \overline{y}_i} (1-\tau) \cdot |y_i - \overline{y}|} \tag{3}$$

where $\hat{y}_i$ and $\overline{y}$ are the fitted values derived from the equation with and without controls, respectively. This represents a local measure of fit since it depends on each quantile τ, differently from the global R^2 commonly used in a standard OLS framework.

Figure 4: Pseudo R-squared

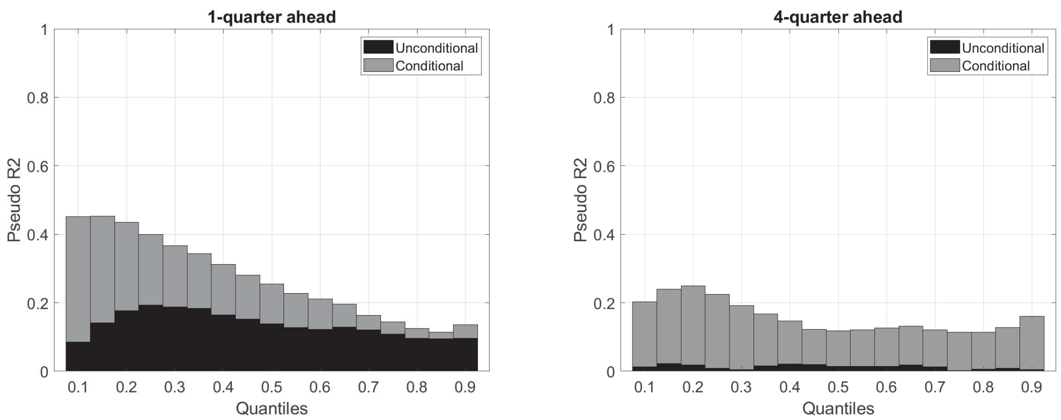


Figure 4 illustrates the pseudo R^2 for both models and both horizons. The fit appears considerably higher for the left part of this distribution, especially for the horizon $h = 1$. Moreover, this fit monotonically decreases over quantiles. This finding characterizes the left asymmetry of this distribution and thus validates the idea that business cycle conditions have an asymmetric effect on the conditional distribution of inflation forecasts.

3 Asymmetry in the inflation distribution

This section examines in depth the estimated conditional distribution of inflation to show his asymmetry in three different ways. First, it looks at the role of conditioning the inflation distribution on economic conditions. Second, it provides a quantification of the evolution of extreme inflation rate scenarios generated by the estimated distribution. Finally, it illustrates two appealing inflation-related policy scenarios.

3.1 Relative entropy

In this part I quantify the implications of conditioning on the state of the business cycle by considering the Kullback-Leibler divergence between the conditional, $f(y)$, and the unconditional distribution, $g(y)$, of inflation forecasts[6]. As described by Adrian et al. [2019], this measure can be used to assess the impact of the conditioning variable on the distribution of inflation. In other words, the relative entropy provides the *information gain* produced by including the current state of the business cycle. Analytically, this can be written as

$$\mathcal{L}_t^D(f_t, g) = \int_{-\infty}^{F^{-1}(0.5)} \left(log\, g(y) - log\, f_t(y)\right) f_t(y) dy \tag{4}$$

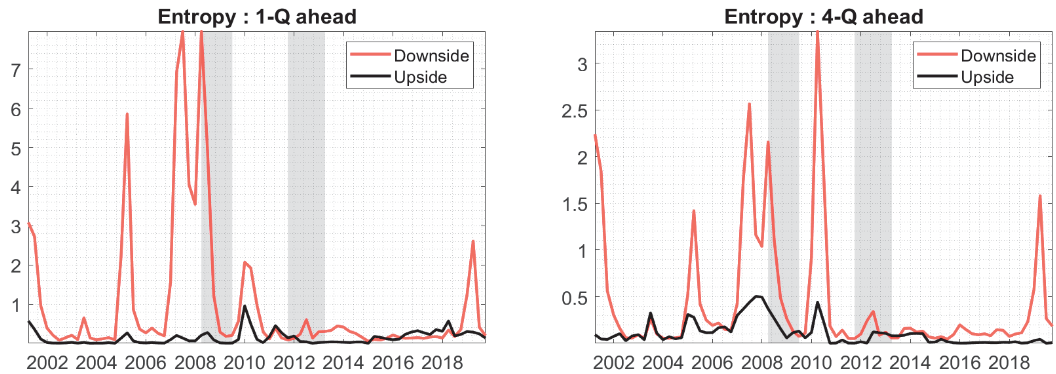
$$\mathcal{L}_t^U(f_t, g) = \int_{F^{-1}(0.5)}^{\infty} \left(log\, g(y) - log\, f_t(y)\right) f_t(y) dy\,. \tag{5}$$

