Discussion of Density Nowcasts and Model Combination: Nowcasting Euro-area GDP growth over the 2008-9 recession, by Gian Luigi Mazzi, James Mitchell and Gaetana Montana

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Uncertainty and Forecasting in Macroeconomics

James and co-authors construct density nowcasts of current quarter GDP growth.

Combination of simple regression models (single indicator models using 'soft' or 'hard' data) with time-varying recursive weights using a logarithmic scoring rule or equal weights.

Approach is general – could include VAR/factors/MIDAS/'bridge equations' etc.

Combined density very flexible as number of regression models is large, and goodness-of-fit evaluated on PITS.

Key advantage of approach – Density nowcasts:

- Agnostic with regard to users loss function.
- Assess uncertainty associated with nowcasts.

Outline

1. Why nowcasting differs to forecasting:
   Missing data, changing database, measurement error, structural breaks.

   Many of these issues handled by James' methodology, but I will briefly discuss the interaction of measurement error and structural breaks.

2. Model combination to allow for "uncertain instabilities":
   James finds 'Occams Window' to eliminate bad models and model selection only performs well later in the quarter after 'hard' data are obtained.

   I will briefly discuss implications for model averaging and combination when there is structural change.

Signal extraction problem at T.

If nowcast differs significantly from outturn:

- outlier due to measurement error?
- more permanent location shift?
- combination of both?

observationally equivalent with one data point.

Measurement errors $\Rightarrow$ autocorrelated residuals **but** only few observations to detect.

Residual analysis needed at end of sample: If last few residuals exhibit increase in variance and autocorrelation, more weight placed on measurement error hypothesis.

Alternatively, indicator-impulse saturation used to detect late onset shifts.
Some cases can be justified *ex ante* (e.g. VAT changes).

Problem:

Measurement error and location shifts at T require different forecasting models.

- Measurement error $\Rightarrow$ EWMA schemes optimal
- Location shift $\Rightarrow$ intercept correction and differencing
  But exacerbates impact of measurement errors

Location shift requires $+$ IC for nowcast period
Measurement error requires $-$ one-off IC to offset error

Resolving conflict between opposite responses is central to accurate nowcasting.

Can we distinguish between location shifts and measurement errors?

- measurement error at T does not 'carry forward', although effects will in dynamic process;
- data at T usually revised: revisions to errors at $T+1$ informative about source of error from T to $T+1$;
- next nowcast error (from $T+1$ to $T+2$) large if source is location shift, $\therefore$ repeated mis-forecasting indicative of location shift;
- extraneous contemporaneous data help to discriminate: discrepancy from existing models persist or disappear;
- variance of measurement errors usually changes as the forecast origin approaches.

Long history of pooling across forecasts from a number of models, Newbold and Harvey (2002), Fildes and Ord (2002), Stock and Watson (1999).

Seen as an insurance policy: guard against worst outcome at cost of better outcomes.

Hendry and Clements (2004) motivate by including robust models that allow for structural breaks.

Some selection is required...

Would you mix a glass of poison with glasses of pure water, and then drink the combination?

James proposes Occam's window which excludes 'poisonous' component models – by $t + 45$ days only 2 of 444 models retained.

But no robust models included in set: intercept corrections / differencing devices.

Averaging aims to capture model uncertainty:

> *"Conditioning on a single selected model ignores model uncertainty which, in turn, can lead to the underestimation of uncertainty when making inferences about quantities of interest".*
> *Hoeting, Madigan, Raftery, and Volinsky (1999)*

Of little comfort if poor models accorded too much importance.

Essential to use selection and retain some robust predictors in averaged set – point forecasting performance improved by *Gets* model selection, see Hendry and Reade (2004).

James' model selection chooses single 'best' model according to logarithmic scoring rule. Instead include all available 'soft' and 'hard' data and select using general-to-specific, allowing for multiple indicators to be retained.

James proposes a general framework for density nowcasting.
Could embed within the framework some robustness in the presence of breaks such as 2008-9 recession:

- Each indicator variable model could be made robust in-sample by impulse-indicator saturation which allows for breaks and outliers.
- The component models could be made robust to out-of-sample breaks by including intercept corrected and differenced models within the combination set.
- Trade-off between recursive and rolling windows as discussed by James.
  Will depend on changes in smallest eigenvalue of regressor second-moment matrix at break, see Castle, Fawcett, and Hendry (2010).
- Trade-off between measurement error and breaks at heart of problem.

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