Advances in Nowcasting Economic Activity: Secular Trends, Large Shocks and New Data

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CONTRIBUTION OF THIS PAPER

- This paper is about nowcasting economic activity

- Propose Bayesian dynamic factor model (DFM), which takes seriously key features of macroeconomic data:

  1. Low-frequency variation in the mean and variance
  2. Heterogeneous responses to common shocks (leads/lags)
  3. Fat tails (outliers and "large" shocks)

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- Evaluate model and its components in comprehensive out-of-sample exercise

  - On fully real-time, unrevised US data 2000-2019
  - Point and density forecasting
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    - On fully real-time, unrevised US data 2000-2019
    - Point and density forecasting
    - Taking advantage of cloud computing
- Apply model out of sample to track the Great Lockdown of 2020 (in progress)
    - Incorporate newly available high-frequency data

THE MODEL

THE MODEL: SPECIFICATION OF BASELINE

- Start from familiar specification of a DFM (e.g. Giannone, Reichlin, and Small, 2008 and Banbura, Giannone, and Reichlin, 2010)
- An n-dimensional vector of quarterly and monthly observables $\mathbf{y}_t$ follows

$$
\begin{aligned}
\Delta(\mathbf{y}_t) &= \mathbf{c} + \boldsymbol{\lambda}\mathbf{f}_t + \mathbf{u}_t \\
(I - \Phi(L))\mathbf{f}_t &= \varepsilon_t \\
(1 - \rho_i(L))u_{i,t} &= \eta_{i,t}, \qquad i = 1, \ldots, n
\end{aligned}
$$

$$
\begin{aligned}
\varepsilon_t &\overset{iid}{\sim} N(0, \boldsymbol{\Sigma}_\varepsilon) \\
\eta_{i,t} &\overset{iid}{\sim} N(0, \sigma^2_{\eta_i}), \qquad i = 1, \ldots, n
\end{aligned}
$$

The Model: Specification of SV

- Consider n-dimensional vector of observables $\mathbf{y}_t$, which follows

$$\Delta(\mathbf{y}_t) = \mathbf{c}_t + \boldsymbol{\lambda}\mathbf{f}_t + \mathbf{u}_t,$$

with

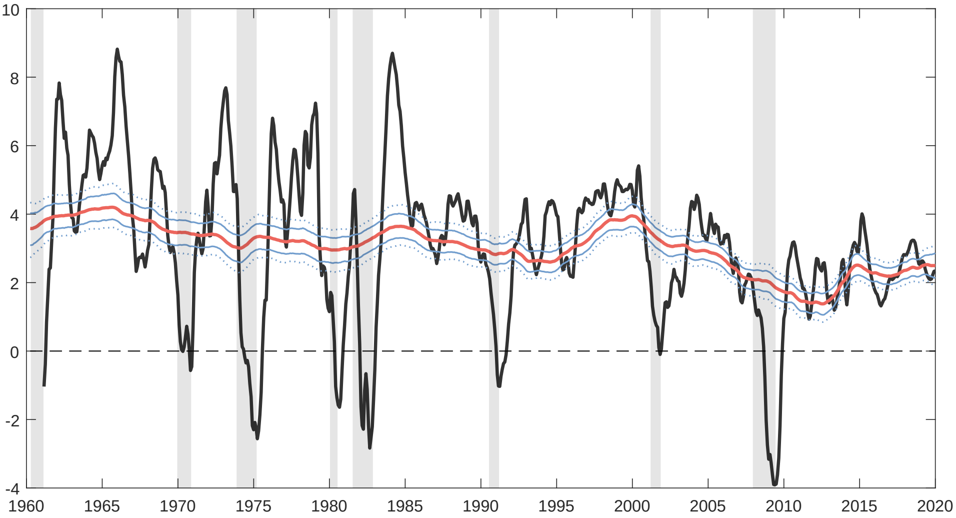
$$\mathbf{c}_t = \begin{bmatrix} \mathbf{B} & \mathbf{0} \\ \mathbf{0} & \mathbf{c} \end{bmatrix} \begin{bmatrix} \mathbf{a}_t \\ 1 \end{bmatrix},$$

