Addressing COVID-19 Outliers in BVARs with Stochastic Volatility

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The results presented here do not necessarily represent the views of the Federal Reserve Bank of Cleveland, the Federal Reserve System, the Deutsche Bundesbank, the Eurosystem, or their respective staffs.
How to make VARs work in turbulent times?

Extreme realizations since March 2020 lead to . . .

- strong effects on parameter estimates
- implausible predictions in constant-variance VARs
- in terms of point and density forecasts
Red diamonds: outliers more than five times the IQR away from median
BVAR FORECASTS FOR PAYROLL GROWTH

parameters from data through Feb (green) or Apr 2020 (black)

Medians and 68% bands, homoskedastic BVAR, data since 1959:03
Some suggest to omit COVID-19 obs from VAR estimation (Schorfheide & Song, 2020)

...or to place less weight on COVID-19 data in parameter estimation (Lenza & Primiceri, 2020)
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• Indeed, this is what VARs with SV would do: down-weight obs with larger variance of residuals
COVID-19 OUTLIERS AS HIGH-VARIANCE EVENTS

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• ...or to place less weight on COVID-19 data in parameter estimation (Lenza & Primiceri, 2020)

• Indeed, this is what VARs with SV would do: down-weight obs with larger variance of residuals

• But, conventional VAR-SV models assume changes in volatility to be highly persistent

• ...with strong effects on projected uncertainty
BVAR FORECASTS FOR PAYROLL GROWTH

parameters from data through Feb (green) or Apr 2020 (black), SV (red)

-200 -100 0 100

Medians and 68% bands, VARs with constant (green/black) or time-varying (red) variance
How to make VARs work in turbulent times?

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We develop approaches with random outliers in SV

- Outliers seen as fast, but transitory changes in SV
- Random outliers are part of the DGP and its predictions
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- Outliers seen as fast, but transitory changes in SV
- Random outliers are part of the DGP and its predictions

We also consider simple options for known outliers

- Exogenously “known” outliers
- Not modeled, not part of the DGP
- Treated with dummies, or missing-data approach
### RELATED LITERATURE

**Extreme data, outliers, and fat tails**


**BVARS with stochastic volatility**

- Cogley & Sargent (2005), Primiceri (2005)
- Carriero, Clark, & Marcellino (2019), Carriero, Chan, Clark, & Marcellino (2021)
AGENDA

1. BVAR models and extreme observations
2. Forecast performance pre COVID
3. Forecasts since spring 2020
4. Robustness
5. Conclusion
6. (Appendix)
### Dynamic model for the vector $y_t$

$$
    y_t = \Pi_0 + \Pi(L)y_{t-1} + v_t, \quad E_{t-1}v_t = 0
$$

### We consider the following variants:

**CONST:**  
$$
    v_t = \Sigma^{0.5} \varepsilon_t, \quad \varepsilon_t \sim N(0, I)
$$
Dynamic model for the vector $y_t$

$$y_t = \Pi_0 + \Pi(L)y_{t-1} + \nu_t, \quad E_{t-1}\nu_t = 0$$

We consider the following variants:

**CONST:** \( \nu_t = \Sigma^{0.5}\epsilon_t \), \( \epsilon_t \sim N(0, I) \)

**SV:** \( \nu_t = A^{-1}\Lambda_t^{0.5}\epsilon_t \), \( \log \lambda_{j,t} \sim RW \)

\( A^{-1} \) lower unit-triangular, \( \Lambda_t \) diagonal
BVAR MODELS AND OUTLIER-ADJUSTED VOLATILITY

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$$\nu_t = A^{-1}\Lambda_t^{0.5}\varepsilon_t, \quad \log \lambda_{j,t} \sim RW$$

$$\nu_t = A^{-1}\Lambda_t^{0.5}O_t\varepsilon_t, \quad o_{j,t} \sim iid$$

$A^{-1}$ lower unit-triangular, $\Lambda_t$, $O_t$ diagonal
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**SVO:**

$$v_t = A^{-1} \Lambda_t^{0.5} O_t \varepsilon_t,$$

$$o_{j,t} \sim iid$$

$$o_{j,t} \sim \begin{cases} 1 & \text{with prob. } 1 - p_j \\ U(2, 20) & \text{with prob. } p_j \end{cases}$$

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**SVO-t:** $v_t = A^{-1}\Lambda_t^{0.5}O_t Q_t \varepsilon_t$, $o_{j,t}, q_{j,t} \sim iid$

$$q_{j,t} \sim \sqrt{IG\left(\frac{\nu_j}{2}, \frac{\nu_j}{2}\right)}$$

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$O_t$ can have more mass on large outliers than $Q_t$

$A^{-1}$ lower unit-triangular, $\Lambda_t$, $O_t$, and $Q_t$ diagonal
Note: Medians. Total: $\Sigma_t = A^{-1}O_tQ_t\Lambda_tQ_tO_tA^{-T}$, pure SV: $\tilde{\Sigma}_t = A^{-1}\Lambda_tA^{-T}$
SIMPLE ALTERNATIVES TO TREAT KNOWN OUTLIERS

Two options when outlier events can be identified prior to estimation . . .

