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Abstract

We propose a method to adjust for data outliers in Bayesian Vector Autoregressions (BVARs), which allows for different outlier magnitudes across variables and rescales the reduced form error terms. We use the method to document several facts about the effect of outliers on estimation and out-of-sample forecasting results using euro area macroeconomic data. First, the COVID-19 pandemic led to large swings in macroeconomic data that distort the BVAR estimation results. Second, these swings can be addressed by rescaling the shocks' variance. Third, taking into account outliers before 2020 leads to mild improvements in the point forecasts of BVARs for some variables and horizons. However, the density forecast performance considerably deteriorates. Therefore, we recommend taking into account outliers only on pre-specified dates around the onset of the COVID-19 pandemic.

Keywords: COVID-19 pandemic, outliers, Bayesian VARs, forecasting, euro area.

JEL classification: C11, C32, C51, E37.

Resumen

Este trabajo propone un método para ajustar los datos atípicos en modelos vectoriales autorregresivos estimados con técnicas bayesianas (BVAR) que supone reescalar por magnitudes diferentes la varianza de los errores de la forma reducida. Se utiliza este método para documentar varios hechos sobre el efecto de los valores atípicos en la estimación y la previsión fuera de muestra utilizando datos macroeconómicos de la zona del euro. En primer lugar, la pandemia de COVID-19 provocó grandes oscilaciones en los datos macroeconómicos que distorsionan los resultados de estimación de los modelos BVAR. En segundo lugar, estas oscilaciones pueden abordarse reescalando la varianza de las perturbaciones. En tercer lugar, si se tienen en cuenta los valores atípicos antes de 2020, se obtienen ligeras mejoras en las previsiones puntuales de los BVAR para algunas variables y horizontes. Sin embargo, el rendimiento de las previsiones de las densidades se deteriora considerablemente. Por lo tanto, recomendamos tener en cuenta los valores atípicos solo en las fechas preestablecidas en torno al inicio de la pandemia de COVID-19.

Palabras clave: pandemia de COVID-19, valores atípicos, BVAR, predicción, área del euro.

Códigos JEL: C11, C32, C51, E37.

1 Introduction

Bayesian Vector autoregressions (BVARs) are a popular way of modeling the dynamic relationships of macroeconomic variables. Since the Covid-19 pandemic has caused swings of unprecedented magnitudes in macroeconomic series, the following questions emerged: can VARs be robustified to the pandemic's outliers, and does an adjustment for outliers, more generally, improve BVARs' forecasting performance prior to 2020?

This paper makes two contributions to address these questions. On the one hand, we study the relevance of an outlier adjustment prior to and after 2020 in a 10-variable Bayesian VAR (with and without stochastic volatility) using quarterly euro area data ranging from 1985:Q1 to 2021:Q3. The variables include five macroeconomic variables, real GDP, consumer price inflation, nominal wages, employment, and foreign demand, as well as the oil price, an exchange rate basket, short- and long-term interest rates, and a stock market index.

We subsequently document three empirical facts. First, relative to the same model estimated on data until 2019:Q4, the parameters' posteriors of both a BVAR without stochastic volatility (BVAR-WOSV) and a BVAR with stochastic volatility (BVAR-SV) change substantially when including the observations of 2020:Q1 onward. Second, using an outlier correction method leads to posterior distributions that are close to the results based on data until 2019:Q4. This underlines the usefulness of an outlier correction specification since the few additional observations of 2020 and 2021 should not drastically alter the posterior distribution based on the previous 136 observations. Third, accounting for outliers prior to 2020 improves the forecasts of the BVAR-WOSV for some variables and horizons; the point forecast performance of the BVAR-SV is essentially unchanged. However, density forecasts considerably deteriorate for both the BVAR-WOSV and BVAR-SV.

As a second contribution, we propose a new method to address outliers within the framework of a BVAR. Our specification rescales the variance-covariance matrix of the reduced form error term vector and the outlier magnitude is allowed to be different across variables. The rescaling of the variance-covariance matrix implies that, for instance, Covid-19 observations are down-weighted in the model estimation and the model's regression coefficients are virtually unchanged. The method is easily amended for the outlier dates to be pre-specified *a priori* instead of estimated alongside the outlier magnitude. Further, since it rescales the reduced form variance it can be readily applied to BVARs with constant volatility or to stochastic volatility specifications that do not use the triangular decomposition of Primiceri (2005). For instance, recent work by Hartwig (2021), Arias et al. (2021), and Ganics and Odendahl (2021) advocates for SV specifications other than the triangular decomposition since they show that the ordering problem due to the triangular decomposition is empirically relevant for forecasting results.

Our paper is most closely related to the work of Carriero et al. (2022a, CCMM hereafter), who were the first to investigate the effect of Covid-19 outliers in BVARs that include stochastic volatility (see also Carriero et al. (2022b) for an additional application of their methodology). However, we differ from them in several important ways. First, we focus on quarterly euro area data. Second, when our outlier specification is used in combination with stochastic volatility, the outlier matrix rescales the reduced form error term instead of the structural shocks and, therefore, is applicable to a wider variety of SV specifications and leaves the contemporaneous correlation of the reduced form error term unaffected.

The present paper is further related to Lenza and Primiceri (2022), the first paper addressing the Covid outlier issue in BVARs. Different from their framework, which obtains parameter estimates by optimizing the marginal likelihood, we focus on the effect of outliers in euro area data and study their relevance both after and prior to 2020. Further, we investigate outlier specifications in a BVAR with stochastic volatility, allowing for different outlier magnitudes across variables and for the outlier dates to be estimated.

Another paper contributing to the topic of outlier specifications includes Bobeica and Hartwig (2021), who use euro area data to show that the Covid-19 outliers cause a substantial change in the estimated coefficients of a BVAR without stochastic volatility unless the regression coefficient prior is set very tight. As a remedy, the authors propose to estimate a BVAR with an error term that is drawn from a Student's t distribution to allow for larger shocks. Different from their work, we investigate the effect of outliers prior to 2020 on the forecasting performance of different BVAR specifications. Further, we can allow for different outlier magnitudes across variables and can easily impose the dates of the outlier occurrence.

Instead of re-scaling the variance of the existing shocks, Ng (2021) considers the Covid-19 outliers to be driven by a new type of shock, a "health" shock, that is not yet captured by the existing shocks in the model. In particular, in a VAR using the monthly U.S. unemployment rate and industrial production, she explicitly controls for the pandemic situation by including the growth rate of the increase of monthly positive Covid-19 tests. The resulting impulse response functions are very similar to the pre-Covid period, indicating that including data on the pandemic development can indeed control for the outliers. Different from Ng (2021), we focus on quarterly and euro area data, and capture Covid-19 outliers via rescaling the variance of existing (reduced form) shocks.

Finally, we are also related to Stock and Watson (2016), who corrected for outliers in an unobserved component model to measure trend inflation. Instead, we apply a matrix version of the outlier correction of Stock and Watson (2016) inspired by but different from Carriero et al. (2022a), to capture the Covid-19 outliers in a multivariate model.

Section 2.1 introduces the BVAR with stochastic volatility and the outlier correction methods. Section 3 shows results of the Covid-19 outliers on the BVAR estimates. Section 4 shows results of a forecast comparison exercise of models with and without an outlier specification prior to 2020. Section 5 shows results when pre-specifying the outlier dates around the onset of the Covid-19 pandemic. Section 6 concludes.

2 Methodology and data

2.1 Bayesian VARs with outlier correction

This section introduces the specifications of the BVAR with constant volatility, stochastic volatility, and with the outlier correction method. For the remainder of the paper, BVAR-SV denotes the BVAR with stochastic volatility and BVAR-WOSV denotes the specification without stochastic volatility. The respective Gibbs samplers and some convergence diagnostics are given in Section A.

BVAR-WOSV: The BVAR without stochastic volatility can be described by:

$$y_t = B_0 + \sum_{i=1}^{p} B_i y_{t-i} + o_t S_t e_t \,,$$

$$s_{n,t} = \begin{cases} 1 & \text{with probability } (1-q_{s,i}) \\ U(2,\bar{u}_s) & \text{with probability } q_{s,i}, \end{cases} \quad \text{for} \quad n = 1, ..., N. \tag{1}$$

$$o_t = \begin{cases} 1 & \text{with probability } (1-q_o) \\ U(2,\bar{u}_o) & \text{with probability } q_o, \end{cases}$$

where B_0 is the $(N \times 1)$ vector of intercepts and the B_k's are the $(N \times N)$ coefficient matrices, $e_t \stackrel{iid}{\sim} \mathcal{N}(0, \Sigma_e)$. For the VAR coefficients, we use a Minnesota-type prior, which shrinks all coefficients of variables in growth rates to zero and the first own-lag coefficient of variables in (log-) levels to 0.8 (see Section 2.2 for details on the variables). Further, let κ_β denote the hyperparameters that control the tightness of the Minnesota-type prior, with $\beta = \text{vec}([B_0, B_1, ..., B_p]')$. We estimate κ_β alongside all the other parameters in the model using the Metropolis-Hastings step from Amir-Ahmadi et al. (2020). The degrees of freedom and scale of the inverse-Wishart prior on Σ_e are set to $N+3$ and the identity matrix, respectively.

S_t is a diagonal matrix with elements $s_{n,t}$, $n = 1, ..., N$, that captures outliers in individual series occurring with probability $q_{s,i}$. Further, $s_{n,t} \sim_{\text{iid}} U(2, \bar{u}_s)$ denotes the uniform prior distribution on the interval $[2, \bar{u}_s]$. o_t is a scalar outlier that occurs with probability q_o and rescales the variance of all series. The outlier probabilities have a Beta distribution as a prior, i.e. $q_i \sim B(a_{s,i}, b_{s,i})$ and $q_o \sim B(a_o, b_o)$, where $B(\cdot)$ denotes the beta distribution, the $q_{s,i}$ are independent across $i = 1, ..., N$ and $q_{s,i}$ and q_o are also independent. The empirical results are not very sensitive to the choice of $\bar{u}_o$ and $\bar{u}_s$, which we set to 20.

The model with outlier specification is labeled BVAR-WOSV-OC. For the BVAR-WOSV without outlier specification, we restrict S_t to be equal to the identity matrix and $o_t = 1$ for all t.

BVAR-SV: The BVAR with stochastic volatility takes the form:

$$\begin{aligned} y_t &= B_0 + \sum_{k=1}^{p} B_k y_{t-k} + o_t S_t A^{-1} \Sigma_t^{\frac{1}{2}} e_t \,, \\ \Sigma_t &\equiv \text{diag}\left(\sigma_{1,t}^2, \ldots, \sigma_{N,t}^2\right) \,, \\ \log(\sigma_{n,t}^2) &= \log(\sigma_{n,t-1}^2) + \eta_{n,t} \quad \text{for} \quad n = 1, \ldots, N \,, \end{aligned}$$

where B_0 and the B_k's are defined as in the BVAR-WOSV, A^{-1} is a lower triangular matrix with ones on the diagonal, $e_t \stackrel{iid}{\sim} \mathcal{N}(0, I_N)$, and $(\eta_{1,t}, ..., \eta_{N,t})' \stackrel{iid}{\sim} \mathcal{N}(0, \Xi)$, where Ξ is not constrained to be diagonal. The prior specification on the stochastic volatility coefficients is $\Xi \sim IW\big((N+3) \cdot 0.01 \cdot I_N, N+3\big)$, i.e. the prior is rather uninformative, where IW denotes the inverse-Wishart distribution. Throughout the paper, we will refer to the square-root of the diagonal elements of $A^{-1}\Sigma_t A^{-1'}$ as the time-varying standard deviation.

S_t and o_t are defined as in eq. (1). Since S_t pre-multiplies $A^{-1}\Sigma_t^{\frac{1}{2}}$ it has a pure scaling effect on $A^{-1}\Sigma_t A^{-1'}$ and S_t can be interpreted as rescaling the reduced form shocks. The $s_{i,t}$ can be drawn sequentially by conditioning on $s_{j,t}$, $j \neq i$; details of the Gibbs sampler are given in Section A.1. In the baseline specification, we use the same values for $a_{s,i}, b_{s,i}$ and a_o, b_o across all $i = 1, ..., N$.

The model with outlier specification is labeled BVAR-SV-OC. For the BVAR-SV without outlier specification, we restrict S_t to be equal to the identity matrix and $o_t = 1$ for all t.

BVAR-SV-CCMM: In the forecast comparison exercise, we are additionally evaluating the performance of an existing methodology by CCMM[1]:

$$y_t = B_0 + \sum_{i=1}^{p} B_i y_{t-i} + A^{-1} S_t \Sigma_t^{\frac{1}{2}} e_t, \tag{2}$$

where S_t is defined as above. Our specification differs from CCMM since our specification pre-multiplies $A^{-1}\Sigma_t^{\frac{1}{2}}$. In other words, we rescale the reduced form shocks and CCMM rescale the structural shocks. The Gibbs sampler used to implement CCMM is given in Section A.2.

2.2 Data

The data vector y_t consists of 10 euro area variables. Five of the variables are in quarter-on-quarter growth rates: real GDP (GDP), seasonally adjusted HICP (HICP), compensation per employee (CPE), number of employees (EMP), and a measure of foreign demand (FD); the other five variables are the log-level of the oil price in US dollars (OIL), the effective exchange rate (EER), the three-month EURIBOR (STN), a synthetic long term rate (LTN) taken from the Area Wide Model database[2], and the log-level of the Stoxx 600 index (STOXX). These 10 series capture real macroeconomic developments, nominal price changes as well as financial developments. The data used for the estimation range from 1985:Q1 to 2021:Q3. Data from 1980:Q1 to 1984:Q4 are used as a training sample for the initialization of the stochastic volatility series.

3 The effect of Covid-19 outliers

In this section, we document how the different model specifications account for potential Covid-19 outliers. We consider two estimation samples for the models: from 1985:Q1 to 2019:Q4 and from 1985:Q1 to 2021:Q3. Throughout the section, the label PreCovid implies that the estimation in-sample ended in 2019:Q4. OC denotes the model with outlier correction and NOC without outlier correction.

3.1 BVAR-WOSV

Figure 1 plots the outlier posterior means of the outliers for the specification OC, displayed whenever the posterior mean is above 1.5. The figure shows large values for the outliers for 2020:Q1, 2020:Q2, and 2020:Q3, and to a lesser extent for 2021:Q3 (see Figure B.1 for a focus of the outlier values in 2020 and 2021). Further, outliers are estimated around the financial crisis period and during the 1990s, in particular for CPE, STN, and LTN.

