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ON THE CONDITIONAL DISTRIBUTION OF EURO AREA INFLATION FORECAST

by Fabio Busetti, Michele Caivano and Lisa Rodano *

Abstract

The paper uses dynamic quantile regressions to estimate and forecast the conditional distribution of euro-area inflation. As in a Phillips curve relationship we assume that inflation quantiles depend on past inflation, the output gap, and other determinants, namely oil prices and the exchange rate. We find significant time variation in the shape of the distribution. Overall, the quantile regression approach describes the distribution of inflation better than a benchmark univariate trend-cycle model with stochastic volatility, which is known to perform very well in forecasting inflation. In an out-of-sample prediction exercise, the quantile regression approach provides forecasts of the conditional distribution of inflation that are superior, overall, to those produced by the benchmark model. Averaging the distribution forecasts of the different models improves robustness and in some cases results in the greatest accuracy of distributional forecasts.

JEL Classification: C32, E31, E37.
Keywords: quantile regression, Phillips curve, time-varying distribution.

Contents

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1 Introduction

The New Keynesian paradigm has made inflation forecasts central for monetary authorities. The optimal monetary policy is inevitably forward looking and targets the agents' forecasts of inflation. Moreover, central banks' announcements of inflation forecasts affect public expectations and thus enhance the effectivennes of monetary policy (see, among others, Clarida *et al.* (1999), Christiano & Fitzgerald (2003), Woodford (2003), Svensson (2007)).

Most central banks regularly publish medium-term inflation forecasts both as point estimates and confidence bands (or 'fan charts'), so as to provide a measure of uncertainty around the central outcome. In some cases the forecast distribution may be asymmetric, reflecting - largely in a judgemental way - the likelihood of alternative macroeconomic scenarios and 'tail events'. For example, the Bank of England publishes fan charts for inflation since 1996 (see Britton *et al.* (1998) and Bank of England (2002)); the Bank of Italy regularly publishes fan charts for real GDP and HICP inflation since 2009 (see Miani & Siviero (2010)).

The econometric literature on forecasting inflation has stressed that, on average, simple univariate timeseries models are hard to outperform. In particular, Atkeson & Ohanian (2001) found that a random walk model for the annual rate of inflation has generally a lower Mean Square Forecast Error (MSFE) than Phillips curve type models over the period 1984-99. Stock & Watson (2007) showed that a univariate trend-cycle model with stochastic volatility provides an accurate description of inflation dynamics over most sample periods. There are, however, periods when Phillips-curve models are more effective at forecasting inflation, particularly when the economy is weak; see Stock & Watson (2007) and Stock & Watson (2008). As regards the stability of the relationship between inflation and economic activity, a flattening of the US Phillips curve after 1984 was identified by Roberts (2006). Time-varying coefficient models have been considered in various studies, e.g. Cogley *et al.* (2010), D'Agostino *et al.* (2013), Granger & Jeon (2011), Stella & Stock (2012). In a recent work Riggi & Venditti (2014) report an increased sensitivity of euro area inflation to the (large negative) outgap gap in the aftermath of the sovereign debt crisis, although they note that the effects of a structural break are difficult to disentangle from those associated to a possible underestimation of the slack in the economy.

All the above papers compare inflation models in terms of point forecasts, e.g. using the MSFE metrics. The focus of this study is, by contrast, the entire conditional distribution of euro area inflation. This can be characterized using dynamic quantile regression models. A Phillips-curve type relation is assumed, where inflation quantiles depend on past inflation and the output gap, as well as on oil prices and the exchange rate. Our results show substantial time-variation in the shape of the distribution on inflation, with changes not limited to volatility but also affecting the degree of kurtosis and, to some extent, asymmetry.

Overall we find that the quantile regression approach better describes the distribution of inflation compared with the benchmark, given by a standard univariate trend-cycle model with stochastic volatility, that is known to be hard to beat in forecasting inflation. In an out-of-sample prediction exercise, the quantile regression approach provides overall superior forecasts of the conditional distribution of inflation. Averaging the forecast distributions of different models improves robustness and in some cases achieves the highest accuracy of distributional forecasts.

To our knowledge, not many papers have applied quantile regression methods to estimate the distribution of macroeconomic variables. The closest work to ours is Manzan & Zerom (2013), where it is shown that economic activity indicators, such as the unemployment rate, are useful for forecasting the distribution of US inflation. Specifically, starting from the results of Atkeson & Ohanian (2001), Manzan & Zerom (2013) constructs quantile regression models for the residuals of a random walk process for annual inflation, using as regressors several types of economic indicators; this is found to yield more accurate predictions of the distribution of inflation, particularly at lower quantiles. Tillmann & Wolters (2014) use quantile regressions to study the persistence of US inflation, finding a structural break at all quantiles in the early 80's. Gaglianone & Lima (2014) construct density forecasts for macroeconomic series using the average in the Survey of Professional Forecasters (SPF) as a covariate. Andrade *et al.* (2014) find that the quantiles of the SPF density forecasts help (point) predictions of future inflations. Finally, Laurent & Koźluk (2012) use quantile regressions to measure GDP forecast uncertainty, using industrial production and other indicators of real activity.

The paper proceeds as follows. Section 2 reviews the quantile regression approach and briefly describes the benchmark univariate trend-cycle model with stochastic volatility. Section 3 contains the in-sample estimation results on the chariczterization of the conditional distribution of inflation. An out-of-sample forecast exercise is carried out in section 4. Section 5 concludes.

2 Modelling the conditional distribution of euro area inflation

This section reviews the quantile regression approach and describes the benchmark forecast model, given by a univariate trend-cycle model with stochastic volatility.

