# 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.*

# RESEARCH AGENDA

## How to make VARs work in turbulent times?

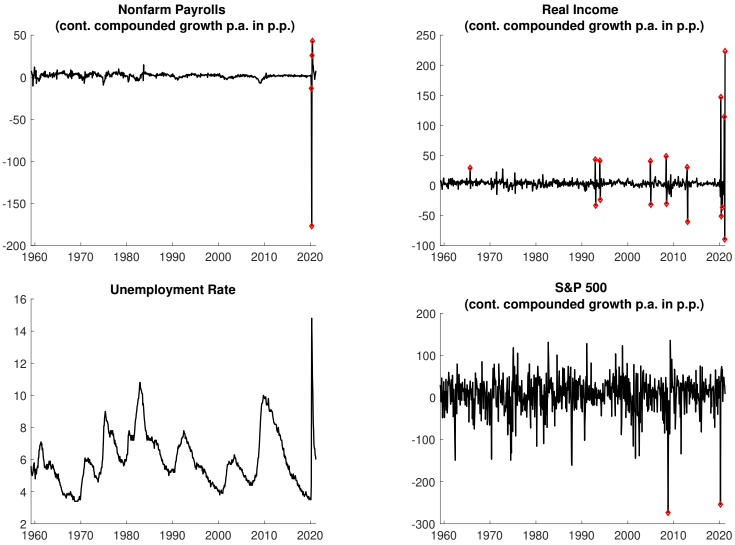
Extreme realizations since March 2020 lead to ...

- strong effects on parameter estimates
- implausible predictions in constant-variance VARs
- in terms of point and density forecasts

# EXTREME DATA SINCE MARCH 2020

## Monthly data 1959:03 – 2021:03



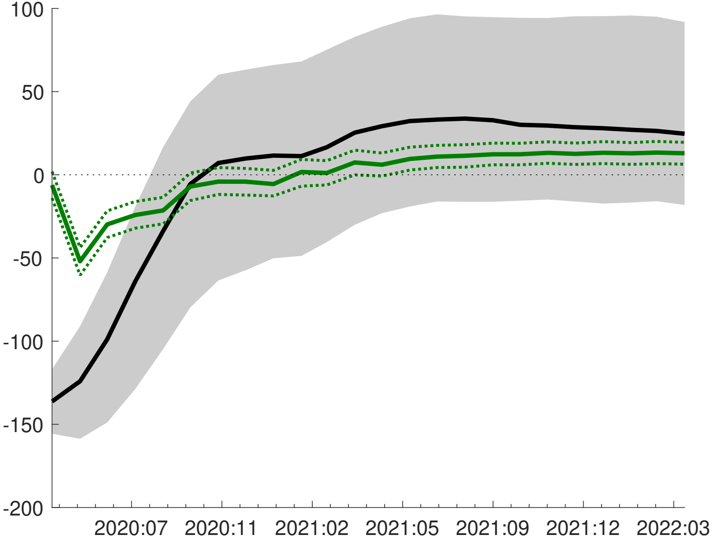



Red diamonds: outliers more than five times the IQR away from median

# BVAR FORECASTS FOR PAYROLL GROWTH

APRIL 2020

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




Medians and 68% bands, homoskedastic BVAR, data since 1959:03

# COVID-19 OUTLIERS AS HIGH-VARIANCE EVENTS

- **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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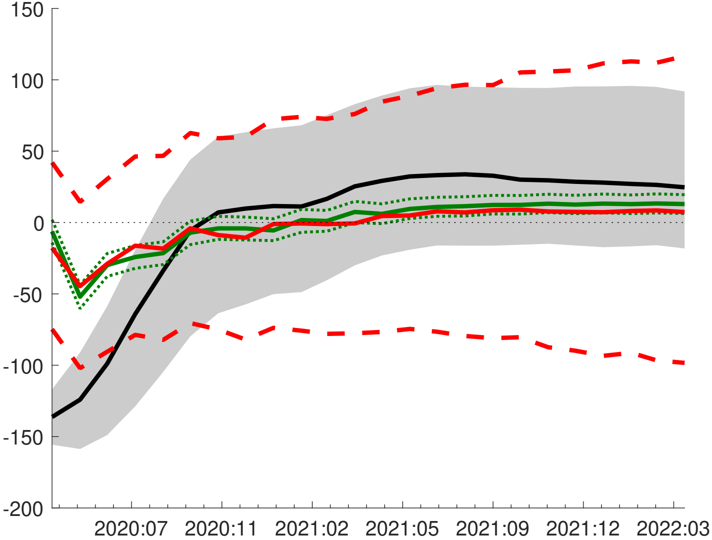
- Some suggest to omit COVID-19 obs from VAR estimation (Schorfheide & Song, 2020)
- . . . or to place less weight on COVID-19 data in parameter estimation (Lenza & Primiceri, 2020)
- Indeed, this is what VARs with SV would do:

  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

APRIL 2020

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




Medians and 68% bands, VARs with constant (green/black) or time-varying (red) variance

# RESEARCH AGENDA AND CONTRIBUTIONS

## 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

## 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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## 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

## We also consider simple options for known outliers

- Exogenously "known" outliers
- Not modeled, not part of the DGP
- Treated as missing data (or with dummies)

