Discussion of

Interpreating Big-Data in the Macro Economy: A Bayesian Mixed Frequency Estimator

by David Kohns and Arnab Bhattacharjee

Daniele Bianchi

School of Economics and Finance
Queen Mary University of London

2019 Modelling with big data and machine learning

Why should we care?

A decision maker $\mathcal{D}$ wants to predict in "real-time" the state of the economy y based on an information set $\boldsymbol{X}$.

A standard approach is

$$y_t = \boldsymbol{\beta}' \boldsymbol{X}_{t-1} + \epsilon_t, \qquad \epsilon_t \sim N(0, \nu_t)$$

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Question:

- Can we exploit big data to assess the state of the economy?... without losing economic intuition

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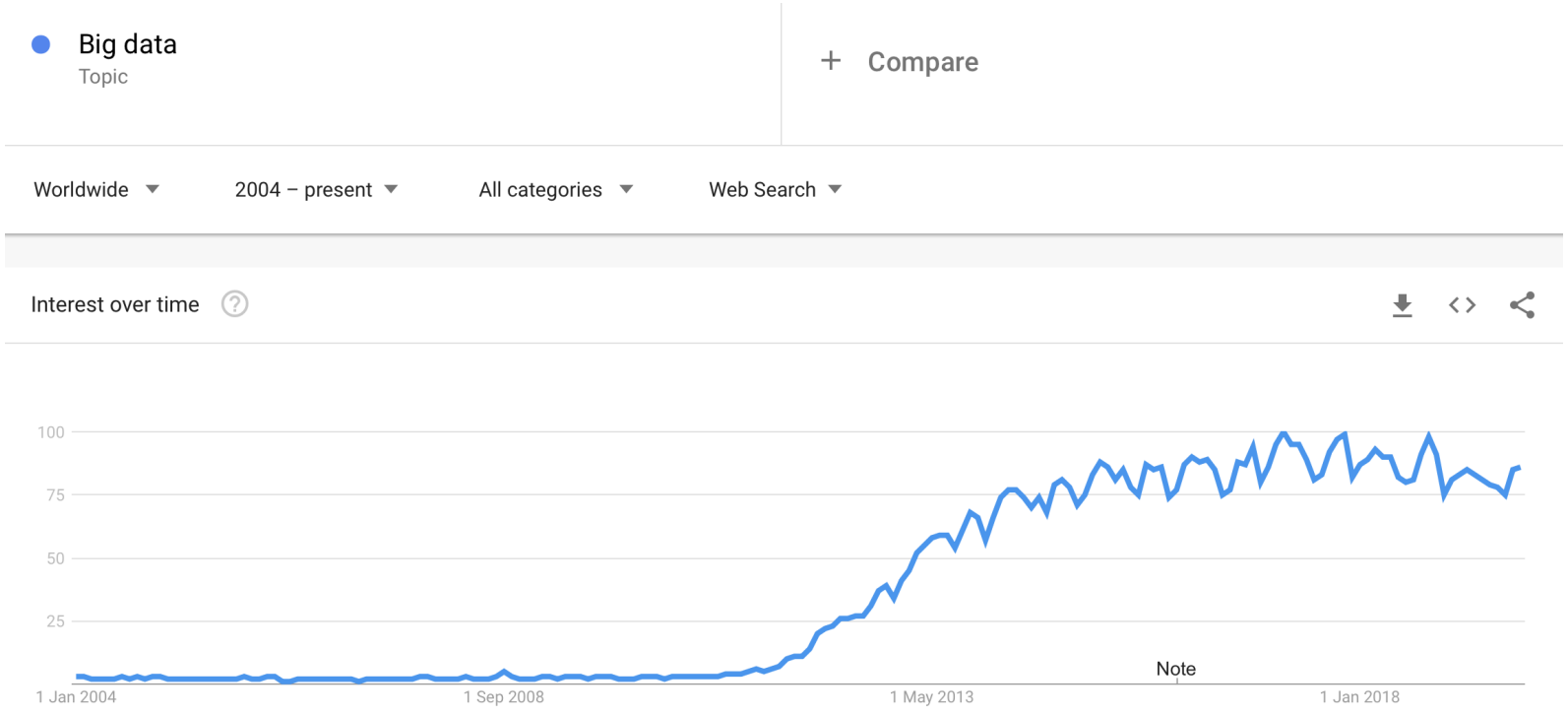

This Paper

Few issues in combining Big Data with macroeconomic variables:

- Data are sampled at different frequencies.
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$$y_t = \mu_t + \boldsymbol{\beta}' \boldsymbol{x}_t + \epsilon_t,$$
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This paper:
The predictors in $\boldsymbol{x}_t$ could be at $\neq$ frequencies (U-MIDAS, Foroni and Marcellino 2014).

My Comments:

Comment 1: Google Search Volume index.