1) Generic missing-data approach  (SV-OutMiss)

- Pre-screen data for outliers, based on historical norms (e.g. distance from median; similar to DFM literature)
- VAR-SV with data augmentation for missing values
- Past outliers taken as given, no future outliers anticipated
- Ignores outlier effects not only in estimation of $\Sigma$ but also in jump-off vector $y_t$ for $E_t(y_{t+h}) = \Pi^h y_t$
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2) COVID-19 dummies (SV-Dummy)
   - COVID-19 generated wild swings in various months
   - Separate dummies for March 2020 to March 2021
   - Otherwise standard VAR-SV with wide priors on dummies (to soak up COVID data)
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6. (Appendix)
SETUP OF OUR FORECAST COMPARISONS

**BVAR estimation**
- Non-conjugate priors (Minnesota-style shrinkage of $\Pi$)
- MCMC estimation with corrected triangular scheme of CCM19/CCCM21 to handle SV in larger systems
- Re-estimated for each forecast origin

**Quasi real-time setup**
- 16 variables; all data from FRED-MD 2021 April vintage
- Monthly observations since 1959:03
- Growing estimation windows
- Forecasts up to two years out ($h = 24$)

**Evaluation window 1985:01 – 2017:12**
  to ignore 2020 realizations
## DATA SET

Monthly obs from 1959:03 to 2021:03; FRED-MD vintage 2021:04

<table>
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<th>Variable</th>
<th>FRED-MD code</th>
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Note: Interest-rate densities are dynamically censored at ELB
## POINT FORECAST COMPARISON
Values below one indicate improvement over SV

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<tr>
<th>Variable / Horizon</th>
<th>SVO-t 3</th>
<th>SVO-t 12</th>
<th>SVO-t 24</th>
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Note: Eval from 1985:01 through 2017:12. Stars denote DMW significance
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## DENSITY FORECAST COMPARISON

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<tr>
<td>Real Income</td>
<td>0.96***</td>
<td>0.94***</td>
<td>0.86***</td>
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<td>0.94***</td>
<td>0.94***</td>
<td>0.87***</td>
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<td>0.91***</td>
<td></td>
<td>0.98*</td>
<td>0.98***</td>
<td>0.94***</td>
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<tr>
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<td>0.96***</td>
<td>0.90***</td>
<td></td>
<td>1.01</td>
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<td>0.96</td>
<td></td>
<td>1.01</td>
<td>0.99</td>
<td>0.96**</td>
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<td>Unemployment Rate</td>
<td>1.00</td>
<td>1.01</td>
<td>1.00</td>
<td></td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
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<tr>
<td>Nonfarm Payrolls</td>
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<td>0.98*</td>
<td>0.93***</td>
<td></td>
<td>0.99</td>
<td>0.98**</td>
<td>0.96***</td>
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<tr>
<td>Hours</td>
<td>0.99</td>
<td>0.98*</td>
<td>0.92***</td>
<td></td>
<td>1.01</td>
<td>0.99</td>
<td>0.97***</td>
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<tr>
<td>Hourly Earnings</td>
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<td>0.93***</td>
<td></td>
<td>1.00</td>
<td>0.99**</td>
<td>0.97***</td>
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<tr>
<td>PPI (Fin. Goods)</td>
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<td>0.98***</td>
<td>0.95***</td>
<td></td>
<td>0.99</td>
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<td>0.98***</td>
<td></td>
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<td>0.97***</td>
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<tr>
<td>Housing Starts</td>
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<td></td>
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<tr>
<td>S&amp;P 500</td>
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<td>0.97***</td>
<td>0.92***</td>
<td></td>
<td>0.99</td>
<td>0.98***</td>
<td>0.96***</td>
<td></td>
</tr>
<tr>
<td>USD / GBP FX Rate</td>
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<td>0.92***</td>
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<td>0.99**</td>
<td>0.97**</td>
<td>0.93***</td>
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<td>1.00</td>
<td>0.99*</td>
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<td>10-Year yield</td>
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<td>Baa Spread</td>
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<td>0.98*</td>
<td>0.98**</td>
<td>0.98*</td>
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Note: Eval from 1985:01 through 2017:12. Stars denote DMW significance
Across variables forecast horizons, we typically find:

- SVO-t did as well as, if not better, than SV
- SV outperformed the CONST benchmark (see paper)
- SV-Outmiss performed similar to SVO-t

Outlier-adjusted SV helpful for outlier-prone variables while not hurting otherwise, and similarly so for missing-data treatment
AGENDA

