Online Appendix for
"Bayesian Compressed Vector Autoregressions"

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Outline

This not-for-publication appendix presents a number of additional results and robustness analysis that were not included in the main paper. The structure of the document is as follows.

Appendix A presents additional results to highlight the predictive accuracy of the various models considered in the paper, focusing one-by-one on the key seven series of interest, i.e. PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, and GS10. Results on point forecast accuracy are presented in Figure A.1 to Figure A.6, while results for density forecast accuracy are in Figure A.7 to Figure A.12.

Appendix B presents results for an Intermediate VAR with 46 variables. Table B.1 and the left side of Table B.3 present evidence on the quality of point forecasts for our seven main variables of interest relative to the AR(1) benchmark. Figure B.1 presents evidence on when the forecasting gains of the Intermediate BCVARs are achieved. Table B.2 and the right hand side of Table B.3 shed light on the quality of the density forecasts of the Intermediate VAR by presenting averages of log predictive likelihoods. Figure B.2 plots the cumulative sums of the multivariate log predictive likelihood differentials for the Intermediate VAR across a number of forecast horizons. Finally, Table B.4 shows the forecast performance of our BCVAR_{tvp-sv} approach in the Intermediate VAR case.

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Appendix C presents results for a number of additional analysis and robustness checks we considered. Figure C.1 and Figure C.2 plot the empirical distributions of m and φ, which define the dimension and the degree of sparsity in the compression matrix, for the Bayesian compressed VARs of different dimensions. They can be interpreted as approximations to the posteriors of these parameters.[1] Next, Figure C.3 and Figure C.4 compare the estimated coefficients of the medium BCVAR using our triangularization scheme for the VAR (defined in equations (6) to (8) of the paper) and the triangularization scheme proposed by Carriero, Clark and Marcellino (2016b), while Table C.1 provides a forecast comparison of the two triangularization schemes. In the table, we label with BCVAR$_{ccm}$ the BCVAR model estimated using the Carriero, Clark, Marcellino (2016b) approach without compressing the covariance terms. Similarly, we label with BCVAR$_{ccm,c}$ the version of the model where we also compress the covariance terms.[2] Next, Figure C.5 compares the impulse responses functions from the BCVAR approach to those obtained using OLS, in the case of the medium VAR. Table C.2 presents results for the out-of-sample forecast performance of the BCVAR methods when considering an alternative weighting scheme to perform BMA, where for each equation of the VAR the forecasts resulting from the different random compressions are averaged according to the univariate BIC computed separately for that equation. In the table, we indicate with BCVAR$_{alt}$ and BCVAR$_{c,alt}$ the two versions of BCVAR, with or without compression on the covariance terms, of this alternative BMA scheme.

To shed light on whether there are statistically significant differences between the multivariate approaches, Table C.3 shows the forecast performance using the BVAR as the benchmark. Table C.4 (which is of the same format and should be compared to Table B.3) summarizes the forecasting performance of our BCVAR approach when the BICs are calculated using the likelihood of the 7 key variables of interest. Table C.5 presents results with the 7 variables of interest ordered last (labeled BCVAR$_{c,v.2}$) compared to those of other

[1] To aid in interpretation note that, in our compressed VARs, there is a different compression matrix in each equation and so, for brevity, the figures average over all equations and are based on the 75% of draws with highest posterior probability. Remember that smaller values of m indicate a higher degree of compression and, for a given m, $\varphi = 0.5$ induces the highest degree of sparsity.

[2] The triangularization proposed by Carriero, Clark and Marcellino (2016b) rewrites the original VAR(1) in equation (4) of the paper as $Y_t = BY_{t-1} + \widehat{A}^{-1}\Sigma\left(\widetilde{E}_t\right) + \Sigma E_t$, where, using the notation defined in the paper, $\widehat{A}^{-1} = A^{-1} - I_n$, and $\widetilde{E}_t$ are residuals which can be estimated recursively (because $\widehat{A}^{-1}$ is lower triangular). Compared to our proposed triangularization, defined in equations (6) to (8) of the paper, this form does not multiply B with A^{-1}, rather it retains the original matrix of VAR coefficients.

approaches. Table C.6, Table C.7, and Table C.8 repeat these robustness checks for TVP-SV versions of our approach. Table C.9 presents forecasting results for the BCVAR model with time variation in both the coefficient and covariance matrix (labeled BCVAR_{tvp-sv} in the table) as well as those with only variation in the error covariance matrix (labeled BCVAR_{sv} in the table). Finally, the top two panels of Table C.9 compare our BCVAR_{tvp-sv} and BCVAR_{sv} approaches to the model of Carriero, Clark and Marcellino (2016b) (labeled BVAR_{ccm}).[3]

Lastly, Appendix D lists the variable definitions and transformation codes for the 129 variables for which complete data was available.

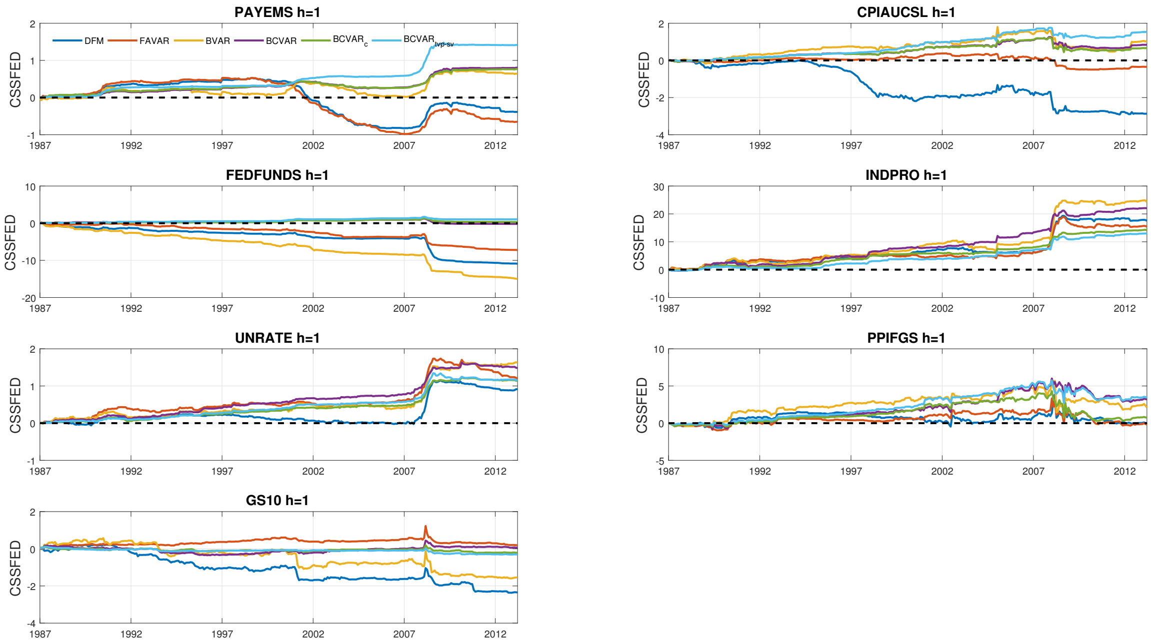
References

Carriero, A., Clark, T. and Marcellino, M. (2016b). Large vector autoregressions with stochastic volatility and flexible priors, Federal Reserve Bank of Cleveland Working Paper, no. 16-17.

[3] For the autoregressive coefficients we use the asymmetric Minnesota prior with shrinkage hyperparameter $\lambda = 0.01$, and prior mean for own lags $\delta = 0.95$. For all other parameters our priors are fairly non-informative and are exactly the same as in Carriero, Clark and Marcellino (2016b). Also, note that the results in Table C.9 for the Medium VAR took 25 hours to run on a PC using a modern Core i7 and 32Gb of RAM.

Appendix A Predictive performance for individual series

Figure A.1. Cumulative sum of squared forecast error differentials, Medium VAR, $h = 1$

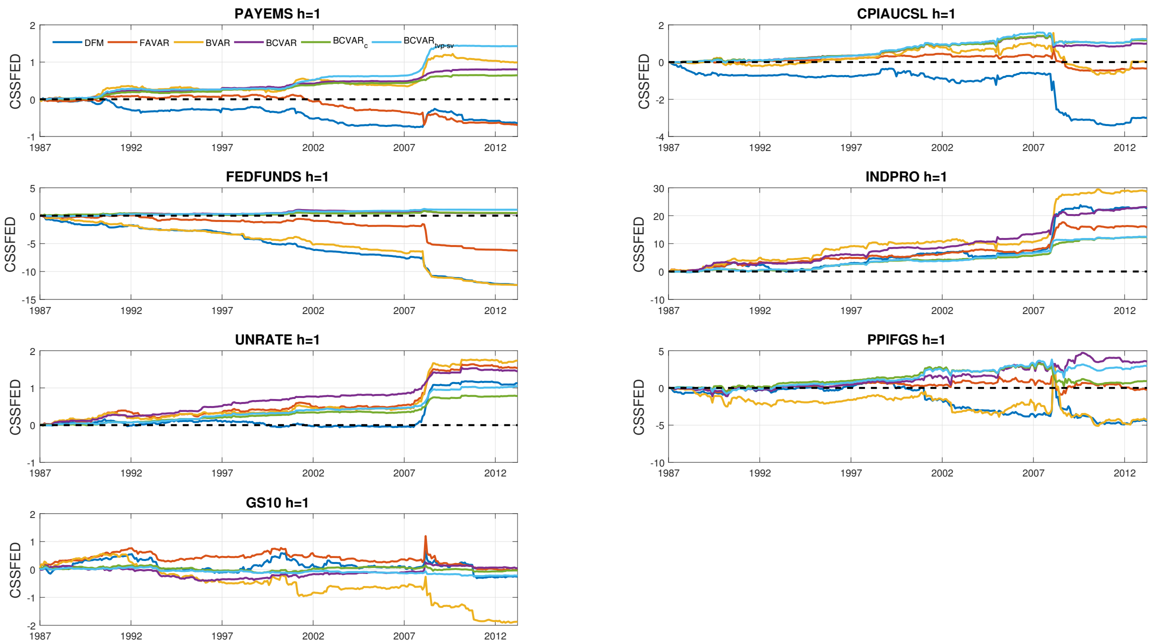


This figure plots the cumulative sum of squared forecast errors generated by the AR(1) model minus the cumulative sum of squared forecast errors generated by model i for a Medium size VAR and forecast horizon $h = 1$,

$$CSSFED_{ijht} = \sum_{\tau=\underline{t}}^{t} \left(e^2_{bcmk,j,\tau+h} - e^2_{i,j,\tau+h} \right)$$

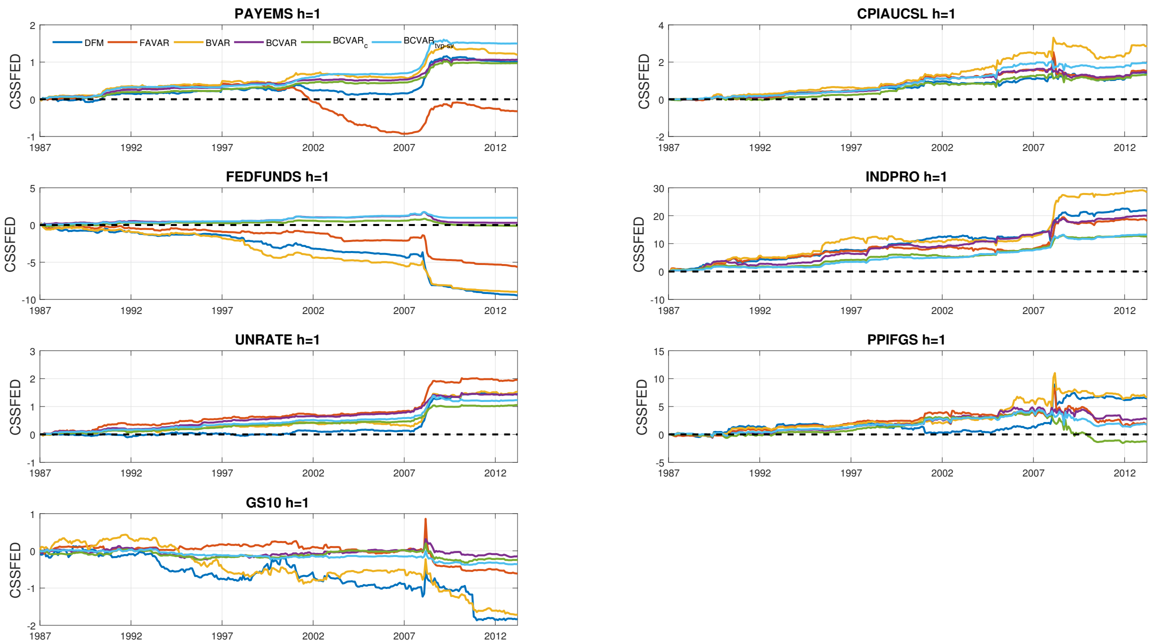
where $t = \underline{t}, ..., \bar{t} - h$. Values above zero indicate that model i generates better performance than the benchmark, while negative values suggest the opposite. $i \in \{\mathrm{DFM}, \mathrm{FAVAR}, \mathrm{BVAR}, \mathrm{BCVAR}, \mathrm{BCVAR}_c, \mathrm{BCVAR}_{tvp-sv}\}$, $j \in \{\mathrm{PAYEMS}, \mathrm{CPIAUCSL}, \mathrm{FEDFUNDS}, \mathrm{INDPRO}, \mathrm{UNRATE}, \mathrm{PPIFGS}, \mathrm{GS10}\}$, $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Each panel displays results for a different series.

