# Measuring the Euro Area Output Gap*

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**Abstract**

We measure the Euro Area (EA) output gap and potential output using a non-stationary dynamic factor model estimated on a large dataset of macroeconomic and financial variables. From 2012 to 2024, we estimate that the EA economy was tighter than policy institutions estimate, suggesting that the slow EA growth results from a potential output issue, not a business cycle issue. Moreover, we find that a decline in trend inflation, not slack in the economy, kept core inflation below 2% before the pandemic and that demand forces account for at least 30% of the post-pandemic increase in core inflation.

## 1 Introduction

The decomposition of GDP in potential output—the level of output consistent with current technologies and "normal" use of capital and labor—and the output gap—the percentage deviation of GDP from its potential—is a fundamental task for policymakers. Potential output tells us how fast an economy can grow in the long run; the output gap helps assess the cyclical position of the economy and, thus, potential inflationary pressures (e.g., Jarociński and Lenza, 2018; Bańbura and

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Bobeica, 2023). Potential output and the output gap are essential for the common Euro Area (EA) monetary policy and the fiscal policy of individual countries—they are among the main pillars of the EA fiscal surveillance framework, ultimately affecting the fiscal capacity of each member country (European Commission, 2018). However, since both quantities are unobserved, policymakers need a model to extract them from the data.

This paper proposes a new measure of potential output and the output gap for the EA based on a non-stationary dynamic factor model estimated on a large dataset of macroeconomic and financial variables. Compared to the prevailing literature, which focuses on theoretical structural models with few variables of interest, we adopt a distinct approach because we let the data speak by leveraging a large information set conditional on a few key macroeconomic priors—for example, the long-run slowdown in output growth (Cette et al., 2016).

We conduct our analysis on a new large-dimensional dataset comprising 118 EA economic indicators from 2001:Q1 to 2024:Q3. Four main results emerge from our analysis: first, our output gap estimate is in line with those published by the European Commission (EC) and the International Monetary Fund (IMF) until the 2011–2012 Sovereign Debt Recession (henceforth, SDR), after which our output gap measure suggests that the EA economy was tighter than estimated by the EC and the IMF. Moreover, we estimate that potential output growth decelerated after the 2008–2009 Global Financial Crisis (henceforth, GFC), and as of 2024:Q3, potential output growth has yet to return to the pre-GFC pace. In other words, our results suggest that the EA has a potential output issue, not a business cycle issue. Hence, if the goal is to achieve better economic conditions in the EA, European countries should implement structural reforms and promote productivity-enhancing investments that have long-run effects, while policies aiming at stimulating household consumption and residential investments will have only short-term effects at best.

Second, we find that, on average, the Okun's law relationship and the Phillips Curve are satisfied in our model, even though we do not impose either of them; hence, cyclical movements in real activity, unemployment, and inflation are interconnected (see, e.g., Bianchi et al., 2023).

Third, we find that core inflation remained below 2% after the GFC, not because there was slack in the economy, but rather because trend inflation decreased by one percentage point—in line with the idea that inflation expectations de-anchored on the downside after the GFC (Ciccarelli and Osbat, 2017; Corsello et al., 2021). Moreover, we show that the output gap contributed to at least 30% of the post-pandemic increase in core inflation, thus supporting existing literature that suggests demand forces played a substantial role in the rise of post-pandemic inflation (Ascari et al., 2023; Giannone and Primiceri, 2024; Bergholt et al., 2025). Finally, our output gap measure yields better inflation forecasts than those derived from commonly used methods. These results confirm that our data-driven measure is economically meaningful and valuable for policy analysis.

Fourth, we find that growth financed through household debt is not sustainable in the long run, which is why incorporating financial indicators in the dataset, particularly credit indicators, is necessary to pin down the output gap.

To measure potential output and the output gap, we first estimate the non-stationary dynamic factor model by Quasi Maximum Likelihood using the EM algorithm jointly with the Kalman smoother (Doz et al., 2012; Barigozzi and Luciani, 2024). Then, we extract a common trend from the estimated common factors and compute the cyclical component by subtracting the common trend from the common factors. Having estimated the common trend and the common cyclical component, we measure potential output as the part of GDP explained by the common trends and the output gap as the part of GDP explained by the common cyclical component. Our model belongs to the class of unobserved component models, which is among the most indicated ones for extracting the transitory component of GDP (Canova, 2025).

This model is an enhanced version of the model Barigozzi and Luciani (2023) used to measure the US output gap, as it does not require a long sample to identify the trend and deals with the Covid pandemic. Specifically, we use a three-step estimation procedure to account for the latter. First, we estimate the model using only pre-Covid data. Second, we estimate the effects induced by the Covid shock (level-shift and increased volatility). Third, we re-estimate the model on the full dataset after purging the data from Covid-induced dynamics.

Our model is large-dimensional and non-stationary, thus allowing us to capture well-established co-movements in macroeconomic variables while retaining data in levels. It is now widely recognized that cross-sectional aggregation of a large number of series allows to consistently disentangle the co-movements in the data from idiosyncratic dynamics (Stock and Watson, 2016) and that to obtain meaningful estimates of potential output and the output gap a large information set is necessary (Buncic and Pagan, 2023). To the best of our knowledge, this is the first paper that estimates the EA output gap with such a rich information set.

Moreover, we go beyond the common practice of pre-transforming data to work with stationary and centered variables. Thus, we can capture features crucial for identifying the common trend, which would be inevitably lost if we were to difference the data to achieve stationarity (Ng, 2018). This is important not only for estimating the output gap but also because accurately accounting for low-frequency movements helps eliminate any potential confounding effect when estimating the relationship between real activity and inflation over the business cycle (Bianchi et al., 2023).

**Related literature.** How to estimate potential output and the output gap has been a hotly debated topic for several decades (see, e.g., Canova, 2025). The literature has proposed two main approaches: a theoretical approach and a statistical approach.

The theoretical approach uses theoretical models, such as production-function-based models used by the EC (Havik et al., 2014) and the IMF (De Masi, 1997) or New-Keynesian DSGE models (Justiniano et al., 2013; Burlon and D'Imperio, 2020; Furlanetto et al., 2021).

The statistical approach uses (univariate or multivariate) statistical models, sometimes paired with some macroeconomic relationships of interest, e.g., the Phillips Curve. For example, many papers rely on univariate models (e.g., Morley et al., 2003; Kamber et al., 2018; Hamilton, 2018; Phillips and Jin, 2021; Phillips and Shi, 2021; Hartl et al., 2022), while few others employ multivariate non-stationary methods, which are either low-dimensional models (Jarociński and Lenza, 2018; González-Astudillo, 2019; Tóth, 2021; Hasenzagl et al., 2022), or medium-size, but stationary, models (Aastveit and Trovik, 2014; Morley and Wong, 2020; Morley et al., 2023). Most of these works focus on the US, while only a few focus on the EA, the most recent being Morley et al. (2023).

**Structure of the paper.** The rest of the paper is organized as follows. In Section 2, we present the data used in our analysis, and in Section 3, we present the model and the estimation strategy. Then, in Section 4, we present our estimate of potential output and the output gap, and in Section 5, we dive deep into the economic content of these estimates, focusing on the Okun's law and the Phillips correlation. Next, we focus on inflation. Section 6 interprets inflation dynamics after the GFC through the lens of our model, and Section 7 assesses the ability of our output gap estimate to forecast inflation. Finally, Section 8 looks into what signals our model takes from financial indicators to estimate the output gap, and Section 9 concludes.

A Supplemental Appendix contains additional details on the model, showing various robustness analyses, and reporting additional results. Specifically, Appendix A provides full details on the dataset, while Appendixes B, C, D, and E provide additional details about the model. Next, Appendixes F, G, and H provide robustness analysis. Lastly, Appendix I compares our output gap estimate with that obtained with alternative statistical methodologies, and Appendix J assesses the reliability of our output gap estimate.

## 2 A large Euro Area dataset

We construct a large macroeconomic dataset of $n = 118$ EA series, observed from 2001:Q1 to 2024:Q3 ($T = 95$). The dataset contains a wide range of macroeconomic indicators, including national account statistics, industrial production and turnover indicators, labor market and compensation indicators, price indexes, oil prices, natural gas prices, house prices, exchange rates, interest rates, a stock market index, monetary aggregates, non-financial assets and liabilities, and confidence indexes.

In terms of broad categories of data, we include in the dataset the usual suspects normally considered for high-dimensional macroeconomic analysis (see, for example, McCracken and Ng, 2016, 2020).

