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

Nikita Perevalov and Philipp Maier \*

### KC Fed Workshop on Central Bank Forecasting

Discussant: Philip Liu<sup>†</sup> International Monetary Fund

pliu@imf.org

October 15, 2010

<sup>\*</sup>Presenter: Nikita Perevalov, Bank of Canada.

<sup>&</sup>lt;sup>†</sup>Discussant: Western Hemisphere Department, IMF.



## 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

$$X_{i,t+h} = \gamma(L)X_{i,t} + \underbrace{\beta(L)F_t}_{\text{useful}??} + \underbrace{\epsilon_{i,t+h}}_{\text{min.}}$$
(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
- $\bullet$  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

| Nowcast  | M1   | M2   | M3   | Forecast $+1Q$ | M1   | M2   | M3   |
|----------|------|------|------|----------------|------|------|------|
| AR RMSE  | 2.6  | 2.6  | 2.6  | AR RMSE        | 2.7  | 2.7  | 2.7  |
| Paper    | -    | -    | -    | Paper          | 2.78 | 2.78 | 2.78 |
| DFM RMSE | 1.7  | 2.0  | 1.8  | DFM RMSE       | 2.2  | 2.4  | 2.2  |
| DFM/AR   | 0.65 | 0.77 | 0.70 | DFM/AR         | 0.81 | 0.89 | 0.81 |
| Paper    | -    | -    | -    | Paper          | 0.61 | 0.53 | 0.66 |

Table 1: DFM vs AR model US GDP nowcast/forecast

- 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



#### **Minor comments**

- 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.