Comment 2: Spike-and-Slab prior.

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- Where is the true source of information?
- Shall we look at "web search" or "news search"?

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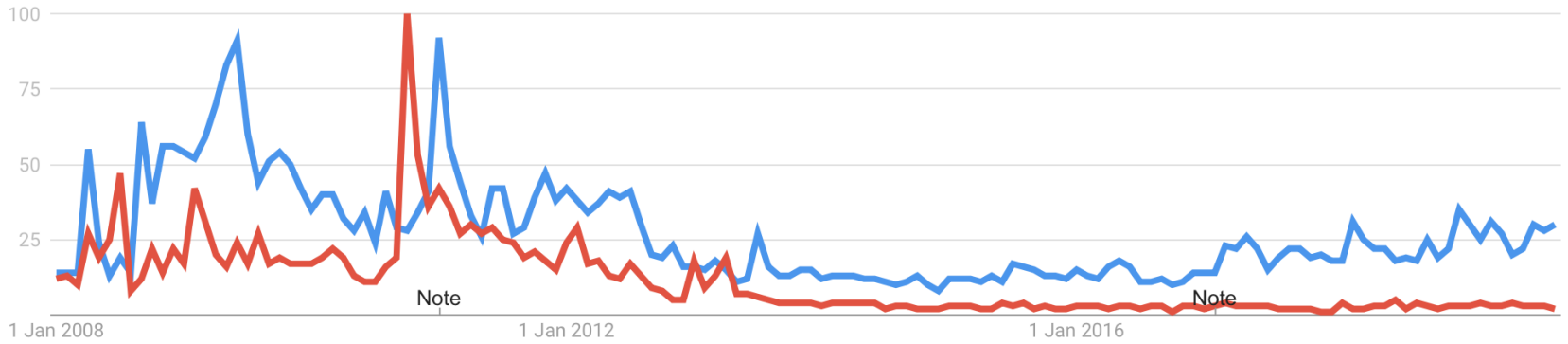
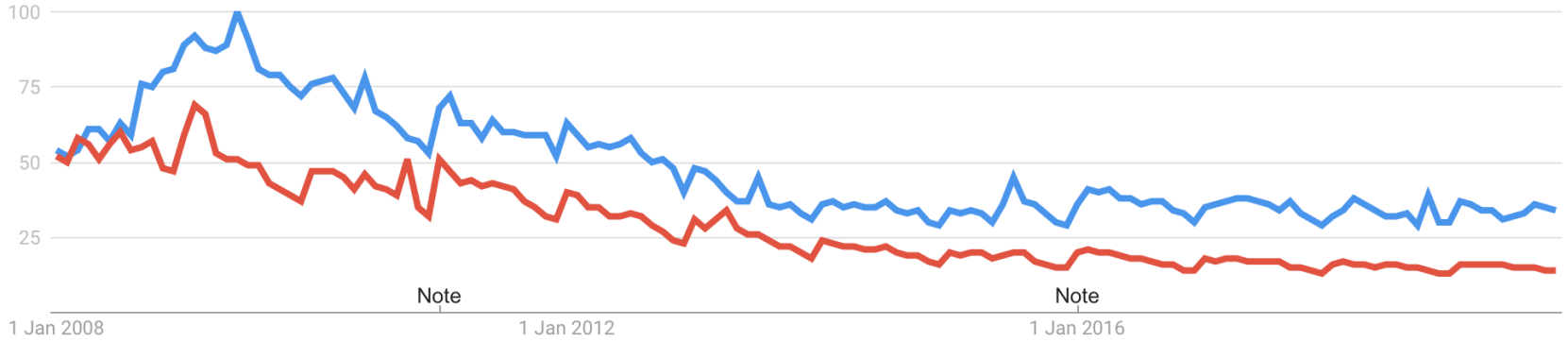
Figure: Foreclosure and Bankruptcy search



(a) Web Search



(b) News Search

Comment 2: Spike-and-Slab prior

Hierarchical mixture of normals
(George and McCulloch 1993), i.e.,

$$\beta_i|\gamma_i \sim (1-\gamma_i)\, N\left(0, \tau^2\right) + \gamma_i N\left(0, c^2\tau^2\right)$$

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- No assumption of sparsity;
  the parameter π is
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- Easy to interpret
- Embeds model and
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Cons:

- crucial the choice of $N\left(0,\tau^2\right)$ vs t-student, inverse-Gamma, Laplace, etc.
- crucial the choice of $p\left(d\pi\right)$; uniform, Beta, etc.
- it is static.

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In the paper:

1. π is fixed
2. Slab distribution $N\left(0, c^2\tau^2\right)$
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- Dynamic spike-and-slab
  (e.g., Korobilis and Koop 2019, Bianchi et al. 2019).

Conclusion

Very interesting paper, recommended reading!!