In terms of which and how many series to include for each category, we use a mix of economic and statistical reasoning. On the one hand, to identify the common factors driving the co-movement in the data, it is crucial to pool information from many indicators; hence, a larger information set should be preferred. On the other hand, a key assumption of the model is the presence of mild cross-sectional correlation among the idiosyncratic components: violating this assumption leads to a deterioration of the model's performance (Boivin and Ng, 2006; Luciani, 2014). Thus, when building a dataset for factor analysis, we face a trade-off between the need for a larger information set and the risk of introducing too much idiosyncratic correlation. For this reason, we selected the variables to include in the dataset to maximize economic signal while limiting the noise, with exceptions motivated by economic reasoning. For instance, we include GDP and its components since their informational content justifies a relatively high level of idiosyncratic correlations. Similarly, consumption and employment are decomposed according to durability and sectoral composition, respectively, while assets and liabilities are decomposed by ownership. In contrast, we keep the consumer price index for energy while dropping the producer price index for energy, as they carry the same signal (their correlation is greater than 0.95). Likewise, we drop the consumer price index for industrial goods because it has a correlation greater than 0.95 with the goods consumer price index.

As for the treatment of the series, we take logarithms for all variables except for confidence indicators and those already expressed in percentage points. We keep all variables in levels except for price indicators, for which we take first differences; i.e., we work with inflation rates. This is a common approach used in the literature to avoid spurious dynamics resulting from the potential $I(2)$ behavior in price indexes (Stock and Watson, 2016; McCracken and Ng, 2016, 2020). Appendix A provides the complete list of variables included in the dataset, along with their sources and treatment.

# 3 Methodology

In Section 3.1, we outline the model and its main features—we discuss all the details, formal assumptions, and further comments in Appendix B. In Section 3.2, we sketch how we estimate the model while referring the reader to Appendix C for a step-by-step guide on how estimation is carried out in practice and Appendix D for the bootstrap procedure used to measure uncertainty around our estimates.

## 3.1 The model

We denote the observed $i$-th time series at a given quarter $t$ as $y_{it}$, with $1 \leq i \leq 118$ and 2001:Q1 $\leq t \leq$ 2024:Q3. In our non-stationary dynamic factor model, each variable is the sum of (i) a secular component $\mathrm{D}_{it}$, which is treated either as deterministic or stochastic, (ii) $q$ common factors $\mathbf{f}_t = (f_{1t} \cdots f_{qt})'$, which capture the macroeconomic long- and short-run co-movements and have a dynamics governed by a VAR, and (iii) an idiosyncratic component $\xi_{it}$, which captures local dynamics or measurement errors and is possibly correlated across $i$ and $t$.

We partition the $n$ series according to two features. First, according to the nature of the secular component, that is, whether $\mathrm{D}_{it}$ is a stochastic or a deterministic process. Second, according to the nature of the idiosyncratic component, that is, whether $\xi_{it}$ has a stochastic trend or it is stationary.

In particular, we model $\mathrm{D}_{it}$ as a local linear trend for GDP to account for the well-documented slowdown in productivity (Cette et al., 2016) and for households' financial liabilities (HHLB) and households' long-term loans (HHLB.LLN), which make up more than 80% of total household's liabilities, whose average growth rate has slowed down consistently since the GFC. For these variables, we say that $i \in \mathcal{L}_1$. Moreover, we model $\mathrm{D}_{it}$ as a local level model for the unemployment rate (UNETOT) to account for relevant labor market features (Cette et al., 2016)—this includes the reallocation of employees across sectors, which contributed to the slowdown in the EA productivity growth—and for all consumer price inflation indexes (HICPOV, HICPNEF, HICPG, HICPSV, HICPNG, HICPFD) as well as oil and natural gas prices (POIL, PNGAS) to account for the slowdown in inflation occurred after the GFC—accounting for low-frequency dynamics in inflation is crucial to avoid potential confounding effects which may alter the relation between inflation and real activity over the business cycle (Bianchi et al., 2023). For these variables, we say that $i \in \mathcal{L}_0$.[1] For all other series, $\mathrm{D}_{it}$ is either a linear trend with a constant slope, in which case we say that $i \in \mathcal{I}_b$, or $\mathrm{D}_{it}$ is just a constant equal to $\mathrm{D}_{i0}$. To determine $\mathcal{I}_b$, we test the significance of the sample mean of $\Delta y_{it}$ (see Appendix A).

As for the idiosyncratic components, if $\xi_{it} \sim I(1)$, then we say that $i \in \mathcal{I}_1$ and we model $\xi_{it}$ as a random walk, while if $\xi_{it} \sim I(0)$, we say that $i \notin \mathcal{I}_1$ and we leave its dynamics unspecified to avoid over-parametrization of the model. To determine $\mathcal{I}_1$, we employ the test proposed by Bai and Ng (2004) for the null hypothesis of an idiosyncratic unit root (see Appendix A).

Furthermore, we capture the effect of the Covid shock, which generated a large shift both in the levels (Ng, 2021; Stock and Watson, 2025), and in the volatility (Lenza and Primiceri, 2022; Carriero et al., 2024) of most macroeconomic EA series, through an additional common factor $g_t$ (Stock and Watson, 2025), and a scalar $s_t$ scaling the conditional volatility of the latent factors (Lenza and Primiceri, 2022). While we model the former to have an impact on all series only in 2020 and 2021, we allow the latter to have an effect that persists even after the recovery from the pandemic. These choices reflect the fact that mobility restrictions and lockdowns in the EA have been on and off until early 2022, while in the US, they were enforced only at the beginning of the pandemic.

Formally, the model reads as follows:

$$
\begin{aligned}
y_{it} &= \mathrm{D}_{it} + \boldsymbol{\lambda}_i' \mathbf{f}_t + \gamma_i g_t \mathbb{I}_{2020:\mathrm{Q1} \le t \le 2021:\mathrm{Q4}} + \xi_{it}, && 1 \le i \le 118, \;\; 2001:\mathrm{Q1} \le t \le 2024:\mathrm{Q3}, && (1)\\
\mathrm{D}_{it} &= \mathrm{D}_{it-1} + b_{i,t-1} \mathbb{I}_{i \in \mathcal{I}_b} + \epsilon_{it}, && \epsilon_{it} \sim (0, \sigma^2_{\epsilon_i} \mathbb{I}_{i \in \mathcal{L}_0}), && (2)\\
b_{it} &= b_{it-1} + \eta_{it}, && \eta_{it} \sim (0, \sigma^2_{\eta_i} \mathbb{I}_{i \in \mathcal{L}_1}), && (3)\\
\mathbf{f}_t &= \sum_{j=1}^{p} \mathbf{A}_j \mathbf{f}_{t-j} + \{ s_t \mathbb{I}_{t \ge 2020:\mathrm{Q1}} + \mathbb{I}_{t < 2020:\mathrm{Q1}} \} \mathbf{u}_t, && \mathbf{u}_t \overset{i.i.d.}{\sim} (\mathbf{0}, \boldsymbol{\Sigma}_u), && (4)\\
\xi_{it} &= \xi_{it-1} \mathbb{I}_{i \in \mathcal{I}_1} + e_{it}, && e_{it} \sim (0, \sigma^2_{e_i}), && (5)
\end{aligned}
$$

where $\mathbb{I}_A = 1$, if $A$ is true, and $\mathbb{I}_A = 0$, otherwise. We set $p = 2$ based on the BIC criterion for a VAR on the estimated factors, and $q = 4$ based on standard information criteria (Bai and Ng,

[1] Appendix H shows robustness results for the estimate of the output gap when removing the time variation in the secular trends.

2002; Hallin and Liška, 2007). Details are in Appendix E.

Furthermore, we assume that one common trend, $\tau_t$, which we model as a random walk, drives the non-stationarity in the factors $\mathbf{f}_t$, an assumption in line with many theoretical models assuming a common trend as the sole driver of long-run dynamics (e.g., Del Negro et al., 2007). In contrast, we remain agnostic on the law of motion of the residual, i.e., the stationary cyclical component, which we denote as $\boldsymbol{\omega}_t$. Specifically, we consider the decomposition:

$$\mathbf{f}_t = \boldsymbol{\psi}\tau_t + \boldsymbol{\omega}_t, \qquad \boldsymbol{\omega}_t \sim (\mathbf{0}, \boldsymbol{\Sigma}_\omega), \tag{6}$$

$$\tau_t = \tau_{t-1} + \nu_t, \qquad \nu_t \sim (0, \sigma_\nu^2). \tag{7}$$

We can then identify the common trend $\tau_t$ by properly initializing the variance $\sigma_\nu^2$, which is analogous to controlling the signal-to-noise ratio. Details are in the next section. This identification strategy for the common trend is consistent with the results of Kim and Kim (2022), who show that extracting a common trend modeled with an unconstrained random walk component overfits GDP, thus producing a potential output that fluctuates too much and generating the so-called "pile-up" problem.