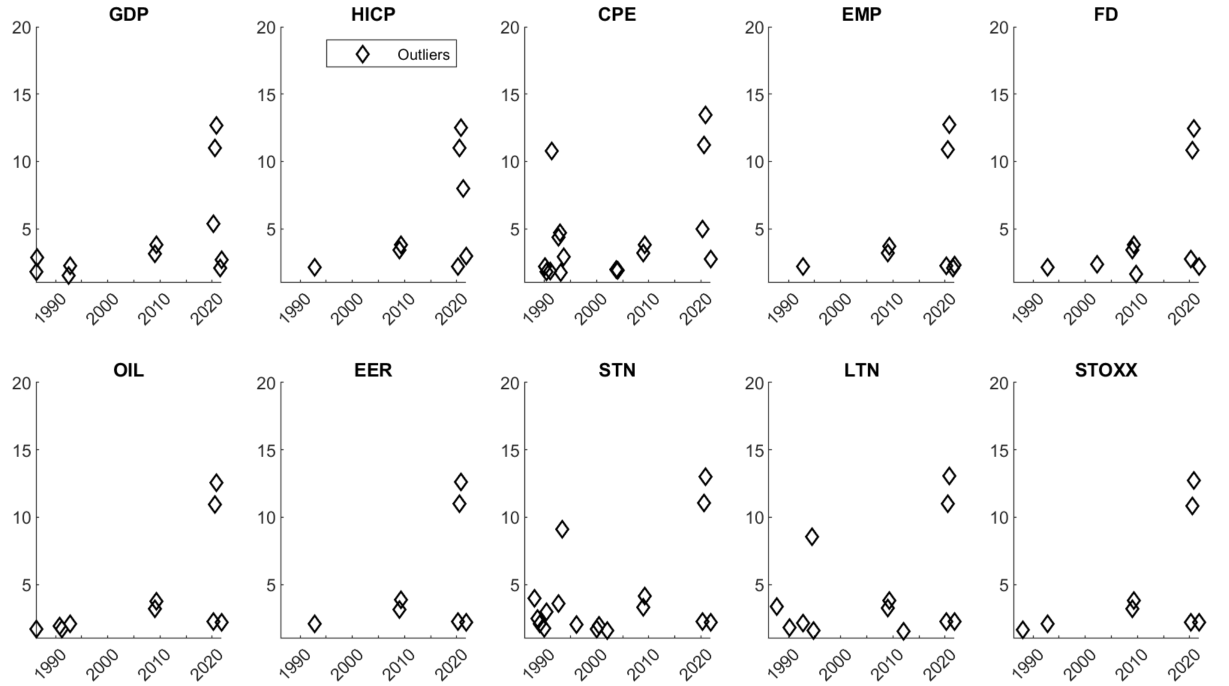
Figure 2 shows the posterior densities of $\sigma_{ii,e}$, for $i = 1, ...N$; the OC-PreCovid (dotted line), OC (dash-dotted line) results are very similar suggesting that the outlier specifications capture the Covid-19 outliers well, whereas the posterior densities of the NOC specifications differ

[1] CCMM propose several alternatives and we focus here on their"SVO" model.

[2] The dataset from the Area Wide Model is available on the website of the Euro Area Business Cycle Network: https://eabcn.org/page/area-wide-model.

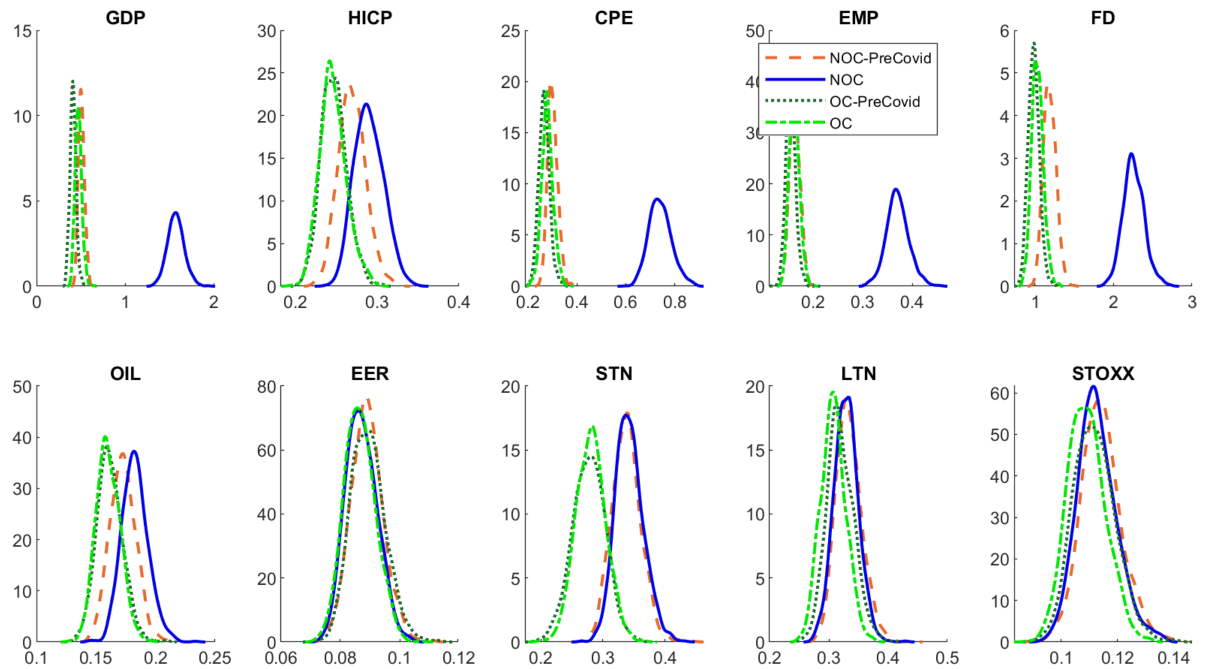
substantially for GDP, CPE, EMP, and FD for the two samples, highlighting the large impact of the few observations of 2020 and 2021 on the model's posterior.[3]

Figure 1: Posterior mean of outliers — BVAR-WOSV



Note: The figure shows the posterior means of $o_t S_t$. For legibility, the plot only shows values when the posterior mean is larger than 1.5.

Figure 2: Posterior densities of $\sigma_{ii,e}$ — BVAR-WOSV

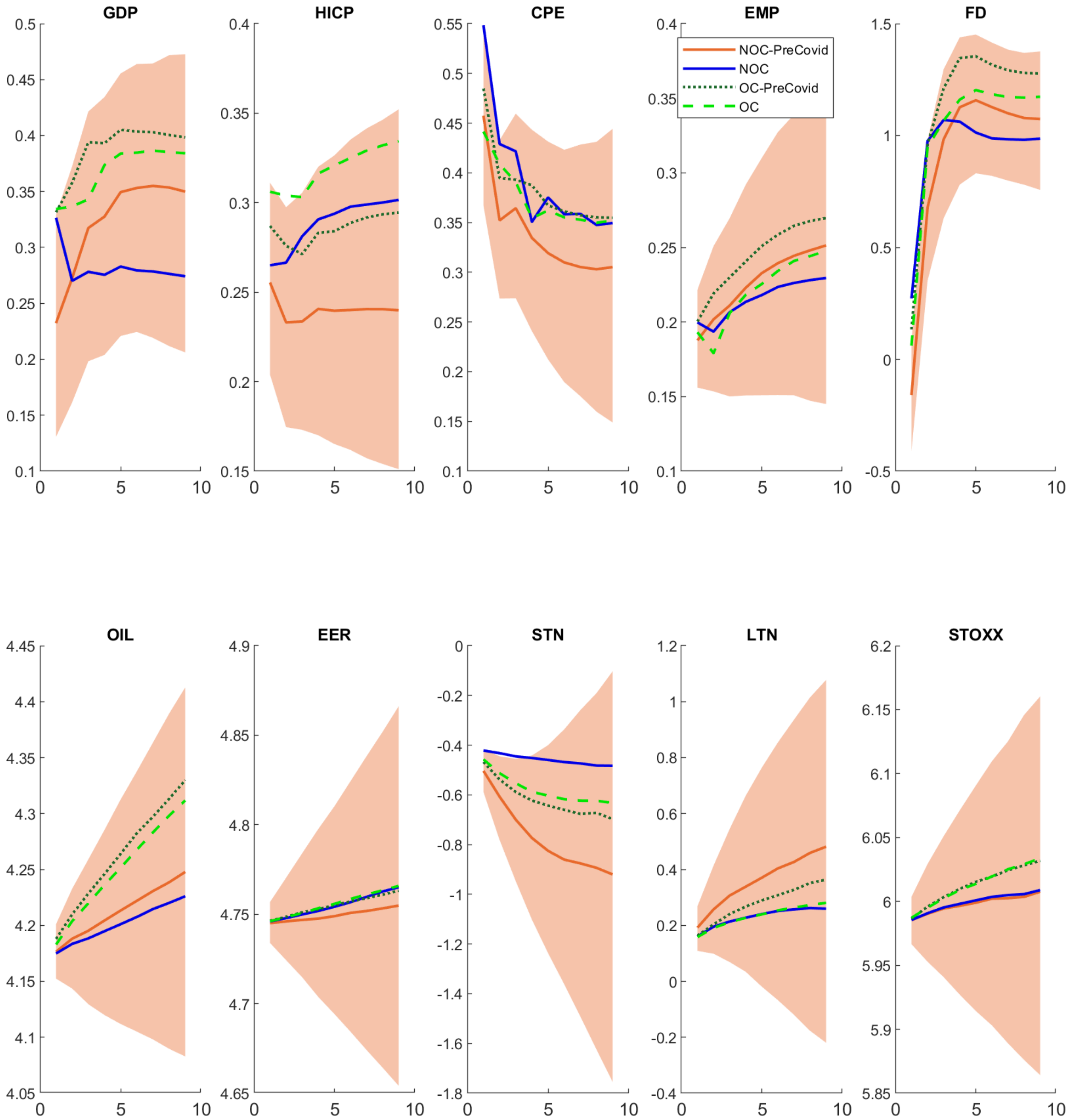


Note: The figure shows the posterior densities of the square root of the diagonal elements of Σ_e.

[3]Figure A.1 and Figure A.2 shows trace plots of $s_{\text{CPE},1991Q2}$ and o_{2020Q3} to give examples of two convergence diagnostics for the outlier draws.

Figure 3 shows pseudo-forecasts, with origin 2019:Q4, for the OC (dashed line), OC-PreCovid (dotted line), and the NOC and NOC-PreCovid specification (solid lines). The pseudo-forecasts allow for a visual comparison of the dynamics of the models estimated under different specifications. The shaded area shows 68% credible intervals for the median forecast of the NOC-PreCovid specification. Comparing the solid lines to each other, shows the effect of the Covid-period observations on the model's posterior; for instance, the lines are considerably different for GDP and HICP underlining the strong effect of the few Covid-19 data points on the model's posterior. Comparing the dashed and dotted line shows that the outlier specification is largely able to dampen the effect of the observations during the pandemic on the model's dynamics.

Figure 3: Pseudo-forecasts — BVAR-WOSV

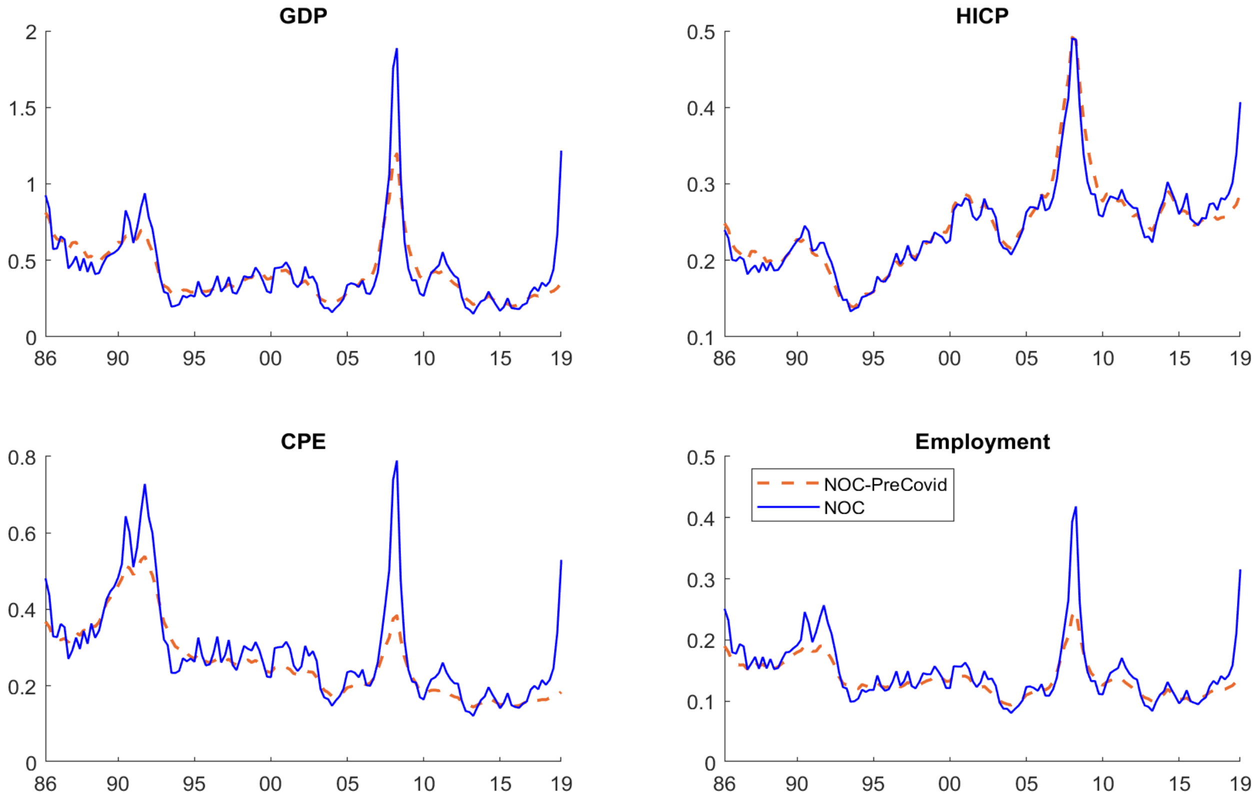


Note: The figure shows the posterior median pseudo-forecasts made using data up to 2019:Q4. The shaded area denotes 68% credible intervals of the median forecast of the PreCovid specification.

3.2 BVAR-SV

In a model with stochastic volatility, the data points of 2020 have a strong effect on the posterior distribution of the volatility series. Figure 4 shows the estimates of the stochastic volatility posterior mean for a subset of the variables of a model estimated on data from 1985:Q1 to 2019:Q4 (NOC-PreCovid, dashed line) and the same model estimated on data up to 2021:Q3 (NOC, solid line). The volatility estimates are plotted until 2019:Q4, for a plot until 2021:Q3 of the NOC specification see Figure B.4. Once 2020 and 2021 observations are included, the volatility series changed throughout the sample, with much larger values around the financial crisis and in the early 1990s for the GDP, CPE, and employment series. The seven new observations since the onset of the Covid-19 crisis have thus a large impact on the model's posterior. The figure also shows that the volatility increase in the NOC model starts well before 2020:Q1: to capture the large volatility increases in 2020, the rather smooth random walk specification used for xstochastic volatility starts to increase well before the onset of the crisis. In other words, the standard random walk (or autoregressive) SV specifications are unable to capture the dynamics of the pandemic in a reasonable way.

