How Should We Model Outliers in Nowcasting?

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* The views expressed in this paper are those of the author and do not necessarily represent the views of the Bank of England or its committees.

Motivation

How is the economy doing now?

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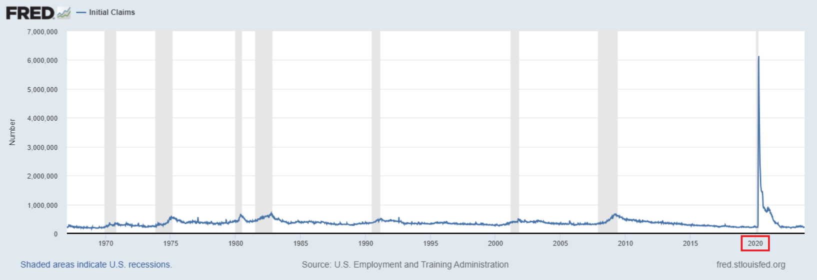


"Both the depth and the duration of the economic downturn are extraordinarily uncertain and will depend in large part on how quickly the virus is brought under control." [Powell's press conference, 2020.4.29]

Now we have models, but...

Two approaches to incorporate outliers to DFMs, with:

1. T-distribution (e.g., Antolin-Diaz et al. 2024)

2. Uniform mixture distribution (e.g. NY Fed Staff Nowcast 2.0)

Now we have models, but...

Two approaches to incorporate outliers to DFMs, with:

1. T-distribution (e.g., Antolin-Diaz et al. 2024)

   "*Student-t model results in a faster tail decay, assigning a larger probability mass to large but not extremely large outliers." (Antolin-Diaz et al. 2024)*

2. Uniform mixture distribution (e.g. NY Fed Staff Nowcast 2.0)

   "*...more geared toward generating sizable outliers at a variable-specific rate of occurrence... we view as conceptually preferable, particularly in the COVID."* (Carriero et al. 2024)

Different implications: **How should we model outliers?**

This paper

Dynamic factor model + features of data: fat tails, outliers
$\longrightarrow$ explicit modeling of outliers, not simply screening

1. Revisit t-dist vs. uniform mix approaches to model outliers:
   $\longrightarrow$ More flexible v. suited for large jumps
2. A hybrid model: t-dist $\times$ uniform mixture
   $\longrightarrow$ accommodate both frequent/small, rare/large outliers

(Pseudo) real-time, out-of-sample forecasting exercise:
$\longrightarrow$ application to France, pre- and post-pandemic

Findings

1. Both t-dist and uniform mixture capture a part of the picture
   $\longrightarrow$ t-dist: (too) frequent outliers, underestimates SV
   $\longrightarrow$ uniform mix: missing moderate/frequent outliers
   $\longrightarrow$ No clear winner between the two

2. The hybrid model outperform all models during the COVID
   $\rightarrow$ both in point & density forecasting: 34–54% v. benchmark
   $\rightarrow$ dominates at every quantile, especially at the upper tail
   $\rightarrow$ stability: isolates COVID from pre-pandemic estimates.

3. Outlier models are crisis insurance
   $\rightarrow$ No clear advantage v. SV-only DFM in pre-COVID

Modelling outliers: t-dist v. uniform mixture

Model specification TVM

Feature (1–2): time-varying mean + stochastic volatility

$$\Delta y_t = c_t + \Lambda(L) f_t + u_t \tag{1}$$

$$(1 - \phi(L)) f_t = \sigma_{\epsilon_t} \epsilon_t, \quad \epsilon_t \sim N(0, 1) \tag{2}$$

Feature (3): outlier in SV (multiplicative)

$$(1 - \rho_i(L)) u_{it} = \sigma_{\eta_{it}} o_{it} \eta_{it}, \quad i = 1, ..., n \tag{3}$$

...and the trend and SV follow random walk

$$a_t = a_{t-1} + v_{a,t}, \quad v_{a,t} \sim N(0, \omega_a^2) \tag{4}$$

$$log \sigma_{\epsilon_t} = log \sigma_{\epsilon_{t-1}} + v_{\epsilon,t}, \quad v_{\epsilon,t} \sim N(0, \omega_\epsilon^2) \tag{5}$$

$$log \sigma_{\eta_t} = log \sigma_{\eta_{t-1}} + v_{\eta,t}, \quad v_{\eta,t} \sim N(0, \omega_\eta^2), \quad i = 1, ..., n \tag{6}$$

T-distribution v. Uniform mixture

Modelling outliers with t-dist (e.g. Antolin-Diaz et al. 2024):

$$\Delta(y_t - o_t) = c_t + \Lambda(L) f_t + u_t, \quad o_{it} \sim t_{\nu_i}(0, \sigma^2_{oi})$$

- Long pedigree in the SV literature (Jacquier et al. 2004)
- Use scale mixture to accommodate t-distributed errors:
  $o_{it} = \sqrt{\psi_{it}} z_{it} \sim t_{vi}(0, \sigma^2_{oi}), \quad \psi_{it} \sim IG, \quad z_{it} \sim N(0, \sigma^2_{oi})$

Limitation of t-outliers:

1. Complicate to justify priors: p(σ^2_{oi}) $\sim$ IG(0.1, ν_i)
   $\longrightarrow$ ADP (2024): $\nu_i = 1$ for monthly, 30 for quarterly (?)

