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?

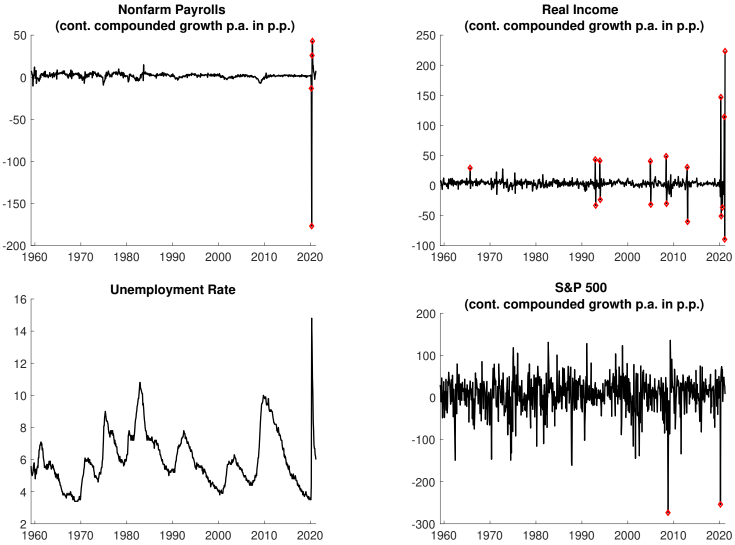
Extreme realizations since March 2020 lead to ...

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

EXTREME DATA SINCE MARCH 2020

U.S.

Monthly data 1959:03 – 2021:03

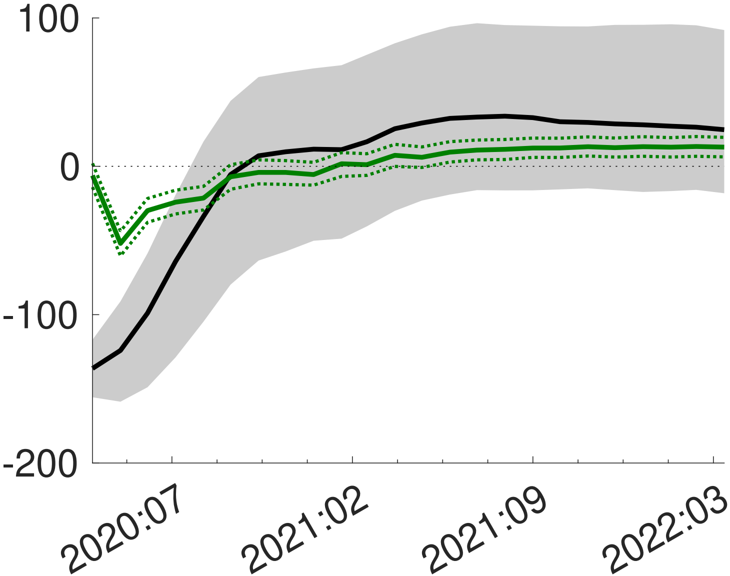


Red diamonds: outliers more than five times the IQR away from median

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

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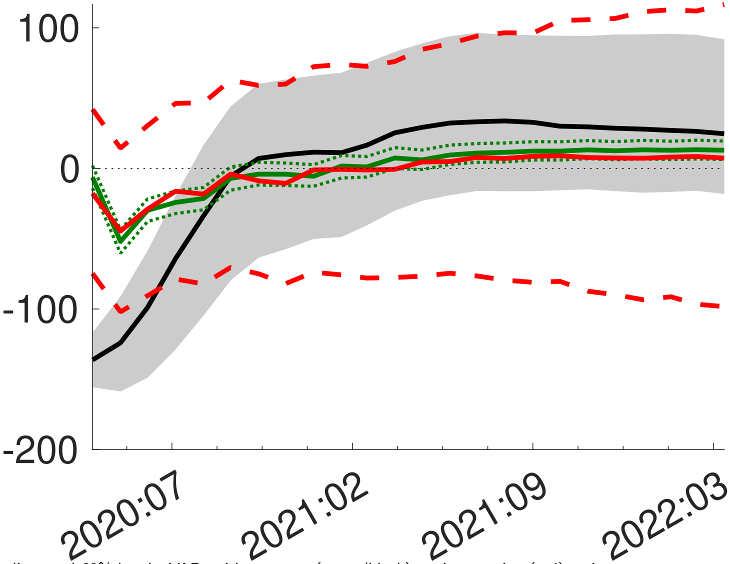
- Some suggest to omit COVID-19 obs from VAR estimation (Schorfheide & Song, 2020)
- . . . or to place less weight on COVID-19 data in parameter estimation (Lenza & Primiceri, 2020)
- Indeed, this is what VARs with SV would do:

  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 with dummies, or missing-data approach

RELATED LITERATURE

Extreme data, outliers, and fat tails

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

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)

BVAR MODELS AND OUTLIER-ADJUSTED VOLATILITY

Dynamic model for the vector y_t

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

We consider the following variants:

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

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A^{-1} lower unit-triangular, Λ_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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$$q_{j,t} \sim \sqrt{IG\left(\frac{\nu_j}{2}, \frac{\nu_j}{2}\right)}$$

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O_t can have more mass on large outliers than Q_t

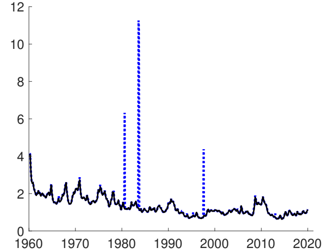
A^{-1} lower unit-triangular, Λ_t, O_t, and Q_t diagonal

FORECAST ERROR VOL DECOMPOSITION

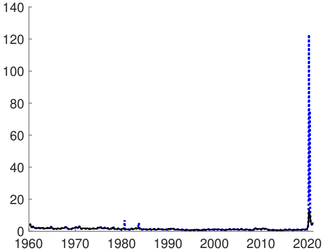
Total Σ_t incl. outliers (colored), pure SV component $\tilde{\Sigma}_t$ (black)

SVO

pre COVID-19

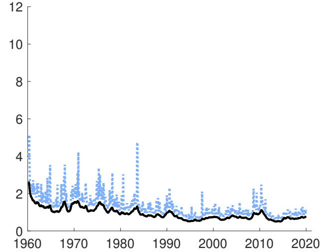


full sample



SV-t

pre COVID-19



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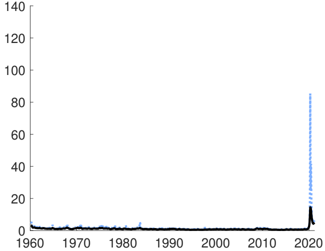

Note: Medians. Total: $\boldsymbol{\Sigma_t = A^{-1} O_t Q_t \Lambda_t Q_t O_t A^{-T}}$, pure SV: $\boldsymbol{\tilde{\Sigma}_t = A^{-1} \Lambda_t A^{-T}}$

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 $\boldsymbol{\Pi}$ but also in jump-off vector $\boldsymbol{y_t}$ for $\boldsymbol{E_t(y_{t+h}) = \Pi^h y_t}$

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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)

AGENDA

1. BVAR models and extreme observations
2. **Forecast performance pre COVID**
3. Forecasts since spring 2020
4. Robustness
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SETUP OF OUR FORECAST COMPARISONS

BVAR estimation

- Non-conjugate priors (Minnesota-style shrinkage of $\boldsymbol{\Pi}$)
- 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 ($\boldsymbol{h = 24}$)

Evaluation window 1985:01 – 2017:12
to ignore 2020 realizations

DATA SET

BACKUP

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 densities are dynamically censored at ELB