Figure 4: Time-varying standard deviation up to 2019:Q4 — BVAR-SV



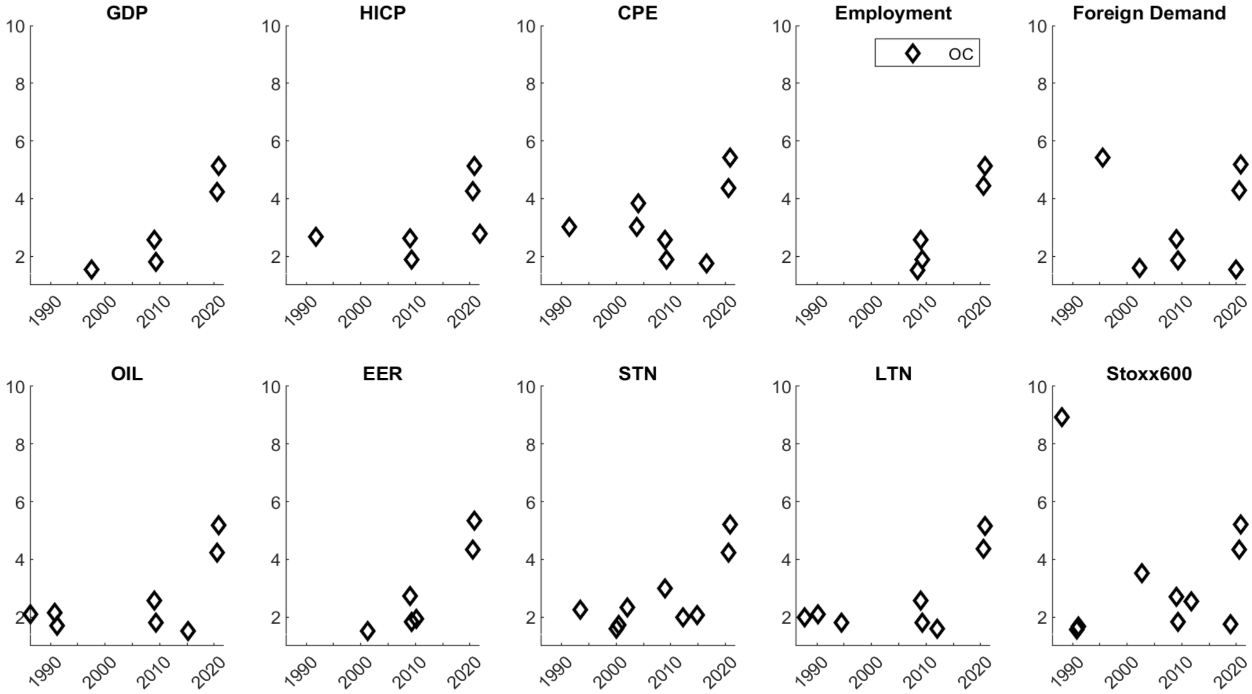
Note: The solid and dashed line show the posterior mean of the time-varying standard deviation of the NOC-PreCovid (dotted line) and NOC (solid line) specification. Estimates were obtained using data until 2019Q4 for the NOC-PreCovid model and until 2021Q3 for the NOC specification. The plot shows the estimated time-varying standard deviation until 2019:Q4 for both specifications.

Figure 5 shows posterior means of outliers estimated via the OC specification. Common outliers appear during the financial crisis and the pandemic, whereas individual outliers appear rather early in the sample for some variables such as CPE, FD, the STN and Stoxx 600.[4]

[4]Figure A.3 and Figure A.4 shows trace plots of $s_{FD,1995Q2}$ and o_{2020Q3} to give two examples of convergence diagnostics for the outlier draws.

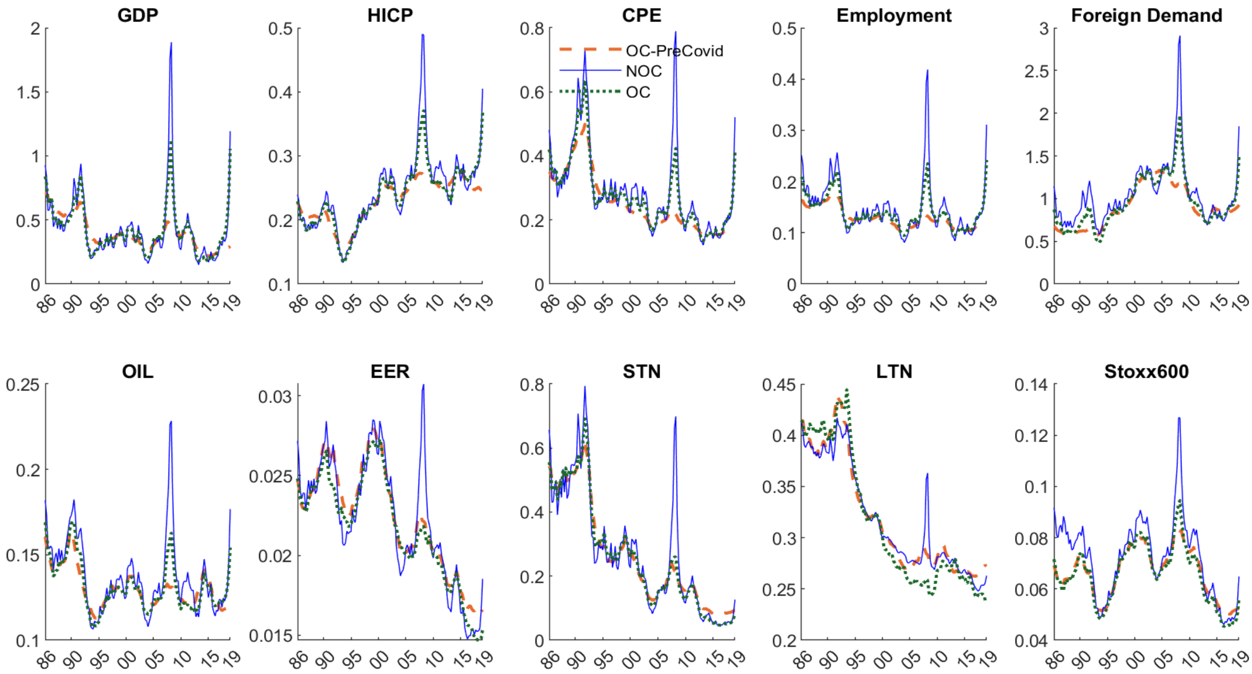
However, Figure 6 suggests that the posterior distribution of the stochastic volatility series is still affected by the 2020 data points since they deviate quite substantially from the OC-PreCovid estimates for some periods and variables, for instance for GDP around the financial crisis of 2008.

Figure 5: Posterior means of outliers — BVAR-SV



Note: The figure shows the posterior means of $o_t S_t$. To increase the legibility of the plot, it only shows posterior means above 1.5.

Figure 6: Time-varying standard deviation — BVAR-SV



Note: The solid, dashed, and dotted lines show the posterior mean of the time-varying standard deviation, excluding the contribution of o_t and S_t for the OC model, until 2019:Q4 of the NOC (solid), OC-PreCovid (dashed), and OC (dotted) specification. Estimates were obtained using data until 2019:Q4 for the OC-PreCovid model and until 2021:Q3 for the NOC and OC specification.

4 Forecast results

In this section, we investigate whether using the outlier correction method before 2020 improves out-of-sample forecasts in an evaluation sample ranging from 2002:Q1 to 2019:Q4. The initial in-sample estimation window ranges from 1985:Q1 to 2001:Q4, and the models are re-estimated each period using a recursive window scheme.[5]

4.1 BVAR-WOSV

Table 1 shows relative MSFEs and CRPSs of the BVAR-WOSV-OC model compared to the plain BVAR-WOSV; boldface numbers indicate a rejection of a test of equal predictive ability at the 10% level.[6] Boldface numbers indicate that the test of Clark and West (2007) rejects the null hypothesis of a one-sided test of equal predictive ability, with the alternative being that the OC model has a better forecasting performance. The results show that the outlier correction improves point forecasts for GDP, employment, the LTN, and Stoxx 600 relative to the plain BVAR-WOSV. However, density forecasts deteriorate for all variables and rather substantially for the exchange rate, interest rates, and stock index.

Figure 7 shows a heatmap of outlier estimates for the quarters of the in-sample (y-axis) and the different in-samples (x-axis) used in the recursive forecasting exercise. Warmer colors denote larger outlier estimates. We observe that the model estimates outliers around the financial crisis for each of the vintages used in the recursive in-sample estimations. In addition, the model starts to identify outliers in the early 1990s but of a smaller magnitude.

Table 1: BVAR-WOSV forecast comparison — 2002:Q1 to 2019:Q4

	Panel A MSFE				Panel B CRPS			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	**0.89**	**0.92**	**0.95**	0.99	**0.94**	0.98	1.01	1.05
HICP	1.04	1.04	1.05	1.14	**1.05**	**1.05**	1.06	1.10
CPE	0.98	0.93	1.02	0.99	1.00	1.04	**1.15**	**1.30**
Employment	1.01	**0.95**	**0.94**	**0.93**	1.02	1.01	1.03	**1.07**
ForeignDemand	1.06	1.01	1.05	1.08	**1.04**	1.03	1.05	**1.08**
OilPrice	1.00	0.99	1.01	1.05	1.02	1.00	1.01	1.05
EER	**0.99**	**0.93**	0.97	0.98	**1.07**	**1.12**	**1.22**	**1.42**
STN	0.95	0.99	1.01	1.06	1.00	**1.06**	**1.12**	**1.20**
LTN	**0.98**	**0.97**	0.97	1.02	**1.02**	**1.04**	**1.09**	**1.20**
Stoxx600	**0.96**	0.98	**0.96**	**0.94**	1.01	**1.04**	**1.09**	**1.21**

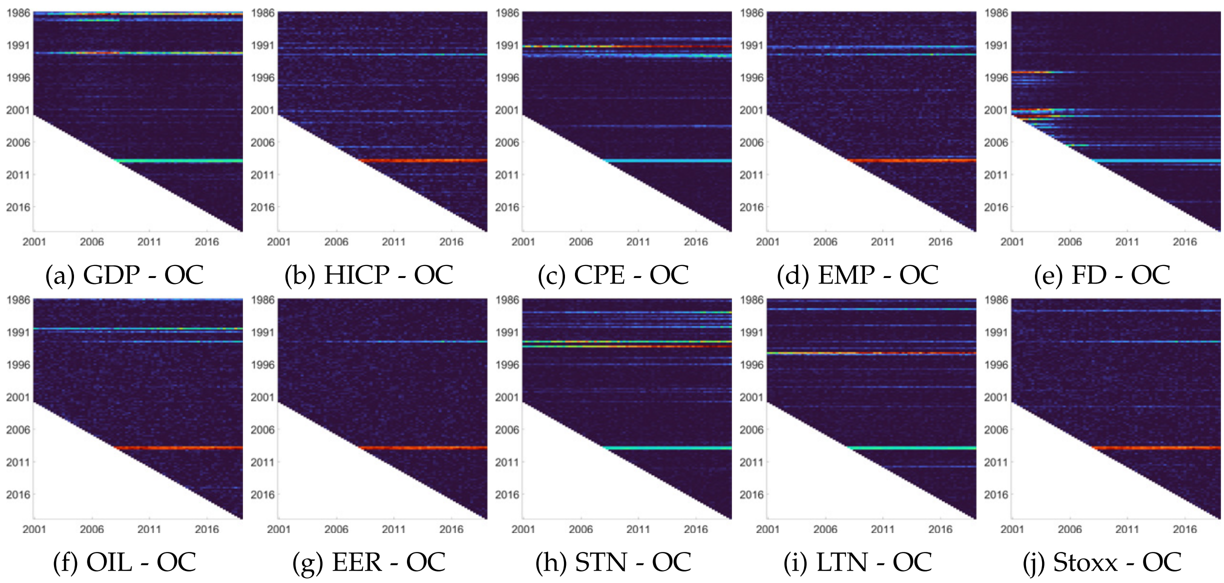
Note: The table shows the ratio of the MSFEs and CRPSs of a BVAR-WOSV-OC and a plain BVAR-WOSV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the BVAR-WOSV-OC. h denotes the forecast horizons. The pseudo out-of-sample period is 2002:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the one-sided test proposed in Clark and West (2007) for the MSFE and the two-sided test of Diebold and Mariano (1995) for the CRPS. A Newey and West (1987) HAC estimator is used to estimate the variance, and statistical significance at the 10% level is indicated by boldface numbers.

[5] These forecasts are based on final vintage data instead of using a real-time dataset.

[6] Since models are nested and estimated using a recursive window estimation scheme, we use the test statistic proposed in Clark and West (2007) for the forecast point comparison exercise. For the CRPS comparison, we use the standard Diebold and Mariano (1995) test since Clark and West (2007) is not applicable in that case.

Table B.1 shows results when the initial in-sample estimation ranges from 1995:Q1 to 2009:Q4, such that the evaluation sample becomes 2010:Q1 to 2019:Q4. Table B.2 shows results over the same, shorter out-of-sample evaluation period but when the in-sample estimation sample is as in the baseline specification. Results are qualitatively similar to Table 1. As shown in Figure 7, some of the estimated outliers occur before 1995 such that there are fewer outliers to be estimated in the shorter in-sample starting in 1995, which is documented in the outlier heatmap given in Figure B.2.

Figure 7: Recursively estimated outliers — BVAR-WOSV



(a) GDP - OC (b) HICP - OC (c) CPE - OC (d) EMP - OC (e) FD - OC

(f) OIL - OC (g) EER - OC (h) STN - OC (i) LTN - OC (j) Stoxx - OC

Note: The figure shows the outlier estimates when the in-sample is recursively increased by one quarter. The x-axis denotes the last observation of the in-sample. The y-axis denotes the time series of in-sample dates. Warmer colors denote larger posteriors of $o_t S_t$, dark blue denotes a value of one, and white denotes observations that were not yet in the in-sample. Moving along the x-axis, for a given date on the y-axis, shows an outlier estimate at a specific point a time but across different in-samples. Moving along the y-axis, for a given date on the x-axis, shows the outlier estimates over time for a given in-sample.

4.2 BVAR-SV

Figure 8 documents that the different outlier specifications estimate outliers throughout all the vintages of the recursive window estimation scheme. To assess whether the estimated outliers lead to an improvement in the models' forecasting performance in the pre-Covid period, Table 2 shows results of a forecast comparison exercise of the BVAR-SV with and without an outlier correction method. Numbers show relative MSFEs and CRPSs of the models as indicated by the panel name; boldface numbers indicate a rejection of a test of equal predictive ability at the 10% level. Overall, there are no considerable improvements for point forecasts using either CCMM or OC. In turn, density forecasts considerably deteriorate using the outlier methods.

Table B.3 and Table B.4 show results when the initial in-sample estimation ranges from 1995:Q1 to 2009:Q4, with an evaluation sample of 2010:Q1 to 2019:Q4. Figure B.5 indicates the outlier magnitudes in the recursive estimation samples. Table B.5 and Table B.6 show results over the same, shorter out-of-sample evaluation period but when the in-sample period is the same as in the baseline specification. Comparing Table B.3 and Table B.5 shows that the in-sample somewhat matters for the relative point forecast performance; the outlier specification fairs relatively better when the in-sample starts in 1995:Q1. Note that in all evaluation and in-sample periods considered, the density forecasts considerably deteriorated.

