Incorporating short data into large mixed frequency VARs for regional nowcasting

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Problem context

- Demand for higher frequency and more timely regional economic data;
- Increasing development and use of econometric models to handle 'mixed–frequency' data;
- Since 2017, we've been working to develop econometric models to produce more timely and higher frequency ITL growth estimates for the UK (Koop et al. 2022; Koop et al. 2020a; Koop et al. 2020b; Koop, McIntyre, and Mitchell 2020);
- Over this period we've seen increasing availability of regional data, but with limited historical coverage (a.k.a.'short' data) creating a lot of 'missingness';
- 'Can we develop econometric models that can make use of these 'short' data to produce more timely and higher frequency (quarterly) ITL1 output growth estimates?'

Problem features

- Key features of the problem we had in mind:
  - Higher frequency and more timely UK-wide data;
  - Aggregation constraint inherent in this problem;
  - Relatively short time series of available regional output data;
  - Some higher frequency output data for the devolved administrations (DAs);
  - Limited time series of regional-level economic predictors;
  - Stability of economic geography over time.
- To which we now add: an increasing number of timely regional predictors becoming available but which have a short time series.

Mixed Frequency Econometrics

- Growing literature on building econometric models which combine data of different frequencies (Schorfheide and Song 2015; Ghysels 2016; Brave, Butters, and Justiniano 2019; McCracken, Owyang, and Sekhposyan 2021);
- Intuition: estimate an econometric model using high and low-frequency variables and use these estimated relationships to "fill in" values for the low-frequency variables;
- Typically these models are used to leverage high-frequency data to provide nowcasts of low-frequency variables (e.g. M/Q), but our application is a different (A/Q);
- Our Koop et al. 2020b model is built on the mixed-frequency state-space model of Schorfheide and Song 2015 and provides the starting point for the model developed in this paper.

Notation

- $t = 1, .., T$ runs at the *quarterly* frequency;
- $r = 1, .., R$ denotes the R regions in the UK;
- $y_t^{UK} = log(Y_t^{UK}) - log(Y_{t-1}^{UK})$ is the quarterly change (log difference) in GVA in the UK;
- $y_t^{r,A} = log(Y_t^{r,A}) - log(Y_{t-4}^{r,A})$ is annual GVA growth in region r. It is observed, but only in quarter 4 of each year, $\boldsymbol{y_t^A} = (y_t^{1,A}, ..., y_t^{R,A})$ is a vector of annual growth rates for the R regions;
- $y_t^r = log(Y_t^r) - log(Y_{t-1}^r)$ is the quarterly change in GVA in region r. It is only observed towards the end of our sample (its availability is different by region pre-2012);
- $\boldsymbol{y_t^Q} = (y_t^1, ..., y_t^R)'$ is a vector of quarterly growth rates for the R regions;
- $\boldsymbol{Z_t^r}$ is a vector of k_r quarterly variables for region r – these are our "short" data.

VAR: Definition

- Begin with a structural VAR relating a vector of N dependant variables $\boldsymbol{y_t}$ to lags of the dependent variable:

$$\boldsymbol{B y_t} = \boldsymbol{A x_t} + \epsilon_t \tag{1}$$

- $\boldsymbol{x_t}$ is a vector containing p lags of $\boldsymbol{y_t}$;
- ϵ_t are assumed $N(\mathbf{0}, \mathbf{\Sigma})$ where $\mathbf{\Sigma}$ is a diagonal matrix;
- $\boldsymbol{B}$ is lower triangular with ones on the diagonal;
- $\boldsymbol{A}$ is an NxNp matrix, giving pN^2 VAR coefficients to be estimated;
- If N and/or p is large the VAR can be seriously overparameterised; we make use of prior shrinkage (results with both adaptive Lasso (AL) & asymmetric conjugate prior (ACP)).

MF-VAR: Definition

- The MF-VAR is where $\boldsymbol{y_t}$ contains a combination of observed (low-frequency) and unobserved or latent (high-frequency) variables:
  - These are linked via the *inter-termporal restriction*:
  - Observed annual growth rate to unobserved quarterly growth rate is approximately (see Mariano and Murasawa 2010; Mariano and Murasawa 2003):

$$y_t^{r,A} = \frac{1}{4}y_t^r + \frac{1}{2}y_{t-1}^r + \frac{3}{4}y_{t-2}^r + y_{t-3}^r + \frac{3}{4}y_{t-4}^r + \frac{1}{2}y_{t-5}^r + \frac{1}{4}y_{t-6}^r \quad (2)$$

- Thus we set $\boldsymbol{y_t} = \left(y_t^{UK}, \boldsymbol{y_t^{Q'}}\right)$ where $\boldsymbol{y_t^{Q}}$ contains the quarterly regional growth rates we wish to estimate.

MF-VAR: Definition

- In our regional model (in contrast to MF-VARs at a national level) we can draw on another source of information based on the fact that UK GVA is the sum of the regions;
  - We call this the 'cross-sectional' restriction.
- How to incorporate this in the econometric model? By following Doran 1992;
- The MF-VAR can be set up as a state space model where the state equations are given by the VAR and the measurement equations are given by the inter-temporal and cross-sectional restrictions;
- This can be estimated using Bayesian methods (we use VB rather than MCMC for computational reasons).