2. Most mass close to 1
   $\longrightarrow$ not the best to deal with unforeseen jumps (COVID)

T-distribution v. Uniform mixture

Stock and Watson (2016):

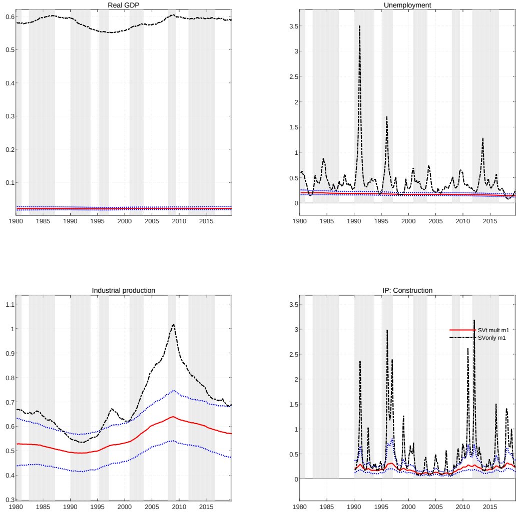
$$o_{it} = \begin{cases} 1 & \text{with probability} \quad 1 - p_i \\ U(2,10) & \text{with probability} \quad p_i \end{cases}$$

Advantage : Equal p on outlier states [2,10], no value below 1
$\longrightarrow$ geared towards extreme and rare jumps

p(p_i| y, θ) $\sim$ beta(α, β) details
$\longrightarrow$ α = num. occurence of outliers in data + prior (pre-sample)
$\longrightarrow$ β = num. non-occurence of outliers in data + prior
$\longrightarrow$ Easier, sensible, variable-specific priors

Limitation: rigid, missing shocks outside the boundary

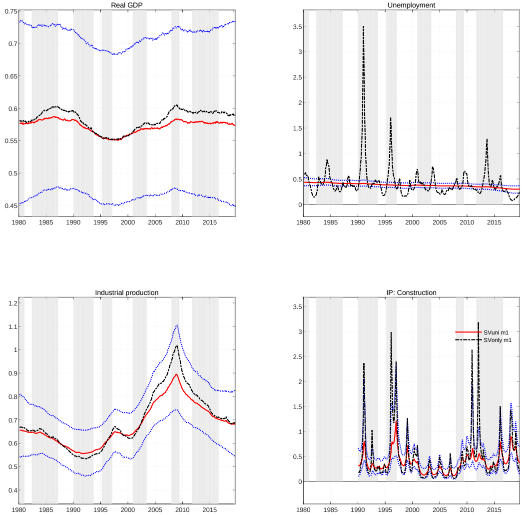
Stochastic volatility: hard indicators (t-dist) M Q



Black = posterior median, **SV-only** model without outliers.
Red and blue = posterior median and 68% bands from the t-dist outlier model.

Sample: 1980.1 – 2019.9. OECD recessions in grey.

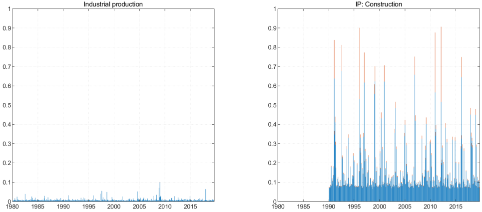
Stochastic volatility: hard indicators (uniform) M Q



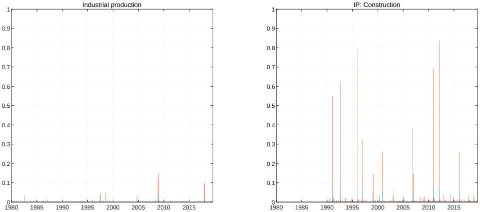
Black = posterior median, **SV-only** model without outliers.
Red and blue = posterior median and 68% bands from the uniform outlier model.

Sample: 1980.1 – 2019.9. OECD recessions in grey.

Posterior probability of outlier states



(a) student-t outliers: too frequent and small



(b) uniform outliers: rare but large

Orange = $p(o > 5)$, Blue = $p(2 < o < 5)$. Sample: 1980.1 – 2019.9.

A hybrid model

So far, outlier in SV:

$$(1-\rho_i(L))u_{it} = \sigma_{\eta_{it}} o_{it} \eta_{it}, \quad \eta_{it} \sim N(0,1)$$

where outlier o_{it} follows:

1. the student-t distribution
2. Uniform mixture

A hybrid model

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1. the student-t distribution
   $\longrightarrow$ draws small–medium outliers frequently
2. Uniform mixture
   $\longrightarrow$ draws large, outliers rarely

The distribution of outliers unknown. Then, what if:

A hybrid model

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The distribution of outliers unknown. Then, what if:

$$(1 - \rho_i(L))u_{it} = \sigma_{\eta_{it}} o_{it}^{med} o_{it}^{big} \eta_{it}, \quad \eta_{it} \sim N(0,1)$$

where each follows student-t and uniform mixture distribution

Average Outlier counts: monthly indicators

Range	SV-t	SV-uniform	Hybrid (t+uniform)	Data (>IQR)
$[2, 5)$	10.5	0.96	8.67	14.2
	[9.25, 11.7]	[0.75, 1.21]	[7.25, 10.0]	
$5+$	0.04	2.79	0.42	0.62
	[0.00, 0.08]	[2.29, 4.12]	[0.25, 0.58]	

Average Posterior predictive outlier counts across 24 monthly variables. posterior median, [16%, 84%].

- Both approaches seems half-right
- Hybrid model sits in-between: large outliers close to the data

Out-of-sample forecasting

Data

Type	Variable	Relevance	Delay	Start	Transformation
Quarterly	Real GDP	89	2	Jan-1980	% QoQ
	Real Investment (Gross Fixed Capital Formulation)		2	Jan-1980	% QoQ
	Total volume of hours worked (employees)		2	Jan-1980	% QoQ
Survey (11)	BdF survey: change in output, manufacturing industry		0	Jan-1980	Level
	BdF survey: expected production		0	Jan-1980	Level
	BdF survey: new orders		0	May-1981	Level
	BdF survey: sentiment indicator for manufacturing	51	0	May-1981	Level
	Composite business climate indicator	11	0	Jan-1980	Level
	Manufacturing: order books and demand		0	Jan-1980	Level
	Manufacturing: general outlook	(97)	0	Jan-1980	Level
	Manufacturing: probable trend		0	Jan-1980	Level
	Services: expected activity		0	Jan-1991	Level
	Services: expected demand	(77)	0	Jan-1991	Level
	Consumer confidence	80	0	Jan-1980	Diff
Consumption	Household consumption: manufactured goods	17	1	Jan-1980	% MoM
Output (7)	Industrial production	60	2	Jan-1980	% MoM
	Capacity utilization		1	Jan-1981	Diff
	Retail sales	55	2	Jan-1980	% MoM
	Car registration	90	1	Jan-1980	% MoM
	Building permits		1	Jan-1994	% MoM
	Industrial production: construction	60	2	Jan-1990	% MoM
	Turnover Index: manufacturing	11	2	Jan-1999	% MoM
Labor (3)	Registered unemployment level for France	37	1	Jan-1980	% MoM
	Active job seekers (A,B,C)		1	Jan-1996	% MoM
	New vacancies		1	Jan-1989	% MoM
Trade (2)	Exports: value goods for France	51	2	Jan-1980	% MoM
	Imports: value goods for France	54	2	Jan-1980	% MoM

