1 Introduction

The COVID-19 pandemic unprecedentedly affected humanity, not only in terms of public health but also economically. Unlike other crises, economic deterioration has been globally synchronised. According to the International Monetary Fund, the world economy contracted by approximately 3.0% in 2020, with both developed and emerging economies falling by 4.8% and 1.9%, respectively. Ensuing recovery was relatively quick owing to the distribution of vaccines and the gradual opening during and after the lockdown. This allowed most economies to bounce back to positive growth rates in one to three quarters, which, given the magnitude of the initial downturn, led to a worldwide growth of 6.0% in 2021— a reflection of extreme macroeconomic data with high levels of uncertainty. These fluctuations, quite naturally, lead economists to raise questions about the macroeconomic effects of the COVID-19 shock, particularly on variables such as the potential output and gap. On simple inspection, it is difficult to label a downturn of that magnitude as trivial for long-run variables. However, the pace of the recovery also makes it challenging to label this shock as highly influential.

With this in mind, we aim to answer whether estimations of the output gap should be adjusted to account for the COVID-19 shock. We intend to determine a way to reconcile the magnitude of the shock with its transitory nature when approximating the potential output.

Our approach must, therefore, cover two fronts: first, how to obtain a good econometric framework for estimating the output gap, and second, how this can be adjusted in a manner that allows incorporating the COVID-19 shock information but prevents it from influencing the model as if it was representative of the data-generating process. For the first point, we rely on a permanent-transitory (PT) decomposition framework to identify the fluctuations of a set of macroeconomic variables (where the output is included) in a Bayesian Structural Vector Autoregression (BSVAR) setup; this is done by following Uhlig (2004). Based on the resulting model, we recover a path for the potential output that covers the COVID-19 period. For the second point, we adjust the model estimation with a scale factor around the rare shock date along the lines of Lenza and Primiceri (2022).

Primarily, our model includes an ample set of variables that contrasts with the usual output gap estimation frameworks, such as univariate statistical filters or production function approaches. This enables us to include additional sources of information in our setup and account for the permanent income hypothesis through the relationship between consumption and long-run output, which, as mentioned by Cochrane (1994), facilitates identifying the permanent component of the output.

Nonetheless, the identification task in the context of SVAR models can be challenging, as these frameworks usually rely on imposing strong assumptions about the nature of shocks that can be too restrictive. For example, it is usual to impose that long-run output is driven only by supply shocks, while demand is only associated with transitory components (e.g., Barsky and Sims, 2011; Blinder and Rudd, 2013; Keating and Valcarcel, 2015; Chen and Gornicka, 2020). However, recent data has vindicated the potential long-term role of demand-driven phenomena; for example, in the Global Financial Crisis (GFC) and the protracted recovery that followed, a weak demand affected both the current output and its future expectations in such a persistent way that it shifted down the path of potential growth (Fontanari, Palumbo, and Salvatori, 2020).[1] The literature has followed suit and has recently pointed out that other shocks, such as demand (Furlanetto, Lepetit, Robstad, Rubio-Ramírez, and Ulvedal, 2021) and monetary (Jordà, Singh, and Taylor, 2020) shocks, can also have long-run effects.

The aforementioned consideration is even more valid in the context of the COVID-19 shock, which was considered a supply-driven shock but eventually showed to involve demand-driven fluctuations.[2] We circumvent this issue of a separate identification of supply and demand shocks and their association with different terms by adopting an agnostic identification approach along the lines of Uhlig (2004), that is, based on the maximization of the explained fraction of long-horizon Forecast Error Variance (FEV) of the gross domestic product (GDP). Such an approach is particularly reasonable for gauging the potential output when we observe shocks such as the COVID-19 downturn that are perceived as a combination of supply- and demand-driven fluctuations (rather than either exclusively).

This identification scheme has been used by recent studies, such as Angeletos, Collard, and

[1]This experience even led to revisiting the literature on hysteresis, such as Cerra, Fatás, and Saxena (forthcoming), Benati and Lubik (2021) and Aikman, Drehmann, Juselius, and Xing (2022).

[2]See Guerrieri, Lorenzoni, Straub, and Werning (2022) and Fornaro and Wolf (2020) for further discussion on demand to output spillovers and stagnation traps.

Dellas (2020) and Brignone and Mazzali (2022) and with the same objective of decomposing the permanent and transitory fluctuations of macroeconomic variables. We follow a similar approach while adjusting the econometric modelling along the lines of Lenza and Primiceri (2022), which allows us to incorporate the COVID-19 downturn in the sample but limits the impact of the rare event on the estimated parameters. The joint application of the identification setup and adjustment for high-magnitude shocks in the context of output gap estimations represents our contribution.

We apply our approach to the seven developed economies and find that a single structural shock is sufficient to characterise the long-run behaviour of GDP. By contrast, the remaining shocks tend to explain their transitory effects more significantly. This result aligns with the findings of Dieppe, Francis, and Kindberg-Hanlon (2021), Angeletos, Collard, and Dellas (2020) and Brignone and Mazzali (2022) for the US and European countries. Based on this result and the structural shocks, we approximate the GDP gap at each date as the weighted sum of the transitory shocks (and use the other shock to recover potential output) with weights based on the associated historical decomposition of the BSVAR model.

We address our main research question and compare the potential output (and gap) estimates with standard gap estimation methods and the BSVAR counterpart with no COVID-19 adjustment. We find that our proposal (PT identification with COVID-19 adjustment) prevents the potential output from falling too rapidly at the onset of the shock and does not induce a fast recovery in subsequent periods, a known drawback of usual univariate filtering techniques, that can also be present in other output gap methods, and leads to reliability and stability issues in the final estimates (see for example Chalmovianský and Němec, 2022; Marcellino and Musso, 2011; Camba-Mendez and Rodriguez-Palenzuela, 2003).

Then, we compare our method with an alternative BSVAR with the same identification scheme but a stochastic volatility setup. This alternative is, in principle, also adjusting for the effect of the COVID-19 episode on the model. However, in contrast to our scaling method around the shock date, the adjustment is entirely endogenous because the variance is time-varying. This model leads to a stronger decrease in the potential output, but even by 2022 shows no sign of recovery, suggesting that the large magnitude of the shock could persistently affect the estimates. In light of this, our model represents a more appropriate alternative for a shock of large magnitude but small persistence that is less representative of the data-generating process of the sample.

Finally, we evaluate our method in a simulation setting to compare it with alternative setups in a more general light —instead of only with the specific COVID-19 episode as a reference. The results indicate that the large-scale shock may induce standard filters to deliver negatively correlated estimators with the target (simulated "true" output gap). When that occurs, our model's structurally identified permanent component corrects the issue by itself, that is, without any large-shock adjustment. However, only through the scale factor adjustment we can obtain sizable gains in terms of the cross-correlations (with the estimand), which at their peak can grow from less than 0.5 (with unadjusted methods) to beyond 0.8.

In summary, these results and exercises consistently indicate that the model's performance is not only associated with the structural identification of the BSVAR but also with the adjustment of the model to include the large shock. The benefits of adjusting the gap estimates in the presence of shocks of unprecedented magnitude are non-trivial. The performance gains terms are present even in models that are already successful at approximating the potential output. In addition, our setup prevents a substantial decrease in the potential output after the outlying downturn and a quick recovery once its transitory nature is made evident; that is, it improves on the known drawbacks of complex counterparts and standard filters.

Related literature Our paper is related to various strands of the literature. At large, this paper belongs to the literature on the estimation of the output gap, and to a greater extent to those based on multivariate approaches.[3] More specifically, our paper is related to studies using PT decomposition-type methods for estimating the output gap; among these papers, Angeletos, Collard, and Dellas (2020), Brignone and Mazzali (2022) and Dieppe, Francis, and Kindberg-Hanlon (2021) use the same approach of this paper, that is, based on explaining the highest possible share of the FEV of the output in the long-run. In contrast, studies such as Morley, Rodríguez-Palenzuela, Sun, and Wong (2023), Berger, Morley, and Wong (2023), and Berger and Ochsner (2022) use a Beveridge-Nelson (BN) type of decomposition based on the optimal forecast at long horizons. Our contribution relative to the first group of these studies is adjusting our baseline model along the lines of Lenza

[3]For an overview of this literature see Álvarez and Gómez-Loscos (2018), Guisinger et al. (2018). For a discussion about multivariate approaches, see Cochrane (1990)

and Primiceri (2022) to include the COVID-19 period in the sample. Simultaneously, relative to the second group, rather than calling the optimal long-run forecast (obtained via BN decomposition) the potential GDP, we structurally identify a model where a limited number of shocks explains the share of the long-run variance.

This study also relates to the literature on the adjustment of econometric models to include COVID-19 periods. In particular, it closely follows the work of Lenza and Primiceri (2022) by scaling the model information around a researcher-specified date but allowing the scale factor parameters to be obtained in a Bayesian setting. Other studies proposing alternative adjustments in this direction are Hartwig (2022), Carriero, Clark, Marcellino, and Mertens (2022), and Ng (2021).

Having said this, it should be mentioned that this is not the only study leveraging in Lenza and Primiceri (2022) to adjust an output gap estimation method. This is also done in Morley, Rodríguez-Palenzuela, Sun, and Wong (2023). There, the authors adjust a VAR-X by the COVID-19 episode and afterward estimate the trend component of the output for the Eurozone using a BN decomposition. Our work is similar in applying jointly Lenza and Primiceri (2022) and an output gap estimation method. However, we differ in a number of relevant dimensions. First, we use an SVAR approach where we identify the structural errors driving the long-run component of GDP (from the forecast-error variance decomposition as in Uhlig, 2004); second, we estimate jointly the model and the scaling factors of Lenza and Primiceri (2022) in a Bayesian setting; and finally, we use a different notion of the potential output (and gap): We construct the potential output (gap) as the permanent (transitory) component resulting from the contribution of the structural shocks that explain the long-run (short-run) behavior of the GDP.

The remainder of this document is organised as follows. We explain the methodology and data sources in Section 2. Section 3 describes the main results, including a comparison of the proposed framework with those yielded by other methods. In Section 4, we evaluate the performance of the proposed method in a simulation exercise, and we conclude in Section 5.

2 Methodology

Our empirical strategy consists of two stages. First, we fit a reduced-form Vector Autoregressive (VAR) model with a scale factor adjustment around the COVID-19 crisis as in Lenza and Primiceri (2022). This allows us to account for the increased variance in the macroeconomic variables around the shock date. Second, we recast our model into an SVAR form by identifying the main structural shocks explaining the output in the long run, which is done along the lines of Uhlig (2004), that is, by maximizing the explained fraction of the total FEV of the GDP at a long-run horizon (e.g., 15 or 25 years ahead).[4]

In the first stage, following Lenza and Primiceri (2022), a scale factor s_t is added to the VAR model's reduced-form residuals to capture the increased uncertainty during the COVID-19 crisis. s_t is set to one in the sample period before the COVID-19 shock (t^*), $s_{t^*} = \bar{s_0}$, $s_{t^*+1} = \bar{s_1}$, $s_{t^*+2} = \bar{s_2}$ and $s_{t^*+j} = 1 + (\bar{s_2} - 1)\rho^{j-2}$ for $j \geq 3$.[5] The scaled (reduced-form) VAR model is given by:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_p Y_{t-p} + s_t u_t, \qquad u_t \sim N(0, \Sigma). \tag{1}$$

The COVID-19 outbreak dates back to the first quarter of 2020 ($t^* = 2020Q1$), therefore, $\bar{s}_0$ is estimated for that date, and $\bar{s}_1$, $\bar{s}_2$ for the next two quarters. From there, the scale factor decays at a rate ρ for all future periods.[6] Thus, $\theta \equiv [\bar{s_0}, \bar{s_1}, \bar{s_2}, \rho]$ is the vector of additional parameters to be estimated jointly with those of the VAR $(B_0, B_1, \ldots, B_p, \Sigma)$. Equation (1) can be estimated as in Giannone, Lenza, and Primiceri (2015) by assuming the prior distributions of the coefficients to be conjugate Normal-Inverse Wishart and by including the scale factors into the posterior hyperparameters. They are jointly estimated using Bayesian techniques by drawing those parameters (that include θ) from their posterior distributions within the context of a Metropolis-Hastings procedure.

[4] It is also possible on other variables, such as household consumption.

[5] This setup allows the scale factor to take three different values in the first three periods after the outbreak and then decay at a rate ρ in subsequent periods. The assumed dynamics behind this scale structure align with the empirical evidence for the year after the onset of the pandemic. Furthermore, notice the parameters are expected to be non-negative, which also aligns with the estimation results and the resulting parameters' distributions shown in Section 3.

[6] As mentioned, alternative adjustments to COVID-19 data for VAR models have emerged in the literature in both frequentist and Bayesian frameworks, several of which are based on the inclusion of additional pandemic-related variables as controls (dummies or indicators). See Ng (2021), Carriero, Clark, Marcellino, and Mertens (2022), and Hartwig (2022).

For the estimation, the priors of β and Σ used are,

$$\Sigma \sim IW(\Psi, d),$$
$$\beta|\Sigma \sim N(b, \Sigma \otimes \Omega),$$

where $\beta \equiv vec([B_0, B_1, \ldots, B_p]')$ and $\gamma \equiv (\Psi, d, b$ and $\Omega)$ are the hyperparameter vectors. As mentioned by these authors, the Minnesota prior assumes that each variable included in the model follows a random walk process, and the prior for θ is defined analogously as a Normal distribution centered at 1.[7] The posterior of θ is used to capture the dynamics of s_t, which is jointly evaluated with the posterior of γ as proposed by Lenza and Primiceri (2022):

$$p(\gamma, \theta|Y) \propto p(Y|\gamma, \theta) \cdot p(\gamma, \theta).$$

After (1) is estimated we proceed with the second stage, consisting of identifying structural shocks (ε_t) linked to the reduced-form errors by an impact matrix A_0 such that $u_t = A_0\varepsilon_t$ and $\Sigma = A_0 A_0'$. It should be noted that there is not a unique A_0 that satisfies these relationships. For any candidate matrix A_0 an alternative matrix $\ddot{A}_0$ exists that can be derived using an orthonormal matrix Q where $A_0 = \ddot{A}_0 Q$ and $QQ' = I$; in that sense, our approach also falls within the "set-identification" category.