and

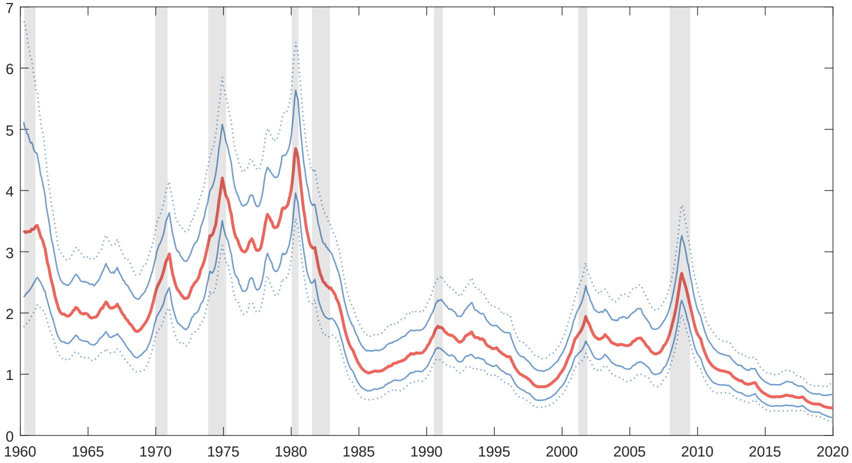
$$\begin{aligned} (I - \Phi(L))\mathbf{f}_t &= \sigma_{\varepsilon_t}\boldsymbol{\varepsilon}_t, \\ (1 - \rho_i(L))u_{i,t} &= \sigma_{\eta_{i,t}}\eta_{i,t}, \quad i = 1, \ldots, n \end{aligned}$$

- The time-varying parameters are specified as random walk processes
- Builds on Antolin-Diaz, Drechsel, and Petrella (2017)

ESTIMATED TREND



ESTIMATED VOLATILITY OF THE FACTOR



- SV captures both secular (McConnell and Perez-Quiros, 2000) and cyclical (Jurado et al., 2014) movements in volatility

THE MODEL: ADDING HETEROGENEOUS DYNAMICS

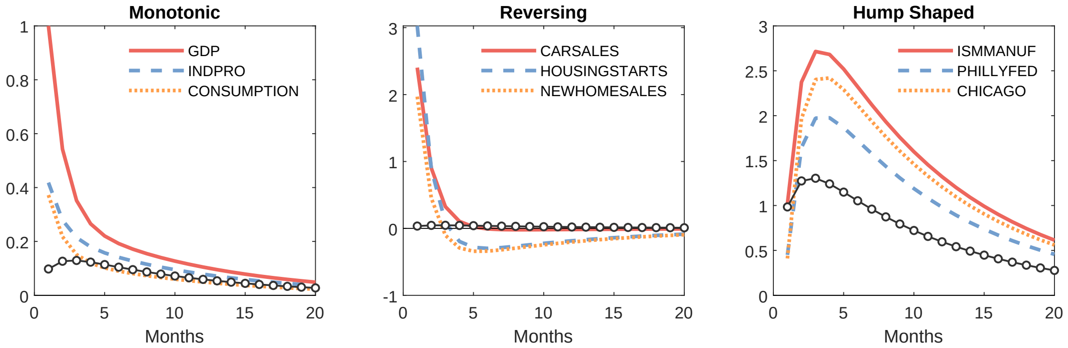
- Modify the observation equation to be

$$\Delta(\mathbf{y}_t) = \mathbf{c}_t + \boldsymbol{\Lambda}(\mathbf{L})\mathbf{f}_t + \mathbf{u}_t,$$

  where $\boldsymbol{\Lambda}(\mathbf{L})$ contains the loadings on contemporaneous and lagged factors

- Camacho and Perez-Quiros (2010) first noticed that survey data was better aligned with a distributed lag of GDP
- D'Agostino et al. (2015) show that adding lags improves performance in the context of a small model