MF-FAVAR: Definition

- The MF-FAVAR is a MF-VAR but with $\boldsymbol{y_t}$ redefined to be: $\boldsymbol{y_t} = \left(y_t^{UK}, \boldsymbol{y_t^{Q'}}, \boldsymbol{f_t'}\right)$, where $\boldsymbol{f_t} = \left(\boldsymbol{f_t'}, \ldots, \boldsymbol{f_t^R}\right)'$ is a vector of regional factors;
- We can have more than one factor per region, hence $\boldsymbol{f_t^r}$ is a vector of n_f factors constructed using $\boldsymbol{Z_t^r}$ for $r = 1, \ldots, R$, these factors are observed quarterly;
- Note that this model is quite large, having at a minimum $N = R + n_f + 1$ dependent variables (with one factor per region we're looking at N=25);
- In practice our models are even larger than this to incorporate more than one factor;
- To help with the over-parameterisation we impose one additional restriction, namely that the regional factors are 'region specific' in that they do not enter the equations for the other regions (we also explore the effect of relaxing this).

Constructing the factors for the MF-FAVAR

- We consider three main approaches to filling in missing data with different patterns of 'missingness':
  - EMPCA (Stock and Watson 2002) ⏩ EMPCA
  - TW (Bai and Ng 2021) ⏩ TW
  - TP (Cahan, Bai, and Ng 2022) ⏩ TP
- Our particular challenge is the 'ragged edge' at the start of the sample for most regional predictors;
- We explored the properties of these approaches across different dimensions (missingness, T, N, etc) in a series of Monte Carlo experiments. ⏩ Monte Carlo Experiments

Data

- Regional data:
  - Annual real GVA growth data from 1999, quarterly from 2012 (DAs have slightly longer time series). Prior to 1999 these data are based on applying a UK deflator to the nominal data;
  - $>$30 additional regional predictors are considered covering: labour market, PMI, Retail Sales, House Prices, claimant count and CBI Business Survey data, etc.
  - Not all are available for all regions, and the length of time series and release delay varies (see next slide).
- UK data:
  - Real and nominal data quarterly from 1967 in growth rates;
  - Additional UK quarterly variables in the MF-VAR: Inflation, interest rates, change in oil prices and exchange rates.

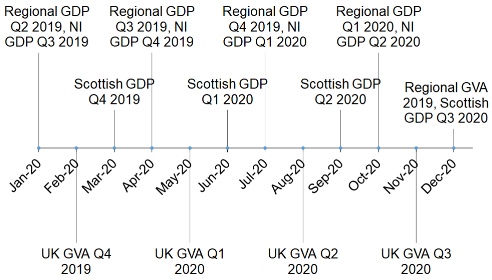
Some of the regional predictors

Table: Regional Indicators: Short and Long Data

Variable	Tab	Description	Frequency	Geographic Coverage (National - N; Regional-R)	Time period	Typical release delay
1	UK Quarterly HPI	Nationwide Building Society House Price Index	Q	N	Q1 1967 -	1 week
10	Employment	16 - 64 Employment Rate Labour Force Survey	Q	R	Q2 1992 - Q4 2021	6 weeks
11	Unemployment	16+ Unemployment Rate Labour Force Survey	Q	R	Q2 1992 - Q4 2021	6 weeks
16	RegCC	Claimant count rate	M	R	Apr 1974 - Jan 2022	2 weeks
17	PayrollEMP	Payroll employment	M	R	July 2014 - Jan 2022	2 weeks
18	PayrollPayMedian	Median payroll pay	M	R	July 2014 - Jan 2022	2 weeks
19	HousePrice	House Price Index	M	R	Jan 1995 - Mar 2022 (most regions, some later)	6 weeks
20	PMIactivity	PMI activity measure (headline)	M	R	Jan 1997 - Jan 2022 (most regions, some later)	2 weeks
24	PMIprices	Prices	M	R	Jan 1997 - Jan 2022 (most regions, some later)	2 weeks
31	Scot_GDP	Scottish monthly GDP	M	R (Scot only)	Jan 2010 - Mar 2022	2 months
33	Scot_RetailSales	Retail sales index for Scotland	Q	R (Scot only)	Q1 2008 - Q1 2020	1 month
35	NI_IOS	Northern Ireland Index of Services	Q	R (NI only)	Q1 2005 - Q4 2021	3 months
37	NI_RSI	Northern Ireland Retail Sales Index	Q	R (NI only)	Q1 2014 - Q4 2021	3 months
40	VAT	VAT Turnover Aggregates	Q	R	Q1 2012 - Q4 2021	5 months

Pseudo-realtime nowcasting exercise

- We produce 3 data–points for each region at each time–step:
  - Backcast – produced in quarter t, relating to quarter t-2;
  - Estimate – produced in quarter t, relating to quarter t-1;
  - Nowcast – produced in quarter t, relating to quarter t.
- To illustrate why we evaluate three data–points:



- We respect the real-time release calendar for our regional and national data (output and predictors);
- We time the model to run upon receipt of the latest UK-wide data.

Results

- Real–time nowcasting and forecasting exercise:
  - Two evaluation metrics evaluating the point (*RMSE*) and density (*CRPS*) nowcasts, lower values better;
  - Evaluation against published quarterly data in real–terms from ONS (presented relative to benchmark Koop et al. 2020b style MF-VAR model); Results
  - Results across different means of calculating regional factors (EMPCA/TW/TP); Results
  - Results with different numbers of factors included; Results
  - Different methods of selecting the regional factors to include (highest eigenvalue v. highest in-sample correlation with UK GVA growth); Results
  - Different priors (Adaptive Lasso (AL) instead of the Assymtetric Conjugate Prior (ACP)). Results

Concluding Remarks

- Context: nowcasting at a regional level is challenging for a number of reasons, but existing econometric models can produce accurate and well-calibrated nowcasts;
- Challenge: increasing availability of new and innovative data sources which might be useful in producing faster estimates of regional economic activity, but the short time-series nature of these data makes their use with time-series models problematic;
- What we do: we explore how different factor approaches can be used to augment existing MF-VAR models to incorporate these new data sources;
- Findings: Where UK data are not available for a given quarter, there are nowcasting gains from conditioning our nowcasts on our regional factors, but not otherwise. Differences across factor methods are small.

