Capturing GDP nowcast uncertainty in real time

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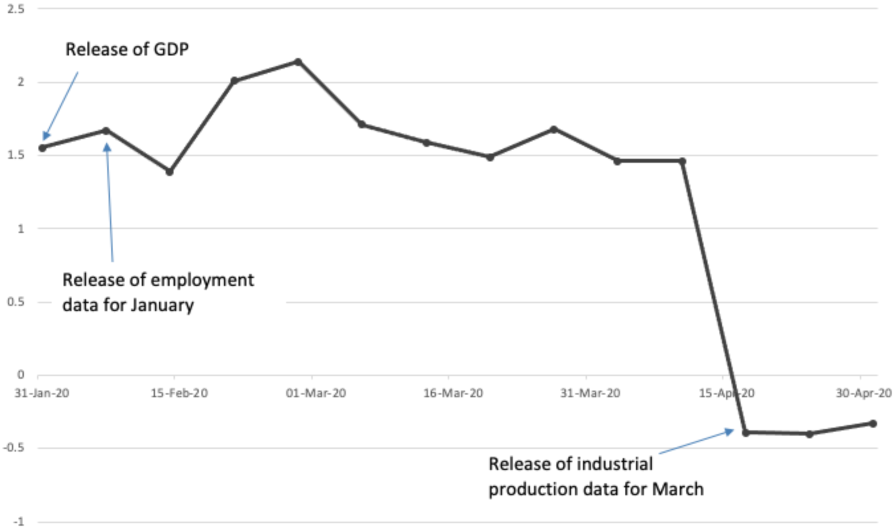
Why do we nowcast GDP ?

- GDP is the main signal on economic activity but is not timely enough.
- Many series related to economic activity are released more frequently and rapidly.
- By modelling the relationship between these related series and GDP it is possible to get an idea of the GDP figure before its publication.
- This is possible using nowcasting methods : A set of techniques for modelling together series sampled at different frequencies and released at different points in time.

An example of GDP nowcast

Figure: NY Fed US GDP nowcast for 2020 Q1 across time

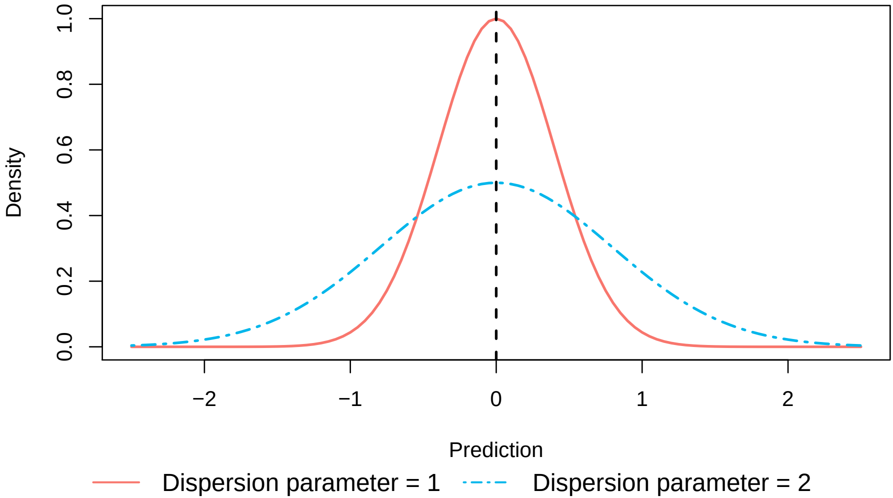


Motivation 1 : Related series provide a signal on nowcasting uncertainty

- Nowcasting methods use related series to improve GDP **point forecasts**.
- But these series carry also a signal on **forecasting uncertainty** which is exploited only partially.
- Large forecasting errors in related series may indicate upcoming large forecasting errors in GDP.