In this context—common to most BSVAR identification setups—we apply our specific identification strategy: Attaining the maximum explained fraction of the long-horizon FEV, along the lines of Uhlig (2004). This method seeks a target q_1 that satisfies:

$$q_1 = \operatorname{argmax} q_1' M q_1 \equiv q_1' \sum_{h=0}^{k} \ddot{A}_0{}' C_h' (e_j e_j') C_h \ddot{A}_0 q_1,$$

$$\text{subject to} \qquad q_1' q_1 = 1,$$

where q_1 is a column of Q that explains the k-step-ahead forecast error of the j-th variable in Y_t (in our case, the log of GDP), whose variance is given by M. Simultaneously, and as in Uhlig (2003), q_1

[7] For stationary series, we must adopt a prior mean of zero for all coefficients. However, as in our case in this article, when we are working with non-stationary series, it is better to set the prior mean to one to shrink towards a random walk. Further details see Giannone, Lenza, and Primiceri (2015).

is the eigenvector associated with the largest eigenvalue of the matrix M; e_j is a selector vector with zeros everywhere and a 1 in the j-th position, and C_h is a component of the long-run impact matrix of the VAR associated to the horizon h.[8] Finally, the constraint guarantees that q_1 is a unit-length column vector that belongs to an orthonormal matrix.

Notably, the method recovers all eigenvalues and eigenvectors of M, which —given the decomposition method— are ordered (from highest to lowest) by their explained share of the FEV for a target variable. The structural shocks are then constructed with these eigenvectors, which implies that they are also sorted by the extent to which they explain the long-run FEV of the target variable. Consequently, once computed, we can gauge the number of shocks that explain a sizable component of the long-run FEV of the GDP and decide how many of these to use for constructing the permanent component of the GDP. At the same time, the rest will determine the transitory one, as explained in detail in the following section.[9]

2.1 Output gap determination within the structural model

The BSVAR and identification setup above yields the structural errors and, more importantly for our objective, associates these to the variables' long-run (permanent) or short-run (transitory) components. We can reconstruct the estimated potential output and output gap based on such information. From this point forward, we denote it as (LP-Adjusted) which is our baseline based on a permanent-transitory (PT) identification (Uhlig, 2004) with a COVID-19 adjustment (as in Lenza and Primiceri, 2022, hence the LP acronym).

First, we compute the historical decomposition (HD) of the model that expresses the observed variables as a weighted sum of all structural shocks:

$$y_{1,t} = HD^{init}_{y_{1,t}} + HD^{\varepsilon^{(1)}}_{y_{1,t}} + HD^{\varepsilon^{(2)}}_{y_{1,t}} + \cdots + HD^{\varepsilon^{(k)}}_{y_{1,t}} \tag{2}$$

where $y_{1,t}$ denotes the first variable in Y_t, $HD^{\epsilon^k}_{y_{1,t}}$ represents the contribution of the k-th structural

[8] Note that $C(L) = I + C_1 L + C_2 L^2 + C_3 L^3 \cdots + C_h L^h + \ldots$ and the moving average representation of the model -in terms of the reduced form residuals- is given by $Y_t = \mu + C(L)u_t$ where μ is the unconditional mean of Y_t implied by the VAR model.

[9] Notice that a single shock will not generally replicate the entire FEV; it will only explain a large proportion. In other words, more shocks can normally be used to increase the percentage of explained FEV if a second or third shock is also found to explain a sizable share of the permanent component of the target.

shock ($\varepsilon^{(k)}$) to its dynamics, and $HD_{y_{1,t}}^{init}$ is the sample analog to the unconditional mean of the variable y_1. Notice that analogous expressions hold for any variable in Y_t. For the sake of exposition, let us denote $y_{1,t}$ as the observed output.

The contribution of each structural error expressed in (2) will depend on the (finite) MA representation of the resulting VAR model,[10] and each component will indicate the impact of one of the structural shocks realized in previous periods on the output in t; for example, the contribution of the k-th structural shock in the output at t is:

$$HD_{y_{1,t}}^{\epsilon^{(k)}} = \sum_{j=0}^{t-1} \theta_{1k}^{(j)} \epsilon_{t-j}^{(k)},$$

with $\theta_{1k}^{(j)}$ denoting the coefficient in the row 1, column k within the j-th matrix in the MA representation of the associated VAR.[11]

Now, the decomposition in (2) is appealing if we care about the dynamics explained by each structural shock but by itself does not disentangle the potential output from the gap dynamics. However, our identification setup indicates which structural errors mainly drive the permanent component and which the transitory, making it possible to split the observed dynamics into each. For example, in the case that only the first structural shock drives the permanent component and the others (second to k-th shock) the transitory, each component of the output (potential GDP and gap) is obtained as,

$$y_{1,t} = \overbrace{HD_{y_{1,t}}^{init} + HD_{y_{1,t}}^{\varepsilon^{(1)}}}^{y_{1,t}^{pot}} + \overbrace{HD_{y_{1,t}}^{\varepsilon^{(2)}} + HD_{y_{1,t}}^{\varepsilon^{(3)}} + \cdots HD_{y_{1,t}}^{\varepsilon^{(k)}}}^{y_{1,t}^{gap}} = y_{1,t}^{pot} + y_{1,t}^{gap}, \tag{3}$$

where $y_{1,t}^{pot}$ would denote the permanent component of output—the potential output— and $y_{1,t}^{gap}$ the transitory component—or the output gap. It should also be noted that this method for obtaining the gap is analogous to the one used to compute these quantities in other VAR-based studies such as Blanchard and Quah (1989), and Chen and Gornicka (2020), the latter based on the identification

[10]Note that for practical applications, this is carried out with finite-horizon analogs or approximations to the usual MA(∞) or Wold representation of the model, in fact, the Historical Decomposition itself is usually defined just as a finite horizon version of this representation.

[11]Such representation is the HD itself and can also be expressed as $Y_t = HD_y^{Init} + \sum_{j=0}^{t-1} \Theta^{(j)} A_0 \varepsilon_{t-j}$.

scheme of Forbes, Hjortsoe, and Nenova (2018).

2.2 Data

We assemble a dataset encompassing nine variables for seven developed economies: United States (USA), Canada (CAN), Australia (AUS), United Kingdom (GBR), Germany (GER), France (FRA), and Italy (ITA).[12] This economies comprises some of the world's most influential advanced economies due to those represent a significant share of the global economy. These economies are characterized by their high levels of industrialization, technological innovation, and well-developed financial systems. They play pivotal roles in international trade and investment, contributing substantially to global economic stability. In addition, the application of our method to various economies allows us to conduct external validation, ensuring that the results are not dependent on a particular country. In the first row of Figures 8 and 9 in the Appendix A, the dynamics of GDP for this group of economies are observed. Although the impact of the COVID-19 shock was widespread globally, it is evident that European countries experienced more significant declines compared to the rest of the developed countries. This could be attributed, in part, to the fact that their population was more affected in terms of infections and deaths during the critical periods before the production of the vaccine. The aforementioned figures (in Appendix A) depict the rest of the variables used in our estimations, which are shown in the units and transformations they enter the econometric model for each economy.

2.3 Empirical strategy

For purposes of the estimation of the actual gap (reported in sections 2.3 and 3), we use the complete set of information (nine variables) and fit i) the model explained in Section 2 that corresponds to our baseline model (LP-Adjusted) based on a permanent-transitory (PT) identification (Uhlig, 2004) with a COVID-19 adjustment (as in Lenza and Primiceri, 2022, hence the LP acronym), ii) a BSVAR model with PT identification but no COVID-19 adjustment (denoted PT-Decomp), and iii) a BSVAR model with a PT identification and a stochastic volatility setup, i.e., without an explicit correction

[12] Typically, the G7 is a group that includes United States, Canada, Japan, Germany, France, the United Kingdom, and Italy. However, Japan has maintained interest rates close to zero for over three decades and experienced deflation, posing challenges for identifying permanent and transitory shocks using our approach. We decided to include Australia, which belongs to the G12 and is geographically the closest to Japan.

at the exact date of the COVID-19 shock (named PT-Stocvol) but where the residuals' variance is allowed to vary over time. On the other hand, for the evaluation stage (section 4), we use only three of the time series in each case: Real output, inflation, and interest rate; and then, we run a Monte Carlo simulation based on a New Keynesian model as in Benati (2008). Finally, in the estimation and evaluation sections, we also consider standard univariate filters (HP and Christiano-Fitzgerald bandpass filter).

In the first stage of the our econometric approach, We set a nine-variable B-SVAR in levels for each economy with a lag length (in most cases of $p = 2$) choice given by the Bayesian and Hannan-Quinn Information criteria and estimate the VAR in levels using a hierarchical modelling approach that allows us to make inferences about the informativeness of the prior distribution of the BSVAR, as proposed by Giannone, Lenza, and Primiceri (2015), which automatically determines a suitable measure of shrinkage by considering a combination of conjugate priors such as a Minnesota prior and tighter priors, when the model includes many coefficients relative to the number of observations. As part of the procedure, we run 20000 draws and keep half of these for estimation after the burn-in step. In addition, we explicitly model the COVID-19 extreme observations as in Lenza and Primiceri (2022). From this first stage, we obtain a reduced-form VAR that has already been adjusted by the scale factor (s_t) and incorporates the pandemic shock.

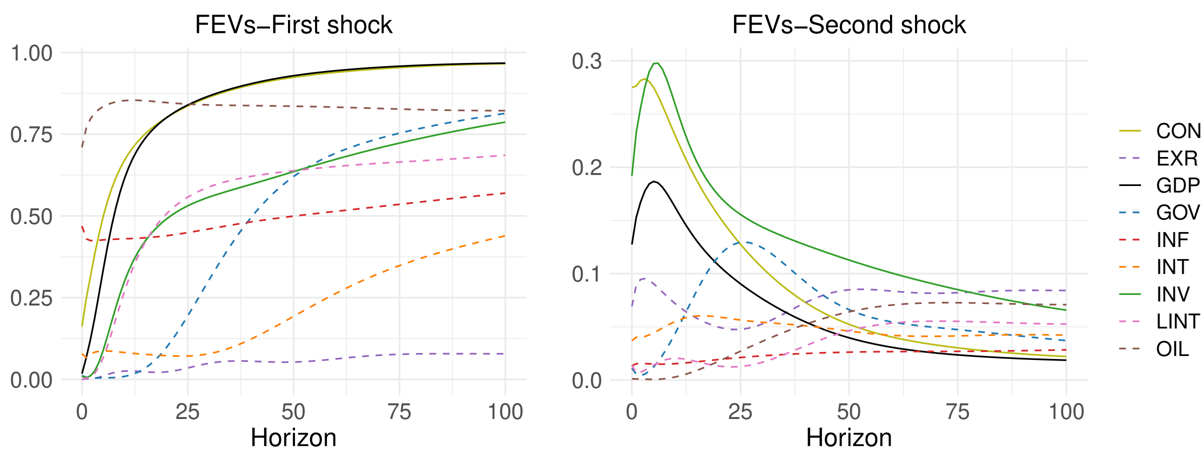
In the second stage, we identify the impact of the matrix of the SVAR by maximizing the explained share of the forecast variance error of the GDP for a 25-year horizon as in Uhlig (2004). Concurrently, we apply two additional restrictions: the proportion of the FEV of consumption accounted for by the first structural error must be greater than the corresponding proportion for output, and the proportion for output must be greater than that for investment. As explained by Cochrane (1994) and King, Plosser, Stock, and Watson (1987), this accounts for the fact that consumption is more closely aligned to the permanent component of GDP, while investment should reflect its most volatile and transitory components. After verifying these restrictions and keeping the draws that comply with them, we conducted PT decomposition and computed the permanent (and transitory) output component (as mentioned in section 2.1).[13]

As aforementioned, the decomposition and resulting impact matrix already consider the ordering

[13]As a check, we increased the number of draws to 100000 and obtained similar results.

of the structural shocks according to their share of the explained variance of the target variable.[14] This can be verified in Figure 1, where we can see that for the US economy only the first structural error is necessary to account for approximately 95% of the long-run (permanent) component of the GDP.[15] In contrast, the next most important shock in explaining the GDP's long-run FEV is instead better associated with the short-run or transitory component. An analogous result holds for the other economies in our sample where the first shock explains between 59% to 96% of the long-run GDP FEV (Figure 10 in Appendix A.2).

Figure 1: Shocks explaining the highest share of long-run GDP FEV (USA)



Note: The Figure shows the Forecast Error Variance (FEV) explained by the two structural shocks with the largest explained share for the long-term GDP. Given a single shock explains almost 100% of GDP for large horizons (left-panel), it is associated as the main driver of the permanent component of output. In contrast, the second highest (right panel) and remaining shocks are instead considered as driving the transitory component of output.

In light of these results, we compute the output gap based on the historical decomposition components attributed to the second to ninth structural shocks —i.e., those explaining only the transitory component of GDP— and use only the first one to recover the potential GDP.[16] To do this, we compute the output gap by rerunning the baseline BSVAR model (LP-Adjusted) and shutting off the first structural shock. Thus, the transitory component is estimated based only on the other eight shocks.[17] On a related point, it should also be noted that the first structural error will explain

[14]This implies that the first structural shock reported by the method is the one with the largest share of explained variance of the long-run GDP, followed by the shock with the second largest share, and so on, until the last shock that explains the smallest share.

[15]In some cases, we show the results only for the US for the sake of a more transparent and simpler exposition. However, the analogous figures and results for the other economies are included in the appendix.

[16]Analogously, the potential GDP can be obtained as the original series minus the transitory component.