References I

Bai, Jushan and Serena Ng (Oct. 2021). "Matrix Completion, Counterfactuals, and Factor Analysis of Missing Data". In: *Journal of the American Statistical Association* 116.536, pp. 1746–1763. DOI: 10.1080/01621459.2021.1967163.

Brave, Scott A., R. Andrew Butters, and Alejandro Justiniano (2019). "Forecasting economic activity with mixed frequency BVARs". In: *International Journal of Forecasting* 35.4, pp. 1692–1707. ISSN: 0169-2070. DOI: https://doi.org/10.1016/j.ijforecast.2019.02.010.

Cahan, Ercument, Jushan Bai, and Serena Ng (2022). "Factor-based imputation of missing values and covariances in panel data of large dimensions". In: *Journal of Econometrics*. DOI: 10.1016/j.jeconom.2022.01.006.

References II

- Diebold, Francis X and Robert S Mariano (1995). "Comparing Predictive Accuracy". In: *Journal of Business & Economic Statistics* 20.1, pp. 134–144. DOI: 10.1198/073500102753410444.
- Doran, Howard E (1992). "Constraining Kalman filter and smoothing estimates to satisfy time-varying restrictions". In: *The Review of Economics and Statistics*, pp. 568–572.
- Ghysels, Eric (2016). "Macroeconomics and the reality of mixed frequency data". In: *Journal of Econometrics* 193.2, pp. 294–314.
- Koop, Gary, Stuart McIntyre, and James Mitchell (2020). "UK regional nowcasting using a mixed frequency vector auto-regressive model with entropic tilting". In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 183.1, pp. 91–119. DOI: 10.1111/rssa.12491.

References III

- Koop, Gary et al. (Aug. 2020a). "Reconciled estimates and nowcasts of regional output in the UK". In: *National Institute Economic Review* 253, R44–R59. DOI: 10.1017/nie.2020.29.
- — (2020b). "Regional output growth in the United Kingdom: More timely and higher frequency estimates from 1970". In: *Journal of Applied Econometrics* 35.2, pp. 176–197. DOI: 10.1002/jae.2748.
- — (2022). "Using stochastic hierarchical aggregation constraints to nowcast regional economic aggregates". In: *International Journal of Forecasting* WP 22-06. DOI: 10.26509/frbc-wp-202206.
- Mariano, Roberto S. and Yasutomo Murasawa (2003). "A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series". In: *Journal of Applied Econometrics* 18.4, pp. 427–443. ISSN: 1099-1255. DOI: 10.1002/jae.695.

References IV

Mariano, Roberto S. and Yasutomo Murasawa (2010). "A Coincident Index, Common Factors, and Monthly Real GDP". In: *Oxford Bulletin of Economics and Statistics* 72.1, pp. 27–46. ISSN: 1468-0084. DOI: 10.1111/j.1468-0084.2009.00567.x.

McCracken, Michael W., Michael T. Owyang, and Tatevik Sekhposyan (2021). "Real-Time Forecasting and Scenario Analysis Using a Large Mixed-Frequency Bayesian VAR". In: *International Journal of Central Banking* 17.71, pp. 1–41. URL: https://www.ijcb.org/journal/ijcb21q5a8.htm.

Schorfheide, Frank and Dongho Song (2015). "Real-Time Forecasting With a Mixed-Frequency VAR". In: *Journal of Business & Economic Statistics* 33.3, pp. 366–380. DOI: 10.1080/07350015.2014.954707.

References V

Stock, J and M Watson (2002). "Macroeconomic Forecasting Using Diffusion Indexes". In: *Journal of Business & Economic Statistics* 20.2, pp. 147–162. DOI: 10.1198/073500102317351921.

Appendix

EMPCA (Stock and Watson 2002)

- PCA is a popular (non-parametric) approach to estimating factors, exploiting correlations across variables to produce estimates of factors;
- When data are missing EMPCA uses an expectations-maximisation (EM) algorithm to fill in the missing data;
- Recall that our regional factors $\boldsymbol{f}_t^r$ are constructed using $\boldsymbol{Z}_t^r$ which contains missing values;
- If $\hat{\boldsymbol{Z}}_t^r$ is $\boldsymbol{Z}_t^r$ where the missing data are replaced with estimates, and $\hat{\boldsymbol{f}}_t^r$ are the estimates of the factors, then EMPCA is an iterative algorithm using PCA on $\hat{\boldsymbol{Z}}_t^r$ to produce $\hat{\boldsymbol{f}}_t^r$;
- Estimates of the missing values are produced as fitted values from a regression of $\hat{\boldsymbol{Z}}_t^r$ on $\hat{\boldsymbol{f}}_t^r$.