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
Hourly Earnings	1.00	1.01**	1.03*	1.00	1.00	1.00
PPI (Fin. Goods)	0.99	1.00	1.00	1.00	1.00	1.00
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***
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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 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

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3. **Forecasts since spring 2020**
4. Robustness
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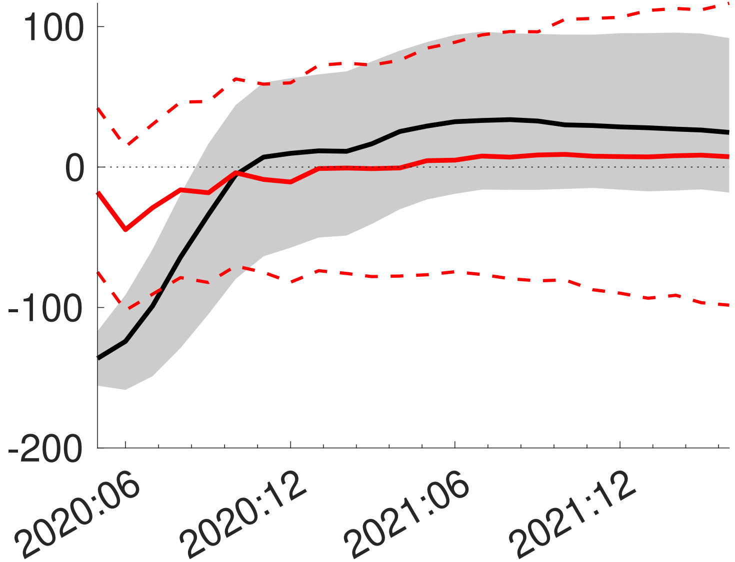
PAYROLL GROWTH FORECASTS

APRIL 2020

SV (red), CONST (black)

