On the advantages of disaggregated data:
Insights from forecasting the U.S. economy in a data-rich environment

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The big picture

What the paper do:

- Evaluate the forecasting performance of factor models for the U.S.
- Study out-of-sample forecast accuracy at disaggregate levels

\[ X_{i,t+h} = \gamma(L)X_{i,t} + \beta(L)F_t + \epsilon_{i,t+h} \]

useful??  min.  (1)

- Compare direct forecasts vs restricted (national accounting) forecasts
Summary of the key results

- Factor models are better relative to AR for more volatile components
  - AR generally projects like a RW, in particular for volatile series (good with $C$ but not at $X$ or $I$)
  - Factor models use more information than AR
  - Evaluation period include the crisis (factor model outperforms around turning points)

- Restricted forecasts suffer or there was little improvements over direct forecasts
  - Positive forecast errors in subcomponents
  - Forecast errors at higher level of aggregation generally “cancel” each other out
General comments

- The paper is well motivated and contributes to the forecasting literature
- Improvements using factor models maybe overstated (around 40% improvement for Q+1)
- How can we produce more accurate GDP forecasts?
Use real-time data

- In real-time, factor models will have less data to work with

- The paper appears to assume a balance panel, timing of information flow plays a critical role for real time application

<table>
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<th>Nowcast</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>Forecast +1Q</th>
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<th>M2</th>
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- If real-time vintages are not available, a couple of suggestions to construct quasi real time data (but still ignores data revisions)
  
  ▶️ The HAVER database records the date when the series was first released
Look at the recent data release calendar, impose this over the evaluation period

**Forecast combination**

- Factor models (extra information) work well for volatile components
- AR models (RW feature) work well for with consumption
- Does combining component forecasts help improve overall GDP forecast?
  - Use RMSEs to weight across different models
  - Combine the forecast of individual components
  - Expand the set of models: Bridge-equations, BVARs etc
• Pre-crisis forecast performance (relative to AR’s) of statistical models are generally pretty bad, what would be the forecast performance if the post-2008 data was excluded?

• Clarify how the weights in the restricted forecasts are constructed and applied, does it change over time?

• The DFM uses 3 factors, would be useful to include more/less (Bai and Ng 2002 type selection criteria) as robustness check.

• A bit more details on the design of the forecast experiment, cut-off for data, timing etc.