Motivation 1 : Related series provide a signal on nowcasting uncertainty

Figure: The effect of dispersion on density forecasts

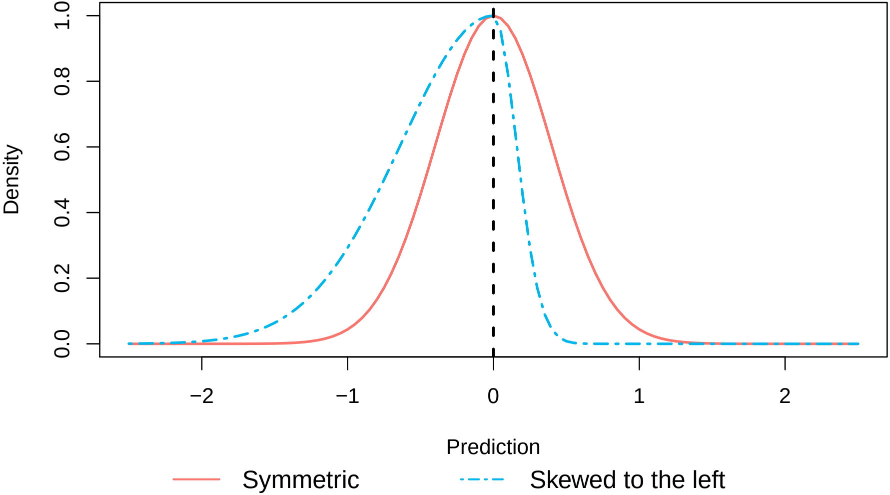


Motivation 2 : Nowcasting uncertainty may be asymmetric and fat-tailed

- There is increasing evidence that macroeconomic data are not normally distributed.
    - Outcomes are asymmetrically distributed round the location (or mean).
    - Extreme events happen more frequently than assumed with a normal distribution.
- This asymmetry :
    - Varies along the business cycle;
    - Has important implications regarding the shape that nowcasting uncertainty takes.
- Increased asymmetry in related series may indicate upcoming asymmetry in GDP density nowcasts.

Motivation 2 : Nowcasting uncertainty may be asymmetric and fat-tailed

Figure: The effect of skewness on density forecasts



This Paper

- I use a **dynamic factor model** to capture cross-sectional dependencies in time series sampled at different frequencies.
- To model non-Gaussian features - specifically fat tails and skewness - I use **score driven** methods.
- Contribution : I explore the modelling of common factors in **scale** and **shape** parameters, controlling the **dispersion** and **asymmetry** of possible outcomes round point forecasts.
  - In the special case of a Gaussian model I derive a convenient approximation for modelling a common volatility component. This technique can be used in many DFMs.
- I investigate the performance of the approach using US real-time data.

Model : A mixed-measurement approach

- The log density of the observation vector $y_t = (y_{1,t}, ..., y_{m,t})'$ is

$$\log p(y_t|Y_{t-1}) = \sum_{i=1}^{m} \delta_{i,t} \log p_i(y_{i,t}|Y_{t-1}), \quad i = 1, ..., m.$$

- The series are cross-sectionally independent conditional on past information.

- Each series follows an Asymmetric Student-t distribution (AST) with distinct location, scale, shape and tail parameters.

- If series i is missing in period t $\delta_{i,t}$ is zero.

Model : A score driven recursion for time-varying parameters

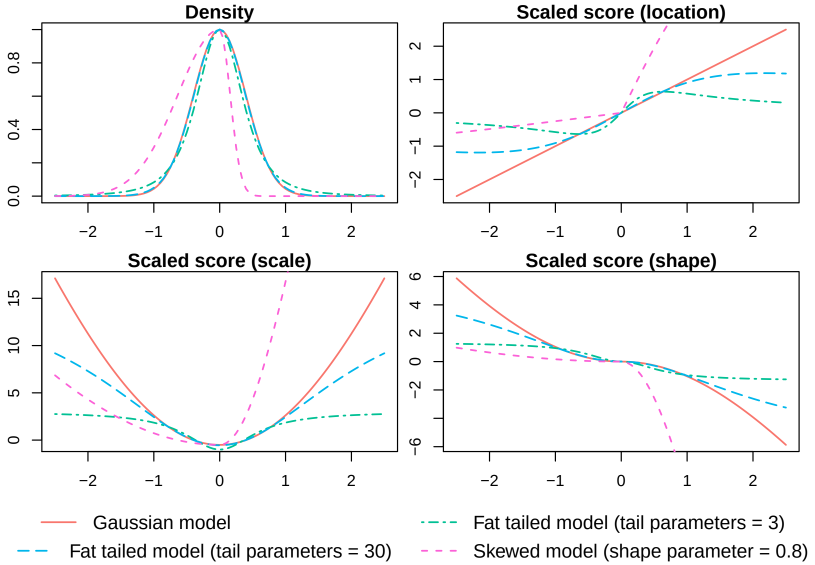
- The vector of time-varying f_t includes location, scale and shape parameters and has a score-driven dynamic (Harvey (2013) and Creal et al. (2013)):