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TW (Bai and Ng 2021)

- The Tall-Wide (TW) algorithm of Bai and Ng 2021 is not iterative and therefore does not have the same computational issues as EMPCA. How does TW work?
  - Each column of the Txk_r matrix of data for a given region, $\boldsymbol{Z_t^r}$, contains all the data for a variable, some of which have no missing data, these are the **Tall** block;
    - Undertake PCA using this block and produce factors $\hat{\boldsymbol{f}}_t^{\boldsymbol{r},\ \boldsymbol{Tall}}$ and factor loadings $\hat{\boldsymbol{\Lambda}}^{\boldsymbol{r},\ \boldsymbol{Tall}}$.
  - Some rows of $\boldsymbol{Z_t^r}$ will similarly not have missing data, these form the **Wide** block.
    - PCA can be done on this block producing factors $\hat{\boldsymbol{f}}_t^{\boldsymbol{r},\ \boldsymbol{Wide}}$ and factor loadings $\hat{\boldsymbol{\Lambda}}^{\boldsymbol{r},\ \boldsymbol{Wide}}$.
  - TW is an algorithm for combining $\hat{\boldsymbol{f}}_t^{\boldsymbol{r},\ \boldsymbol{Tall}}$, $\hat{\boldsymbol{\Lambda}}^{\boldsymbol{r},\ \boldsymbol{Tall}}$, $\hat{\boldsymbol{f}}_t^{\boldsymbol{r},\ \boldsymbol{Wide}}$ and $\hat{\boldsymbol{\Lambda}}^{\boldsymbol{r},\ \boldsymbol{Wide}}$ in an optimal way (using least squares regression) and produce a single regional factor.
- Bai and Ng 2021 show this approach has desirable asymptotic properties, but depends on the number of columns/rows.

TP (Cahan, Bai, and Ng 2022)

- The Tall Project (TP) approach is similar to TW, $\hat{\boldsymbol{f}}_t^{\boldsymbol{r},\ \boldsymbol{Tall}}$ and $\hat{\boldsymbol{\Lambda}}^{\boldsymbol{r},\ \boldsymbol{Tall}}$ are key but addresses the issue where the *wide* block is thin;
- It does this using auxiliary regressions for the observed values of each individual variable (other than those in the *tall* block) on the *tall* block factors;
- The auxiliary regression for variable i can be used to fill in the missing value for variable i, and thus $\hat{\boldsymbol{Z}}_t^{\boldsymbol{r}}$ has no missing values;
- Regional factors are then constructed using PCA on $\hat{\boldsymbol{Z}}_t^{\boldsymbol{r}}$.

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Monte Carlo Simulations

Table: EMPCA: Trace R^2, and computation times (seconds), $r = 2$

			Trace R^2 EMPCA					Computation Time			
T	n	τ	missing: 0	20%	40%	60%	80 %	20%	40%	60%	80 %
50	12	0.00	0.83	0.60	0.49	0.43	0.35	0.06	0.17	0.15	0.27
50	12	0.30	0.73	0.49	0.42	0.25	0.31	0.15	0.16	0.23	0.30
50	12	0.60	0.68	0.39	0.37	0.24	0.30	0.20	0.24	0.25	0.29
50	12	0.90	0.53	0.39	0.39	0.32	0.31	0.12	0.22	0.16	0.35
50	102	0.00	0.93	0.68	0.46	0.41	0.15	6.50	14.12	17.27	not
50	102	0.30	0.93	0.52	0.43	0.35	0.29	6.95	13.66	not	not
50	102	0.60	0.90	0.45	0.38	0.40	0.20	11.04	14.13	17.55	not
50	102	0.90	0.51	0.33	0.31	0.25	0.18	17.93	21.19	not	not
100	12	0.00	0.85	0.61	0.58	0.45	0.31	0.23	0.28	0.61	0.74
100	12	0.30	0.76	0.46	0.53	0.28	0.21	0.30	0.42	0.80	0.85
100	12	0.60	0.53	0.35	0.29	0.21	0.22	0.88	0.78	1.21	0.90
100	12	0.90	0.48	0.38	0.34	0.32	0.23	0.28	0.40	0.92	0.86
100	102	0.00	0.96	0.72	0.58	0.82	0.66	55.39	not	not	not
100	102	0.30	0.95	0.63	0.58	0.66	0.64	54.40	not	not	not
100	102	0.60	0.93	0.52	0.50	0.60	0.74	57.00	not	not	not
100	102	0.90	0.67	0.35	0.36	0.65	0.72	not	not	not	not
200	12	0.00	0.91	0.73	0.60	0.51	0.39	0.70	0.91	1.79	1.15
200	12	0.30	0.85	0.63	0.51	0.35	0.33	1.37	2.88	2.48	2.79
200	12	0.60	0.60	0.46	0.31	0.31	0.36	3.27	5.08	2.92	4.26
200	12	0.90	0.54	0.41	0.34	0.28	0.35	2.41	2.73	2.28	2.58
200	102	0.00	0.97	0.78	0.77	0.86	0.50	142.89	not	not	not
200	102	0.30	0.97	0.75	0.74	0.88	0.53	237.86	not	not	not
200	102	0.60	0.95	0.69	0.70	0.87	0.47	257.62	not	not	not
200	102	0.90	0.63	0.47	0.36	0.45	0.26	not	not	not	not

