Discussion of "Macroeconomic nowcasting with big data through the lens of a sparse factor model" by Laurent Ferrara and Anna Simoni

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Outline of the discussion

- Summary of the paper
  - Methodology
  - Main findings
- My comments
  - Nowcasting: Alchemy or science?
  - The evaluation of the model
    - Real time?
    - More timely official data?

Summary of the paper

- The paper asks the question: Can Google Trends data be useful in macroeconomic nowcasting?
- To assess this $\Rightarrow$ Combine Google data with "official" soft and hard data to assess their relative importance.
  - Summarise the Google data with some factors.
  - Estimate a different *factor-augmented bridge regression* for each week of the quarter with these factors and the data available at that point in time.
  - Pseudo real time evaluation against (some) competing nowcasting models

Methodology

1. Extract factors from Google search data with Sparse Principal Component Analysis (Zou et al. 2006)
   1. Pre-select a subsample of Google data before estimating a factor model (3 pre-selection methods considered).
   2. Start from ordinary principal components analysis, which can be formulated as regression-type optimisation problem.
   3. $\Rightarrow$ Enforce sparsity by adding two terms to the PCA minimisation problem: ℓ_1 type penalty and a Ridge-type quadratic penalty to deal with possible multicollinearity
2. For every week of the quarter w estimate:
   $Y_t = \alpha_{0,w} + \alpha'_{1,w} F_t^w + \alpha_{2,w} S_t + \alpha_{3,w} IP_t + \varepsilon_t$
   Because of frequency mismatch, the twelve models include different numbers of predictors.
3. Compare with 1) bridge regression with ordinary PCA factors and 2) bridge regression with LASSO ℓ_1 type penalty (no factors) and across pre-selection method.

Main findings

- Accuracy improvements with Google trends data in the first three weeks of the quarter, *when the model incorporates no other information*
- The improvement in forecasting accuracy due to Google Trends data is negligible once the first soft data is available.
- Pre-selection of the Google data that go in the factor model helps.

Nowcasting: Alchemy or science?

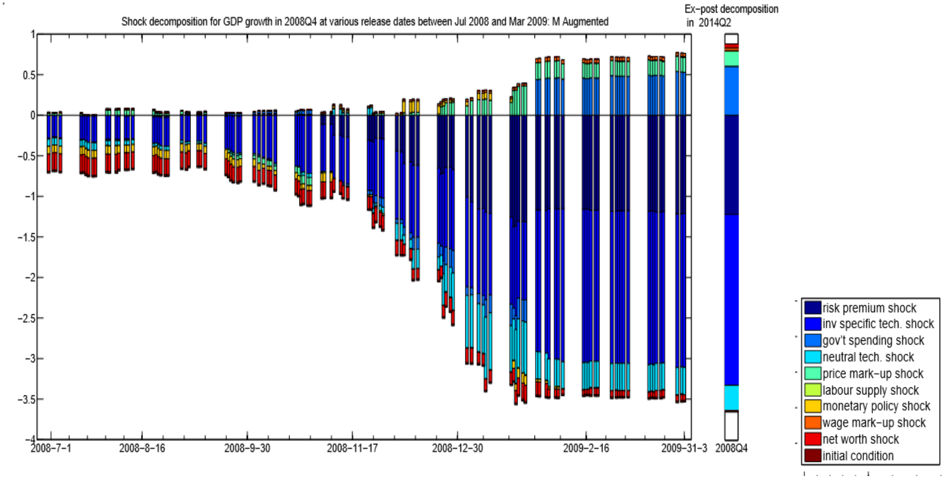
- There are a lot of moving parts in this paper: google trends, pre-selection methods, a factor model, shrinkage, and processing of the news that changes according to the day of the month.
- *"While this approach uses data, it is not scientific in the sense of being replicable, using well-understood methods, quantifying uncertainty, being amenable to later evaluation [...] and being internally inconsistent".* Stock and Watson (2017, JEP)
- But should we give up internal consistency and coherency?
- Stock and Watson (2017, JEP) point to the improvements of the methods for real-time macroeconomic monitoring as one of the 10 key developments in time-series econometrics in the last 20 years.