It is important to stress that we do not impose any parametric model for the dynamic evolution of either $\nu_t$ or $\boldsymbol{\omega}_t$. Regarding $\nu_t$, we notice that if we modeled it as an ARMA process, our approach would be equivalent to Morley et al. (2024) approach, who achieve identification by rescaling the estimated parameters of an estimated ARMA for $\Delta\tau_t$ (see Appendix F for a comparison between the two approaches). Regarding $\boldsymbol{\omega}_t$ we notice that the common practice of modeling it as an AR(2) poses identification problems since the same state-space representation can also be obtained with an ARMA(2,1) specification (Kim and Kim, 2022).

The model we just described is a modified version of the model Barigozzi and Luciani (2023) (BL) used to estimate the output gap in the US. We modified BL's model to overcome two important limitations. First, their model relies on estimating cointegrating relationships to identify the common trends, thus requiring long time series to get a reliable estimate. As such, BL's model can be estimated only on US macroeconomic data for which more than 50 years of quarterly data are available. Second, BL estimate their model on pre-Covid data; thus, to incorporate more recent observations, some modification is needed to handle the different co-movements brought about by the Covid pandemic. In this paper, we solve both limitations by introducing (6)-(7), which we can estimate even on short samples, and by incorporating recently proposed methods to handle the Covid period in the estimation strategy.

Combining Equations (1) and (6), we obtain the decomposition of each observed variable:

$$y_{it} \;=\; \mathrm{D}_{it} + \boldsymbol{\lambda}_i'\boldsymbol{\psi}\tau_t + \boldsymbol{\lambda}_i'\boldsymbol{\omega}_t + \gamma_i g_t \mathbb{I}_{2020:\mathrm{Q1}\leq t \leq 2021:\mathrm{Q4}} + \xi_{it}. \tag{8}$$

Focusing on GDP, we define potential output, $\mathrm{PO}_t$, and the output gap, $\mathrm{OG}_t$, as:

$$\mathrm{PO}_t \;=\; \mathrm{D}_{\mathrm{GDP},t} + \boldsymbol{\lambda}_{\mathrm{GDP}}'\boldsymbol{\psi}\tau_t, \tag{9}$$

$$\mathrm{OG}_t \;=\; \boldsymbol{\lambda}_{\mathrm{GDP}}'\boldsymbol{\omega}_t. \tag{10}$$

Hence, in our framework, potential output is the sum of the time-varying secular trend of GDP ($\mathrm{D}_{\mathrm{GDP},t}$), which captures the long-run decline in EA output growth, and the part of GDP driven by the common trend component ($\tau_t$); the output gap is the part of GDP driven by the stationary cyclical component ($\boldsymbol{\omega}_t$).

From the definition of potential output (9) and output gap (10), we left out the idiosyncratic component, $\xi_{\mathrm{GDP},t}$, and the Covid component, $\gamma_{\mathrm{GDP}} g_t$. While the idiosyncratic component is likely to be just a measurement error (Aruoba et al., 2016), hence, it is clear why we are leaving it out; the exclusion of the Covid shock deserves an explanation.

The Covid component represents the co-movements from 2020:Q1 to 2021:Q4 that neither potential output nor the output gap captures. In principle, this component could be allocated to the output gap, which would be equivalent to assuming that the productive capacity of the EA "froze" due to the lockdowns. While this view is commonly accepted by European institutions (Thum-Thysen et al., 2022), it is still unclear whether, and by what amount, the EA productive capacity has been affected by the Covid shock. Thus, we remain agnostic on the allocation of the Covid component between potential output and the output gap, and we will present it as a standalone component.

### 3.2 Estimating the model

To estimate potential output and the output gap, we first estimate the DFM (1)-(5) using a three-step estimation procedure, and then we estimate the model for the common trend (6)-(7) on the estimated factors.

**Estimating the dynamic factor model.** To estimate the model in (1)-(5), we need to extract the latent states $\mathbf{f}_t$, $g_t$, $\mathrm{D}_{\mathrm{i},t}$ (if $i \in \mathcal{L}_1$ or $i \in \mathcal{L}_0$), and $\xi_{it}$ (if $i \in \mathcal{I}_1$), and estimate the parameters $\boldsymbol{\lambda}_i$, $\gamma_i$, $\mathbf{A}_j$, $s_t$, $\boldsymbol{\Sigma}_u$, $\sigma^2_{e_i}$, $a_i$, and $b_i$ (if $i \in \mathcal{I}_b$), while we calibrate $\sigma^2_{\epsilon_i}$ (if $i \in \mathcal{L}_0$) and $\sigma^2_{\eta_i}$ (if $i \in \mathcal{L}_1$)

following Del Negro et al. (2017).[2] To do so, we use a three-step estimation procedure that we summarize below.

Step 1: Estimate the model up to 2019:Q4 (pre-Covid step). We obtain a preliminary estimate of the parameters using non-stationary PCA (Bai and Ng, 2004; Barigozzi et al., 2021; Onatski and Wang, 2021). Then, we run the EM algorithm, jointly with the Kalman smoother, as described in Barigozzi and Luciani (2024) in the high-dimensional case.

Step 2: Estimate the Covid factor and volatility (Covid step). Using the parameter estimated over the pre-Covid period, we apply the Kalman filter and smoother to extract the latent states using data up to the end of the sample. To address the influence of the Covid outliers on the estimates, we truncate the Kalman smoother at 2020:Q1, and then we continue the backward iterations by re-initializing the Kalman smoother using the Kalman filter estimate for 2019:Q4. This truncation avoids any backward spurious effect from the Covid period to the pre-Covid estimates but creates a structural break in the estimated secular components in 2020:Q1. For this reason, we adjust the level of the smoothed secular components by judgmentally allocating the break in 2020:Q1 to the idiosyncratic component, as suggested by Ahn and Luciani (2024).[3]

At this point, we have an estimate of the states over the entire sample given the information set prior to the Covid shock. This implies that the co-movements in the Covid period are left unaccounted for and are captured by the idiosyncratic component $\xi_{it}$. Thus, since Covid was a common shock affecting most of (if not all) the series in the dataset, we estimate the Covid factor $\widehat{g}_t$ and its loadings $\widehat{\gamma}_i$ by PCA on the variance-covariance matrix of the idiosyncratic component for the period 2020:Q1-2021:Q4, following Stock and Watson (2025).

Lastly, we estimate the Covid volatilities $\widehat{s}_t$ for the period 2020:Q1-2024:Q3 by maximum likelihood and by using the factors extracted using pre-Covid parameters. We find that $\widehat{s}_t$ jumps from 1 to about 3.5 at the onset of the Covid pandemic, and then remain larger than 2 until the end of 2022, thus justifying our choice of imposing a time-varying volatility until the end of the sample. In Appendix G, we show how our measures would change if we do not explicitly model

[2] We calibrate the variances of the stochastic secular components so that when $i \in \mathcal{L}_1$, the standard deviation of the secular trend is approximately 1% over 100 years, while when $i \in \mathcal{L}_0$, the standard deviation of the secular trend is approximately 1% over 50 years.

[3] An alternative approach we could have taken consists of adjusting for outliers on a series-by-series basis. However, we did not pursue this option because much of the additional volatility during the Covid shock is "economic" volatility induced by the pandemic, not measurement error (Ng, 2021). A univariate outlier adjustment method cannot distinguish between the two, so it likely removes economically relevant information. Indeed, if we do univariate outlier adjustment, we get that the Covid factor is essentially zero, and the output gap is flat as if nothing happened.

the effect of Covid, or if we use the exponential decay parametrization proposed by Lenza and Primiceri (2022).

Step 3: Full sample estimation. We estimate all the parameters and latent states up to the end of the sample, by using data net of the Covid component, i.e., with $y_{it} - \widehat{\gamma}_i \widehat{g}_t$. Specifically, by using the factors estimated over the whole sample in Step 2 rescaled by $\widehat{s}_t$ in the last part of the sample, we estimate the parameters, $\widehat{\boldsymbol{\lambda}}_i$, $\widehat{\mathbf{A}}_j$, $\widehat{\boldsymbol{\Sigma}}_u$, $\widehat{\sigma}^2_{e_i}$, $\widehat{a}_i$, and $\widehat{b}_i$, by maximizing the expected likelihood. Finally, with the estimated parameters in hand, we obtain a final estimate of the states, $\widehat{\mathbf{f}}_t$, $\widehat{\mathrm{D}}_{i,t}$, and $\widehat{\xi}_{it}$, through the Kalman smoother again truncated in 2020:Q1 and reinitialized before iterating backward, as explained in Step 2.