27 total: 11 soft, 16 hard variables (quarterly = 3). Sample: 1980.1 – 2019/2022.9

Out-of-sample analysis

- Same data, pseudo real-time (no revisions but delay)
- Bayesian approach: priors shrinking towards basic DFM
- Expanding window: based on 1980.1 – 2004.12 sample,
  $\rightarrow$ extend the sample when new data released, up to:
  (1) 2019.9 and (2) 2022.6
- Forecasting horizon: up to 1Q, but also backcasts
  $\rightarrow$ last month of the reference quarter = "month 0"
- 7 models: 3 outlier methods, SV, constant DFM (+ screening)
  $\rightarrow$ from complex (left) to simple (right) models

Out-of-sample performance: pre-COVID

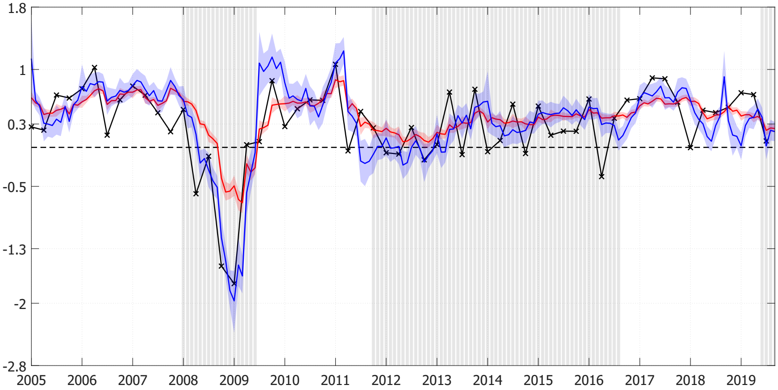
Horizon/model	t+uniform	Full (t-dist)	Full (uniform)	SV miss	SV	Basic miss	Basic DFM
(a) point forecasting: relative RMSE							RMSE
-5 month	1.015	0.986	0.951	0.949	0.952	0.998	0.484
-4 month	0.973	0.961	0.957	0.950	0.953	0.999	0.459
-3 month	0.958	0.959	0.928	0.935	0.929	1.001	0.422
-2 month	1.000	0.945	0.879	0.877	0.880	0.996	0.374
-1 month	0.895	0.881	0.877	0.877	0.876	0.993	0.347
0 month (end of reference Q)	0.905	0.900	0.873	0.873	0.874	0.995	0.340
1 month	0.889	0.899	0.865	0.872	0.866	0.987	0.338
(b) density forecasting: relative CRPS						CRPS	
-5 month	1.009	0.987	0.946	0.945	0.950	0.994	0.268
-4 month	0.971	0.962	0.955	0.952	0.952	1.002	0.259
-3 month	0.955	0.948	0.922	0.931	0.925	1.002	0.249
-2 month	0.922	0.883	0.850	0.850	0.853	1.000	0.235
-1 month	0.800	0.802	0.829	0.830	0.829	1.002	0.233
0 month (end of reference Q)	0.816	0.818	0.826	0.829	0.832	1.001	0.234
1 month	0.806	0.822	0.817	0.827	0.822	0.988	0.233

Estimation period: 2005.1 – 2019.9, Based on the sample: 1980.1 – 2004.12.

- All outlier models dominate basic DFM
- Not much improvement v. SV-only models without outliers
  $\longrightarrow$ modest improvement in density forecasting at $h = 0$

Pseudo real-time nowcasts, pre-COVID (v. basic DFM)

uniform

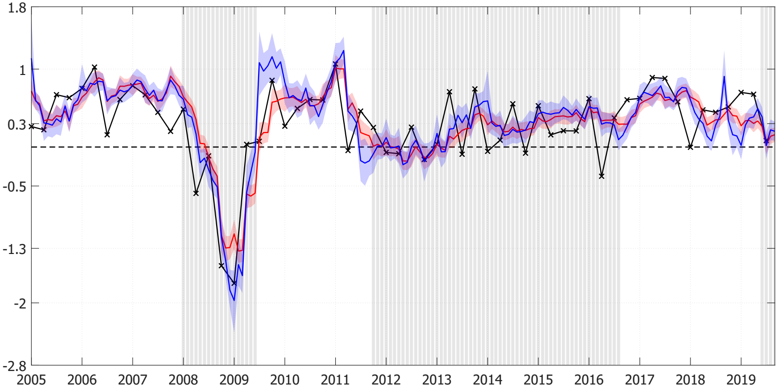


Estimation period: 2005.1 – 2019.9. Black = real GDP growth.

Red = Basic DFM, Blue = Hybrid (t+uniform). Shades = OECD recessions.

- Great Recession: better timing, trough/rebound

Pseudo real-time nowcasts, pre-COVID (v. SV-DFM)



Estimation period: 2005.1 – 2019.9. Black = real GDP growth.

Red = DFM with SV, Blue = Hybrid (t+uniform). Shades = OECD recessions.

- Not much gain except the trough

Tail forecasting quality: pre-COVID

DFMs	τ=.05	τ=.10	τ=.90	τ=.95
Hybrid	0.446^{***}	0.588^{***}	0.836^{*}	0.660^{***}
SV-t	0.451^{***}	0.588^{***}	0.816^{**}	0.655^{***}
SV-uniform	0.543^{***}	0.624^{***}	0.954	0.873
SV-only DFM	0.550^{***}	0.634^{***}	0.956	0.879
Basic DFM	0.129	0.138	0.070	0.054

Mean quantile score (Giacomini-Komunjer 2005) relative to Basic DFM. h=0 horizon.