Monte Carlo Simulations

Table: Trace R^2: TW and TP, $r = 2$

			Trace R^2 TW					Trace R^2 TP				
T	n	τ	missing: 0	20%	40%	60%	80 %	missing: 0	20%	40%	60%	80 %
50	12	0.00	0.80	0.67	0.61	0.55	0.41	0.77	0.70	0.58	0.47	0.36
50	12	0.30	0.70	0.65	0.46	0.46	0.38	0.62	0.54	0.55	0.42	0.27
50	12	0.60	0.41	0.43	0.29	0.35	0.30	0.36	0.40	0.42	0.34	0.26
50	12	0.90	0.54	0.38	0.32	0.35	0.27	0.42	0.31	0.35	0.28	0.30
50	102	0.00	0.93	0.81	0.66	0.61	0.36	0.93	0.82	0.71	0.62	0.45
50	102	0.30	0.92	0.80	0.68	0.57	0.34	0.93	0.80	0.66	0.58	0.42
50	102	0.60	0.91	0.80	0.60	0.46	0.26	0.89	0.77	0.62	0.53	0.34
50	102	0.90	0.60	0.55	0.42	0.28	0.28	0.54	0.54	0.50	0.49	0.28
100	12	0.00	0.87	0.76	0.65	0.50	0.46	0.83	0.74	0.70	0.59	0.50
100	12	0.30	0.67	0.67	0.54	0.39	0.36	0.73	0.64	0.61	0.52	0.42
100	12	0.60	0.47	0.42	0.42	0.37	0.38	0.43	0.37	0.37	0.39	0.37
100	12	0.90	0.48	0.43	0.36	0.33	0.24	0.42	0.33	0.39	0.40	0.39
100	102	0.00	0.95	0.84	0.78	0.61	0.41	0.95	0.86	0.73	0.65	0.55
100	102	0.30	0.95	0.85	0.74	0.56	0.47	0.95	0.84	0.71	0.62	0.48
100	102	0.60	0.93	0.83	0.73	0.51	0.43	0.94	0.80	0.70	0.56	0.45
100	102	0.90	0.69	0.57	0.46	0.41	0.37	0.68	0.59	0.47	0.42	0.38
200	12	0.00	0.88	0.79	0.73	0.63	0.51	0.89	0.78	0.67	0.57	0.44
200	12	0.30	0.82	0.67	0.64	0.52	0.40	0.82	0.70	0.57	0.46	0.38
200	12	0.60	0.47	0.43	0.46	0.30	0.32	0.50	0.50	0.41	0.33	0.34
200	12	0.90	0.54	0.41	0.47	0.30	0.32	0.41	0.46	0.35	0.31	0.32
200	102	0.00	0.96	0.86	0.72	0.64	0.49	0.97	0.86	0.73	0.64	0.45
200	102	0.30	0.96	0.84	0.73	0.58	0.38	0.97	0.86	0.73	0.57	0.44
200	102	0.60	0.95	0.83	0.69	0.59	0.34	0.95	0.84	0.68	0.54	0.39
200	102	0.90	0.65	0.69	0.51	0.39	0.24	0.73	0.65	0.61	0.42	0.35

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Main Results

Table: Main Results

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
RMSFE (multiplied by 100)														
Benchmark MF-VAR														
	Nowcast	2.84	1.82	2.10	1.87	1.96	2.08	3.35	1.80	1.72	2.46	1.63	1.71	2.11
	Estimate	0.84	0.48	0.54	0.58	0.41	0.38	1.21	0.40	0.57	0.68	0.16	0.38	0.55
	Backcast	0.42	0.30	0.35	0.36	0.26	0.27	0.79	0.19	0.31	0.34	-	-	0.36
MF-FAVAR: VAT lag=5 months														
TP	Nowcast	1.72	1.63	1.66	1.70	1.61	1.65	2.44	1.53	1.54	1.82	1.23	1.38	1.66
	Estimate	0.62	0.56	0.62	0.67	0.46	0.41	1.10	0.41	0.59	0.63	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.28	0.26	0.70	0.21	0.35	0.32	-	-	0.36
CRPS (multiplied by 100)														
Benchmark MF-VAR														
		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
	Nowcast	1.21	0.87	0.99	0.91	0.89	0.91	1.23	0.84	0.86	1.07	0.61	0.72	0.93
	Estimate	0.43	0.29	0.31	0.33	0.27	0.26	0.51	0.26	0.32	0.37	0.11	0.20	0.30
	Backcast	0.23	0.17	0.19	0.19	0.16	0.15	0.28	0.14	0.18	0.20	-	-	0.19
MF-FAVAR: VAT lag=5 months														
TP	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.80*	1.04*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19

Notes:$*$ denote rejection of the null of equal forecast accuracy against the benchmark MF-VAR model at the 0.10 significance level using a two-sided Diebold and Mariano 1995 test.

Back

Comparison across factor methods

Table: Comparison across factor methods

MF-FAVAR: VAT lag=5 months														
RMSFE (multiplied by 100)														
EMPCA	Nowcast	1.68	1.62	1.67	1.72	1.61	1.64	2.45	1.52	1.54	1.82	1.24	1.36	1.66
	Estimate	0.62	0.55	0.62	0.67	0.45	0.40	1.10	0.41	0.59	0.62	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.27	0.26	0.70	0.21	0.35	0.32	-	-	0.35
TW	Nowcast	1.71	1.62	1.67	1.69	1.61	1.64	2.45	1.53	1.54	1.83	1.23	1.36	1.66
	Estimate	0.62	0.55	0.62	0.66	0.45	0.40	1.10	0.42	0.59	0.63	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.35
TP	Nowcast	1.72	1.63	1.66	1.70	1.61	1.65	2.44	1.53	1.54	1.82	1.23	1.38	1.66
	Estimate	0.62	0.56	0.62	0.67	0.46	0.41	1.10	0.41	0.59	0.63	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.28	0.26	0.70	0.21	0.35	0.32	-	-	0.36
CRPS (multiplied by 100)														
EMPCA	Nowcast	0.85*	0.81*	0.84	0.85	0.79*	0.79*	1.05*	0.74*	0.79*	0.88*	0.51*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	Nowcast	0.87*	0.81*	0.84	0.84	0.78*	0.79*	1.05*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.80*	1.04*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19