Table 2: BVAR-SV forecast comparison — MSFE — 2002:Q1 to 2019:Q4

	Panel A CCMM/BVAR				Panel B OC/BVAR			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	**0.99**	1.00	**0.98**	**0.97**	**0.99**	1.00	**0.99**	**0.99**
HICP	1.00	1.02	1.03	1.04	1.01	1.01	1.00	1.01
CPE	0.99	1.03	1.06	1.08	0.98	1.04	1.03	1.05
Emp	1.00	1.00	1.00	**0.98**	1.02	1.01	1.00	**0.98**
FD	1.01	1.03	1.03	1.02	1.00	1.01	1.01	1.01
Oil	1.03	1.03	1.04	1.07	1.02	1.02	1.02	1.03
EER	1.03	1.03	1.07	1.10	1.01	1.01	1.03	1.01
STN	0.97	1.00	1.04	1.07	1.00	1.02	1.04	1.02
LTN	1.00	0.99	0.98	1.00	1.01	1.00	1.02	1.02
Stoxx	1.01	1.00	**0.98**	0.99	1.01	1.01	1.00	**0.98**

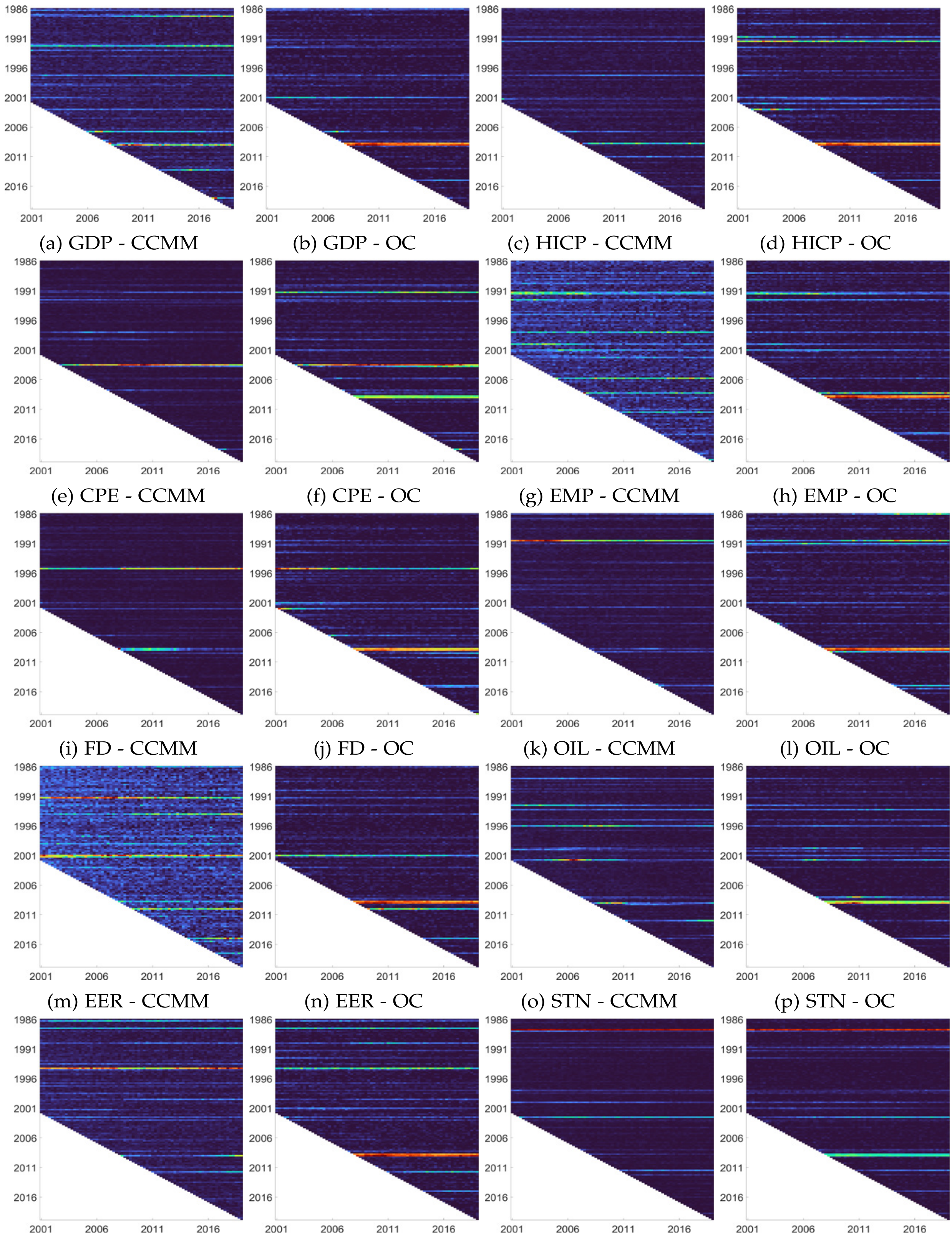
Note: The table shows the ratio of the MSFEs of a BVAR-SV with CCMM and OC and a plain BVAR-SV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the ratio indicated by the Panel name. h denotes the forecast horizons. The pseudo out-of-sample period is 2002:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the one-sided test proposed in Clark and West (2007) and a Newey and West (1987) HAC to estimate the variance. Statistical significance at the 10% level is indicated by boldface numbers.

Table 3: BVAR-SV forecast comparison — CRPS — 2002:Q1 to 2019:Q4

	Panel A CCMM/BVAR				Panel B OC/BVAR			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	0.99	1.01	1.00	0.98	1.00	1.03	1.03	1.01
HICP	0.99	1.00	1.01	1.03	1.00	1.00	1.00	1.01
CPE	1.01	**1.04**	**1.07**	**1.14**	1.01	**1.03**	**1.05**	**1.10**
Emp	1.00	1.00	1.00	**1.05**	**1.01**	1.01	1.01	**1.05**
FD	**1.04**	**1.05**	**1.05**	1.01	1.02	1.02	**1.03**	1.01
Oil	1.01	1.02	1.01	1.02	**1.02**	**1.02**	1.00	1.00
EER	**1.03**	**1.04**	**1.08**	**1.19**	**1.02**	**1.03**	**1.05**	**1.10**
STN	0.99	1.03	1.03	1.03	**1.03**	**1.05**	**1.03**	1.01
LTN	1.01	1.01	**1.04**	**1.08**	**1.03**	**1.04**	**1.06**	**1.07**
Stoxx	1.01	**1.03**	**1.06**	**1.16**	**1.03**	**1.06**	**1.08**	**1.15**

Note: The table shows the ratio of the CRPSs of a BVAR-SV with CCMM and OC and a plain BVAR-SV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the ratio indicated by the Panel name. h denotes the forecast horizons. The pseudo out-of-sample period is 2002:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the Diebold and Mariano (1995) test and a Newey and West (1987) HAC to estimate the variance. Statistical significance at the 10% level is indicated by boldface numbers.

Figure 8: Recursively estimated outliers — BVAR-SV



(a) GDP - CCMM (b) GDP - OC (c) HICP - CCMM (d) HICP - OC

(e) CPE - CCMM (f) CPE - OC (g) EMP - CCMM (h) EMP - OC

(i) FD - CCMM (j) FD - OC (k) OIL - CCMM (l) OIL - OC

(m) EER - CCMM (n) EER - OC (o) STN - CCMM (p) STN - OC

(q) LTN - CCMM (r) LTN - OC (s) Stoxx - CCMM (t) Stoxx - OC

Note: The figure shows for each variable-method combination the outlier estimates when the in-sample is recursively increased by one quarter. The x-axis denotes the last observation of the in-sample. The y-axis denotes the time series of in-sample dates. Warmer colors denote larger posteriors of $o_t S_t$, i.e. dark blue denotes a value of one. Moving along the x-axis, for a given date on the y-axis, shows outlier estimates at a specific point a time but across different in-samples. Moving along the y-axis, for a given date on the x-axis, shows the outlier estimates over time for a given in-sample.

5 Pre-specified outlier dates

Since the effect of the outlier specifications on the models' forecasting performance is mixed, we present results for a specification that allows for outliers only during pre-specified dates in 2020 and 2021. In other words, this specification allows for an adjustment for outliers caused by the Covid-19 pandemic but not outside of the specified dates. This amounts to setting

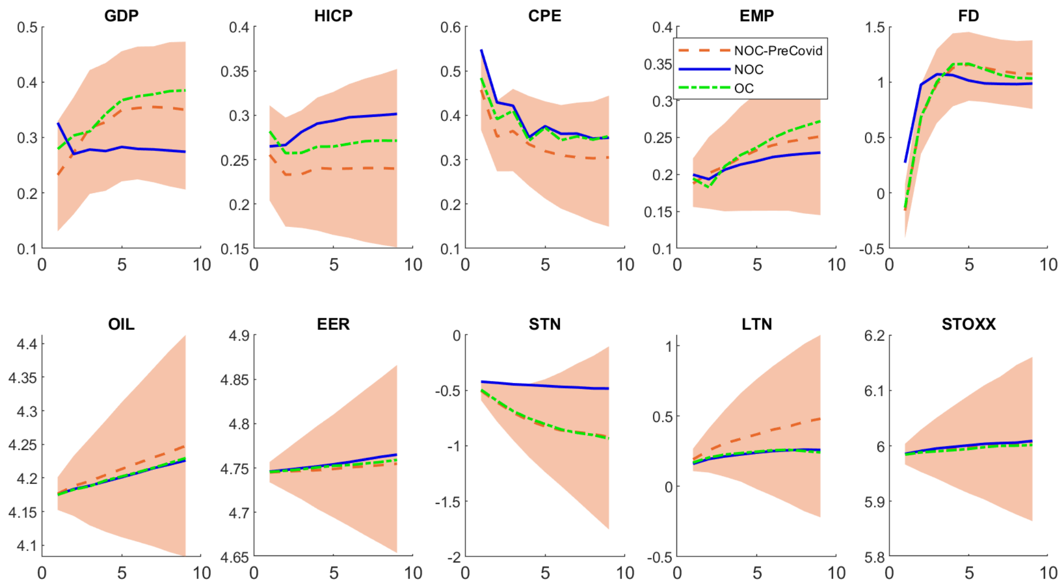
$$s_{n,t} = \begin{cases} U(1,20) & \text{if} \quad t \in \tau, \\ 1 & \text{otherwise,} \end{cases} \quad \text{for} \quad n = 1, ..., N. \qquad (3)$$
$$o_t = \begin{cases} U(1,20) & \text{if} \quad t \in \tau, \\ 1 & \text{otherwise,} \end{cases}$$

where τ is a set of dates on which we impose that $s_{n,t}$ and o_t are drawn from a uniform distribution $U(1,20)$. In the results presented below, τ includes 2020Q1 to Q4 and 2021Q1.

5.1 BVAR-WOSV

Figure 9 shows posterior medians of pseudo-forecasts, with origin 2019:Q4, for different BVAR-WOSV specifications: NOC-PreCovid (dashed line), OC (dash-dotted line), and NOC (solid line). The OC and NOC models are estimated on data up to 2021:Q3, and the NOC-PreCovid specification is estimated on data up to 2019:Q4. The shaded area shows 68% credible intervals for the PreCovid median forecasts. The posterior median forecasts of NOC differ substantially in terms of shape and location from NOC-PreCovid for GDP, HICP, FD, and STN. In addition, for CPE, FD, and the STN, the NOC specification lies outside of NOC-PreCovid's credible intervals.

Figure 9: Pseudo-forecasts — BVAR-WOSV — pre-specified outlier dates

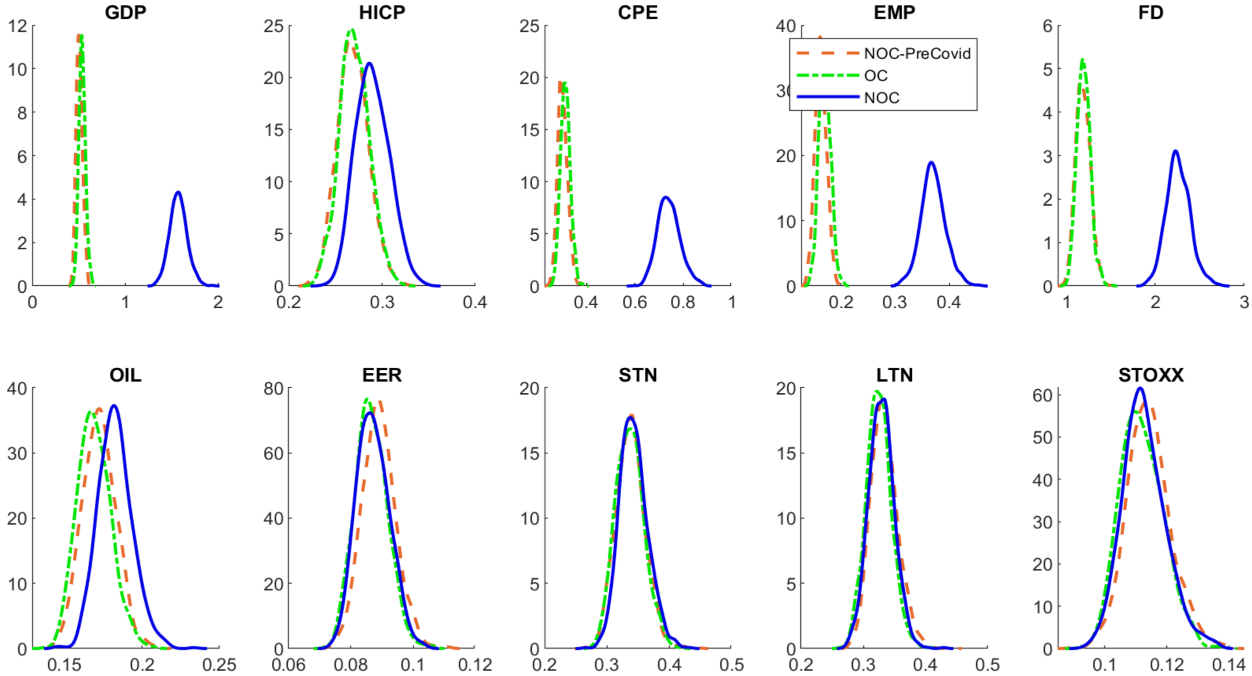


Note: The figure shows the posterior median pseudo-forecasts with origin 2019:Q4. The shaded area denotes 68% credible intervals of the median forecast of the NOC-PreCovid specification.

Figure 10 shows the posterior densities of the square root of the diagonal elements of Σ_e for three different models. Without any outlier correction (NOC), the posterior density of the variance increases drastically for the variables GDP, CPE, EMP, and FD due to the data points during the Covid-19 pandemic. In turn, OC shows posterior densities that are comparable to the NOC-PreCovid estimates.

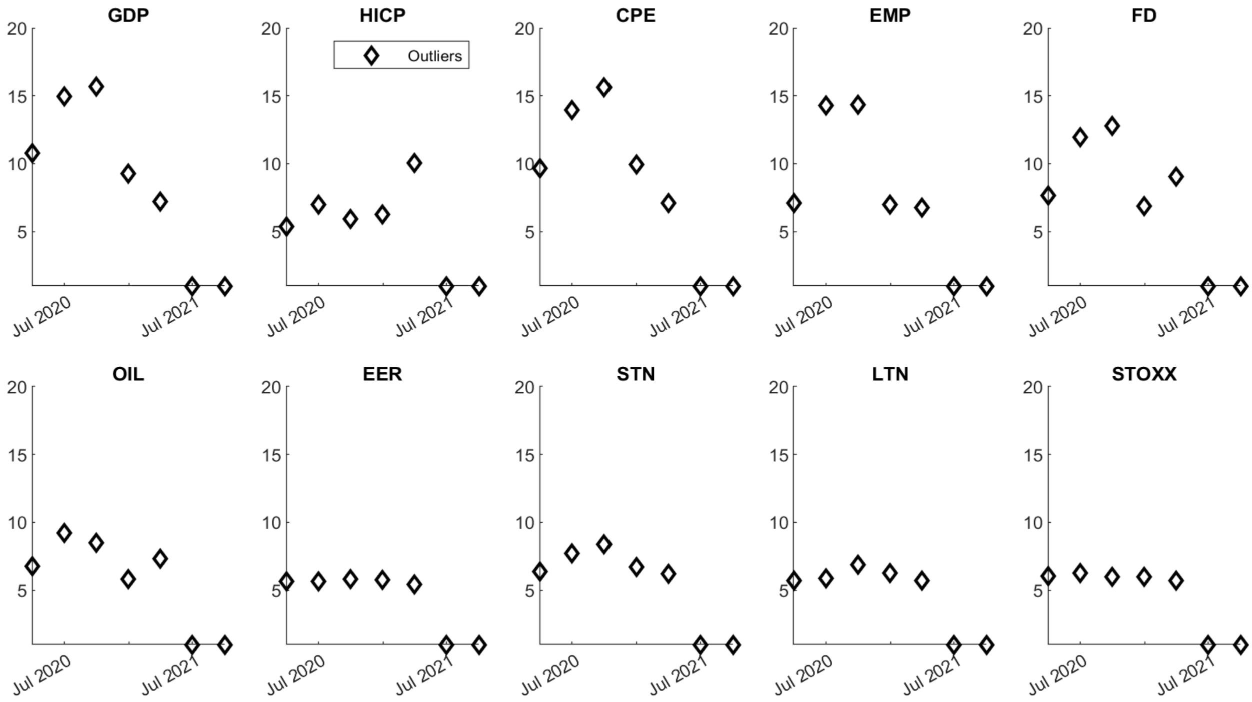
Figure 11 shows the posterior means of the estimated outliers. The outliers are particularly large for GDP, CPE, EMP, FD, and OIL.

