Colombian output gap in Covid times: A permanent-transitory decomposition approach *

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August 17, 2024

Abstract

This paper estimates the output gap for the Colombian economy between 1995 and 2022, explicitly modeling the COVID-19 period where results show a significant 18.8% decrease in the output gap. Our proposed modelling framework comprises a Bayesian Structural Vector Autoregressions with an identification setup based on a permanent-transitory decomposition that exploits the long-run relationship of consumption with output and whose residuals are scaled up around the COVID-19 period. Our results indicate that (i) a single structural error is sufficient to explain the permanent component of the gross domestic product (GDP); (ii) the adjusted method allows for the incorporation of the COVID-19 period without assuming sudden changes in the modelling setup after the pandemic; and (iii) the proposed adjustment generates approximation improvements relative to standard filters or similar models with no adjustments or alternative ones, but where the specific rare observations are not known. Importantly, abstracting from any adjustment may lead to over- or underestimating the gap, too-quick gap recoveries after downturns, or too-large volatility around the median potential output estimations.

JEL Codes: E2, E3, E32, E36, O41

Key words: Bayesian methods, business cycles, potential output, output gaps, structural estimation

*The author(s) thank Luca Benati from the University of Bern for the academic supervision of this paper. This research was conducted through a coaching program under the Bilateral Assistance and Capacity Building for Central Banks (BCC), financed by SECO, and the Graduate Institute in Geneva. The author(s) also appreciate the comments of Cédric Tille and Jean-Paul Renne. The views expressed in this paper are solely those of the author(s) and do not necessarily reflect those of Banco de la República or its board of directors.

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1 Introduction

The COVID-19 pandemic exposed the interconnectedness of the global economy. As the virus spread, nations worldwide faced synchronized economic downturns. The International Monetary Fund (IMF) reported a worldwide economic contraction of 3.0% in 2020, with developed and emerging economies both suffering significant losses. The Colombian economy was no exception and was hit significantly by this crisis, falling by $7,0\%$, the lowest number in the country's economic history. However, also thanks to globalization and technological progress, the world was able to find vaccines and cope with the gradual opening after the lockdown of the first half of 2020. As a consequence, the rebound of the economy was surprisingly important in such a way that in 2021 also positive rates never seen before were observed. For instance, the world economy grew $6,0\%$ which was significantly higher than its average since 2001 ($3,5\%$). So, for two years the world economy not only suffered high levels of uncertainty but also the presence of extreme macroeconomic data both in the downturn and in the subsequent rebound which has raised a question about what happened to the output gap (or potential GDP growth) of the economy?

First of all, we can start by describing that the measurement of output gap is probably one of the unobserved economic variables which has become a huge challenge for economist mainly because its estimation involves more uncertainty and controversy in the profession. So, the Covid shock makes it even more difficult to measure this variable than ever due to the high uncertainty in the disaggregation of shocks into permanent components and transitory ones.

Second, the standard and traditional economy theory suggest that potential output is influenced entirely by supply forces while demand shocks did not, therefore the latter is associated with the transitory component that causes the fluctuations around the potential GDP that explains the output gaps (Blanchard and Quah (1989), Barsky and Sims (2011), Blinder and Rudd (2013), Chen and Gornicka (2020)). Nevertheless, the role of demand has been vindicated due to the observed losses and prolonged crisis after the financial crisis in 2008 where the weakness of demand not only affected the current output but also deteriorated its future expectations, in such a way that it shifted down the path of potential growth (Fontanari, Palumbo, and Salvatori (2020)). In fact, this empirical trait again promoted the hypothesis of hysteresis where different type of shocks may have a permanent repercussion on output, in particular those associated with crises and deep recessions and not necessarily only those on the supply side (Blanchard and Summers (1986), Ball (2009), Summers (2015), Benati and Lubik (2021)).

The foregoing becomes more relevant in the current context of the Covid shock which was initially considered a supply shock but the facts showed a feedback to the demand which encouraged an increase in the economic literature about demand spillovers during this episode. Fornaro and Wolf (2020) model a drop in the productivity growth rate as a consequence of pandemic shock under a new Keynesian model framework. The authors model a negative endogenous feedback between the current and the expected growth path in future due to a contraction in demand by the fall in future productivity which cause a stagnation trap. Guerrieri et al. (2022) show how a supply shock that reduce potential GDP in one sector of the economy could diminish demand in other sectors, in turn, can cause additional drops in GDP potential. According to the authors, the destruction of jobs and businesses exacerbates the initial shock and spreads the recession when the elasticity of substitution between sectors is relatively low, the intertemporal elasticity of substitution is relatively high, and markets are incomplete.

With this in mind, we estimate the output gap for Colombian economy by using a Bayesian Vector Auto-regressive model (BSVAR) with a relative large eight-variable set as well as we model the extreme observations which were seen during the Covid pandemic following Granados and Parra-Amado (2024). Unlike the more popular methods for estimating potential GDP (or output gap) such as HP filter (Hodrick and Prescott (1997)), CF filter (Christiano and Fitzgerald (2003)) or a production function approach which are based only on real GDP (univariate methods) or in a small set of variables, we include a relatively large set of eight variables that enables us to recognize the hypothesis of permanent income and the key relationship between consumption and GDP growth long-run path in order to find a permanent-transitory decomposition (Cochrane (1994)). Also, we take into account variables like exchange rate and oil prices for the fact the Colombian economy is an small open economy dependent on oil as its main export product.

On the empirical ground, a key limitation in SVAR framework is related to the identification scheme which we need to impose strong assumption in order to identify a specific shocks such as supply, demand or monetary policy shocks. Among the most common identification alternatives are contemporaneous effects as Choleski or short restrictions (Sims (1980), Christiano et al. (1996, 1999)), sign restrictions (Uhlig (2005)), long-run restrictions (Blanchard and Quah (1989)), through heteroskedasticity (Rigobon (2003)), instruments for shocks (Romer and Romer (2004, 2010)), and others (Beaudry and Portier (2006), Gertler and Karadi (2015), Lütkepohl and Netšunajev (2017)). Considering this, building on Granados and Parra-Amado (2024), our empirical approach employs an agnostic identification strategy similar to Uhlig (2003, 2004)[1] and models extreme COVID observations as in Lenza and Primiceri (2022). With this strategy, we enable to handle the extreme volatility of covid shocks and then identify the structural shocks by those that explained the variability of Colombian GDP in the long-run in a flexible identification scheme without impose strong restrictions and and separating it from economic theory.