Figure A.2. Cumulative sum of squared forecast error differentials, Intermediate VAR, $h = 1$



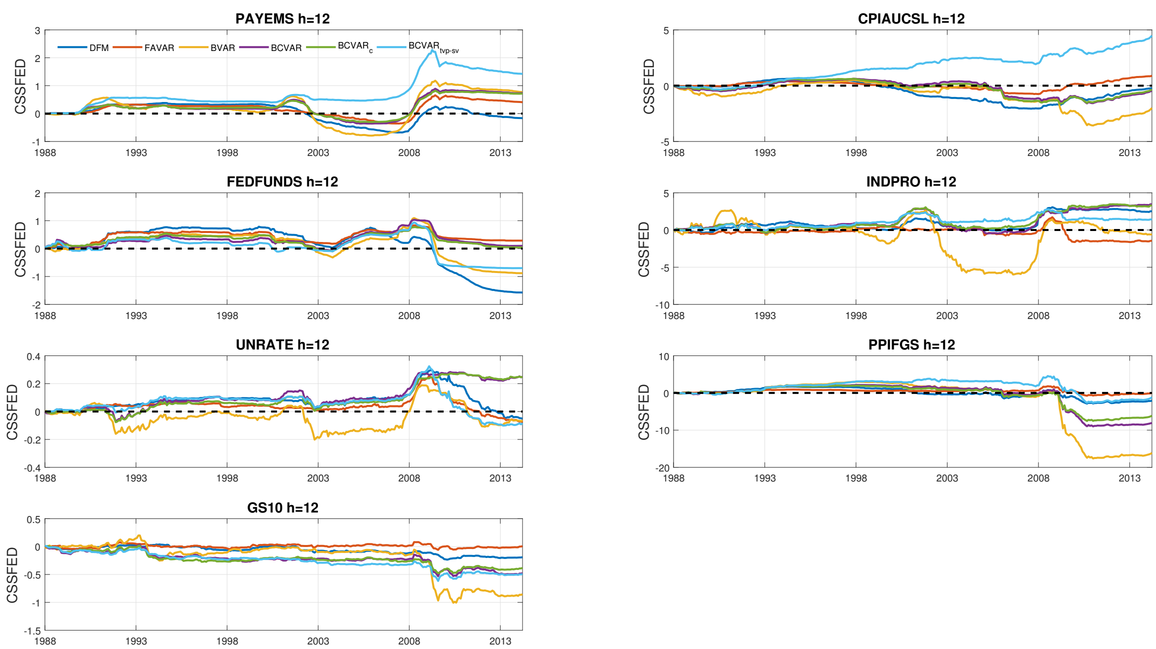
This figure plots the cumulative sum of squared forecast errors generated by the AR(1) model minus the cumulative sum of squared forecast errors generated by model i for an Intermediate size VAR and forecast horizon $h = 1$. $i \in \{\mathrm{DFM}, \mathrm{FAVAR}, \mathrm{BVAR}, \mathrm{BCVAR}, \mathrm{BCVAR}_c, \mathrm{BCVAR}_{tvp-sv}\}$. See notes to Figure A.1 for additional details.

Figure A.3. Cumulative sum of squared forecast error differentials, Large VAR, $h = 1$



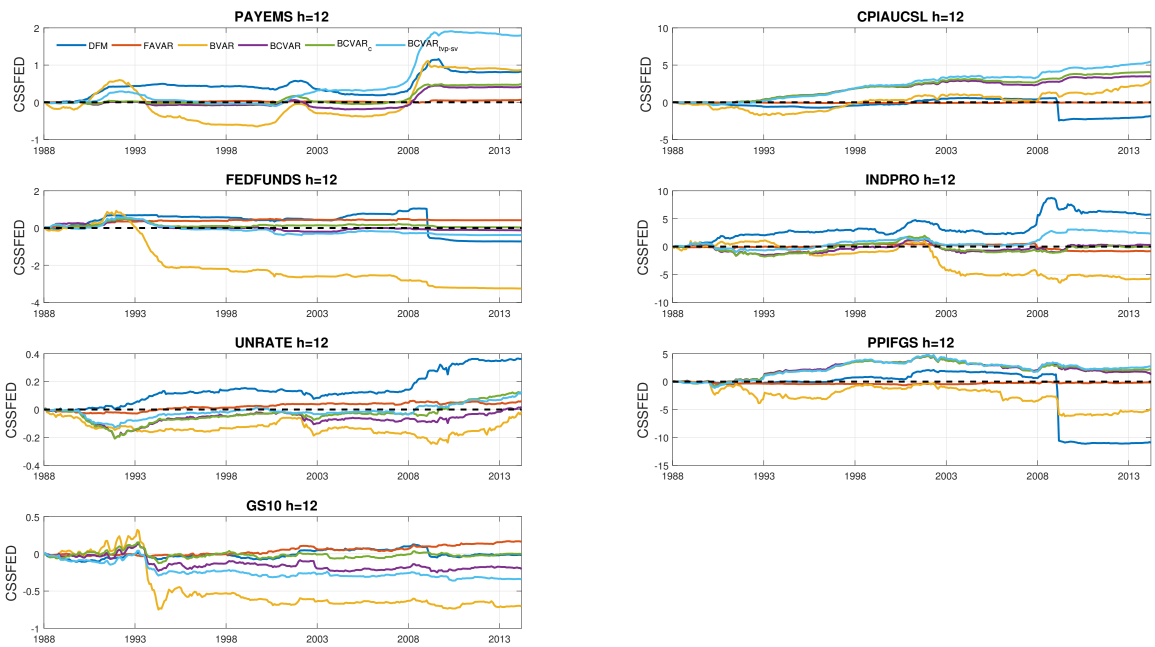
This figure plots the cumulative sum of squared forecast errors generated by the AR(1) model minus the cumulative sum of squared forecast errors generated by model i for a Large size VAR and forecast horizon $h = 1$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.1 for additional details.

Figure A.4. Cumulative sum of squared forecast error differentials, Medium VAR, $h = 12$



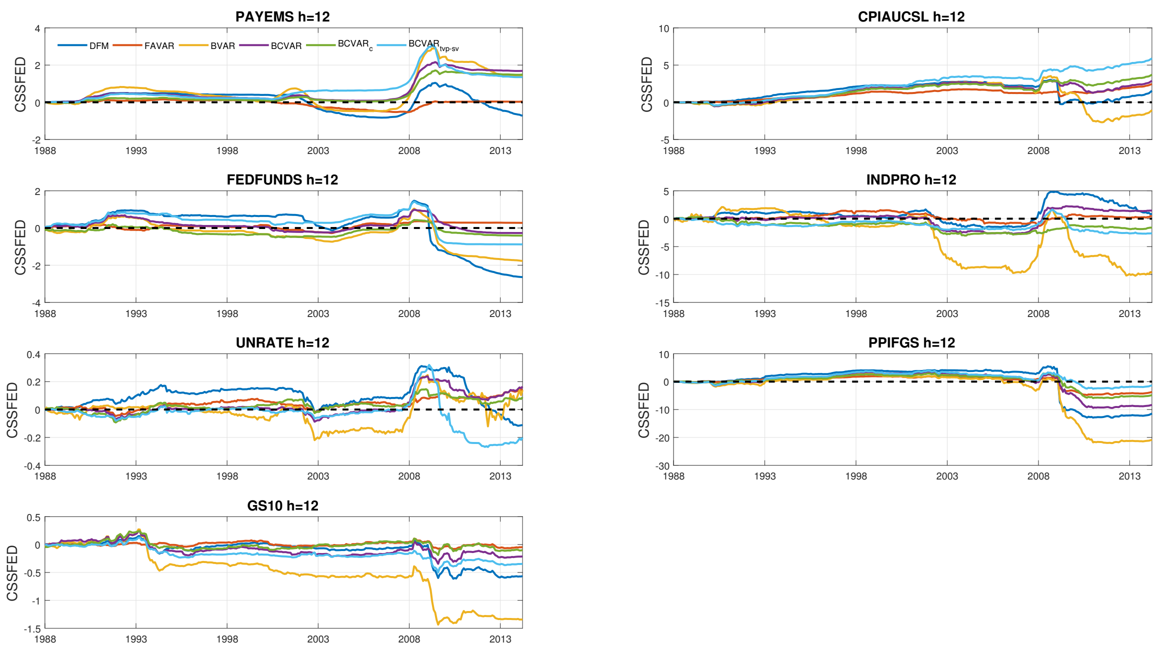
This figure plots the cumulative sum of squared forecast errors generated by the AR(1) model minus the cumulative sum of squared forecast errors generated by model i for a Medium size VAR and forecast horizon $h = 12$. $i \in \{\mathrm{DFM}, \mathrm{FAVAR}, \mathrm{BVAR}, \mathrm{BCVAR}, \mathrm{BCVAR}_c, \mathrm{BCVAR}_{tvp-sv}\}$. See notes to Figure A.1 for additional details.

Figure A.5. Cumulative sum of squared forecast error differentials, Intermediate VAR, $h = 12$



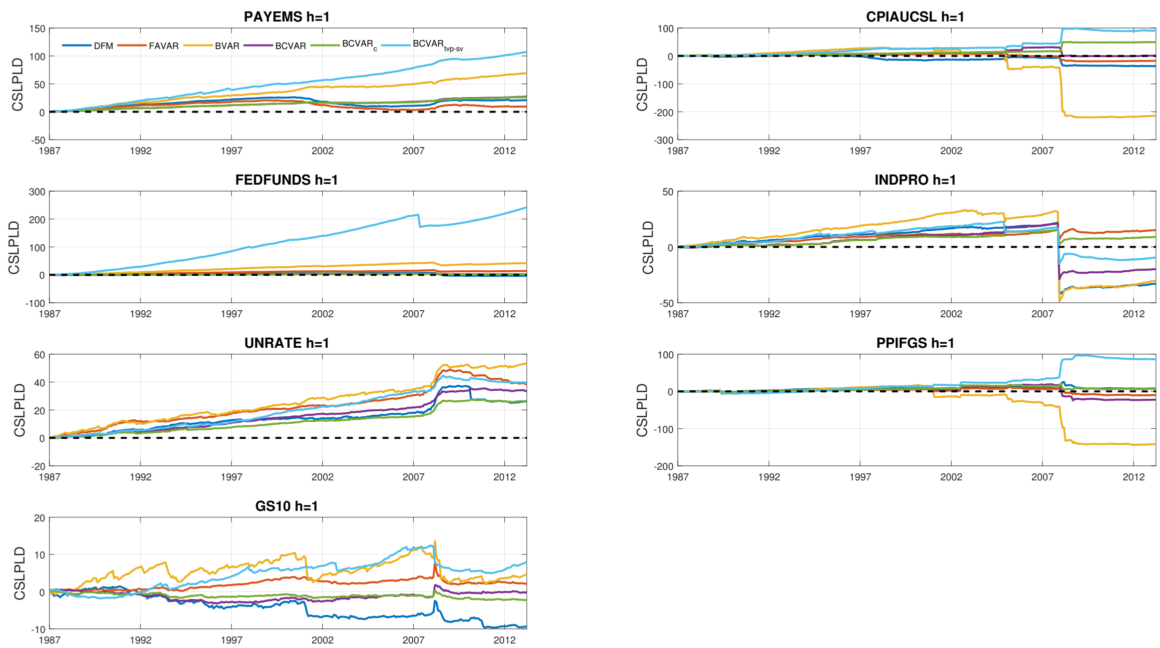
This figure plots the cumulative sum of squared forecast errors generated by the AR(1) model minus the cumulative sum of squared forecast errors generated by model i for an Intermediate size VAR and forecast horizon $h = 12$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.1 for additional details.

Figure A.6. Cumulative sum of squared forecast error differentials, Large VAR, $h = 12$



This figure plots the cumulative sum of squared forecast errors generated by the AR(1) model minus the cumulative sum of squared forecast errors generated by model i for a Large size VAR and forecast horizon $h = 12$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.1 for additional details.

Figure A.7. Cumulative sum of log predictive likelihood differentials, Medium VAR, $h = 1$

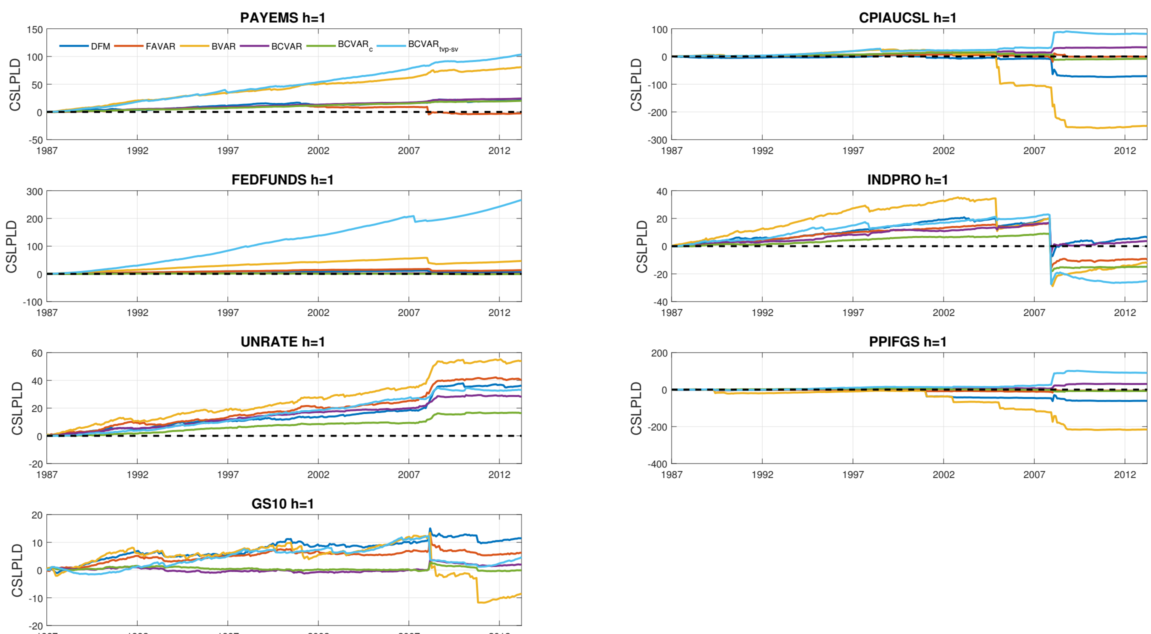


This figure plots the cumulative sum of log predictive likelihoods generated by model i minus the cumulative sum of log predictive likelihoods generated by the AR(1) model for a Medium size VAR and forecast horizon $h = 1$,

$$CSLPLD_{ijht} = \sum_{\tau=\underline{t}}^{t} (LPL_{i,j,\tau+h} - LPL_{bcmk,j,\tau+h})$$

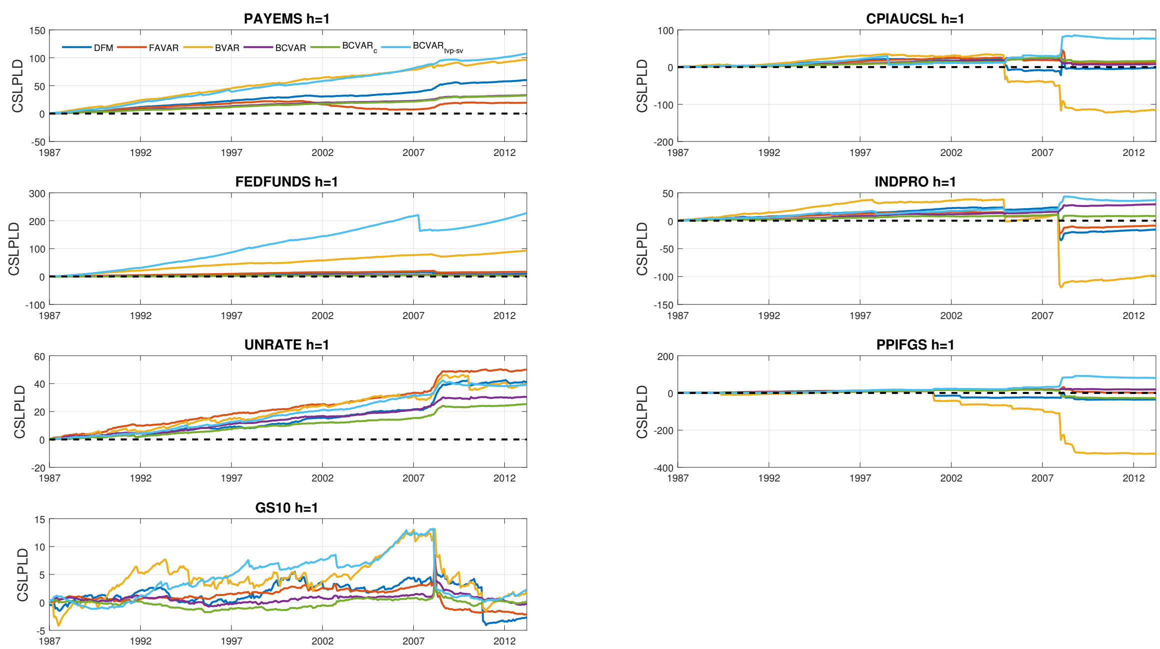
where $t = \underline{t}, ..., \bar{t} - h$. Values above zero indicate that model i generates better performance than the benchmark, while negative values suggest the opposite. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$, $j \in \{PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10\}$, $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Each panel displays results for a different series.