$$f_{t+1} = Bf_t + As_t,$$

$$s_t = S_t \Delta_t, \quad \Delta_t = \frac{\partial \log p(y_t | Y_{t-1})}{\partial f_t}, \quad S_t = \mathrm{E}\left[\Delta_t \Delta_t' | Y_{t-1}\right]^{-1}.$$

- The score is a function of prediction errors (generally nonlinear).

The effect of deviating from the Normal distribution on the score



Model : Dynamic factor models for location, scale and shape parameters

- Each time-varying parameter is decomposed into a idiosyncratic trend and a common component:

$$
\begin{aligned}
\lambda^j_{i,t+1} &= \lambda^j_{i,t} + A^j_{\lambda i} s^j_{\lambda i,t}, &\qquad& \text{(trend)},\\
\rho(L)\pi^j_{t+1} &= A^j_{\pi} s^j_{\pi,t}, && \text{(common component)},
\end{aligned}
$$

  For each series ($i = 1, ..., m$) and for each parameter ($j = \mu, \boldsymbol{\sigma}, \boldsymbol{\alpha}$).

- These unobserved components are then linked to the parameters :

$$
\begin{aligned}
\mu_{i,t} &= f_i(\lambda^{\mu}_{i,t}, \pi^{\mu}_t) \quad \text{(locations)},\\
\boldsymbol{\sigma_{i,t}} &= \boldsymbol{g_i(\lambda^{\sigma}_{i,t}, \pi^{\sigma}_t)} \quad \textbf{(scales)},\\
\boldsymbol{\alpha_{i,t}} &= \boldsymbol{h_i(\lambda^{\alpha}_{i,t}, \pi^{\alpha}_t)} \quad \textbf{(shapes)}.
\end{aligned}
$$

Addressing the issue of temporal aggregation

- Each series follows the predictive model :

$$y_{i,t} = \mu_{i,t} + \sigma_{i,t}\epsilon_{i,t}, \qquad \text{or} \quad y_{i,t} = \mu_{i,t} + v_{i,t}.$$

- GDP is quarterly whereas the related series are monthly.

- For location parameters Mariano and Murasawa (2003) popularised a precise approximation :

$$\mu_{i,t} = \frac{1}{3}\tilde{\mu}_{i,t} + \frac{2}{3}\tilde{\mu}_{i,t-1} + \tilde{\mu}_{i,t-2} + \frac{2}{3}\tilde{\mu}_{i,t-3} + \frac{1}{3}\tilde{\mu}_{i,t-4}.$$

where $\mu_{i,t}$ is the quarterly parameter and $\tilde{\mu}_{i,t} = \lambda^{\mu}_{i,t} + \Phi_i \pi^{\mu}_{t+1}$ the monthly parameter.

Addressing the issue of temporal aggregation

- If all series are normally distributed the following approximation for scale parameters works:

$$\sigma_{i,t} = \sqrt{\frac{1}{9}\tilde{\sigma}^2_{i,t} + \frac{4}{9}\tilde{\sigma}^2_{i,t-1} + \tilde{\sigma}^2_{i,t-2} + \frac{4}{9}\tilde{\sigma}^2_{i,t-3} + \frac{1}{9}\tilde{\sigma}^2_{i,t-4}}.$$

  where $\sigma_{i,t}$ is the quarterly parameter and $\tilde{\sigma}_{i,t} = \exp(\lambda^{\sigma}_{i,t} + \Phi_i \pi^{\sigma}_{t+1})$ the monthly parameter.