As result, we find that a single shock is enough to describe the fluctuations in the Colombian business cycle which is similar to other studies such as Angeletos et al. (2020) and Brignone and Mazzali (2022). So, we build the output gap by rerunning our model, setting to zero that single shock (with the highest percentage of explanation of GDP variability in the long-run) and obtaining the cyclical component of GDP logarithm's. The latter is subtracted from the log observed GDP

[1]This approach find the structural errors by using the maximization of fraction of long-horizon Forecast Error Variance (FEV) of a specific variable. In particular, we focus on GDP FEV in a 25 years horizon.

and we recover the log of the potential GDP. In particular, the COVID-19 pandemic caused a sharp decrease in the Colombian gap, reaching a low of -18.9% in the second quarter of 2020. However, this decline was temporary, unlike the persistent downturn seen in previous recessions, and then the gap rebounded quicky. Through a counterfactual analysis, we determined that COVID-19 had a negative impact of 1.4 percentage points on Colombia's potential economic growth.

This article is organized as follows. In the next section, we show a brief literature review. In section 3, we introduce the methodology proposed by Granados and Parra-Amado (2024) which combines two methods: addressing extreme values in covid pandemic as Lenza and Primiceri (2022) and the identification scheme in VAR models proposed by Uhlig (2003, 2004). In section 4, we introduce the data, the model and its empirical approach, and the main results and findings. Our conclusions are drawn in the final section.

2 Literature review

As mentioned before, it is quite common to associate potential GDP with the trend component of observed GDP which is used to calculate the output gap defined as the deviation of real GDP from its potential output. From the policy perspective, many central banks use the output gap measure as a source or indicator of inflationary pressures, which could condition their monetary stance by assessing the response of observed GDP to shocks and how those fluctuations could reflect a conservative or undesirable change from the optimal path of output. Likewise, output gap indicates the economy's position on business cycle which enables us to evaluate how close or far the current fiscal deficit is from that considered as neutral.

From an empirical perspective, as potential GDP is a latent variable from which the output gap is also derived, both statistical and economic models have emerged as a tool for its measurement. As pointed out by Kiley (2013), the concepts of potential output gap stemming from definitions that are not only different, but they also lead to different conclusions and assessments oftentimes. According to this author, those concepts can be grouped in three main gap estimation approaches: filtering or statistical approach, the production function approach, and the New Keynesian approach. In a similar vein, Álvarez and Gómez-Loscos (2018) survey the gap estimation methods and provide a classification according to features such as complexity, decision variables or type of modeling (e.g., univariate, multivariate, see the Appendix B).

A popular tool to measure the output gap is by production function approach which estimates the output deviation from a level consistent with current technologies and full usage of resources of capital and labor (CBO (2001, 2014), Havik et al. (2014)). However, from an empirical perspective, these measures are usually associated with the common wisdom of a trend GDP where the gap is defined by the deviation of output from its long-run trend (e.g., filtering approaches such as Beveridge and Nelson (1981), Hodrick and Prescott (1997), Baxter and King (1999), Christiano and Fitzgerald (2003), among others). In line with this, it is common some analysts and policy practitioners is to conceive the potential output as a smooth trend (Basu and Fernald (2009)). This implies that supply factors and technology changes do not present significant fluctuations over time, and therefore, short-run fluctuations of output gap are mainly driven by demand shocks. Although empirically those univariate filters are usually used, their main criticism comes from the fact that they typically show a low transitory variability (Cochrane (1990)[2]).

In a structural multivariate model this notion also began to be conceived. For example, Blanchard and Quah (1989) show that under the traditional Keynesian view of fluctuations, they interpret the permanent shocks as supply disturbances which are the only sources that affect the potential output while those shocks defined as transitory are linked with demand disturbances. However, they also recognize that there could be cases in which demand shocks affect GDP in the long term, although in such a case they consider that those shocks would be small compared to those defined as supply shocks.

Our starting point is the seminal article of Cochrane (1994) which examines how to decompose permanent and transitory components in GNP unraveling the consumption's behaviour. Thus, it results a useful measure of the trend in GNP based on the permanent income interpretation. According to Cochrane (1994), under a random walk consumption's dynamics, if consumption shows no change, the consumers interpret any contemporary shock or movement in GNP as transitory.

Uhlig (2003, 2004) identify the permanent and transitory shocks in US economy by maximizing the FEV of real GNP over five-years horizon. As a result, it is possible to explain around 90% of the GNP variability by using the largest two shocks of the FEV. Although this method is entirely empirical and does not contemplate structural restrictions from economic theory in the identification process, the author suggests that the first shock seems like a productivity shock while the second could be attributed to inflationary or wage push shock. Following this identification scheme, Angeletos et al. (2020) find that a single shock can be used to explains macroeconomic fluctuations. This common propagation mechanism in macroeconomic data was defined as Main Business Cycle shock (MBC) by the authors. It is neither a supply-side shock nor a standard inflationary-type demand shock, and they point out deficiencies in the traditional mechanisms since there is a disconnection between the variables of the economic cycle and inflation or TFP. Brignone and Mazzali (2022) expand Angeletos et al. (2020) in a high dimensional framework by using dynamic factor model over a set of 136 variables. They found the the economy seems to be mainly driven in the long-run by just one supply-side permanent shock. In this aspect, our research follows this branch of the literature in which the identification mechanism is agnostic and data-driven and the business cycle is explained by a single permanent shock.

In recent years, empirical evidence suggests that the use of multivariate models produces more reasonable estimates of the output gap, since they include a broad set of relevant information to

[2]Cochrane (1990) compares univariate and multivariate filters and finds much larger cyclical components in the latter ones where including variable as consumption enable to assess whether shocks to GNP are persistent.

capture the reduced-form dynamics of macroeconomic variables and identify aggregate shocks (Jarociński and Lenza (2018), Morley and Wong (2020), Barigozzi and Luciani (2021), Furlanetto et al. (2022)). In particular, Morley and Wong (2020) apply Beveridge and Nelson (1981) decomposition based on a large BVAR to estimate the U.S. output gap taking into account the FEV of the GDP one-step ahead. The authors mitigate the possibility of over-fitting output growth by Bayesian shrinkage.