2.1 Quantile regression[1]

Let $F(y)$ be the cumulative distribution function of the random variable y. For any $0 < \alpha < 1$, the quantile of order α of y, denoted as $Q_\alpha(y)$, is defined by the inverse of the distribution function, $Q_\alpha \equiv F^{-1}(\alpha) = \inf\{y : F(y) \geq \alpha\}$. Given a set of i.i.d. observations y_t, $t = 1, 2, ..., T$, the sample quantile, $\widehat{Q}_\alpha$, is obtained by sorting them in ascending order; equivalently, it is given by the solution of the following minimization problem,

$$\begin{aligned}
\widehat{Q}_\alpha &= \arg\min_Q \left\{ \sum_{t=1}^{T} \rho_\alpha (y_t - Q) \right\} \\
&= \arg\min_Q \left\{ \sum_{y_t \geq Q} \alpha |y_t - Q| + \sum_{y_t < Q} (1-\alpha) |y_t - Q| \right\},
\end{aligned}$$

where $\rho_\alpha(u) = u(\alpha - 1(u > 0))$ is the so-called *check function*, with $1(u > 0)$ being the usual indicator function. For the median, the check function $\rho_{0.5}(u)$ corresponds to the loss function of the Least Absolute Deviation estimator, $\widehat{Q}_{0.5} = \arg\min \sum_{t=1}^{T} |y_t - Q|$.

In the quantile regression approach, introduced by Koenker & Bassett (1978), the quantiles are modelled in terms of some parametric function of observable covariates, z_t, e.g.

$$Q_\alpha(y_t | z_t) = \beta_0(\alpha) + \beta_1(\alpha)' z_t,$$

where the regression coefficients depend on the quantile order α. The parameters are estimated by the same minimization procedure described above, i.e.

$$\left(\widehat{\beta}_0(\alpha), \widehat{\beta}_1(\alpha)'\right) = \arg\min_{\beta_0, \beta_1} \left\{ \sum_{t=1}^{T} \rho_\alpha \left(y_t - \beta_0(\alpha) - \beta_1(\alpha)' z_t\right) \right\}.$$

[1] Koenker (2005) is a detailed monograph on quantile regression methods.

Under regularity conditions, the estimated parameters are $\sqrt{T}$ - consistent and have a Gaussian limit distribution. The asymptotic covariance matrix depends on the error density function, so it can be difficult to estimate. As an alternative to the asymptotic results, bootstrap methods can be used to obtain the standard errors of the parameters; see e.g. Buchinsky (1995).

A goodness of fit measure for quantile regression, proposed by Koenker & Machado (1999), is based on the 'residual absolute sum of weighted differences', $RASW_\alpha = \sum_{y_t \geq \widehat{Q}_{\alpha,t}} \alpha \left| y_t - \widehat{Q}_{\alpha,t} \right| + \sum_{y_t < \widehat{Q}_{\alpha,t}} (1-\alpha) \left| y_t - \widehat{Q}_{\alpha,t} \right|$, where $\widehat{Q}_{\alpha,t} = \widehat{\beta}_0 (\alpha) + \widehat{\beta}_1 (\alpha)' z_t$ is the fitted α-quantile at time t. This 'pseudo R^2 measure' (constructed as the coefficient of determination in least squares analysis) is defined as

$$R^2_\alpha = 1 - \frac{RASW_\alpha}{TASW_\alpha}, \tag{1}$$

where $TASW_\alpha$ is the total sum of weighted differences, obtained by plugging the unconditional quantile in the $RASW_\alpha$ formula above. Thus R^2_α ranges between 0 and 1.

By estimating quantile regressions for several α's, varying in the interval (0,1), the entire conditional distribution of y_t can be traced out.

In the actual estimates quantiles might cross at some points in time, i.e. it can happen that $\widehat{Q}_{\alpha_1,t} > \widehat{Q}_{\alpha_2,t}$ for $\alpha_1 < \alpha_2$. For these cases a correction is needed, such as the one in Chernozhukov *et al.* (2010).

2.2 A trend-cycle model with stochastic volatility

The year-on-year rate of inflation π_t is modelled in terms of a time-varying location μ_t (that can be interpreted as 'trend inflation') and volatility σ_t as follows:

$$\pi_t = \mu_t + \sigma_t \varepsilon_t, \quad t = 1, ..., T. \tag{2}$$

The model is estimated by maximum likelihood, resorting to the dynamic conditional score (DCS) methodology developed by Harvey (2013) and Creal *et al.* (2013). Accordingly, we directly specify the filter for updating the estimates of the time-varying parameters in terms of the score of the conditional distribution of inflation. In particular, we assume:

$$\pi_t = \mu_{t|t-1} + exp(\lambda_{t|t-1}) \varepsilon_t, \tag{3}$$

$$\mu_{t+1|t} = \omega_\mu(1-\phi_\mu) + \phi_\mu \mu_{t|t-1} + \kappa_\mu u_{t,\mu}, \tag{4}$$

$$\lambda_{t+1|t} = \omega_\lambda(1-\phi_\lambda) + \phi_\lambda \lambda_{t|t-1} + \kappa_\lambda u_{t,\lambda}, \tag{5}$$

where $u_{t,\mu}$ and $u_{t,\lambda}$ are linear functions of the score of the conditional distribution. If $\varepsilon_t \sim N(0,1)$, then $u_{t,\mu} = \pi_t - \mu_{t|t-1} = v_t$ and $u_{t,\lambda} = v_t^2 exp(2\lambda_{t|t-1})$ and the model becomes an AR(1) process with GARCH(1,1) errors. A maximum likelihood estimation assuming a Gaussian distribution yields (numerical standard errors in brackets) $\omega_\mu = 0.0258(0.0014)$, $\phi_\mu = 0.8408(0.0425)$, $\omega_\lambda = -5.004(0.5739)$, $\phi_\lambda = 0.996(0.0365)$, $\kappa_\mu = 0.9747(0.1229)$ and $\kappa_\lambda = 0.2689(0.039)$.