ESTIMATED HETEROGENEOUS DYNAMICS



- Substantial heterogeneity in IRFs of to innovations in the cyclical factor

THE MODEL: ALLOWING FOR OUTLIERS

- Modify the observation equation to be

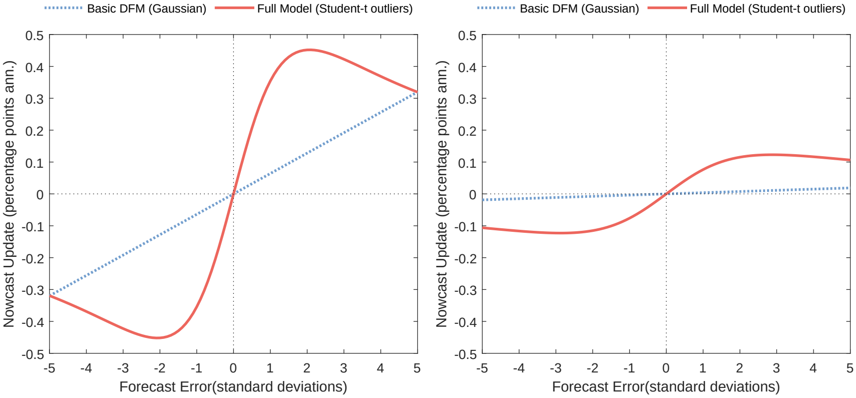
$$\Delta(\mathbf{y}_t - \mathbf{o}_t) = \mathbf{c}_t + \mathbf{\Lambda}(\mathbf{L})\mathbf{f}_t + \mathbf{u}_t,$$

  where the elements of $\mathbf{o}_t$ follow t-distributions:

$$o_{i,t} \overset{iid}{\sim} t_{\nu_i}(0, \omega_{o,i}^2), \qquad i = 1, \ldots, n$$

- The degrees of freedom of the t-distributions, ν_i, are estimated jointly with the other parameters of the model

NEWS DECOMPOSITIONS: WHAT FAT TAILS ACHIEVE



- Update of nowcast nonlinear and nonmonotic in forecast error of releases
- Some (hard) data gets more importance

THE MODEL: SUMMARY OF NOVEL FEATURES

1. Macro data: low-frequency variation in mean and variance
   - Model: time-varying parameters
2. Macro data: different leads and lags across indicators
   - Model: variables load on factor lags
3. Macro data: recurring outliers in level and difference
   - Model: t-distributed component

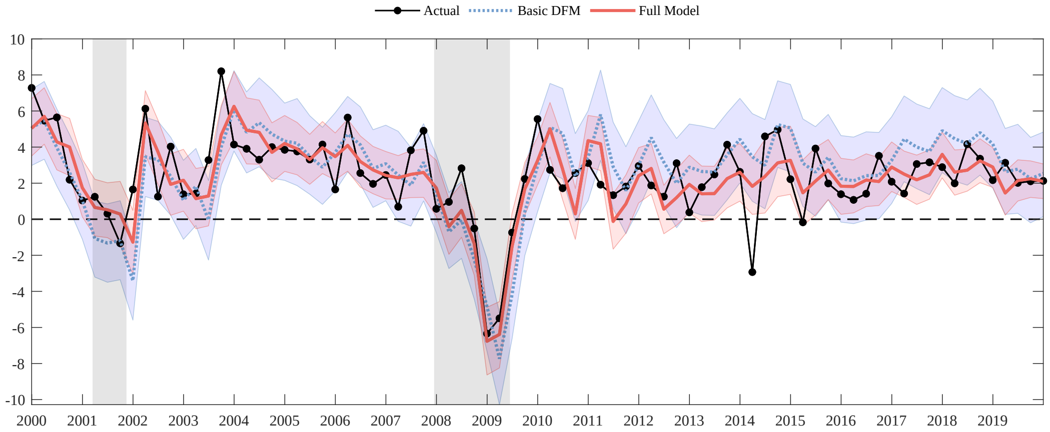
REAL-TIME EVALUATION EXERCISE

A REAL real-time exercise

- **The model is fully re-estimated every time new data is released/revised**
- The exercise starts in Jan 2000 and ends in Dec 2019: on average there is a data release on 15 different dates every month $\Rightarrow$ 3600 vintages of data
- Thanks to efficient implementation, it takes just 20 min Gibbs sampler on a single computer (we use 8,000 iterations/draws)
  - Hierarchical implementaiton of the Gibbs sampler
  - Vectorized version of the Kalman filter
- Would still mean almost 2 months of time to run the evaluation
  - Use Amazon Web Services cloud computing platform