where the downside entropy $\mathcal{L}_t^D$ refers to the difference between the unconditional and conditional distribution for the left part of the distribution (namely from the first percentile to the median) and the upside entropy $\mathcal{L}_t^U$ which is the analogous for the right part of the distribution. Figure 5 points out one main evidence: the downside entropy (red line) is significantly more volatile than the upside entropy (black line) which indeed remains stable over time. This confirms that economic conditions do not provide any information gain about the upper quantiles of the

[6]The Kullback-Leibler divergence, also known as relative entropy or information divergence, is a measure of the non-symmetric difference between two distributions. It is generally used because differently from other measures of distance, it has a direct counterpart in the logarithmic scoring rule, which is commonly used for evaluating density forecasts (see Amisano and Giacomini [2007]).

inflation distribution, while they are extremely important for the bottom ones. In other words, the variation of the conditional distribution is mainly driven by the movements in the left tail and not by those in the right tail which remains relatively constant over time.

Figure 5: Downside (red) and upside (black) entropy



Note: the grey shaded areas corresponds to the CEPR recession periods in the euro area

3.2 Expected shortfall and longrise

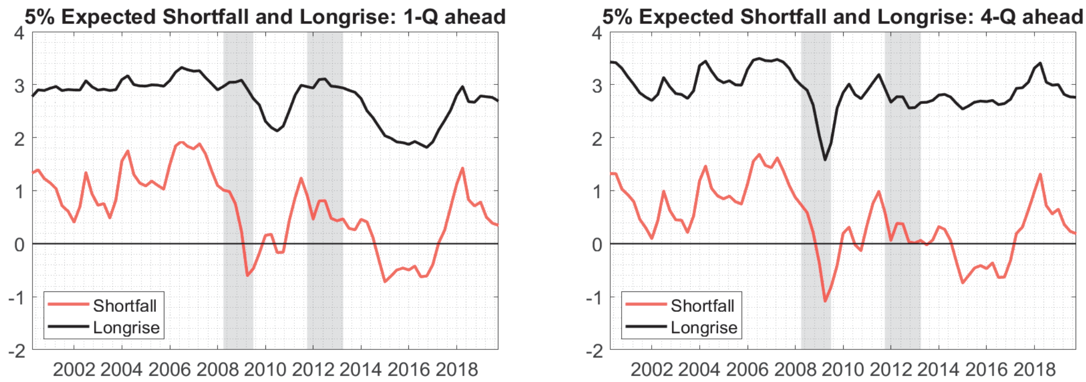
The estimated conditional distribution can also be used to quantify the expected values of extreme scenarios, namely either low or high values of inflation that a forecaster might predict according to this quantile-regression model. This is implemented by considering the expected shortfall and expected longrise which are two measures commonly used in the finance literature to represent the expected return on the portfolio in the worst (or best) $\tau\%$ of cases. In practice, these two measures can be defined as

$$SF_t = \int_0^{0.05} F_t^{-1}(\tau)\, d\tau \qquad LR_t = \int_{0.95}^{1} F_t^{-1}(\tau)\, d\tau \tag{6}$$

and they correspond to the integral of the inverse cumulative distribution function $F_t^{-1}(\cdot)$ at its extreme 5-percentile tails, i.e. from 1 to the 5-th percentile and from 95-th to the 100 percentile.

Figure 6 shows that for both horizons the expected longrise remains roughly stable over time fluctuating around values of 3% while the expected shortfall is much more volatile in the interval between -1% and 1%. The main message of these two figures is that the expectation of low inflation is sensitive to the fluctuations in the business cycle whereas the upside risk is less responsive to changes in economic conditions.