Figure A.8. Cumulative sum of log predictive likelihood differentials, Intermediate VAR, $h = 1$



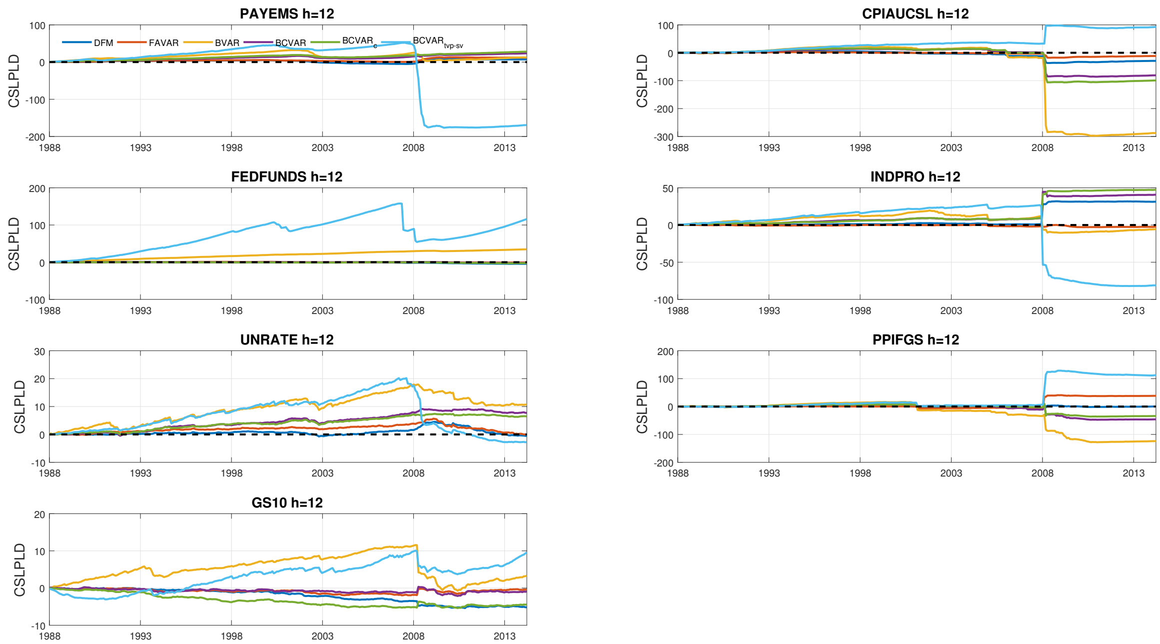
This figure plots the cumulative sum of log predictive likelihoods generated by model i minus the cumulative sum of log predictive likelihoods generated by the AR(1) model for an Intermediate size VAR and forecast horizon $h = 1$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.7 for additional details.

Figure A.9. Cumulative sum of log predictive likelihood differentials, Large VAR, $h = 1$



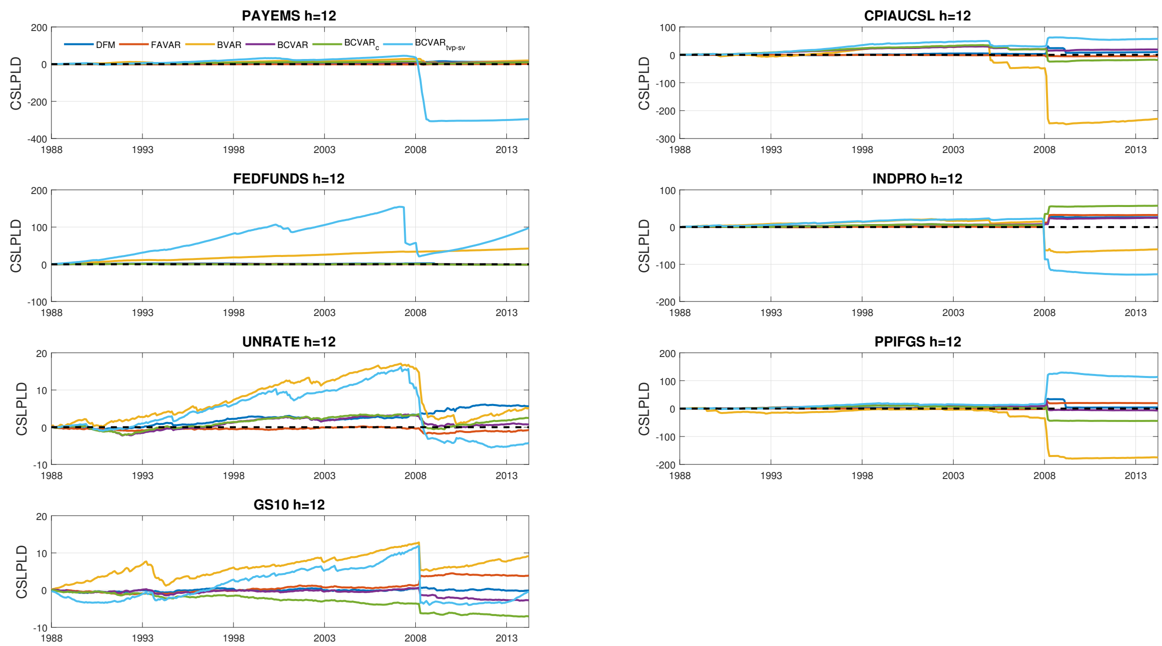
This figure plots the cumulative sum of log predictive likelihoods generated by model i minus the cumulative sum of log predictive likelihoods generated by the AR(1) model for a Large size VAR and forecast horizon $h = 1$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.7 for additional details.

Figure A.10. Cumulative sum of log predictive likelihood differentials, Medium VAR, $h = 12$



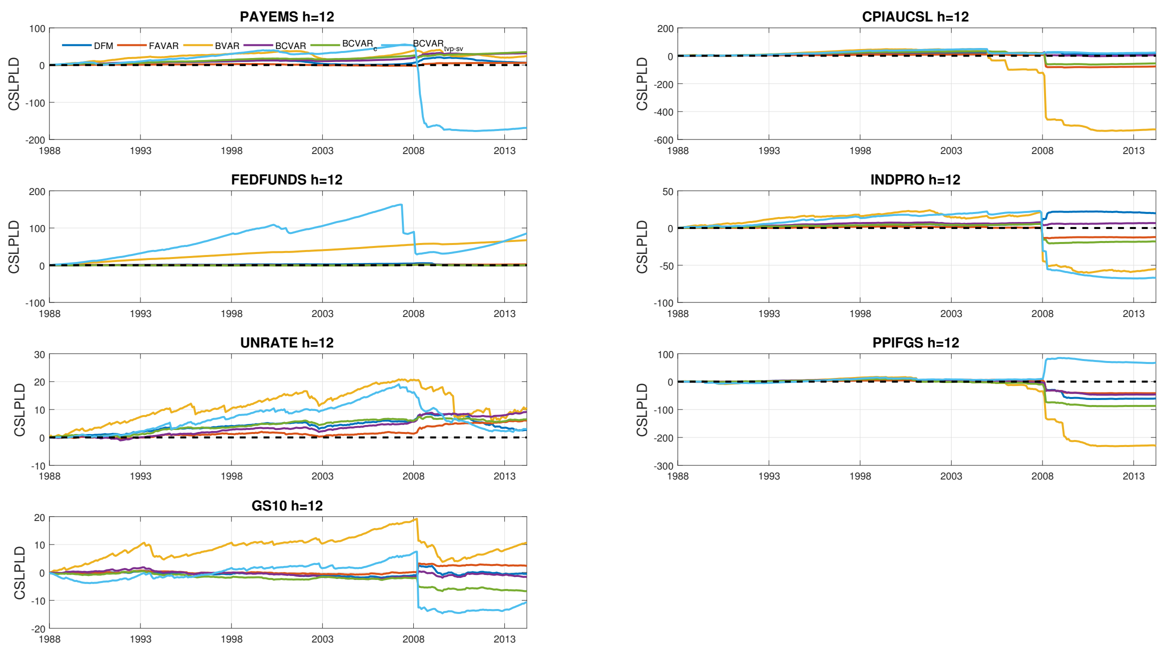
This figure plots the cumulative sum of log predictive likelihoods generated by model i minus the cumulative sum of log predictive likelihoods generated by the AR(1) model for a Medium size VAR and forecast horizon $h = 12$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.7 for additional details.

Figure A.11. Cumulative sum of log predictive likelihood differentials, Intermediate VAR, $h = 12$



This figure plots the cumulative sum of log predictive likelihoods generated by model i minus the cumulative sum of log predictive likelihoods generated by the AR(1) model for an Intermediate size VAR and forecast horizon $h = 12$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.7 for additional details.

Figure A.12. Cumulative sum of log predictive likelihood differentials, Large VAR, $h = 12$



This figure plots the cumulative sum of log predictive likelihoods generated by model i minus the cumulative sum of log predictive likelihoods generated by the AR(1) model for a Large size VAR and forecast horizon $h = 12$. $i \in \{\text{DFM}, \text{FAVAR}, \text{BVAR}, \text{BCVAR}, \text{BCVAR}_c, \text{BCVAR}_{tvp-sv}\}$. See notes to Figure A.7 for additional details.

Appendix B Results for Intermediate VAR

Table B.1. Out-of-sample point forecast performance, Intermediate VAR

Variable	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
			$h=1$					$h=2$		
PAYEMS	1.137	1.146	**0.792****	0.831***	0.864***	0.869	0.914	**0.512*****	0.747***	0.762***
CPIAUCSL	1.148	1.017	1.000	0.951	**0.942***	1.165	1.085	1.099	0.911**	**0.898*****
FEDFUNDS	2.449	1.731	2.449	0.949	**0.944**	1.961	1.376	2.532	0.963	**0.924**
INDPRO	0.824**	0.877***	**0.778*****	0.820***	0.904***	0.855	0.918*	**0.771****	0.907**	0.935*
UNRATE	0.851**	0.798***	**0.770*****	0.809***	0.897***	0.803**	0.841***	**0.794****	0.857***	0.893***
PPIFGS	1.042	1.002	1.041	**0.967**	0.991	1.157	1.057	1.166	1.013	**1.006**
GS10	1.015	1.001	1.113	**0.997**	1.002	0.999	1.023	1.116	**0.996**	1.009
			$h=3$					$h=6$		
PAYEMS	0.780	0.842*	**0.467*****	0.717***	0.732***	0.841	0.920*	**0.604****	0.764**	0.783***
CPIAUCSL	1.132	1.061	1.146	**0.923****	0.926**	1.045	1.018	0.988	0.897***	**0.885*****
FEDFUNDS	1.714	1.063	2.174	1.001	**0.989**	1.247	0.974	1.234	0.998	**0.963**
INDPRO	0.900	0.944	**0.852**	0.927**	0.938*	**0.939**	0.981	0.980	0.975	0.971
UNRATE	0.855*	0.911**	**0.840***	0.906**	0.930**	0.906**	0.956***	**0.887****	0.927**	0.962
PPIFGS	1.143	**1.003**	1.168	1.004	1.007	1.104	1.008	1.088	1.001	**0.993**
GS10	1.040	**1.024**	1.211	1.050	1.047	1.038	**1.009**	1.098	1.031	1.022
			$h=9$					$h=12$		
PAYEMS	0.877	0.962**	**0.762**	0.858*	0.863**	0.926	0.994	**0.922**	0.962	0.956
CPIAUCSL	1.047	0.998	0.910	0.848***	**0.841*****	1.065	1.002	0.898	0.880***	**0.860*****
FEDFUNDS	1.113	1.008	1.179	**0.970**	1.025	1.062	**0.964***	1.281	1.010	0.997
INDPRO	**0.962**	1.009	1.003	0.987	0.988	**0.957**	1.006	1.043	0.998	1.000
UNRATE	**0.949****	0.987	0.965	0.979	0.987	**0.954****	0.992	1.002	0.998	0.985
PPIFGS	1.059	1.002	1.049	**0.973**	0.973	1.096	1.002	1.042	0.989	**0.981**
GS10	0.998	0.998	1.043	**0.995**	1.022	1.001	**0.990**	1.043	1.012	1.000

This table reports the ratio between the MSFE of model i and the MSFE of the benchmark AR(1) for the Intermediate VAR, computed as

$$MSFE_{ijh} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} e^2_{i,j,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} e^2_{bcmk,j,\tau+h}},$$

where $e^2_{i,j,\tau+h}$ and $e^2_{bcmk,j,\tau+h}$ are the squared forecast errors of variable j at time τ and forecast horizon h generated by model i and the AR(1) model, respectively. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$}, $j \in$ {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}, and $h \in \{1, 2, 3, 6, 9, 12\}$. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest MSFE across all models for a given variable-forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table B.2. Out-of-sample density forecast performance, Intermediate VAR