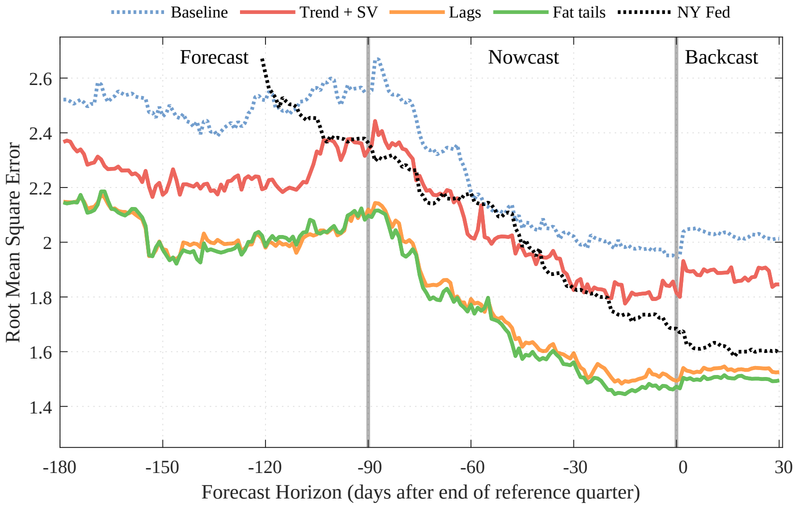
EVALUATION RESULTS

FORECASTS VS. ACTUAL OVER TIME (US)



- Long run trend eliminates the upward bias in GDP forecasts after the crisis
- Lead-lag dynamics improve the mode's performance around turning points

COMPARISON OF DIFFERENT MODELS

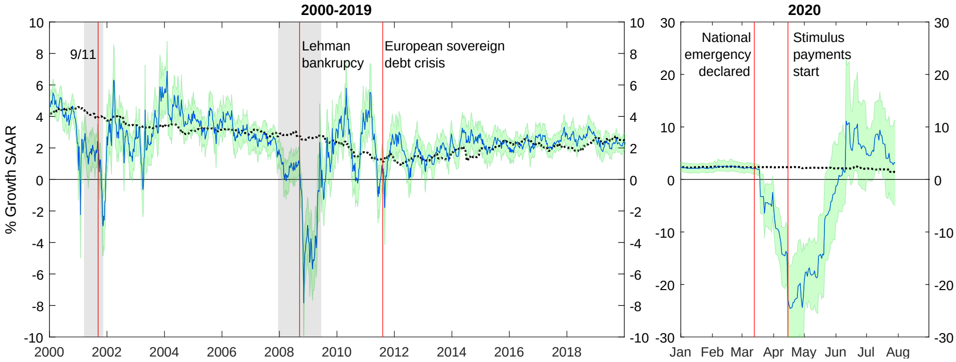


THE GREAT LOCKDOWN

NOWCASTING DURING THE GREAT LOCKDOWN

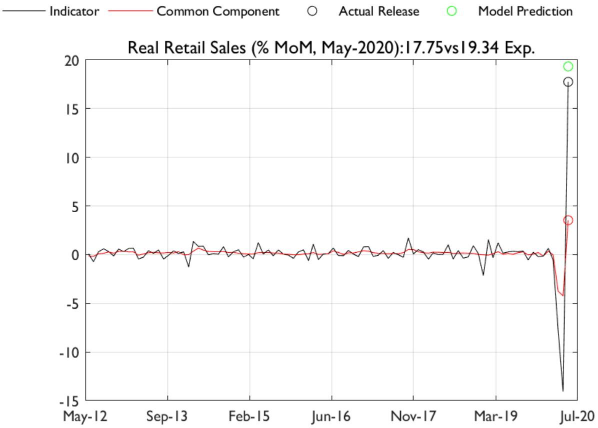
- Many formal models produce nonsensical results
- We have been exploring two avenues
  1. How novel model components help tracking activity in 2020
     - In particular heterogeneous dynamics and fat tails
  2. How to incorporate 'alternative data' in the DFM machinery
     - Novel data sources with very small history have become available