Figure 6: Expected Shortfall (red) and Longrise (black)



Note: the grey shaded areas corresponds to the CEPR recession periods in the euro area

3.3 Policy-scenario probabilities

Price stability is the main target of the majority of central banks. In the euro area, the European Central Bank (ECB) is the institution which pursues medium- and long-term price stability, with the mandate to keep headline inflation "close but below to two percent". Recent episodes as the Europe's Double-Dip recessions and oil turmoils in the period 2014-2015 had a considerable impact on the level of prices and brought the inflation rate also in negative territory.

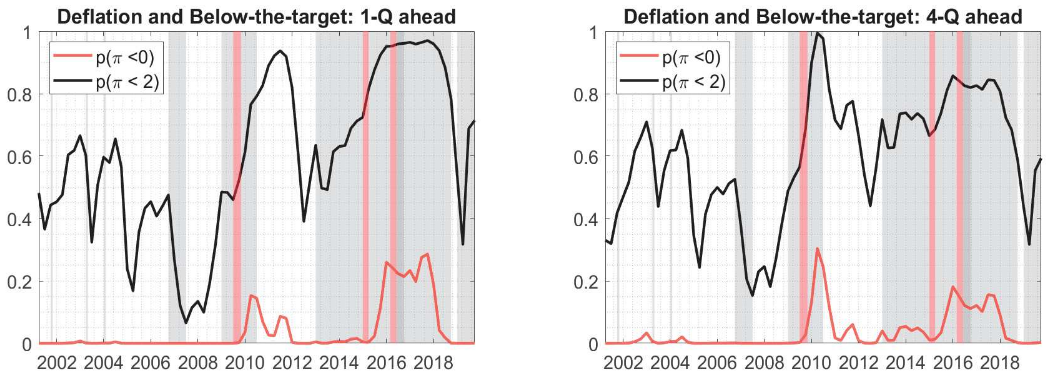
With this is mind, this section uses the estimated conditional distribution to propose the quantification of two relevant policy scenarios, namely the risk of deflation ($\pi < 0$) and the probability of being below the target ($\pi < 2$), which for simplicity is assumed to be at a 2 percent inflation rate. Using the same notation of equation 6, this can be specified as

$$F_t^{DEFL}(0) = \int_{-\infty}^{(0)} f_t(y)dy \qquad F_t^{BT}(2) = \int_{-\infty}^{(2)} f_t(y)dy\,. \tag{7}$$

where $f_t(y)$ is the conditional distribution of inflation and $F_t^{DEFL,BT}(\cdot)$ is the corresponding cumulative distribution function. Figure 6 illustrates the quantitative results in following way: the red line represents the probability of a future inflation rate in negative territory while the black line corresponds to the probability of an inflation rate below the 2% target. Similarly, the red and the grey shaded areas represent the periods in which the euro area was in deflationary time and below the target, respectively.

The charts present similar results for both horizons. The probability of being below the target is well-captured: indeed, the odds of having inflation below 2% is generally above 0.5 for all the period after 2013, which is commonly known as

Figure 7: Policy-scenario analysis



Note: the red shaded areas correspond to deflationary periods and the grey shaded areas represent the periods in which the inflation rate was below 2%.

"missing inflation". Similarly, the probability of deflation rises in 2009 related to the severity of the recession and then it spikes again in 2016 in the period of very low inflation due to some turmoil in oil dynamics.

4 Out-of-sample

The empirical results presented so far are obtained using an in-sample estimation approach. Although this is extremely useful for understanding the properties of the estimated distribution of inflation forecasts, it does not fully replicate the true experience of a forecaster. For this reason, this section proposes an out-of-sample exercise to assess the forecasting abilities of this quantile model. The forecasting exercise evaluates the performance of the model over a period of seven years, i.e. 28 quarters between 2012Q4 and 2019Q3, using a recursive estimation procedure with a focus on two specific dimensions: (i) the quantile score, which assesses the forecast accuracy across different quantiles, and (ii) the probability integral transformation (PIT), that measures the calibration of the predictive density.