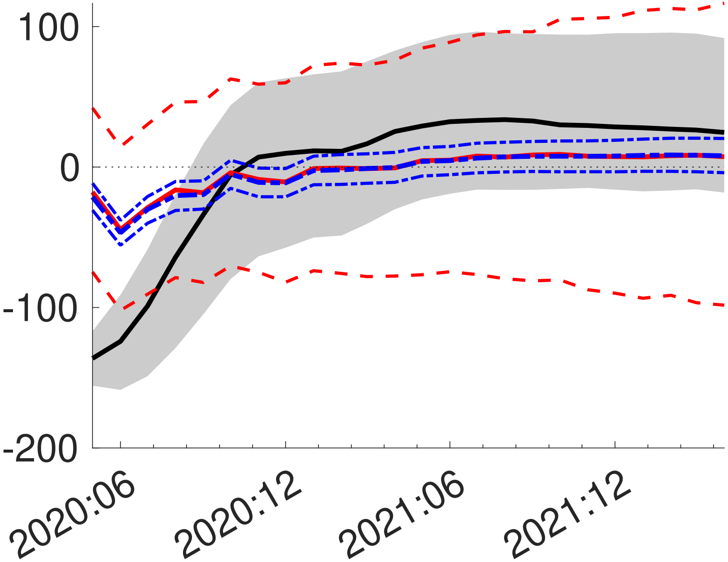


Note: Medians and 68% bands

PAYROLL GROWTH FORECASTS

APRIL 2020

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



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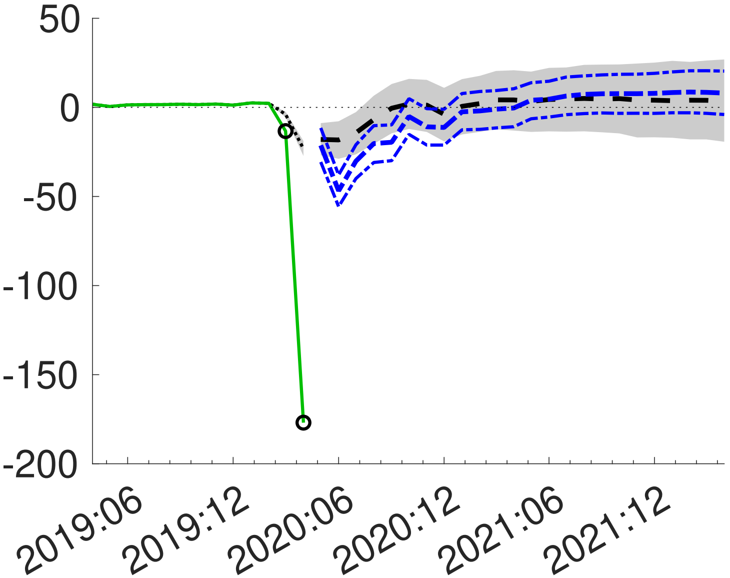
PAYROLL FORECASTS W/KNOWN OUTLIERS

APRIL 2020

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

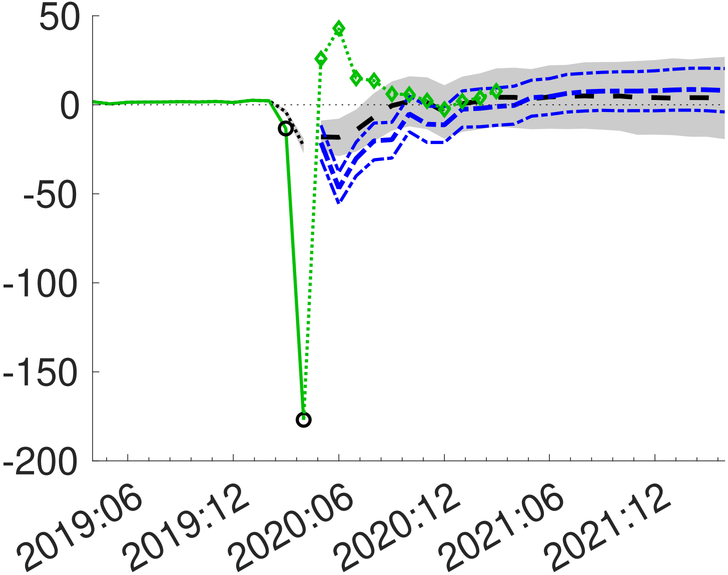


Note: Medians and 68% bands. Circles: Pre-identified outlier data

PAYROLL FORECASTS W/KNOWN OUTLIERS

APRIL 2020

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



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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 $h \leq 6$)

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

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Caveat: Only few realizations observed so far

AGENDA

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, $\boldsymbol{o_t}$, that simultaneously scales all variables up or down