Is there a trade-off between accuracy and coherency?

The last 20 years have seen the development of platforms for real-time forecasting that combine formal models for big data and Filtering into nowcasting.

- Aruoba, Diebold & Scotti (2009): dynamic factor model blending weekly, monthly and quarterly stock and flow data.
- Banbura et al. (2013) handle in a systematic daily, weekly, monthly and quarterly data, essentially all the information that moves markets.
- Brave, Butters & Justiniano (2016) nowcast with a mixed-frequency BVAR, exploiting Schorfheide and Song (2015) to do exact Bayesian posterior mixed-frequency analysis in a high-dimensional model.
- Giannone, Monti & Reichlin (JME, 2016): nowcasting with a DSGE model!

Interpreting 2008Q4 in real time



Real time model evaluation

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1. Recursive estimation
2. Real-time data flow
3. Real-time data
4. Ex-ante model specification

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1. **Recursive estimation**
2. **Real-time data flow**
3. Real-time data
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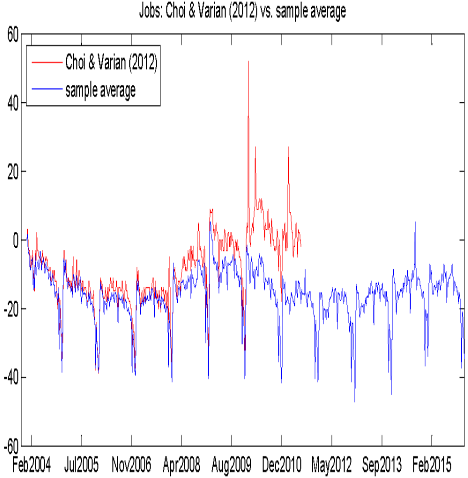
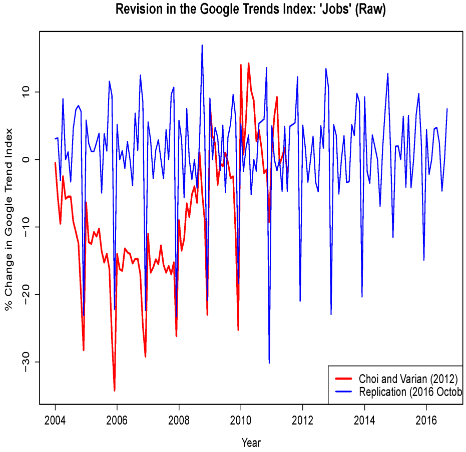
Google trends data

- Product of numerous algorithms and decisions invisible to the user and that are adapted in time (Lazar et al. 2014)
- Data revisions are large, what you observe today is different from what was available at the time the forecasts were made.
  - Noise might be large, need to clean from seasonality and outliers.
  - Unlike official data, which go through systematic quality checks, these series are not audited.

Google trends data

Li (2016) Van Norden (2017) http://econbrowser.com/archives/2017/05/guest-contribution-big-data-and-fake-forecasts





Real time model evaluation

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Real time model evaluation

1. **Recursive estimation**
2. **Real-time data flow**
3. **Real-time data** $\Rightarrow$ Would be great to have vintages!
4. Ex-ante model specification

Other official data?

- Paper finds that Google trends data are useful when other data are not available $\rightarrow$ exploit their **timeliness**.
- Only one survey series is used, and it is not the most timely.
- We know that for the US there is a plethora of high frequency private sector weekly and daily data to be exploited.
  - e.g. Stock and Watson (2014) – Weekly Economic Index