Regarding the covid period, Berger et al. (2023) build a nowcast model to US output gap by combining Beveridge and Nelson (1981) decomposition and mixed-frequency Bayesian VAR (Ghysels (2016), Cimadomo et al. (2022)). They estimate a steep decline of the US output gap in 2020Q2 between -10.1% and -8.3% conditional to the set of information from April to June 2020. They show that monthly indicators such as consumer sentiment, credit risk spread and the unemployment rate are useful for nowcasting the output gap in real time. Similar results for the German economy have been reported in Berger and Ochsner (2022) by using the same methodology. They find that the output gap dropped from 1.17 to -8.78% due to covid shock which implies it only marginally affected potential output but is accounted for by a massive decline in the output gap. These articles take into account a large set of information to determine in real time the impacts of the covid by using monthly variables but do not explicitly model the covid. On the contrary, Morley et al. (2022) propose a take a two-step approach where first the authors use a hybrid of Bayesian and maximum likelihood estimation (MLE) approaches discussed in Lenza and Primiceri (2022) to model the covid shock, and second, they decompose the GDP growth following Beveridge and Nelson (1981) in order to fit the GDP trend-permanent component of the euro zone. Our research is similar in that we use a two-stage method, but differs in that instead of using the above decomposition, we rely on Uhlig (2003, 2004) identification scheme.

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3 Methodology

To calculate the output gap, we employ a permanent-transitory decomposition approach as outlined in Granados and Parra-Amado (2024) which is divided into two stages. First, we use a reduced-form Vector Autoregressive (VAR) model that includes a scale factor to account for COVID-19-induced volatility. As in Lenza and Primiceri (2022), the traditional VAR include a s_t term as follows:

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

where s_t is set to one in the sample period before the COVID-19 shock (t^*), and subsequently, latent parameters ($\theta \equiv [\bar{s_0}, \bar{s_1}, \bar{s_2}, \rho]$) are estimated to capture the increased uncertainty during the COVID-19 period, which then diminishes as the economy recovers. As usual in this framework, we fit the scale factors for the first three quarters in COVID period starting at the first quarter of 2020

($t^* = 2020Q1$) and a decay parameter ρ for the next quarters. Thus, the unobserved parameters are $s_{t^*} = \bar{s_0}$, $s_{t^*+1} = \bar{s_1}$, $s_{t^*+2} = \bar{s_2}$ and $s_{t^*+j} = 1 + (\bar{s_2} - 1)\rho^{j-2}$ for $j \geq 3$.

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 in a Metropolis-Hasting procedure. The priors of β and Σ can be described as

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

where $\beta \equiv vec([B_0, B_1, \ldots, B_p]')$ and $\gamma \equiv (\Psi, d, b \text{ and } \Omega)$ are the hyperparameter vectors. 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):

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

Second, we recast the model of equation (1) into an SVAR form by identifying the main shock explaining the Colombian business cycle in the long run, which is done, along the lines of Uhlig (2003, 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). Recall that the structural errors (ε_t) are related to the reduced-form errors (u_t) in equation (1) through the impact matrix (A_0) that establishes $u_t = A_0\varepsilon_t$ and $\Sigma = A_0 A_0'$. Uhlig (2003, 2004) use an alternative matrix $\ddot{A}_0$ which can be found by using an orthonormal matrix Q where $A_0 = \ddot{A}_0 Q$ and $QQ' = I$ through maximization of the following expression:

$$q_1 = \text{argmax}\, q_1' M q_1 \equiv q_1' \sum_{h=0}^{k} \ddot{A}_0{}' C_h' (e_j e_j') C_h \ddot{A}_0 q_1$$
$$\text{subject to} \qquad q_1' q_1 = 1$$

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, as shown in Uhlig (2003), q_1 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.[3] 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 higher to lower fractions, explained by the FEV of the target variable. Thus, we can verify whether one or more shocks explain a larger component of the long-run FEV of the GDP. In other words, this approach identifies the shock that best explains the long-run component of the target variable. This is done in the following section.

4 Results

4.1 Data and empirical strategy

We set an eight-variable B-SVAR in levels for the period 1995Q2 to 2022Q1 using Colombian data.[4] The variables included are GDP, household consumption (CON), government consumption (GOV), investment (INV), inflation (CPI), real exchange rate (RER), interbank interest rate (ITB), and Brent oil price. The domestic account variables (first five in the VAR) were obtained from the Colombian National Statistics Department (DANE), the exchange rate and interest rate from the Central Bank of Colombia (Banco de la República), and the oil price from Bloomberg.

We select a lag length of two (p = 2) following 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 the 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. We ran 20.000 draws and kept half for estimation after burn-in. In addition, we explicitly modelled 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 st and incorporates the pandemic shock.

In the second stage, we identified the impact of the matrix of the SVAR by maximizing the explained share of the forecast variance error of the GDP for a 25 years horizon, as in Uhlig (2003, 2004). As part of the procedure, we restrict that the share of the FEV one step ahead of consumption explained by the first structural error, or (the majority of the) permanent component, is larger than that of the output and for the latter to be larger than that of the 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

[3] Note that $C(L) = I + C_1L + C_2L^2 + C_3L^3 \cdots + C_hL^h + \ldots$ and the moving average representation of the model is given by $Y_t = B(L)^{-1}u_t = C(L)u_t$.

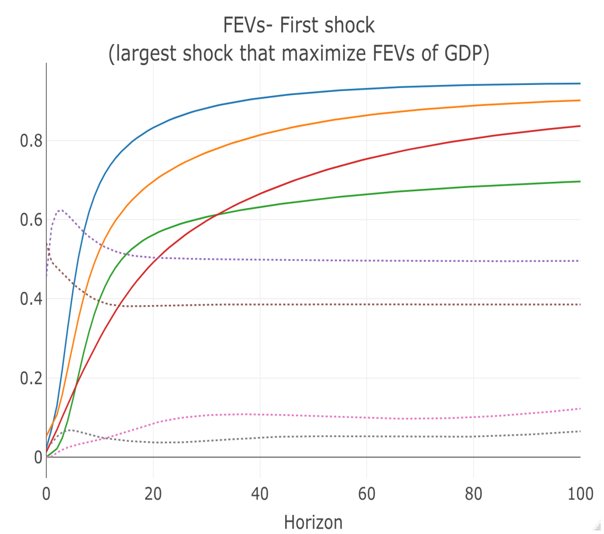
[4] We report unit root and cointegration tests that are consistent with our model choice in Appendix A

the draws that comply with them, we conducted PT decomposition and computed the permanent (and transitory) output component.[5]

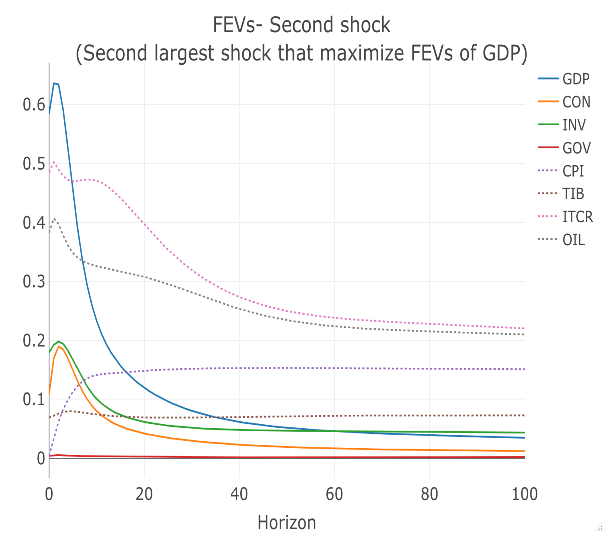
As aforementioned, the decomposition and resulting impact matrix already consider the ordering of structural shocks according to their share of the explained variance of the target variable. This can be verified in Figure 1, where we can see that only the first structural error is necessary to account for approximately 90% of the long-run (permanent) component of the GDP. Concurrently, the next most important shock explain the GDP's FEV in the short run which is more resembling the transitory output component.