**Estimating the common trend.** Having estimated the model parameters and unobserved states, we can now estimate the common trend. To this end, we estimate the state-space model in (6)-(7) using the EM algorithm by replacing the true factors with the estimated factors. In particular, we initialize $\sigma^2_\nu$ in such a way that the standard deviation of the trend is approximately 1% over 100 years (Del Negro et al., 2017).

At convergence of the EM algorithm, we obtain a final estimate of the parameters, $\widehat{\boldsymbol{\psi}}$, $\widehat{\boldsymbol{\Sigma}}_\omega$, and $\widehat{\sigma}^2_\nu$, and using these estimates, we have a final estimate of the trend $\widehat{\tau}_t$ and of the cyclical component $\widehat{\boldsymbol{\omega}}_t = \widehat{\mathbf{f}}_t - \widehat{\boldsymbol{\psi}}\widehat{\tau}_t$, obtained through the Kalman smoother. Given the estimates of the common trend and the cyclical common component, we compute our final estimates of potential output and the output gap according to (9) and (10), respectively.

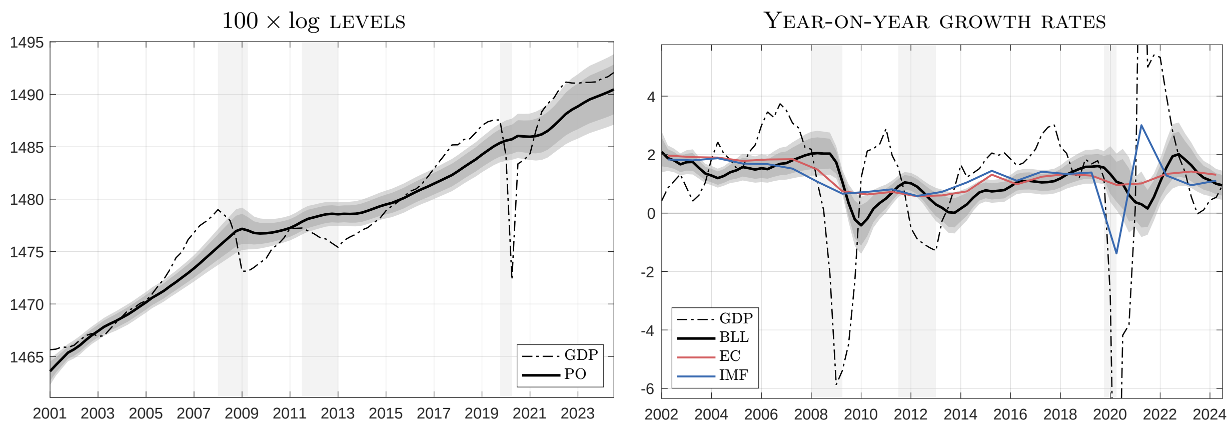
As shown in Barigozzi and Luciani (2024), the estimation procedure we just outlined delivers consistent estimators of all parameters and of the factors, provided that $n$ and $T$ grow to infinity and the EM algorithm is initialized with the estimator of the loadings and factors introduced by Barigozzi et al. (2021). Furthermore, to prove this result, we neither have to impose the Gaussianity assumption nor have to require uncorrelatedness of the idiosyncratic components ($\xi_{it}$ if $i \notin \mathcal{I}_1$ or $e_{it}$ if $i \in \mathcal{I}_1$) across $i$ or $t$. Rather, we just have to impose standard moment conditions, such as existence and summability of 4th-order cumulants.

# 4 Potential output and output gap of the Euro Area

Figure 1 presents our potential output estimate (black line), both in 100 × log levels (left plot) and in year-on-year (YoY) growth rates (right plot). The right plot also includes potential output growth estimates from the EC (red line) and IMF (blue line).

Three main results emerge from Figure 1. First, potential output growth decelerated after the GFC, and the SDR further compounded this deceleration—average potential output growth was 2.1% in 2008, and the subsequent peak was 1.6% right before the Covid pandemic. This result is consistent with the results of Elfsbacka Schmöller and Spitzer (2021), who show that the decline in total factor productivity that occurred during the two recessions induced hysteresis effects on the level of GDP. Second, while the EC and IMF also estimate a slowdown in potential growth after the GFC, they do not estimate any effects of the SDR on potential growth. Third, it is still too soon to determine whether the Covid recession had a long-term effect on potential output growth—the prevailing institutional perspective is that it did not (Thum-Thysen et al., 2022)—because while potential growth rebounded fast after the Covid shock, reaching a peak in 2022:Q4 at 2%, it then slowly declined to 0.95% in 2024:Q3, below the pre-Covid pace.

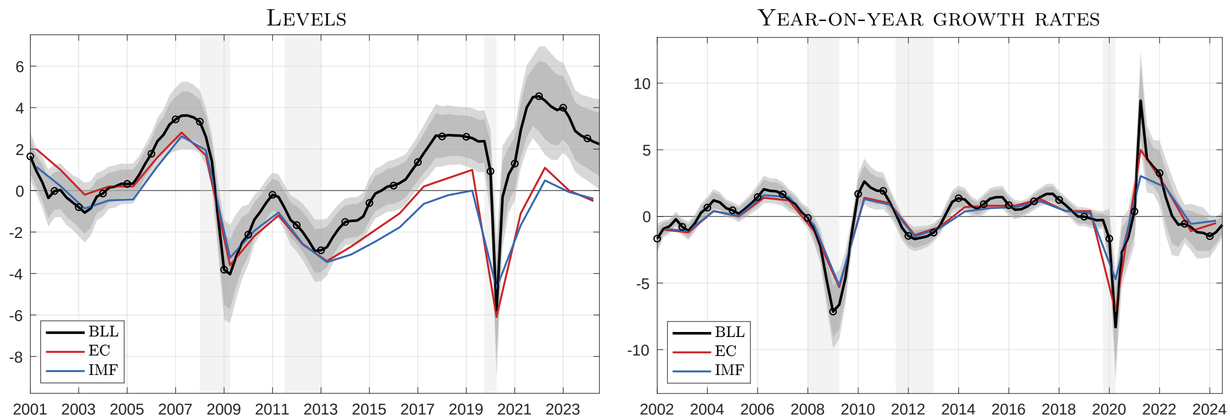
Figure 1: *Potential output*




Notes: In all charts, the black solid line is our estimate of potential output, the grey shaded areas are the 68% and 84% confidence bands, and the dashed black line is GDP—we truncated the y-axis in the right chart for readability. In the right chart, the blue and red lines are the potential output estimates published by the European Commission and the IMF, respectively. The IMF estimate of YoY potential output growth reported in the right chart is the result of our own calculation. Indeed, the IMF publishes only an estimate of the output gap from which we backed out potential output. Thus, the blue line in the right chart does not account for any adjustment for Covid that the IMF might have done.

Figure 2 presents the estimated output gap, together with the estimates from the EC and the IMF. Our output gap estimate looks similar to those of the EC and IMF in that the dating of the turning points perfectly coincides. Moreover, the three estimates closely align until the SDR, as they all suggest a substantial overheating of the economy in the pre-GFC period, followed by a persistently negative output gap during the two recessions. However, our measure increased after the SDR, hovering at about 2% from 2017 to the Covid pandemic, thus signaling a much tighter economy than the EC or the IMF. Likewise, our measure indicates a much tighter economy after the Covid shock than the EC and the IMF.