# RELATED LITERATURE

## BVARS with stochastic volatility

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

## Extreme data, outliers, and fat tails

- Lenza & Primiceri (2020), Schorfheide & Song (2020), Bobeica & Hartwig (2021)
- Antolin-Diaz, Drechsel, & Petrella (2021),
  Huber, Koop, Onorante, Pfarrhofer, & Schreiner (2020)
- Guerrón-Quintana & Zhong (2020), Mitchell & Weale (2021)
- Jacquier, Polson, & Rossi (2004), Karlsson & Mazur (2020),
  Cúrdia, Del Negro & Greenwald (2014),
  Clark & Ravazzolo (2015)
- Stock & Watson (2002, 2016), Breitung & Eickmeier (2011)
  Artis, Banerjee, & Marcellino (2005)

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# AGENDA

1. **BVAR models and extreme observations**
2. **Forecast performance**
3. **Model fit**
4. **Robustness**
5. **Conclusion**
6. **(Appendix)**

# BVAR MODELS AND OUTLIER-ADJUSTED VOLATILITY

## Dynamic model for the vector $y_t$

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

## We consider the following variants:

CONST: $\boldsymbol{v_t = \Sigma^{0.5} \varepsilon_t}$, $\qquad \boldsymbol{\varepsilon_t \sim N(0, I)}$

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

# ROLE OF HETEROSKEDASTICITY IN VARS

DIGRESSION

## Stylized setup: scalar, one observation, known variance etc.

### Inference about slope coefficients $\pi$ in stylized setup:

$$y_t = \pi \, y_{t-1} + v_t$$

- Given $y_{t-1}$, $v_t \sim N(0, \sigma_t^2)$, $\sigma_t^2$ known
- Prior: $\pi | y_{t-1} \sim N(\underline{\pi}, \underline{\omega}^2)$

**Observed value $y_t$ is noisy signal about $\pi$**

**Stylized setup: scalar, one observation, known variance etc.**

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**Observed value $y_t$ is noisy signal about $\pi$**

## Inference about $\pi$ is a signal extraction problem

$$E(\pi | y_t, y_{t-1}) = (1-\kappa)\,\underline{\pi} + \kappa\, \frac{y_t\, y_{t-1}}{y_{t-1}^2}$$

$$\text{with} \quad \kappa = \frac{\underline{\omega}^2}{\sigma_t^2 / y_{t-1}^2 + \underline{\omega}^2}$$

**Less weight on time-$t$ data point,**
**the noisier the signal (the larger $\sigma_t^2$)**

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

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

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

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

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

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

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

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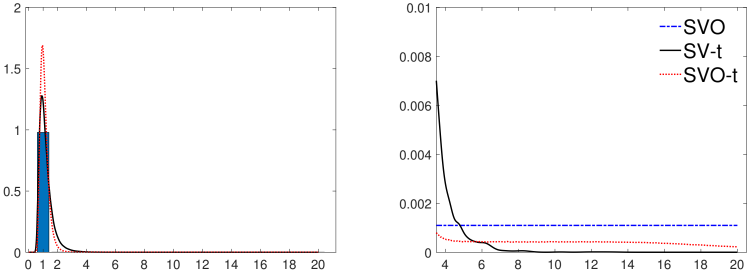
# SVO VS. SV-$t$

## Densities for $o_{j,t}$ (SVO), $q_{j,t}$ (SV-$t$), and $o_{j,t} \cdot q_{j,t}$ (SVO-$t$)

**$o_{j,t}$ can place more mass on large outliers than $q_{j,t}$**

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

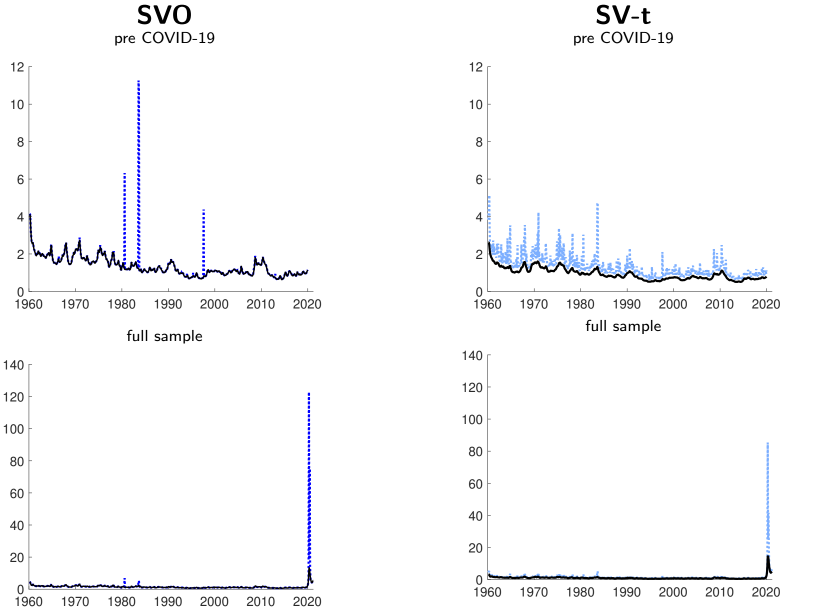



- SVO prior: 1 outlier every 4 years
- For SVO-t: prior mean lowered to 1 outlier every 10 years
- Here: all calibrated to generate same 2nd moment as SVO (will be estimated in our empirical application)