4.1 Quantile score

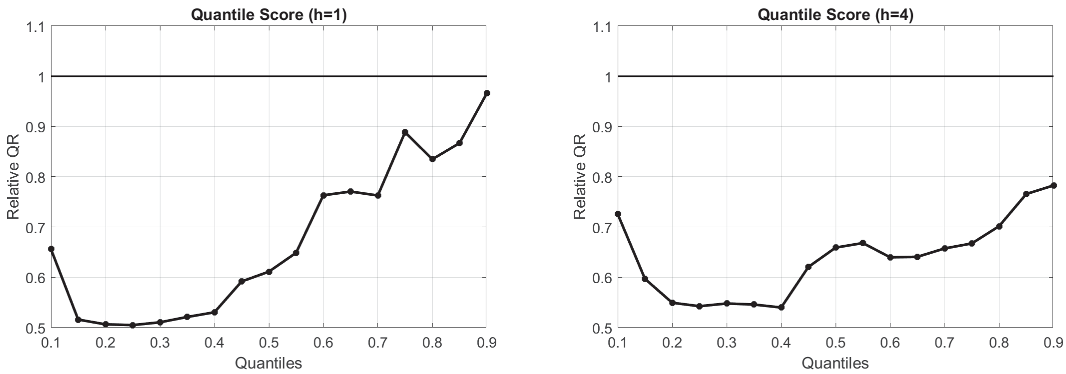
In the case of a non-parametric distribution, the standard approach to evaluate the performance of a model is to use the predictive score which corresponds to the value of the predictive density generated by the model at the realized value of inflation following the logic that the higher the score, the more accurate the model is. However, in the presence of a considerable asymmetry as in this case, looking at the score per *sè* is not very informative. Indeed, the most appropriate way to evaluate these model is to assess the specific performance across quantiles (see Gneiting and

Raftery [2007] and Busetti et al. [2015]). In practice, this corresponds to consider the loss function $L(\tau)$ evaluated as

$$L(\tau) = \sum_{y_t \geq Q_{\tau,t}} \tau |y_t - \hat{Q}_{\tau,t}| + \sum_{y_t < Q_{\tau,t}} (1-\tau)|y_t - \hat{Q}_{\tau,t}| \quad (8)$$

where $\hat{Q}_{\tau,t}$ is the out-of-sample prediction for each quantile τ at each time t. Clearly, the logic of this loss function is the lower $L(\tau)$, the better the performance. To quantify the accuracy gain obtained by conditioning on the business cycle, figure 8 shows the ratio between the quantile score of the conditional model and the unconditional model. Two results appear clear: first, the accuracy gain (black line) is below one for both horizons at each quantile. This implies that the conditional distribution has an overall superior performance with respect to the unconditional distribution. Second, this accuracy gain is more marked for the lower quantiles, in general around 40 per cent for the left part of the distribution while it is considerably lower for the upper quantiles.

Figure 8: Relative quantile score



Note: the black line indicates the relative quantile score. A number below one indicates that the conditional model outperforms the unconditional model in terms of the quantile score.

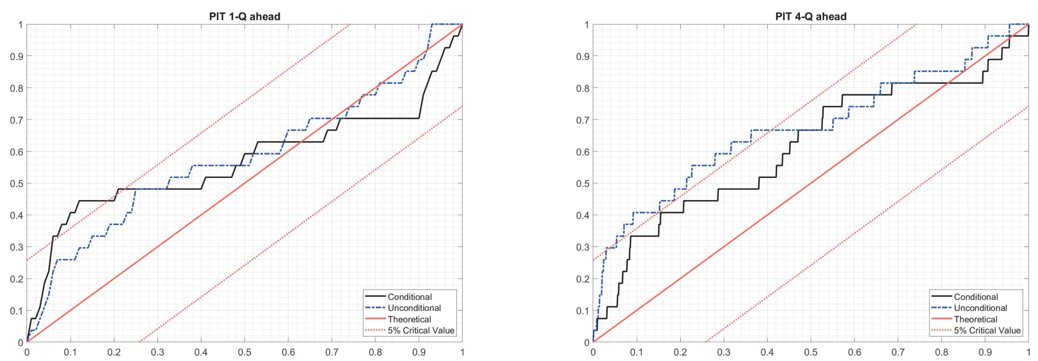
4.2 Probability integral transformation

This part analyzes the calibration of the predictive distribution by looking at the empirical cumulative distribution of the probability integral transformation (PIT), a tool introduced by Diebold et al. [1998]. In a nutshell, this measure indicates the percentage of observations that are below any given quantile τ and it is used to evaluate whether the empirical predictive distribution matches the true (unobserved) distribution that generates the data. In other words, this is equivalent to test whether the generated distribution z_{t+h}, which is obtained as