FIGURE 2: *Output gap*

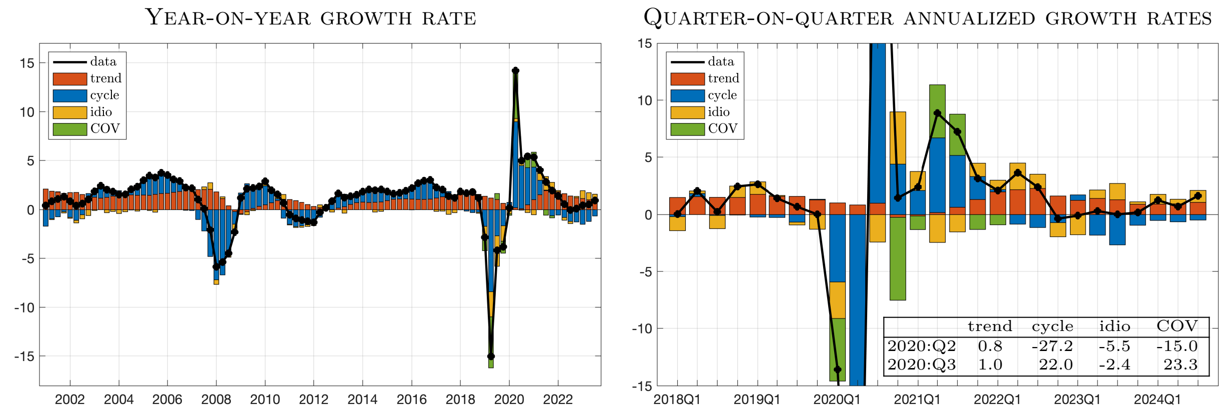



NOTES: The black line is our estimate of the output gap (OG) in levels (left plot) and YoY growth rates (right plot)—the level of the output gap is the percentage deviation from potential, the YoY growth rates is $\mathrm{OG}_t - \mathrm{OG}_{t-4}$. Each black marker denotes one year (four quarters), starting from 2001:Q1. The grey shaded areas are the 68% and 84% confidence bands. The red and blue lines are the output gap estimates published by the European Commission and the IMF, respectively.

To conclude, Figure 3 decomposes GDP growth into the contribution of potential output, the output gap, the Covid factor, and the idiosyncratic component. During the Covid pandemic, the output gap subtracted 27.2 percentage points (p.p.) from quarter-on-quarter (QoQ) annualized GDP growth in 2020:Q2 (inset box, right chart). With QoQ annualized GDP growth rate declining at a -47%, a 27.2 p.p. contribution from the output gap seems dubious. However, as explained in Section 3.2, our output gap estimate captures only business-as-usual co-movements, while the Covid factor captures the additional co-movements induced by the Covid shock. As shown by the inset box in the right plot in Figure 3, the Covid factor accounts for an additional -15 p.p. of the QoQ GDP growth rate plunge in 2020:Q2. Since then, the Covid factor added around 23 p.p. in 2020:Q3, and its contribution declined in the following six quarters, alternating between negative contribution when mobility restrictions were in place and positive contribution during the reopening.

In summary, Figures 1–3 show that the EA has a potential output issue, not a business cycle issue. Since the seminal work of Blanchard and Quah (1989), it is common to assume that supply shocks have permanent effects, while demand shocks have only transitory effects. Empirical studies support this assumption. Specifically, Forni et al. (2025) show that the impulse response functions to a supply (demand) shock are almost identical to those of a permanent (transitory shock). Additionally, Benati and Lubik (2021) find that it is essentially impossible to detect aggregate demand shocks that permanently affect GDP.

Figure 3: *Decomposition of GDP growth*




Notes: The black line with dot markers is GDP growth. The bars represent the contribution of each component to GDP growth. The left plot shows YoY growth rates, while the right plot shows QoQ growth at an annual rate. Growth rates are computed using the log approximation.

Based on this evidence, we assume that the common trend $\tau_t$—hence, potential output—is mainly driven by supply forces, while the cyclical common component $\boldsymbol{\omega}_t$—hence, the output gap—is mainly driven by demand forces. Consequently, to achieve better economic conditions in the EA, European countries should implement structural reforms and promote productivity-enhancing investments that have long-run effects. In contrast, policies aiming at stimulating household consumption and residential investments will have only short-term effects at best because, as we will show in Section 8, growth financed through household debt is not sustainable in the long run.

## 5 What about the Okun's law and the Phillips curve?

Our estimate of the output gap has a different meaning than that of the EC and IMF, which derive the output gap and potential output according to the so-called "production function approach" (Kiley, 2013). In production-function-based models, the output and unemployment gaps are related through the Okun's law, and the output gap is related to inflation through the Phillips curve. Thus, in these models, the unemployment gap decreases whenever the output gap increases, and vice-versa, and low inflation suggests a negative output gap, while high inflation indicates a positive gap.

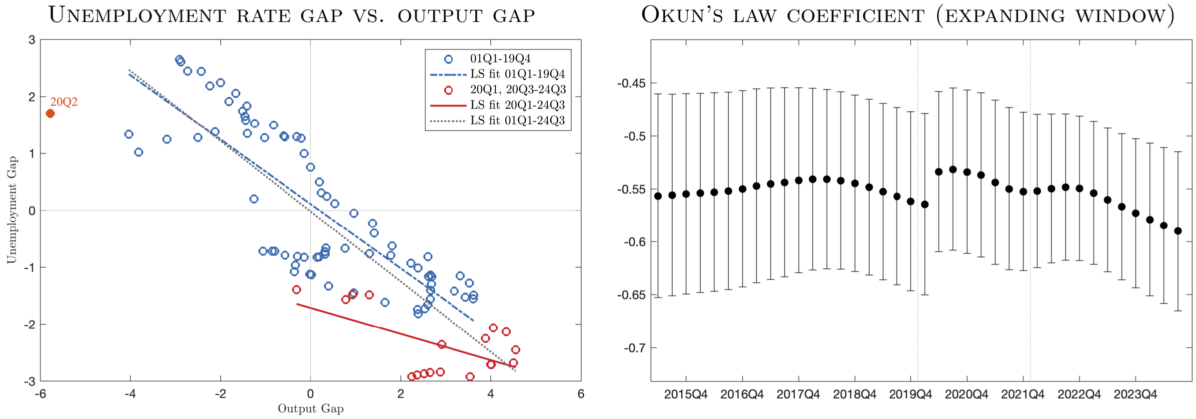
In our model (like any statistical model), we do not impose any Okun's law or Phillips curve. Thus, we must be careful when we compare our estimate with that of the EC or the IMF because their output gap measures are designed to indicate potential inflation pressure, whereas ours is not. Nonetheless, in Sections 5.1 and 5.2, we show that, on average, our model satisfies the Okun's law relationship and exhibits Phillips correlation.

## 5.1 The Okun's law

The left plot in Figure 4 shows that in our model, the unemployment rate gap and the output gap are negatively correlated; that is, our model captures the Okun's law relationship in the data. Over the whole sample, on average, for every percentage point increase in the output gap, the unemployment gap decreases 0.6 p.p. (grey dotted line). Moreover, this correlation has decreased after Covid from -0.56 (blue dash-dotted line) to -0.23 (red solid line), suggesting a (temporary) disconnect between the labor and goods and services market post-Covid in the EA as also noted by Berson et al. (2024). The right plot in Figure 4 shows the expanding window estimate of the Okun's law coefficient $\beta$ in the regression $(\mathrm{UR}_t - D_{\mathrm{UR},t}) = \alpha + \beta \mathrm{OG}_t + \varepsilon_{\mathrm{UR},t}$, where $D_{\mathrm{UR},t}$ is the time-varying mean of the unemployment rate defined in (2). On average, the Okun's law coefficient varies between -0.55 to -0.60.[4]

Figure 4: *Okun's Law*

Unemployment rate gap vs. output gap — Okun's law coefficient (expanding window)




Notes: The left chart shows the Okun's law relationship with the output gap on the horizontal axis and the unemployment rate gap on the vertical axis. Each circle corresponds to an output gap - unemployment gap pair at a given time $t$. The grey dotted, blue dashed-dotted, and red solid lines are the least squares fit lines for the full, pre-Covid, and post-Covid samples, respectively, obtained by omitting the observation for 2020:Q2 (orange dot).

The right chart shows the least squares estimate, based on an expanding window starting from 2015:Q1, of the Okun's law slope $\beta$ given by the regression $(\mathrm{UR}_t - D_{\mathrm{UR},t}) = \alpha + \beta \mathrm{OG}_t + \varepsilon_{\mathrm{UR},t}$, where $D_{\mathrm{UR},t}$ is the time-varying mean of the unemployment rate defined in (2). Each dot is an estimate of $\beta$ while the whiskers are $\pm$ one HAC standard errors.