3 In-sample estimation results

For euro area inflation we estimate the following prediction model of conditional quantiles, motivated by Phillips curve arguments:

$$Q_\alpha(\pi_{t+h}) = \beta_0(\alpha) + \beta_1(\alpha)\pi_t + \beta_2(\alpha) y_t + \beta_3(4) oil_t + \beta_4 ex_t, \tag{6}$$

where π_t is inflation (the year-on-year change of the logarithm of the Harmonized Index of Consumer Prices), y_t the output gap, oil_t the change in oil prices in euro, ex_t the change of the nominal effective exchange rate of the euro. The model is estimated with quarterly data over the period 1990-2014 for $\alpha = .05, .10, .15, ..., .85, .90, .95$ and $h = 1, 2, 3, 4$. The regressors y_t, oil_t and ex_t are meant to capture the effects of, respectively, demand pressure, commodity prices and the exchange rate[2]. The model is dynamic in the sense that the inflation quantiles depend on the past level of inflation, in addition to the other covariates.[3]

Overall we model 19 conditional quantiles that are used for obtaining 1,2,3,4-step ahead forecasts for the conditional distribution of inflation. The estimated coefficients have the correct sign and they are, in most cases, statistically significant at least at the 10% level. Clearly, given the relatively

[2] Data on HICP and GDP are taken from Eurostat. The output gap is computed as the log-difference between actual and potential GDP, with the latter calculeted by a standard Hodrick-Prescott filter. The source for oil prices is Thomson Financial Datastream, while the nominal effective exchange rate is the 19-trading partners measure published in the ECB's Statistical Data Warehouse.

[3] An alternative way of proceeding would be to explicitly model the time dependence of quantiles. This could be done non-parametrically as in Yu & Jones (1998), De Rossi & Harvey (2009), or using the non-linear parametric approach of Engle & Manganelli (2004).

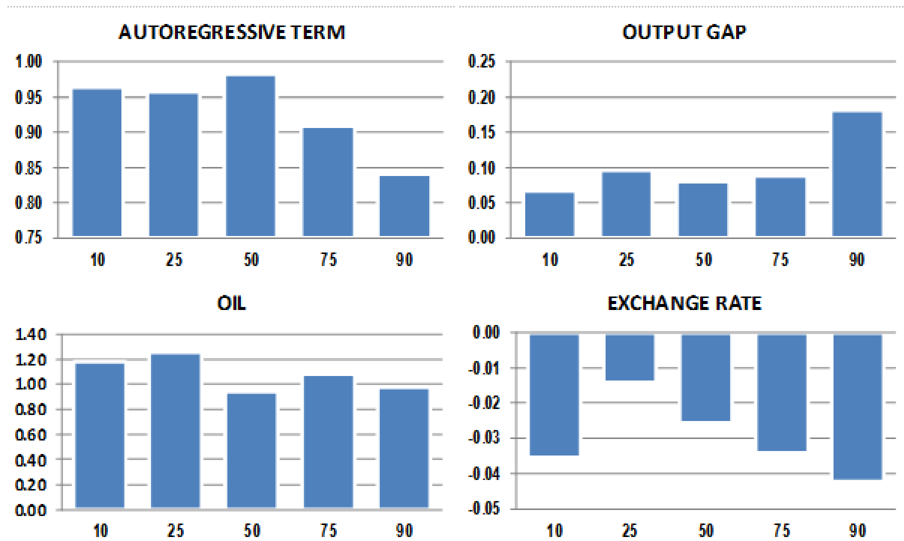

Figure 1: Quantile regression coefficients at $\alpha = .10, .25, .50, .75, .90$

small number of observations, estimation noise could be an issue for precise estimation of the outer quantiles.

A subset of the coefficients, for different probability orders α and for $h = 1$, are shown in Figure 1. The 'pseudo-autoregressive' terms $\beta_1(\alpha)$ are relatively large; interestingly, persistence seems higher in the lower parts of the distribution compared with higher quantiles; the response to the output gap is stronger in the right tail of the distribution. The coefficients for oil and the exchange rate have the correct sign, positive the former and negative the latter. Compared with oil prices, the response of inflation to the exchange rate is less uniform across quantiles, being higher in the tails.

The properties of the conditional distribution are described in detail in the subsection below, where they are compared with the univariate trend-cycle model with stochastic volatility (denoted as LLSV) that accounts for time variation only in the location and scale of the distribution.

As concerns the goodness of fit of the estimated models, the pseudo R^2 measure (1) for the quantile regression and for LLSV models is reported in Table 1 for $h = 1$. Other than the baseline prediction model (6), denoted as QR_0, we also consider an alternative specification where exogenous regressors can enter contemporaneously (QR_1).[4] This may be viewed as being

[4]For $h = 1, 2, 3, 4$, the QR_1 model takes the following specification: $Q_\alpha(\pi_{t+h}) =$

close to the standard approach to inflation forecasting in central banks, with inflation being projected conditional on assumed future paths for commodity prices, the exchange rate and the output gap. Note that while QR_1 is expected to have a clear advantage over QR_0 within sample, this is not necessarily the case in genuine out-of-sample forecasts where the performance can be negatively affected by the noise embedded in the assumptions for the conditioning variables.

The QR_1 is the most accurate model, at all quantile orders. If the exogenous regressors are not allowed to enter contemporaneously (QR_0) the models' fit inevitably deteriorates, particularly in the lower part of the distribution. The QR_0 specification is however superior to the univariate trend-cycle model (LLSV).