Note: SVO builds on Stock & Watson (2016), SV-t follows Jacquier, Polson & Rossi (2004)

# FORECAST ERROR VOL DECOMPOSITION — PAYROLL GROWTH

**total $\Sigma_t$ incl. outliers (colored), pure SV component $\tilde{\Sigma}_t$ (black)**




Note: Medians. Total: $\boldsymbol{\Sigma_t = A^{-1} O_t Q_t \Lambda_t Q_t O_t A^{-T}}$, pure SV: $\boldsymbol{\tilde{\Sigma}_t = A^{-1} \Lambda_t A^{-T}}$

# MISSING-DATA APPROACH FOR KNOWN OUTLIERS

## VAR-SV with missing data: “SV-OutMiss”

- **Pre-screen data for outliers**, based on historical norms (e.g. distance from median; similar to DFM literature)
- **If outlier, treat data point $z_t^j$ as missing data**

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- **Special case of additive measurement errors $e_t$**:

$$z_t^j = y_t^j + \phi_t^j \cdot e_t^j$$

with $\phi_t^j \to \infty$ if outlier, $\phi_t^j = 0$ if otherwise

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$$E_t(y_{t+h}) = \Pi^h E(y_t | z^t)$$

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**Past outliers taken as given,**
**none anticipated in future**

# AGENDA

1. BVAR models and extreme observations

2. **Forecast performance**
   - before COVID-19
   - since COVID-19

3. Model fit

4. Robustness

5. Conclusion

6. (Appendix)

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

| Variable | FRED-MD code | Transformation | RW Prior |
|---|---|---|---|
| Real Income | RPI | $\Delta \log(x_t) \cdot 1200$ | |
| Real Consumption Exp. | DPCERA3M086SBEA | $\Delta \log(x_t) \cdot 1200$ | |
| IP | INDPRO | $\Delta \log(x_t) \cdot 1200$ | |
| Capacity Utilization | CUMFNS | | yes |
| Unemployment Rate | UNRATE | | yes |
| Nonfarm payrolls | PAYEMS | $\Delta \log(x_t) \cdot 1200$ | |
| Hours | CES0600000007 | | |
| Hourly Earnings | CES0600000008 | $\Delta \log(x_t) \cdot 1200$ | |
| PPI: Finished Goods | WPSFD49207 | $\Delta \log(x_t) \cdot 1200$ | yes |
| PCE prices | PCEPI | $\Delta \log(x_t) \cdot 1200$ | yes |
| Housing Starts | HOUST | $\log(x_t)$ | yes |
| SP500 | SP500 | $\Delta \log(x_t) \cdot 1200$ | |
| U.S. / U.K. Forex | EXUSUKx | $\Delta \log(x_t) \cdot 1200$ | |
| 5-Year yield | GS5 | | yes |
| 10-Year yield | GS10 | | yes |
| Baa spread | BAAFFM | | yes |

Note: Interest-rate forecasts are dynamically censored at ELB

# SETUP OF OUR FORECAST COMPARISONS

## BVAR estimation

- Non-conjugate priors (Minnesota-style shrinkage of $\mathbf{\Pi}$)
- Gibbs samplers

## Quasi real-time setup

- Growing estimation windows (i.e., recursive scheme)
- Forecasts up to two years out ($\boldsymbol{h = 24}$)

**Evaluation window 1985:01 – 2017:12**

to ignore 2020-21 realizations

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# POINT FORECAST COMPARISON

**RELATIVE RMSE**

## Values below one indicate improvement over SV

| | SVO-t | | | SV-OutMiss | | |
|---|---|---|---|---|---|---|
| Variable / Horizon | 3 | 12 | 24 | 3 | 12 | 24 |
| Real Income | 1.00 | 1.01** | 0.93* | | | |
| Real Consumption | 1.00 | 1.00 | 1.01 | | | |
| IP | 0.99 | 1.00 | 0.96*** | | | |
| Capacity Utilization | 0.99 | 1.00 | 0.97 | | | |
| Unemployment Rate | 0.99 | 0.99 | 0.99 | | | |
| Nonfarm Payrolls | 1.00 | 1.01 | 0.98 | | | |
| Hours | 1.00 | 0.99 | 1.00 | | | |
| Hourly Earnings | 1.00 | 1.01** | 1.03* | | | |
| PPI (Fin. Goods) | 0.99 | 1.00 | 1.00 | | | |
| PCE Prices | 1.00 | 1.01 | 1.03* | | | |
| Housing Starts | 0.99 | 0.99 | 1.03*** | | | |
| S&P 500 | 1.00 | 1.00 | 1.01** | | | |
| USD / GBP FX Rate | 1.00 | 1.00 | 0.86 | | | |
| 5-Year yield | 1.00 | 1.01 | 0.97 | | | |
| 10-Year yield | 1.00 | 1.01 | 0.98 | | | |
| Baa Spread | 0.99 | 0.99 | 0.97 | | | |

