# Nowcasting Euro Area GDP Growth Using Bayesian Quantile Regression

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#### Nowcasting GDP via quantile regression

- Eurostat's Flash estimates of quarterly GDP growth for the euro area are currently published 30 days after the end of the quarter. For many years, from 2003-2016, they were published at 45 days
- Ahead of these estimates many higher-frequency indicators become available
- This paper uses an application to explore the utility of quantile regression methods in producing density nowcasts of quarterly GDP growth from higher frequency indicators

### Quantile regression (QR)

- QR allows for nonlinearities between the indicators and GDP growth
  - The relative importance of different indicators can vary by quantile of GDP growth
- We emphasise the construction of full predictive densities from these QRs
- We propose a Bayesian QR nowcasting strategy that accommodates
  - 1 the mixed-frequency, and
  - 2 "ragged-edge" nature of
  - 3 the increasingly big datasets that characterise recent nowcasting applications



#### **U-MIDAS QR**

• We relate the conditional  $\tau$ -th quantile of quarterly GDP growth in quarter t,  $y_t$ , to  $x_t^m$ , a vector of monthly indicators, where m = 1, 2, 3 denotes the month in quarter t (plus lags of GDP)

$$Q_{y_t}(\tau|\Omega_t) = \beta_{0,\tau} + \beta_{1,\tau} x_t^1 + \beta_{2,\tau} x_t^2 + \beta_{3,\tau} x_t^3, \tau \in (0,1)$$

- We follow Mazzi et al. (2014 OBES) and consider a large set of 124 monthly indicators, including business confidence data, IP data and financial market data for both the euro aggregates and its largest economies
- We use real-time data for all variables (involved us collecting euro area vintage data)
- We adopt a Bayesian estimator and consider various shrinkage priors to avoid parameter proliferation



#### Bayesian QR (BQR)

- Bayesian inference proceeds by forming the likelihood using asymmetric Laplace densities
- We use the mixture representation of Kozumi and Kobayashi (2011 JSCS)
- We implement different shrinkage priors on  $V_{\beta}$ , where  $\beta_{\tau} \sim N(0, V_{\beta})$
- All can lead to the inclusion of different indicators in different parts of the GDP growth distribution
- Estimation via standard MCMC (Gibbs sampling) methods

### Shrinkage priors

#### We consider three forms of shrinkage prior

- 1 Lasso, adaptive Lasso and elastic net. Parameter-specific (or local) shrinkage priors
- 2 Horseshoe and Dirichlet-Laplace. Shrinks small coefficients (or uninformative indicators) to zero, with fat-tails to avoid over-shrinkage of large coefficients associated with important indicators
- 3 SSVS. A normal mixture prior, the Stochastic Search Variable Selection prior is a discrete mixture of a peaked prior around zero and a vague proper prior

#### Density nowcasts I

• Having estimated the BQR in-sample (t = 1, ..., T) for a given quantile  $\tau$ , quantile nowcasts can be computed given  $x_{T+1}$ :

$$\widehat{Q}_{y_{T+1}}(\tau | \Omega^{j}_{T+1})^{r} = \widehat{\beta}^{r}_{0}(\tau) + \widehat{\beta}^{r}_{1}(\tau) x^{1}_{T+1} + \widehat{\beta}^{r}_{2}(\tau) x^{2}_{T+1} + \widehat{\beta}^{r}_{3}(\tau) x^{3}_{T+1}$$

where  $\widehat{\beta}_k^r$  (k=0,...,3) denotes the r-th MCMC draw from the posterior parameter distribution and  $\Omega^j_{T+1}$  denotes the j-th available information set. We consider nowcasts at j=1 (t-15 days) and j=2 (t+15 days)

- Recall that the quarter T+1 values of the indicator variables are published ahead of the quarter T+1 values for  $y_t$  and are exploited when nowcasting. The density nowcasts can be evaluated when  $y_{T+1}$  is subsequently published
- We consider two methods of constructing a predictive density from the BQR quantile nowcasts

#### Density nowcasts II

- 1 Collect r=1,...,R MCMC draws of the quantile nowcast  $\widehat{Q}_{y_{T+1}}(\tau|\Omega^j_{T+1})^r$  across  $\tau\in[0.05,0.10,...,0.90,0.95]$  and then construct the full posterior density nowcast from this stacked vector use a Gaussian kernel to smooth
- 2 Follow Adrian et al. (AER 2019) and fit a skew-t density to 5 (we also try 19) conditional mean quantile forecasts

#### Out-of-sample results I

- We compare the accuracy of the density nowcasts of euro area GDP growth from BQR (with the 6 priors) against
- 1 The density forecast combination strategy of Mazzi et al. (2014 OBES)
  - Takes linear combinations of the density nowcasts generated from 124 linear Gaussian regression models relating quarterly GDP growth separately to each monthly or quarterly indicator
- 2 Factor (principal component) augmented classical quantile and linear regressions
  - Likely effective in *dense* data environments
- 3 An AR(1) Gaussian density



#### **Evaluation**

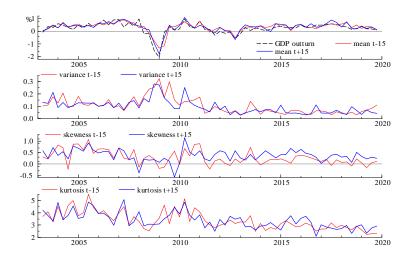
- Evaluate the point and density estimates against Eurostat's first official estimate using
  - 1 RMSE
  - 2 Average logarithmic score
  - 3 Average cumulative ranked probability score
  - Two variants of the quantile weighted probability score (Gneiting and Ranjan, 2007 JBES) that emphasise left tail events and both tails
- The evaluation sample starts in 2003q2, as this is when Eurostat first published its Flash estimate for GDP growth and ends in 2019q4
- More on the pandemic to come...



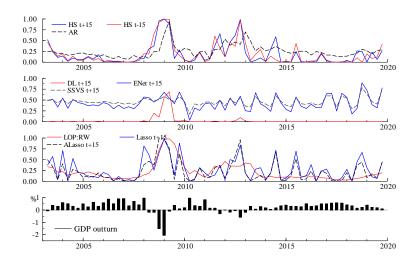
#### Nowcast accuracy

- In summary, we find
  - 1 BQR with global-local priors delivers the most accurate nowcasts at both horizons according to all five evaluation metrics
  - **2** The choice of prior matters
  - 3 BQR outperforms the density forecast combinations and the factor-augmented linear and quantile regressions suggestive of a *sparse* rather than *dense* dataset and of gains to shrinkage out-of-sample
  - 4 Using a skewed-t does not work as well as using the MCMC draws
  - **6** Accuracy is better at t+15 days than at t-15 days

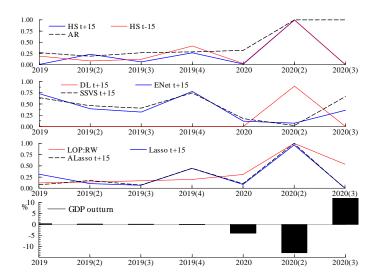
#### Temporal evolution of moments from BQR (HS prior)



## Growth-at-Risk: Prob of negative growth



### COVID-19: Prob of negative growth



#### Conclusion

- Bayesian QRs with global-local priors produce accurate density nowcasts of euro area GDP growth, including over the GFC and COVID-19 recessions
- Future work should consider the use of weekly, even daily indicators