α	QR_1	QR_0	LLSV
.05	0.72	0.57	0.61
.10	0.73	0.64	0.62
.15	0.73	0.66	0.63
.20	0.73	0.66	0.63
.25	0.72	0.66	0.62
.30	0.71	0.66	0.61
.35	0.71	0.65	0.60
.40	0.70	0.65	0.59
.45	0.70	0.65	0.59
.50	0.69	0.64	0.59
.55	0.69	0.64	0.59
.60	0.69	0.65	0.59
.65	0.69	0.65	0.59
.70	0.69	0.66	0.59
.75	0.70	0.66	0.60
.80	0.70	0.67	0.60
.85	0.70	0.66	0.59
.90	0.69	0.67	0.58
.95	0.68	0.66	0.53

Table 1. Goodness of fit at the various quantiles of the distribution

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$\beta_0(\alpha) + \beta_1(\alpha)\pi_t + \beta_2(\alpha) y_{t+h-1} + \beta_3(4) oil_{t+h} + \beta_4 ex_{t+h}$

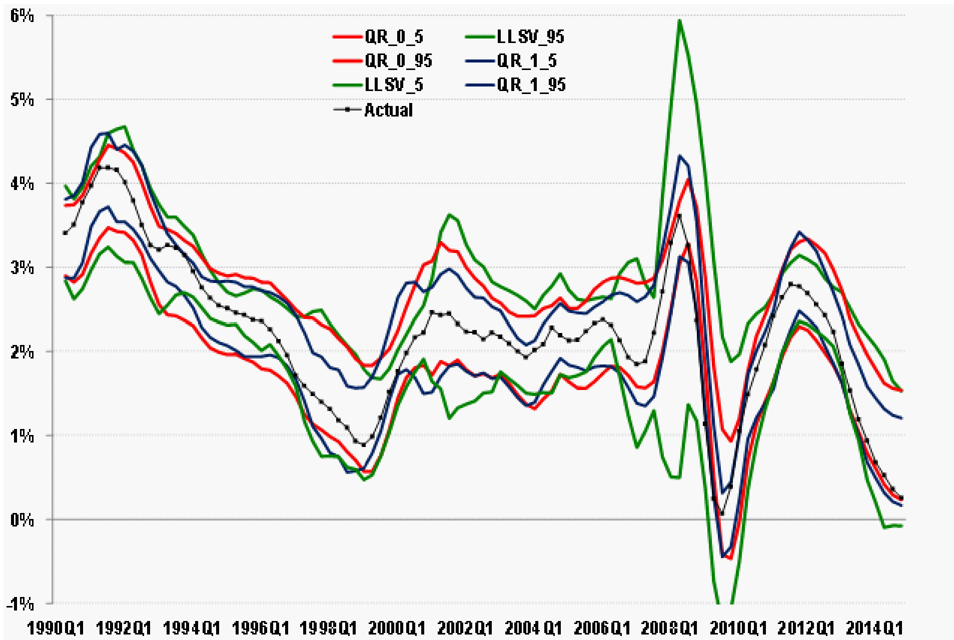

Figure 2: Outer quantiles (.05 and .95) and realized values of inflation; centered moving averages of three terms.

3.1 Gauging the time–variation in the conditional distribution

In general, our results show substantial time-variation in the shape of the distribution of inflation; besides movements in volatility, time variation appears to affect higher moments of the distribution as well. The outer quantiles (α equal to .05 and .95) are shown in figure 2 for QR_0, QR_1 and LLSV, together with the level of inflation. In most periods the quantiles of QR_0, QR_1 and LLSV move relatively closely together; this regularity breaks down during periods of high volatility in the exogenous variables, not accounted for in the LLSV model. Large swings of the exogenous regressors are also associated with inflation falling in the upper or the lower tail of the distribution.

The dispersion, measured by the interquartile range, is shown in figure 3. The time-variation of volatility is quite extreme in the LLSV model, but is also a feature of QR_0 and, to a lower extent, of QR_1.

Figure 4 shows a simple measure of symmetry of the distribution, $\varsigma = Q_{.10} + Q_{.90} - 2Q_{.50}$; a value greater than zero indicates positive skewness, i.e. that the right tail is longer than the left one. The conditional distribution

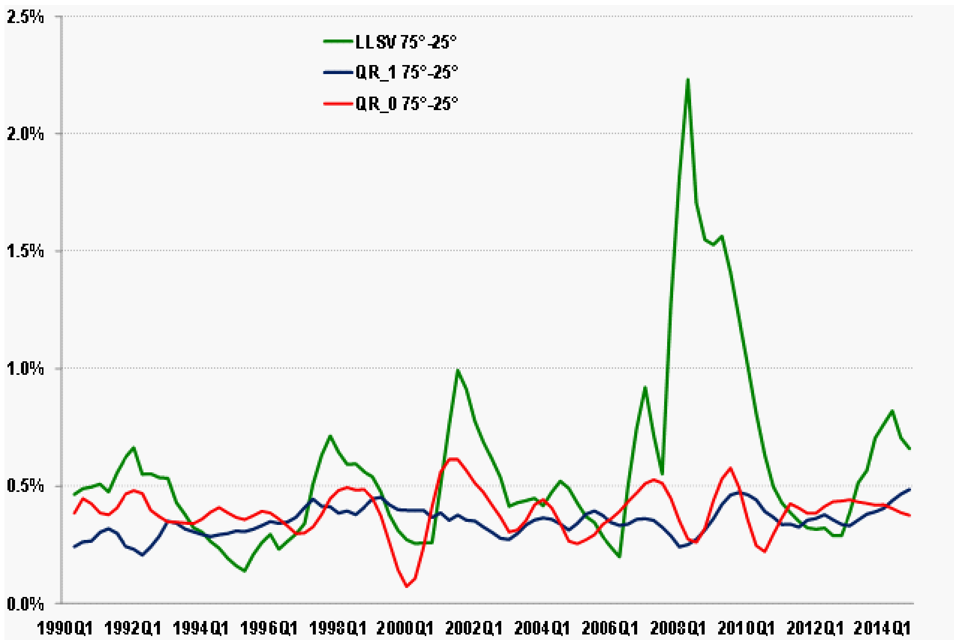

Figure 3: Interquartile ranges; centered moving averages of three terms.

implied by the QR_1 model tends to be positively skewed, whereas skewness changes frequently sign for QR_0. The distribution of LLSV is symmetric by construction.