- When the model is non-Gaussian monthly series are aggregated into rolling quarterly figures. Labonne and Weale (2020) show that the loss in precision should be small.

Estimation : Weighted maximum likelihood

- Estimation via weighted maximum likelihood (Blasques et al. (2016)) :

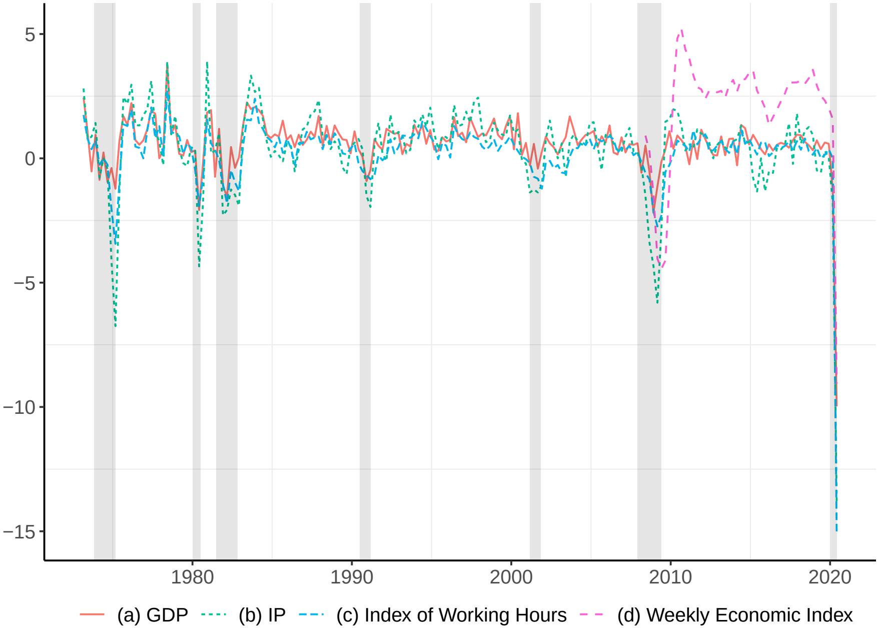
$$\log p^{w}(y_t|Y_{t-1}) = \delta_{i,t}\log p_1(y_{1,t}|Y_{t-1}) + W\sum_{i=2}^{m}\delta_{i,t}\log p_i(y_{i,t}|Y_{t-1}).$$

- The objective is nowcasting GDP not the related series; these are used to help only.
- The related series' contribution to the log likelihood is reduced using W.

Real-time US economic data

- The model is composed of four series :
  - GDP Advance Estimate (Quarterly);
  - Industrial production (IP) (Monthly);
  - The weekly index of working hours (IWH) (Monthly);
  - the Weekly Economic Indicator (WEI) (Monthly).
- GDP, IP and IWH are from 1973 Q2 to 2020 Q2 wheareas WEI is from 2010 Q2 up to Q2 2020.
- Vintages retrieved from the Federal Reserve Bank of Philadelphia.
- Real-time estimation from 2000 up to 2020 Q2.

Data : Levels



5
0
−5
−10
−15
1980
1990
2000
2010
2020
(a) GDP
(b) IP
(c) Index of Working Hours
(d) Weekly Economic Index

Model specifications

- Three models with scale and shape common factors :
  - (a) : AST DFM with Scale+Shape CFs;
  - (b) : AST DFM (Sk Covs) with Scale+Shape CFs;
  - (c) : DFM with SV and Scale CF ;
- Three benchmark models :
  - (d) : AST DFM (Sk Covs) with SV and TV shape;
  - (e) : DFM with SV;
  - (f) : St-t DFM with SV;