[17]The methodology is not limited to selecting a single shock to identify the permanent component of GDP in the long run. For example, in the case of Italy, it could consider employing the first two shocks (84%) as the first shock explains

most of the long-run FEV of the GDP (target variable) but not necessarily the largest share of the FEV for other variables. The relative importance of the shocks to the other variables can be seen in the FEV decomposition per variable, as shown in Figure 13 for the US economy and Figures 14 to 19 (in the Appendix A.5) for the other countries in our sample.[18]

3 Results

3.1 Baseline Results

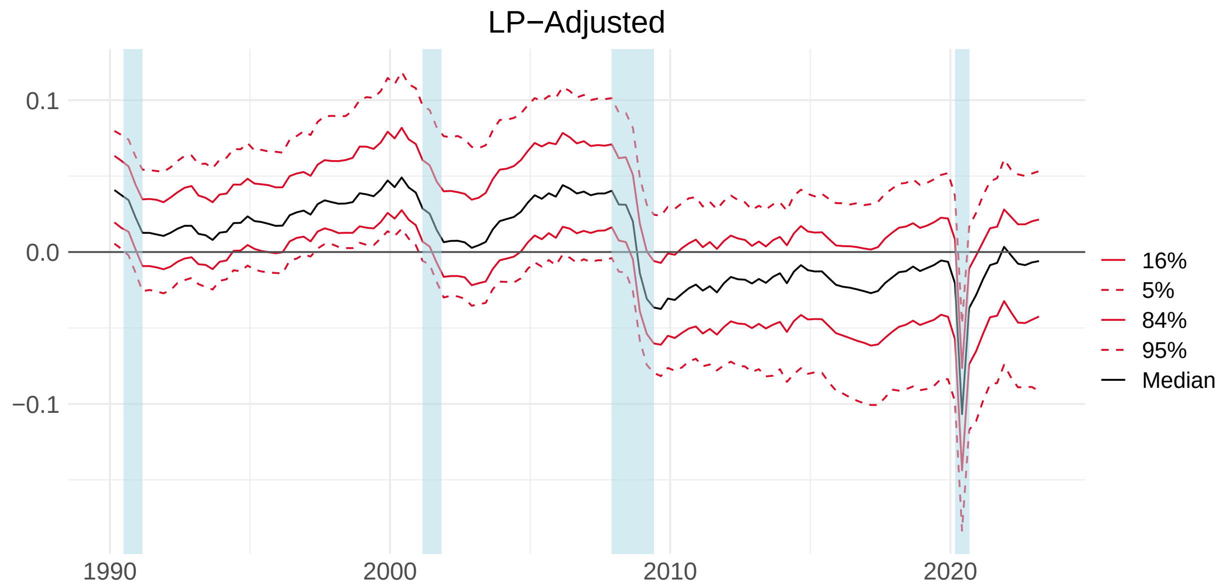
Figure 2 shows the output gap for the US economy obtained from our proposed baseline BSVAR model. This approach —labeled LP-Adjusted— incorporates both a PT decomposition and a scale factor adjustment, which deals with the observations during the COVID-19 period. Before COVID-19, the estimated output gap reflects the early 1990s and 2000s recessions and the global financial crisis (GFC) in 2008.[19] Another notable feature of our method is its ability to gauge the uncertainty associated with the estimate over time. As observed, there is a significant increase in volatility during the COVID-19 period compared to previous periods.

59% of the long-term GDP variations, while the second accounts for nearly 25%. In this case, the transitory component (output gap) is explained by using seven shocks (from the third to ninth structural shocks).

[18]We leave additional results that are related to other variables and shocks for the appendix as we are only concerned with approximating the target variable here (GDP).

[19]Those crises correspond to the shaded areas in Figure 3 associated with the turning points determined by the National Bureau of Economic Research (NBER) for recession. The NBER recession data are available at http://www.nber.org/cycles/cyclesmain.html

Figure 2: Baseline results: Output gap for US economy



Notes: The Figure shows the results of the baseline BSVAR model with Permanent-Transitory decomposition and Covid-19 adjustment (LP-Adjusted). The solid black line represents the median estimates. The solid and dotted red lines represent the percentiles of 5%, 16%, 84% and 95%, respectively.

During the COVID-19 pandemic, the US gap underwent a steep decline (-10.6%) in the second quarter of 2020; however, unlike in the 2008 recession, the downturn was not persistent. Instead, it bounced back in the following quarters. As in most economies, the decrease is largely explained by lockdown measures, while the gradual reopening of the economy induces the recovery. It is worth highlighting that, unlike the aftermath of the 2008 financial crisis that led to a negative gap persisting for more than a decade, a partial closure of the US GDP gap was observed following the COVID-19 pandemic. A similar pattern is obtained for the other six economies, although many of them show a positive output gap in 2023Q1 (see Figure 11 in Appendix A.3). Consequently, the average output gap for the seven countries fell to -13.6% during the second quarter of 2020. This downturn was most pronounced in the United Kingdom, where the gap plummeted to -24%. In contrast, Australia experienced the least impact, with a gap registering at -7.8%.

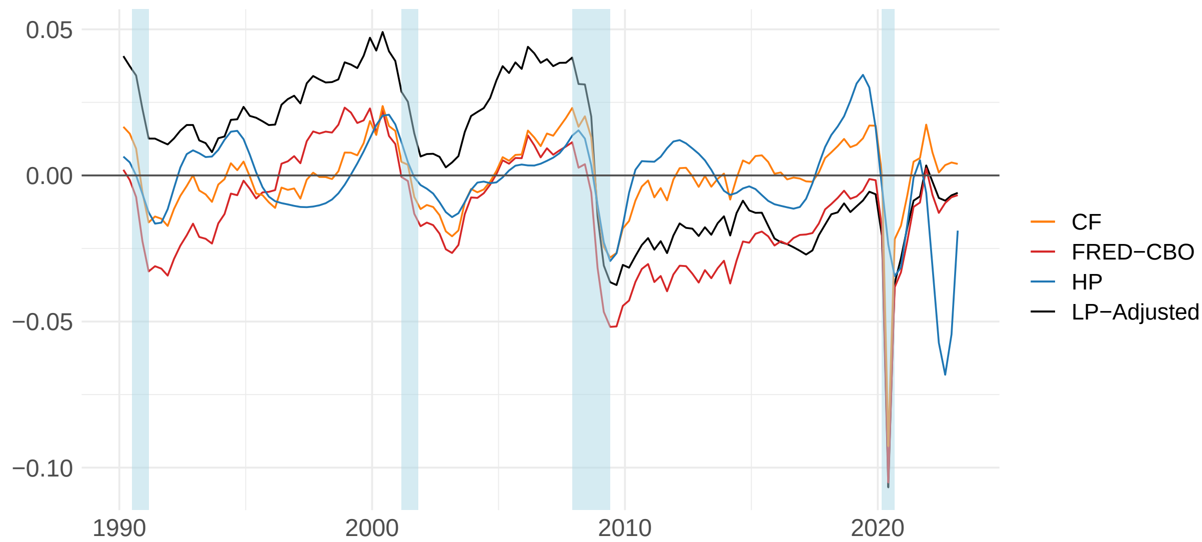
3.1.1 Comparison with alternative estimation methods

We also compare our estimations with those generated by usual filtering techniques, namely the Hodrick-Prescott (HP) and Christiano-Fitzgerald (CF) filters, as well as to an estimation computed using the real potential GDP as released by the U.S. Congressional Budget Office (FRED-CBO).[20] The output gap estimates for the compared methods and our proposal are shown in Figure 3. We can see that the univariate filters (HP, CF) tend to deliver a large gap right before COVID-19 and a swift and sizable subsequent recovery, which sends that gap onto positive territory (and at or beyond 2%) in a few quarters. These features may indicate an overestimation of the gap, specifically when we see that the other estimates, including our proposal, do not display such behaviour, and instead suggest a dynamic yet more moderate recovery. Notably, when tying these results to the associated potential output dynamics, they indicate that our proposal does not lower the potential output significantly during the pandemic period, which reflects the adjustment of the model to incorporate the COVID-19 observations in the estimation sample without assuming drastic changes in its data-generating process.

Concerning the official CBO estimate, it is important to note that our model consistently generates a negative gap after the 2008 financial crisis, in accordance with the economic consensus which is related to recent studies on hysteresis and the scarring effects of protracted recessions (e.g., Cerra, Fatás, and Saxena, 2023; Aikman, Drehmann, Juselius, and Xing, 2022). Similarly, using the CBO estimate as a benchmark, the correlation with our model's estimate is notably higher than the filters (86% vs 30% and 75%). Similar findings are obtained for the other six economies (see Figure 11 in Appendix A.3).

[20]We take the data from the FRED webpage (https://fred.stlouisfed.org/graph/?g=f1cZ)

Figure 3: Comparison methodologies for output gap estimation (USA)



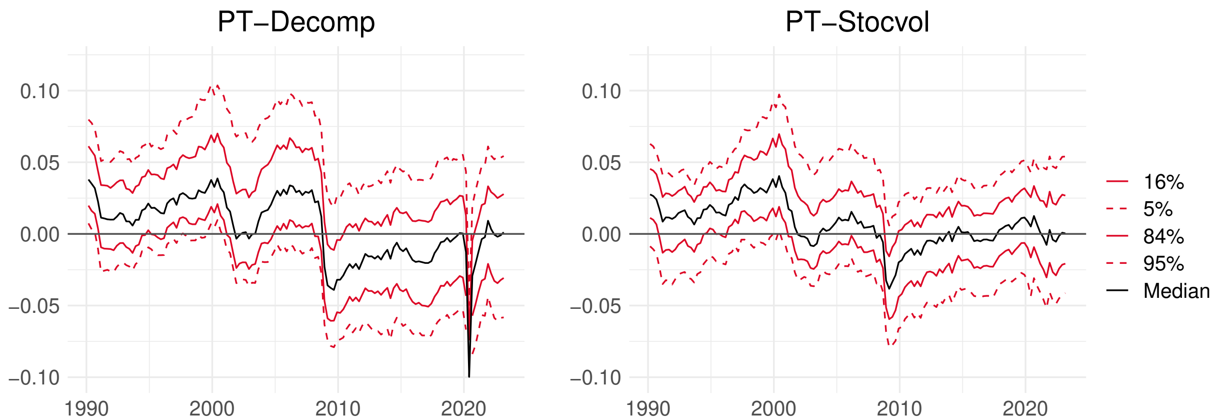
Notes: The black line represents the median of the baseline model (LP-Adjusted). The orange and blue represent the Hodrick-Prescott (HP) and Christiano-Fitzgerald (CF) univariate filters. The red one is the output gap using the real potential GDP estimated by the U.S. Congressional Budget Office (CBO). Shaded areas indicate U.S. recessions and the COVID-19 period.

Finally, we compare the proposed BSVAR model (LP-Adjusted) with two models using the same type of identification setup (PT decomposition as in Uhlig, 2004). The first alternative is a BSVAR without a scaling adjustment for the COVID-19 episode (PT-Decomp). The second is a model where instead of using a scale factor at a known —large shock— date to adjust for the pandemic observations, an implicit time-varying uncertainty adjustment is allowed through a stochastic volatility structure of the errors (PT-Stocvol).

The associated output gaps of the two BSVAR alternatives are shown in Figure 4. A contrast between the baseline and the alternatives emerges at first sight: both the PT-Decomp and the PT-Stocvol generate a less negative gap during the COVID-19 outbreak, which implies that in those cases, the potential output is affected more drastically relative to our baseline model. Hence, as with some of the simpler filters, the alternatives tend to overestimate the impact of the shock on the long-run output.

Regarding the volatility around the estimates, the PT-Decomp displays the largest uncertainty, as reflected by wider percentile ranges than in the baseline. On the other hand, the PT-Stocvol successfully mitigates volatility (yielding at a similar range as the baseline); however, it is the method where the estimated potential output is affected the most during the downturn. Therefore, we do not obtain an adequate estimate of the output gap from the stochastic volatility setup. Comparable results are obtained for the remaining six economies.

Figure 4: US Output gap - two alternative BSVAR models



Notes: The left panel shows the results of the BSVAR model with Permanent-Transitory decomposition and no COVID-19 adjustment (PT-Decomp). The right panel shows the results of the Stochastic Volatility BSVAR with Permanent-Transitory decomposition and no Covid-19 adjustment (PT-Stocvol). The solid black line represents the median estimates. The solid and dotted red lines represent the percentiles of 5%, 16%, 84%, and 95%, respectively.

3.1.2 Outlier observations around the COVID pandemic

Given that our main concern is to study the adjustment of potential output estimates to drastic magnitude shocks, such as those observed in the COVID-19 outbreak, verifying the estimates of the scale factors generated by our baseline estimates can be insightful. Principally, if scaling is irrelevant, the posterior estimates should suggest $\bar{s}_0 = \bar{s}_1 = \bar{s}_2 = 1$; otherwise, they should be sizeable. We estimate these parameters as in Lenza and Primiceri (2022) and present our estimate of scale factors in Figure 5.

The parameters posteriors are drawn based on a Metropolis-Hastings algorithm with a Minnesota Prior. Thus, we estimated the scaling factors jointly with other hyperparameters in a hierarchical structure. The resulting posteriors for $\bar{s}_0, \bar{s}_1, \bar{s}_2$ peak around 1.5, 13, and 7, respectively, indicating that, in effect, it is relevant for this sample to scale up the errors around the COVID-19 observations to account for the steep increase in volatility of that period, but that may not characterise its data-generating process, nor should it drastically influence the BVAR estimates. A country-by-country

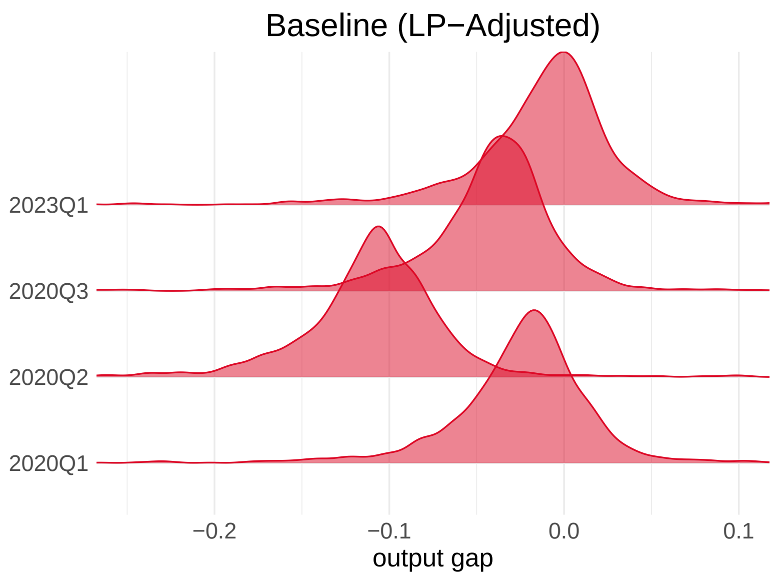
Figure 5: Posterior distribution of the overall volatility scaling factors

Notes: Each column represents the scale parameters $\theta \equiv [\bar{s_0}, \bar{s_1}, \bar{s_2}, \rho]$. Each row represents the results for each country. The vertical dotted black line marks the mode of the distribution.

analysis shows that Italy and France were the most adversely impacted in 2020Q1, exhibiting an estimated parameter $\bar{s}_0$ nearly twice as high as in the rest of the economies. We must remember that these nations were the most severely affected by the virus at the pandemic's outset. Similarly, the estimates for the UK reflect an increased volatility during the second and third quarters of 2020 compared to the other countries. Finally, the decay coefficient (ρ) for the US peaks around 0.5, which, together with $\bar{s}_2$, implies that the scale factor falls by half after 2020Q3 and subsequently non-linearly towards one. In contrast, for other European countries, the parameter may denote a greater persistence of the pandemic effects. Among the latter cases, the one with the most saliently persistent impact is Italy.