Finally, Figure 5 plots the right tail thickness index $\xi = (Q_{.95} - Q_{.50})\,/\,(Q_{.75} - Q_{.50})$ and the left tail one. Interestingly in many periods the right tail appears much thicker than implied by a Gaussian distribution, where $\xi = 2.43$.

One important issue is whether the movements observed in the conditional quantiles are in some sense 'statistically significant' or whether they are just related to estimation noise. Clearly, the bulk of the time-variation depicted in Figure 2 is related to a changing conditional mean. The measures of dispersion, asymmetry and tail thickness are instead constructed using differences between quantiles, so that the effect of the conditional mean is washed out.

Busetti & Harvey (2010) have recently proposed statistical tests for the null hypothesis of constant quantiles against the alternative of 'permanent' movements, in the form of either random walk component or determistic shifts. Applying these tests to the residuals of an OLS estimate of the same type as the ones used for the quantile regressions we find evidence of instability of the quantiles, although not overwhelming. Looking at single

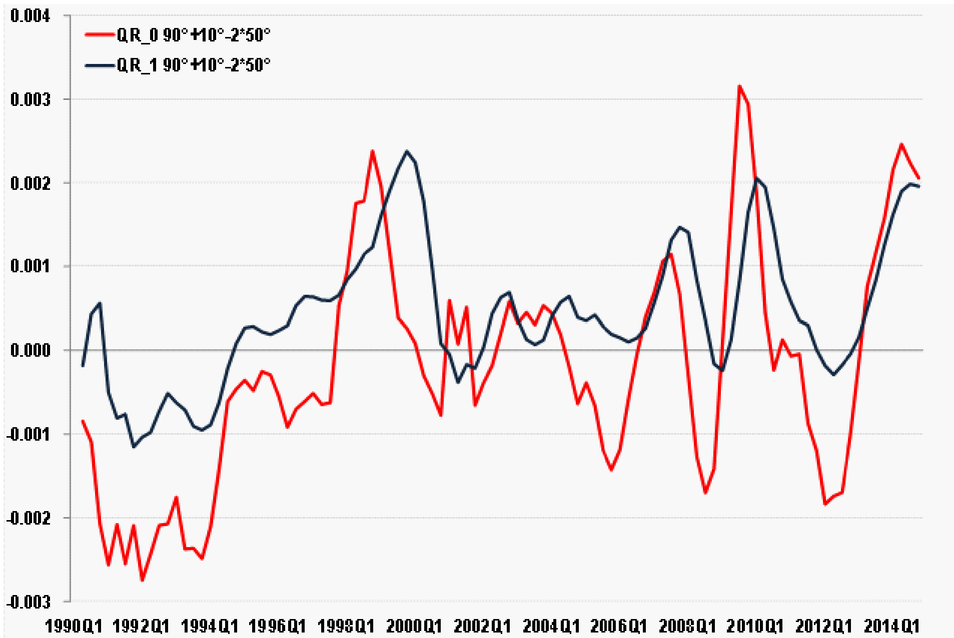

Figure 4: Skewness; centered moving averages of three terms.

quantiles we reject the null hypothesis at least at 10% significance only for $\alpha = .25$. But a multivariate test that jointly considers several quantiles (.10, .25, .50, .75, .90) also rejects the null hypothesis. Rejections occur also for the statistics based on the interquartile range (or the .05-.95 range) and for tail thickess, but not for skewness. It must however be stressed that in a sample of just 100 observations the power of these tests is expected not to be large.

Finally, an approximation of the conditional density functions of the three models is shown in Figure 6 for $t = 2008Q3$ and $t = 2014Q4$, respectively.[5] While in both periods the distribution implied by the LLSV model displays the largest dispersion (as seen also in Fig. 3), the difference with respect to the quantile regression models appears to be especially striking in 2008Q3; this finding suggests that in 2008Q3 most of the volatility of inflation is due to movements in its exogenous determinants, such as oil prices and the exchange rate, which are correctly controlled for in quantile regressions but not in the LLSV model. By contrast, in 2014Q4 the volatility of inflation

[5] This is obtained by Monte Carlo draws from the (piecewise linear) conditional cumulative distribution implied by the fitted quantiles.

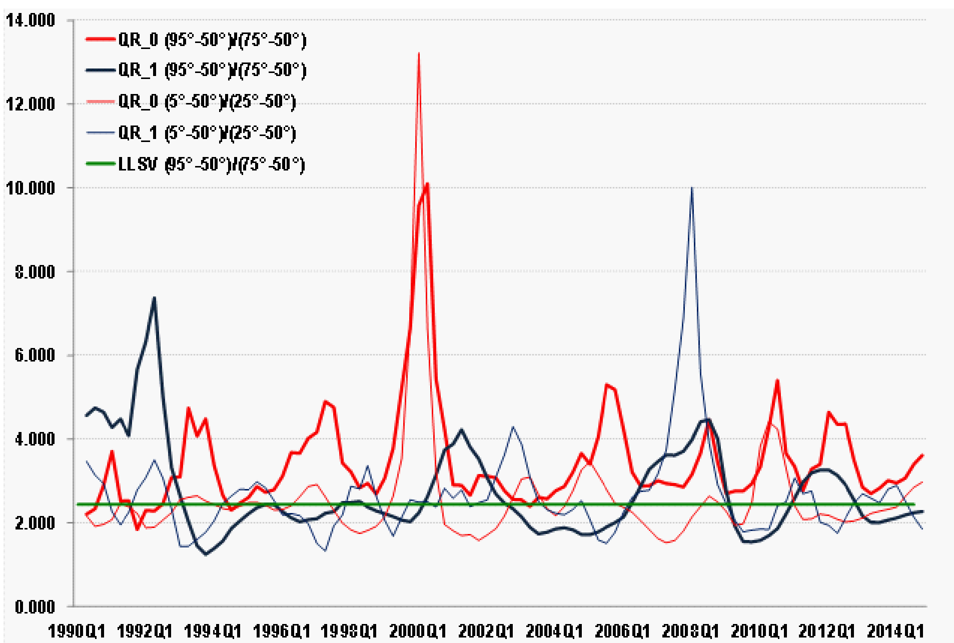

Figure 5: Right and left tail thickness; centered moving averages of three terms.