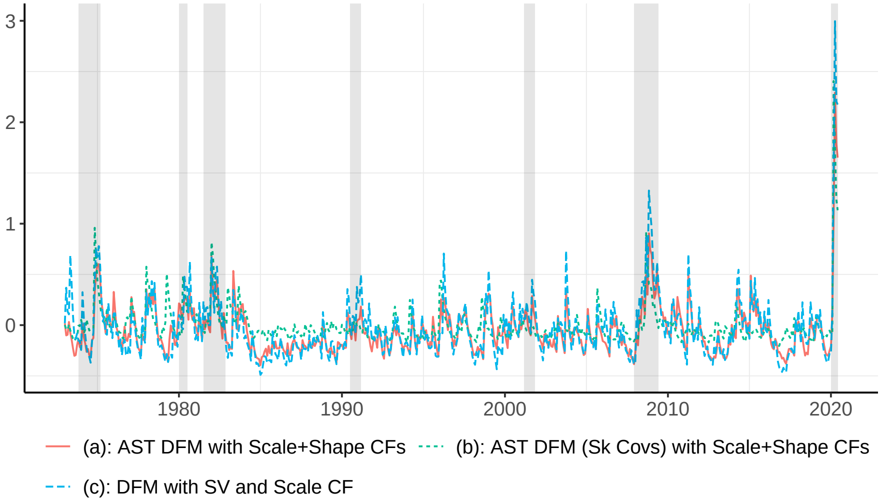
In-sample analysis : Estimation results

Table: Comparison of the model specifications using the full-sample results.

Model	L.L.	L.L. GDP	AIC	BIC
(a): AST DFM with Scale+Shape CFs	-381.4	-124	854.7	1097.5
(b): AST DFM (Sk Covs) with Scale+Shape CFs	-402.3	-124.6	892.7	1124.9
(c): DFM with SV and Scale CF	-578.1	-136.3	1220.2	1389.1
(d): AST DFM (Sk Covs) with SV and TV shape	-548.9	-135.9	1159.8	1323.4
(e): DFM with SV	-580.1	-138	1212.1	1349.4
(f): St-t DFM with SV	-569	-139.4	1196	1349.1

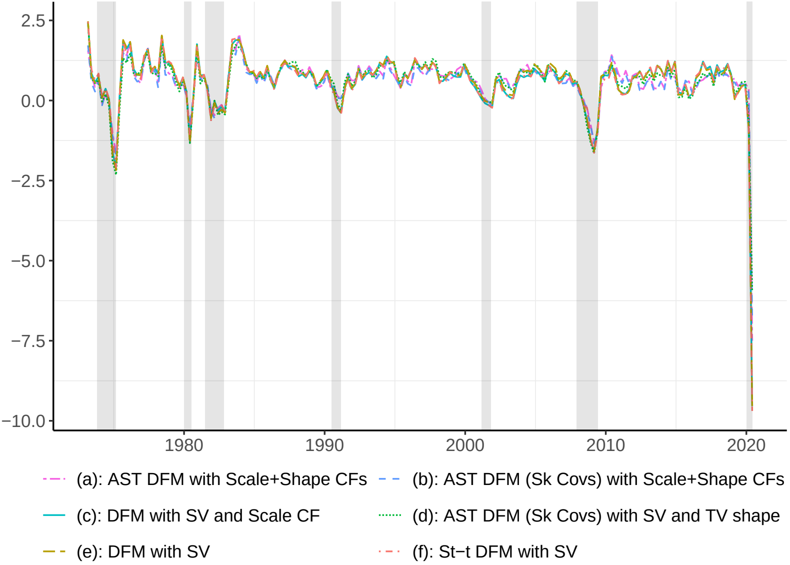
In-sample analysis : Scale common factor

Figure: Scale common factors. Rolling quarterly estimate for model (a) and (b) and monthly estimate for model (c).