In light of these results, we compute the output gap based on the second to eighth structural shocks and use only the first one to recover the potential GDP.[6] On a related point, it should also be noted that the first structural error will explain the majority of the long-run FEV of the GDP (target variable), but not necessarily the largest share of the FEVfor 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 9 in the Appendix C.1.[7]

Figure 1: Contribution of FEV explanation over each variable (first two largest shocks that maximize FEV of GDP)



(a) First shock (permanent)



(b) Second shock (transitory)

Note: The left panel shows the contribution to the FEV of each variable by the structural error identified as the one with the highest percentage of explanation for the FEV of GDP. The right panel shows the second-largest shock that explains the GDP's FEV.

[5]As a check, we increased the number of draws to 100.000 and obtained similar results.

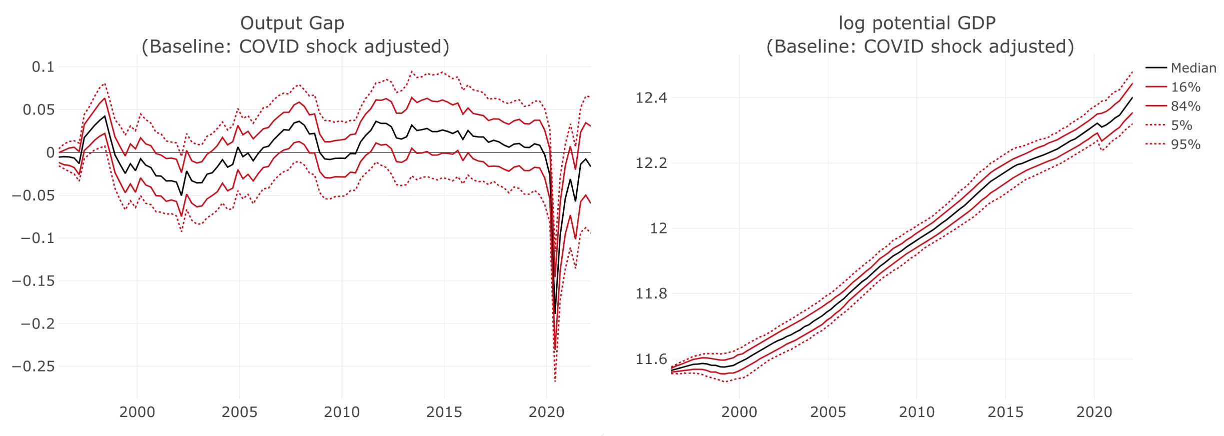
[6]Analogously, the potential GDP can be obtained as the original series minus the transitory component.

[7]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, but also because the trade-off of this method is that you compromise a structural interpretation of the shocks as separable types of drivers (e.g. monetary, financial, global, local, supply, or demand, among others), as by construction, the method only gauges the overall importance of shocks at different horizons.

4.2 Baseline Results

Figure 2 shows the output gap and potential GDP for the Colombian economy obtained from our proposed BSVAR, using a combined PT decomposition and a scale factor adjustment to include and adjust for the COVID-19 period observations. Before COVID-19, our estimated gap and potential output reflected the recession of the late 1990s, a slight deterioration during the GFC.[8] In both cases, we can see decreases in the gap dynamics and dips in the potential output. An additional gap decrease occurred during 2016, reflective of a reduction in terms of trade due to exogenous shocks in the international price of oil.[9] In general, these dynamics are aligned with previous business cycle dating exercises carried out for Colombia (e.g., Alfonso et al., 2013), despite the high uncertainty one may expect to see around these estimates also reflected in the amplitude of the percentile intervals shown in the figure.

Figure 2: Baseline results: Output gap and potential GDP for Colombia



(a) Output gap **(b)** Potential GDP

Notes: The solid black line represents the median estimates. The solid and dotted red lines represent the percentiles of 5% , 95% , 16% and 84% , respectively.

During the COVID-19 pandemic, the gap underwent a steep decline (-18.9%) in the second quarter of 2020; however, unlike in the 1999 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 recovery is induced by the gradual reopening of the economy. The potential output also displays different dynamics than the 90s recession as it dips down, but more mildly and less persistently during the lockdown quarters. In the late nineties, the potential GDP growth went negative, contrasting with the pandemic when it only decelerated (from 3.5% in 2019 to 2.2% in 2020). The recovery paths are also in contrast with the potential output trending upward

[8] For the Colombian case, our main downturns of reference are the 1999 and GFC crises. The former is one of the worst recessions to date, while the latter is relatively mild compared with the dynamics of advanced economies.

[9] Colombia's main export commodity is crude oil and related products.

and gap closing by 2022Q1.

4.2.1 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 a production function approach (PF).[10] 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 rapid and sizeable subsequent recovery, which sends that gap onto positive territory (and at or beyond 5%) 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, these results indicate that our proposal does not lower the potential output significantly during the period, which is related to adjusting the model to incorporate COVID-19 observations in the estimation sample without assuming drastic changes in its data-generating process.