The dynamics of the output gap distribution during the pandemic. To further illustrate the impact of the COVID-19 shock on the output gap, we can depict the distributions of the draw estimates for dates around the episode as shown in Figure 6. We show the estimated empirical distribution for the quarter of the shock (2020Q1), the subsequent two quarters, and the first quarter of 2023 as a reference for a date when the potential output dynamics are, in principle, back to normal (here, we implicitly recognise the transitory nature of the pandemic shock).

Figure 6: Distribution of the US output gap estimation during COVID-19 shock and 2023Q1.



Notes: The green line represents the median of the baseline model (LP-Adjusted). Tthe orange and blue represents the Hodrick-Prescott (HP) and Christiano-Fitzgerald (CF) univariate filters. The red one is the output gap using the real potential GDP estimated by the U.S. Congressional Budget Office (CBO). Shaded areas indicate U.S. recessions.

As we can see in the figure, the gap distribution shifts noticeably to the left during the pandemic, implying that the potential GDP was not strongly affected by the downturn (and instead, the gap lowered in line with the observed GDP). In addition, the distribution spread increased, reflecting an increase in uncertainty around the estimate during the pandemic. Afterwards, we observe the distribution shifting back to pre-COVID-19 levels, although it still reflects increased volatility. In summary, we can see that the impact on the mean gap was transitory but with a somewhat larger uncertainty remaining. Nonetheless, this greater uncertainty is approximately one percentage point higher than before, rather than orders of magnitude higher, as may be suggested by a model without a scale factor adjustment for the COVID-19 downturn.

4 Evaluation of the method

Evaluating the relative performance of our estimates is a challenging task as our target, the potential GDP, is an unobserved variable, and thus, there is no well-defined target against which to perform a "horse race" using a set of competing methods. However, an assessment of these methods is still in order, and alternative evaluation methods can be proposed. These usually imply assuming knowledge of relevant features of the potential output that can be tested.

One route taken by the literature (e.g., Chen and Gornicka, 2020; Camba-Mendez and Rodriguez-Palenzuela, 2003; Pichette, Robitaille, Salameh, and St-Amant, 2019) comprises setting up a Phillips Curve with the output gap on the right-hand side of the equation. Subsequently, an estimation method of the output gap is assessed according to its capacity to forecast inflation in the context of the Phillips Curve. Here, we assume that the output gap is a relevant variable for determining inflation and that the relationship captured in the Phillips curve is stable over time; that is, the curve setup is an appropriate device for testing the relationship between the output gap and inflation.

Although that is a feasible venue, it also opens discussions about how stable the Phillips Curve in each country is, or even considering whether such a relationship exists (e.g., McLeay and Tenreyro, 2020), or if its slope has flattened over time (Hazell, Herreño, Nakamura, and Steinsson, 2022). These discussions are particularly relevant in recent times when the trade-off between output stabilisation and inflation is strongly felt worldwide. However, such debates are beyond the scope of our study and may divert attention from what we aim for in this study, approximating the potential output.

Alternatively, and along similar lines as Canova (2020), we take a more direct approach and assume to count with an available true measure of the potential output, which would be approximated with a set of (econometric) output gap methods that use other economic variables as input, and whose estimates are assessed based on their co-movement with the actual output gap. We do this in the context of a Monte Carlo simulation, where the set of economic variables and "true" potential output are simulated based on an economic general equilibrium model.

4.1 The model used to simulate the output gap

We consider a standard three-equation New Keynesian DSGE model along the lines of Benati (2008), but where the output is assumed to have a unit root component that behaves as a random walk with a drift:

$$y_t^P = \delta + y_{t-1}^P + v_t, \qquad v_t \sim WN(0, \sigma_v^2), \tag{4}$$

The associated log-linearized model is given by:

$$\pi_t = \frac{\beta}{1+\alpha\beta}\pi_{t+1|t} + \frac{\alpha}{1+\alpha\beta}\pi_{t-1} - \kappa\hat{y}_t + u_t, \qquad u_t \sim WN(0, \sigma_u^2), \tag{5}$$

$$\hat{y}_t = \gamma\hat{y}_{t+1|t} + (1-\gamma)\hat{y}_{t-1} - \sigma^{-1}(R_t - \pi_{t+1|t}) - (1-\gamma)\Delta y_t^P, \tag{6}$$

$$R_t = \rho R_{t-1} + (1-\rho)\left[\phi_\pi \pi_t + \phi_y \hat{y}_t\right] + \epsilon_{R,t}, \qquad \epsilon_{R,t} \sim WN(0, \sigma_R^2). \tag{7}$$

The first two equations, the hybrid Phillips curve and dynamic IS, feature both backward and forward-looking components. In contrast, the monetary policy rule is given by a Taylor rule with smoothing. π_t is inflation, R_t is the nominal rate, and the real GDP is Y_t which in the model is rescaled by its unit root component (Y^P) as $\hat{y}_t = \ln\left(Y_t/Y_t^P\right)$ to achieve stationarity. The latter implies that $\hat{y}_t$ is the output gap or the output as a deviation of the potential GDP given by its stochastic trend. The other variables are set as log-deviations of their non-stochastic steady-state values.

The model parameters are approximated with a combination of calibration and estimation. The estimated parameters of the model, $\Theta = \{\sigma_R^2, \sigma_u^2, \sigma_v^2, \kappa, \sigma, \alpha, \gamma, \rho, \phi_\pi, \phi_y\}$, were obtained for each considered economy using Bayesian methods. The posterior mode is found via simulated annealing as in Benati (2008), and the posterior distribution of Θ is characterized by implementing a Random-Walk Metropolis-Hastings algorithm as in An and Schorfheide (2007). Both simulated annealing and Metropolis simulations require the evaluation of the likelihood (and posterior) of the model based on its Sims canonical form and associated state-space representation. On the other hand, we use a calibrated value of 0.99 for the discount factor.

Table 1 shows median —across country-specific estimates— the parameters' priors, posterior modes, and percentiles obtained in our estimations. An additional step in the simulations is the scale factor adjustment of the variances, which is revised every 10% of the iterations and adjusted depending on the fraction of accepted draws in the subset draws. With that, the average acceptance ratio across —country-specific— simulations is 0.229.

Table 1: Prior, Posterior modes and standard deviations for the parameters (median values)

		Prior		Posterior	
Parameter	Prior Density	Mode	Standard Deviation	Mode	90% coverage percentiles
σ_R^2	Inverse Gamma	0.01	0.01	0.0008	[0.0007, 0.00011]
σ_u^2	Inverse Gamma	0.01	0.01	0.0010	[0.0008, 0.0012]
σ_v^2	Inverse Gamma	0.01	0.01	0.0012	[0.0010, 0.0014]
κ	Gamma	0.10	0.10	0.191	[0.120, 0.322]
σ	Gamma	1	2	4.294	[3.036, 7.891]
α	Beta	0.90	0.05	0.901	[0.776, 0.952]
γ	Beta	0.50	0.25	0.750	[0.690, 0.854]
ρ	Beta	0.7500	0.10	0.688	[0.618, 0.762]
ϕ_π	Gamma	1.50	0.25	2.278	[1.888, 2.687]
ϕ_y	Gamma	0.50	0.15	0.589	[0.389, 0.826]

Note: The average acceptance ratio of the Metropolis algorithm across countries estimates is 0.229-. The values reported correspond to the median values across country-specific estimations of the economic model.

4.2 Evaluation method of the output gap estimations

Based on each estimated New Keynesian model (one for each country in our sample), a Monte Carlo simulation is carried out, where, in each iteration, a sample (33 years long) of the model variables is simulated and a corresponding "true" output gap is obtained. The simulated observable economic variables are then used as inputs for a set of competing econometric methods that estimate the output gap of the simulated model. For each iteration, the cross-correlation between each econometric estimate of the output gap and the simulated —actual— output gap is calculated and recorded.

In other words, in each simulation, we use the economic model to obtain an output gap and other consistent economic variables with the former.[21] Then, we feed the econometric methods —that includes our proposal— with the observable economic variables to generate an estimated output gap. Finally, we assess the estimates of all methods in terms of the co-movement between their estimated gap and the actual gap (simulated).

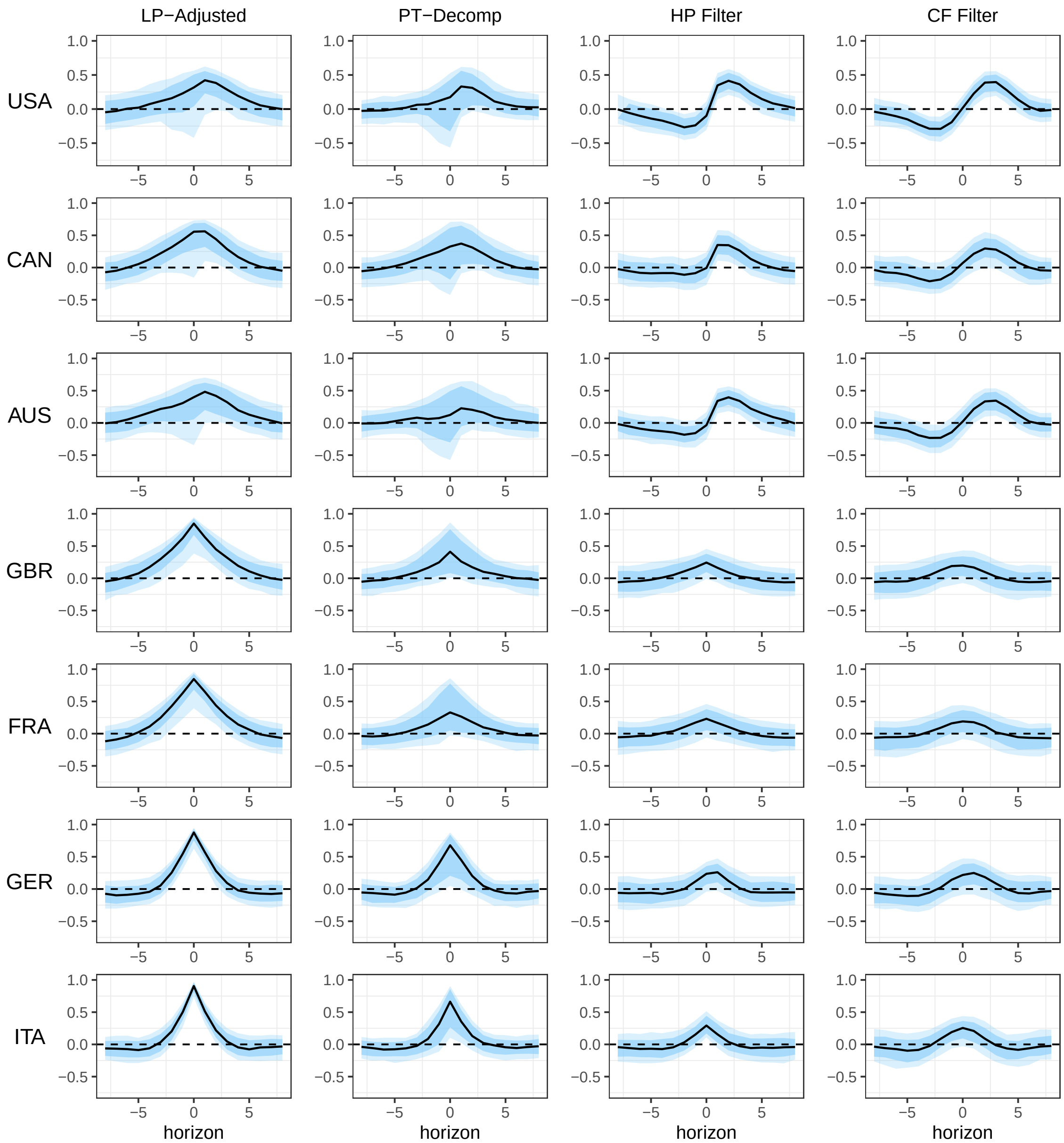
The methods compared are: (i) our proposal, a Permanent-transitory decomposition with a Lenza and Primiceri (2022) type adjustment for large shocks episodes with a known date (LP-Adjusted), (ii) a Permanent-Transitory decomposition via a BSVAR (PT-Decomp), (iii) a Hodrick-Prescott filter (HP), and (iv) a Christiano-Fitzgerald Band Pass filter (CF). The latter two filters are more frequently used and widely available methods of estimation of the potential output. In contrast, the Permanent-Transitory decomposition is relatively more complex as it aims to achieve a structural identification for an SVAR based on the long-run forecasts of the output. Finally, our proposed method combines the structural long-run forecast identification approach with an estimation adjustment to account for the presence of drastically large scale shocks whose date is known.

Notably, the identification method in the SVAR models methods (i) and (ii) (or LP-Adjusted and PT-Decomp) are the same. Thus, we are carrying two tests here: First, whether it is worthwhile to focus on a structural identification method despite its higher complexity, and second, if it is also relevant to adjust the estimates of the model for the presence of very large shocks.

Finally, to make the experiment more relevant in our context of interest (an economy affected by an unprecedented scale shock), we incorporate a large-scale shock in each simulation that mimics the dynamics of the COVID-19 episode. For this, we apply a short-lived high-magnitude negative productivity shock at the end of each simulated sample, which, after impacting the variables (e.g., the output), still allows them to approach their previous trend values by the last date but without depicting a full recovery.

[21] Here, by consistent, we mean that these are generated within each iteration by the same shocks.