Figure 10: Posterior densities of $\sigma_{ii,e}$ — BVAR-WOSV — pre-specified outlier dates



Note: The figure shows the posterior densities of the square root of the diagonal elements of Σ_e for different BVAR-WOSV specifications.

Figure 11: Posterior densities of outliers — BVAR-WOSV — pre-specified outlier dates

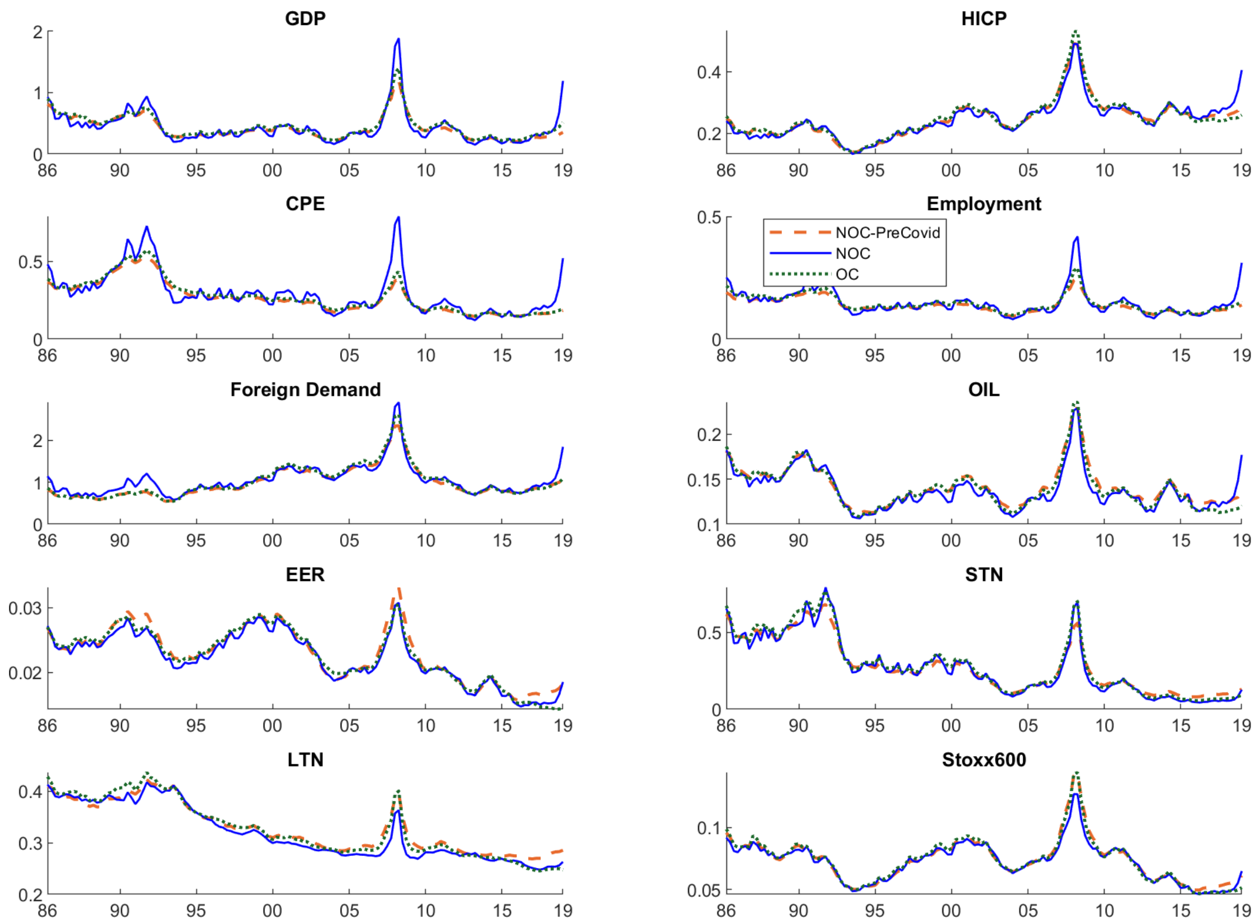


Note: The figure shows the posterior means of $o_t S_t$ from 2020Q1 to 2021Q3.

5.2 BVAR-SV

Figure 12 plots the stochastic volatility posterior mean estimates for three different models: the BVAR-SV estimated on data up to 2019:Q4 (NOC-PreCovid), the BVAR-SV with pre-specified outlier dates (OC) and without outliers (NOC) estimated on data up to 2021:Q3. The figure shows that without outlier specification, the 2020 and 2021 observations lead to large changes in the posterior of the estimated volatility series even for periods well before 2020; for instance, the spike in the stochastic volatility is particularly large for real GDP growth around the financial crisis for the NOC model. To capture the effect of the Covid-19 data points, the NOC specification's stochastic volatility increases substantially in 2020 to down-weigh the effect of the large swings of the 2020:Q1, Q2, and Q3 observations on the regression coefficients and the likelihood. This leads to a larger posterior mean of Ξ, the variance-covariance matrix of the shocks to the stochastic volatility equation, which in turn also increases the posterior estimates of the volatility outside of the Covid-19 periods.

Figure 12: Time-varying standard deviation until 2019:Q4 — BVAR-SV — pre-specified outlier dates

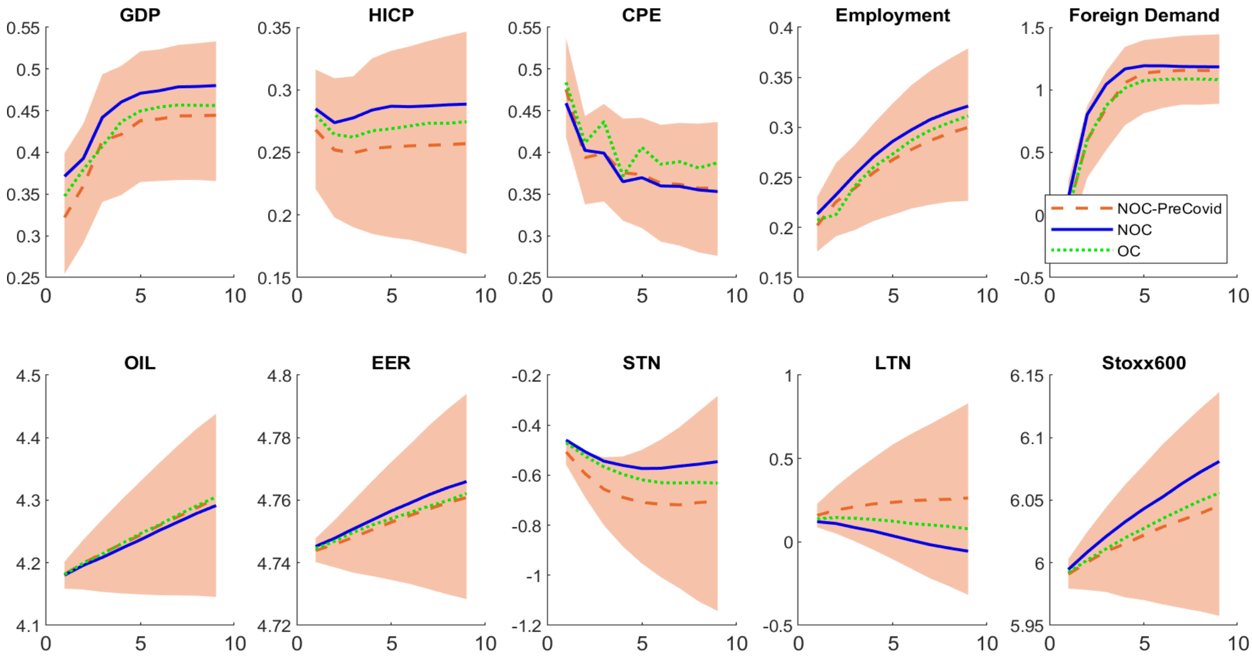


Note: The plot shows the posterior mean of the time-varying standard deviation, excluding the contribution of o_t and S_t for the OC model, of a NOC-PreCovid (dashed line), an OC (dotted line), and a NOC (solid line) specification. Estimates were obtained using data until 2019:Q4 for the NOC-PreCovid model and until 2021:Q3 for the OC and NOC specification.

Figure 13 shows pseudo-forecasts, with origin 2019:Q4, for the NOC-PreCovid (dashed line), OC (dotted line), and the NOC (solid line) specification. The shaded area shows 68% credible intervals for the median forecast of the NOC-PreCovid specification. The shape and levels of the forecasts are largely similar across the different specifications and in-samples. Notably, the forecasts of NOC are very similar to the NOC-PreCovid specification since the stochastic volatility captures the outliers (see Figure 4).

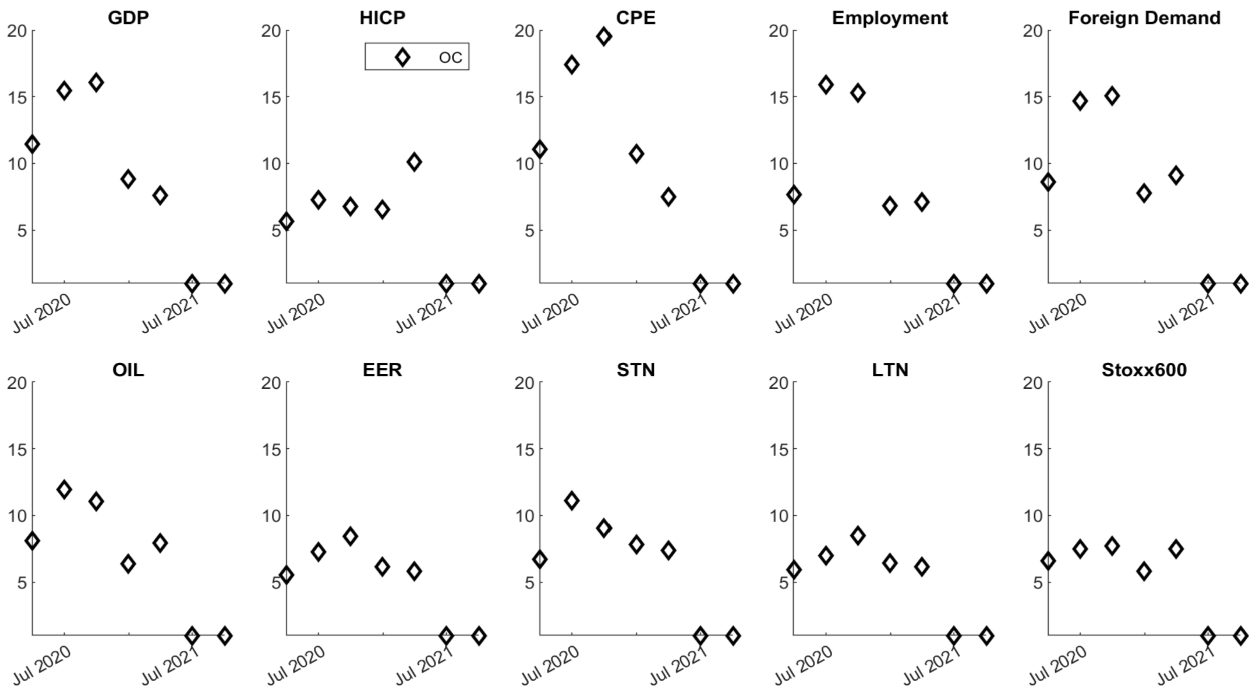
Figure 14 shows that the posterior means for the outliers for 2020:Q1 to 2021:Q3 are of considerable size for all variables.

Figure 13: Pseudo-forecasts — BVAR-SV — pre-specified outlier dates



Note: The figure shows the posterior median pseudo-forecasts made using data up to 2019:Q4. The shaded area denotes 68% credible intervals of the median forecast of the PreCovid specification.

Figure 14: Posterior means of outliers — BVAR-SV — pre-specified outlier dates



Note: The solid line shows the posterior means of $o_t S_t$ from 2020:Q1 to 2021:Q3.

6 Conclusion

The pandemic that started in 2020 drew attention to the issue of potential data outliers, i.e. large unprecedented swings that can severely affect the estimation of (linear) econometric models. In this paper, we present a methodology to account for data outliers and documented several empirical facts about the potential presence of outliers in an estimation of Bayesian VARs using euro area data.

First, the Covid-19 pandemic caused movements in macroeconomic data that distort the estimation results of BVARs. If the researcher does not account for the observations of 2020 in the modeling approach, these observations will substantially change the model parameters' posterior distributions.

Second, the outliers can be accounted for by rescaling the shocks' variance. The methodology presented in this paper rescale the reduced form error variance and can be implemented in models with and without stochastic volatility as well as for stochastic volatility specifications that do not rely on the triangular decomposition of Primiceri (2005).

Third, allowing for outliers prior to 2020 leads to improvements of the point forecasts of a BVAR without stochastic volatility for some variables and horizons. There are no improvements for the point forecasts of a BVAR that already includes stochastic volatility. Further, for both models the density forecasts considerably deteriorate for several variables. Based on these results, we recommend to allow for outliers only on pre-specified dates around the onset of the Covid-19 pandemic.

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Appendix A Gibbs sampler and convergence diagnostics

A.1 Gibbs sampler for OC

Standard steps of the Gibbs sampler are not explained in detail here and time subscripts are suppressed for simplicity:

1. Draw from $\pi(\beta, A, S, o, q_S, q_o, s_{\text{mixt}}|y, \Sigma)$, where s_{mixt} is the indicator for the mixture components (not the outliers) needed for the mixture approximation when drawing the stochastic volatility.
   (a) Draw β, A, S, o, q_s, q_o marginal of s_{mixt}.
      i. Draw β from $\pi(\beta|y, \Sigma, A, S, o, \kappa_\beta) \sim N_{pn^2+n}(\hat{\beta}, \hat{V}_\beta)$. Implementation is standard.
      ii. Draw A from $\pi(A|y, \beta, \Sigma, S, o)$. Implementation is standard.
      iii. Draw S from $\pi(S|y, \beta, \Sigma, A, q_S, o)$. S is drawn via a grid-approximation of the posterior distribution. See details below.
      iv. Draw q_S from $\pi(q_S|S)$. See details below.
      v. Draw o from $\pi(o|y, \beta, \Sigma, A, S, q_o)$. o is drawn via a grid-approximation of the posterior distribution. See details below.
      vi. Draw q_o from $\pi(q_o|o)$. See details below.
   (b) Draw s_{mixt} from $\pi(s_{\text{mixt}}|y, \beta, \Sigma, A, S, o)$. Implementation is standard.
2. Draw Σ from $\pi(\Sigma|y, \Sigma_\eta, \beta, A, S, o, s_{\text{mixt}})$ via Durbin and Koopmann (2002). Implementation is standard.
3. Draw Ξ from $\pi(\Xi|\Sigma) \sim IW_n(\hat{\tau}_\eta, \hat{S}_{V_\eta})$. Implementation is standard.
4. Draw κ_β from $\pi(\kappa_\beta|\beta)$ following Amir-Ahmadi et al. (2020).