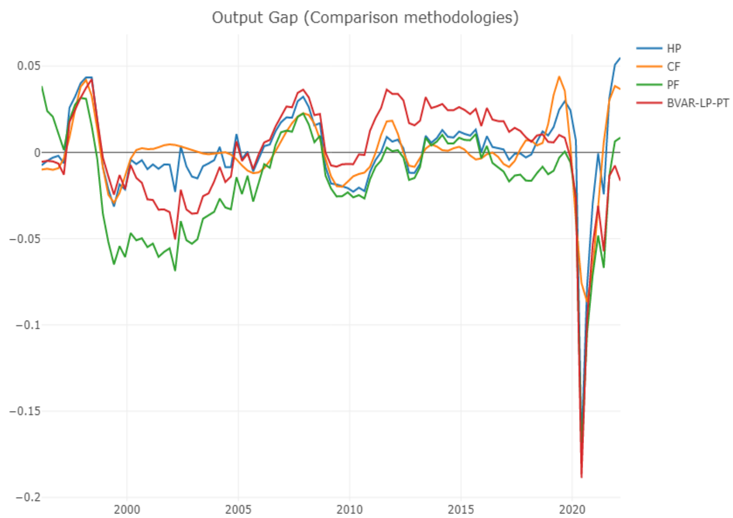
By contrast, the PF function seems to draw the gap in the opposite direction and could indicate its underestimation. First, it is below all competing methods throughout the sample, but primarily, it lowers the gap too steeply during every downturn (1999, 2008, 2016, COVID-19). These patterns also contrast with our proposal; thus, we see our method as a middle point. In particular, concerning the PF method, our proposal has the advantage of including more information in the model and pinpointing the long-run behavior of the GDP through its link to consumption. While the PF, conversely, can be too quick to associate the bulk, if not all, of the fluctuations in capital and labor inputs to the short-run behavior of the GDP, which is counterfactual 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).

Finally, we compared the proposed BSVAR model with two models of the same type. That is models with the same identification setup (PT decomposition as in Uhlig, 2003). We consider an alternative BSVAR without a scaling adjustment for the COVID-19 episode and another where, instead of using a scale factor, the model is allowed to feature stochastic volatility (BSVAR-SV).

The associated output gaps and potential outputs of the two B-SVAR alternatives are shown in Figure 4 and 5. A large contrast between the baseline and the alternatives emerges at first sight: both the BSVAR (unadjusted) and the BSVAR-SV generate a less negative gap during the COVID-19 outbreak, which implies that the potential output is affected more drastically relative to our baseline model. In that sense, as with some of the simpler filters, the alternatives tend to overestimate the impact of the shock on the long-run output.

[10]The PF approach reconstructs the potential output from the individual inputs of GDP, aside from the total productivity, in the context of a Cobb-Douglas technology setup

Figure 3: Comparison methodologies for output gap estimation



Regarding the volatility around the estimates, the BSVAR (unadjusted) displays the largest uncertainty, as reflected by percentile ranges that are twice as large as in the baseline. Nevertheless, the BSVAR-SV successfully mitigates volatility (at a similar range span as the baseline); however, it is the method where the potential output is affected the most during the downturn.

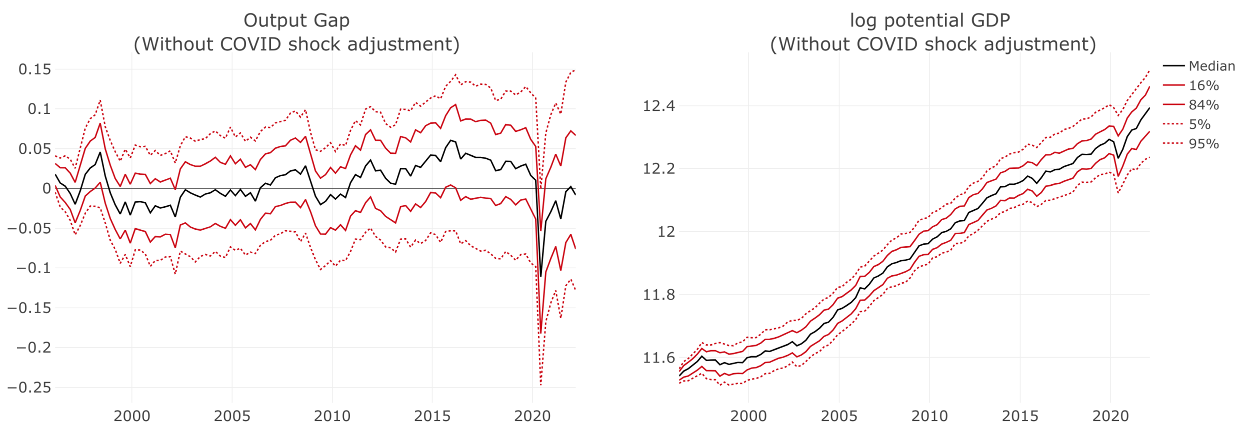


Figure 4: Output gap and Potential GDP- BSVAR without scale factor

4.2.2 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 (and shrinkage) in Figure 6.

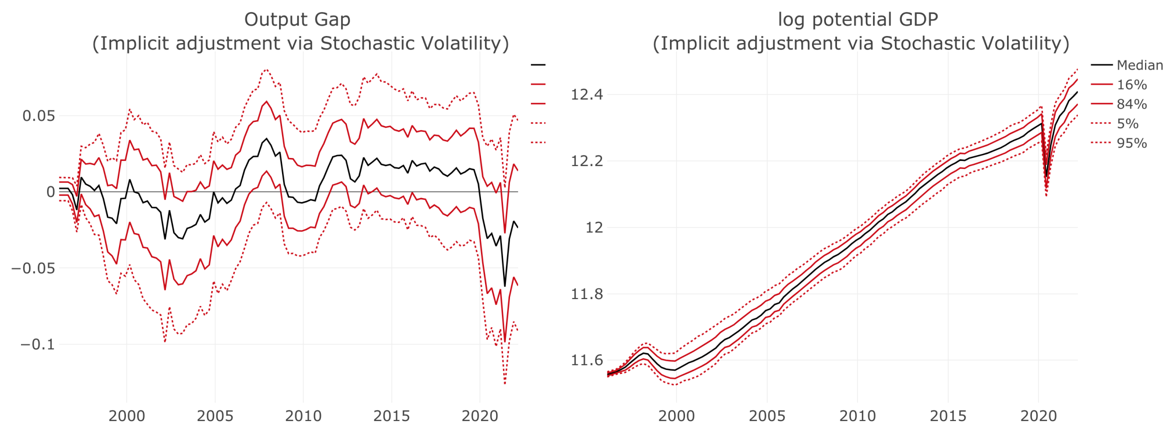
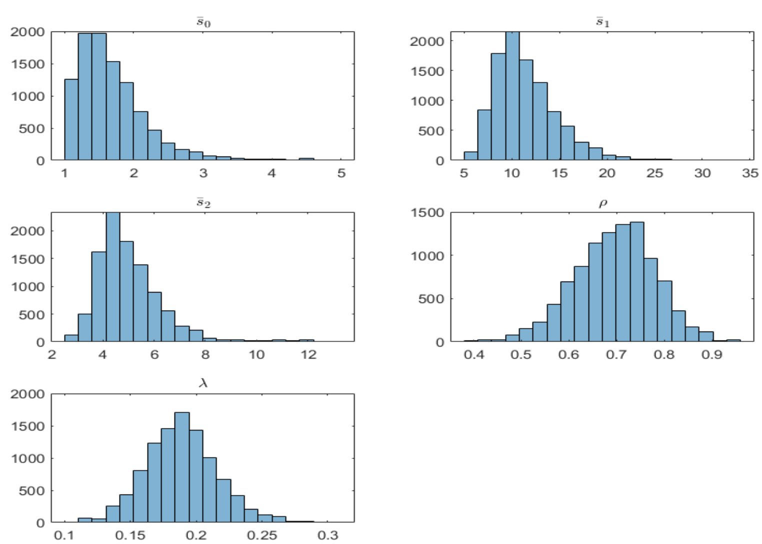