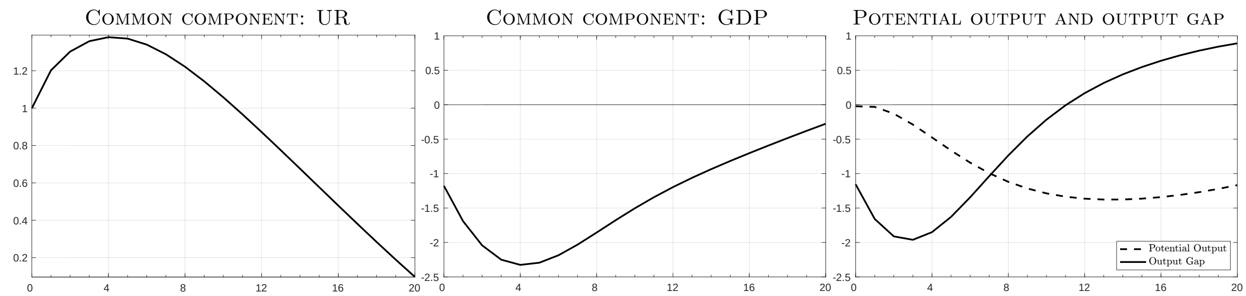
To further corroborate the intuition that there is a tight relationship between our output gap estimate and labor market indicators, Figure 5 shows the Generalized Impulse Response Functions (GIRFs) of the common component of the unemployment rate, GDP, potential output, and the output gap to a 1 p.p. shock to the common component of the unemployment rate.[5] Results

[4] We also estimated the relationship between the output gap and hours worked gap and find a positive correlation in line with the results of Morley et al. (2023).

[5] The lag-$h$ GIRF of all variables is obtained by computing the differences between the $h$-step ahead forecast of their common component conditional on a shock to a given variable at time $T+1$ minus the $h$-step ahead unconditional forecast of the common component, i.e., when no shock is imposed. Both forecasts are computed conditional on all

confirm that our model, on average, associates an unemployment rate increase with an output gap decrease. After the shock, the common component of the unemployment rate remains 1 p.p. (or more) above the baseline for about a year and a half before decreasing and slowly returning to zero. In response, GDP decreases and keeps decreasing, reaching a through a year after the shock; then, it slowly returns to baseline. The model attributes most of the GDP response to movements in the output gap, while potential output slightly decreases only after a few quarters. The shock is fully absorbed in about 4 years.

FIGURE 5: *Generalized Impulse Response Functions to a shock to the unemployment rate*




NOTES: The black solid/dashed lines are the GIRFs to a 1 p.p. shock to the common component of the unemployment rate. The major ticks in the x-axis represent quarters after the shock.

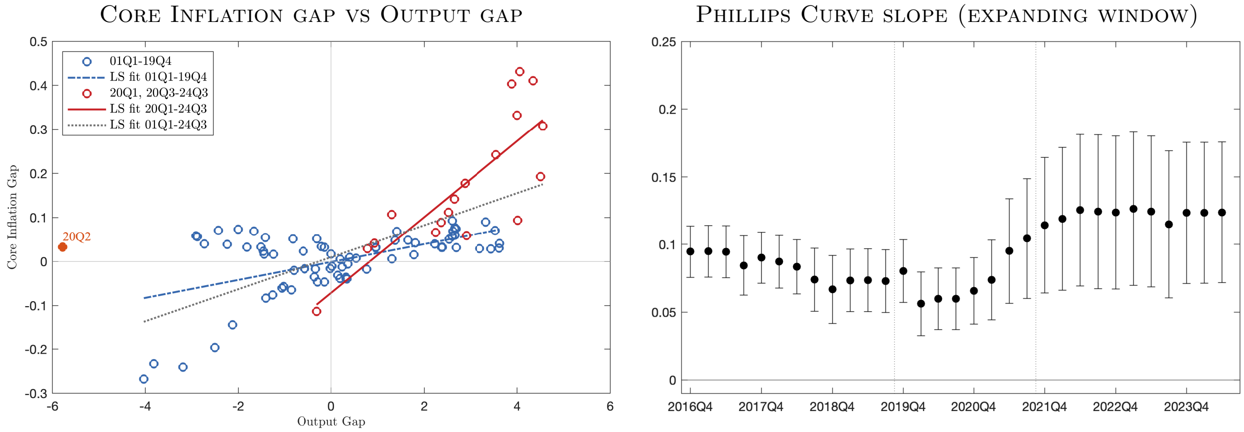
## 5.2 The Phillips curve

The left plot in Figure 6 shows that in our model, the core inflation rate gap (i.e., the cyclical common component of core inflation) and the output gap are positively correlated; that is, there is Phillips correlation in the data, and our model captures it. Over the whole sample, on average, for every percentage point increase in the output gap, the core inflation gap increases 4 basis points (dotted grey line). Moreover, this correlation has increased significantly after Covid from 0.022 (dashed-dotted blue line) to 0.079 (solid red line). The right plot in Figure 6 shows the expanding window estimate of the slope of the Phillips curve $\alpha$ in the following expectation-augmented specification (e.g., Conti, 2021): $\pi_t = c + \alpha \mathrm{OG}_t + \beta \pi_{t-1} + \gamma \pi_t^e + \varepsilon_{\pi,t}$, where $\pi_t$ is core inflation and $\pi_t^e$ are the long-run (5-year ahead) inflation expectations in the Survey of Professional Forecasters. The results suggest that the relationship between inflation and the output gap has strengthened after Covid, a point also made by Lane (2024).

To further corroborate the intuition that there is a relationship between our output gap estimate and inflation indicators, Figure 7 shows the GIRFs of the common component of core inflation,

information available at time $T$ (the last observation in our sample) by means of the Kalman filter (Bańbura et al., 2015; Crump et al., 409).

Figure 6: *Phillips Curve*

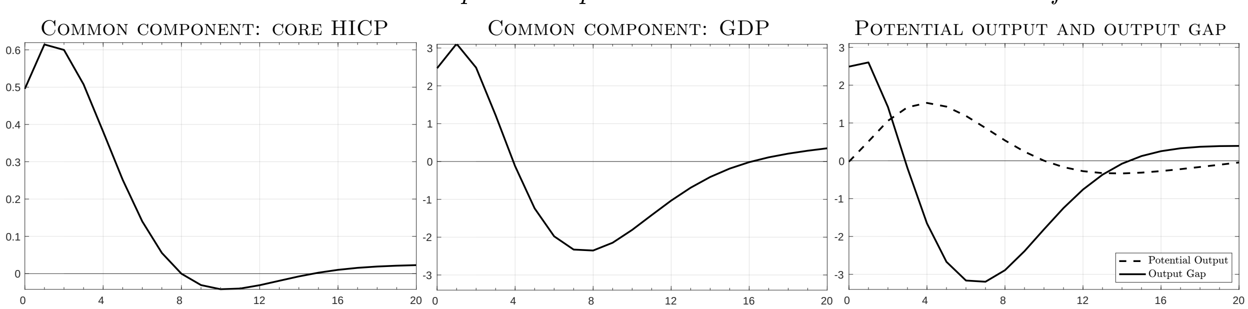



Notes: The left chart shows the Phillips curve relationship with the output gap on the horizontal axis and the core inflation gap on the vertical axis. Each circle corresponds to an output gap - core inflation gap pair at time $t$. The grey dotted, blue dashed-dotted, and red solid lines are the least squares fit lines for the full, pre-Covid, and post-Covid samples, respectively, obtained by omitting the observation for 2020:Q2 (orange dot).

The right chart shows the least squares estimate, based on an expanding window starting from 2015:Q1, of the slope of the Phillips curve given by the following expectation-augmented specification: $\pi_t = c + \alpha \mathrm{OG}_t + \beta \pi_{t-1} + \gamma \pi_t^e + \varepsilon_{\pi,t}$, where $\pi_t$ is core inflation and $\pi_t^e$ are the long-run (5-year ahead) inflation expectations in the Survey of Professional Forecasters. Each dot is an estimate of $\alpha$ while the whiskers are $\pm$ one HAC standard errors.

GDP, potential output, and the output gap to a 0.5 p.p. shock to the common component of core inflation. Results confirm that our model, on average, associates an increase in inflation with an output gap increase. The GIRF of the common component of core inflation peaks one quarter after the shocks before decreasing and slowly returning to zero. In response, GDP initially increases, but after about a year, it starts decreasing, reaching a trough about 2 years after the shock—the shock is fully absorbed in 5 years. The response of potential output is negative and persistent. The output gap initially increases, then decreases, and increases again before returning to zero.

Figure 7: *Generalized Impulse Response Functions to a shock to core inflation*




Notes: The black solid/dashed lines are the GIRF to a 0.5 p.p. shock to the common component of core inflation. The major ticks in the x-axis represent quarters after the shock.

# 6 Inflation dynamics through the lens of our model

In Section 5.2, we show that, although we did not create it specifically to signal inflationary pressures, our output gap measure does provide insights related to inflation dynamics. In light of these results, further inspection of Figure 2 raises two important questions: How can we reconcile an output gap of 2% between 2017 and 2019 when inflation was just 1%, well below the 2% ECB target? How does our model interpret post-pandemic inflation dynamics?