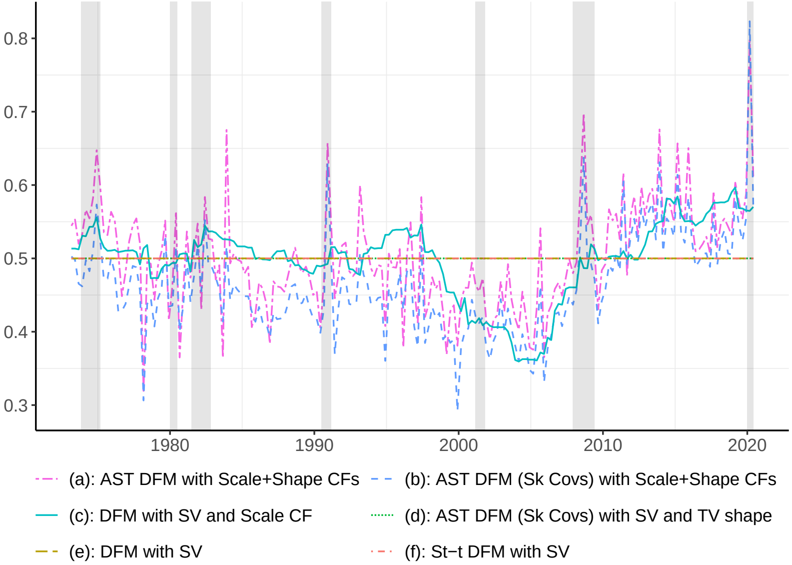
In-sample analysis : Locations

Figure: Quarterly figures corresponding to calendar quarters.