Figure 5: Output gap and Potential GDP-Stochastic volatility BSVAR without scale factor

The parameters posteriors are drawn based on a Metropolis Hastings algorithm with a Minnesota Prior. Thus, we estimated the scaling factors together with other hyperparameters in a hierarchical structure. The resulting posteriors for $\bar{s}_0, \bar{s}_1, \bar{s}_2$ peak around 1.5, 10, and 4.5, 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. Nonetheless, the posterior of the decay coefficient (ρ) peaks around 0.75, which, together with $\bar{s}_2$, implies that the volatility scale factor falls by a third after 2020Q3 and then non-linearly towards one.[11]

Figure 6: Posterior distribution of the overall standard deviation of Minnesota prior and volatility scaling factors

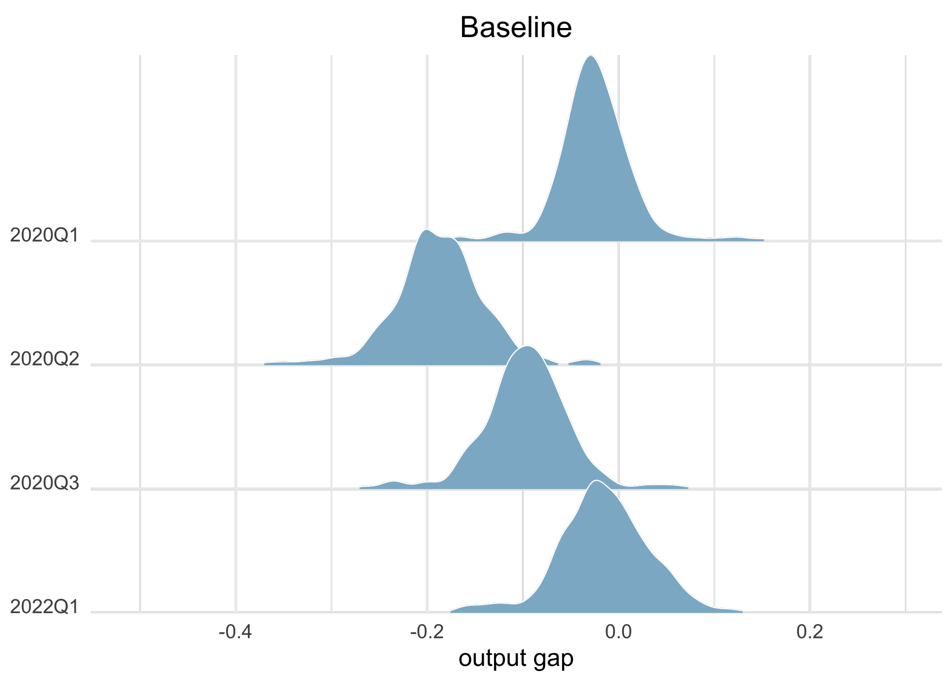


[11]We also obtain the posterior for the shrinkage parameter of Minnesota prior (λ), depicting a mode around 0.19.

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 7. We reveal the quarter of the shock (2020Q1), the subsequent two quarters, and the first quarter of 2022 as a reference for a date when the potential output dynamics are, in principle, back to normal (here implicitly recognise the transitory nature of the pandemic shock).[12]

As we can see in the figure, the distribution of the gap has a large shift to the left, implying that the potential GDP was not largely 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 shifts 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, although a somewhat larger uncertainty remains. Nonetheless, the larger uncertainty is approximately one percentage point higher than before, rather than orders of magnitude larger, as may be induced by a model without a scale factor adjustment for the COVID-19 downturn.

Figure 7: Distribution of the output gap estimation during COVID-19 shock and 2022Q1.



4.3 Counterfactual exercise (no covid) vs baseline model

In this subsection we compute a counterfactual output gap where the COVID downturn is abstracted from. We re-run our permanent-transitory decomposition through the BSVAR model by setting to zero the shocks linked with the transitory component, using sample information until

[12]As an additional exercise, we present a counterfactual exercise in Appendix 4.3, where we discuss the gap and potential output that would have been observed in the absence of the pandemic shock.

December 2019 and forecasting nine quarters ahead. Notably, the Colombian potential GDP would have grown 3.6% in 2020 which represents a loss of 1.4% compared to the baseline model. We find similar results assuming that potential GDP would have grown at the average rate of the last decade.

In a world without COVID we obtain the potential GDP would have grown 3.6% in 2020, i.e., 1.4% higher than in our baseline model with COVID (which grows by 2.2%). In terms of the output gap, the counterfactual shows a median around zero which contrasts with the estimates of the COVID period that show a median of -18.8%.