To answer these questions, in Figure 8, we plot the decomposition of core inflation (HICPNEF) implied by our model:

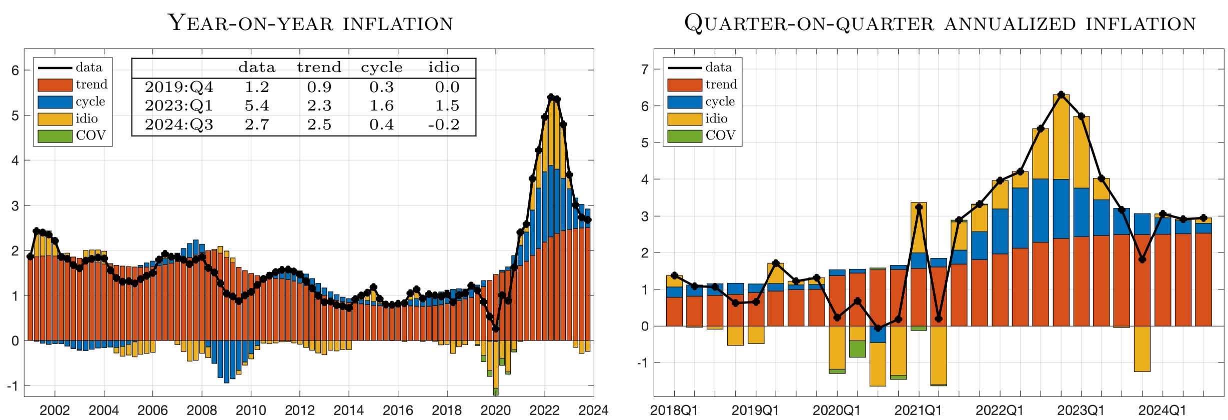
$$y_{\text{HICPNEF},t} = \bar{\pi}^c_t + \tilde{\pi}^c_t + \gamma_{\text{HICPNEF}} g_t \mathbb{I}_{2020:\text{Q1} \leq t \leq 2021:\text{Q4}} + \xi_{\text{HICPNEF},t}, \tag{11}$$

$$\bar{\pi}^c_t = \text{D}_{\text{HICPNEF},t} + \boldsymbol{\lambda}'_{\text{HICPNEF}} \boldsymbol{\psi} \tau_t, \tag{12}$$

$$\tilde{\pi}^c_t = \boldsymbol{\lambda}'_{\text{HICPNEF}} \boldsymbol{\omega}_t, \tag{13}$$

where $\bar{\pi}^c_t$ is trend inflation, and $\tilde{\pi}^c_t$ is the inflation gap. Similar to Hasenzagl et al. (2019), we estimate that after the GFC, trend inflation decreased from 2% to about 1% in 2016, a level at which it stabilized until the Covid pandemic. This result aligns with the findings of Ciccarelli and Osbat (2017) and Corsello et al. (2021), who show that inflation expectations de-anchored on the downside after the SDR. Thus, we conclude that after the GFC, core inflation remained below 2% primarily because trend inflation decreased, not because there was slack in the economy, which explains why we estimate an output gap above 2% when core inflation was 1%.

FIGURE 8: *Decomposition of core inflation*




Notes: The black line with dot markers is core inflation. The bars represent the contribution of each component to core inflation. The left plot shows YoY inflation, while the right plot shows QoQ inflation at an annual rate.

Next, we turn our attention to post-pandemic inflation dynamics. As shown in the inset box of the left chart in Figure 8, YoY core inflation increased about 4.2 p.p. between 2019:Q4 and 2023:Q1. Trend inflation and the core inflation gap jointly account for about 65% of this 4.2 p.p. increase, while idiosyncratic factors drive the remaining portion. Since its 5.4% peak in 2023:Q1, YoY core inflation decreased to 2.7% in 2024:Q3. The core inflation gap accounts 40 basis points of this decline, and the idiosyncratic components for 250 basis points, while trend inflation increased 20 basis points.

As we explained at the end of Section 4, the cyclical common component—therefore, the core inflation gap—primarily reflects demand forces. Under this assumption, the results of the decomposition in Figure 8 show that demand forces accounted for at least 30% of the post-pandemic increase in core inflation, thus supporting existing literature that indicates that demand dynamics played a significant role in the inflation surge following the pandemic (Ascari et al., 2023; Giannone and Primiceri, 2024; Bergholt et al., 2025).

Figure 8 clearly shows that other significant factors shaping post-pandemic inflation dynamics are idiosyncratic. For example, lingering Covid-specific effects (e.g., supply chain bottlenecks) that are not captured by the Covid factor. Another possibility is that the concurrent sharp rise in oil and natural gas prices following the onset of the Russia-Ukraine war induced second-round effects beyond those experienced in the pre-Covid sample. Finally, labor market tightness might have induced a non-linear response of prices that our linear model fails to capture. These factors might have a more or less persistent effect. Thus, our estimate of the role of demand forces should be considered a lower bound.

# 7 Has our output gap measure predictive power for inflation?

Any output gap measure *must* be good at predicting inflation to be considered a credible indicator of current/future inflationary pressure. Thus, to assess the forecasting properties of our output gap estimate, we replicate the analysis conducted in Bańbura and Bobeica (2023), and we employ the following model:

$$\pi_{t+4} = \alpha\pi_t + \beta OG_t + v_{t+4}, \tag{14}$$

where $\pi_t = 100\log(P_t/P_{t-1})$ is the quarter-on-quarter inflation rate in quarter $t$, $P_t$ is the harmonized consumer price index (either headline or core), $\pi_{t+4} = \sum_{i=1}^{4}\pi_{t+i}$ is year-on-year inflation in quarter $t+4$, and $OG_t$ is the output gap. Bańbura and Bobeica (2023) labeled model (14) the "benchmark model," and they show that, despite being very simple, it delivers decent forecasts compared to more complex alternative models.

Our exercise compares the inflation forecast obtained using the benchmark model (14) with a forecast obtained by replacing our estimate of the output gap with different univariate and multivariate statistical models: the HP filter, the filter by Hamilton (2018), the boosted HP filter by Phillips and Shi (2021), the Butterworth filter as recommended by Canova (2025), and the large Bayesian VAR approach by Morley et al. (2023)—Appendix I describes these alternative models. We carry out the forecasting exercise on expanding windows, where the first window is a 60-quarter window. We look at the forecasting performance of the different output gap measures over two distinct samples: a pre-Covid sample, 2015:Q4–2019:Q4, and a post-Covid sample, 2022:Q1–2024:Q3.

Table 1 compares the forecasting performance of the different output gap measures in terms of relative Root Mean Squared Error (RMSE)—numbers lower than one indicate a better forecasting performance when using our output gap estimate. As shown in rows (1)-(8), in the pre-Covid period, when inflation was low and stable, our output gap measure performed better than all the other alternatives in forecasting headline inflation and better than most alternatives when forecasting core inflation. However, in the post-Covid period, when inflation surged and then declined, our model outperformed all the other measures, sometimes substantially.

Table 1: *4-quarter ahead year-on-year inflation forecasting*
*Relative Root Mean Squared Errors*

| | | 2015:Q4-2019:Q4 | | 2022:Q1-2024:Q3 | |
|---|---|---|---|---|---|
| | Output Gap Measure | Headline | Core | Headline | Core |
| (1) | HP Filter ($\lambda = 1600$) | 0.91 | 1.00 | 0.97 | 0.89 |
| (2) | HP Filter ($\lambda = 51200$) | 0.92 | 1.01 | 0.94 | 0.89 |
| (3) | Hamilton Filter | 0.99 | 0.97 | 0.97 | 0.90 |
| (4) | Boosted HP Filter ($\lambda = 1600$) | 0.90 | 0.95 | 0.89 | 0.87 |
| (5) | Boosted HP Filter ($\lambda = 51200$) | 0.90 | 0.99 | 0.91 | 0.88 |
| (6) | Christiano-Fitzgerald Filter | 0.90 | 0.82 | 0.98 | 0.88 |
| (7) | Butterworth Filter | 0.95 | 0.95 | 0.96 | 0.88 |
| (8) | Multivariate Beveridge-Nelson | 0.91 | 0.97 | - | - |

Notes: The table shows the relative RMSE of forecasting year-on-year inflation using (14), where $\text{OG}_t$ is either our output gap estimate, or an alternative output gap estimate. Our benchmark output gap estimate is always the numerator of the RMSE, thus numbers lower than 1 indicate a better forecasting performance when using our benchmark output gap estimate. Rows (1)–(8) compare our benchmark estimate with alternative models. In row (8) forecasts are obtained with the output gap measure by Morley et al. (2023) which is available only until 2021:Q3. Therefore, we only present results for the pre-Covid forecasting exercise.