Figure 7: Cross-correlation between the output gap estimates and their simulated target



Note: median (black), 68% coverage, and 90% coverage percentiles of the cross-correlations between the output gap estimate of each method and the simulated output gap of the economic model.

The results for all the countries in our sample are reported in Figure 7, where, for each country in a row panel, we show the cross-correlation between the true (simulated) output gap and the one estimated by the econometric methodology in each column. Each plot shows the cross-correlations across simulated samples, with the black line depicting the median estimates and the blue areas the 68% and 90% coverage percentiles. Ideally, we want to have a positive and high cross-correlation at all horizons with the smallest possible uncertainty across iterations.

We find two salient patterns. First, the standard filtering techniques (HP and CF) can be distorted by the large-scale shock and generate negatively correlated estimators with the target in some cases, and even in short horizons.[22] In those cases, the feature of the HP and CF filters of yielding too-sharp and quick reversions of the gap in a single period —after the large-scale shock is revealed to be transitory— is the reason behind the deterioration of the output estimates. This drawback is corrected by the methods that decompose the permanent and transitory components of the output (LP-Adjusted and PT-Decomp.), thereby mitigating the reliability and stability issues of output gap methodologies suggested by studies such as Marcellino and Musso (2011).

Now, it should be mentioned that the correlation sign reversion does not occur in all cases, and in fact, it will also not appear if we instead perform the experiment without large-scale shocks. However, even if this issue does not emerge, we still see that there is a cross-correlation gain when switching from the standard filters (HP, CF) to those using a permanent-transitory identification scheme.

The added value of adjusting the estimator. A second salient pattern we obtain is that when we use our proposal —i.e., we complement the identification in the BSVAR model with the Lenza and Primiceri (2022) adjustment— there is both a decrease in the implied volatility of the estimator (something we verified in prior sections with observed data) and a substantial cross-correlation gain. In fact, in the best cases, the peak correlation can jump up to beyond 0.8 from values surrounding 0.5 at best (depending on the alternative method considered). To see this, we can notice how the correlation in the first column is higher than in the other ones for all rows.

In summary, the results of this experiment favor both the identification method for computing the output gap and also the addition of the adjustment via the scaling factor as in our proposal, which ultimately will outperform the other alternatives for all countries. Thus, in this case, it is worthwhile to use a relatively more complex but structural estimation method. Moreover, it is even better to complement it with the adjustment for the large-scale shock.

[22] As a check, we repeated the experiment without the large-scale shock, in which case the abrupt reversion to negative correlations does not occur. Such estimations and figures are available upon request.

5 Concluding remarks

This study examines whether potential output models should be adjusted to account for rare, large-magnitude shocks, such as those experienced during the COVID-19 lockdown in 2020. Ideally, we would like to include a complete set of observations in the model while preventing observations of unprecedented magnitude —that do not resemble the sample data-generating process— from affecting the quality of the econometric modelling framework under consideration.

To investigate this question, we utilize a model that integrates a wide range of information sources within a structural framework in line with the approach of Uhlig (2004). Our identification strategy leverages the relationship between consumption and output to distinguish the permanent and transitory components of GDP. Building on this framework, we introduce an adjustment by applying a scaling factor to the residuals, explicitly focusing on the period around the COVID-19 pandemic outbreak, in line with the methodology proposed by Lenza and Primiceri (2022).

Our results, based on a sample of seven developed economies, indicate that only one structural error is enough to account for most of the long-run behaviour of GDP (and potential output) and that the remaining shocks majorly explain transitory fluctuations (i.e., the gap). At the same time, simulation exercises show that the adjusted model outperforms both simple filtering alternatives and similarly complex models that abstract from adjusting the large-scale shock periods or that do so in alternative setups that do not explicitly account for outlying observations at the specific dates of the high-magnitude episodes (e.g., models with stochastic volatility). Concurrently, our setup prevents quick output gap reversals after downturns or drastic changes in the potential output after high-magnitude transitory observations. In that sense, while our setup aligns with the findings of recent studies on the scarring effects of economic downturns (e.g., Cerra, Fatás, and Saxena, 2023; Aikman, Drehmann, Juselius, and Xing, 2022), it still prevents the unprecedented-magnitude observations from affecting the resulting model substantially.

It is relevant to mention that, in our proposal, we can better approximate the potential GDP (and gap) by trading off the possibility of disentangling output dynamics into separate structural drivers with economic interpretation (e.g., monetary, financial, global, supply, and demand, etc.). Not being able to carry out such a type of exercise is the cost of accessing our identification strategy, which is strictly concerned with an endogenous determination of the horizon profile of the structural shocks. In that spirit, a separation of the output dynamics into interpretable fundamental drivers where we can also draw the main lessons from this study—that allow mitigating the approximation costs of *ad-hoc* changes in the term horizon of the shocks, as commonly done in other structural identification setups—is left for future research.

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A Baseline model: Results

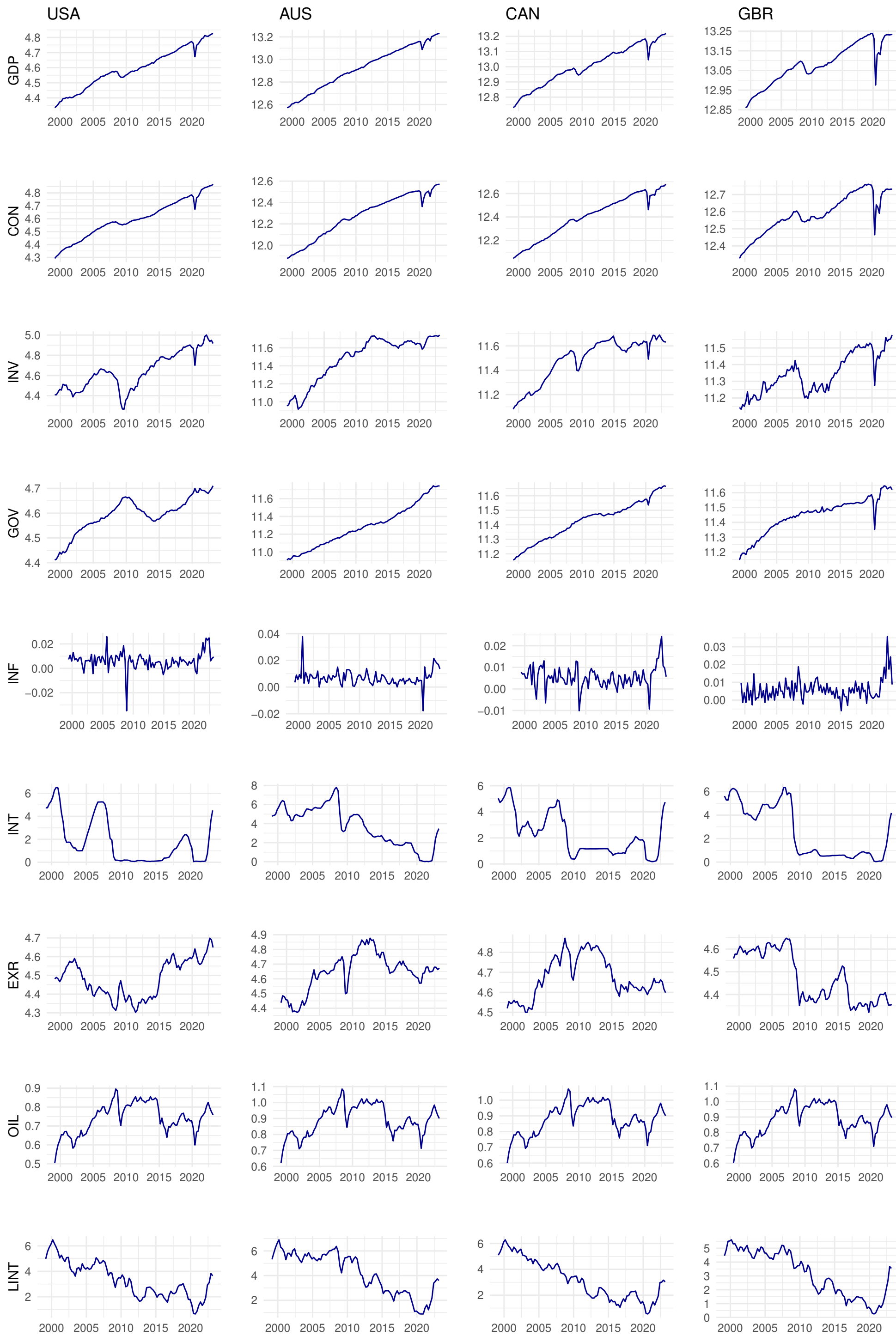
A.1 Data

Country	Data Source
USA	Bureau of Economic Analysis (BEA), Federal Reserve Bank of St. Louis (FRED), OECD
CAN	Statistics Canada, datastream
AUS	Australian Bureau of Statistics, datastream
GBR	Office for National Statistics, datastream
GER	Eurostat, OECD, datastream
FRA	Eurostat, OECD, datastream
ITA	Eurostat, OECD, datastream
Oil price (OIL)	Bloomberg; it is deflacted by each country CPI

OECD: The Organisation for Economic Co-operation and Development

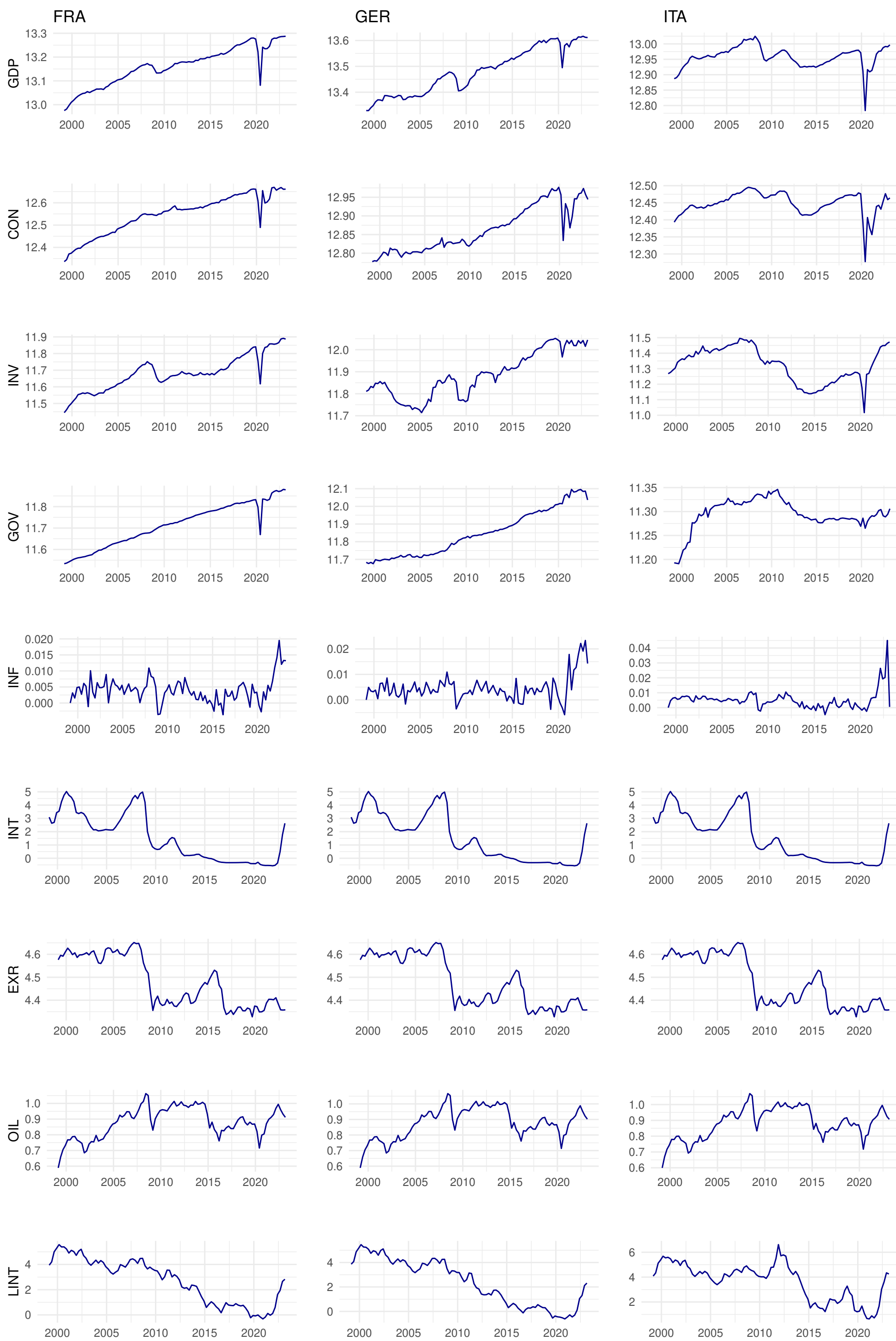
Table 2: Sources of economic indicators for selected advanced countries

Figure 8: Data for USA, AUS, CAN and GBR



Notes: All data, except interest rates and inflation, are in logs.