Back

Varying the number of factors

Table: RMSFE (multiplied by 100)

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
MF-FAVAR (p=1 lag, n_f=5, VAT lag = 5 months)														
EMPCA	Nowcast	1.69	1.61	1.67	1.71	1.60	1.63	2.46	1.52	1.53	1.82	1.24	1.36	1.65
	Estimate	0.62	0.55	0.63	0.67	0.45	0.40	1.10	0.41	0.59	0.62	0.15	0.33	0.55
	Backcast	0.34	0.31	0.38	0.42	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.36
TW	Nowcast	1.71	1.62	1.68	1.71	1.61	1.64	2.45	1.53	1.54	1.82	1.23	1.37	1.66
	Estimate	0.61	0.56	0.63	0.67	0.45	0.40	1.11	0.41	0.59	0.62	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.42	0.28	0.26	0.70	0.22	0.35	0.32	-	-	0.36
TP	Nowcast	1.71	1.61	1.66	1.70	1.60	1.63	2.44	1.54	1.53	1.82	1.23	1.36	1.65
	Estimate	0.62	0.56	0.62	0.67	0.46	0.40	1.10	0.42	0.60	0.63	0.15	0.34	0.55
	Backcast	0.34	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.36
MF-FAVAR (p=1 lag, n_f=2, VAT lag = 5 months)														
EMPCA	Nowcast	1.68	1.62	1.67	1.72	1.61	1.64	2.45	1.52	1.54	1.82	1.24	1.36	1.66
	Estimate	0.62	0.55	0.62	0.67	0.45	0.40	1.10	0.41	0.59	0.62	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.27	0.26	0.70	0.21	0.35	0.32	-	-	0.35
TW	Nowcast	1.71	1.62	1.67	1.69	1.61	1.64	2.45	1.53	1.54	1.83	1.23	1.36	1.66
	Estimate	0.62	0.55	0.62	0.66	0.45	0.40	1.10	0.42	0.59	0.63	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.35
TP	Nowcast	1.72	1.63	1.66	1.70	1.61	1.65	2.44	1.53	1.54	1.82	1.23	1.38	1.66
	Estimate	0.62	0.56	0.62	0.67	0.46	0.41	1.10	0.41	0.59	0.63	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.28	0.26	0.70	0.21	0.35	0.32	-	-	0.36

Back

Varying the number of factors

Table: CRPS (multiplied by 100)

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
MF-FAVAR (p=1 lag, n_f=5, VAT lag = 5 months)														
EMPCA	Nowcast	0.86*	0.81*	0.84	0.84	0.78*	0.79*	1.06*	0.74*	0.79*	0.88*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.34	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	Nowcast	0.86*	0.81*	0.84	0.84	0.79*	0.79*	1.05*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.35	0.31	0.33	0.35	0.29	0.26	0.50	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.81*	0.83*	0.84	0.78*	0.79*	1.05*	0.74*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35*	0.29	0.26	0.50	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.28	0.14	0.19	0.19	-	-	0.19
MF-FAVAR (p=1 lag, n_f=2, VAT lag = 5 months)														
EMPCA	Nowcast	0.85*	0.81*	0.84	0.85	0.79*	0.79*	1.05*	0.74*	0.79*	0.88*	0.51*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	Nowcast	0.87*	0.81*	0.84	0.84	0.78*	0.79*	1.05*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.80*	1.04*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19

Back

Factor selection approaches

Table: RMSFE (multiplied by 100)

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
MF-FAVAR, Correlation, VAT lag = 5 months)														
EMPCA	Nowcast	1.70	1.63	1.68	1.73	1.61	1.64	2.45	1.53	1.55	1.83	1.24	1.36	1.66
	Estimate	0.62	0.55	0.63	0.68	0.46	0.40	1.10	0.41	0.60	0.62	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.42	0.28	0.25	0.70	0.22	0.35	0.31	-	-	0.36
TW	Nowcast	1.71	1.63	1.67	1.70	1.62	1.63	2.44	1.53	1.54	1.83	1.24	1.37	1.66
	Estimate	0.62	0.56	0.63	0.67	0.46	0.40	1.10	0.41	0.59	0.62	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.36
TP	Nowcast	1.72	1.63	1.67	1.70	1.61	1.64	2.43	1.54	1.53	1.84	1.23	1.36	1.66
	Estimate	0.62	0.55	0.62	0.67	0.45	0.40	1.09	0.41	0.59	0.64	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.27	0.25	0.69	0.22	0.35	0.32	-	-	0.35
MF-FAVAR, Eigenvalue, VAT lag = 5 months)														
EMPCA	Nowcast	1.68	1.62	1.67	1.72	1.61	1.64	2.45	1.52	1.54	1.82	1.24	1.36	1.66
	Estimate	0.62	0.55	0.62	0.67	0.45	0.40	1.10	0.41	0.59	0.62	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.27	0.26	0.70	0.21	0.35	0.32	-	-	0.35
TW	Nowcast	1.71	1.62	1.67	1.69	1.61	1.64	2.45	1.53	1.54	1.83	1.23	1.36	1.66
	Estimate	0.62	0.55	0.62	0.66	0.45	0.40	1.10	0.42	0.59	0.63	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.35
TP	Nowcast	1.72	1.63	1.66	1.70	1.61	1.65	2.44	1.53	1.54	1.82	1.23	1.38	1.66
	Estimate	0.62	0.56	0.62	0.67	0.46	0.41	1.10	0.41	0.59	0.63	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.28	0.26	0.70	0.21	0.35	0.32	-	-	0.36