Step 1.a.(iii), which simplifies to $\pi(S|y, \beta, \Sigma, A, q_S, o) \propto \pi(y|S, \beta, \Sigma, A, q_S, o)\pi(S|q_S)$, requires some clarification. For $\pi(y|S, \beta, \Sigma, A, o, q_S)$, we can write

$$y_t - \Pi X_t = v_t = o_t S_t A^{-1} \Sigma_t^{1/2} e_t \tag{4}$$

where $X_t = [1, y'_{t-1}, ..., y'_{t-p}]'$ and $\Pi = [B_0, B_1, ..., B_p]$, where $e_t \sim N(0, I)$, such that v_t has a multivariate Normal distribution with mean zero and variance $o_t S_t A^{-1} \Sigma_t$. The $s_{i,t}$ need to be drawn conditionally on the $s_{j,t}, j \neq i$ because the elements of v_t are contemporaneously correlated. Since the conditional posterior of $s_{i,t}$ is proportional to the product of a multivariate Normal and a uniform distribution, we approximate the conditional posterior over a grid of values for $s_{i,t}$ (see Stock and Watson (2016) for a related approximation of a conditional posterior).

Let $\pi_{\tilde{v}_t}(s_{i,t})$ denote $v_t|(o_t, S_t, A, \Sigma_t) \sim N(0, o_t^2 S_t A^{-1} \Sigma_t A^{-1'} S_t)$, where $s_{i,t}$ denotes the function's argument since we want to evaluate $\pi_{\tilde{v}_t}(s_{i,t})$ over a grid of values for $s_{i,t}$. In particular, the $s_{i,t}$ can be drawn iteratively for $i = 1, ..., N$ as follows:

I. Evaluate $\pi_{\tilde{v}_t}(s_{i,t}^{(j)})$ at grid points $s_{i,t}^{(1)}, ..., s_{i,t}^{(j)}, ..., s_{i,t}^{(J_{\text{grid}})}$ given $\tilde{v}_t, o_t, \Sigma_t, A$, and $S_{-i,t}$, where $S_{-i,t}$ denotes the draws $s_{j,t}$ for which $j \neq i$ from the previous sweep, $s_{i,t}^{(1)} = 1$ and the rest of the grid points are taken from the interval $[2, \bar{u}_s]$. Given the prior structure on $s_{i,t}$, the prior density, denoted by $w_{i,t}^{(j)}$, of $s_{i,t}^{(j)}$ is $w_{i,t}^{(1)} = (1 - q_{s,i})$ and $w_{i,t}^{(j)} = q_{s,i}/(J-1)$, $j \neq 1$, otherwise.

II. Compute $\tilde{\pi}_j = \frac{\pi_{\tilde{v}_{i,t}}(s_{i,t}^{(j)}) w_{i,t}^{(j)}}{\sum_{k=1}^{J_{\text{grid}}} \pi_{\tilde{v}_{i,t}}(s_{i,t}^{(k)}) w_{i,t}^{(j)}}$ for all $j = 1, ..., J_{\text{grid}}$.

III. Compute $\bar{\tilde{\pi}}_j = \sum_{k=1}^{j} \tilde{\pi}_k$ for all $j = 1, ..., J_{\text{grid}}$ and draw $u \sim U(0,1)$.

IV. Select $s_{i,t}^{(j)}$ as the new draw if $\bar{\tilde{\pi}}_{j-1} \leq u < \bar{\tilde{\pi}}_j$ with $\bar{\tilde{\pi}}_0 = 0$.

In step 1.(a).(iv): draw from the beta distribution $\pi(q_{s,i}|s_i)$, for $i = 1, ..., N$, where $q_{s,i}$ is the probability of an outlier in variable i and $s_i = \{s_{i,1}, ..., s_{i,t}, ..., s_{i,T}\}$. If the outlier dates are assumed to be known *a priori*, the step 1.(a).(iv) is dropped from the Gibbs sampler. Sampling o_t works analogously.

A.2 Gibbs sampler to implement CCMM

To implement the specification of CCMM we use the following Gibbs sampler:

1. Draw from $\pi(\beta, A, s_{\text{mixt}}|y, \Sigma)$, where the s_{mixt} denotes the indicators for the mixture components (not the outliers) needed for the mixture approximation when drawing the stochastic volatility.
   (a) Draw β, A marginal of s_{mixt}.
      i. Draw β from $\pi(\beta|y, \Sigma, A, S, \kappa_\beta) \sim N_{pn^2+n}(\hat{\beta}, \hat{V}_\beta)$. Implementation is standard.
      ii. Draw A from $\pi(A|y, \beta, \Sigma, S)$. Implementation is standard.
   (b) Draw s_{mixt} from $\pi(s_{\text{mixt}}|y, \beta, \Sigma, A, S)$. Implementation is standard.
2. Draw Σ from $\pi(\Sigma|y, \Sigma_\eta, \beta, A, S, s_{\text{mixt}})$ via Durbin and Koopmann (2002). Implementation is standard.
3. Draw Ξ from $\pi(\Xi|\Sigma) \sim IW_n(\hat{\tau}_\eta, \hat{S}_{V_\eta})$. Implementation is standard.
4. Draw S from $\pi(S|y, \beta, \Sigma, A, q, s_{\text{mixt}})$. S is drawn using a discrete approximation to the posterior. See details below.
5. Draw q from $\pi(q|S)$. See details below.
6. Draw κ_β from $\pi(\kappa_\beta|\beta)$ following Amir-Ahmadi et al. (2020).

In this specification, conditional on $y, \beta, \Sigma, A, s_{\text{mixt}}$, we can write

$$A(y_t - \Pi X_t) = \tilde{v}_t = S_t \Sigma_t^{1/2} e_t = S_t \Sigma_t^{1/2} e_t = [s_{1,t}\sigma_{1,t}e_{1,t}, ..., s_{N,t}\sigma_{N,t}e_{N,t}]'. \tag{5}$$

Since the $e_t \sim N(0, I)$, we can write $\log(\tilde{v}_{i,t}^2)|(s_{\text{mixt},i,t}, \sigma_{i,t}, s_{i,t}) \sim N(\mu_{i,\text{mixt},t} + \log(s_{i,t}^2) + \log(\sigma_{i,t}^2)\ ,\ \sigma_{i,mixt,t}^2)$, where $\mu_{i,\text{mixt},t}$ and $\sigma_{i,mixt,t}^2$ denote the respective mixture components for equation i at time t. Let $\pi_{\tilde{v}_{i,t}}(s_{i,t})$ denote $\log(\tilde{v}_{i,t}^2)|(s_{\text{mixt},i,t}, \sigma_{i,t}, s_{i,t})$. The values for $s_{i,t}$ can then be drawn as follows:

I. Evaluate $\pi_{\tilde{v}_{i,t}}(s_{i,t}^{(j)})$ at grid points $s_{i,t}^{(1)}, ..., s_{i,t}^{(j)}, ..., s_{i,t}^{(J_{\text{grid}})}$ and $\tilde{v}_{i,t}, \sigma_{i,t}$, and $s_{\text{mixt},i,t}$. As in Section A.1, the prior density of $s_{i,t}$ is denoted by $w_{i,t}^{(j)}$.

II. Compute $\tilde{\pi}_j = \frac{\pi_{\tilde{v}_{i,t}}(s_{i,t}^{(j)}) w_{i,t}^{(j)}}{\sum_{k=1}^{J_{\text{grid}}} \pi_{\tilde{v}_{i,t}}(s_{i,t}^{(k)}) w_{i,t}^{(j)}}$ for all $j = 1, ..., J_{\text{grid}}$.

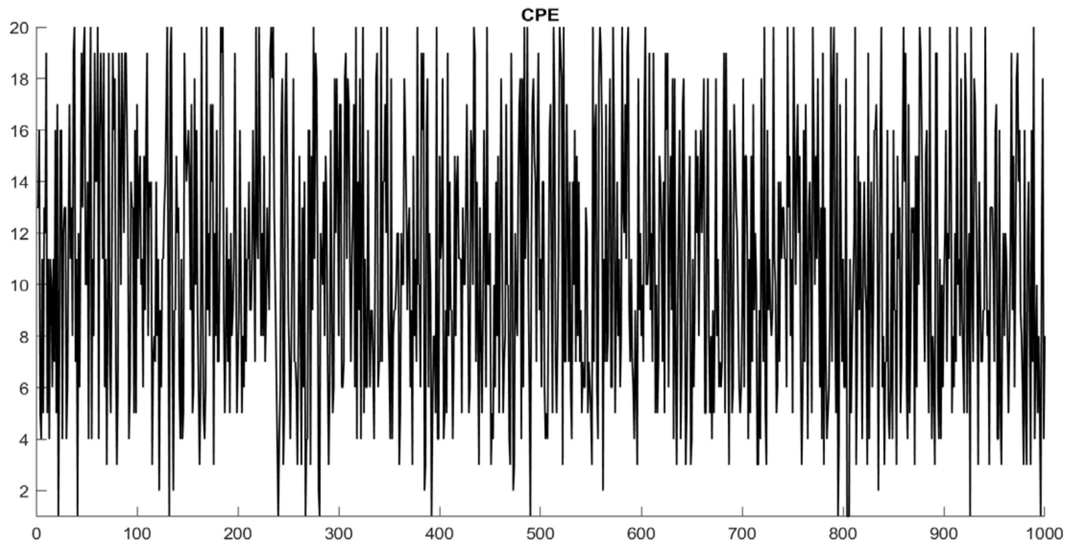
III. Compute $\bar{\tilde{\pi}}_j = \sum_{k=1}^{j} \tilde{\pi}_k$ for all $j = 1, ..., J_{\text{grid}}$ and draw $u \sim U(0,1)$.

IV. Select $s_{i,t}^{(j)}$ as the new draw if $\bar{\tilde{\pi}}_{j-1} \leq u < \bar{\tilde{\pi}}_j$ with $\bar{\tilde{\pi}}_0 = 0$.

Sampling q from $\pi(q|S)$ can be done as in Section A.1.

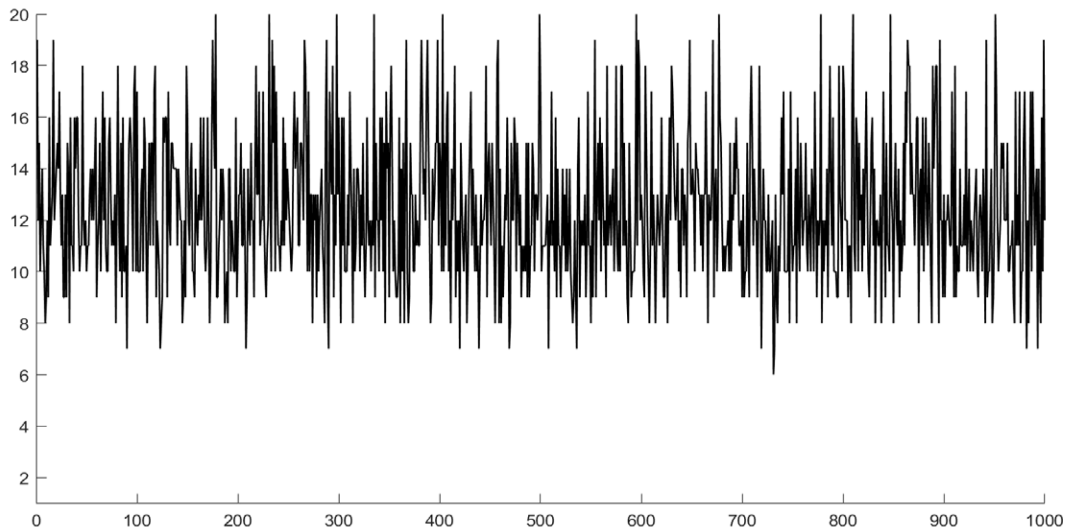
A.3 BVAR-WOSV with outlier correction — convergence diagnostics

Figure A.1: Trace plot of draws of $s_{\text{CPE},t}$ — BVAR-WOSV-OC — 1991Q2



Note: The figure shows a trace plot for outliers $s_{\text{CPE},t}$, with t = 1991:Q2, based on 1,000 posterior draws. The estimation sample is 1985:Q1 to 2021:Q3.

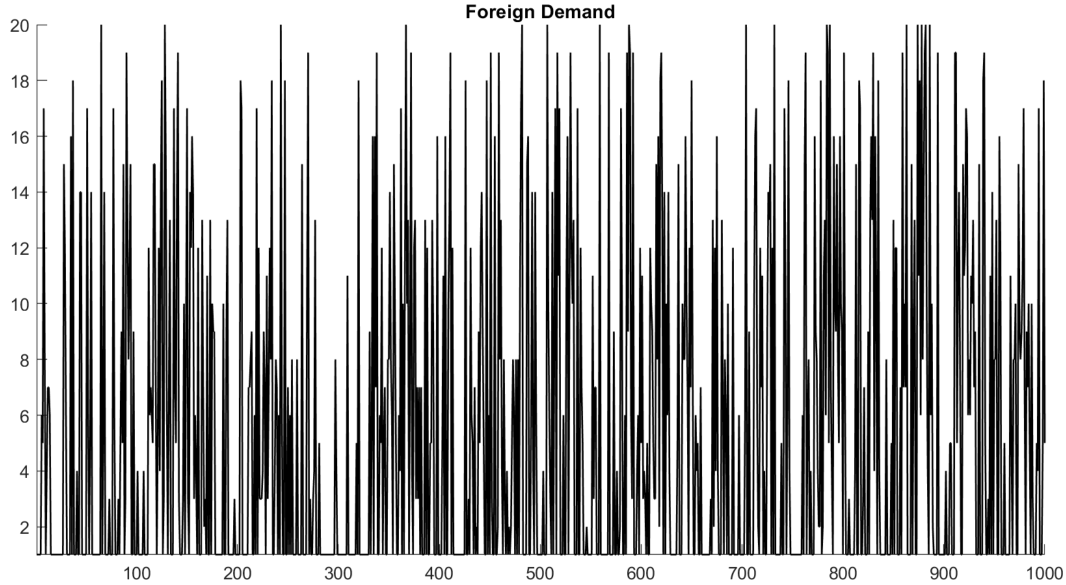
Figure A.2: Trace plot of draws of $o_{\text{CPE},t}$ — BVAR-WOSV-OC — 2020Q3



Note: The figure shows a trace plot for outliers o_t, with t = 2020:Q3 based on 1,000 posterior draws. The estimation sample is 1985:Q1 to 2021:Q3.