Note: Eval from 1985:01 through 2017:12. Stars denote DMW significance

# POINT FORECAST COMPARISON

RELATIVE RMSE

## Values below one indicate improvement over SV

| | SVO-t | | | SV-OutMiss | | |
|---|---|---|---|---|---|---|
| Variable / Horizon | 3 | 12 | 24 | 3 | 12 | 24 |
| Real Income | 1.00 | 1.01** | 0.93* | 1.00 | 1.01 | 0.94 |
| Real Consumption | 1.00 | 1.00 | 1.01 | 0.99 | 1.00 | 1.00 |
| IP | 0.99 | 1.00 | 0.96*** | 1.00 | 0.99 | 0.98* |
| Capacity Utilization | 0.99 | 1.00 | 0.97 | 1.02 | 0.98 | 0.97 |
| Unemployment Rate | 0.99 | 0.99 | 0.99 | 1.00 | 0.99* | 1.00 |
| Nonfarm Payrolls | 1.00 | 1.01 | 0.98 | 1.00 | 0.99 | 0.98 |
| Hours | 1.00 | 0.99 | 1.00 | 1.01 | 1.00 | 1.01 |
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| PCE Prices | 1.00 | 1.01 | 1.03* | 0.99 | 1.02** | 1.02 |
| Housing Starts | 0.99 | 0.99 | 1.03*** | 1.00 | 0.99 | 1.00 |
| S&P 500 | 1.00 | 1.00 | 1.01** | 1.00 | 1.00 | 1.01 |
| USD / GBP FX Rate | 1.00 | 1.00 | 0.86 | 0.99* | 1.00 | 0.84 |
| 5-Year yield | 1.00 | 1.01 | 0.97 | 0.99* | 1.00 | 0.96 |
| 10-Year yield | 1.00 | 1.01 | 0.98 | 0.99 | 1.00 | 0.98 |
| Baa Spread | 0.99 | 0.99 | 0.97 | 0.99 | 0.99* | 1.01 |

Note: Eval from 1985:01 through 2017:12. Stars denote DMW significance

# DENSITY FORECAST COMPARISON

RELATIVE CRPS

## Values below one indicate improvement over SV

| | SVO-t | | | SV-OutMiss | | |
|---|---|---|---|---|---|---|
| Variable / Horizon | 3 | 12 | 24 | 3 | 12 | 24 |
| Real Income | 0.96*** | 0.94*** | 0.86*** | 0.94*** | 0.94*** | 0.87*** |
| Real Consumption | 0.99 | 0.97*** | 0.91*** | 0.98* | 0.98*** | 0.94*** |
| IP | 0.99* | 0.96*** | 0.90*** | 1.01 | 0.98*** | 0.96*** |
| Capacity Utilization | 0.99 | 1.00 | 0.96 | 1.01 | 0.99 | 0.96** |
| Unemployment Rate | 1.00 | 1.01 | 1.00 | 0.99 | 0.99 | 0.99 |
| Nonfarm Payrolls | 1.00 | 0.98* | 0.93*** | 0.99 | 0.98** | 0.96*** |
| Hours | 0.99 | 0.98* | 0.92*** | 1.01 | 0.99 | 0.97*** |
| Hourly Earnings | 0.99** | 0.98*** | 0.93*** | 1.00 | 0.99** | 0.97*** |
| PPI (Fin. Goods) | 0.99* | 0.98*** | 0.95*** | 0.99 | 0.99** | 0.97*** |
| PCE Prices | 1.00 | 1.00 | 0.98*** | 0.99** | 0.99 | 0.97*** |
| Housing Starts | 1.00 | 1.01 | 1.01* | 1.00 | 0.99 | 0.99 |
| S&P 500 | 0.99** | 0.97*** | 0.92*** | 0.99 | 0.98*** | 0.96*** |
| USD / GBP FX Rate | 0.99* | 0.97*** | 0.92*** | 0.99** | 0.97** | 0.93*** |
| 5-Year yield | 1.00 | 1.01* | 1.01 | 0.99 | 1.00 | 0.99* |
| 10-Year yield | 1.01 | 1.01 | 1.01* | 1.00 | 1.00 | 0.99 |
| Baa Spread | 0.99 | 0.99 | 0.97** | 0.98* | 0.98** | 0.98* |

Note: Eval from 1985:01 through 2017:12. Stars denote DMW significance

# TAKE AWAYS: FORECAST PERFORMANCE PRIOR 2020
## Evaluating the out-of-sample forecast with origins from 1985–2017 . . .

Across variables and forecast horizons, we typically find:

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

**Outlier-adjusted SV helpful for outlier-prone variables**

**while not hurting otherwise,**

**and similarly so for missing-data treatment**

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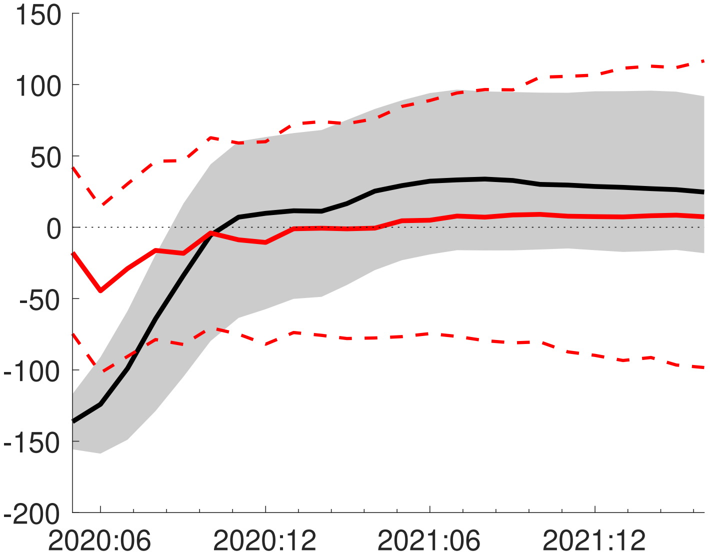
# PAYROLL GROWTH FORECASTS