Variable	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
			$h=1$					$h=2$		
PAYEMS	0.065***	-0.008	**0.254*** **	0.076***	0.063***	0.138***	0.079***	**0.406*** **	0.140***	0.137***
CPIAUCSL	-0.223	-0.002	-0.787	**0.104** **	-0.026	-0.800	0.061	-2.100	0.032	**0.182** **
FEDFUNDS	0.022	0.042**	**0.147** **	0.004	-0.002	-0.002	**0.018**	-0.026	0.000	0.009
INDPRO	**0.020**	-0.030	-0.039	0.011	-0.047	0.162***	0.064	**0.181** **	0.065***	0.090**
UNRATE	0.114***	0.127***	**0.170*** **	0.089***	0.051***	0.118***	0.080***	**0.150*** **	0.083***	0.058***
PPIFGS	-0.191	-0.021	-0.679	**0.096* **	-0.024	-0.477	-0.091	-1.105	**0.053**	-0.048
GS10	**0.036* **	0.020	-0.027	0.006	0.000	0.017	0.014	0.017	**0.021**	-0.003
			$h=3$					$h=6$		
PAYEMS	0.141***	0.060***	**0.416*** **	0.159***	0.160***	0.082**	0.029	**0.300*** **	0.121***	0.140***
CPIAUCSL	-0.246	-0.086	-1.873	**-0.073**	-0.075	-0.091	0.078	-0.826	**0.087** **	-0.061
FEDFUNDS	-0.046	0.011	**0.029**	0.004	0.006	-0.007	-0.002	**0.159*** **	0.003	0.012*
INDPRO	-0.022	0.005	-0.056	**0.010**	-0.021	**0.069** **	-0.128	-0.315	-0.063	-0.149
UNRATE	0.081***	0.035**	**0.119*** **	0.061***	0.054***	0.039***	0.017**	**0.092*** **	0.042***	0.023**
PPIFGS	-0.193	-0.061	-1.087	**0.029**	-0.125	-0.064	**0.049**	-0.791	0.007	-0.099
GS10	-0.001	-0.010	-0.028	**0.000**	-0.008	-0.005	-0.005	**0.004**	-0.004	-0.009
			$h=9$					$h=12$		
PAYEMS	0.059**	0.019	**0.165*** **	0.095***	0.097***	0.044	0.003	**0.063**	0.034*	0.032
CPIAUCSL	-0.157	**-0.040**	-0.872	-0.104	-0.158	0.032	-0.016	-0.721	**0.059**	-0.058
FEDFUNDS	-0.006	-0.006	**0.145*** **	-0.002	-0.003	-0.001	-0.002	**0.133*** **	-0.003	-0.004
INDPRO	**0.085**	0.029	-0.178	0.027***	0.050	0.083	0.102	-0.188	0.078	**0.180**
UNRATE	0.033***	-0.002	**0.050** **	0.017**	0.013*	**0.018** **	-0.002	0.017	0.002	0.008
PPIFGS	-0.036	**-0.021**	-0.647	-0.047	-0.047	0.014	**0.061**	-0.549	-0.021	-0.138
GS10	0.004	-0.001	**0.034**	0.001	-0.017	0.000	0.012	**0.029**	-0.009	-0.022

This table reports the average log predictive likelihood (ALPL) differential between model i and the benchmark AR(1) for the Intermediate VAR , computed as

$$ALPL_{ijh} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(LPL_{i,j,\tau+h} - LPL_{bcmk,j,\tau+h} \right),$$

where $LPL_{i,j,\tau+h}$ and $LPL_{bcmk,j,\tau+h}$ are the log predictive likelihoods of variable j at time τ and forecast horizon h generated by model i and the AR(1) model, respectively. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$}, $j \in$ {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}, and $h \in \{1, 2, 3, 6, 9, 12\}$. All density forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the highest ALPL across all models for a given variable-forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table B.3. Out-of-sample forecast performance: Multivariate results

Fcst h.	*Intermediate VAR*									
	WMSFE					*MVALPL*				
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.160	1.048	1.103	**0.906*****	0.939***	0.710***	0.820***	**0.988*****	0.933***	0.253***
h= 2	1.117	1.033	1.148	**0.919*****	0.924***	0.847***	0.844***	0.895***	**1.011*****	0.360***
h= 3	1.083	0.981	1.126	**0.934****	0.939***	0.886***	0.835***	0.945***	**1.023*****	0.264***
h= 6	1.016	0.980**	0.977	0.937**	**0.935****	0.937***	0.828***	**1.187*****	1.054***	0.276***
h= 9	0.999	0.994	0.979	**0.939****	0.951**	0.935***	0.828***	**1.198*****	1.043***	0.271***
h=12	1.009	0.993*	1.026	0.975	**0.965****	0.886***	0.837***	**1.017*****	0.956***	0.157*

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark AR(1) model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$}, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark AR(1), computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

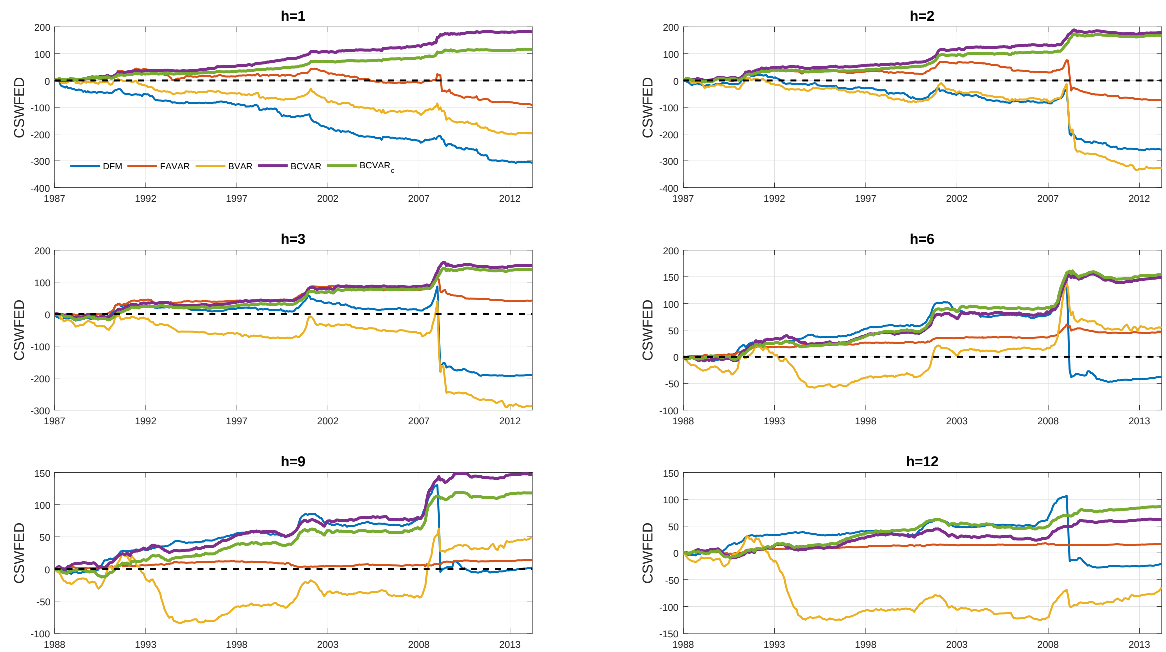
where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given forecast horizon. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table B.4. Out-of-sample forecast performance: Compressed TVP-SV VAR

Variable	*Intermediate VAR*											
	MSFE						*ALPL*					
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.699*****	0.566***	0.565***	0.648**	**0.739****	**0.837**	**0.326*****	0.387***	0.335***	-0.064	-0.508	-0.929
CPIAUCSL	**0.939**	**0.870*****	**0.862*****	**0.843*****	**0.796*****	**0.809*****	**0.257**	**0.486**	**0.306**	**0.244**	**0.345**	**0.181**
FEDFUNDS	**0.875****	**0.847****	**0.843****	**0.932**	**0.968**	1.033	**0.838*****	**0.616****	**0.531***	**0.380**	0.073	**0.307**
INDPRO	0.904***	0.930*	0.936*	0.962	0.983	0.982	-0.079	-0.085	-0.189	-0.348	-0.290	-0.399
UNRATE	0.862***	0.863***	0.899**	0.926**	0.959**	0.984	0.104***	0.104***	0.078***	0.052***	0.031	-0.013
PPIFGS	0.972	**0.985**	**0.983**	**0.987**	**0.958**	**0.976**	**0.285**	**0.400**	**0.371**	**0.361**	**0.379**	**0.359**
GS10	1.013	1.007	1.037	1.023	1.012	1.021	0.015	0.009	-0.049	-0.008	-0.013	-0.001
Multivariate	0.910***	**0.878*****	**0.877*****	**0.896*****	**0.908*****	**0.941****	**1.633*****	**1.635*****	**1.511*****	**1.215*****	0.966***	0.674

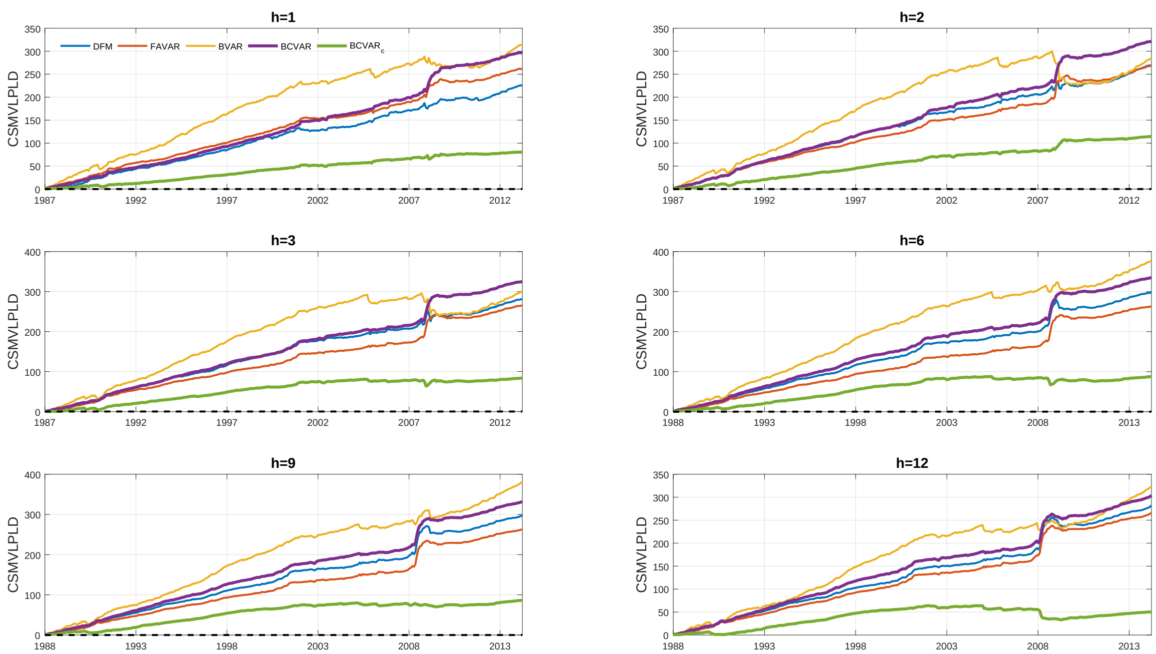
The left half of this table reports the ratio between the univariate or multivariate weighted mean squared forecast error of the BCVAR_{tvp-sv} model and the univariate or multivariate weighted mean squared forecast error of the benchmark AR(1) model. The right half of the table shows the univariate or multivariate average log predictive likelihood differentials between the BCVAR_{tvp-sv} model and the benchmark AR(1) model. h denotes the forecast horizons, with $h \in \{1, 2, 3, 6, 9, 12\}$. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate all instances where the BCVAR_{tvp-sv} model outperforms all alternative models (DFM, FAVAR, BVAR, BCVAR, BCVAR_c), for any given variable/forecast horizon combination. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Figure B.1. Cumulative sum of weighted forecast error differentials, Intermediate VAR



This figure plots the cumulative sum of weighted forecast errors generated by the AR(1) model minus the cumulative sum of weighted forecast errors generated by model i for the Intermediate VAR. We define the weighted forecast error of model i and the AR(1) model at time $\tau + h$ as $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$, where $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$}, and $h \in \{1, 2, 3, 6, 9, 12\}$. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Each panel displays results for a different forecast horizon.

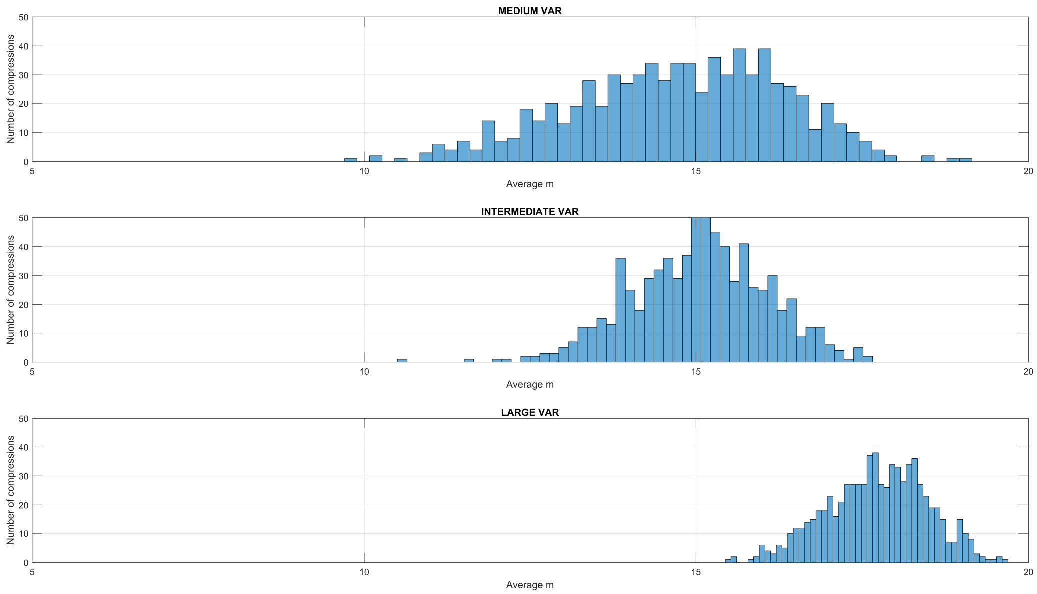
Figure B.2. Cumulative sum of multivariate log predictive likelihood differentials, Intermediate VAR



This figure plots the cumulative sum of the multivariate log predictive likelihoods generated by model i minus the cumulative sum of the multivariate log predictive likelihoods computed from an AR(1) model for the Intermediate VAR. $i \in \{\text{DFM, FAVAR, BVAR, BCVAR, BCVAR}_c\}$, $h \in \{1, 2, 3, 6, 9, 12\}$, and the multivariate log predictive likelihoods are computed under the assumption of joint normality, as described in the text. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Each panel displays results for a different forecast horizon.