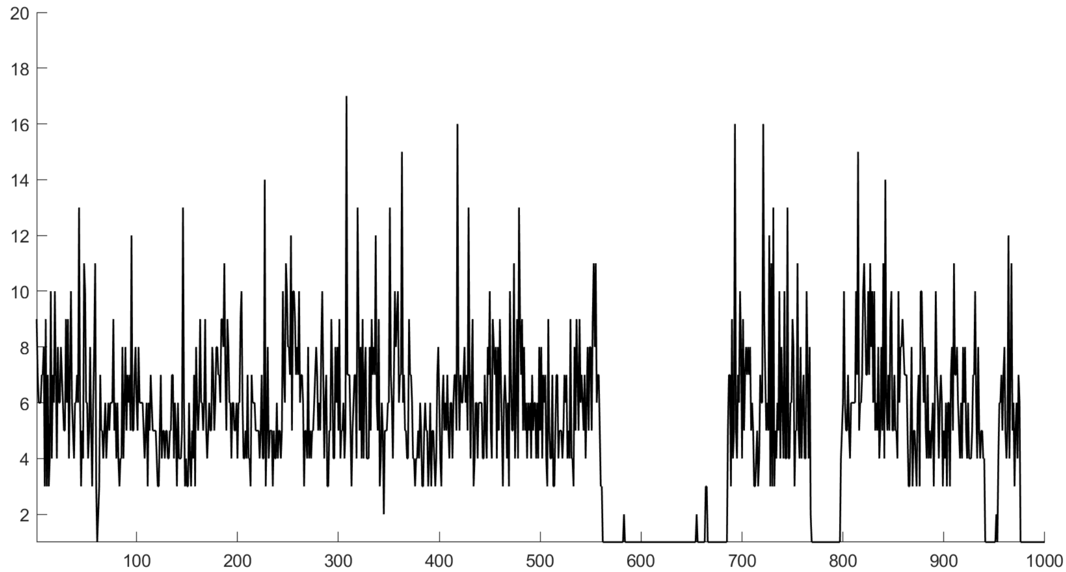
A.4 BVAR-SV with outlier correction — convergence diagnostics

Figure A.3: Trace plot of draws of $s_{\mathrm{FD},t}$ — BVAR-SV — 1995Q2



Note: The figure shows a trace plot for outliers $s_{\mathrm{FD},t}$, with t = 1995:Q2 for 1,000 posterior draws. The estimation sample is 1985:Q1 to 2021:Q3.

Figure A.4: Trace plot of draws of o_t — BVAR-SV — 2020Q3

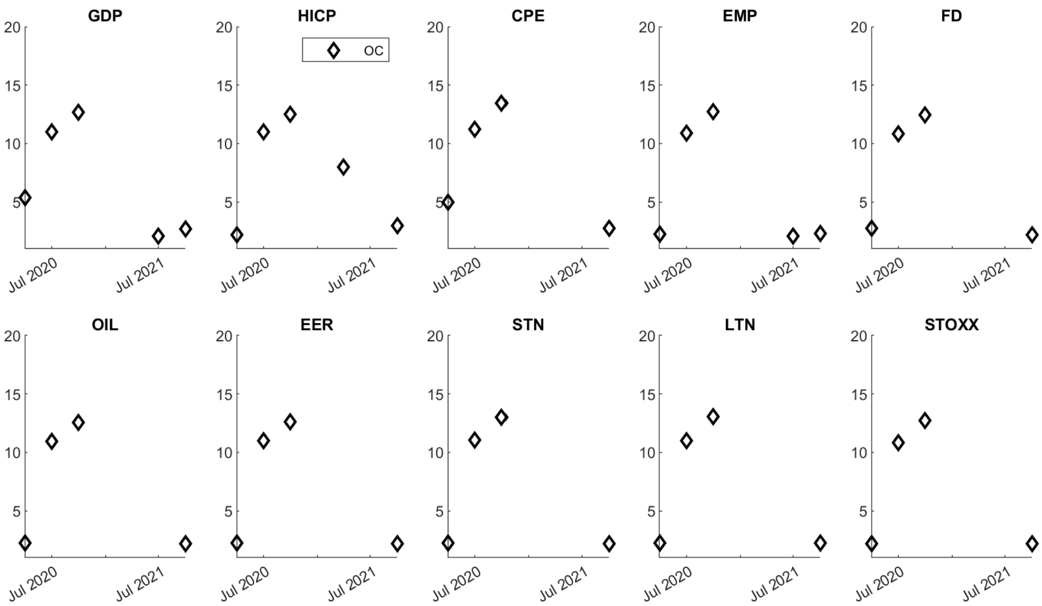


Note: The figure shows a trace plot for outliers o_t, with t = 2020:Q3 for 1,000 posterior draws. The estimation sample is 1985:Q1 to 2021:Q3.

Appendix B Additional results

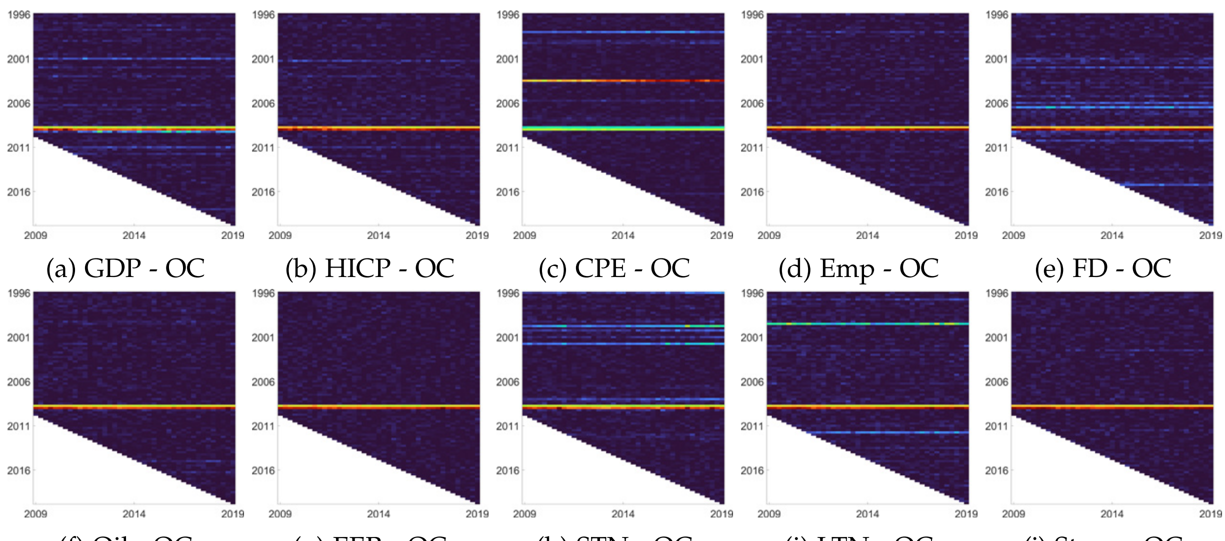
B.1 BVAR-WOSV

Figure B.1: Posterior means of outliers — BVAR-WOSV



Note: The figure shows the posterior means of the outlier draws from 2020:Q1 to 2021:Q3.

Figure B.2: Recursively estimated outliers — BVAR-WOSV



(a) GDP - OC (b) HICP - OC (c) CPE - OC (d) Emp - OC (e) FD - OC

(f) Oil - OC (g) EER - OC (h) STN - OC (i) LTN - OC (j) Stoxx - OC

Note: The figure shows for each variable-method combination, the outlier estimates when the in-sample is recursively increased by one quarter. The x-axis denotes the last observation of the in-sample. The y-axis denotes the time series of in-sample dates. Warmer colors denote larger posteriors of $o_t S_t$, dark blue denotes a value of one, and white denotes observations that were not yet in the in-sample. Moving along the x-axis, for a given date on the y-axis, shows outlier estimate at a specific point a time but across different in-samples. Moving along the y-axis, for a given date on the x-axis, shows the outlier estimates over time for a given in-sample.

Table B.1: BVAR-WOSV forecast comparison — IS starts 1995 — MSFE — 2010:Q1 to 2019:Q4

	Panel A MSFE				Panel B CRPS			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	**0.96**	**0.96**	**0.97**	0.97	0.97	**0.95**	0.98	0.99
HICP	**0.93**	**0.96**	**0.97**	**0.95**	**0.97**	0.99	1.00	1.00
CPE	1.00	**0.98**	0.99	0.99	**1.02**	1.02	**1.06**	**1.14**
Employment	**0.97**	**0.98**	0.98	0.98	1.01	0.98	0.96	0.99
ForeignDemand	**0.97**	0.98	**0.96**	0.97	0.97	0.97	0.97	0.99
OilPrice	1.03	1.07	1.16	1.38	1.03	1.03	**1.03**	**1.21**
EER	1.00	1.03	1.04	**0.91**	**1.04**	**1.14**	**1.31**	**1.63**
STN	**0.98**	**0.95**	**0.88**	**0.72**	**0.97**	**0.93**	**0.87**	0.90
LTN	**0.99**	**0.98**	**0.97**	**0.95**	**0.97**	**0.95**	**0.92**	0.93
Stoxx600	**0.99**	1.00	1.03	1.00	1.01	1.01	**1.06**	**1.22**

Note: The table shows the ratio of the MSFEs and CRPSs of a BVAR-WOSV with OC and a plain BVAR-WOSV in Panel A and Panel B. Numbers smaller than one indicate a superior performance of the OC specification. h denotes the forecast horizons. The pseudo out-of-sample period is 2010:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the one-sided test proposed in Clark and West (2007) for Panel A and a Diebold and Mariano (1995) test for Panel B, using a Newey and West (1987) HAC estimator for the variance, and statistical significance at the 10% level is indicated by boldface numbers.

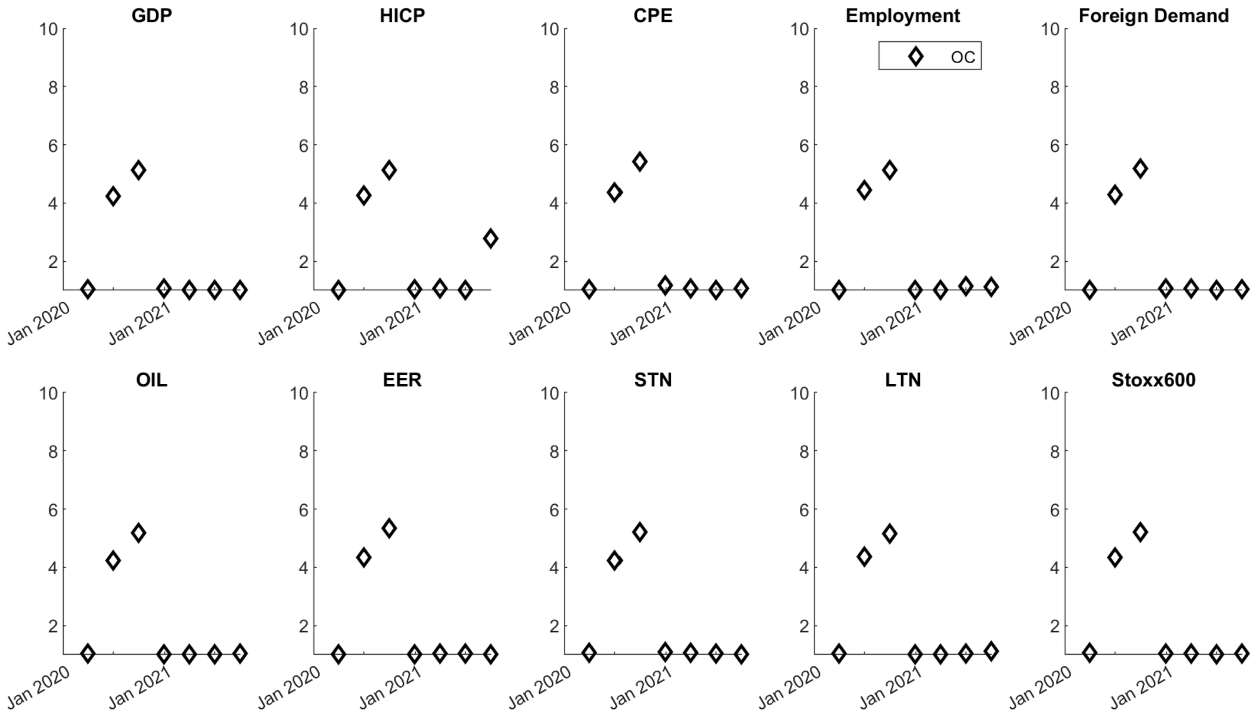
Table B.2: BVAR-WOSV forecast comparison — IS start 1985— MSFE — 2010:Q1 to 2019:Q4

	Panel A MSFE				Panel B CRPS			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	**0.93**	**0.96**	0.97	0.98	0.94	0.99	1.01	1.02
HICP	1.04	1.10	1.15	1.41	1.04	1.07	1.10	**1.21**
CPE	1.04	1.03	1.17	1.37	1.03	**1.07**	**1.19**	**1.37**
Employment	**0.98**	**0.92**	**0.86**	**0.86**	1.01	1.03	1.05	1.07
ForeignDemand	1.24	1.45	1.66	1.62	**1.09**	**1.18**	**1.25**	**1.27**
OilPrice	1.01	1.04	1.07	1.27	1.00	1.03	1.08	**1.20**
EER	0.99	**0.94**	**0.93**	1.04	**1.07**	**1.12**	**1.22**	**1.44**
STN	1.38	1.69	1.99	3.57	1.02	**1.15**	**1.32**	**1.63**
LTN	0.98	0.98	1.02	1.09	1.02	**1.03**	**1.09**	**1.19**
Stoxx600	**0.95**	1.01	**0.94**	**0.84**	**1.03**	**1.08**	**1.15**	**1.28**

Note: The table shows the ratio of the MSFEs and CRPSs of a BVAR-WOSV with OC and a plain BVAR-WOSV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the OC specification. h denotes the forecast horizons. The pseudo out-of-sample period is 2010:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the one-sided test proposed in Clark and West (2007) for Panel A and a Diebold and Mariano (1995) test for Panel B, using a Newey and West (1987) HAC estimator for the variance, and statistical significance at the 10% level is indicated by boldface numbers.

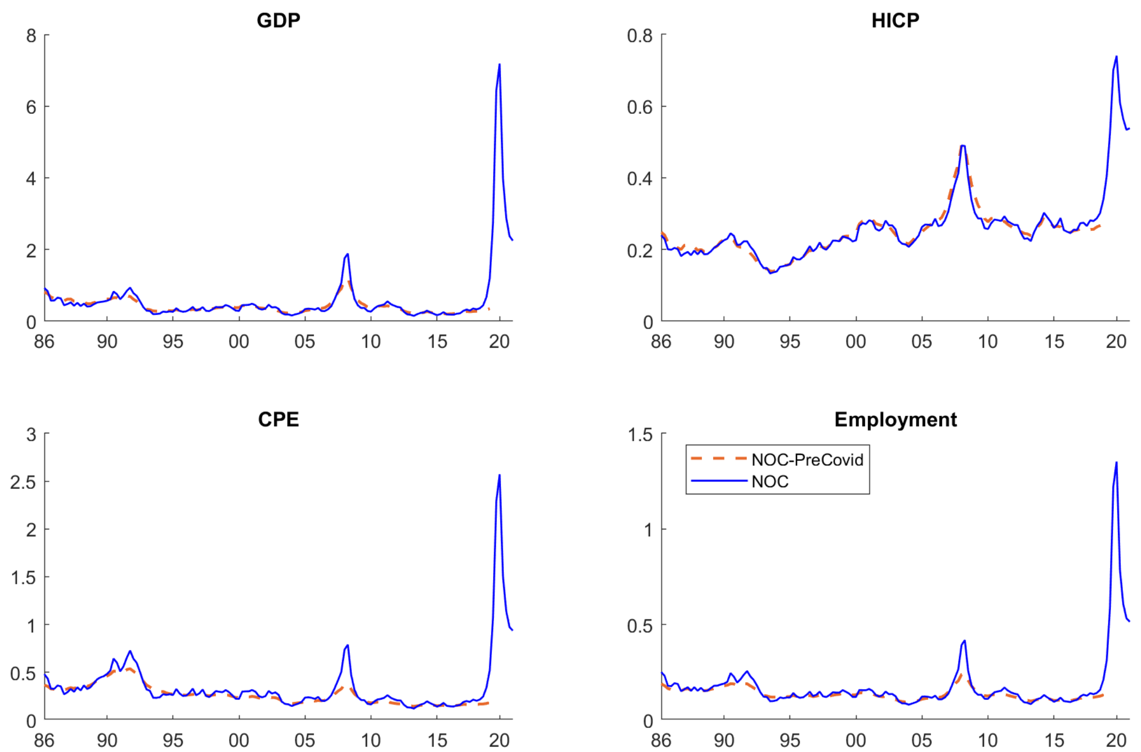
B.2 BVAR-SV

Figure B.3: Posterior means of outliers — BVAR-SV



Note: The figure shows the posterior means of $o_t S_t$ from 2020:Q1 to 2021:Q3.