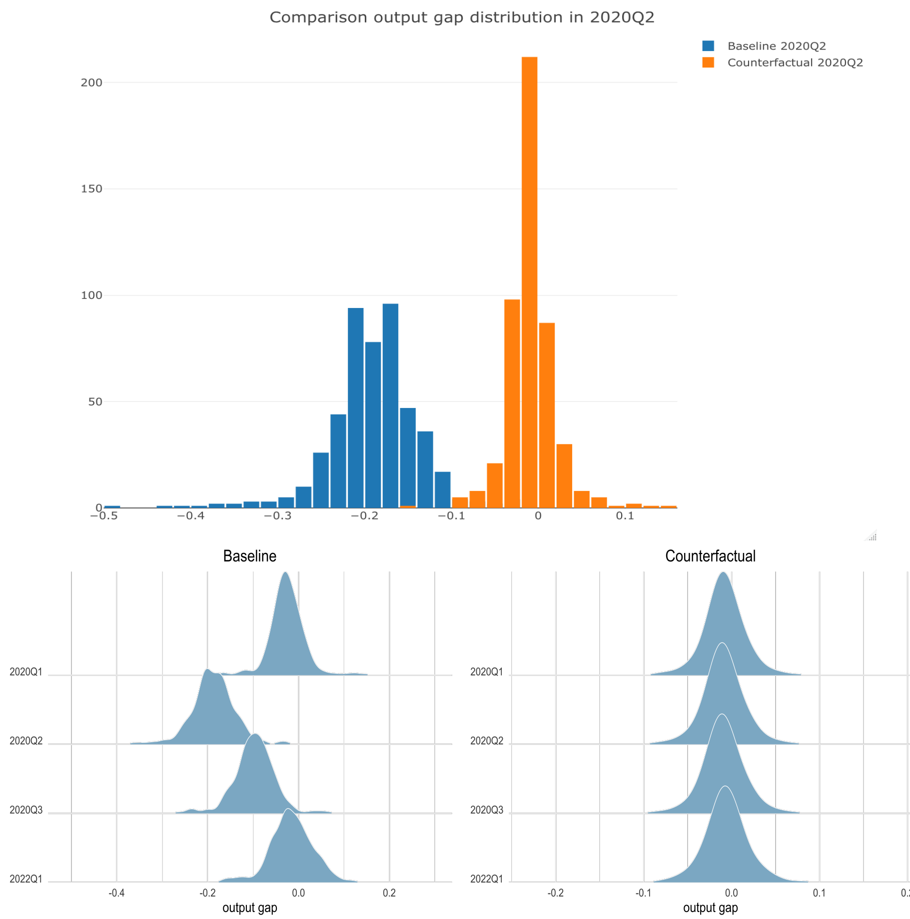


Figure 8: Counterfactual exercise vs baseline model

5 Concluding remarks

This study examined 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. It aimed to include a complete set of observations in the model while preventing observations of unprecedented magnitudes (that do not resemble the sample data-generating process) from affecting the quality of the resulting econometric modelling framework.

To address this question, we considered a baseline model incorporating ample information sources into a structural framework that allows for the application of an identification strategy that exploits the relationship between consumption and output to recover the permanent and transitory components of GDP, as in Uhlig (2003, 2004). Based on this setup, we adjusted the model with a scaling factor of the residuals around the COVID-19 pandemic outbreak along the lines of Lenza and Primiceri (2022). Our results 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). Our setup prevents quick output gap reversals after downturns or drastic changes in the potential output after high-magnitude transitory observations. In particular, during COVID times, our findings indicate an 18.8% decline in the output gap during the pandemic. Furthermore, our statistical analysis reveals a 1.4 percentage point reduction in potential GDP due to the COVID-19 crisis.

While our identification strategy has its limitations, particularly in terms of decomposing output dynamics in economic structural drivers (e.g. monetary, financial, global, supply, and demand), it provides a simple way to find a agnostic structural identification that explain the FEV of the GDP in the long-run. Although we can estimate the output gap with a reasonable accuracy, future research can explore these drivers in more detail, building on our findings to refine the approximation and minimize the drawbacks of arbitrary shock horizon adjustments common in other approaches.

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A Additional descriptive data

Table 1: Unit root test

Variable-Test	ADF		PP		KPSS		ERS	
	Level	First Diff	Level	First Diff	Level	First Diff	Level	First Diff
GDP	0.9609	0.0000	0.9684	0.0000	1.16079	0.101328	198.0309	0.505899
CON	0.9962	0.0000	0.9984	0.0000	1.152888	0.313152	158.1545	0.478252
INV	0.8669	0.0000	0.842	0.0000	0.971256	0.145345	26.53758	0.495762
GOV	0.8951	0.0000	0.6729	0.0000	1.188665	0.136647	715.5667	0.679222
CPI	0.2782	0.0006	0.4451	0.0000	0.826933	0.075889	45.25559	0.030919
TIB	0.0948	0.0000	0.0664	0.0000	0.77068	0.322704	9.37788	0.866045
ITCR	0.3569	0.0000	0.2941	0.0000	0.723053	0.222996	75.03317	0.92045
OIL	0.1299	0.0000	0.2149	0.0000	0.246352	0.069921	1.960358	0.556965

Note: * For ADF and PP the data in table corresponds to p-values, and the test statistic are reported for KPSS (1%: 0.739, 5%:0.463, 10%: 0.347) and ERS (1%: 1.9472, 5%:3.1142, 10%: 4.1812)
Source: Authors' calculations.

Table 2: Cointegration test

	GDP CON INV				GDP CON INV GOV CPI TIB ITCR OIL			
Unrestricted Cointegration Rank Test (Trace)	Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	p-value*	Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	p-value*
	None	0.191276	30.49843	0.0415				
	At most 1	0.081933	8.844121	0.38	None *	0.556582	260.3158	0
	At most 2	0.001222	0.124712	0.724	At most 1 *	0.455536	177.3651	0
					At most 2 *	0.342743	115.3538	0.0012
					At most 3 *	0.238327	72.54651	0.0298
					At most 4	**0.199753**	**44.7783**	**0.0946**
					At most 5	0.131228	22.0492	0.2958
					At most 6	0.066799	7.700448	0.498
					At most 7	0.00634	0.648709	0.4206
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)	Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	p-value*	Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	p-value*
	None	0.191276	21.6543	0.0422	None *	0.556582	82.95069	0
	At most 1	**0.081933**	**8.719409**	**0.3103**	At most 1 *	0.455536	62.01128	0.0005
	At most 2	0.001222	0.124712	0.724	At most 2 *	0.342743	42.80733	0.024
					At most 3	**0.238327**	**27.7682**	**0.2244**
					At most 4	0.199753	22.72911	0.1853
					At most 5	0.131228	14.34875	0.3371
					At most 6	0.066799	7.051739	0.483
					At most 7	0.00634	0.648709	0.4206
*MacKinnon-Haug-Michelis (1999) p-values								

Source: Authors' calculations.

B Survey: methods

Table 3: Univariate estimation methods

	Model based	Decision variables	Complexity	Need or advisability of using forecats
Hodrick & Prescott	No	Smoothness parameter	Low	Yes
Baxter & King	No	Pass band Filter length	Low	Yes
Butterworth filtering	No	Pass band Filter length	High	Yes
Wavelet-based methods	No	Wavelet basis	High	Yes
Linear detrending	Yes	None	Low	No
Beveridge & Nelson	Yes	ARIMA model	High	Yes
Structural time series	Yes	STS model	High	No
Hamilton	Yes	Regime switching model	High	No
Kim & Nelson	Yes	Regime switching model	High	No

Source: Álvarez and Gómez-Loscos (2018).