$$z_{t+h} = \int_{-\infty}^{y_{t+h}} f_{t+h}(y_{t+h})dy, \tag{9}$$

is distributed as an *iid* Uniform $(0, 1)$ distribution. To test for the correct specification of the conditional predictive density, I adopt the test proposed by Rossi and Sekhposyan [2019] which preserves the estimation error of the parameters used to construct the densities and focuses on evaluating the *absolute* performance of the model's predictive density[7]. In this context, a perfectly calibrated density should be equal to the 45-degree line, therefore any deviation from the bisector line suggests a bias in the predictive density. Figure 9 shows the results for the conditional (black line) and unconditional (blue dashed line) distribution together with the critical values (red dotted lines). A line outside these 5% critical values indicates the rejection of the null hypothesis of correct calibration, therefore considering the model as not correctly calibrated.

Figure 9: Probability integral transformation



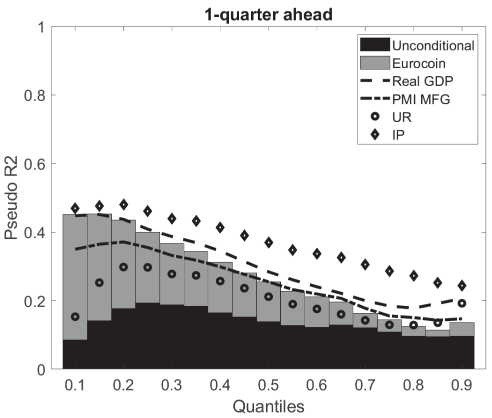
Interestingly, the overall difference in terms of calibration between the two distributions is relatively small. However, for the horizon $h = 1$ the test rejects the null hypothesis of correct calibration for the conditional distribution due to the left part of the distribution. Viceversa, the null hypothesis is rejected only for the unconditional distribution for $h = 4$. One explanation of these results is that the business cycle conditions lead the conditional model to be relatively pessimist on the inflation outlook, generating a left asymmetry. In the second case, the lack of correct calibration is probably due to the persistency of inflation.

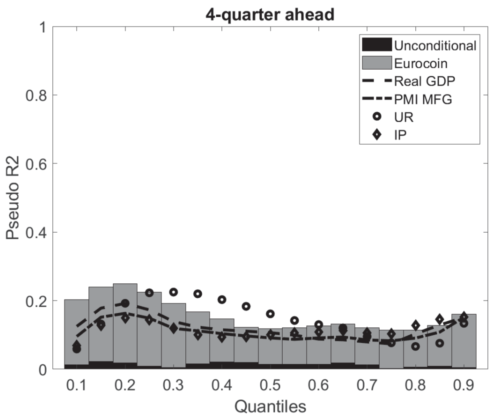
[7] Critical values (red dotted lines in the graphs) are obtained using the method proposed by Rossi and Sekhposyan [2019] which also provide an interesting review of the related literature.

5 Robustness checks

The results obtained so far are based on the €-*coin* as the indicator of the business cycle in the euro area. Although its validity has been extensively analyzed (see Altissimo et al. [2010]), it is interesting to study whether the left asymmetry of the distribution of inflation forecasts is also robust to other main business cycle variables. For this reason, the analysis of Section 3 is repeated by conditioning on a list of standard business cycle indicators for the euro area: more precisely, I consider real GDP, industrial production, unemployment rate and ISM PMI manufacturing index[8]. To assess the robustness of the results, figure 10 presents the pseudo R-squared statistic as in section 2.3. In this case, the pseudo-R^2 of the unconditional and the conditional model are compared to the corresponding values for the models with the other business cycle indicators. These two charts confirm the main result of the paper, namely the existence of an left asymmetry in the distribution of inflation forecasts which is generated by the deterioration of the business cycle. In some cases the evidence of a left asymmetry appears less strong than the case of the €-*coin* but this is due to the fact that the latter is obtained by including a large variety of indicators of business cycle, therefore it appears to better capture the current state of the economy.

Figure 10: Robustness over business cycle indicators





[8] A complete description of the variables is available in the Data Appendix.