Figure B.4: Time-varying standard deviation up to 2021:Q3 — BVAR-SV



Note: The solid and dashed line show the posterior mean of the time-varying standard deviation of the NOC-PreCovid (dotted line) and NOC (solid line) specification. Estimates were obtained using data until 2019Q4 for the NOC-PreCovid model and until 2021Q3 for the NOC specification. The plot shows the estimated time-varying standard deviation until 2019:Q4 for the NOC-PreCovid specification and until 2021:Q3 for the NOC specification.

Table B.3: BVAR-SV forecast comparison — IS start 1995 — MSFE — 2010:Q1 to 2019:Q4

	Panel A CCMM/BVAR				Panel B OC/BVAR			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	**0.92**	**0.91**	**0.89**	0.84	0.98	0.98	**0.95**	0.97
HICP	1.04	1.02	1.08	1.10	1.00	**0.99**	1.03	1.06
CPE	1.12	1.12	1.04	**0.93**	**0.96**	0.99	**0.97**	1.00
Emp	**0.91**	0.92	0.84	0.83	**0.96**	**0.96**	0.93	1.00
FD	1.03	0.98	1.06	1.00	1.00	1.00	**0.98**	1.00
Oil	1.08	1.12	1.10	1.12	1.02	1.05	1.05	1.05
EER	0.98	0.99	1.04	1.10	1.00	1.01	1.01	1.00
STN	1.25	1.13	1.02	1.06	1.07	1.02	1.00	1.00
LTN	1.05	1.07	1.05	0.99	1.00	1.01	1.00	1.01
Stoxx	0.99	**0.98**	**0.96**	0.99	1.01	1.00	1.02	1.03

Note: The table shows the ratio of the MSFEs of a BVAR-SV with CCMM and OC and a plain BVAR-SV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the ratio indicated by the panel name. h denotes the forecast horizons. The pseudo out-of-sample period is 2010:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the one-sided test proposed in Clark and West (2007) and a Newey and West (1987) HAC to estimate the variance. Statistical significance at the 10% level is indicated by boldface numbers.

Table B.4: BVAR-SV forecast comparison — IS start 1995 — CRPS — 2010:Q1 to 2019:Q4

	Panel A CCMM/BVAR				Panel B OC/BVAR			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	0.99	1.00	1.00	1.01	1.00	1.00	0.98	1.01
HICP	**1.02**	**1.02**	**1.06**	**1.07**	1.00	1.00	**1.01**	**1.03**
CPE	1.09	**1.09**	**1.10**	**1.09**	0.98	1.01	1.01	**1.03**
Emp	0.98	1.01	1.01	1.06	0.99	1.00	1.01	1.06
FD	**1.03**	**1.03**	**1.06**	**1.05**	**1.03**	**1.04**	**1.03**	**1.05**
Oil	**1.05**	**1.09**	**1.11**	**1.15**	**1.03**	**1.06**	**1.07**	1.07
EER	1.02	**1.03**	**1.10**	**1.35**	**1.02**	**1.03**	**1.05**	**1.15**
STN	**1.13**	**1.10**	**1.08**	1.04	**1.10**	**1.08**	**1.05**	0.99
LTN	**1.04**	**1.04**	1.02	0.95	1.01	1.00	0.98	0.95
Stoxx	**1.03**	**1.05**	**1.09**	**1.22**	**1.05**	**1.07**	**1.09**	**1.15**

Note: The table shows the ratio of the CRPSs of a BVAR-SV with CCMM and OC and a plain BVAR-SV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the ratio indicated by the panel name. h denotes the forecast horizons. The pseudo out-of-sample period is 2010:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the Diebold and Mariano (1995) test and a Newey and West (1987) HAC to estimate the variance. Statistical significance at the 10% level is indicated by boldface numbers.

Table B.5: BVAR-SV forecast comparison — MSFE — 2010:Q1 to 2019:Q4

	Panel A CCMM/BVAR				Panel B OC/BVAR			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	1.00	1.02	0.99	1.00	1.02	1.00	**0.93**	**0.91**
HICP	1.00	1.01	0.99	1.01	0.99	1.04	1.07	1.09
CPE	1.02	1.02	0.99	0.98	1.04	1.05	1.05	1.04
Emp	1.01	0.99	**0.96**	**0.98**	0.99	0.98	**0.92**	**0.92**
FD	**0.98**	**0.97**	**0.96**	1.00	1.10	1.17	1.13	1.08
Oil	1.02	1.03	1.01	1.00	1.06	1.10	1.13	1.17
EER	1.00	1.00	1.00	1.01	1.03	1.03	1.05	1.11
STN	1.02	1.00	1.02	1.04	1.12	1.13	1.13	1.23
LTN	1.00	0.99	1.01	1.01	1.00	0.98	0.97	0.98
Stoxx	1.01	1.02	1.00	0.98	1.02	1.00	0.97	0.96

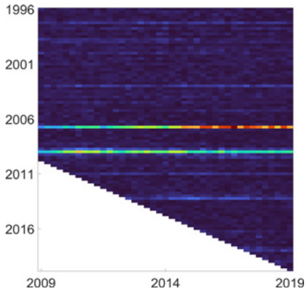
Note: The table shows the ratio of the MSFEs of a BVAR-SV with CCMM and OC and a plain BVAR-SV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the ratio indicated by the Panel name. h denotes the forecast horizons. The pseudo out-of-sample period is 2010:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the one-sided test proposed in Clark and West (2007) and a Newey and West (1987) HAC to estimate the variance. Statistical significance at the 10% level is indicated by boldface numbers.

Table B.6: BVAR-SV forecast comparison — CRPS — 2010:Q1 to 2019:Q4

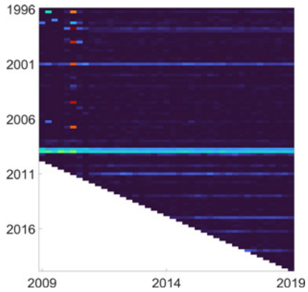
	Panel A CCMM/BVAR				Panel B OC/BVAR			
Variable	h=1	h=2	h=4	h=8	h=1	h=2	h=4	h=8
GDP	1.00	**1.01**	1.00	1.01	1.01	1.00	0.97	0.99
HICP	1.00	1.00	1.00	1.01	0.99	1.02	**1.05**	**1.05**
CPE	1.02	**1.03**	1.02	**1.04**	**1.03**	**1.05**	**1.08**	**1.10**
Emp	1.00	1.00	1.01	1.02	1.00	1.00	1.01	1.04
FD	1.00	1.01	1.01	**1.02**	**1.05**	**1.10**	**1.07**	**1.05**
Oil	**1.01**	**1.03**	1.02	1.01	1.02	**1.07**	**1.08**	**1.09**
EER	1.00	1.01	**1.02**	**1.10**	**1.03**	**1.03**	**1.07**	**1.22**
STN	**1.03**	**1.05**	**1.05**	**1.05**	1.04	**1.07**	**1.10**	**1.15**
LTN	**1.01**	1.01	1.02	1.01	1.01	1.01	1.01	1.01
Stoxx	**1.03**	**1.06**	**1.11**	**1.19**	**1.02**	**1.05**	**1.11**	**1.25**

Note: The table shows the ratio of the CRPSs of a BVAR-SV with CCMM and OC and a plain BVAR-SV in Panel A and Panel B. Numbers smaller than one indicate superior performance of the numerator of the ratio indicated by the Panel name. h denotes the forecast horizons. The pseudo out-of-sample period is 2010:Q1 to 2019:Q4 for $h = 1$ and respectively shorter for $h = 2, ..., 8$. Equal predictive ability is tested using the Diebold and Mariano (1995) test and a Newey and West (1987) HAC to estimate the variance. Statistical significance at the 10% level is indicated by boldface numbers.

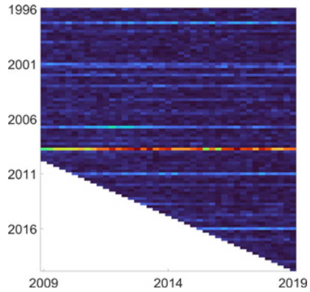
Figure B.5: Recursively estimated outliers — IS start 1995 — BVAR-SV



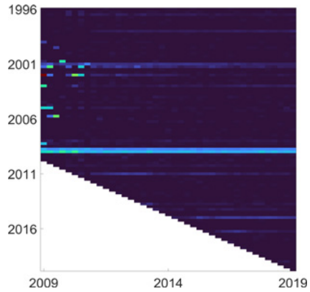
(a) GDP - CCMM



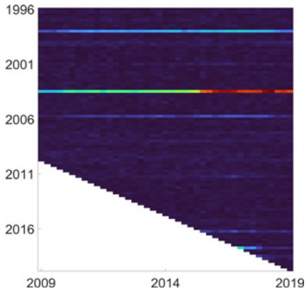
(b) GDP - OC



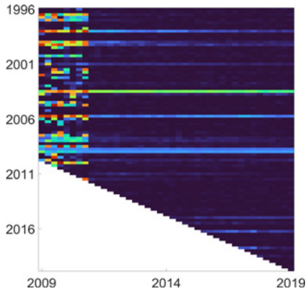
(c) HICP - CCMM



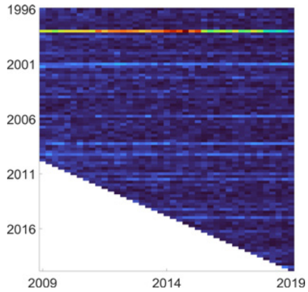
(d) HICP - OC



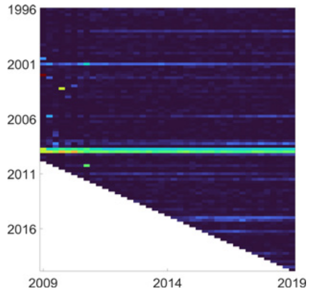
(e) CPE - CCMM



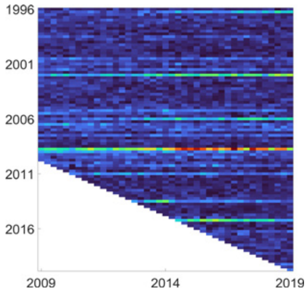
(f) CPE - OC



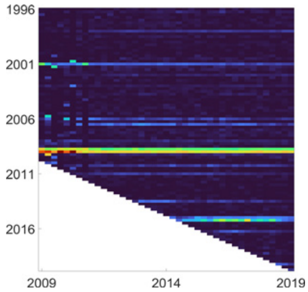
(g) EMP - CCMM



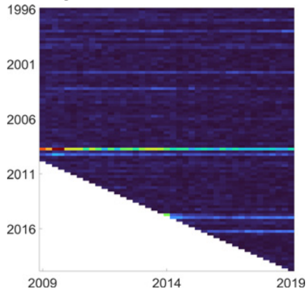
(h) EMP - OC



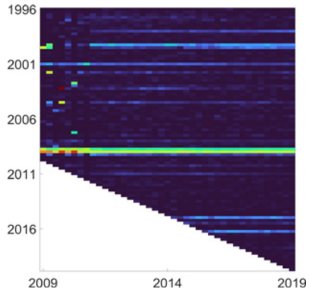
(i) FD - CCMM



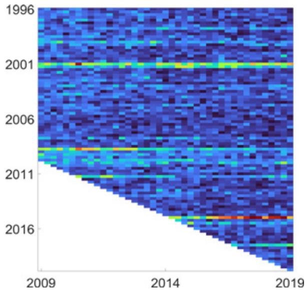
(j) FD - OC



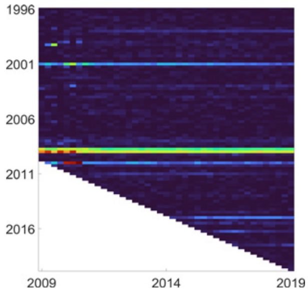
(k) OIL - CCMM



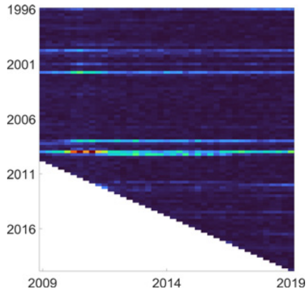
(l) OIL - OC



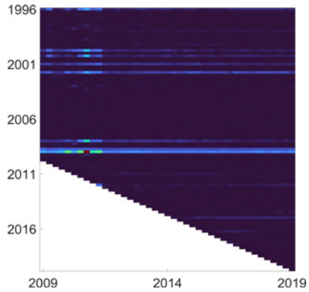
(m) EER - CCMM



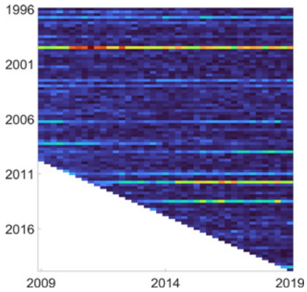
(n) EER - OC



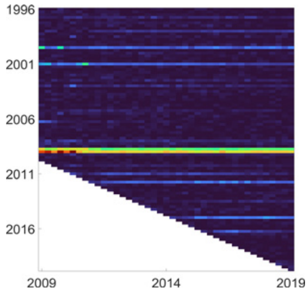
(o) STN - CCMM



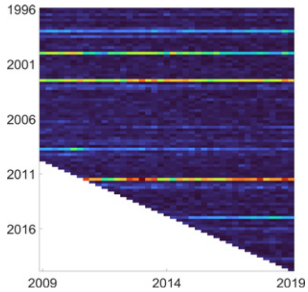
(p) STN - OC



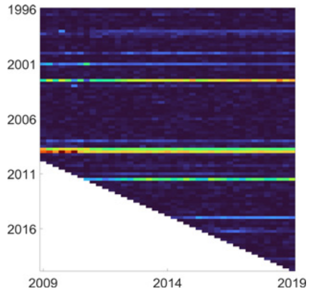
(q) LTN - CCMM



(r) LTN - OC



(s) Stoxx - CCMM



(t) Stoxx - OC

Note:The figure shows for each variable-method combination the outlier estimates when the in-sample is recursively increased by one quarter. The x-axis denotes the last observation of the in-sample. The y-axis denotes the time series of in-sample dates. Warmer colors denote larger posteriors of $o_t S_t$, i.e. dark blue denotes a value of one. Moving along the x-axis, for a given date on the y-axis, shows outlier estimates at a specific point a time but across different in-samples. Moving along the y-axis, for a given date on the x-axis, shows the outlier estimates over time for a given in-sample.

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