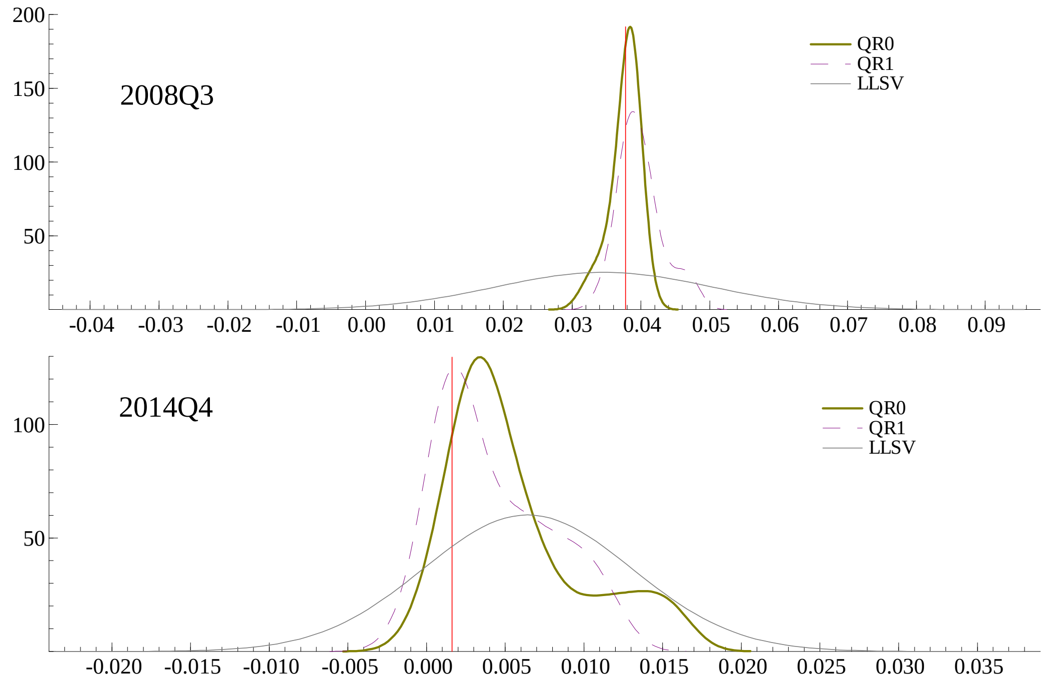

Figure 6: Forecast densities for 2008Q3 and 2014Q4; the red line is the realized value.

does not seem dominated by movements in its exogenous deteminants (see also Fig. 4): the main difference between the distributions implied by two class of models lies in the left tail, which is much longer for the (forcedly symmetric) LLSV model, while the more flexible quantile regression models are able to detect a non-negligible positive skewness.

4 Out-of-sample properties of the forecast distributions

In this section we evaluate the performance of the models in a genuine, real-time, out-of-sample forecast exercise. Each model is re-estimated at each point in time and standard conditioning assumptions are made for the exogenous variables: (1) the output gap is computed in real-time using a standard HP filter, (2) oil prices are derived from market's futures contracts;

(3) the exchange rate is kept constant at the most recent values (random walk projection). These assumptions are the same as those underlying the corresponding (quarterly) Eurosystem macroeconomic projection exercise. Clearly, such assumptions do not affect the LLSV model; QR_0 is only affected by the assumptions on the output gap, whose real-time estimates may differ sensibly from those based on the final data. The evaluation sample is relatively small, limited to the period 2010-2014.

We consider forecasts provided by QR_0, QR_1, a Phillips curve with constant variance (PC), the univariate trend-cycle model (LLSV) and two (equal weighted) combinations of forecast distributions, denoted as FC-01 and FC-01L. The first combines the distributions of QR_0 and QR_1; the second those of QR_0, QR_1 and LLSV. They are obtained by quantile averaging, as suggested in Busetti (2014).

For each model and forecast horizon $h = 1, 2, 3, 4$ the check loss function $L(\alpha)$ is evaluated,

$$L(\alpha) = \sum_{y_t \geq \widehat{Q}_{\alpha,t}} \alpha \left| y_t - \widehat{Q}_{\alpha,t} \right| + \sum_{y_t < \widehat{Q}_{\alpha,t}} (1-\alpha) \left| y_t - \widehat{Q}_{\alpha,t} \right|, \quad \alpha = .05, .10, ..., .90, .95,$$

where $\widehat{Q}_{\alpha,t}$ is the real time forecast of the α-order quantile. The lower the loss function the better the forecast of the conditional quantile. The results for all models and quantile orders α are reported in the appendix, where the losses are computed as ratios to the LLSV model; thus an entry lower than 1 means that the corresponding model is better than LLSV, and viceversa for entries greater than 1.

Averaging the loss functions over α's allows to get an overall measure of out-of-sample performance of the forecast distribution. This corresponds to the weighted quantile scoring function (WQS) of Gneiting & Raftery (2007), defined as

$$WQS = \int_0^1 L(\alpha)\omega(a)da,$$

where $\omega(a)$ are the weights. Table 2 reports results for: (1) uniform weights, $\omega(a) = 1$; (2) $\omega(\alpha) = \alpha(1-\alpha)$ which concentrates the weight in the middle of the distributions; (3) $\omega(\alpha) = (1-2\alpha)^2$ where more weight is placed in the tails. The *lower* WQS the better is the distributional forecast.