APRIL 2020

## SV (red), CONST (black)

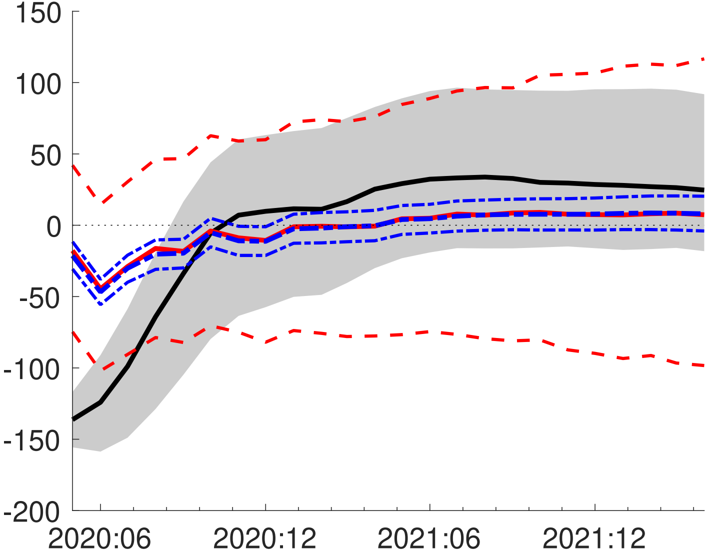



Note: Medians and 68% bands

# PAYROLL GROWTH FORECASTS

APRIL 2020

## SVO-t (blue), SV (red), CONST (black)

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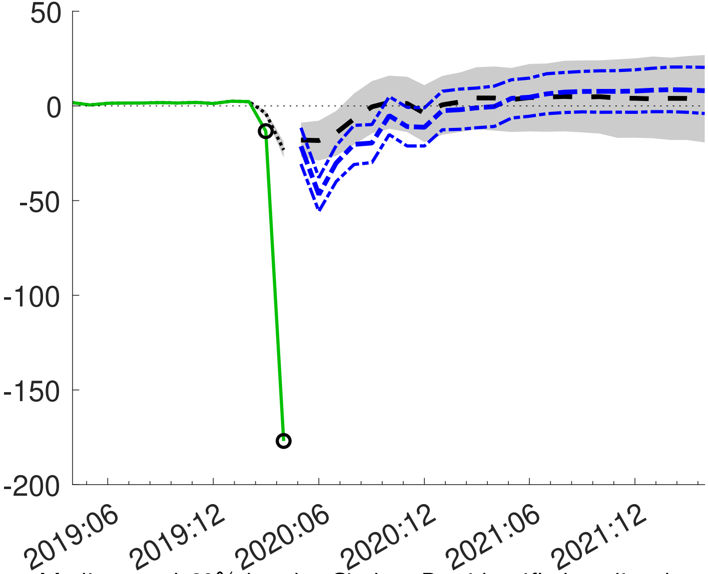
# PAYROLL FORECASTS W/KNOWN OUTLIERS

**APRIL 2020**

## SVO-t (blue), SV-OutMiss (black)

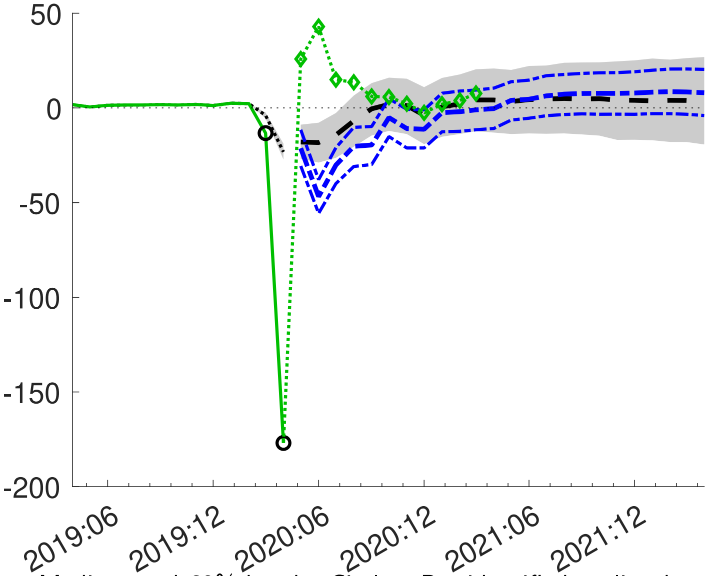



Note: Medians and 68% bands. Circles: Pre-identified outlier data

# PAYROLL FORECASTS W/KNOWN OUTLIERS

APRIL 2020

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




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

# PAYROLL GROWTH FORECASTS W/KNOWN OUTLIERS

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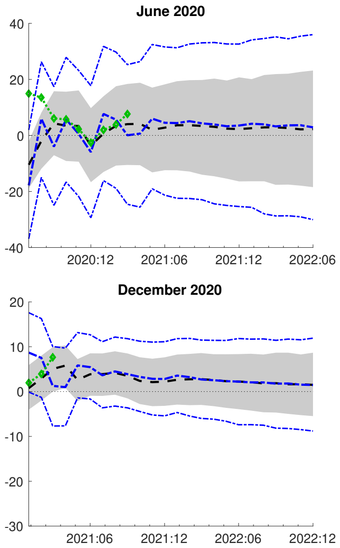