Appendix C Additional analysis

Figure C.1. Average compression size (m) for top 75% compressions

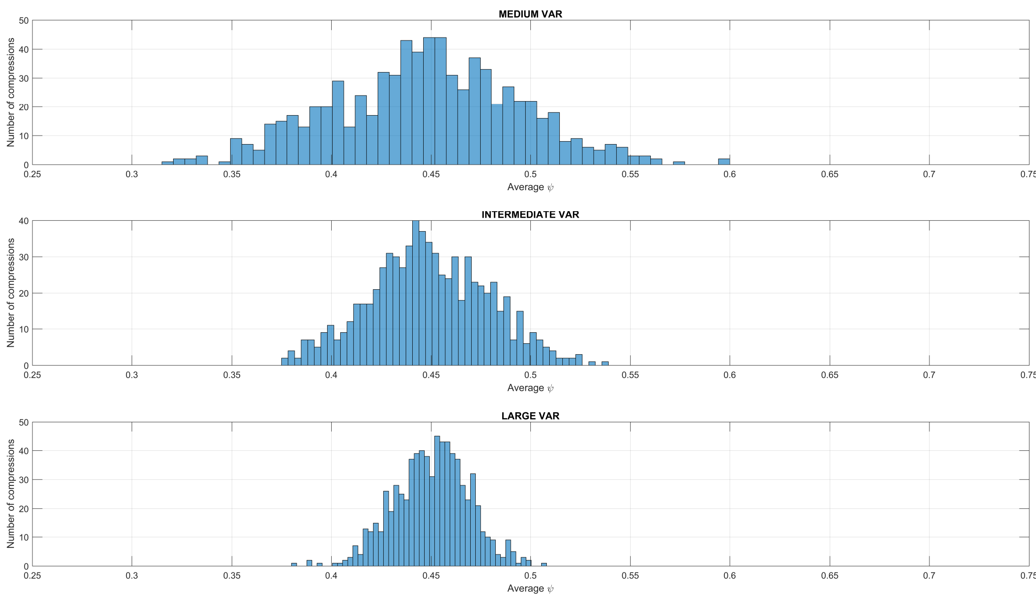


This figure display the empirical distribution of the average number of rows of the random compression matrices Φ_i, $i = 1, ..., n$ averaged across all n equations of the VAR, and according to the top 75% compressions, ranked in terms of the VAR overall BIC. For each of the n equations in the VAR, the model specification is

$$Y_{i,t} = \Theta_i^c \left(\Phi_i Z_t^i\right) + \sigma_i E_{i,t} \qquad i = 1, ..., n$$

where Z_t^i denotes the subset of the vector Z_t which applies to the i-th equation of the VAR: $Z_t^1 = (Y_{t-1})$, $Z_t^2 = \left(Y_{t-1}', -Y_{1,t}\right)'$, $Z_t^3 = \left(Y_{t-1}', -Y_{1,t}, -Y_{2,t}\right)'$, and so on. Similarly, Φ_i is a matrix with m rows and column dimension that conforms with Z_t^i.

Figure C.2. Average sparsity (φ) for top 75% compressions

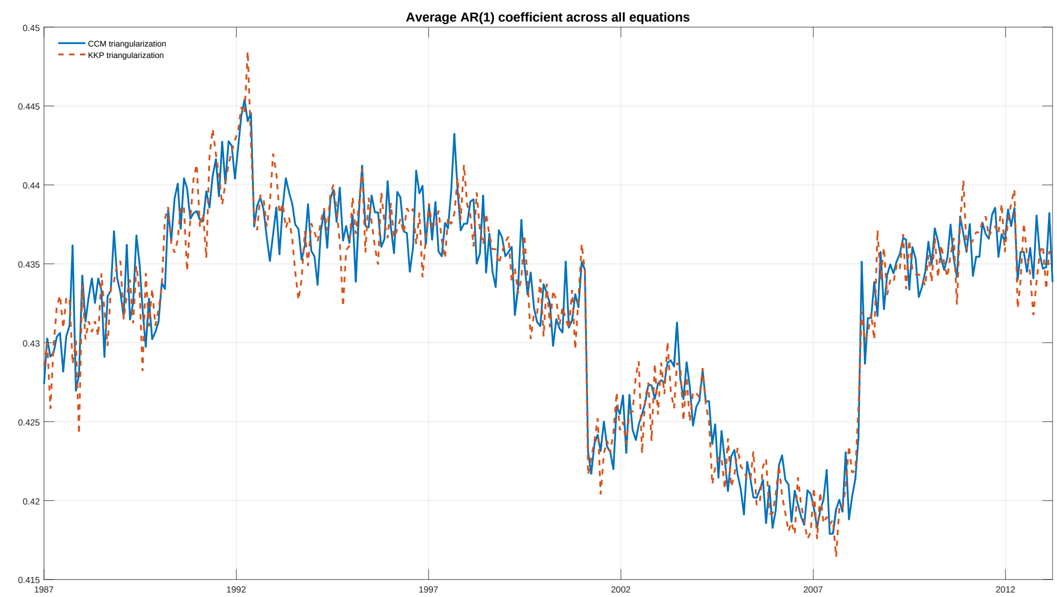


This figure display the empirical distribution of the average sparsity factor φ of the matrix Φ_i, $i = 1, ..., n$ averaged across all n equations of the VAR, and according to the top 75% compressions, ranked in terms of the VAR overall BIC. For each of the n equations in the VAR, the model specification is

$$Y_{i,t} = \Theta_i^c \left(\Phi_i Z_t^i \right) + \sigma_i E_{i,t} \quad i = 1, ..., n$$

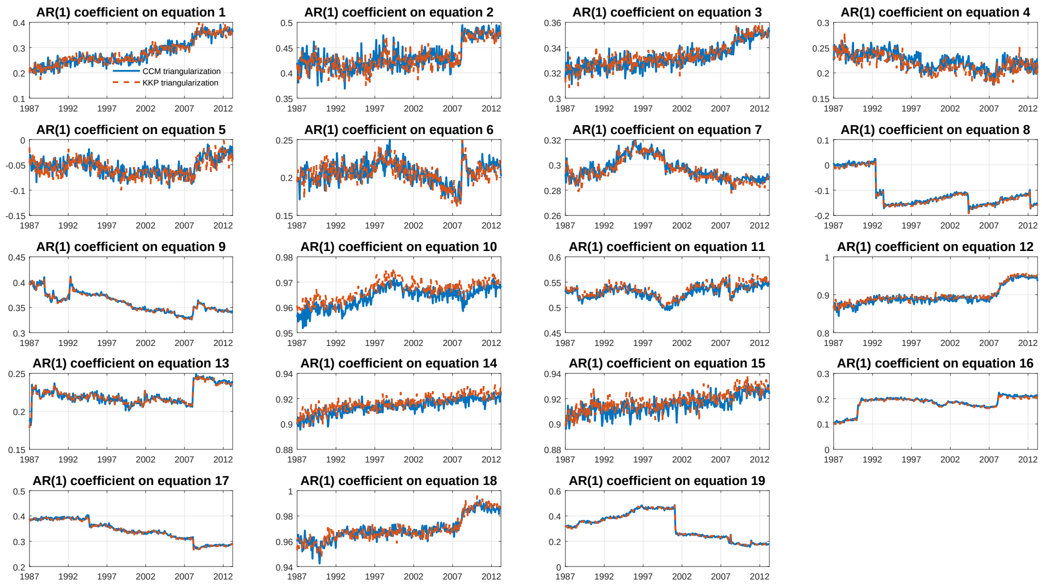
where Z_t^i denotes the subset of the vector Z_t which applies to the i-th equation of the VAR: $Z_t^1 = (Y_{t-1})$, $Z_t^2 = \left(Y_{t-1}^{'}, -Y_{1,t} \right)^{'}$, $Z_t^3 = \left(Y_{t-1}^{'}, -Y_{1,t}, -Y_{2,t} \right)^{'}$, and so on. Similarly, Φ_i is a matrix with m rows and column dimension that conforms with Z_t^i.

Figure C.3. Average AR(1) coefficients across equations, Medium VAR



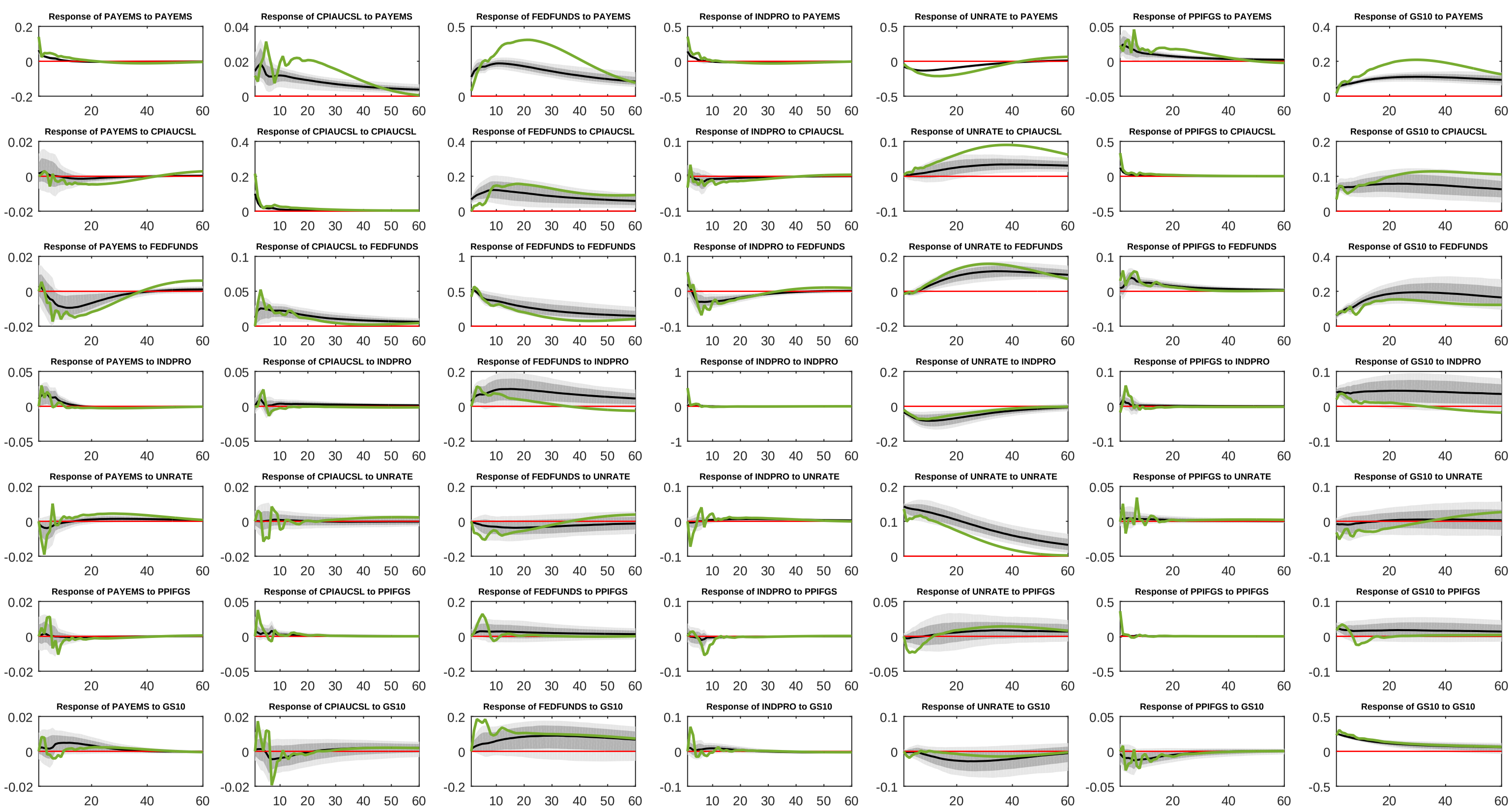
This figure displays the average of all 19 first own lag coefficients using the Carriero, Clark and Marcellino (2016b) and our triangularization algorithms in the Medium VAR. For the first method this is the average of all elements B_{ii} for $i = 1, ..., 19$ where $B = B^c\Phi$. For the second method this is the average of all elements B_{ii} for $i = 1, ..., 19$ where $B = A^{-1}(\Gamma^c\Phi)$. The x-axis represents the 318 observations in the evaluation sample.

Figure C.4. AR(1) coefficients across equations, Medium VAR



This figure displays each of the 19 first own lag coefficients using the Carriero, Clark and Marcellino (2016b) and our triangularization algorithms in the Medium VAR. For the first method these are the elements B_{ii} for $i = 1, ..., 19$ where $B = B^c\Phi$. For the second method these are the elements B_{ii} for $i = 1, ..., 19$ where $B = A^{-1}(\Gamma^c\Phi)$. The x-axis represents the 318 observations in the evaluation sample.

Figure C.5. Impulse response functions, Medium VAR



This figure depicts the impulse response functions for the seven variables of interest (PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10), obtained using the Medium VAR. Shaded areas denote the 68% posterior probability intervals of the impulse response functions from the Medium BCVAR for the seven variables of interest, with the posterior median represented by the black line. Green lines are the mean impulse responses from the same VAR estimated with OLS.