Back

Factor selection approaches

Table: CRPS (multiplied by 100)

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
MF-FAVAR, Correlation, VAT lag = 5 months)														
EMPCA	Nowcast	0.87*	0.81*	0.84	0.85	0.79*	0.79*	1.05*	0.75*	0.80*	0.88*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.34	0.35	0.29	0.26	0.49	0.26	0.33	0.35	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.79*	1.05*	0.74*	0.80*	0.88*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.34	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.21	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.81*	0.83	0.84	0.79*	0.79*	1.04*	0.74*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
MF-FAVAR, Eigenvalue, VAT lag = 5 months)														
EMPCA	Nowcast	0.85*	0.81*	0.84	0.85	0.79*	0.79*	1.05*	0.74*	0.79*	0.88*	0.51*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	Nowcast	0.87*	0.81*	0.84	0.84	0.78*	0.79*	1.05*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.80*	1.04*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19

Back

Allowing every region's factors to impact all others

Table: RMSFE (multiplied by 100)

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
VB MF-FAVAR-full - AL-ACP (p=1 lag, n_f=2, VAT lag = 5 months)														
EMPCA	Nowcast	1.69	1.60	1.66	1.70	1.59	1.60	2.45	1.50	1.52	1.77	1.21	1.29	1.63
	Estimate	0.64	0.56	0.63	0.68	0.46	0.40	1.12	0.43	0.62	0.61	0.15	0.32	0.55
	Backcast	0.34	0.31	0.38	0.42	0.28	0.26	0.71	0.23	0.35	0.31	-	-	0.36
TW	Nowcast	1.70	1.59	1.65	1.68	1.60	1.60	2.42	1.50	1.51	1.78	1.20	1.30	1.63
	Estimate	0.63	0.56	0.63	0.67	0.46	0.40	1.11	0.42	0.60	0.62	0.15	0.33	0.55
	Backcast	0.34	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.34	0.32	-	-	0.36
TP	Nowcast	1.71	1.59	1.65	1.67	1.60	1.61	2.41	1.49	1.50	1.78	1.20	1.30	1.63
	Estimate	0.63	0.56	0.62	0.67	0.47	0.40	1.10	0.41	0.60	0.62	0.15	0.33	0.55
	Backcast	0.34	0.31	0.38	0.41	0.28	0.26	0.70	0.22	0.35	0.32	-	-	0.36
VB MF-FAVAR-own (p=1 lag, n_f=2, VAT lag = 5 months)														
EMPCA	Nowcast	1.68	1.62	1.67	1.72	1.61	1.64	2.45	1.52	1.54	1.82	1.24	1.36	1.66
	Estimate	0.62	0.55	0.62	0.67	0.45	0.40	1.10	0.41	0.59	0.62	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.27	0.26	0.70	0.21	0.35	0.32	-	-	0.35
TW	Nowcast	1.71	1.62	1.67	1.69	1.61	1.64	2.45	1.53	1.54	1.83	1.23	1.36	1.66
	Estimate	0.62	0.55	0.62	0.66	0.45	0.40	1.10	0.42	0.59	0.63	0.15	0.33	0.54
	Backcast	0.33	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.35
TP	Nowcast	1.72	1.63	1.66	1.70	1.61	1.65	2.44	1.53	1.54	1.82	1.23	1.38	1.66
	Estimate	0.62	0.56	0.62	0.67	0.46	0.41	1.10	0.41	0.59	0.63	0.15	0.34	0.55
	Backcast	0.33	0.31	0.38	0.41	0.28	0.26	0.70	0.21	0.35	0.32	-	-	0.36

Allowing every region's factors to impact all others

Table: CRPS (multiplied by 100)

		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
VB MF-FAVAR-full - AL-ACP (p=1 lag, n_f=2, VAT lag = 5 months)														
EMPCA	Nowcast	0.86*	0.81*	0.83	0.84	0.78*	0.79*	1.06*	0.73*	0.78*	0.87*	0.50*	0.57*	0.79
	Estimate	0.36	0.31	0.34	0.36	0.29	0.26	0.50	0.27	0.34	0.35	0.11	0.19	0.31
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.28	0.15	0.19	0.19	-	-	0.19
TW	Nowcast	0.86*	0.81*	0.83	0.83	0.78*	0.79*	1.05*	0.74*	0.78*	0.88*	0.50*	0.58*	0.78
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.27	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.21	0.21	0.17	0.15	0.27	0.15	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.81*	0.83	0.83	0.78*	0.79*	1.05*	0.73*	0.78*	0.88*	0.50*	0.58*	0.78
	Estimate	0.36	0.31	0.33	0.35	0.30	0.26	0.50	0.26	0.33	0.36	0.11	0.19	0.31
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
VB MF-FAVAR-own (p=1 lag, n_f=2, VAT lag = 5 months)														
EMPCA	Nowcast	0.85*	0.81*	0.84	0.85	0.79*	0.79*	1.05*	0.74*	0.79*	0.88*	0.51*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	Nowcast	0.87*	0.81*	0.84	0.84	0.78*	0.79*	1.05*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.80*	1.04*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
	Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
	Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19

