Data rich forecasting

XII Annual Inflation Targeting Seminar Banco Central do Brasil

Simon Price Bank of England and City University

> Rio de Janeiro 13 May 2010

Disclaimer

These comments are solely the views of the discussant and should not be thought to represent those of the Bank of England or Monetary Policy Committee members.



Who I am

- I'm not primarily an econometrician I'm a practitioner. A forecaster and an economist.
- However, I do have experience using data rich models.



Two excellent papers both forecasting inflation with large data sets

- Eliana González Bayesian model averaging
- Francisco Marcos Rodrigues Figueiredo Factor models and PLS

Delighted to see that each paper draw on work by my co-authors.

- Jana Eklund and also myself, Vincent Labhard and George Kapetanios (predictive likelihood).
- Jan Groen and George Kapetanios (partial least squares)



The problem and some solutions

Lars Svensson (IJCB 2005): 'Large amounts of data about the state of the economy and the rest of the world ... are collected, processed, and analyzed before each major decision.'

- Eyeballing vast quantities of data in lengthy meetings.
- Expert tinkering with ad hoc small models.

More systematically, use statistical methods.

- 1. Model selection ('pretest') and information criteria.
- 2. Ridge and Bayesian regression
- 3. Bagging.
- 4. Automatic model selection à la Hendry.
- 5. Model averaging of various types.
- 6. Various flavours of factor models.
- 7. Partial least squares.
- 8. Bayesian estimation of large VARs.



The problem and some solutions

Lars Svensson (IJCB 2005): 'Large amounts of data about the state of the economy and the rest of the world ... are collected, processed, and analyzed before each major decision.'

- Eyeballing vast quantities of data in lengthy meetings.
- Expert tinkering with ad hoc small models.

More systematically, use statistical methods.

- 1. Model selection ('pretest') and information criteria.
- 2. Ridge and Bayesian regression
- 3. Bagging.
- 4. Automatic model selection à la Hendry.
- Model averaging of various types.
- 6. Various flavours of factor models.
- 7. Partial least squares.
- 8. Bayesian estimation of large VARs



The problem and some solutions

Lars Svensson (IJCB 2005): 'Large amounts of data about the state of the economy and the rest of the world ... are collected, processed, and analyzed before each major decision.'

- Eyeballing vast quantities of data in lengthy meetings.
- Expert tinkering with ad hoc small models.

More systematically, use statistical methods.

- 1. Model selection ('pretest') and information criteria.
- 2. Ridge and Bayesian regression.
- 3. Bagging.
- 4. Automatic model selection à la Hendry.
- 5. Model averaging of various types.
- 6. Various flavours of factor models.
- 7. Partial least squares.
- 8. Bayesian estimation of large VARs.



What the econometric solutions have in common

- Everything is connected. So the right model includes all variables in the data set. But while this might reduce bias, because of multicollinearity it also reduces precision. And estimation may not be feasible. The curse of dimensionality.
- But because of multicollinearity we can reduce the parameter space because variables have common components.
- What we're looking for are ways of shrinking the problem.



The incredible shrinking methods

- Model averaging emphasises a small number of forecasts.
- (Although simple averages do well in practice.)
- Variable selection picks a small number of variables.
- Factor methods reduce the joint variance to a few components.
- Partial least squares selects the most relevant factors.
- Bayesian regression shrinks the parameters to a few important ones.



A unified framework

An empirical comparison of methods for forecasting using many predictors

James H. Stock and Mark Watson (2005)

• This paper has 'some preliminary results' for a unified framework for similar models - eg, pretest, IC methods, BMA, bagging, and empirical Bayes models - with a neat result that all the models can be characterised in terms of a shrinkage representation $(\psi(t_i))$ away from the OLS regression.

$$\hat{Y}_{T+1|T} = \sum_{i=1}^{n} \psi(t_i) \hat{\delta}_i P_{T+1} + o_p(1)$$



Another unified framework

Forecasting using a large number of predictors - is Bayesian regression a valid alternative to principal components?

Christine De Mol, Domenico Giannone and Lucrezia Reichlin (2006).

- Principal Components Regressions
 PCs are extracted from X'X with associated eigenvalues.
 All the selected principal components given equal weight the rest zero.
- Ridge/Bayesian regression
 Weights decline as the eigenvalues fall. But not to zero.
- Lasso regression
 Variables excluded as well (small parameters zero).

Forecasts based on a few aggregates of variables versus a few variables (or parameters).

Yet another

Revisiting Useful Approaches to Data-Rich Macroeconomic Forecasting

Jan Groen and George Kapetanios (2009).

- Factors use all the data but are not targeted.
- Ridge regression shrinks parameters towards zero (parsimony): all data enter, with targeting.
- Partial least squares selects orthogonal combinations of all the data (like factors); weights determined by covariances with forecast variable(like a regression).
- Forecast combination can be thought of as a special PLS case (approximating one-factor PLS).
- If there is a factor structure methods are asymptotically equivalent.
- If not, then PLS (or ridge regression) still works.



It's the results that matter

But it's really quite hard to generalise. Analytical results are limited: Monte Carlo results specific to experiment.

So what matters is the actual experience in a particular country.



It's the results that matter

But it's really quite hard to generalise. Analytical results are limited: Monte Carlo results specific to experiment.

So what matters is the actual experience in a particular country.