6 Conclusions

Recent years of low inflation rates have posed new important questions for scholars (see Ciccarelli and Osbat [2017] for the euro area). Evaluating possible risks to inflation has become of primary importance, especially for policymakers. Quantitatively, this is commonly measured by the predictive density which corresponds to an estimate of the expected probability distribution of the target variable.

This paper proposes a comprehensive analysis of the evolution of the distribution of inflation forecasts conditional on macroeconomic conditions to formally evaluate the risk to inflation conditional on the current state of the economy. More specifically, I first adopt a quantile-regression approach to appropriately capture the effects of changes in economic conditions on all quantiles of the inflation distribution. Then, I use the quantile function to estimate the conditional distribution of inflation forecasts. The main finding is that there is a significant time-variation in the shape of the distribution which is mainly due to the relation of the lower quantiles of inflation with the business cycle. In other words, the conditional distribution presents a dynamics of the downside risk which is sensitive to the current state of the economy while the upside risk remains stable over time. This evidence is generally robust to several business cycle indicators.

This paper also performs some other interesting exercises using the estimated conditional distribution. First, it shows the implication of conditioning on the business cycle by means of the relative entropy. Second, it quantifies the probability of possible but extreme inflation outcomes and lastly it performs some relevant policy scenario analyses to study the ability of the model in capturing inflation dynamics.

Last but not least, the main finding of this paper might have some important policy implications. The asymmetric behaviour of the inflation distribution might be related to the different effectiveness of the monetary policy. Indeed, the evidence of this paper supports the idea that the central bank seems more in control of prices during period of booms, while it appears somehow less effective during downturns, since it can not avoid the possibility of periods of low inflation. However, the sensitivity of this point and the centrality for policy purposes represent a stimulating point for future research.

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Data Appendix

The data are taken from the ECB Statistical Data Warehouse. The sample covers the period Q1.1999-Q3.2019, using quarterly observations.

- **HICP**: Euro area (changing composition) - HICP - Overall index, Monthly index, backdated, fixed euro conversion rate used for weights, European Central Bank, Working day and seasonally adjusted;

- ***€-coin***: Euro area (changing composition), Centre for Economic Policy Research and Banca d'Italia, Coincident indicator of business cycle, based on quarterly changes in cyclical component of the GDP, see Altissimo et al. [2010];

  For the robustness exercise:

- **real GDP** Gross domestic product at market prices - Euro area 19 (fixed composition) Chain linked volume (rebased), Non transformed data, Calendar and seasonally adjusted data;

- **ISM PMI Manufacturing**: Euro area 19 (fixed composition), Markit, Manufacturing - output, Total, Seasonally adjusted, not working day adjusted;

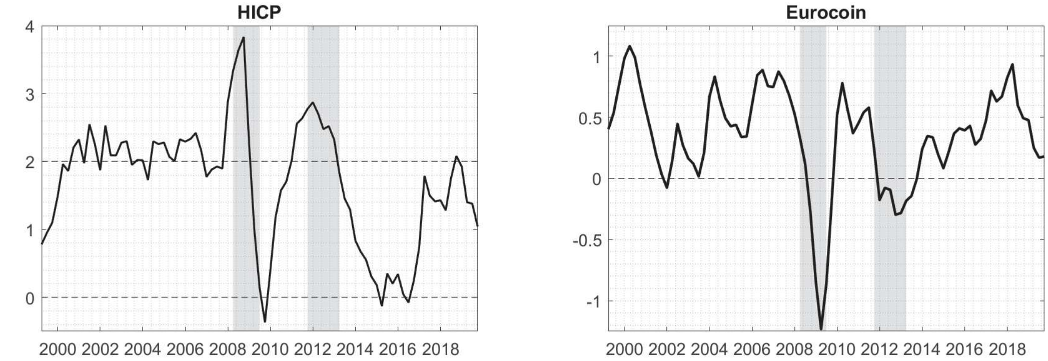
- **Industrial production**: Euro area 19 (fixed composition) - Industrial Production Index, Total Industry (excluding construction); Working day and seasonally adjusted;

- **Unemployment rate**: Euro area 19 (fixed composition) - Standardised unemployment, Rate, Seasonally adjusted, not working day adjusted, percentage of civilian workforce;