- Outlier-augmented models beat Basic DFM at every quantile
- No clear advantage v. SV-only DFM, except the upper tails
- No clear advantage of Hybrid model within outlier models *yet*

Out-of-sample performance: full

Horizon/model	t+uniform	Full (t-dist)	Full (uniform)	SV miss	SV	Basic miss	Basic DFM
(a) point forecasting: relative RMSE							RMSE
-5 month	1.046	1.206	1.899	1.916	1.328	1.040	2.766
-4 month	1.251	2.452	1.595	2.342	2.320	1.684	2.722
-3 month	0.564	0.682	0.733	1.633	0.956	1.014	2.827
-2 month	0.421	0.483	2.027	4.375	0.635	1.199	2.214
-1 month	0.967	1.731	1.103	2.162	1.632	1.025	2.133
0 month (end of reference Q)	0.435	0.558	0.562	2.324	0.572	2.002	1.626
1 month	0.404	0.423	0.570	1.689	0.785	1.451	1.930
(b) density forecasting: relative CRPS						CRPS	
-5 month	1.002	1.092	1.220	1.252	1.181	1.005	0.835
-4 month	1.051	1.629	1.196	1.610	1.482	1.187	0.804
-3 month	0.768	0.822	0.792	1.197	0.932	1.014	0.785
-2 month	0.582	0.590	1.248	2.327	0.726	1.145	0.673
-1 month	0.758	1.187	0.804	1.553	1.301	1.015	0.648
0 month (end of reference Q)	0.574	0.662	0.672	1.570	0.691	1.503	0.557
1 month	0.514	0.530	0.616	1.236	0.828	1.228	0.643

Estimation period: 2005.1 – 2022.9, Based on the sample: 1980.1 – 2004.12.

Best model in point and density forecasting after h = 3

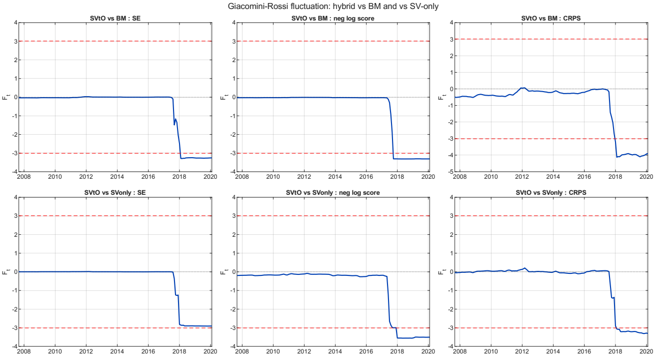
Subsample decomposition: where the gain lives

DFMs	Full	Pre-COVID	COVID	Post-COVID
(a) Nowcast RMSE v. Basic DFM				
Hybrid	0.682^{*}	0.944	0.660^{*}	1.077
SV-t	1.136	0.919	1.139	1.242
SV-uniform	1.481	0.882^{**}	1.502	1.143
SV-only	1.112	0.882^{**}	1.118	1.123
(b) Nowcast CRPS v. Basic DFM				
Hybrid	0.640^{**}	0.851^{**}	0.459^{**}	1.093
SV-t	0.818	0.840^{**}	0.748	1.219
SV-uniform	0.924	0.838^{***}	0.937	1.171
SV-only	0.914	0.841^{***}	0.914	1.195

Stars: DM-HLN Test (1997). *, **, *** at 10%, 5%, 1%. Nowcast horizon.

Crisis is where the hybrid model pays off.

Time-varying relative performance



64-months Rolling-window fluctuation statistic (Giacomini & Rossi 2010).

Hybrid v. Basic (top), SV-only (bottom). Two-sided 5% band ± 3.01.

- Outliers are crisis insurance:
  Hybrid beats basic/SV DFM in COVID-containing windows

Tail forecasting quality: full sample

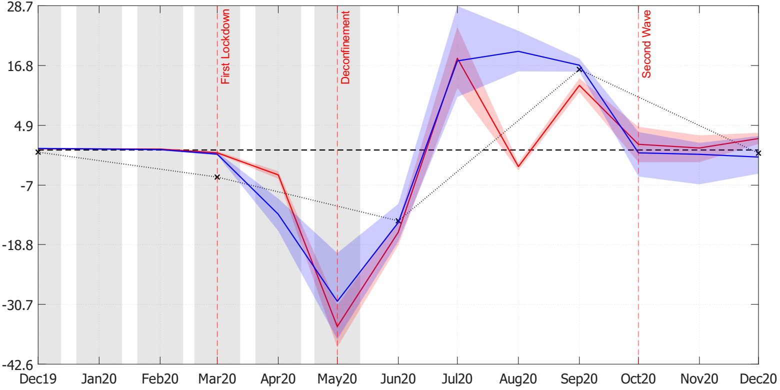
DFMs	τ=.05	τ=.10	τ=.90	τ=.95
Hybrid	0.413^{**}	0.492^{**}	0.606	0.452^{*}
SV-t	0.452^{**}	0.553^{**}	0.976	0.903
SV-uniform	0.513^{**}	0.615^{**}	1.102	0.942
SV-only DFM	0.557^{**}	0.628^{**}	1.234	1.221
Basic DFM	0.361	0.371	0.214	0.186

Mean quantile score (Giacomini-Komunjer 2005) relative to Basic DFM. h=0 horizon.

- Hybrid leads at all τ; upper-tail gap widest

  $\longrightarrow$ better captures COVID recovery (summer 2020)

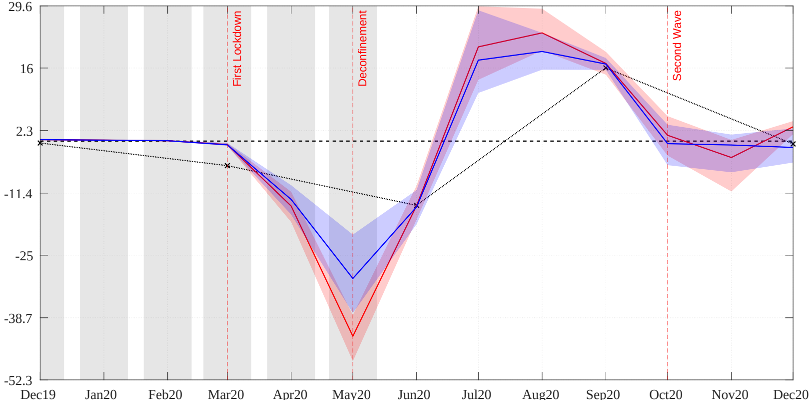
Pseudo real-time nowcasts, COVID uniform



Estimation period: 2019.9 – 2022.9. Black = real GDP growth.

