

“Dynamic Prediction Pools: An Investigation of Financial Frictions and Forecasting Performance” by Marco Del Negro, Raiden Hasegawa, and Frank Schorfheide

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Combining forecasts from different models

The predictive density of y' given data y and models \mathcal{M}_k , $k = 1, \dots, K$:

$$p(y' | y) = \sum_k \pi(\mathcal{M}_k | y) p(y' | \mathcal{M}_k, y) \quad (1)$$

where

$$\pi(\mathcal{M}_k | y) = \frac{p(y | \mathcal{M}_k) \pi(\mathcal{M}_k)}{\sum_k p(y | \mathcal{M}_k) \pi(\mathcal{M}_k)}$$

The weights in (1) are the models' posterior probabilities, determined by the marginal likelihoods and the models' prior probabilities.

Marginal likelihood example

If \mathcal{M}_k is an AR model of y ,

$$p(y | \mathcal{M}_k) = p(y_T, \dots, y_1 | y^0, \mathcal{M}_k)$$

$$= \prod_{t=0}^{T-1} p(y_{t+1} | y^t, \mathcal{M}_k)$$

$$= \prod_{t=0}^{T-2} p(y_{t+2}, y_{t+1} | y^t, \mathcal{M}_k) = \prod_{t=0}^{T-3} p(y_{t+3}, y_{t+2}, y_{t+1} | y^t, \mathcal{M}_k) = \dots$$

Marginal likelihood measures the overall out-of-sample predictive performance of a model (*not* predictive performance at a particular horizon).

Challenges

1. Each model being compared must be a model of *the same data* y .
2. It must be that “each of the discrete [models] makes scientific sense, and there are no (...) models in between.” Gelman et al. (1995), p.176.
 - (a) If the space of models is too sparse, posterior probabilities of models tend to come out implausibly decisive and to display a bang-bang pattern over time.

It is clear *in principle* how to confront these challenges.

Confronting the challenges in practice

- Geweke and Amisano (2011) form a weighted sum of predictive densities (here, $K = 2$):

$$\lambda * p(y_{1,t+h} | y_1^t, y_2^t, \mathcal{M}_1) + (1 - \lambda) * p(y_{1,t+h} | y_1^t, y_3^t, \mathcal{M}_2)$$

where $\lambda \in [0, 1]$, $h \geq 1$, and maximize the product of these sums w.r.t. λ .

- This paper proposes:

$$\lambda_t * p(y_{1,t+h} | y_1^t, y_2^t, \mathcal{M}_1) + (1 - \lambda_t) * p(y_{1,t+h} | y_1^t, y_3^t, \mathcal{M}_2)$$

plus a law of motion for λ_t .

Implementation

- Nonlinear state-space system: the 2nd expression on the previous slide is the measurement equation, the law of motion for λ_t is the transition equation.
- Use a particle filter to infer $\lambda_{1:T}$, also infer parameters of the law of motion for λ_t .
- When inferring parameters of \mathcal{M}_1 and \mathcal{M}_2 , neglect information in $\lambda_{1:T}$. This is reasonable.

Application

- Forecast growth rates of Y and P using DSGE models: $SW\pi$ and $SWFF$.
 - $SWFF$ has an extra observable: corporate bond spread.
 - Sample starts in 1964Q1, forecast evaluation in 1992Q1-2011Q2, real-time data.
- The dynamic pool yields good forecasts.
- λ_t varies considerably over time, while staying away from 0 and 1.

Takeaways

- This is a very useful methodology.
- Paying *some* attention to the corporate bond spread was a good idea throughout the evaluation period.
- Paying *a lot* of attention to the corporate bond spread was a good idea already before the Lehman crisis.
- Let's not stop here, let's learn from the evidence and improve our models.

Back to the challenges: sparsity

- The space of models seems too sparse.
- I agree that a nonlinear encompassing model (e.g., a DSGE with regime switches) seems worth exploring in the future.
- One could also use that model as a prior for a less restricted model (e.g., a VAR with regime switches), with the weight of the prior distributed continuously and inferred rather than fixed.
 - In analogy to the DSGE-VAR of Del Negro and Schorfheide (2004).

Back to the challenges: modelling all the data y

- In principle, it is possible to form an encompassing model and to think of models omitting particular elements of y as restricted versions of the encompassing model.
- Jarociński and Maćkowiak (2014) show that the posterior probability of the relevant restriction can be expressed analytically in a Gaussian VAR with a conjugate prior.
 - Like this paper, we find that the corporate bond spread was useful for forecasting Y and P already before the Lehman crisis.