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# FORECAST PERFORMANCE 2020:03 – 2021:02

**Typically, across all 16 variables . . .**

## 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 $h \leq 6$)

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## Predictive densities

- **SV: very wide**
- **When COVID-19 obs are dummied out: very tight** (see paper)
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## Predictive densities

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- When COVID-19 obs are dummied out: very tight (see paper)
- SVO-t and SV-OutMiss: in between
- **Near-term CRPS:** Some advantage of SVO-t over SV, with SV-OutMiss at least as strong

**Caveat: Only few realizations observed so far**

# AGENDA

1. BVAR models and extreme observations
2. Forecast performance
3. **Model fit**
4. Robustness
5. Conclusion
6. (Appendix)

# MODEL FIT MEASURED BY PREDICTIVE SCORES

## Differences in log-scores $\sum_t \log p(y_t|y_{t-1}, M)$ of model $M$ relative to SV

| | Models | | | | |
|---|---|---|---|---|---|
| **Samples** | **SVO-t** | **SVO** | **SV-t** | **SV-OutMiss*** | **CONST** |
| **Full sample** | | | | | |
| 1975-2021 | | | | | |
| **G Inflation** | | | | | |
| 1975-1984 | | | | | |
| **G Moderation** | | | | | |
| 1985-2007 | | | | | |
| **GFC** | | | | | |
| 2008-2014 | | | | | |
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References: Geweke & Amisano (2010), Kass & Raftery (1995). *SV-OutMiss scores only from 1985 onwards.

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**SVO-t with consistent strength in turbulent times**

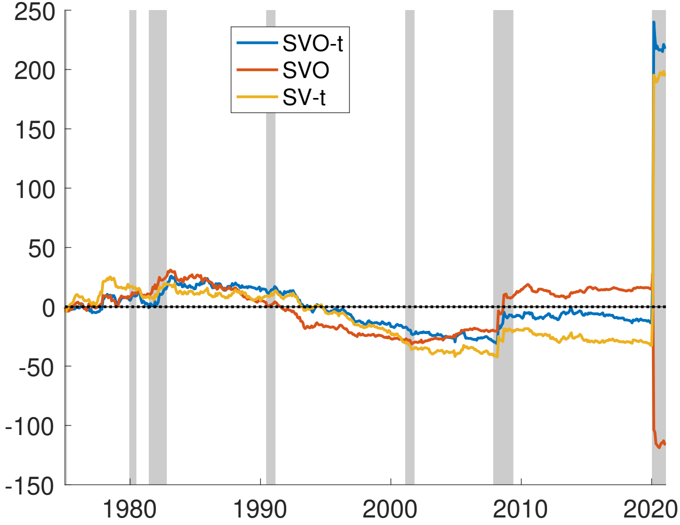
(Great Inflation, GFC and COVID-19)

**Great Moderation: SV best, followed by SV-OutMiss**

References: Geweke & Amisano (2010), Kass & Raftery (1995). *SV-OutMiss scores only from 1985 onwards.

# PREDICTIVE SCORES OVER TIME

**Differences in log-scores $\sum_t \log p(y_t|y_{t-1}, M)$ of model $M$ relative to SV**




**Outlier adjusted SV strongest in turbulent times**

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# ROBUSTNESS

## We also consider . . .

### Common vs variable-specific outliers

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

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

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

### Other model variants

- **VAR in levels:** ongoing work, results similar to baseline
- **SV w/AR(1)**: mean-reversion in SV helps, with further room for improvement through outlier-adjusted SV
- **Ordering of variables in VAR**: Not too sensitive

# AGENDA

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# CONCLUSIONS

## Benefits of outlier-adjusted SV in BVARs

- Detects outliers as random, not known, events
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## Alternative: missing-data approach

- Require outliers to be known/identified ex-ante
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**Makes BVARs work through turbulent times**

# APPENDIX

- **Outliers in post-war data**
- **Individual vs common outliers**
- **Payroll forecasts in 2020/2021**
- **Forecast errors since COVID-19**
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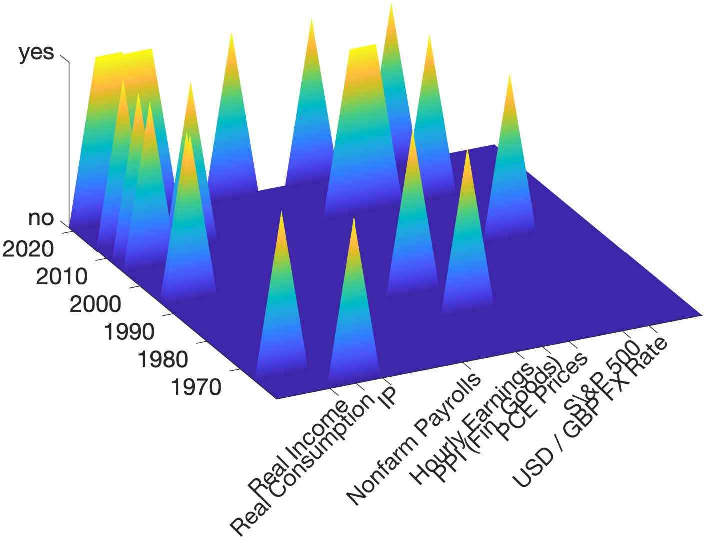
# OUTLIERS IN POST-WAR DATA