The table also reports two standard measures of fit for density forecasts, the *logarithmic score*, and the *linear score*, defined as $\textit{Log-S} = \frac{1}{T}\sum_t \log f_{t|t-h}(y_t)$

and *Lin-S* $= \frac{1}{T}\sum_t f_{t|t-h}(y_t)$, where $f_{t|t-h}(.)$ is the conditional density function for h-step ahead predictions; the *higher* is *Log-S* (or *Lin-S*) the better is the forecast. The intuition is that the model with higher out-of-sample log-score (or lin-score) on average assigns higher probability to the events that really occurred; see e.g. Mitchell & Hall (2005). Note that in our set-up these measure are affected by the noise resulting from interpolating the distribution between quantiles.

For 1-step ahead forecasts, $h = 1$, QR_1 appears to produce the most accurate distribution forecasts according to the WQS measure; the forecast combination between QR_0, QR_1 and LLSV is instead superior according to the log-score and lin-score metrics. In terms of the weighted quantile score, at all forecast horizons QR_1 seems preferable than the benchmark $LLSV$ model (which however works well for $h = 3, 4$ using the log-score and lin-score metrics[6]). The QR_1 achieves the higher lin-score for $h = 2$ while QR_0 seems preferable for $h = 4$ according to the WQS metrics. In general, the simple PC model does quite well in multi-step ahead forecasts. In terms of forecast combination, it seems preferable to jointly consider QR_0, QR_1 and LLSV.

[6] The detailed results of the appendix show that, for $h \geq 2$, LLSV tends to do relatively better in the right tail of the distribution and worse in the left one.

		QR1	QR0	PC	LLSV	FC-01	FC-01L
	Weighted Quantile Score						
	Whole distribution	**0.32**	0.37	0.33	0.39	0.33	0.35
	Center	**0.06**	0.07	0.07	0.08	0.07	0.07
h=1	Tails	**0.06**	0.08	0.07	0.08	0.07	0.07
	Logarithmic Score	4.22	4.04	4.45	4.34	4.30	**4.55**
	Linear Score	0.90	0.62	0.93	0.82	0.81	**0.99**
	Weighted Quantile Score						
	Whole distribution	0.69	0.77	**0.65**	0.76	0.72	0.73
	Center	0.14	0.15	**0.13**	0.15	0.14	0.14
h=2	Tails	0.15	0.17	**0.14**	0.17	0.15	0.15
	Logarithmic Score	3.81	3.69	**4.13**	4.05	3.63	3.77
	Linear Score	**0.79**	0.47	0.65	0.65	0.50	0.52
	Weighted Quantile Score						
	Whole distribution	1.01	1.03	**0.99**	1.06	1.01	1.01
	Center	0.20	0.20	**0.19**	0.20	0.20	0.20
h=3	Tails	0.22	0.22	0.22	0.25	0.22	**0.21**
	Logarithmic Score	3.38	3.28	3.89	**4.00**	3.32	3.60
	Linear Score	0.37	0.36	0.52	**0.59**	0.35	0.47
	Weighted Quantile Score						
	Whole distribution	1.26	**1.22**	1.31	1.32	1.23	1.24
	Center	0.25	**0.24**	0.25	0.25	0.24	0.24
h=4	Tails	0.28	**0.28**	0.29	0.32	0.28	0.28
	Logarithmic Score	3.72	3.38	3.83	**4.02**	3.61	3.79
	Linear Score	0.52	0.40	0.48	**0.59**	0.43	0.48

Table 2. Predictive performance

5 Concluding remarks

Since the end of 2011, euro area inflation has gradually fallen and has remained for a prolonged period of time in a region not consistent with the monetary policy objective of price stability. Over this period, forecasting models have often failed to correctly track inflation in the euro area, signaling increased uncertainty around the prospects for price developments. In this paper we have considered a quantile regression approach for forecasting the distribution of euro area inflation, conditional on a set of covariates. This allows to quantify the uncertainty surrounding central projections of inflation, to study the relation between inflation and its determinants in the various regions of the inflation distribution and to produce forecasts for the probability of events away from the conditional mean.

Our in-sample results show substantial time-variation in the shape of the distribution of inflation, beyond the movements in volatility. The distribution of euro area inflation appears to be on average positively skewed, with a right tail somewhat thicker than the left one. Based on the results of a 'stability test' for quantiles we find that the distribution is not constant over time.

The conditional quantile regression approach allows to better describe the underlying features of the distribution of inflation compared with a pure time series benchmark model with stochastic volatility. We find that the dynamics of inflation appears to be more persistent in the lowest quantiles of the distribution; it may therefore be harder for monetary policy to counter negative shocks pushing inflation below its conditional mean, than it is the case for positive ones. The inflation process also seems more reactive to cyclical conditions in the right tail of the distribution; the response to exchange rate movements is stronger when inflation is in the tails.

In an out-of-sample prediction exercise, quantile regressions overall provide superior forecasts of the conditional distribution of inflation than the benchmark model. Averaging the forecast distributions of different models is however useful to improve robustness and, in some cases, to achieve the highest accuracy of distributional forecasts.

As a possible extension to our analysis, quantiles could be estimated using a multivariate approach along the lines of White *et al.* (2012). This would allow to jointly identify the dynamics of inflation and output and study their comovements over different regions of the multivariate distribution. We leave this issue for future research.

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Appendices

A Estimation results

The following table reports, for quantile orders $\alpha = 0.10, 0.25, 0.50, 0.75, 0.90$ and forecast horizon $h = 1$, the estimated coefficient for the model QR_1 (standard error in brackets). Estimated coefficients for other quantiles and forecast horizon ara available upon request.