Red = SV-only, Blue = hybrid model. Shades = OECD recessions.

Pseudo real-time nowcasts, COVID



Estimation period: 2005.1 – 2022.9. Black = real GDP growth.

Red = t-outliers, Blue = hybrid model. Shades = OECD recessions.

Crisis insurance: SV-path stability

When I add COVID first wave,
how much does a model shift pre-COVID estimates?

Model	Real GDP	IP	Unemployment	IP-Constr.
Hybrid	8.7%	33.8%	22.8%	35.2%
SV-t	11.5%	35.8%	56.3%	19.7%
SV-uniform	75.1%	38.7%	51.9%	33.8%
SV-only	47.4%	28.5%	56.8%	36.6%
Basic DFM	42.0%	30.6%	55.5%	67.3%

Median |% change| of posterior median σ_η, (Sep-2019 fit v. May-2020 fit)
for overlapping samples: 1980.1 – 2019.9.

- Hybrid isolates COVID: GDP σ_η shifts only 8.7%

Conclusion

Conclusion

This paper:

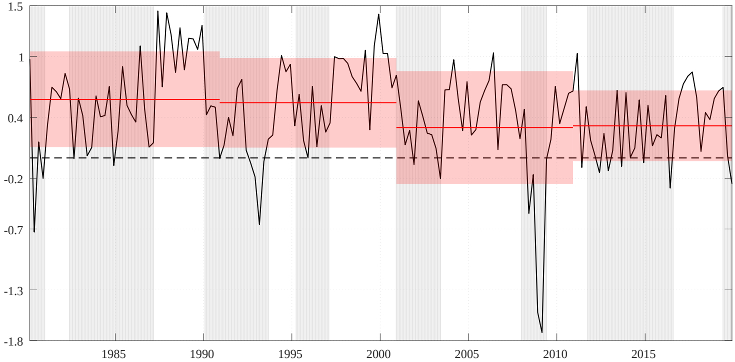
- Evaluate t-dist vs. uniform mix approaches to model outliers
- A hybrid model: t-dist $\times$ uniform mixture
  $\longrightarrow$ accommodate both frequent/small, rare/large outliers

Key results:

1. Both t-dist and uniform mixture capture a part of the picture
   $\longrightarrow$ No clear winner between the two in terms of forecasting
2. The hybrid model outperform all models during the COVID
   $\longrightarrow$ dominant across quantiles, especially at the upper tail
3. Outlier models are crisis insurance
   $\rightarrow$ No clear advantage v. SV-only DFM in pre-COVID

Feature (1): Time-varying mean

back



Sample: 1980.1 – 2019.12. Black = real GDP growth, Red = 10-year means.
Shade in Red: std.deviation, in Grey: OECD Recession dates

Treatment of outliers: Jacquier et al.(2004) Back to model

A standard SV model:

$$\Delta y_t = \sqrt{h_t}\epsilon_t, \quad \epsilon_t \sim N(0,1)$$

$$logh_t = logh_{t-1} + v_t,$$

SV model with fat-tails (without subtracting outliers):

$$\Delta y_t = \sqrt{h_t}\sqrt{o_t}z_t, \quad z_t \sim N(0,1)$$

$$o_t \sim IG \quad or \quad \nu/o_t \sim \chi^2_\nu$$

- SV: large y_t means large SV ($= h_t$)
- fat-tail: o_t takes large y_t before increasing SV
  $\rightarrow$ ability to 'resist' outliers: lower variability in h_t

Mixed Frequency and Missing Data

Back to model

Mariano and Murasawa (2003):

$$y_t^Q = \frac{1}{3} y_t^M + \frac{2}{3} y_{t-1}^M + y_{t-2}^M + \frac{2}{3} y_{t-3}^M + \frac{1}{3} y_{t-4}^M$$

- y_t^Q: *observed* quarterly variables
- y_t^M: *unobserved* monthly values

Recall: $y_t = c_t + \Lambda f_t + u_t$. Then,

$$\begin{aligned} y_t^Q = {} & \frac{1}{3}\lambda_y' f_t + \frac{2}{3}\lambda_y' f_{t-1} + \lambda_y' f_{t-2} + \frac{2}{3}\lambda_y' f_{t-3} + \frac{1}{3}\lambda_y' f_{t-4} \\ & + \frac{1}{3} u_{yt} + \frac{2}{3} u_{y,t-1} + u_{y,t-2} + \frac{2}{3} u_{y,t-3} + \frac{1}{3} u_{y,t-4} \end{aligned}$$

$\uparrow$ in size of state vector: 4 lags of f_t and u_t. Computation costs.

Mixed Frequency and Missing Data

Back to model

This paper: apply approximation to u_t^Q instead of y_t^Q.

Apply the Kalman filter to the following state-space representation:

$$u_{i,t}^Q = Hx_{i,t} + \xi_{i,t}, \quad \xi_{i,t} \sim N(0, R)$$

$$x_{i,t} = Ax_{i,t-1} + e_{i,t}, \quad e_{i,t} \sim N(0, Q)$$

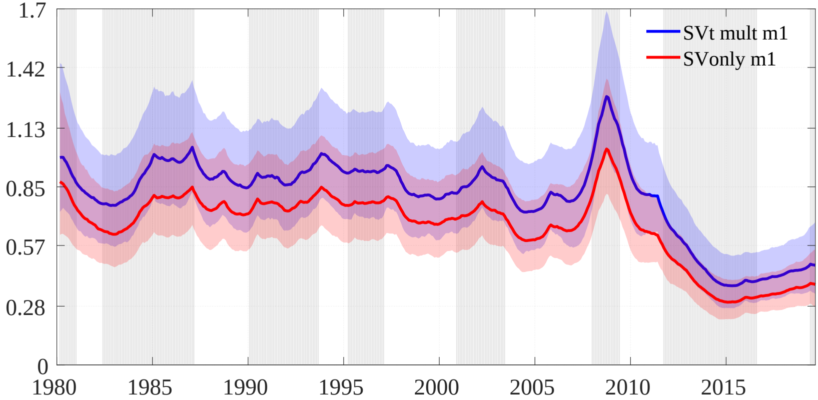
with $x_{i,t} = [u_{i,t}^M \ u_{i,t-1}^M \ u_{i,t-2}^M \ u_{i,t-3}^M \ u_{i,t-4}^M]'$, $\mathrm{H} = [\frac{1}{3} \ \frac{2}{3} \ 1 \ \frac{2}{3} \ \frac{1}{3}]$.