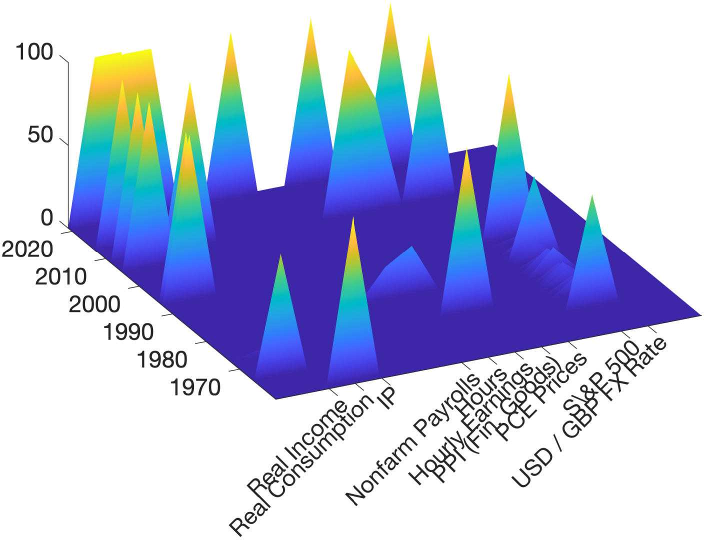
## Occurrence of observations more than 5 times the IQR away from median




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

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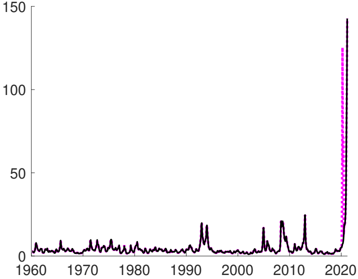
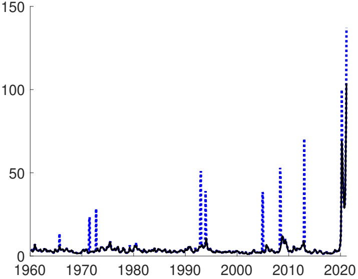
- Maybe ok for selected variables during COVID-19
- Less plausible for broader set of variables
- For example, FE vol decomposition for real income:

**SV-o**




**SVO**



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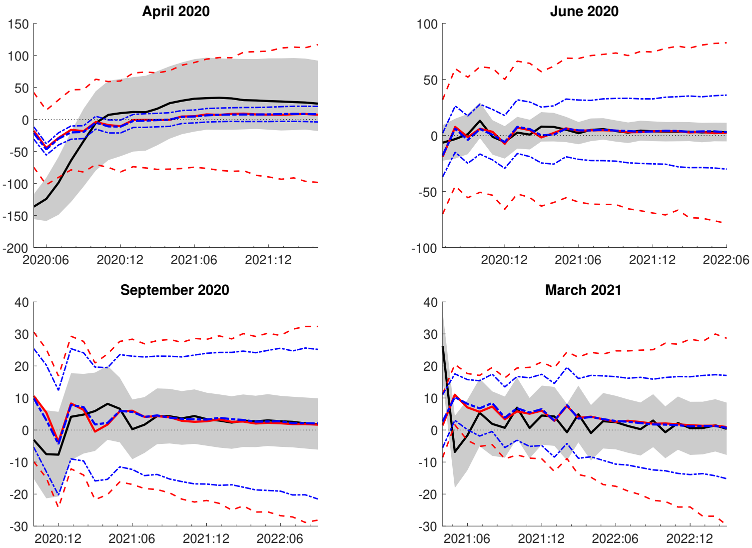


Note: Medians and 68% bands

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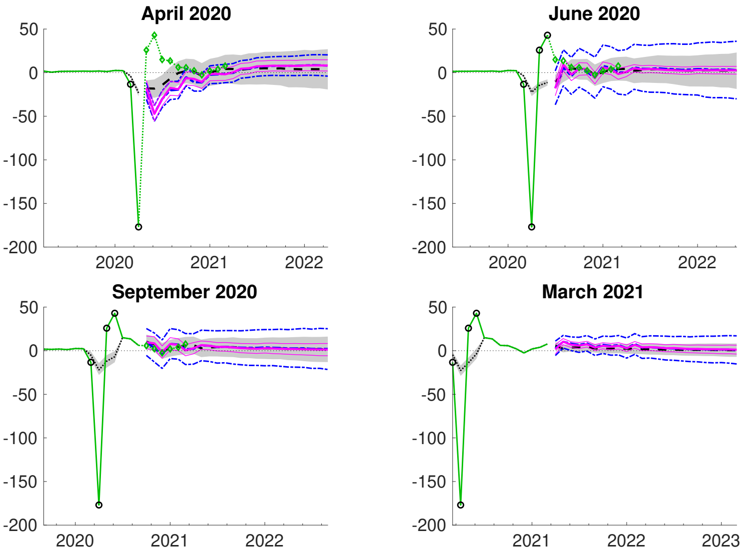