1. BVAR models and extreme observations
2. Forecast performance pre COVID
3. Forecasts since spring 2020
4. Robustness
5. Conclusion
6. (Appendix)
Note: Medians and 68% bands
Note: Medians and 68% bands
PAYROLL FORECASTS W/KNOWN OUTLIERS
SVO-t (blue), SV-OutMiss (black)

Note: Medians and 68% bands. Circles: Pre-identified outlier data
PAYROLL FORECASTS W/KNOWN OUTLIERS

SV-Dummies (purple), SVO-t (blue), SV-OutMiss (black), realized (green)

Note: Medians and 68% bands. Circles: Pre-identified outlier data
## Point forecasts

- **Very similar**: for all of our SV variants (SV, SVO-t, SV-Dummy)
- **Some differences compared to SV-Outmiss**, which proved more accurate so far (RMSE, for $h \leq 6$)

## Predictive densities

- SV: very wide
- SV-Dummy: extremely tight
- SVO-t and SV-OutMiss: in between
- Some advantage of SVO-t over SV, (CRPS $h \leq 6$) with SV-OutMiss at least as strong

**Caveat**: Only few realizations observed so far
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FORECAST PERFORMANCE 2020:03 – 2021:02
Typically, across all 16 variables . . .

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ROBUSTNESS
In paper and appendices we also consider . . .

Variants of outlier-adjusted SV: SVO and SV-t

- Close performance, on average, in the pre-2020 sample for point and density forecasts
- SVO a little weaker than SVO-t at longer horizons, and SV-t quite close to SVO-t

Common vs variable-specific outliers

- Common outlier posits one scalar factor, $o_t$, that simultaneously scales all variables up or down

  $$v_t = o_t \cdot A_t^{-1} \Lambda_t^{0.5} \varepsilon_t \quad \varepsilon_t \sim N(0, I)$$

- Maybe ok for tightly selected variables during COVID-19
- Less plausible for broader set of variables
AGENDA

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6. (Appendix)
CONCLUSIONS

Benefits of outlier-adjusted SV in BVARs

- Detects outliers as random, not known, events
- Delineates transitory spikes from persistent changes in SV
- Pre-COVID-19: a little better, no worse than regular SV
- Since COVID-19: more plausible forecast densities

Alternative: missing-data approach

- Require outliers to be known/identified ex-ante
- Outliers not modeled, densities assume standard VAR-SV
- Robust performance

Makes BVARs work through turbulent times
Outliers in post-war data

Specification of SVO vs SV-t models

Individual vs common outliers

Payroll forecasts in 2020/2021

Forecast errors since COVID-19
OUTLIERS IN POST-WAR DATA
Occurrence of observations more than 5 times the IQR away from median

Measured over full sample of monthly data 1959:03–2021:03. Later we use growing samples in quasi-real time.
OUTLIERS IN POST-WAR DATA

Odds of observations counted as outlier in growing samples starting 1985

Occurrence of observations more than 5 times the IQR away from median
Outliers in post-war data

**Specification of SVO vs SV-t models**

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**SVO VS. SV-\( t \)**

Densities for \( o_t \) (SVO), \( q_t \) (SV-\( t \)), and \( o_t \cdot q_t \) (SVO-\( t \))

\( o_t \) can place more mass on large outliers than \( q_t \)

(Right panel zooms in on right tail of left panel.)

- SVO prior sees 1 outlier every 4 years
- For SVO-\( t \): prior mean lowered to 1 outlier every 10 years
- Here: SV-\( t \) and SVO-\( t \) calibrated to same variance as SVO (will be estimated in our empirical application)
APPENDIX

- Outliers in post-war data
- Specification of SVO vs SV-t models
- Individual vs common outliers
- Payroll forecasts in 2020/2021
- Forecast errors since COVID-19
• Common outlier posits one scalar factor, $o_t$, that simultaneously scales all variables up or down:

$$v_t = o_t \cdot A^{-1} \Lambda_t^{0.5} \varepsilon_t \quad \varepsilon_t \sim N(0, I)$$

• Maybe ok for selected variables during COVID-19

• Less plausible for broader set of variables

• For example, FE vol decomposition for real income:

![Graph showing SV-o and SVO trends from 1960 to 2020](image-url)
Outliers in post-war data

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Forecast errors since COVID-19
PAYROLL GROWTH FORECASTS
SVO-t (blue), SV (red), CONST (black)

Note: Medians and 68% bands
PAYROLL GROWTH FORECASTS W/KNOWN OUTLIERS
SV-Dummies (magenta), SVO-t (blue), SV-OutMiss (black), realized

April 2020
June 2020
September 2020
March 2021

Medians and 68% bands. Circles depict pre-identified past outliers
Outliers in post-war data

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FORECAST ERRORS SINCE COVID-19
Absolute errors of one-step ahead forecasts made March 2020 to Feb 2021

Payroll growth

Hourly Earnings

PCE price inflation

Housing starts
**CONCLUSIONS**

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