Forecasting with Model Uncertainty: Representations and Risk Reduction, by Hirano and Wright

A Discussion

Juan F. Rubio-Ramírez [1,2]

[1]Duke University

[2]Federal Reserve Bank of Atlanta

June 13, 2014

Introduction

- Imagine a researcher that wants to:
  - Select a model
  - Estimate the parameters of the model
  - Using it for prediction
  - When only having access to weak predictors
- The authors compare (basically) three forecasting schemes:
  - In-Sample
  - Out-of-sample
  - Split-sample

Introduction

- The authors compare the methods with and without bagging
- Develop asymptotic representations for easy comparison
- They also do a small sample analysis (I really like this)
- Model uncertainty is modeled as uncertainty of which variables to include
    - Theoretically the authors consider k potential predictors
    - All of them asymptotically local to 0, i.e. $\beta = T^{1/2}b$
    - My understanding is that this is the way to model weak predictors (hard to distinguish from 0 even with large samples)

Results

- Results:
  - Without bagging In-Sample outperforms
    - This results replicates in Inoue and Kilian (2004, 2006). Out-of-Sample is wasting data
  - This is an important result because most applications use Out-of-Sample type of procedures to select and estimate the model
  - With bagging all three methods improve but out-of-Sample and split-sample improve more. Ranking changes
    - Bagging means building a few artificial pseudo-sample
  - Results do not change much when using small-samples

Some Things...

- It is true and clear that bagging is good for Out-of-Sample and Split-Sample (reduces Squared Root of MSPE)
- Not clear from the graphs that this is the case for In-Sample (at least for small *b*s and large *b*s does not reduce Squared Root of MSPE)
- Not sure I can understand why this is the case, I would like a deeper explanation of this issue
- My hope was that more information (that it is the idea of bagging) smaller Squared Root of MSPE regardless of the method
- In the numerical exercise the authors assume that $\Sigma_{xx} = 0$ (lagged variables???)
- Small sample analysis is missing parameter uncertainty (being a bayesian, I could not resist this one)

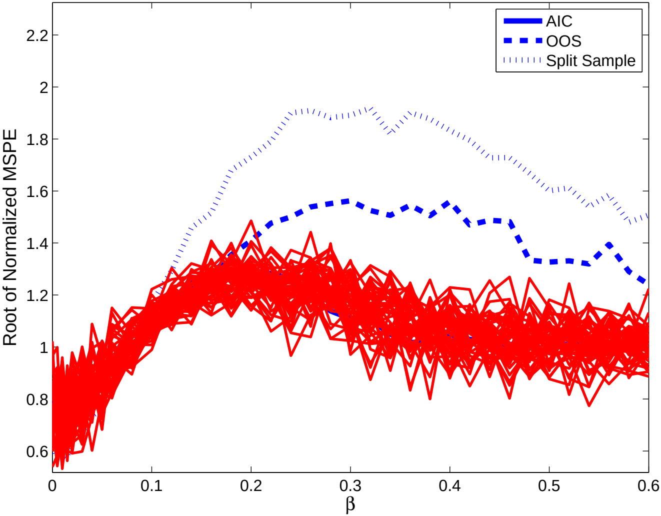
Adding Parameter Uncertainty

- As mentioned, the analysis is missing parameter uncertainty
- I performed a small exercise for the comparison of the three methods for the case without bagging
- I assumed that the posterior distribution of β was normal
- Centered on the true value (mean β)
- A degree of parameter uncertainty (measured as standard deviation of distribution) of 15 percent

Adding Parameter Uncertainty

- Thanks to the authors for sharing the codes (not usual)
- I made draws from posterior of β (100 draws)
- Computed Squared Root of MSPE of the In-Sample method (without bagging)
- Compare with Out-of-Sample and Split-Sample

Comparison when Parameter Uncertainty is Considered



Results of Adding Parameter Uncertainty

- When parameter uncertainty is considered:
  - The three methods are now hard to distinguish (at least for small values of β)
- Important: I have only considered parameter uncertainty for one of the three methods (underestimating the effects of parameter uncertainty)
- Important: Only without bagging
- Important: Using a home-made bayesian framework (I took many short cuts)
- I just want to highlight that it would be important to (also) consider parameter uncertainty for Out-of-Sample and Split-Sample and for the approach with bagging

Conclusions

- Most researcher use a type of Out-of-Sample approach to estimate and select models for forecasting
- The results in Inoue and Kilian (2004, 2006) challenge this approach
- The paper shows that the common practice can be justified when bagging is used (both asymptotically and small samples)

- Some questions related to bagging with In-Sample
- Other questions related with parameter uncertainty when small samples are considered