Then obtain monthly-interpolated quarterly value $y_t^M = \hat{\lambda}_y \hat{f}_t + \hat{u}_{i,t}^M$.

Conjugate prior: beta prior example Back to model

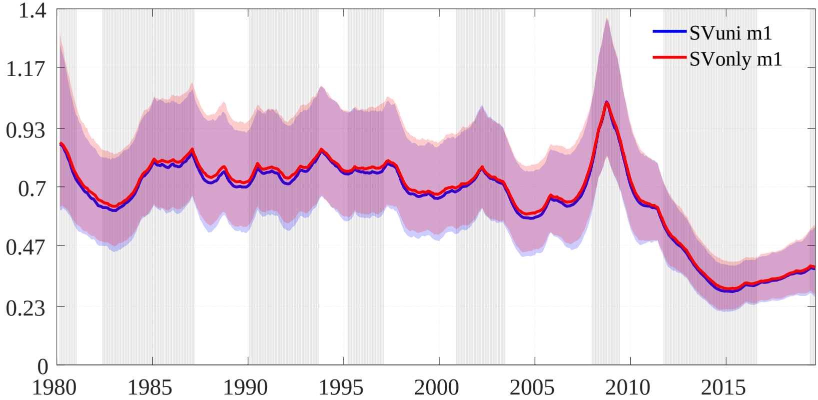
- parameter θ = probability of heads
- Assume the beta (a,b) prior: p(θ) $\propto \theta^{(a-1)}(1-\theta)^{(b-1)}$
- Bernoulli likelihood: L(θ|y) $\propto \theta^{y}(1-\theta)^{(n-y)}$
  $\rightarrow$ y = success, n-y = failure (tails)
- Posterior $\propto$ likelihood $\times$ prior: Beta (y+a, (n-y)+b)
  $\rightarrow$ posterior = "dummy observations"

Volatility of the common activity factor (t-dist) back



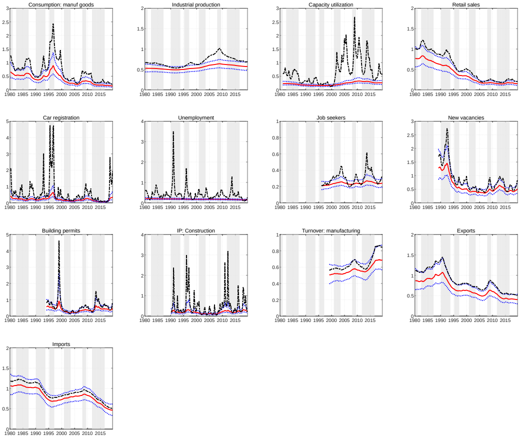
Red = baseline SV-only model, Blue = model with t-outliers.
Posterior median and 90% posterior bands.
Sample: 1980.1 – 2019.9. OECD recessions in grey.

Volatility of the common activity factor (uniform) back



Red = baseline SV-only model, Blue = model with uniform outliers.
Posterior median and 90% posterior bands.
Sample: 1980.1 – 2019.9. OECD recessions in grey.

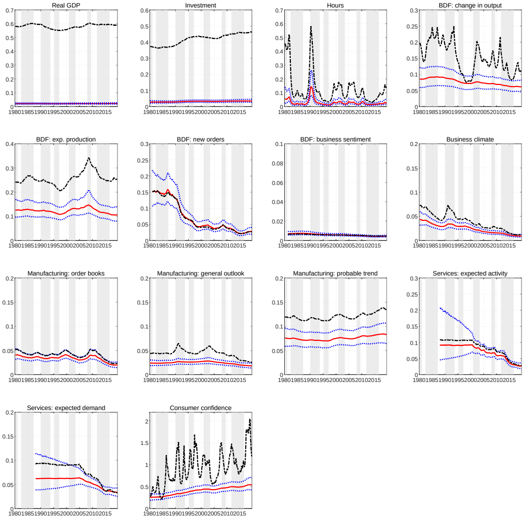
Stochastic volatility: monthly hard indicators (t-dist) back



Black = posterior median, SV-only model without outliers.
Red and blue = posterior median and 68% bands from the full model.

Sample: 1980.1 – 2019.9. OECD recessions in grey.

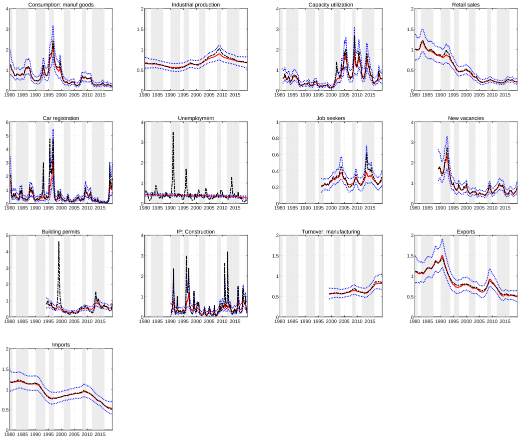
Stochastic volatility: quarterly/soft indicators (t-dist) back



Black = posterior median, SV-only model without outliers.
Red and blue = posterior median and 68% bands from the full model.

Sample: 1980.1 – 2019.9. OECD recessions in grey.