Figure 9: Data for FRA, GER and ITA

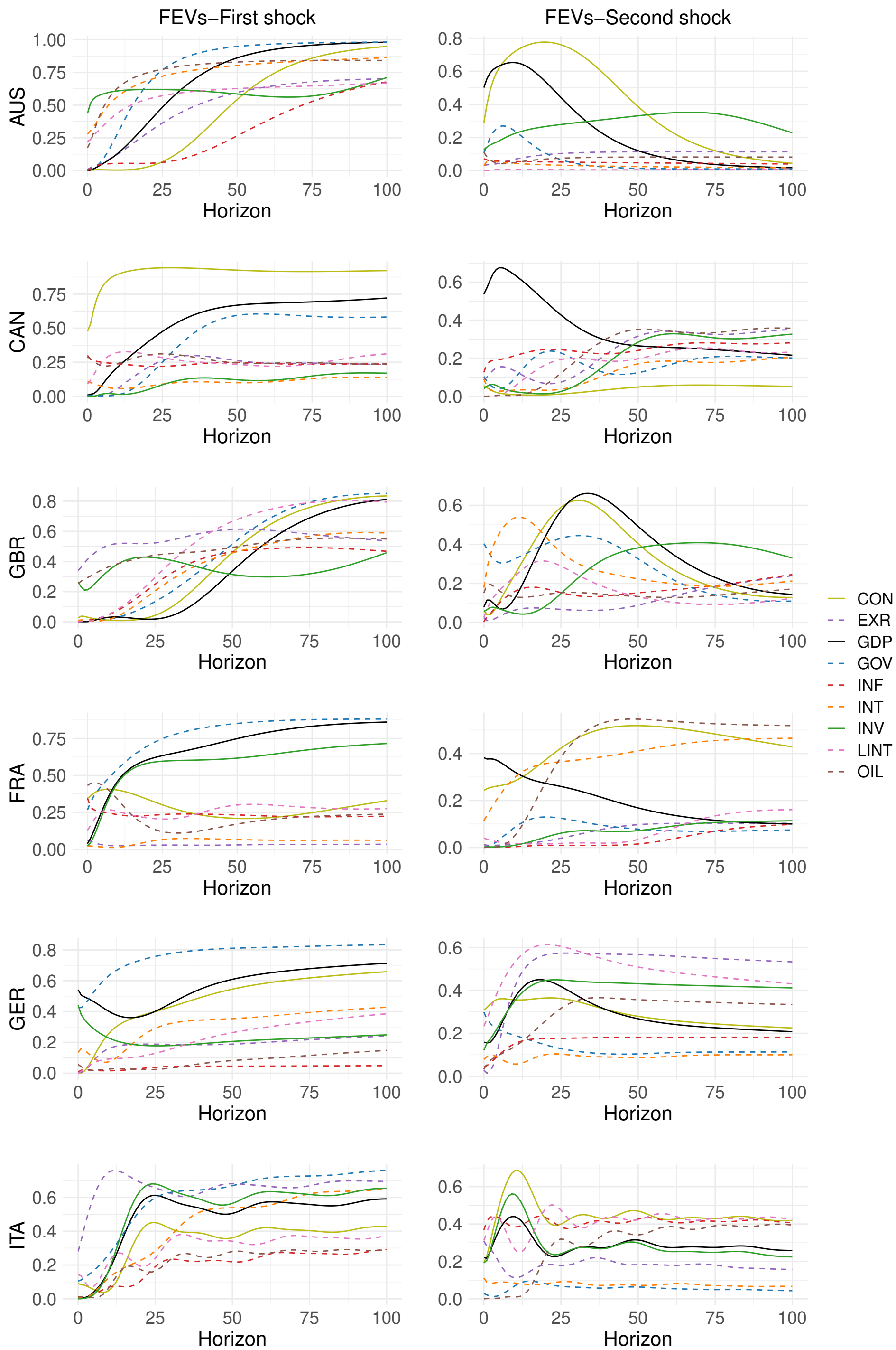


Notes: All data, except interest rates and inflation, are in logs.

A.2 Explained share of Forecast Error Variances: Other economies

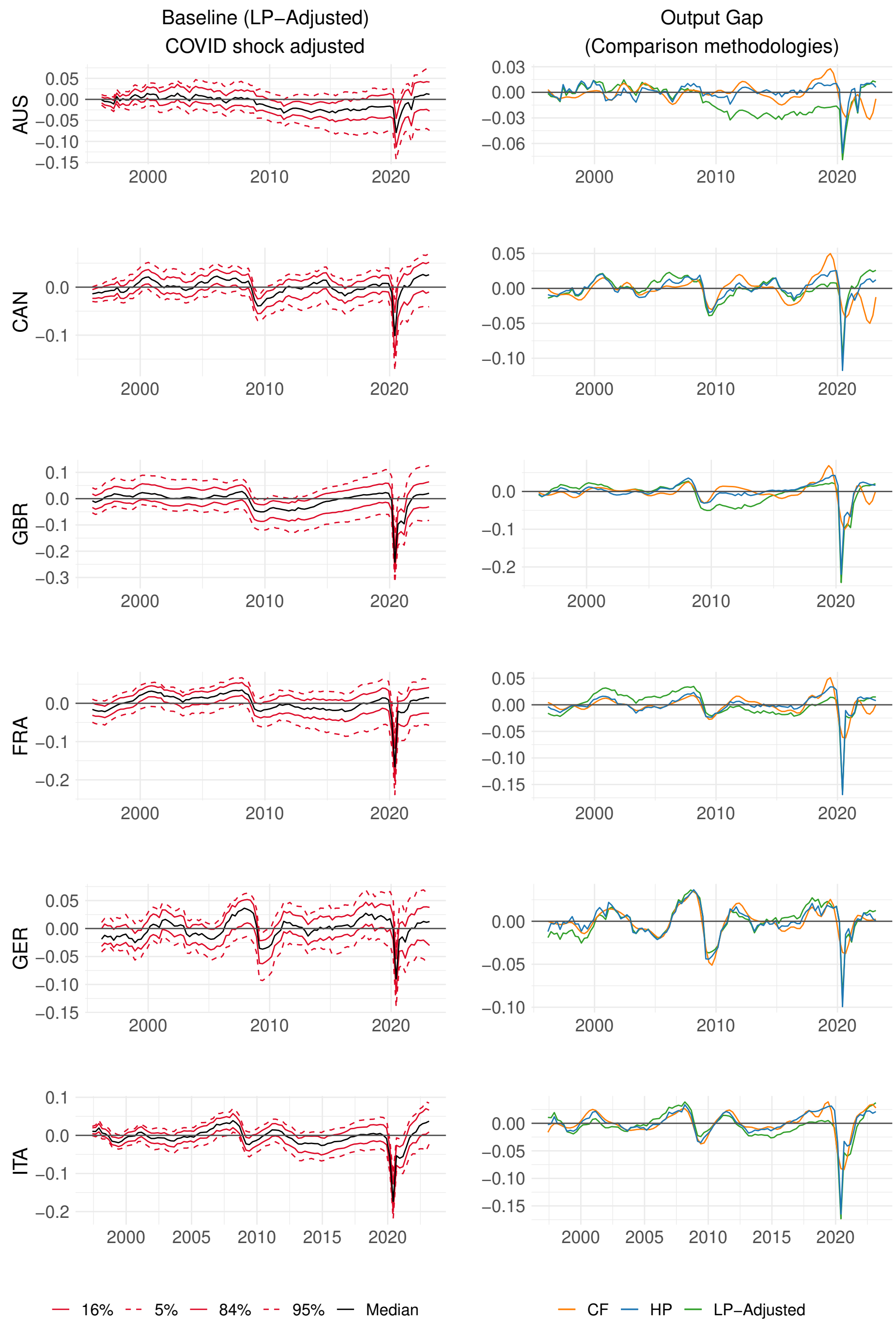
Here, we show the explained FEV share by the two first structural shocks for the rest of the countries in our sample. The selected shocks are those that explain the highest share of the long-run GDP.

Figure 10: Contribution of FEV explanation over each variable for the rest of six economies



A.3 Estimated output gap: Other economies

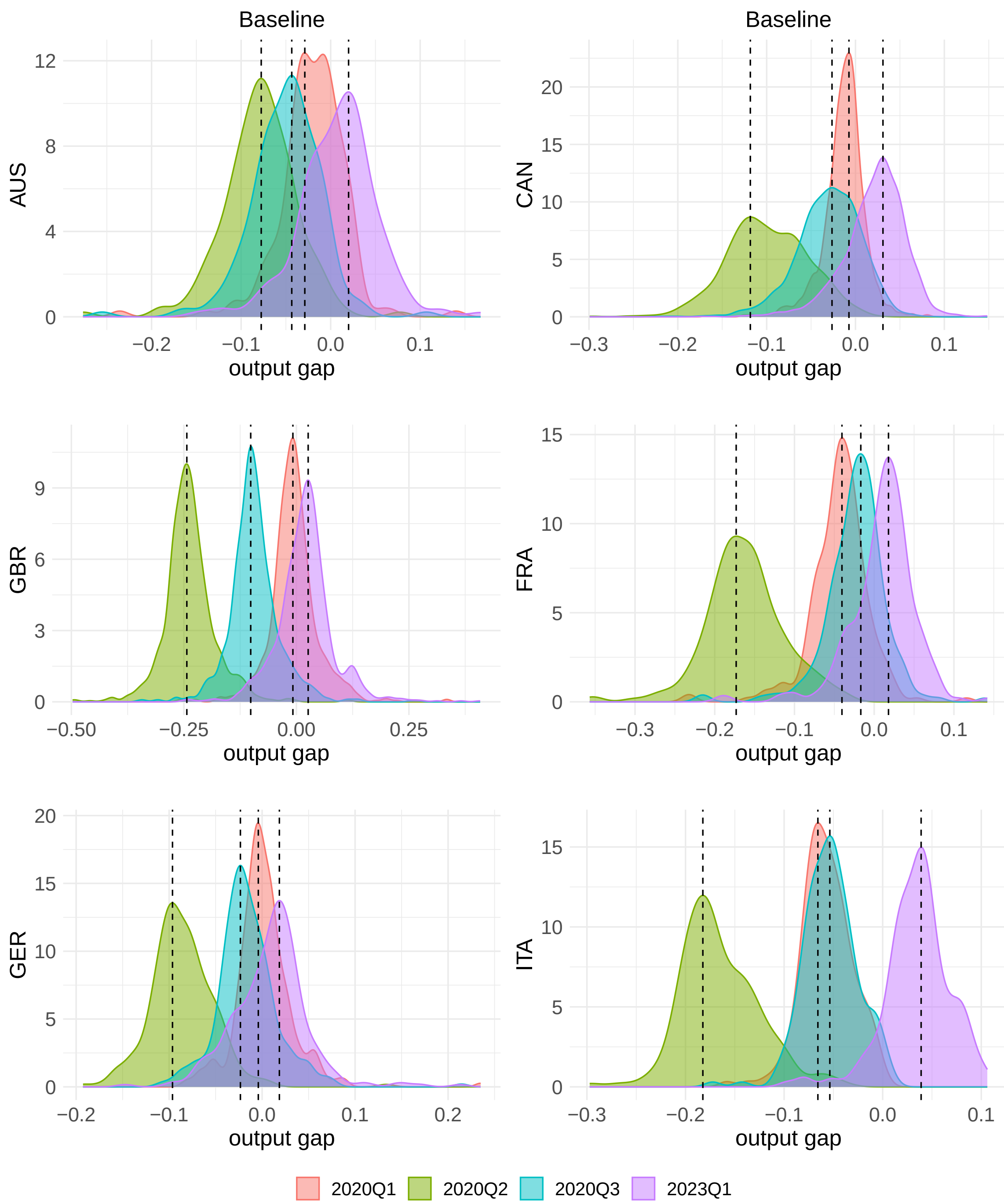
Figure 11: Baseline results: Output gap for the other six economies



Notes: Left panel: The Figures show the results of the baseline BSVAR model with Permanent-Transitory decomposition and Covid-19 adjustment (LP-Adjusted). The solid black line represents the median estimates. The solid and dotted red lines represent the percentiles of 5%, 16%, 84%, and 95%, respectively. Right panel: The Figures show the results of the baseline model (LP-Adjusted) in comparison to the Hodrick-Prescott (HP) and Christiano-Fitzgerald (CF) univariate filters.

A.4 Distributions of the output gap 2020-2023: Other economies

Figure 12: Distribution of the output gap estimation for selected quarters



A.5 Forecast Error Variance decomposition for the baseline model

Figure 13: Forecast Error Variance decomposition (FEVs) by variable (USA)

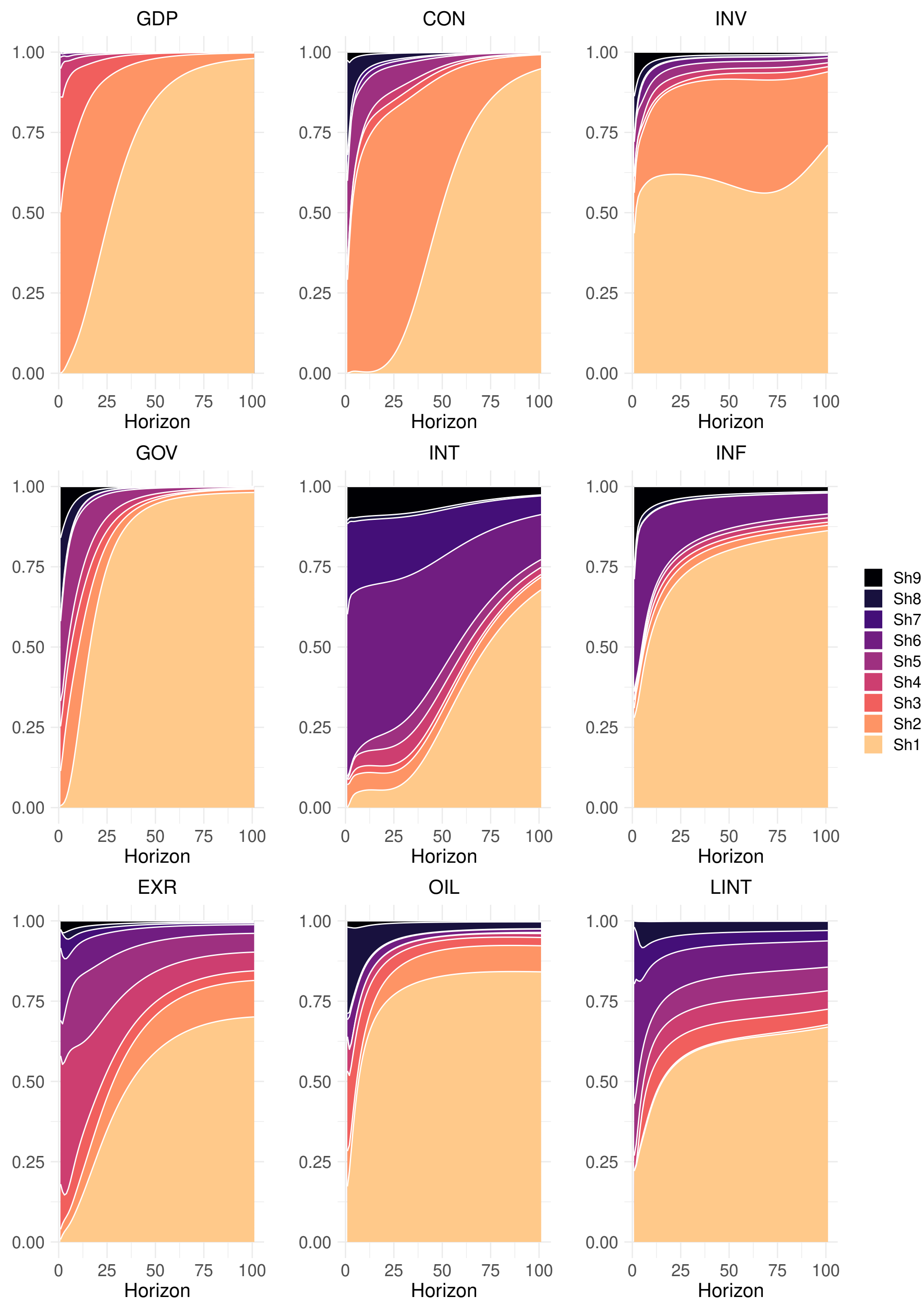


Figure 14: Forecast Error Variance decomposition (FEVs) by variable (AUS)