Data from Stock and Watson WEI

Private Sector Weekly & Daily Data

Description of Variables

Series Name	Frequency	Release Date	Transformation
A. Consumer Spending Variables			
Gallup Consumer Spending	Daily	Early afternoon next day	-
ICHS Same-Store Retail Sales	Weekly	Tuesday Following Week	Year-over-Year Change (%)
Johnson Redbook Same-Store Retial Sales	Weekly	Tuesday Following Week	Year-over-Year Change (%)
Composite Sales Index (Redbook + ICHS)	*Weekly*	-	Year-over-Year Change (%)
MBA Purchase Applications	Weekly	Wednesday Following Week	-
B. Consumer Confidence Variables			
Gallup Economic Confidence	Daily	1PM Following Day	-
Rasmussen Consumer Index	Daily	11AM Same Day	-
Bloomberg Consumer Comfort Index	Weekly	Thursday Following Week	
C. Employment Variables			
Gallup Job Creation Index	Daily	1PM Following Day	-
Unemployment Insurance (Initial Claims)	Weekly	Thursday Following Week	-
D. Industrial Production Variables			
Raw Steel Production	Weekly	Monday Following Week	Year-over-Year Change (%)
Lumber Production: Western Woods	Weekly	Thursday Following Week	Year-over-Year Change (%)
Car Production	Weekly	Tuesdsay Following Week	Year-over-Year Change (%)
E. Financial Variables			
Chicago Fed National Financial Conditions Index	Weekly	Thursday Following Week	-
CBOE Market Volatility Index (VIX)	Daily	COB Same Day	-
Moody's BAA-AAA Corp. Bond Spread	Daily	COB Same Day	-
10YR-3Mo. Secondary Treasury Spread	Daily	COB Same Day	-

Data for EU

TRADING ECONOMICS | CALENDAR | INDICATORS | MARKETS | FORECASTS | Search | APPS

Time	Country	Event	Actual	Previous	Consensus	Forecast
07:45 AM	FR	Current Account MAY		€-1.1B		€-1.8B
09:00 AM	IT	Retail Sales MoM MAY		-0.7%		0.4%
09:00 AM	IT	Retail Sales YoY MAY		-4.6%		1.2%
Monday July 09 2018			Actual	Previous	Consensus	Forecast
07:00 AM	DE	Balance of Trade MAY		€20.4B		€21.2B
07:00 AM	DE	Balance of Trade s.a MAY		€19.4B		
07:00 AM	DE	Exports MoM s.a MAY		-0.3%		
07:00 AM	DE	Imports MoM s.a MAY		2.2%		
07:00 AM	DE	Current Account MAY		€22.7B		€14.6B
Tuesday July 10 2018			Actual	Previous	Consensus	Forecast
05:30 AM	NL	Manufacturing Production YoY MAY		5%		5.5%
07:45 AM	FR	Industrial Production MoM MAY		-0.5%		0.8%
09:00 AM	IT	Industrial Production YoY MAY		1.9%		2.9%
09:00 AM	IT	Industrial Production MoM MAY		-1.2%		-0.1%
09:40 AM	ES	12-Month Letras Auction		-0.348%		
09:40 AM	ES	6-Month Letras Auction		-0.468%		
10:00 AM	EA	ZEW Economic Sentiment Index JUL		-12.6		4.5
10:00 AM	DE	ZEW Current Conditions JUL		80.6		82.5
10:00 AM	DE	ZEW Economic Sentiment Index JUL		-16.1		-10.2
Wednesday July 11 2018			Actual	Previous	Consensus	Forecast
10:40 AM	DE	10-Year Bund Auction		0.48%		
10:45 AM	IT	12-Month BOT Auction		0.550%		
	EA	ECB Non-Monetary Policy Meeting				
Thursday July 12 2018			Actual	Previous	Consensus	Forecast

My Conclusion

Google search data are very useful when official data are not available:

- Emerging economies, e.g. Carriere-Sallow & Labbé 2013.
- Lagged data, e.g. Coble & Pincheira (2017) predict US building permit data.
- Measuring unobserved variables: e.g. Uncertainty (Baker, Bloom, Davies, 2016)

This paper makes progress in the evaluation their relevance for nowcasting, but...

- Given the relevance of data revisions, it would be great to have this assessment with actual real-time