Discussion of "Multivariate Bayesian Predictive Synthesis in Macroeconomic Forecasting"

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- Great paper!

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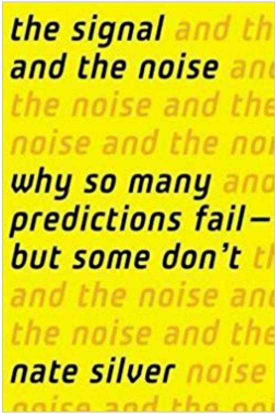

FiveThirtyEight

2018 World Cup Predictions

Soccer Power Index (SPI) ratings and chances of advancing for every team, updating live.

How this works Find out which team you should root for ESPN coverage

Standings | Matches

		TEAM RATING			KNOCKOUT STAGE CHANCES				
TEAM	GROUP	SPI	OFF.	DEF.	MAKE ROUND OF 16	MAKE QUARTER-FINALS	MAKE SEMI-FINALS	MAKE FINAL	WIN WORLD CUP
Uruguay 3 pts.	A	80.0	2.3	0.6	94%	36%	16%	6%	2%
Russia 3 pts.	A	72.3	2.0	0.8	92%	35%	15%	5%	2%
Egypt 0 pts.	A	61.4	1.6	0.9	12%	2%	<1%	<1%	<1%
Saudi Arabia 0 pts.	A	48.8	1.4	1.3	3%	<1%	<1%	<1%	<1%
Spain 0 pts.	B	91.3	3.2	0.5	87%	68%	46%	28%	17%
Portugal 0 pts.	B	83.5	2.4	0.5	70%	44%	24%	11%	5%

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- Implication 2: Mean forecast is less precise than the optimal forecast, since $h + Ns - \frac{(N-1)^2 hs}{Nh+s} < h + Ns$.
- Related to the current paper, each agent i provides a density forecast $h_i(\pi)$. Given that these density forecasts are [highly] correlated, the policy maker should combine the information behind these forecasts.

Policy Maker's Loss Function

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- The key is to realize that the uncertainty faced by a policy maker in using the average forecast is the uncertainty associated with a typical forecaster of the panel; see, Lahiri, Peng and Sheng (2018).

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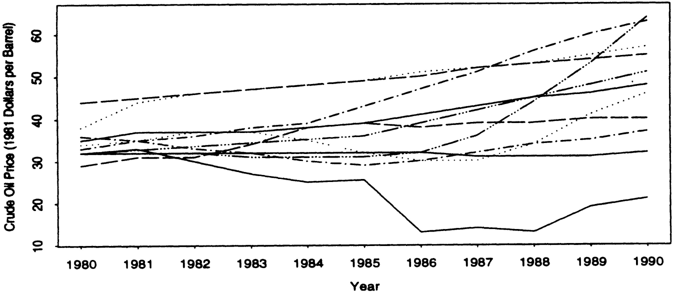
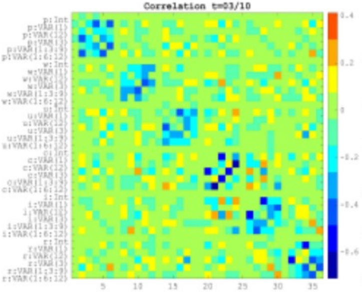
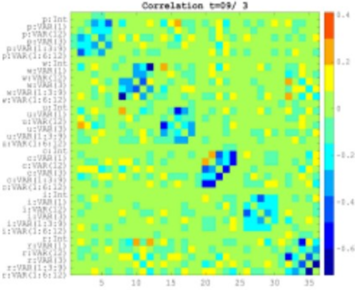


Fig. 1. Forecasts of the price of oil by each of the 10 EMF models under the reference scenario, 1980–90: the lower full curve is the actual price

Measuring Interdependence across Agents/Variables

- Comparing estimates of interdependence of 2003 vs. 2009





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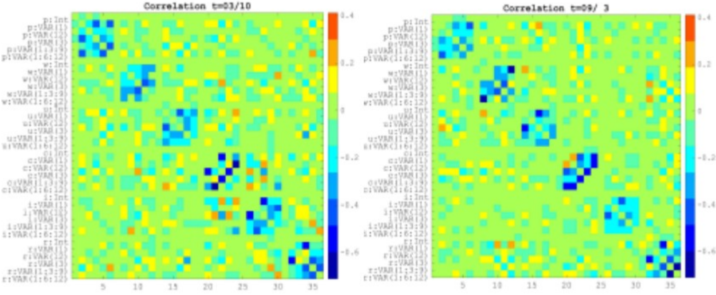

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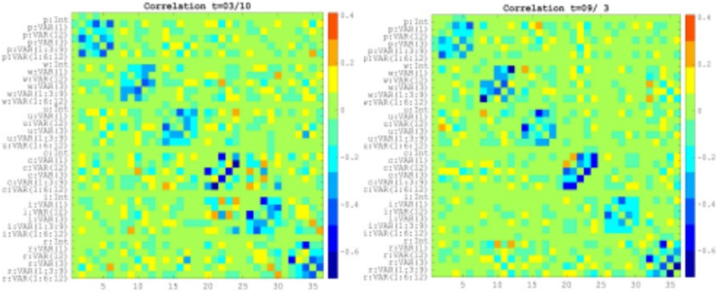

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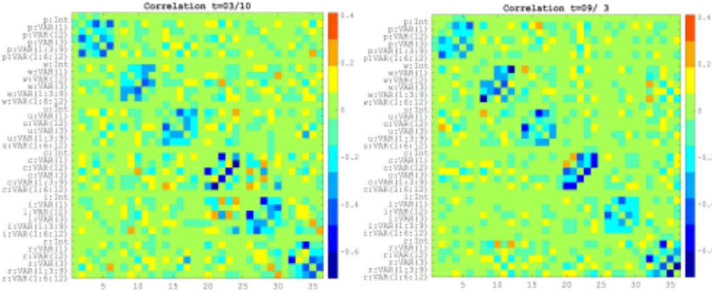

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- Explore the connection between changes in the interdependence pattern and regime changes in the economy.

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- Consider the random walk model as the benchmark; see Faust and Wright (2013) that in forecasting inflation, ridiculously simple forecasts are hard to beat.
- Compare the BPS forecasts with those of experts; see Ang, Bekaert and Wei (2007) that survey inflation forecasts are generally more accurate than model-based forecasts.