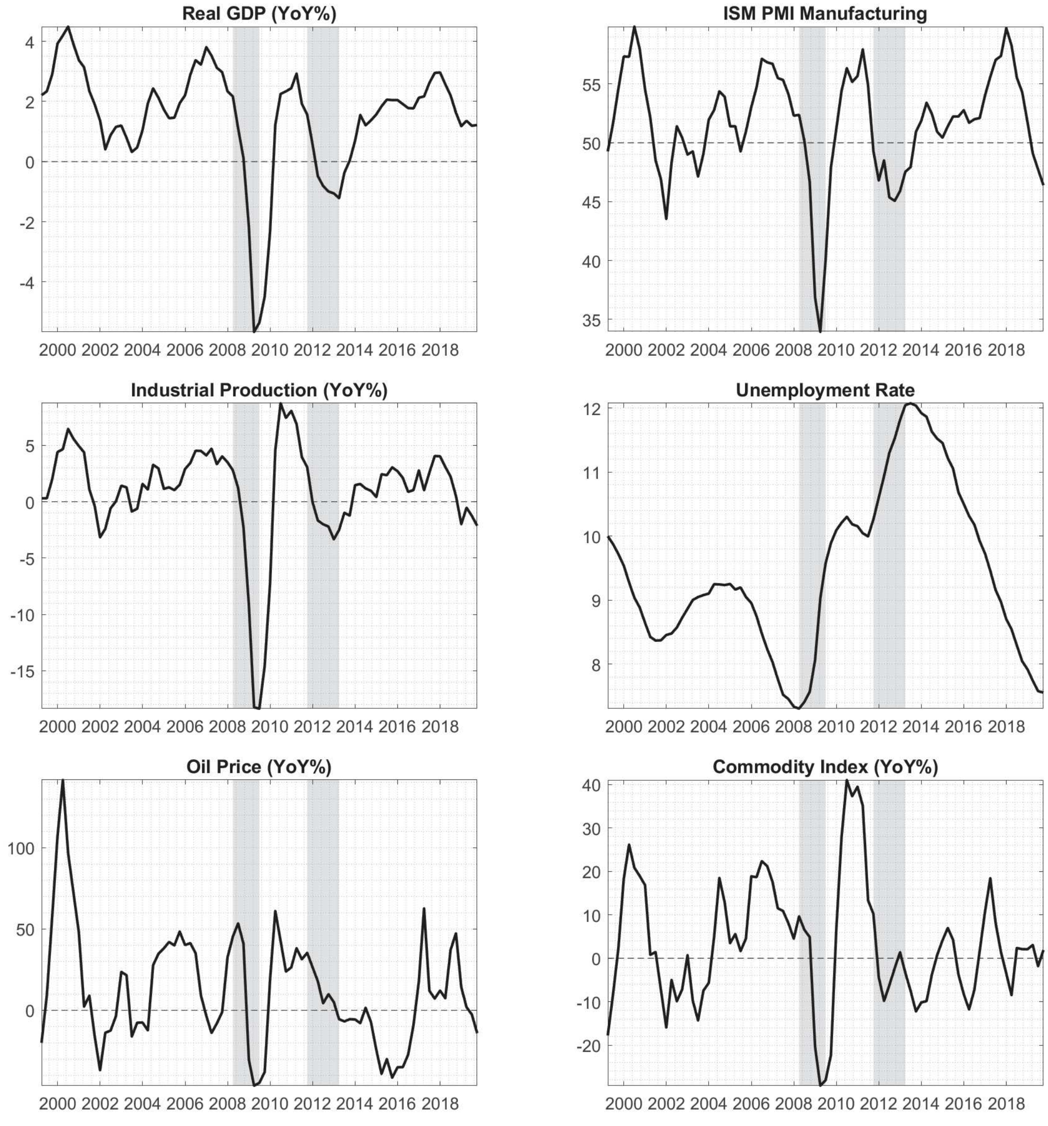
- **Oil price index**: annual growth rate of the Brent oil price converted in Euro;

- **ECB commodity price index**: annual growth rate of the ECB commodity price index, import weighted, Euro denominated, neither seasonally nor working day adjusted.

Figure 11: Raw data



Data for the section on robustness checks



Note: the grey shaded areas corresponds to the recession periods in the euro area as defined by the CEPR business cycle dating committee.

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