Table C.1. Out-of-sample forecast performance: Multivariate results, alternative triangularization schemes

Fcst h.	*Medium VAR*							
	WMSFE				*MVALPL*			
	$BCVAR_{ccm}$	$BCVAR$	$BCVAR_{ccm,c}$	$BCVAR_c$	$BCVAR_{ccm}$	$BCVAR$	$BCVAR_{ccm,c}$	$BCVAR_c$
h= 1	0.941***	**0.916*****	0.934***	0.935***	0.659***	**0.925*****	0.300***	0.285***
h= 2	0.933***	0.929**	**0.925*****	0.926***	0.806***	**1.021*****	0.426***	0.401***
h= 3	0.949*	0.944*	0.950	**0.940***	0.810***	**1.046*****	0.417***	0.356***
h= 6	**0.953**	0.961	0.964	0.954	0.753***	**1.009*****	0.288***	0.296***
h= 9	0.958	**0.957**	0.961	0.960	0.738***	**1.017*****	0.242***	0.254***
h=12	1.001	0.996	**0.994**	0.994	0.663***	**0.886*****	0.182***	0.176***
	Intermediate VAR							
	WMSFE				*MVALPL*			
	$BCVAR_{ccm}$	$BCVAR$	$BCVAR_{ccm,c}$	$BCVAR_c$	$BCVAR_{ccm}$	$BCVAR$	$BCVAR_{ccm,c}$	$BCVAR_c$
h= 1	0.946***	**0.906*****	0.939***	0.939***	0.730***	**0.933*****	0.265***	0.253***
h= 2	0.940***	**0.919*****	0.924***	0.924***	0.851***	**1.011*****	0.333***	0.360***
h= 3	0.936***	**0.934****	0.937**	0.939***	0.850***	**1.023*****	0.293***	0.264***
h= 6	0.937***	0.937**	0.941**	**0.935****	0.882***	**1.054*****	0.278***	0.276***
h= 9	0.949**	**0.939****	0.941**	0.951**	0.879***	**1.043*****	0.261***	0.271***
h=12	0.975**	0.975	0.971*	**0.965****	0.825***	**0.956*****	0.168**	0.157*
	Large VAR							
	WMSFE				*MVALPL*			
	$BCVAR_{ccm}$	$BCVAR$	$BCVAR_{ccm,c}$	$BCVAR_c$	$BCVAR_{ccm}$	$BCVAR$	$BCVAR_{ccm,c}$	$BCVAR_c$
h= 1	0.963**	**0.907*****	0.935***	0.940***	0.511***	**0.996*****	0.290***	0.303***
h= 2	0.939**	0.909***	0.917**	**0.908*****	0.648***	**1.139*****	0.371***	0.406***
h= 3	0.934*	**0.916****	0.923*	0.922**	0.697***	**1.179*****	0.319***	0.368***
h= 6	0.942	**0.933**	0.949	0.940	0.633***	**1.131*****	0.301***	0.269***
h= 9	0.946	**0.938**	0.939	0.943	0.608***	**1.076*****	0.253***	0.243***
h=12	0.968	0.969	**0.963**	0.968	0.544***	**1.009*****	0.145	0.145

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark AR(1) model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in \{\text{BCVAR}_{ccm}, \text{BCVAR}, \text{BCVAR}_{ccm,c}, \text{BCVAR}_c\}$, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark AR(1), computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given VAR size - forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.2. Out-of-sample forecast performance: Multivariate results, alternative BMA schemes

Fcst h.	*Medium VAR*							
	WMSFE				*MVALPL*			
	$BCVAR_{alt}$	$BCVAR$	$BCVAR_{c,alt}$	$BCVAR_c$	$BCVAR_{alt}$	$BCVAR$	$BCVAR_{c,alt}$	$BCVAR_c$
h= 1	0.930***	**0.916*** **	0.934***	0.935***	0.339***	**0.925*** **	0.278***	0.285***
h= 2	0.934***	0.929**	0.930***	**0.926*** **	0.367***	**1.021*** **	0.396***	0.401***
h= 3	0.948*	0.944*	0.946**	**0.940***	0.353***	**1.046*** **	0.349***	0.356***
h= 6	**0.948**	0.961	0.949	0.954	0.276*	**1.009*** **	0.251**	0.296***
h= 9	**0.945***	0.957	0.946**	0.960	0.241	**1.017*** **	0.222*	0.254***
h=12	**0.982**	0.996	0.983	0.994	0.110	**0.886*** **	0.121	0.176***
	Intermediate VAR							
	$BCVAR_{alt}$	$BCVAR$	$BCVAR_{c,alt}$	$BCVAR_c$	$BCVAR_{alt}$	$BCVAR$	$BCVAR_{c,alt}$	$BCVAR_c$
h= 1	0.919***	**0.906*** **	0.940***	0.939***	0.358***	**0.933*** **	0.270***	0.253***
h= 2	0.923***	**0.919*** **	0.929***	0.924***	0.407***	**1.011*** **	0.358***	0.360***
h= 3	**0.934*** **	0.934**	0.934***	0.939***	0.327***	**1.023*** **	0.312***	0.264***
h= 6	**0.933** **	0.937**	0.936***	0.935**	0.351***	**1.054*** **	0.308***	0.276***
h= 9	**0.939** **	0.939**	0.940***	0.951**	0.354***	**1.043*** **	0.331***	0.271***
h=12	0.971**	0.975	0.966***	**0.965** **	0.194	**0.956*** **	0.170	0.157*
	Large VAR							
	$BCVAR_{alt}$	$BCVAR$	$BCVAR_{c,alt}$	$BCVAR_c$	$BCVAR_{alt}$	$BCVAR$	$BCVAR_{c,alt}$	$BCVAR_c$
h= 1	**0.907*** **	0.907***	0.918***	0.940***	0.410***	**0.996*** **	0.365***	0.303***
h= 2	0.909***	0.909***	**0.904*** **	0.908***	0.472***	**1.139*** **	0.444***	0.406***
h= 3	0.914**	0.916**	**0.908** **	0.922**	0.423***	**1.179*** **	0.437***	0.368***
h= 6	0.927	0.933	**0.923***	0.940	0.378***	**1.131*** **	0.356***	0.269***
h= 9	0.928*	0.938	**0.923** **	0.943	0.337**	**1.076*** **	0.310**	0.243***
h=12	**0.951**	0.969	0.951*	0.968	0.231	**1.009*** **	0.211	0.145

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark AR(1) model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in \left\{\text{BCVAR}_{alt}, \text{BCVAR}, \text{BCVAR}_{c,alt}, \text{BCVAR}_c\right\}$, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark AR(1), computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given VAR size - forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.3. Out-of-sample forecast performance: Multivariate results, BVAR as the benchmark

Fcst h.	*Medium VAR*									
	WMSFE					*MVALPL*				
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.023	0.942*	1.000	**0.810*** **	0.826***	-0.428	-0.209	0.000	**-0.054**	-0.694
h= 2	0.943	0.943	1.000	0.833***	**0.830*** **	-0.235	-0.249	0.000	**-0.047**	-0.666
h= 3	0.965	0.969	1.000	0.887*	**0.883***	-0.207	-0.223	0.000	**-0.051**	-0.740
h= 6	1.010	0.975	1.000	0.944	**0.938**	-0.162	-0.193	0.000	**-0.021**	-0.734
h= 9	1.022	0.982	1.000	**0.962**	0.964	-0.171	-0.163	0.000	**-0.004**	-0.767
h=12	0.986	**0.951**	1.000	0.959	0.957	-0.050	-0.060	0.000	**-0.041**	-0.751
	Intermediate VAR									
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.052	0.951	1.000	**0.821*** **	0.852***	-0.278	-0.168	0.000	**-0.055**	-0.735
h= 2	0.973	0.900**	1.000	**0.801*** **	0.805**	-0.048	-0.051	0.000	**0.116**	-0.536
h= 3	0.962	0.872**	1.000	**0.829** **	0.834*	-0.059	-0.110	0.000	**0.078**	-0.682
h= 6	1.040	1.004	1.000	0.960	**0.958**	-0.250	-0.359	0.000	**-0.133**	-0.911
h= 9	1.020	1.015	1.000	**0.959**	0.971	-0.263	-0.370	0.000	**-0.154**	-0.926
h=12	0.983	0.968	1.000	0.950	**0.940**	-0.131	-0.180	0.000	**-0.061**	-0.861
	Large VAR									
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.032	0.993	1.000	**0.892*** **	0.925**	0.045	0.030	0.000	**0.091**	-0.602
h= 2	0.985	0.946	1.000	0.863***	**0.862*** **	0.109	0.027	0.000	**0.195**	-0.538
h= 3	0.985	0.927	1.000	**0.876** **	0.882*	0.074	0.025	0.000	**0.205**	-0.606
h= 6	1.037	0.932	1.000	**0.910***	0.917	0.126	0.165	0.000	**0.301**	-0.561
h= 9	1.039	0.956	1.000	**0.930**	0.934	0.092	0.075	0.000	**0.197**	-0.636
h=12	1.003	0.938	1.000	0.924	**0.923**	0.225	0.201	0.000	**0.300**	-0.564

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark BVAR model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$}, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark BVAR model, computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given VAR size - forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.4. Out-of-sample forecast performance: Multivariate results, alternative BIC

Fcst h.				*Medium VAR*						
			WMSFE					*MVALPL*		
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.158	1.066	1.132	**0.918*****	0.930***	0.551***	0.770***	**0.979*****	0.906***	0.306***
h= 2	1.051	1.052	1.115	**0.927****	0.933**	0.832***	0.818***	**1.068*****	1.031***	0.382***
h= 3	1.027	1.031	1.064	**0.942***	0.944*	0.890***	0.874***	**1.097*****	1.048***	0.354***
h= 6	1.027	0.992	1.017	**0.955**	0.955	0.868***	0.837***	**1.030*****	1.002***	0.279***
h= 9	1.017	0.977	0.995	**0.956**	0.960	0.850***	0.858***	**1.021*****	0.976***	0.253***
h=12	1.025	**0.988**	1.039	1.001	0.995	0.877***	0.867***	**0.927*****	0.923***	0.192***
				Intermediate VAR						
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.160	1.048	1.103	**0.907*****	0.941***	0.710***	0.820***	**0.988*****	0.919***	0.245***
h= 2	1.117	1.033	1.148	0.921***	**0.920*****	0.847***	0.844***	0.895***	**1.018*****	0.346***
h= 3	1.083	0.981	1.126	0.936**	**0.931*****	0.886***	0.835***	0.945***	**1.023*****	0.275***
h= 6	1.016	0.980**	0.977	0.937**	**0.936****	0.937***	0.828***	**1.187*****	1.064***	0.291***
h= 9	0.999	0.994	0.979	**0.946****	0.947**	0.935***	0.828***	**1.198*****	1.056***	0.248***
h=12	1.009	0.993*	1.026	0.974	**0.967****	0.886***	0.837***	**1.017*****	0.948***	0.176**
				Large VAR						
	DFM	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR*	*BCVAR$_c$*
h= 1	1.049	1.009	1.017	**0.901*****	0.925***	0.950***	0.935***	0.905***	**1.001*****	0.323***
h= 2	1.037	0.996	1.053	**0.905*****	0.905***	1.053***	0.971***	0.944***	**1.124*****	0.390***
h= 3	1.030	0.970	1.045	0.914**	**0.905****	1.049***	0.999***	0.974***	**1.139*****	0.369***
h= 6	1.063	0.955	1.026	0.934	**0.927**	0.957***	0.995***	0.830***	**1.153*****	0.306***
h= 9	1.049	0.965	1.009	0.938	**0.926***	0.972***	0.954***	0.879***	**1.089*****	0.263***
h=12	1.052	0.984	1.049	0.974	**0.948**	0.934***	0.910***	0.709**	**0.992*****	0.144

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark AR(1) model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$}, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark AR(1), computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given VAR size - forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.5. Out-of-sample forecast performance: Multivariate results, 7 key variables ordered last

Fcst h.	*Medium VAR*									
	WMSFE					*MVALPL*				
	DFM	*FAVAR*	*BVAR*	*BCVAR$_c$*	*BCVAR$_{c,v.2}$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR$_c$*	*BCVAR$_{c,v.2}$*
h= 1	1.158	1.066	1.132	**0.935*****	0.935***	0.551***	0.770***	**0.979*****	0.285***	0.301***
h= 2	1.051	1.052	1.115	**0.926*****	0.926***	0.832***	0.818***	**1.068*****	0.401***	0.403***
h= 3	1.027	1.031	1.064	0.940*	**0.939****	0.890***	0.874***	**1.097*****	0.356***	0.357***
h= 6	1.027	0.992	1.017	**0.954**	0.956	0.868***	0.837***	**1.030*****	0.296***	0.279***
h= 9	1.017	0.977	0.995	0.960	**0.953**	0.850***	0.858***	**1.021*****	0.254***	0.237***
h=12	1.025	**0.988**	1.039	0.994	0.995	0.877***	0.867***	**0.927*****	0.176***	0.166**
	Intermediate VAR									
	DFM	*FAVAR*	*BVAR*	*BCVAR$_c$*	*BCVAR$_{c,v.2}$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR$_c$*	*BCVAR$_{c,v.2}$*
h= 1	1.160	1.048	1.103	0.939***	**0.936*****	0.710***	0.820***	**0.988*****	0.253***	0.293***
h= 2	1.117	1.033	1.148	**0.924*****	0.945***	0.847***	0.844***	**0.895*****	0.360***	0.313***
h= 3	1.083	0.981	1.126	**0.939*****	0.957**	0.886***	0.835***	**0.945*****	0.264***	0.267***
h= 6	1.016	0.980**	0.977	**0.935****	0.952**	0.937***	0.828***	**1.187*****	0.276***	0.242***
h= 9	0.999	0.994	0.979	**0.951****	0.965*	0.935***	0.828***	**1.198*****	0.271***	0.264***
h=12	1.009	0.993*	1.026	**0.965****	0.977	0.886***	0.837***	**1.017*****	0.157*	0.142
	Large VAR									
	DFM	*FAVAR*	*BVAR*	*BCVAR$_c$*	*BCVAR$_{c,v.2}$*	*DFM*	*FAVAR*	*BVAR*	*BCVAR$_c$*	*BCVAR$_{c,v.2}$*
h= 1	1.049	1.009	1.017	**0.940*****	0.945***	**0.950*****	0.935***	0.905***	0.303***	0.304***
h= 2	1.037	0.996	1.053	**0.908*****	0.940*	**1.053*****	0.971***	0.944***	0.406***	0.371***
h= 3	1.030	0.970	1.045	**0.922****	0.947	**1.049*****	0.999***	0.974***	0.368***	0.317***
h= 6	1.063	0.955	1.026	**0.940**	0.953	0.957***	**0.995*****	0.830***	0.269***	0.267***
h= 9	1.049	0.965	1.009	**0.943**	0.961	**0.972*****	0.954***	0.879***	0.243***	0.217**
h=12	1.052	0.984	1.049	**0.968**	0.973	**0.934*****	0.910***	0.709**	0.145	0.143*

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark AR(1) model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in$ {DFM, FAVAR, BVAR, $\text{BCVAR}_c, \text{BCVAR}_{c,v.2}$}, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark AR(1), computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given VAR size - forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.6. Out-of-sample forecast performance: Compressed TVP-SV VAR, BVAR as the benchmark