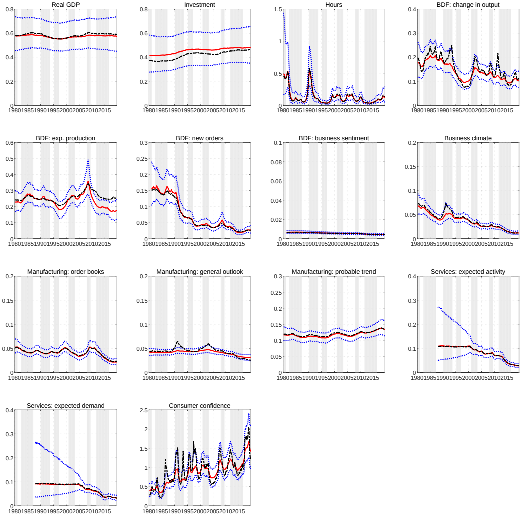
Stochastic volatility: monthly hard (uniform) back



Black = posterior median, SV-only model without outliers.
Red and blue = posterior median and 68% bands from the full model.

Sample: 1980.1 – 2019.9. OECD recessions in grey.

Stochastic volatility: quarterly/soft (uniform) back

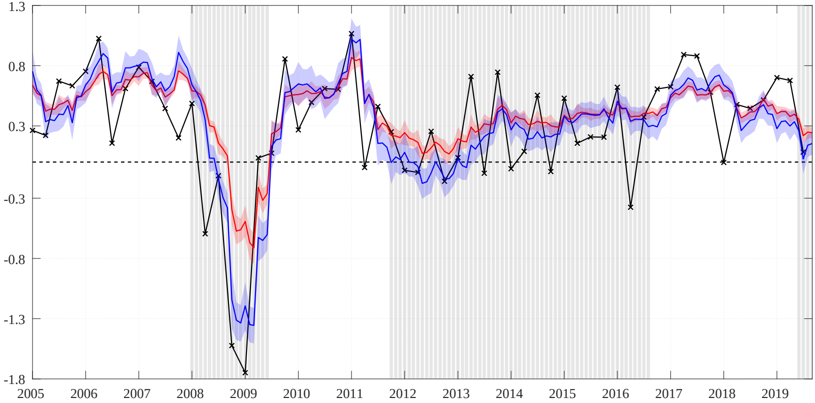


Black = posterior median, SV-only model without outliers.
Red and blue = posterior median and 68% bands from the full model.

Sample: 1980.1 – 2019.9. OECD recessions in grey.

Pseudo real-time nowcasts, pre-COVID

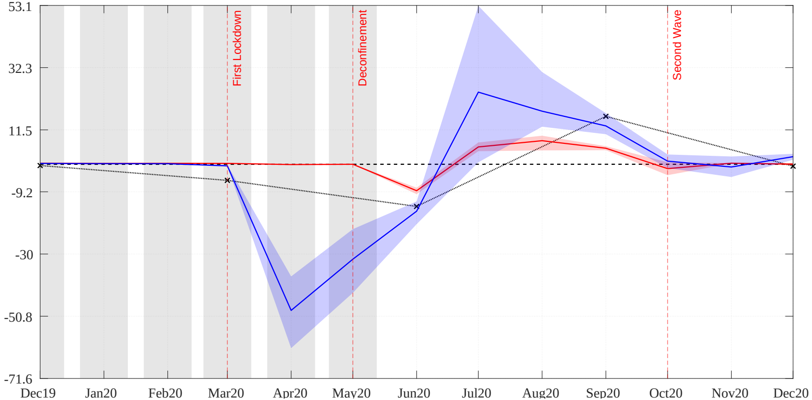
back



Estimation period: 2005.1 – 2019.9. Black = real GDP growth.

Red = Basic, Blue = Full (uniform). Shades = OECD recessions.

Pseudo real-time nowcasts, post-COVID back



Estimation period: 2019.9 – 2022.9. Black = real GDP growth.

Red = Basic, Blue = Full (uniform). Shades = OECD recessions.

Out-of-sample point forecasting: pre-COVID back

Horizon/model	Full (t-dist)	Full (uniform)	SV miss	SV	Basic miss	Basic DFM
(a) point forecasting: RMSE						
-5 month	0.4774	0.4607	0.4598	0.4612	0.4835	0.484
-4 month	0.4407	0.4392	0.4359	0.4374	0.4583	0.459
-3 month	0.4052	0.3920	0.3951	0.3922	0.4230	0.422
-2 month	0.3533	0.3287	0.3278	0.3290	0.3725	0.374
-1 month	0.3054	0.3039	0.3041	0.3037	0.3443	0.347
0 month (end of reference Q)	0.3061	0.2969	0.2970	0.2974	0.3383	0.340
1 month	0.3036	0.2924	0.2948	0.2927	0.3336	0.338
(b) point forecasting: MAFE						
-5 month	0.3651	0.3467	0.3438	0.3458	0.3391	0.3402
-4 month	0.3394	0.3274	0.3270	0.3271	0.3281	0.3302
-3 month	0.3219	0.2982	0.2997	0.2983	0.3054	0.3050
-2 month	0.2803	0.2542	0.2532	0.2531	0.2749	0.2742
-1 month	0.2464	0.2431	0.2423	0.2422	0.2632	0.2633
0 month (end of reference Q)	0.2566	0.2378	0.2389	0.2396	0.2592	0.2596
1 month	0.2491	0.2337	0.2364	0.2347	0.2552	0.2577

Estimation period: 2005.1 – 2019.9, Based on the sample: 1980.1 – 2004.12.

Out-of-sample density forecasting: pre-COVID

back

Horizon/model	Full (t-dist)	Full (uniform)	SV miss	SV	Basic miss	Basic DFM
(a) density forecasting: log score						
-5 month	-0.826	-0.853	-0.871	-0.887	-2.245	-2.176
-4 month	-0.792	-0.983	-0.987	-0.994	-2.695	-2.332
-3 month	-0.804	-1.181	-1.227	-1.233	-3.561	-3.988
-2 month	-0.774	-1.604	-1.694	-1.715	-7.750	-8.319
-1 month	-1.011	-2.452	-2.534	-2.506	-15.319	-15.209
0 month (end of reference Q)	-1.102	-2.907	-2.983	-3.032	-23.034	-21.222
1 month	-1.448	-2.988	-3.090	-3.018	-22.273	-23.052
(b) density forecasting: CRPS						
-5 month	0.2643	0.2534	0.2530	0.2544	0.2660	0.268
-4 month	0.2486	0.2468	0.2461	0.2462	0.2591	0.259
-3 month	0.2362	0.2296	0.2319	0.2304	0.2497	0.249
-2 month	0.2075	0.1998	0.1996	0.2003	0.2348	0.235
-1 month	0.1870	0.1933	0.1935	0.1934	0.2338	0.233
0 month (end of reference Q)	0.1914	0.1932	0.1939	0.1946	0.2341	0.234
1 month	0.1913	0.1901	0.1925	0.1912	0.2300	0.233

Estimation period: 2005.1 – 2019.9, Based on the sample: 1980.1 – 2004.12.