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

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

AGENDA

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

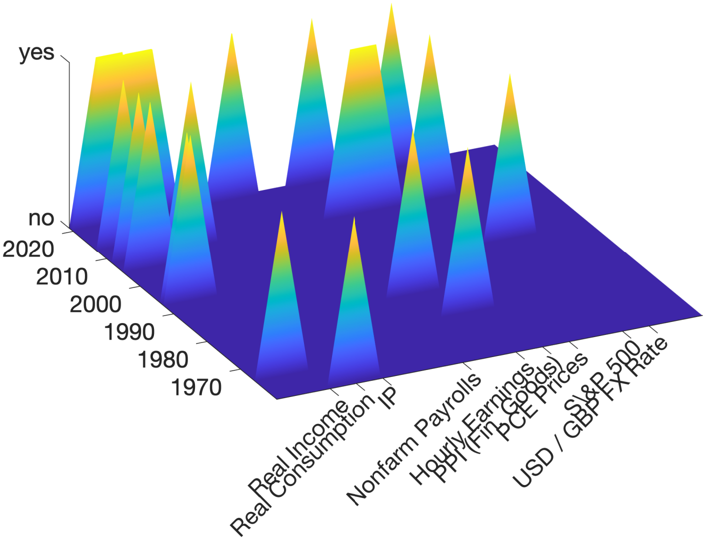
APPENDIX

- **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**

OUTLIERS IN POST-WAR DATA

BACKUP

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

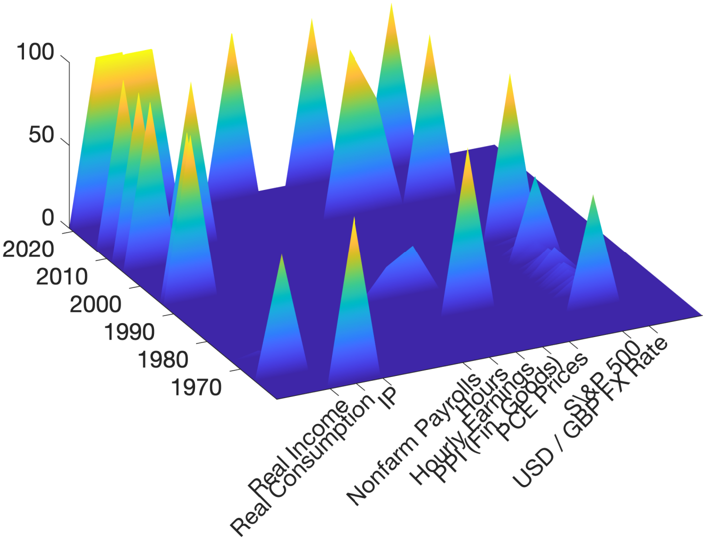


Measured over full sample of monthly data 1959:03–2021:03. Later we use growing samples in quasi-real time.

OUTLIERS IN POST-WAR DATA

BACKUP

Odds of observations counted as outlier in growing samples starting 1985



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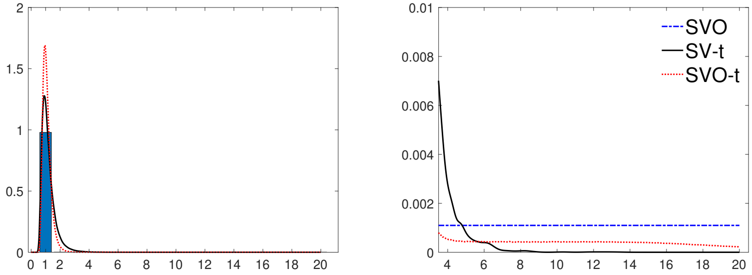
SVO VS. SV-t

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)

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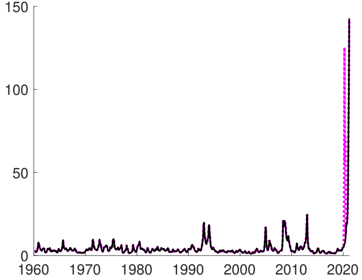
INDIVIDUAL VS COMMON OUTLIER MODEL

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

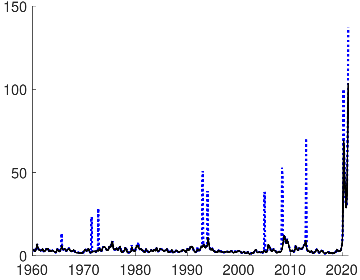
$$\boldsymbol{v_t = o_t \cdot A^{-1} \Lambda_t^{0.5} \varepsilon_t \qquad \varepsilon_t \sim N(0, I)}$$