Variable	*Medium VAR*											
	MSFE						*ALPL*					
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.810****	1.020	1.082	**0.948**	**0.933**	**0.937**	**0.120*****	**0.025**	-0.012	-0.167	-0.514	-0.573
CPIAUCSL	**0.973**	**0.873****	**0.848*****	**0.823****	**0.811*****	**0.790*****	**0.959**	**1.880**	**1.444**	**1.051**	**1.026**	**1.197**
FEDFUNDS	**0.319*****	**0.364*****	**0.497****	0.833*	0.975	0.985	**0.629*****	**0.479***	**0.308**	**0.263**	**0.184**	**0.256**
INDPRO	1.109	1.121	1.009	0.956	0.957	0.985	0.068	-0.175	-0.127	-0.281	-0.262	-0.237
UNRATE	1.081	1.053	1.031	0.992	0.999	1.003	-0.043	-0.026	-0.014	**0.001**	-0.003	-0.042
PPIFGS	**0.987**	**0.914***	**0.908*****	**0.879***	**0.889***	0.886*	**0.718****	**1.074**	**0.884***	**1.091**	**0.820**	**0.744**
GS10	0.932	0.941	0.912	0.924	**0.971**	0.979	**0.011**	-0.007	-0.063	-0.060	-0.046	**0.020**
Multivariate	**0.800*****	**0.793*****	**0.838****	**0.901***	**0.928****	**0.931****	**0.674*****	**0.634*****	**0.476*****	**0.194**	**0.028**	-0.077
	Intermediate VAR											
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.883**	1.106	1.211	1.072	**0.970**	**0.909**	**0.072****	-0.019	-0.081	-0.364	-0.674	-0.992
CPIAUCSL	**0.939**	**0.791***	**0.752***	**0.853***	**0.875****	**0.900***	**1.043****	**2.586**	**2.179**	**1.070**	**1.217**	**0.902**
FEDFUNDS	**0.357*****	**0.334****	**0.388****	**0.755****	**0.821****	0.806*	**0.692*****	**0.642****	**0.502**	**0.221**	-0.072	**0.174**
INDPRO	1.162	1.206	1.098	0.981	0.981	0.942	-0.041	-0.266	-0.133	-0.033	-0.113	-0.211
UNRATE	1.118	1.087	1.070	1.044	0.994	0.981	-0.066	-0.046	-0.041	-0.040	-0.019	-0.030
PPIFGS	0.935	**0.845***	**0.842****	**0.907**	**0.913***	**0.937***	**0.963*****	**1.505***	**1.458***	**1.152**	**1.026**	**0.908**
GS10	0.910	0.902	0.856***	0.932**	0.971	0.979	0.041	-0.007	-0.021	-0.011	-0.047	-0.030
Multivariate	0.825***	**0.765*****	**0.779****	**0.918****	**0.927****	**0.917****	**0.645*****	**0.739*****	**0.566****	**0.027**	-0.232	-0.344
	Large VAR											
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.915**	1.177	1.157	1.059	1.026	1.010	**0.036**	-0.066	-0.073	-0.213	-0.574	-0.607
CPIAUCSL	1.052	**0.907***	**0.863****	**0.813****	**0.783****	**0.768***	**0.603***	**2.482**	**2.656**	**2.539**	**1.534**	**1.735**
FEDFUNDS	**0.429*****	0.418***	**0.505****	0.771*	0.928	0.934	**0.424****	**0.330**	**0.261**	**0.258**	-0.175	**0.058**
INDPRO	1.152	1.159	1.072	0.974	0.938	0.950	**0.427**	0.094	-0.249	-0.169	-0.022	-0.036
UNRATE	1.050	1.106	1.053	1.071	1.045	1.044	-0.003	-0.061	-0.028	-0.034	-0.011	-0.024
PPIFGS	1.048	**0.927**	**0.923****	**0.875****	**0.866****	**0.856***	**1.282****	**2.176***	**1.686***	**1.940**	**1.612**	**0.937**
GS10	0.926	0.899	**0.850****	0.868**	0.943	0.944	**0.001**	**0.046**	0.044	0.033	-0.010	-0.067
Multivariate	**0.887*****	**0.838*****	**0.847****	**0.899***	**0.923****	**0.922***	**0.761*****	**0.722****	**0.618****	**0.386***	0.123	0.004

The left half of this table reports the ratio between the univariate or multivariate weighted mean squared forecast error of the BCVAR_{tvp-sv} model and the univariate or multivariate weighted mean squared forecast error of the benchmark BVAR model. The right half of the table shows the univariate or multivariate average log predictive likelihood differentials between the BCVAR_{tvp-sv} model and the benchmark BVAR model. h denotes the forecast horizons, with $h \in \{1, 2, 3, 6, 9, 12\}$. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate all instances where the BCVAR_{tvp-sv} model outperforms all alternative models (DFM, FAVAR, BVAR, BCVAR, BCVAR_c), for any given VAR size/variable/forecast horizon combination. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.7. Out-of-sample forecast performance: Compressed TVP-SV VAR, alternative BIC

Variable	*Medium VAR*											
	MSFE						*ALPL*					
	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
PAYEMS	**0.742*** **	0.586***	0.572***	**0.646** **	**0.773* **	**0.890**	**0.323*** **	**0.384*** **	0.324***	-0.032	-0.557	-0.759
CPIAUCSL	**0.919*** **	**0.874*** **	**0.889*** **	**0.860** **	**0.836*** **	**0.850*** **	**0.278* **	**0.247** **	**0.416**	**0.159* **	**0.270**	**0.190* **
FEDFUNDS	**0.889**	**0.872**	**0.947**	1.024	1.001	1.106	**0.601** **	**0.635** **	**0.539* **	**0.320**	**0.321**	**0.193**
INDPRO	0.911**	0.933	0.974	0.981	0.992	0.991	-0.021	-0.100	-0.170	-0.614	-0.477	-0.186
UNRATE	0.839***	0.847**	0.885*	0.937	0.982	1.020	0.113***	0.105***	0.086***	0.051**	0.038	-0.002
PPIFGS	0.985	**0.995**	**1.014**	**0.998**	**0.996**	1.012	**0.277** **	**0.348**	**0.386**	**0.334**	**0.369**	**0.324**
GS10	1.022	1.033	1.047	1.036	1.012	1.038	0.007	-0.009	-0.089	-0.049	-0.016	-0.059
Multivariate	**0.913*** **	**0.888*** **	**0.906** **	**0.919* **	**0.934**	**0.979**	**1.581*** **	**1.703*** **	**1.527*** **	**1.144*** **	1.008***	0.819**
	Intermediate VAR											
	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
PAYEMS	**0.741*** **	0.586***	0.594***	0.655***	**0.736** **	**0.848**	**0.313*** **	0.386***	0.251**	-0.149	-0.614	-0.957
CPIAUCSL	**0.943**	**0.869*** **	**0.873*** **	**0.844*** **	**0.782*** **	**0.819*** **	**0.224**	**0.427**	**0.326**	**0.316**	**0.193*** **	**0.247**
FEDFUNDS	**0.878** **	**0.853** **	**0.852* **	**0.957**	**0.986**	1.065	**0.689*** **	**0.655*** **	**0.633*** **	**0.562*** **	**0.214**	**0.397**
INDPRO	0.920***	0.928**	0.933*	0.969	**0.959**	0.984	**0.069**	-0.124	-0.174	-0.389	-0.258	-0.301
UNRATE	0.870***	0.898**	0.915**	0.925**	0.971	0.986	0.105***	0.092***	0.080***	0.051***	0.017	-0.009
PPIFGS	0.974	1.005	**0.986**	**0.970**	**0.962**	**0.979**	**0.258**	**0.363**	**0.338**	**0.361**	**0.355**	**0.311**
GS10	1.017	1.021	1.045	1.017	1.014	1.012	-0.013	-0.038	-0.048	-0.049	0.006	-0.034
Multivariate	0.919***	**0.891*** **	**0.887*** **	**0.899*** **	**0.907*** **	**0.949** **	**1.569*** **	**1.572*** **	**1.457*** **	1.160***	0.972***	0.711*
	Large VAR											
	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
PAYEMS	**0.718*** **	0.569***	0.557***	0.658*	0.768	0.879	**0.329*** **	0.396***	0.340***	0.069	-0.279	-0.547
CPIAUCSL	0.923*	**0.858*** **	**0.862*** **	**0.863* **	**0.816*** **	**0.811*** **	**0.260* **	**0.431* **	**0.442**	**0.347**	**0.409**	**0.248**
FEDFUNDS	**0.904**	**0.891**	0.905	1.007	1.016	1.074	**0.648** **	**0.642** **	**0.447**	**0.469**	**0.322**	**0.290**
INDPRO	0.908***	0.929*	0.940	1.003	1.016	1.016	-0.038	-0.204	-0.043	-0.252	-0.250	-0.400
UNRATE	0.850***	0.868*	0.901	0.961	0.978	1.027	0.115***	0.096***	0.076***	0.053**	0.035	0.007
PPIFGS	0.980	**1.002**	**0.997**	**1.001**	**1.004**	**1.018**	**0.250* **	**0.344**	**0.370**	**0.329**	**0.403**	**0.228**
GS10	1.023	1.032	**1.036**	1.044	1.018	1.018	-0.002	0.003	-0.005	-0.025	0.011	-0.022
Multivariate	0.914***	**0.889*** **	**0.887** **	0.927	0.937	0.969	**1.629*** **	**1.690*** **	**1.562*** **	**1.224*** **	1.023***	0.700*

The left half of this table reports the ratio between the univariate or multivariate weighted mean squared forecast error of the BCVAR_{tvp-sv} model and the univariate or multivariate weighted mean squared forecast error of the benchmark AR(1) model. The right half of the table shows the univariate or multivariate average log predictive likelihood differentials between the BCVAR_{tvp-sv} model and the benchmark AR(1) model. h denotes the forecast horizons, with $h \in \{1, 2, 3, 6, 9, 12\}$. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate all instances where the BCVAR_{tvp-sv} model outperforms all alternative models (DFM, FAVAR, BVAR, BCVAR, BCVAR_c), for any given VAR size/variable/forecast horizon combination. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.8. Out-of-sample forecast performance: Compressed TVP-SV VAR, 7 key variables ordered last

Variable	*Medium VAR*											
	MSFE						*ALPL*					
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.727*****	0.584***	0.564***	**0.658****	**0.775***	**0.878**	**0.322*****	**0.380*****	0.337***	0.043	-0.351	-0.546
CPIAUCSL	**0.906*****	**0.875*****	**0.871*****	**0.861*****	**0.830*****	**0.853*****	**0.259***	**0.327****	**0.442**	**0.138****	**0.317***	**0.117**
FEDFUNDS	**0.906**	**0.872**	**0.922**	0.997	0.969	1.050	**0.699*****	**0.480**	**0.560****	**0.447**	0.105	**0.263**
INDPRO	0.891***	0.929*	0.934	0.967	0.991	0.988	-0.045	-0.177	-0.264	-0.480	-0.443	-0.196
UNRATE	0.872***	0.879*	0.895*	0.961	0.968	1.003	0.105***	0.095***	0.087***	0.054***	**0.047****	0.010
PPIFGS	0.979	**0.994**	**0.990**	**0.995**	**0.999**	1.006	**0.282****	**0.351**	**0.388**	**0.323**	**0.390**	**0.323**
GS10	1.012	1.023	1.032	1.013	0.993	1.022	-0.039	-0.009	-0.021	-0.060	0.019	-0.010
Multivariate	**0.912*****	**0.891*****	**0.889*****	**0.915***	**0.925***	**0.965**	**1.634*****	**1.659*****	**1.566*****	**1.173*****	0.990***	0.799**
	Intermediate VAR											
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.771*****	0.600***	0.591***	0.644**	**0.748****	**0.868**	**0.301*****	0.360***	0.292***	0.128	-0.340	-0.969
CPIAUCSL	0.949	**0.882*****	**0.874*****	**0.849*****	**0.805*****	**0.813*****	**0.251***	**0.456**	**0.342**	**0.284**	**0.273**	**0.227**
FEDFUNDS	**0.893****	**0.834****	**0.862***	**0.937**	1.024	1.042	**0.840*****	**0.700*****	**0.528***	**0.439**	0.072	**0.203**
INDPRO	0.895***	0.962	0.975	0.988	0.989	1.004	0.028	-0.005	-0.110	-0.359	-0.258	-0.278
UNRATE	0.873***	0.899**	0.946	0.935**	0.970	1.004	0.098***	0.089***	0.056**	0.038*	0.014	-0.003
PPIFGS	**0.961**	**0.978**	**0.970**	**0.954**	**0.947****	**0.977**	**0.274**	**0.404**	**0.390**	**0.342**	**0.375**	**0.289**
GS10	1.012	1.045	1.041	1.029	1.011	1.005	**0.041****	0.010	-0.052	**0.008**	-0.019	-0.010
Multivariate	**0.918*****	**0.897*****	**0.895*****	**0.899*****	**0.919****	**0.952***	**1.602*****	**1.551*****	**1.458*****	1.167***	0.910***	0.674*
	Large VAR											
	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
PAYEMS	**0.724*****	0.601***	0.566***	0.683*	0.785	0.898	**0.310*****	0.384***	0.338***	0.091	-0.259	-0.504
CPIAUCSL	0.931*	**0.864*****	**0.903****	**0.859****	**0.795*****	**0.813*****	**0.229**	**0.348***	**0.307**	**0.300**	**0.347**	**0.154**
FEDFUNDS	**0.959**	**0.929**	**0.938**	1.020	1.028	1.085	**0.628****	**0.574****	**0.523**	**0.513***	**0.367**	-0.220
INDPRO	0.904**	0.969	0.955	1.041	1.015	1.038	**0.162***	-0.133	-0.167	-0.158	-0.349	-0.338
UNRATE	0.876**	0.879*	0.900	0.947	1.020	1.013	0.103***	0.087***	0.081***	0.048**	-0.006	0.018
PPIFGS	0.973	1.021	**0.990**	**1.027**	**0.977**	**1.003**	**0.219**	**0.331**	**0.360**	**0.265**	**0.386**	**0.251**
GS10	**1.028**	1.039	1.062	1.045	1.021	1.043	0.001	**0.016**	-0.057	-0.035	-0.090	-0.042
Multivariate	**0.925*****	**0.910*****	**0.904****	**0.939**	**0.940**	0.977	**1.554*****	**1.570*****	**1.485*****	**1.138*****	0.910***	0.714**

The left half of this table reports the ratio between the univariate or multivariate weighted mean squared forecast error of the BCVAR$_{tvp-sv}$ model and the univariate or multivariate weighted mean squared forecast error of the benchmark AR(1) model. The right half of the table shows the univariate or multivariate average log predictive likelihood differentials between the BCVAR$_{tvp-sv}$ model and the benchmark AR(1) model. h denotes the forecast horizons, with $h \in \{1, 2, 3, 6, 9, 12\}$. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate all instances where the BCVAR$_{tvp-sv}$ model outperforms all alternative models (DFM, FAVAR, BVAR, BCVAR, BCVAR$_c$), for any given VAR size/variable/forecast horizon combination. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Table C.9. Out-of-sample forecast performance: Multivariate results, alternative SV models