TRACKING DAILY ACTIVITY



- Model with fat-tails produces stable estimates, is able to capture features like the strong rebound of economic activity during the partial re-opening

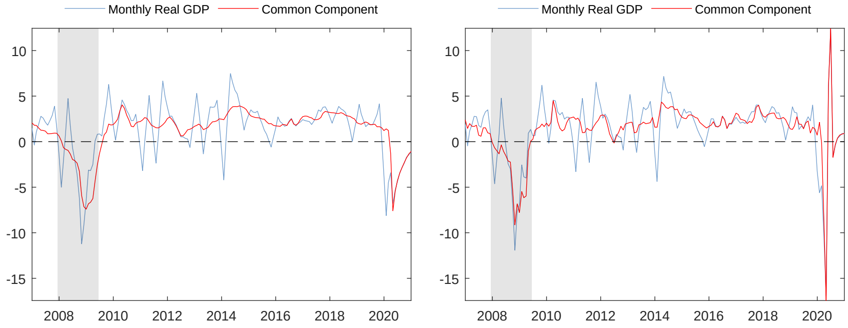
FAT TAILED OBSERVATIONS



- Model correctly captured rebound in retail sales based on history of similar outliers

NOWCASTS AS OF JUNE 2020

BASIC DFM (LEFT) VS. FULL MODEL (RIGHT)



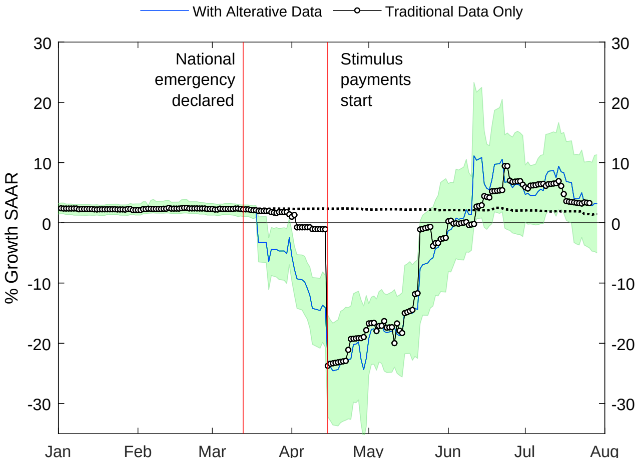
- Persistent decline or more V-shaped recovery?
- Heterogeneous dynamics capture rebound in GDP despite persistent decline in other series (in particular surveys)

USING NEW DATA SOURCES IN THE DFM

Monthly Indicator	Start	High Frequency Proxy	Freq.	Start	Estimated
Real Consumption (excl. durables)	Jan 67	Credit Card Spending (OI)	D	Jan 20	N
Payroll Empl. (Establishment Survey)	Jan 47	Homebase	D	Mar 20	N
Civilian Empl. (Household Survey)	Feb 48	Dallas Fed RPS	BW	Apr 20	N
Unemployed	Feb 48	Dallas Fed RPS	BW	Apr 20	N
Initial Claims for Unempl. Insurance	Feb 48	Weekly Claims (BLS)	W	Jan 67	N
U. of Michigan: Consumer Sentiment	May 60	Rasmussen Survey	D	Oct 04	Y
Conf. Board: Consumer Confidence	Feb 68	Rasmussen Survey	D	Oct 04	Y
U.S. Vehicle Miles Traveled	Jan 70	Apple Mobility Trends	D	Jan 20	N

- "New data" has short history
- Key idea: use new data in combination with similar "traditional" series

USING NEW DATA SOURCES IN THE DFM



- Incorporating new data enables faster tracking of the collapse in real time

CONCLUSION

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- We propose a Bayesian DFM, which explicitly incorporates:
  1. Low-frequency variation in the mean and variance
  2. Heterogeneous responses to common shocks
  3. Outlier observations and fat tails
- We provide a thorough evaluation of the novel model features for the nowcasting process and demonstrate how they improve point and density nowcasts in real time
- Assessment of US activity in 2020 is in progress
  - Some promising insights so far

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