Out-of-sample point forecasting: full sample back

Horizon/model	Full (t-dist)	Full (uniform)	SV miss	SV	Basic miss	Basic DFM
(a) point forecasting: RMSE						
-5 month	3.3347	5.2520	5.2986	3.6733	2.8766	2.766
-4 month	6.6743	4.3425	6.3752	6.3158	4.5847	2.722
-3 month	1.9276	2.0719	4.6172	2.7033	2.8664	2.827
-2 month	1.0688	4.4881	9.6858	1.4062	2.6536	2.214
-1 month	3.6929	2.3537	4.6124	3.4823	2.1873	2.133
0 month (end of reference Q)	0.9078	0.9130	3.7779	0.9293	3.2543	1.626
1 month	0.8157	1.0999	3.2592	1.5153	2.7994	1.930
(b) point forecasting: MAFE						
-5 month	1.0806	1.3226	1.3501	1.1407	0.8873	0.9244
-4 month	1.6074	1.2093	1.4959	1.3530	1.1311	0.9075
-3 month	0.7929	0.8089	1.1182	0.8786	0.8486	0.8480
-2 month	0.5057	1.0224	1.8311	0.5804	0.8212	0.7292
-1 month	0.9206	0.6419	1.1349	0.9448	0.7278	0.6950
0 month (end of reference Q)	0.4567	0.4647	0.9741	0.4729	0.8791	0.6024
1 month	0.4453	0.4854	0.8828	0.6015	0.8268	0.6783

Estimation period: 2005.1 – 2022.9, Based on the sample: 1980.1 – 2004.12.

Out-of-sample density forecasting: full sample back

Horizon/model	Full (t-dist)	Full (uniform)	SV miss	SV	Basic miss	Basic DFM
(a) density forecasting: log score						
-5 month	-21.463	-28.105	-30.715	-29.218	-65.136	-244.853
-4 month	-24.854	-37.859	-38.779	-38.305	-100.828	-462.350
-3 month	-5.565	-8.832	-8.653	-8.866	-53.639	-318.273
-2 month	-8.049	-16.548	-17.443	-17.694	-79.132	-559.888
-1 month	-12.247	-23.190	-26.051	-28.649	-190.255	-871.559
0 month (end of reference Q)	-4.454	-6.801	-8.377	-6.449	-134.327	-367.203
1 month	-2.020	-3.642	-20.577	-12.662	-108.009	-419.691
(b) density forecasting: CRPS						
-5 month	0.9115	1.0188	1.0450	0.9860	0.8390	0.835
-4 month	1.3096	0.9614	1.2940	1.1914	0.9540	0.804
-3 month	0.6457	0.6224	0.9400	0.7321	0.7966	0.785
-2 month	0.3972	0.8403	1.5662	0.4886	0.7708	0.673
-1 month	0.7695	0.5212	1.0064	0.8430	0.6578	0.648
0 month (end of reference Q)	0.3693	0.3745	0.8752	0.3850	0.8379	0.557
1 month	0.3408	0.3960	0.7950	0.5328	0.7903	0.643

Estimation period: 2005.1 – 2022.9, Based on the sample: 1980.1 – 2004.12.

DM / DM-HLN / GW unconditional tests

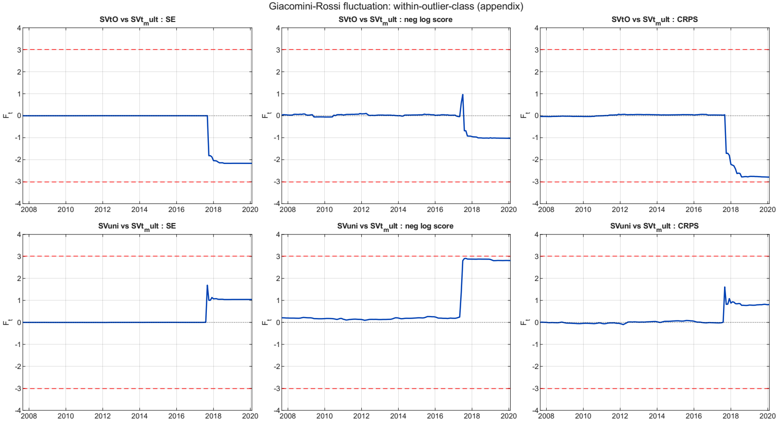
$d_t = L_A(t) - L_B(t)$. Negative stat $\Rightarrow$ A beats B. *, **, *** = 10/5/1%.

Pair (A vs B)		SE stat	SE p	neg log S stat	neg log S p	CRPS stat	CRPS p
Hybrid vs BM	DM	-1.80^{*}	.072	-1.85^{*}	.065	$\mathbf{-2.51}^{**}$	**.012**
	DM-HLN	-1.79^{*}	.074	-1.84^{*}	.067	-2.50^{**}	.013
	GW-HAC	-1.40	.162	-1.18	.238	-1.54	.123
Hybrid vs SV-t	DM	-1.19	.236	-0.54	.590	-1.52	.130
SV-uni vs SV-t	DM	0.57	.568	$+1.77^{*}$	.077	0.45	.650
SV-t vs BM	DM	0.36	.716	-1.85^{*}	.065	-1.11	.269
SV-uni vs BM	DM	0.95	.340	-1.83^{*}	.068	-0.55	.580

DM: Diebold-Mariano (1995); DM-HLN: Harvey-Leybourne-Newbold (1997) small-sample correction;

GW-HAC: Giacomini-White (2006) with Newey-West lag 4. All on 213 Nowcast origins.

GR fluctuation: within-outlier class



Hybrid vs SV-t and SV-uni vs SV-t.