Fcst h.	*Small VAR*					
	WMSFE			*MVALPL*		
	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$
h= 1	**0.917*****	0.942***	0.918***	**2.047*****	1.696***	1.719***
h= 2	0.930***	0.944***	**0.895*****	**1.907*****	1.654***	1.745***
h= 3	0.936***	0.951**	**0.901*****	**1.845*****	1.563***	1.645***
h= 6	0.946***	0.971	**0.912*****	**1.608*****	1.228***	1.386***
h= 9	0.968***	0.981	**0.936*****	**1.385*****	0.978***	1.143***
h=12	0.992	0.999	**0.960***	**0.931***	0.811*	0.930***
	Medium VAR					
	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$
h= 1	1.070	0.935***	**0.905*****	1.599***	1.522***	**1.653*****
h= 2	1.089	0.922***	**0.884*****	1.521***	1.558***	**1.701*****
h= 3	1.123	0.931**	**0.892*****	1.236***	1.399***	**1.573*****
h= 6	1.125	0.937*	**0.916***	1.041***	1.129***	**1.224*****
h= 9	1.031	0.947*	**0.924***	**1.078*****	0.938***	1.049***
h=12	1.007	0.981	**0.967**	**1.039*****	0.760**	0.851***
	Intermediate VAR					
	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$
h= 1		0.942***	**0.910*****		1.520***	**1.633*****
h= 2		0.924***	**0.878*****		1.512***	**1.635*****
h= 3		0.927***	**0.877*****		1.324***	**1.511*****
h= 6		0.919**	**0.896*****		1.119***	**1.215*****
h= 9		0.932**	**0.908*****		0.895***	**0.966*****
h=12		0.959**	**0.941****		**0.718***	0.674
	Large VAR					
	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$	$BVAR_{ccm}$	$BCVAR_{sv}$	$BCVAR_{tvp\text{-}sv}$
h= 1		0.942***	**0.902*****		1.488***	**1.667*****
h= 2		0.924**	**0.883*****		1.543***	**1.666*****
h= 3		0.919**	**0.885****		1.394***	**1.593*****
h= 6		0.939	**0.922**		1.118***	**1.216*****
h= 9		0.938	**0.932**		0.894***	**1.002*****
h=12		**0.950**	0.967		**0.722***	0.713*

The left half of this table reports the ratio between the multivariate weighted mean squared forecast error (WMSFE) of model i and the WMSFE of the benchmark AR(1) model, computed as

$$WMSFE_{ih} = \frac{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{i,\tau+h}}{\sum_{\tau=\underline{t}}^{\bar{t}-h} we_{bcmk,\tau+h}},$$

where $we_{i,\tau+h} = \left(e'_{i,\tau+h} \times W \times e_{i,\tau+h}\right)$ and $we_{bcmk,\tau+h} = \left(e'_{bcmk,\tau+h} \times W \times e_{bcmk,\tau+h}\right)$ denote the weighted forecast errors of model i and the benchmark model at time $\tau+h$, $e_{i,\tau+h}$ and $e_{bcmk,\tau+h}$ are the $(N \times 1)$ vector of forecast errors, and W is an $(N \times N)$ matrix of weights. We set $N = 7$, to focus on the following key seven series, {PAYEMS, CPIAUCSL, FEDFUNDS, INDPRO, UNRATE, PPIFGS, GS10}. In addition, we set the matrix W to be a diagonal matrix featuring on the diagonal the inverse of the variances of the series to be forecast. $\underline{t}$ and $\bar{t}$ denote the start and end of the out-of-sample period, $i \in \{\text{BVAR}_{ccm}, \text{BCVAR}_{sv}, \text{BCVAR}_{tvp-sv}\}$, and $h \in \{1, 2, 3, 6, 9, 12\}$. The right half of the table shows the multivariate average log predictive likelihood differentials between model i and the benchmark AR(1), computed as

$$MVALPL_{ih} = \frac{1}{\bar{t} - \underline{t} - h + 1} \sum_{\tau=\underline{t}}^{\bar{t}-h} \left(MVLPL_{i,\tau+h} - MVLPL_{bcmk,\tau+h}\right),$$

where $MVLPL_{i,\tau+h}$ and $MVLPL_{bcmk,\tau+h}$ denote the multivariate log predictive likelihoods of model i and the benchmark model at time $\tau + h$, and are computed under the assumption of joint normality. All forecasts are generated out-of-sample using recursive estimates of the models, with the out of sample period starting in 1987:07 and ending in 2014:12. Bold numbers indicate the lowest WMSFE and highest MVALPL across all models for any given VAR size - forecast horizon pair. * significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Appendix D Data and transformations

Table D.1. **Output and Income**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
1	5	X	X	RPI	Real Personal Income	PI
2	5		X	W875RX1	RPI ex. Transfers	PI less transfers
6	5	X	X	INDPRO	IP Index	IP: total
7	5			IPFPNSS	IP: Final Products and Supplies	IP: products
8	5			IPFINAL	IP: Final Products	IP: final prod
9	5			IPCONGD	IP: Consumer Goods	IP: cons gds
10	5			IPDCONGD	IP: Durable Consumer Goods	IP: cons dble
11	5			IPNCONGD	IP: Nondurable Consumer Goods	IP: cons nondble
12	5			IPBUSEQ	IP: Business Equipment	IP: bus eqpt
13	5			IPMAT	IP: Materials	IP: matls
14	5			IPDMAT	IP: Durable Materials	IP: dble matls
15	5			IPNMAT	IP: Nondurable Materials	IP: nondble matls
16	5			IPMANSICS	IP: Manufacturing	IP: mfg
17	5			IPB51222S	IP: Residential Utilities	IP: res util
18	5			IPFUELS	IP: Fuels	IP: fuels
19	1		X	NAPMPI	ISM Manufacturing: Production	NAPM prodn
20	1			CAPUTLB00004S	Capacity Utilization: Manufacturing	Cap util

Table D.2. **Labor Market**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
21	1	X	X	HWI	Help-Wanted Index for US	Help wanted indx
22	1		X	HWIURATIO	Help Wanted to Unemployed ratio	Help wanted/unemp
23	5		X	CLF16OV	Civilian Labor Force	Emp CPS total
24	5			CE16OV	Civilian Employment	Emp CPS nonag
25	2	X	X	UNRATE	Civilian Unemployment Rate	U: all
26	1			UEMPMEAN	Average Duration of Unemployment	U: mean duration
27	5			UEMPLT5	Civilians Unemployed $\leq$ 5 Weeks	U $\leq$ 5 wks
28	5			UEMP5TO14	Civilians Unemployed 5-14 Weeks	U 5-14 wks
29	5			UEMP15OV	Civilians Unemployed > 15 Weeks	U > 15 wks
30	5			UEMP15T26	Civilians Unemployed 15-26 Weeks	U 15-26 wks
31	5			UEMP27OV	Civilians Unemployed > 27 Weeks	U > 27 wks
32	5			CLAIMSx	Initial Claims	UI claims
33	5	X	X	PAYEMS	All Employees: Total nonfarm	Emp: total
34	5			USGOOD	All Employees: Goods-Producing	Emp: gds prod
35	5			CES1021000001	All Employees: Mining and Logging	Emp: mining
36	5			USCONS	All Employees: Construction	Emp: const
37	5			MANEMP	All Employees: Manufacturing	Emp: mfg
38	5			DMANEMP	All Employees: Durable goods	Emp: dble gds
39	5			NDMANEMP	All Employees: Nondurable goods	Emp: nondbles
40	5			SRVPRD	All Employees: Service Industries	Emp: services
41	5			USTPU	All Employees: TT&U	Emp: TTU
42	5			USWTRADE	All Employees: Wholesale Trade	Emp: wholesale
43	5			USTRADE	All Employees: Retail Trade	Emp: retail
44	5			USFIRE	All Employees: Financial Activities	Emp: FIRE
45	5			USGOVT	All Employees: Government	Emp: Govt
46	1		X	CES0600000007	Hours: Goods-Producing	Avg hrs
47	1			AWOTMAN	Overtime Hours: Manufacturing	Overtime: mfg
48	1			AWHMAN	Hours: Manufacturing	Avg hrs: mfg
49	1			NAPMEI	ISM Manufacturing: Employment	NAPM empl
128	5			CES0600000008	Ave. Hourly Earnings: Goods	AHE: goods
129	5			CES2000000008	Ave. Hourly Earnings: Construction	AHE: const
130	5			CES3000000008	Ave. Hourly Earnings: Manufacturing	AHE: mfg

Table D.3. **Housing**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
50	4	X		HOUST	Starts: Total	Starts: nonfarm
51	4			HOUSTNE	Starts: Northeast	Starts: NE
52	4			HOUSTMW	Starts: Midwest	Starts: MW
53	4			HOUSTS	Starts: South	Starts: South
54	4			HOUSTW	Starts: West	Starts: West
55	4	X		PERMIT	Permits	BP: total
56	4			PERMITNE	Permits: Northeast	BP: NE
57	4			PERMITMW	Permits: Midwest	BP: MW
58	4			PERMITS	Permits: South	BP: South
59	4			PERMITW	Permits: West	BP: West

Table D.4. **Consumption, Orders and Inventories**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
3	5		X	DPCERA3M086SBEA	Real PCE	Real Consumption
4	5		X	CMRMTSPLx	Real M&T Sales	M&T sales
5	5		X	RETAILx	Retail and Food Services Sales	Retail sales
60	1	X		NAPM	ISM: PMI Composite Index	PMI
61	1		X	NAPMNOI	ISM: New Orders Index	NAPM new ordrs
62	1		X	NAPMSDI	ISM: Supplier Deliveries Index	NAPM vendor del
63	1		X	NAPMII	ISM: Inventories Index	NAPM Invent
65	5			AMDMNOx	Orders: Durable Goods	Orders: dble gds
67	5			AMDMUOx	Unfilled Orders: Durable Goods	Unf orders: dble
68	5			BUSINVx	Total Business Inventories	M&T invent
69	1			ISRATIOx	Inventories to Sales Ratio	M&T invent/sales

Table D.5. **Money and Credit**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
70	5	X	X	M1SL	M1 Money Stock	M1
71	5		X	M2SL	M2 Money Stock	M2
73	5		X	M2REAL	Real M2 Money Stock	M2 (real)
74	5		X	AMBSL	St. Louis Adjusted Monetary Base	MB
75	5		X	TOTRESNS	Total Reserves	Reserves tot
77	5	X	X	BUSLOANS	Commercial and Industrial Loans	C&I loan plus
78	5			REALLN	Real Estate Loans	DC&I loans
79	5		X	NONREVSL	Total Nonrevolving Credit	Cons credit
80	1		X	CONSPI	Credit to PI ratio	Inst cred/PI
132	5			MZMSL	MZM Money Stock	N.A.
133	5			DTCOLNVHFNM	Consumer Motor Vehicle Loans	N.A.
134	5			DTCTHFNM	Total Consumer Loans and Leases	N.A.
135	5	X		INVEST	Securities in Bank Credit	N.A.

Table D.6. **Interest rates and Exchange rates**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
85	2	X	X	FEDFUNDS	Effective Federal Funds Rate	Fed Funds
86	2		X	CP3M	3-Month AA Comm. Paper Rate	Comm paper
87	2		X	TB3MS	3-Month T-bill	3 mo T-bill
88	2		X	TB6MS	6-Month T-bill	6 mo T-bill
89	2		X	GS1	1-Year T-bond	1 yr T-bond
90	2		X	GS5	5-Year T-bond	5 yr T-bond
91	2	X	X	GS10	10-Year T-bond	10 yr T-bond
92	2		X	AAA	Aaa Corporate Bond Yield	Aaa bond
93	2		X	BAA	Baa Corporate Bond Yield	Baa bond
94	1			COMPAPFF	CP - FFR spread	CP-FF spread
95	1			TB3SMFFM	3 Mo. - FFR spread	3 mo-FF spread
96	1			TB6SMFFM	6 Mo. - FFR spread	6 mo-FF spread
97	1			T1YFFM	1 yr. - FFR spread	1 yr-FF spread
98	1			T5YFFM	5 yr. - FFR spread	5 yr-FF spread
99	1	X		T10YFFM	10 yr. - FFR spread	10 yr-FF spread
100	1			AAAFFM	Aaa - FFR spread	Aaa-FF spread
101	1			BAAFFM	Baa - FFR spread	Baa-FF spread
103	5		X	EXSZUS	Switzerland / U.S. FX Rate	Ex rate: Switz
104	5		X	EXJPUS	Japan / U.S. FX Rate	Ex rate: Japan
105	5	X	X	EXUSUK	U.S. / U.K. FX Rate	Ex rate: UK
106	5		X	EXCAUS	Canada / U.S. FX Rate	EX rate: Canada

Table D.7. **Prices**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
107	5	X	X	PPIFGS	PPI: Finished Goods	PPI: fin gds
108	5		X	PPIFCG	PPI: Finished Consumer Goods	PPI: cons gds
109	5		X	PPIITM	PPI: Intermediate Materials	PPI: int materials
110	5		X	PPICRM	PPI: Crude Materials	PPI: crude materials
111	5	X		oilprice	Crude Oil Prices: WTI	Spot market price
112	5			PPICMM	PPI: Commodities	PPI: nonferrous
113	1			NAPMPRI	ISM Manufacturing: Prices	NAPM com price
114	5	X	X	CPIAUCSL	CPI: All Items	CPI-U: all
115	5			CPIAPPSL	CPI: Apparel	CPI-U: apparel
116	5			CPITRNSL	CPI: Transportation	CPI-U: transp
117	5			CPIMEDSL	CPI: Medical Care	CPI-U: medical
118	5			CUSR0000SAC	CPI: Commodities	CPI-U: comm.
119	5			CUUR0000SAD	CPI: Durables	CPI-U: dbles
120	5			CUSR0000SAS	CPI: Services	CPI-U: services
121	5			CPIULFSL	CPI: All Items Less Food	CPI-U: ex food
122	5			CUUR0000SA0L2	CPI: All items less shelter	CPI-U: ex shelter
123	5			CUSR0000SA0L5	CPI: All items less medical care	CPI-U: ex med
124	5			PCEPI	PCE: Chain-type Price Index	PCE defl
125	5			DDURRG3M086SBEA	PCE: Durable goods	PCE defl: dlbes
126	5			DNDGRG3M086SBEA	PCE: Nondurable goods	PCE defl: nondble
127	5			DSERRG3M086SBEA	PCE: Services	PCE defl: service

Table D.8. **Stock Market**

Series id	*Tcode*	*Medium*	*Intermediate*	*FRED*	*Description*	*GSI:Description*
81	5	X	X	S&P 500	S&P: Composite	S&P 500
82	5		X	S&P: indust	S&P: Industrials	S&P: indust
83	1		X	S&P div yield	S&P: Dividend Yield	S&P div yield
84	5		X	S&P PE ratio	S&P: Price-Earnings Ratio	S&P PE ratio