Discussion of “Tails of inflation forecasts and tales of monetary policy” by Andrade, Ghysels and Idier

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Their Story

- The authors introduce $I@R$ measures of risk/uncertainty and density forecast asymmetry
  - and test their utility (point forecasting inflation and interest rates) using individual SPF data
- Forecast asymmetries important (especially post ZLB)
  - central banks routinely talk about inflation risks and the balance of these
    - even when the statistical evidence for asymmetries in their density forecasts appears small; see Mitchell & Hall (2005, OBES); Knüppel & Schultefrankenfeld (2012, IJCB)
  - the authors find time-varying asymmetries in the (US) SPF inflation densities - and that these explain inflation and interest rate outturns

Risk versus (Knightian) uncertainty

- Distinction too often blurred
  - *Imprecise probabilities*: Do we really think respondents 100% believe their (rounded?) forecasts in the outer bins?
  - MPC at BoE don't even quantify 10% outer tail risks (see Mitchell & Weale, 2016)

- But I focus discussion on
  1. econometrics of how we aggregate and use the individual SPF densities
  2. how we might/should evaluate and then improve upon the authors' $I@R$ measures

Should we average probabilities or quantiles? I

- i.e., should we extract the quantiles then aggregate? Or aggregate then extract the quantiles?

- It matters theoretically and empirically... relates to the broader literature (incl. in management science) on forecast (or expert) density combination

Should we average probabilities or quantiles? II

- Linear Opinion Pool commonly used to aggregate, including by FRB Philadelphia when publishing *aggregate* SPF density

$$G(y)^{LOP} = \sum_{i=1}^{N} w_i G_i(y)$$

where $G_i(y)$ are the cumulative distribution forecasts of forecaster i, where $\sum_{i=1}^{N} w_i = 1$

  - Option 1: could compute $I@R(p)$ from $G(y)^{LOP}$

- But authors, in effect, choose to aggregate the N forecast densities using the "Quantile Opinion Pool" (Galvao et al., 2016; Lichtendahl et al., 2013 Management Science; Busetti, 2016)

Should we average probabilities or quantiles? III

- QOP combines the forecasters' quantile functions

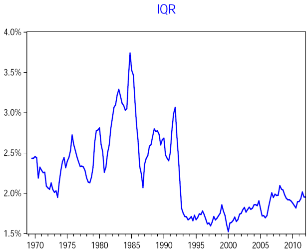
$$G(y)^{-1} = \sum_{i=1}^{N} w_i G_i^{-1}(p)$$

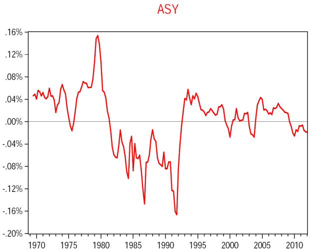
where p is the probability level

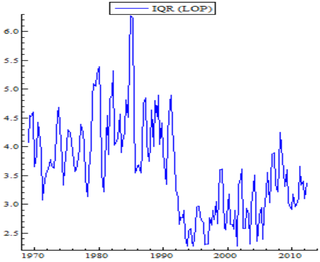
  - Authors' Option 2: $I@R(p) = \sum_{i=1}^{N} w_i G_i^{-1}(p)$, with $w_i = 1/N$

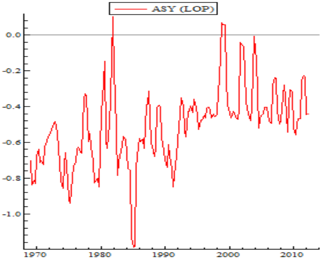
- QOP always delivers sharper densities than LOP (Lichtendahl et al. 2013); QOP can preserve distributional form of individual densities, unlike LOP

Uncertainty and Asymmetry: QOP vs LOP









Evaluating I@R - and associated risk measures I

- Why should $I@R(p)/ASY$ explain the conditional *mean* of inflation or the target interest rate?

- Because of misspecification (poor calibration) of $I@R(p)$? Or asymmetric central bank preferences - as authors discuss?
  - Looks like $I@R(p)$ is poorly calibrated, as 30% of outturns fall in the 10% tails
    - Test (conditional) coverage using Christoffersen (1998, IER) type LR tests?
    - Use *proper* scoring rules? Gneiting & Ranjan (2011, JBES) decompositions of CRPS; Diks et al. (2011, JoE) censored likelihood
  - Shouldn't $I@R(p)$, if well-calibrated, explain the p-th quantile not the mean inflation outturn?
    - It is "optimal" to take the p-th quantile as your forecast if you have an asymmetric piecewise linear loss function (Gneiting 2011 JASA)
    - Does this make sense for central banks?

Evaluating I@R - and associated risk measures II

- Knüppel & Schultefrankenfeld (2012, IJCB) evaluate "risk" (Pearson mode skewness) forecasts *via* a modified Mincer-Zarnowitz regression

$$\left(\frac{\pi_{t+h} - \text{mode}_{t+h|t}}{\sigma_{t+h|t}}\right) = \alpha + \beta\left(\frac{\text{mean}_{t+h|t} - \text{mode}_{t+h|t}}{\sigma_{t+h|t}}\right) + \varepsilon_{t+h}$$

with forecast "optimality" (but under quadratic loss) implying $\alpha = 0$ and $\beta = 1$

- i.e., if the point forecast is the *mode*, then upside (downside) risks should on average be followed by outturns that are greater (less) than the point forecasts
- What's the evaluation test for the authors' Bowley-based risk measure, *ASY*?

Can we improve *I@R*, *ASY*...? I

- Use measures of "risk" that can be directly evaluated (*ex post*) using calibration tests?
- And/or should, like the threshold rather than quantile based risk measure of Kilian and Manganelli (2007, JMCB), the authors' risk measure relate to the user's risk preferences?

Can we improve *I@R*, *ASY*...? II

- Given the errors frequently made when forecasting second moments, can forecasters in practice produce meaningful forecasts of third moments?

- Consider alternative combination strategies, including trimming?
  - Overconfidence. Isn't this an argument for use of the LOP rather than the QOP? Galvao et al. (2016) find a Beta Opinion Pool works well...

- Consider alternative weights on the individual forecasters?
  - Opschoor et al. (2014) choose w_i to maximise the accuracy of tail forecasts

Implications for macro models

- Need increasingly to move beyond (approximately) Gaussian models that deliver (approximately) symmetric forecast densities