Table 4: Multivariate estimation methods

	Underlying economic theory	Decision variables	Complexity
Okun's Law	Okun's Law	VAR model	Medium
Production function	Production function	Production function Cyclically adjusted inputs	High
Blanchard & Quah	Supply and demand shocks	SVAR model	High
Phillips curve	Phillips curve	Output gap time series process	High
Natural rate of interest	Natural rate of interest	Lags in the Phillips curve, Output gap time series process	High
RBC model	General equilibrium	VECM model	High
DSGE model	General equilibrium	Model specification	High

Source: Álvarez and Gómez-Loscos (2018).

C Baseline model: Results

C.1 Forecast Error Variance decomposition (FEVs)

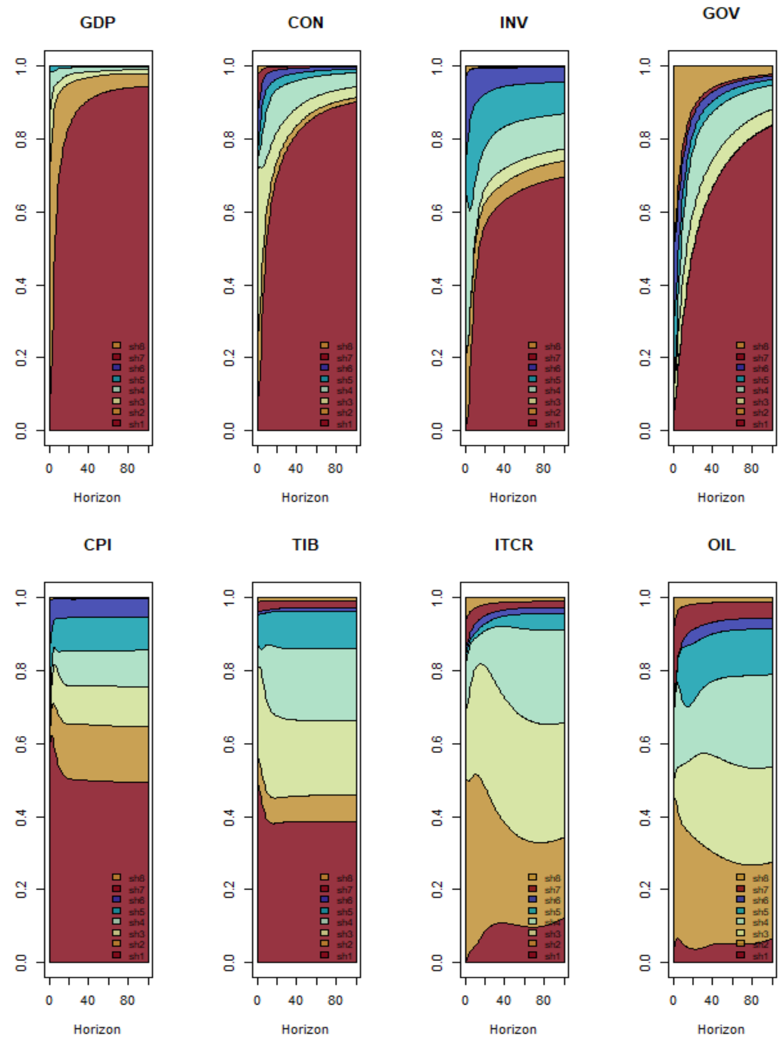

Figure 9: Forecast Error Variance decomposition (FEVs) by variable

D Other models: Results

D.1 Comparison between adjusted gap measures and SVAR-Permanent-Transitory decomposition

We consider a measure of output gaps similarity described in Mink, Jacobs, and de Haan (2012). The measure is given by:

$$\varphi_{it} = 1 - \frac{|g_i(t)g_r(t)|}{\sum_{i=1}^{n} |g_i(t)|},$$

where $g_i(t)$ is the output gap in period t that is compared with an output gap of reference $g_r(t)$, and n refers to the number of countries in an economic region where the comparison is made. In our simpler case, $n = 1$. The similarity φ_{it} will take values equal lower to one, and will approach one where the output gaps are more similar (in fluctuations and amplitude).

For completeness, we also consider the correlation. In both cases, we estimate each indicator over a rolling window (of four years for the similarity and of eight years for the correlation).[13]

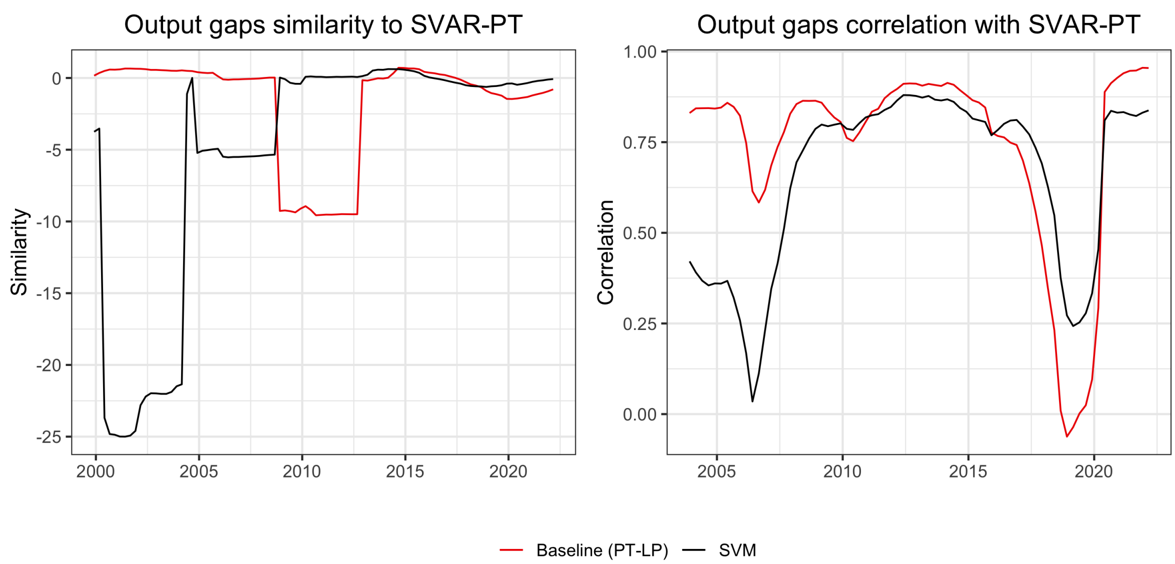

Figure 10: Comparison measures between adjusted SVAR models and SVAR-PT

[13]The result is robust to different windows' sizes; we also considered windows of sizes 12, 20, and 24 quarters for each measure but chose 16 and 32 to strike a balance between the data lost in the calculation and the amount of information considered in each estimate. On the other hand, we also compared a synchronicity measure but do not report it as the signs between either adjusted gap measure and the benchmark show a coincidence ratio of over 90%.