Back

Prior sensitivity

Table: RMSFE (multiplied by 100)

			VB MF-FAVAR (p=1 lag, n_f=2, VAT lag = 5 months)												
	Prior		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
EMPCA	AL	Nowcast	1.74	1.63	1.71	1.70	1.69	1.88	2.53	1.80	1.60	1.60	1.20	1.42	1.71
		Estimate	0.81	0.52	0.53	0.57	0.43	0.49	1.14	0.49	0.55	0.54	0.16	0.35	0.55
		Backcast	0.46	0.28	0.31	0.35	0.27	0.27	0.72	0.24	0.32	0.28	-	-	0.35
TW	AL	Nowcast	1.74	1.60	1.70	1.67	1.69	1.86	2.51	1.77	1.60	1.58	1.20	1.40	1.69
		Estimate	0.81	0.51	0.53	0.56	0.44	0.50	1.13	0.49	0.55	0.54	0.16	0.35	0.55
		Backcast	0.45	0.27	0.31	0.34	0.27	0.27	0.72	0.24	0.32	0.28	-	-	0.35
TP	AL	Nowcast	1.74	1.61	1.65	1.65	1.67	1.86	2.53	1.79	1.57	1.60	1.20	1.39	1.69
		Estimate	0.80	0.52	0.54	0.58	0.43	0.50	1.15	0.49	0.56	0.54	0.16	0.34	0.55
		Backcast	0.45	0.27	0.32	0.36	0.27	0.27	0.72	0.24	0.33	0.28	-	-	0.35
EMPCA	ACP	Nowcast	1.68	1.62	1.67	1.72	1.61	1.64	2.45	1.52	1.54	1.82	1.24	1.36	1.66
		Estimate	0.62	0.55	0.62	0.67	0.45	0.40	1.10	0.41	0.59	0.62	0.15	0.33	0.54
		Backcast	0.33	0.31	0.38	0.41	0.27	0.26	0.70	0.21	0.35	0.32	-	-	0.35
TW	ACP	Nowcast	1.71	1.62	1.67	1.69	1.61	1.64	2.45	1.53	1.54	1.83	1.23	1.36	1.66
		Estimate	0.62	0.55	0.62	0.66	0.45	0.40	1.10	0.42	0.59	0.63	0.15	0.33	0.54
		Backcast	0.33	0.31	0.38	0.41	0.28	0.25	0.70	0.22	0.35	0.32	-	-	0.35
TP	ACP	Nowcast	1.72	1.63	1.66	1.70	1.61	1.65	2.44	1.53	1.54	1.82	1.23	1.38	1.66
		Estimate	0.62	0.56	0.62	0.67	0.46	0.41	1.10	0.41	0.59	0.63	0.15	0.34	0.55
		Backcast	0.33	0.31	0.38	0.41	0.28	0.26	0.70	0.21	0.35	0.32	-	-	0.36

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Prior sensitivity

Table: CRPS (multiplied by 100)

VB MF-FAVAR (p=1 lag, n_f=2, VAT lag = 5 months)															
	Prior		NE	NW	York	EM	WM	EE	LON	SE	SW	WA	SCOT	NI	Average
EMPCA	AL	Nowcast	0.84	0.81*	0.86*	0.88	0.83*	0.81*	1.10*	0.87*	0.88	0.86*	0.52	0.62*	0.82
		Estimate	0.41	0.30	0.31*	0.35*	0.29	0.25	0.51	0.30*	0.36	0.35	0.11	0.19	0.31
		Backcast	0.24	0.17	0.18	0.21*	0.17	0.14	0.28	0.16	0.21*	0.19	-	-	0.19
TW	AL	Nowcast	0.85	0.80*	0.85*	0.87	0.83*	0.81*	1.10*	0.86*	0.88	0.85*	0.52	0.62*	0.82
		Estimate	0.41	0.29	0.32	0.35	0.29	0.25	0.51	0.30*	0.35	0.35	0.11	0.20	0.31
		Backcast	0.24	0.16	0.18	0.21	0.17	0.14	0.28	0.16	0.21	0.19	-	-	0.19
TP	AL	Nowcast	0.85	0.80*	0.84*	0.86	0.82*	0.81*	1.10*	0.86*	0.87	0.86*	0.52	0.61*	0.82
		Estimate	0.41	0.30	0.32*	0.35*	0.29	0.25	0.51	0.30*	0.36	0.35	0.11	0.19	0.31
		Backcast	0.24	0.16	0.19	0.21*	0.17	0.14	0.28	0.16	0.21*	0.19	-	-	0.19
EMPCA	ACP	Nowcast	0.85*	0.81*	0.84	0.85	0.79*	0.79*	1.05*	0.74*	0.79*	0.88*	0.51*	0.59*	0.79
		Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
		Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TW	ACP	Nowcast	0.87*	0.81*	0.84	0.84	0.78*	0.79*	1.05*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
		Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
		Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19
TP	ACP	Nowcast	0.87*	0.82*	0.84	0.84	0.79*	0.80*	1.04*	0.75*	0.79*	0.89*	0.50*	0.59*	0.79
		Estimate	0.36	0.31	0.33	0.35	0.29	0.26	0.49	0.26	0.33	0.36	0.11	0.19	0.30
		Backcast	0.20	0.18	0.20	0.21	0.17	0.15	0.27	0.14	0.19	0.19	-	-	0.19

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