α	Autoregressive term	Output gap	Oil prices	Exchange rate
.10	0.96	0.07	1.18	−0.04
	(0.04)	(0.03)	(0.30)	(0.01)
.25	0.96	0.10	1.26	−0.01
	(0.03)	(0.03)	(0.23)	(0.01)
.50	0.98	0.08	0.94	−0.03
	(0.04)	(0.03)	(0.26)	(0.01)
.75	0.91	0.09	1.08	−0.03
	(0.04)	(0.03)	(0.30)	(0.02)
.90	0.84	0.18	0.98	−0.04
	(0.06)	(0.05)	(0.41)	(0.02)

B Out-of-sample losses as ratios to the LLSV model

The following tables show, for all quantile orders $\alpha = 0.05, ..., 0.95$ and forecast horizon $h = 1, ..., 4$, the ratio $\frac{L_m(\alpha)}{L_{LLSV}(\alpha)}$, where $L_{LLSV}(\alpha)$ is the loss function of the $LLSV$ model and $L_m(\alpha)$ is the loss function of model m,with $m = QR0$, $QR1$, $QR1$, $FC-01$, $FC-01L$.

1 step ahead					
α	QR1	QR0	PC	FC-01	FC-01L
5th	0.66	0.83	0.73	0.73	0.83
10th	0.62	0.71	0.68	0.63	0.71
15th	0.63	0.69	0.69	0.63	0.75
20th	0.68	0.74	0.79	0.68	0.79
25th	0.68	0.77	0.77	0.73	0.77
30th	0.72	0.80	0.76	0.72	0.80
35th	0.74	0.81	0.78	0.74	0.81
40th	0.72	0.79	0.79	0.76	0.83
45th	0.79	0.86	0.83	0.83	0.86
50th	0.86	0.90	0.86	0.86	0.93
55th	0.86	0.90	0.86	0.90	0.93
60th	0.89	0.93	0.89	0.89	0.93
65th	0.92	1.00	0.92	0.96	0.96
70th	0.91	1.09	1.00	1.00	1.00
75th	1.00	1.20	1.05	1.05	1.05
80th	1.06	1.35	1.06	1.12	1.06
85th	1.00	1.43	1.07	1.07	1.07
90th	0.91	1.36	0.91	1.09	1.00
95th	1.03	1.64	0.76	1.04	1.03

2 steps ahead					
α	QR1	QR0	PC	FC-01	FC-01L
5th	0.44	0.55	0.33	0.44	0.44
10th	0.48	0.55	0.39	0.48	0.64
15th	0.51	0.68	0.49	0.56	0.71
20th	0.57	0.76	0.57	0.67	0.78
25th	0.64	0.78	0.64	0.72	0.80
30th	0.71	0.87	0.71	0.79	0.87
35th	0.78	0.85	0.74	0.81	0.87
40th	0.83	0.91	0.80	0.87	0.91
45th	0.89	0.96	0.83	0.93	0.94
50th	0.92	1.02	0.87	0.96	0.98
55th	0.96	1.08	0.92	1.02	1.02
60th	1.02	1.12	0.96	1.06	1.04
65th	1.13	1.18	1.02	1.16	1.09
70th	1.17	1.22	1.07	1.20	1.12
75th	1.28	1.31	1.17	1.28	1.19
80th	1.29	1.42	1.23	1.32	1.23
85th	1.32	1.56	1.36	1.44	1.28
90th	1.59	2.00	1.65	1.76	1.53
95th	2.25	2.25	2.38	2.00	1.63

3 steps ahead					
α	QR1	QR0	PC	FC-01	FC-01L
5th	0.27	0.30	0.23	0.27	0.32
10th	0.44	0.65	0.41	0.52	0.65
15th	0.66	0.67	0.51	0.66	0.77
20th	0.74	0.77	0.62	0.75	0.83
25th	0.78	0.80	0.70	0.78	0.86
30th	0.82	0.83	0.76	0.82	0.87
35th	0.85	0.88	0.81	0.86	0.92
40th	0.89	0.93	0.86	0.92	0.94
45th	0.94	0.99	0.93	0.96	0.97
50th	1.00	1.04	0.97	1.01	1.01
55th	1.09	1.10	1.04	1.09	1.06
60th	1.11	1.11	1.11	1.11	1.08
65th	1.18	1.13	1.17	1.15	1.10
70th	1.22	1.22	1.24	1.22	1.13
75th	1.26	1.26	1.30	1.26	1.14
80th	1.28	1.30	1.40	1.28	1.16
85th	1.44	1.38	1.53	1.41	1.21
90th	1.58	1.42	1.79	1.50	1.25
95th	2.08	1.75	2.50	1.83	1.42

4 steps ahead					
α	QR1	QR0	PC	FC-01	FC-01L
5th	0.38	0.44	0.23	0.41	0.51
10th	0.53	0.60	0.43	0.56	0.68
15th	0.67	0.74	0.56	0.69	0.79
20th	0.76	0.78	0.67	0.76	0.83
25th	0.80	0.81	0.75	0.80	0.86
30th	0.86	0.84	0.84	0.84	0.90
35th	0.91	0.89	0.90	0.89	0.92
40th	0.94	0.91	0.95	0.91	0.94
45th	0.98	0.94	1.01	0.95	0.97
50th	1.01	0.96	1.06	0.98	0.99
55th	1.06	0.99	1.11	1.01	1.01
60th	1.10	1.03	1.17	1.05	1.04
65th	1.16	1.08	1.23	1.12	1.08
70th	1.21	1.12	1.29	1.16	1.10
75th	1.26	1.18	1.38	1.21	1.15
80th	1.25	1.21	1.47	1.23	1.15
85th	1.27	1.25	1.59	1.27	1.14
90th	1.39	1.21	1.79	1.30	1.12
95th	1.67	1.22	2.22	1.39	1.11

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