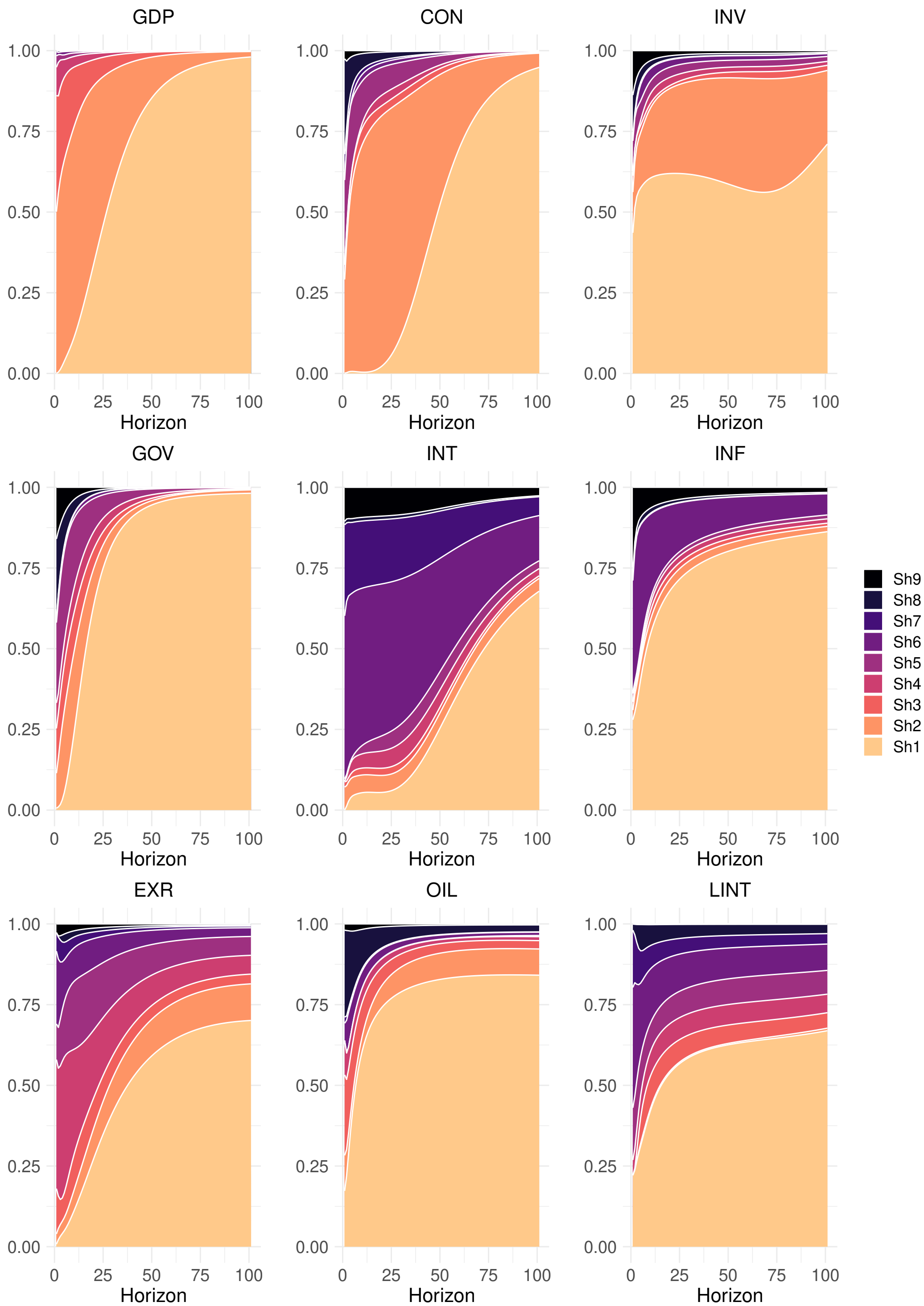


Figure 15: Forecast Error Variance decomposition (FEVs) by variable (CAN)

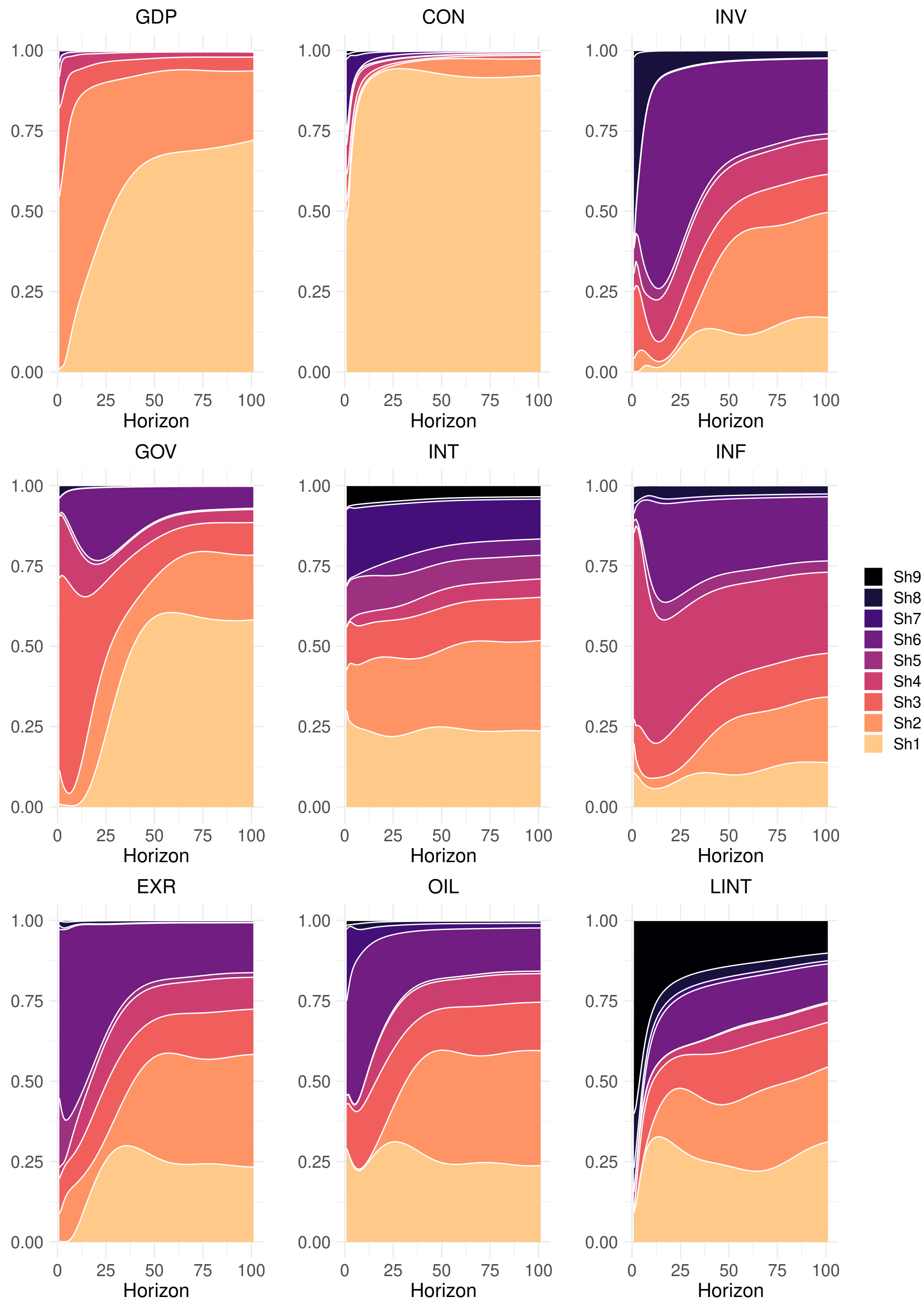


Figure 16: Forecast Error Variance decomposition (FEVs) by variable (GBR)

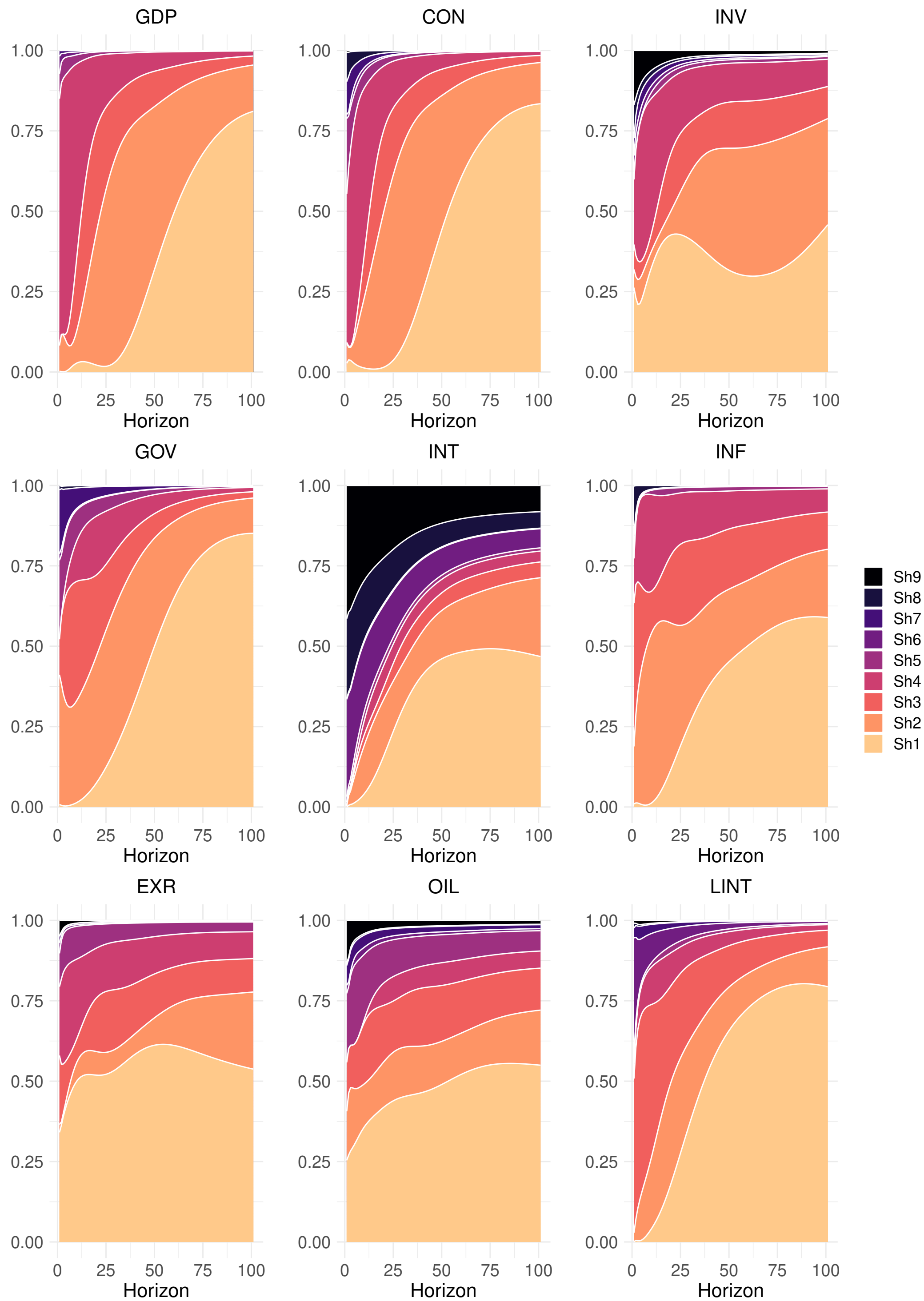


Figure 17: Forecast Error Variance decomposition (FEVs) by variable (FRA)

