CONTRIBUTION OF THIS PAPER

- This paper is about nowcasting economic activity
- Propose Bayesian dynamic factor model (DFM), which features explicitly:
  1. Low-frequency variation in the mean and variance
  2. Heterogeneous responses to common shocks (leads/lags)
  3. Fat tails
- Evaluate model and its components in comprehensive out-of-sample exercise
  - 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
  - New components critical to track activity during this period
  - 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 \(y_t\) follows

\[
\Delta(y_t) = c + \lambda f_t + u_t
\]

\[
(I - \Phi(L))f_t = \varepsilon_t
\]

\[
(1 - \rho_i(L))u_{i,t} = \eta_{i,t}, \quad i = 1, \ldots, n
\]

\[
\varepsilon_t \overset{iid}{\sim} N(0, \Sigma_{\varepsilon})
\]

\[
\eta_{i,t} \overset{iid}{\sim} N(0, \sigma_{\eta_i}^2), \quad i = 1, \ldots, n
\]
The Model: Specification of SV

Consider $n$-dimensional vector of observables $y_t$, which follows

$$\Delta(y_t) = c_t + \lambda f_t + u_t,$$

with

$$c_t = \begin{bmatrix} B & 0 \\ 0 & c \end{bmatrix} \begin{bmatrix} a_t \\ 1 \end{bmatrix},$$

and

$$(I - \Phi(L))f_t = \sigma \varepsilon_t \varepsilon_t,$$

$$(1 - \rho_i(L))u_{i,t} = \sigma \eta_{i,t} \eta_{i,t}, \quad i = 1, \ldots, n$$

The time-varying parameters are specified as random walk processes

Builds on Antolin-Diaz, Drechsel, and Petrella (2017)
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

\[ \Delta(y_t) = c_t + \Lambda(L)f_t + u_t, \]

where \( \Lambda(L) \) 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
Modify the observation equation to be

\[ \Delta(y_t - o_t) = c_t + \Lambda(L)f_t + u_t, \]

where the elements of \( o_t \) follow \( t \)-distributions:

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

The degrees of freedom of the \( t \)-distributions, \( \nu_i \), are estimated jointly with the other parameters of the model.
NEWS DECOMPOSITIONS: WHAT FAT TAILS ACHIEVE

- Update of nowcast nonlinear and nonmonotonic in forecast error of releases
- Some (hard) data gets more importance
INTERACTIONS BETWEEN THE NEW COMPONENTS

- Standard DFM model heavily influenced by persistent and timely surveys

- **Heterogeneous dynamics** “rebalance” the panel, by allowing higher weight to “hard” variables, such as IP, retail sales, etc...
  - ...but hard variables are prone to fat tailed observations

- **Fat-tailed component** captures these infrequent, large observations.
  - This stabilizes the nowcast against high frequency outliers
  - Interacts with the SV, which captures lower frequency changes in volatility
INTERACTIONS BETWEEN THE NEW COMPONENTS
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 → 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 implementation 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 WITH EXTERNAL BENCHMARKS

Survey Expectations and NY Fed Model
THE GREAT LOCKDOWN
INSIGHTS ON NOWCASTING IN 2020: TWO AVENUES

1. Novel model components help tracking activity in 2020
   - Many formal models simply produce nonsensical results
   - Combination of SV, heterogeneous dynamics and fat tails allow for stable tracking

2. How to incorporate ‘alternative data’ in the DFM machinery
   - Novel data sources with very small history have become available
   - Tie together with observations of closely-related traditional series
   - Contributes to more timely assessment of the downturn
Model with fat-tails produces stable estimates, is able to capture features like the strong rebound of economic activity during the partial re-opening
The volatility of underlying economic activity can be measured in real time. It shot up massively during the COVID lockdown and has stayed elevated since.
FAT TAILED OBSERVATIONS

▶ Model captured rebound in retail sales based on history of similar patterns
Persistent decline or more V-shaped recovery?

Heterogeneous dynamics capture rebound in GDP despite persistent decline in other series (in particular surveys)
### Monthly Indicator

<table>
<thead>
<tr>
<th>Monthly Indicator</th>
<th>Start</th>
<th>High Frequency Proxy</th>
<th>Freq.</th>
<th>Start</th>
<th>Estimated</th>
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</thead>
<tbody>
<tr>
<td>Real Consumption (excl. durables)</td>
<td>Jan 67</td>
<td>Credit Card Spending (OI)</td>
<td>D</td>
<td>Jan 20</td>
<td>N</td>
</tr>
<tr>
<td>Payroll Empl. (Establishment Survey)</td>
<td>Jan 47</td>
<td>Homebase</td>
<td>D</td>
<td>Mar 20</td>
<td>N</td>
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<tr>
<td>Civilian Empl. (Household Survey)</td>
<td>Feb 48</td>
<td>Dallas Fed RPS</td>
<td>BW</td>
<td>Apr 20</td>
<td>N</td>
</tr>
<tr>
<td>Unemployed</td>
<td>Feb 48</td>
<td>Dallas Fed RPS</td>
<td>BW</td>
<td>Apr 20</td>
<td>N</td>
</tr>
<tr>
<td>Initial Claims for Unempl. Insurance</td>
<td>Feb 48</td>
<td>Weekly Claims (BLS)</td>
<td>W</td>
<td>Jan 67</td>
<td>N</td>
</tr>
<tr>
<td>U. of Michigan: Consumer Sentiment</td>
<td>May 60</td>
<td>Rasmussen Survey</td>
<td>D</td>
<td>Oct 04</td>
<td>Y</td>
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<tr>
<td>Conf. Board: Consumer Confidence</td>
<td>Feb 68</td>
<td>Rasmussen Survey</td>
<td>D</td>
<td>Oct 04</td>
<td>Y</td>
</tr>
<tr>
<td>U.S. Vehicle Miles Traveled</td>
<td>Jan 70</td>
<td>Apple Mobility Trends</td>
<td>D</td>
<td>Jan 20</td>
<td>N</td>
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<tr>
<td>Real Cons. of Food Services</td>
<td>Dec 69</td>
<td>Open Table Reservations</td>
<td>D</td>
<td>Jan 20</td>
<td>N</td>
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</tbody>
</table>

- “New data” has short history
- Key idea: use new data in combination with similar “traditional” series
Incorporating new data enables faster tracking of the collapse in real time.
REFERENCES