Colombia: model averaging

- Eliana finds that model averaging outperforms the RW benchmark by substantial margins.
- BMA works well at most horizons, better than simple averaging, dynamic factors and benchmark random walks.
- Predictive outperforms marginal likelihood which is not obvious, as PL carries a sample penalty.
- Our own (Kapetanios, Labhard and Price) ITMA doesn't do too badly but BMA beats it.



Specific points: Eliana

- I'd have liked an AR benchmark, which often beats the RW.
- The forecast variable is the 12 month rate suggest using one-month rate (which requires some seasonal adjustment).
- In practice worth experimenting with periods for training and hold-out.
- Why only take the first 20 models?
- The different results on the two runs suggest the burn in was too short.

A few more relevant remarks below that apply to both papers



Brazil: factors

- The issue of variable selection is important.
- · Francisco shows that for Brazil 'targeted' factors work well.
- Nice illustration that you cannot generalise (ie, Groen and Kapetanios report PLS works very well for the US).



Other specific points: Francisco

- The forecast variable is the 12 month rate (I think) suggest using one-month rate (which requires some seasonal adjustment).
- Ridge regressions are a kind of targeted approach, with a degree of parsimony. Might be worth exploring this, although shrinkage factor ad hoc.
- About a comment in the introduction: SVARs don't help in forecasting!

A few more relevant remarks below that apply to both papers.



Need to use real-time data.

I think neither paper handles this too well.

Two aspects.

- Revisions. Not an issue for inflation in many countries, nor for many data such as surveys and financial series, but does apply to some data.
- Flows of data in the period the 'ragged edge'.
- I suspect in practice this is more important, especially short horizons.

Need to use real-time data.

I think neither paper handles this too well.

Two aspects.

- Revisions. Not an issue for inflation in many countries, nor for many data such as surveys and financial series, but does apply to some data.
- Flows of data in the period the 'ragged edge'.
- I suspect in practice this is more important, especially short horizons.

Need to use real-time data.

I think neither paper handles this too well.

Two aspects.

- Revisions. Not an issue for inflation in many countries, nor for many data such as surveys and financial series, but does apply to some data.
- Flows of data in the period the 'ragged edge'.
- I suspect in practice this is more important, especially short horizons.

Need to use real-time data.

I think neither paper handles this too well.

Two aspects.

- Revisions. Not an issue for inflation in many countries, nor for many data such as surveys and financial series, but does apply to some data.
- Flows of data in the period the 'ragged edge'.
- I suspect in practice this is more important, especially short horizons

Need to use real-time data.

I think neither paper handles this too well.

Two aspects.

- Revisions. Not an issue for inflation in many countries, nor for many data such as surveys and financial series, but does apply to some data.
- Flows of data in the period the 'ragged edge'.
- I suspect in practice this is more important, especially for short horizons.

What matters is 'judgement'

Comparing Greenbook and reduced form forecasts using a large realtime dataset

Jon Faust and Jonathan Wright (2007)

A real time evaluation of Bank of England forecasts of inflation and growth

Jan Groen, George Kapetanios and Simon Price, IJF 2009.

- FW: data-rich beats univariate but Greenbook best.
- Groen et al: Inflation Report best, often by wide margins.
- We find the team way outperforms statistical models for the inflation nowcast. But for many components (petrol, food, utilities ...) pretty much have the data.
- In the long-run, the MPC know what their own target is.

so I'd like to know if the data rich methods beat the Brazilian and Colombian experts at short horizons.

What matters is 'judgement'

Comparing Greenbook and reduced form forecasts using a large realtime dataset

Jon Faust and Jonathan Wright (2007)

A real time evaluation of Bank of England forecasts of inflation and growth

Jan Groen, George Kapetanios and Simon Price, IJF 2009.

- FW: data-rich beats univariate but Greenbook best.
- Groen et al: Inflation Report best, often by wide margins.
- We find the team way outperforms statistical models for the inflation nowcast. But for many components (petrol, food, utilities ...) pretty much have the data.
- In the long-run, the MPC know what their own target is.

So I'd like to know if the data rich methods beat the Brazilian and Colombian experts at short horizons.

What matters (for growth, anyway) is the nowcast

Comparing Greenbook and reduced form forecasts using a large realtime dataset

Jon Faust and Jonathan Wright (2007)

- Greenbook growth forecasts beat statistical models.
- But this is mainly because the economists at the Board get the current quarter right. They are 'bean counters'.
- In the UK, we have very early first releases and timely surveys, and experts know how the ONS puts published data together (eg, look at industrial production).
- Consequently the team's nowcast hard to beat.

Dynamic factor models may help with the output nowcast

Short-term forecasts of euro area GDP growth Elena Angelini, Gonzalo Camba-Méndez, Domenico Giannone, Gerhard Rünstler and Lucrezia Reichlin

- ECB did a systematic analysis of short-term forecasting methods for euro area country growth and inflation.
- Found for inflation this was a hopeless task.
- For GDP a dynamic factor model with a state-space element to handle the ragged edge does well in many countries (but not all).
- The ragged edge matters a lot!
- Doesn't beat our experts though.



Unhappy policymakers

- · Policymakers like and need stories.
- None of these methods fit for that task.
- One possible way forward is the FAVAR.



Overall: two careful and informative papers

- Data rich methods add value relative to the benchmarks examined.
- Clear prescriptions for the two countries.
- Interesting results.
- Both work in progress so I look forward to seeing the next versions.



Obrigado





Fim