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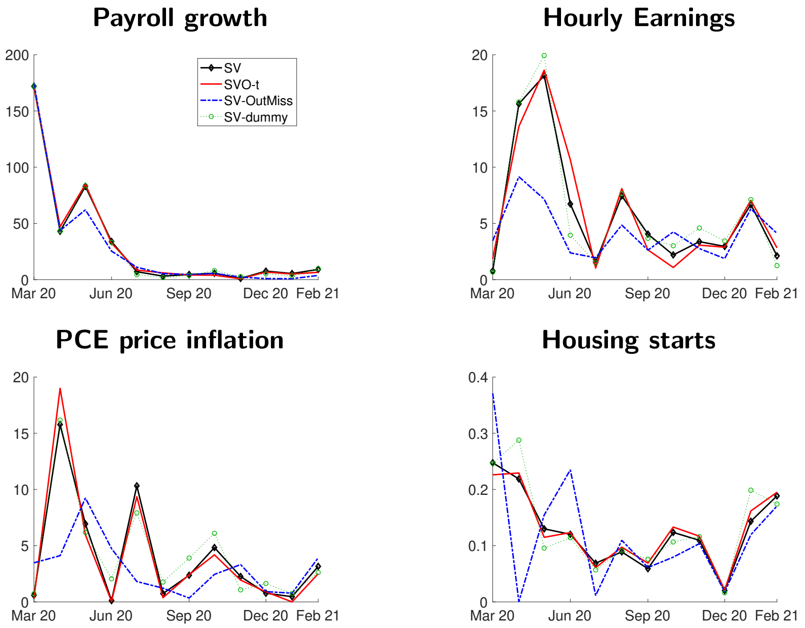
# FORECAST ERRORS SINCE COVID-19

## Absolute errors of one-step ahead forecasts made March 2020 to Feb 2021



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# CHANGES IN ORDER OF VARIABLES IN VAR

## VAR-SV not invariant to order of elements in $y_t$

- Well-known concern: Inference on

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

  not invariant to ordering of variables

- Primiceri (2005), Arias, Rubio-Ramirez, & Shin (2021)

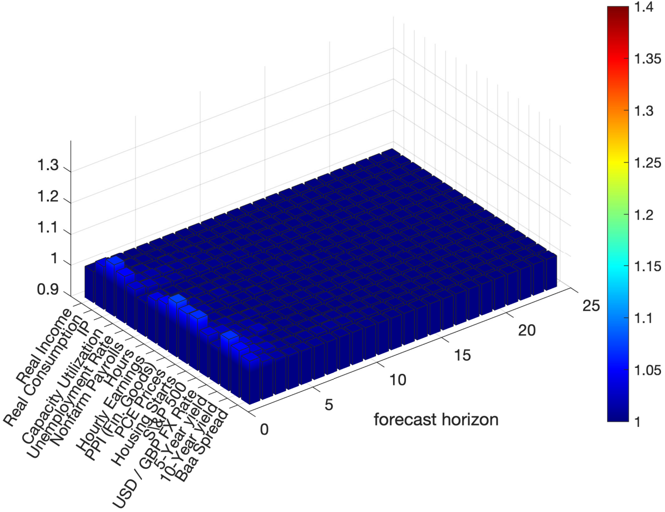
## We consider random permutations

- N=640 permutations
- Two forecast origins: March 2021 and April 2020
- Compare predictive densities with "potential scale reduction factors" (PSRF) of Gelman & Rubin (1992)

**No significant differences per March 2021**
**only some per April 2020**

# DISPERSION BETWEEN DENSITIES W/REORDERING

## Forecast origin: March 2021




Gelman-Rubin PSRF across 640 permutations. Optimal value: 1.0

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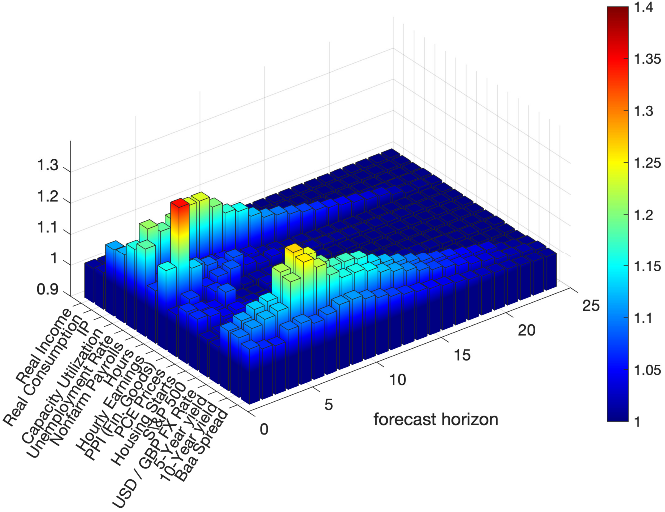
## Forecast origin: April 2020

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