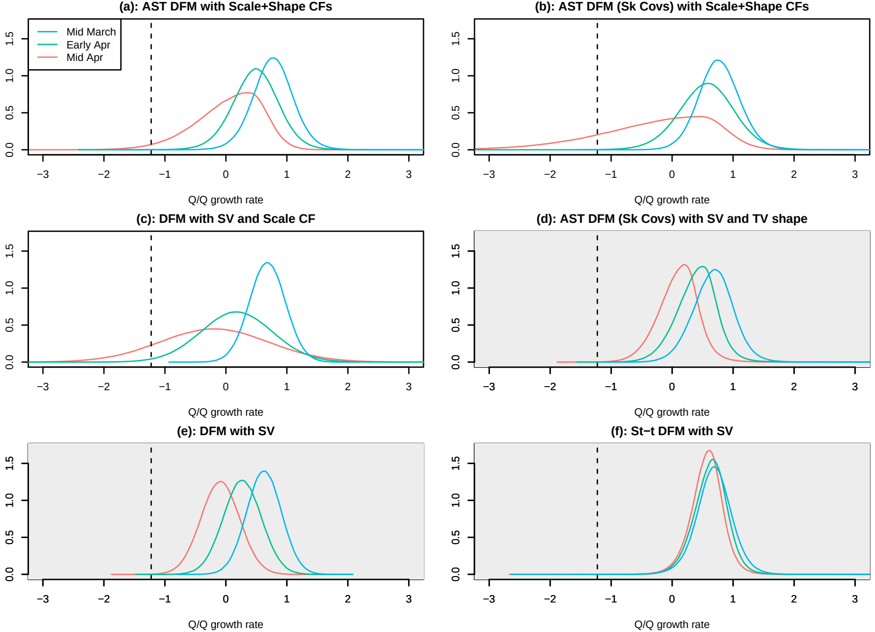


In-sample analysis : Shapes

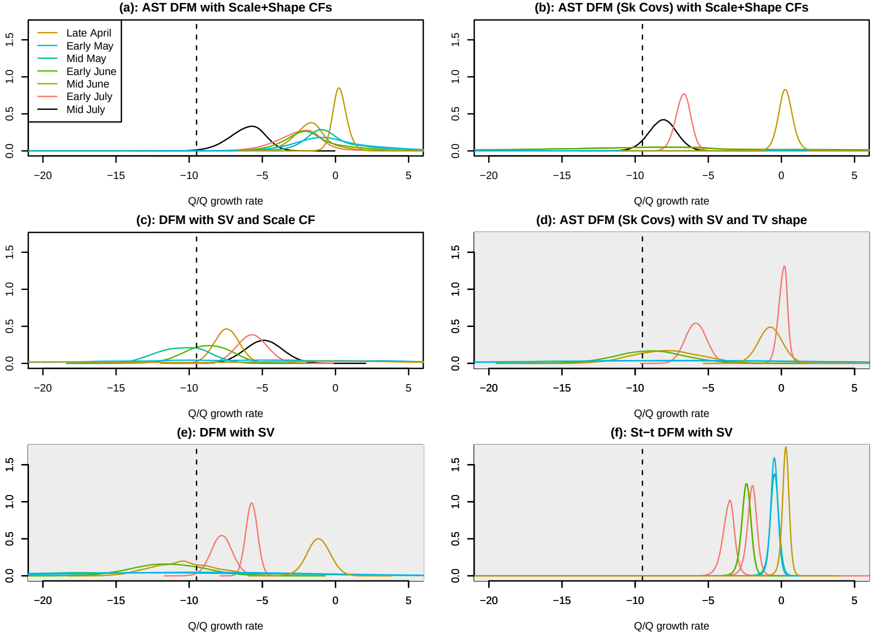
Figure: Quarterly figures corresponding to calendar quarters.



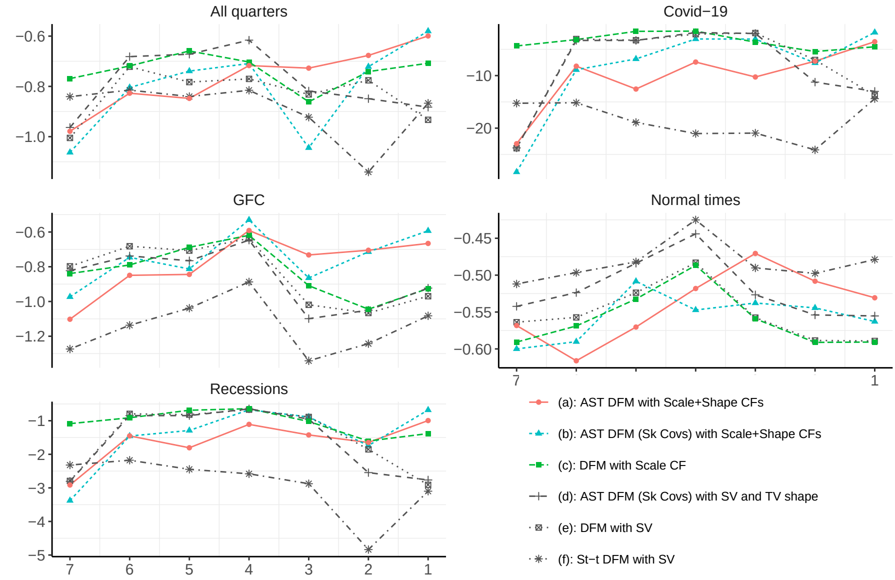
Real-time results : US March nowcast



Real-time results : US June nowcast



Real-time results : Average log score



Real-time results : Average Log Score

	7	6	5	4	3	2	1
Model (a)	-5.71	-2.39	-3.33	-2.07	-2.72	-2.16	-1.27
Model (b)	-6.87	-2.50	-2.04	-1.10	-1.28	-2.26	-0.84
Model (c)	-1.53	-1.23	-0.83	-0.80	-1.40	-1.88	-1.62
Model (d)	-5.78	-1.22	-1.21	-0.83	-1.08	-3.25	-3.63
Model (e)	-5.80	-1.16	-1.22	-0.93	-1.04	-2.26	-3.83
Model (f)	-4.04	-3.96	-4.74	-5.15	-5.31	-6.37	-3.98

Figure: Average log score across all periods at each nowcasting step. The darker the background colour the higher the log score.

Conclusion

- Modelling scale and shape common factors improves estimation of nowcasting uncertainty.
  - This gain materialises at the end of the nowcasting window and during recessions.
- The gain from modelling a shape common factor outweights the loss in precision stemming from the aggregation of the related series.
- Modelling fat tails in the related series complicates the identification of turning points.

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