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

SV-o



SVO



APPENDIX

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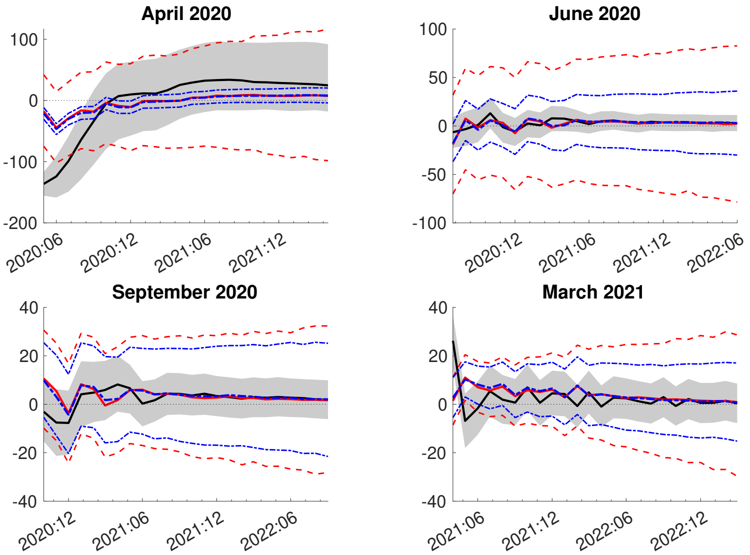
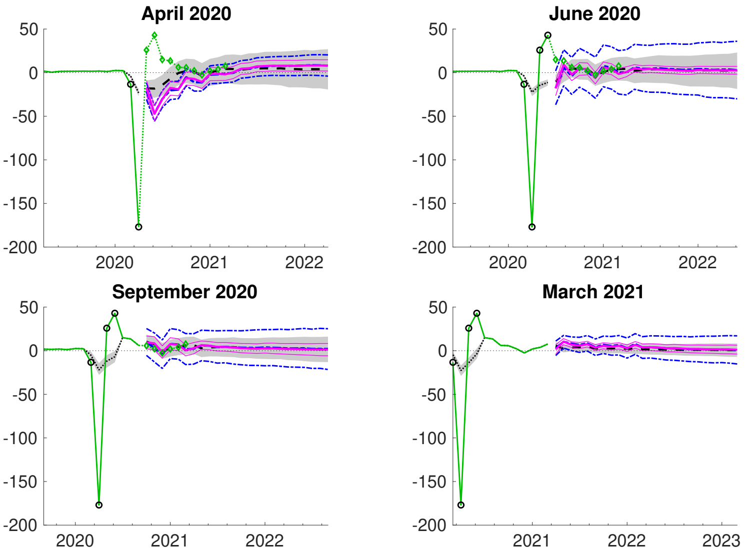
PAYROLL GROWTH FORECASTS
SVO-t (blue), SV (red), CONST (black)



Note: Medians and 68% bands

PAYROLL GROWTH FORECASTS W/KNOWN OUTLIERS

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



Medians and 68% bands. Circles depict pre-identified past outliers

APPENDIX

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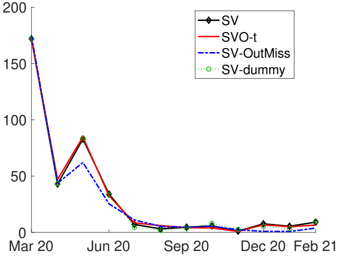
FORECAST ERRORS SINCE COVID-19

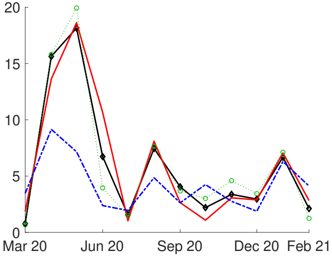
BACKUP

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

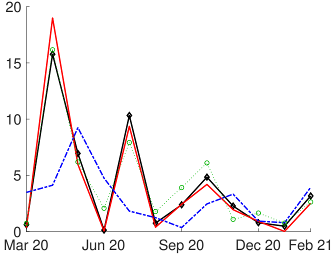
Payroll growth



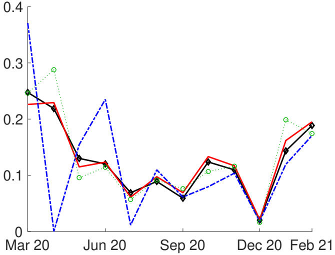
Hourly Earnings



PCE price inflation



Housing starts



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