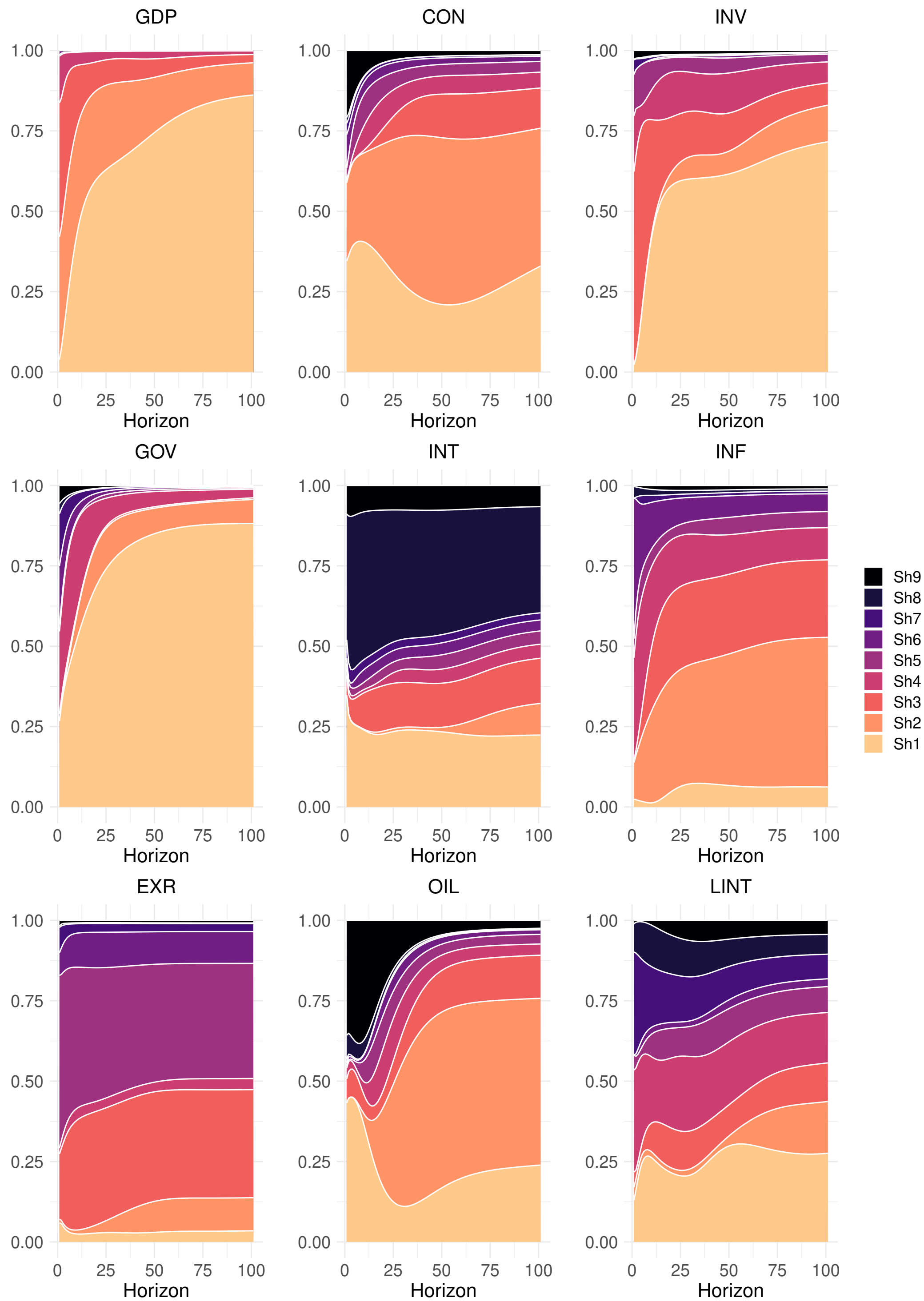


Figure 18: Forecast Error Variance decomposition (FEVs) by variable (GER)

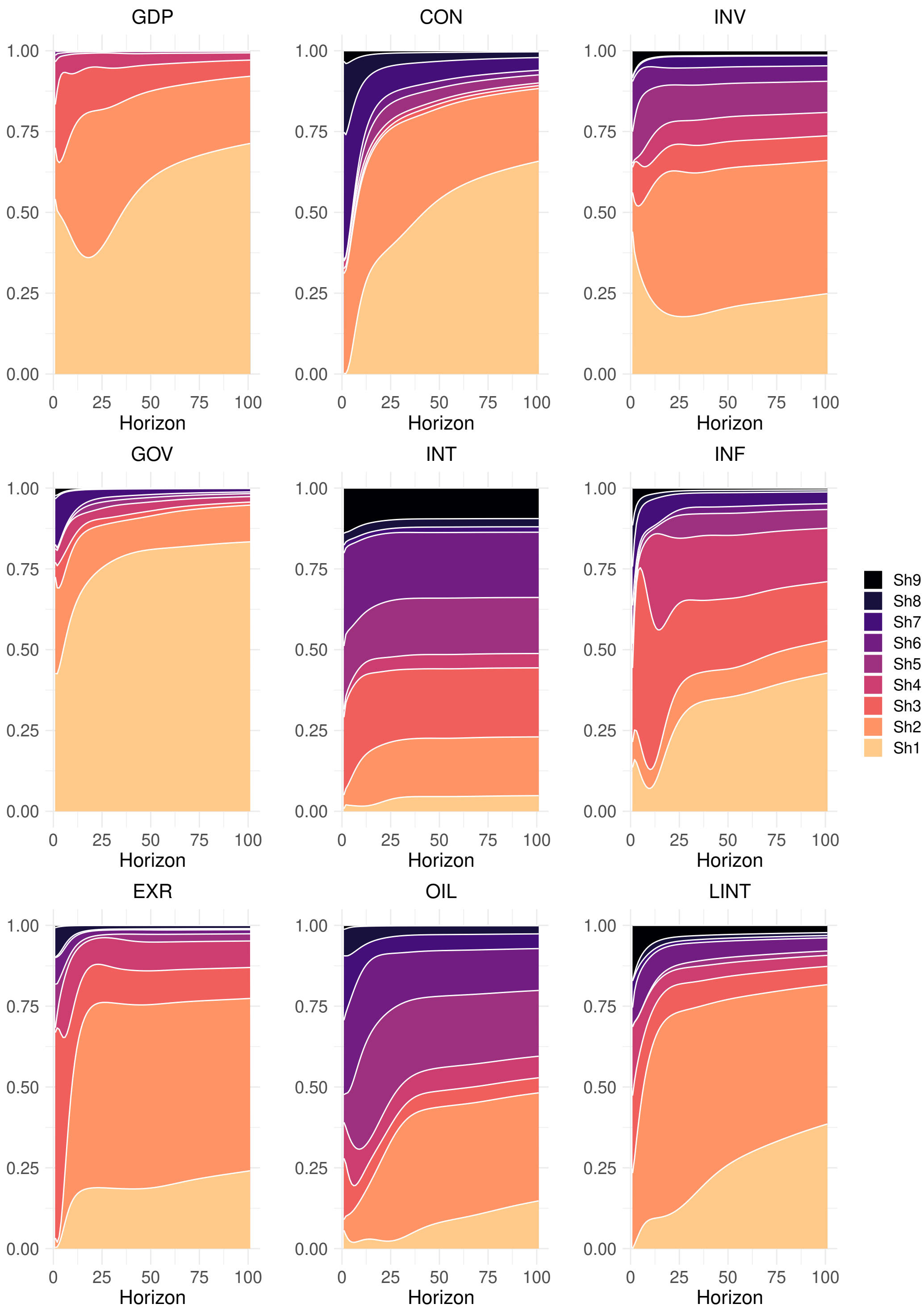
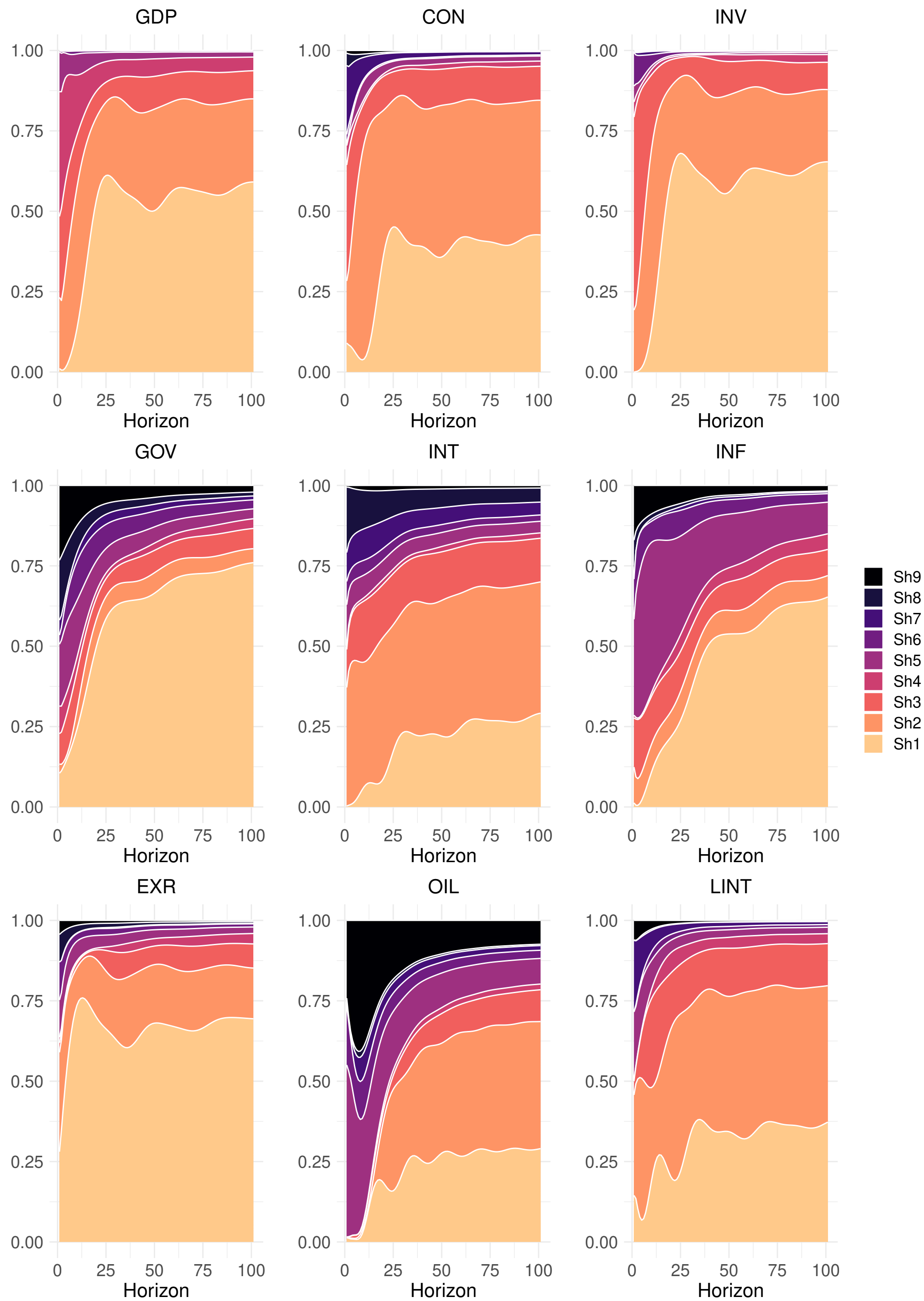
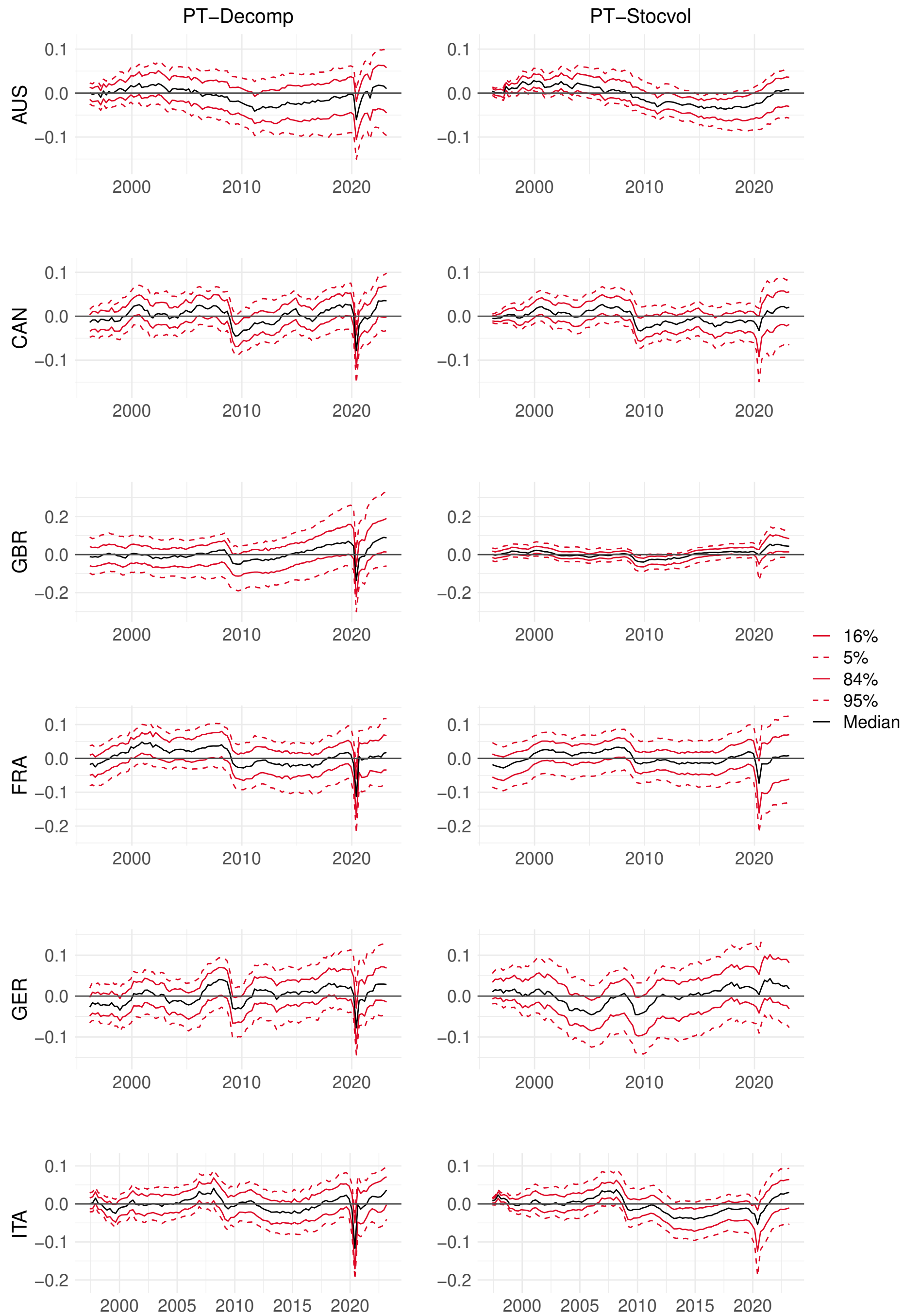


Figure 19: Forecast Error Variance decomposition (FEVs) by variable (ITA)



B Other models: Permanent-transitory SVAR without COVID-19 adjustment and with Stochastic Volatility.

Figure 20: Output gap - two alternative BSVAR models (PT-Decomp and PT-Stocvol)



Notes: Left panel: The Figures show the results of the BSVAR model with Permanent-Transitory decomposition but without Covid-19 adjustment (PT-Decomp). Right panel: The Figures show the results of the BSVAR model with Permanent-Transitory decomposition and Stochastic volatility but without Covid-19 adjustment (PT-Stocvol). The solid black line represents the median estimates. The solid and dotted red lines represent the percentiles of 5%, 16%, 84% and 95%, respectively.