In conclusion, the results in this section prove that our output gap measure is not only a measure of the cyclical position of the economy but also a reliable inflation gauge.

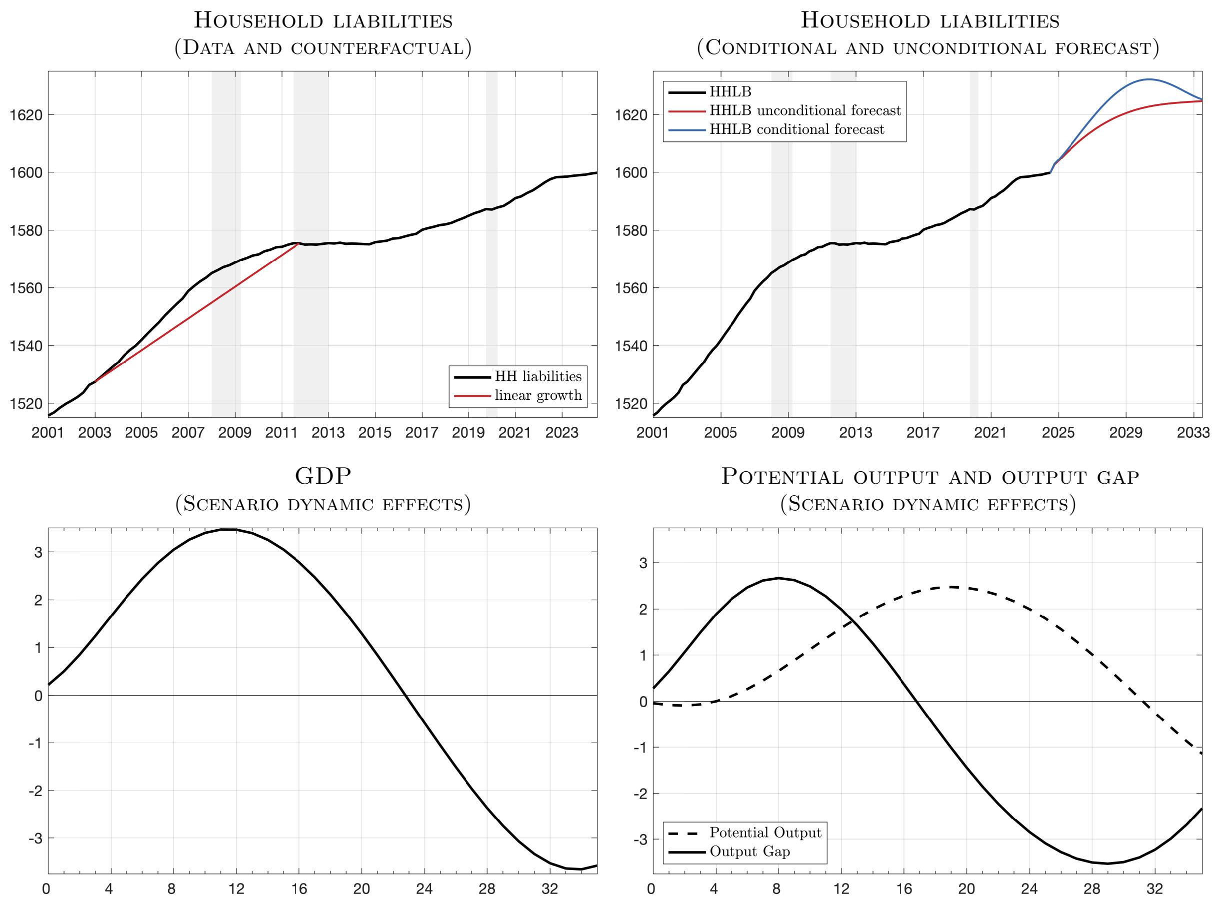
# 8 The role of credit indicators

Borio et al. (2017) argue that financial indicators are crucial to meaningfully assess the business cycle, as credit expansions often lead to economic overheating, especially from the late 1990s onward. In support of this result, Berger et al. (2022) find that a large share of the US economy overheating in the build-up of the financial crisis was due to financial imbalances in the credit and housing market. Moreover, Claessens et al. (2012), Rünstler and Vlekke (2018), and Winter et al. (2022) find that the business and financial cycles are correlated and co-move in the medium run.

To understand what signals our model takes from financial indicators to estimate the output gap, we focus on household liabilities because they have become an important driver of the business cycle in many advanced economies since the early 2000s (Mian et al., 2017). Indeed, while in the 1990s, non-financial corporations were the main driver of the financial cycle, households were behind both the pre-GFC excess leverage, which boosted household demand, and the subsequent deleveraging, which curtailed household's demand (Mian and Sufi, 2018; Plagborg-Møller et al., 2020; Reichlin et al., 2020). In terms of the EA area, Gambetti and Musso (2017) find that loan supply shocks significantly affect the EA business cycle.

Figure 9 shows the impact of a scenario in which household liabilities increase faster than projected in the baseline for about 3½ years. In this scenario, household liabilities reach a level about 6¼ p.p. higher than in the baseline before returning to baseline after about 8 years.[6]

Figure 9: *Scenario analysis*




NOTES: In the upper-left chart, the black line is the data (in 100×log-levels), and the red line is a linear path starting from the value of household liabilities in 2003:Q1 and ending in 2011:Q4. In the upper-right chart, the black line are the data,the blue line is the scenario we simulate, and the red line is the forecast of household liabilities when no alternative scenario is imposed. In the lower charts, the black solid/dashed lines are the dynamic effects of the simulated scenario.

The lower charts in Figure 9 show the dynamic effects of this scenario on the log level of GDP and on

[6] To calibrate this scenario, we computed the difference between the actual times series of household liabilities between 2003:Q1 and 2011:Q4 and a counterfactual scenario in which household liabilities would have grown linearly during this period (the red line in the upper-left chart of Figure 9). Then, we smoothed this difference with a 5-th order degree polynomial and added it to the unconditional forecast of household liabilities (the red line in the upper-right chart in Figure 9), which gives us a path for household liabilities (blue line) conditional on which we can obtain forecasts for all the variables in the model.

the output gap and potential output.[7] Specifically, GDP increases for a little over three years, reaching a peak at 3 p.p. above the baseline. Then, it declines and, after six years, turns negative. The response of the output gap mimics that of GDP, but it is a little faster. Potential output slowly increases for the first five years and then returns to the baseline. These results show that growth financed through household debt is not sustainable in the long run.

To conclude, we repeat the inflation forecasting exercise in Table 1 using the output gap estimated when omitting all credit indicators. We find that, in this case, the predictive performance of the output gap is about 5% worse than our benchmark measure. This result supports our claim that including credit variables in the dataset when estimating the output gap is crucial, as the model including credit indicators outperforms the model excluding credit indicators.

# 9 Conclusions

This paper proposes a new measure of potential output and the output gap for the EA based on letting a large number of macroeconomic and financial indicators speak. To do so, we estimate a large-dimensional non-stationary dynamic factor model, which allows us to capture co-movements across series while incorporating relevant macroeconomic priors, such as the long-run decline in output growth.

Our output gap estimate is in line with those published by the EC and the IMF in most of the sample. However, our estimate diverges significantly after the SDR when our output gap measure suggests that the EA economy was tighter than estimated by the EC and the IMF. This result suggests that the EA has a potential output issue, not a business cycle issue. Hence, if the goal is to achieve better economic conditions in the EA, European countries should implement structural reforms and promote productivity-enhancing investments that have long-run effects. In contrast, policies aiming at stimulating household consumption and residential investments will have only short-term effects at best, as our findings indicate that growth financed through household debt is not sustainable in the long run.

Moreover, although we did not create our output gap measure specifically to signal inflationary pressures, it does provide insights related to inflation dynamics because, on average, the Phillips Curve is satisfied. In particular, we find that core inflation remained below 2% after the GFC, not because there was slack in the economy, but rather because trend inflation decreased by one percentage point—in line with the idea that inflation expectations de-anchored on the downside after the GFC (Ciccarelli and Osbat, 2017; Corsello et al., 2021). Finally, we show that the output gap contributed to at least 30% of the post-pandemic increase in core inflation, thus supporting existing literature that suggests demand forces played a substantial role in the rise of post-pandemic inflation (Ascari et al., 2023; Giannone and Primiceri, 2024; Bergholt et al., 2025).

[7] This is equivalent to computing the effect of a sequence of shocks. Hence, it is estimated the same way we estimated the GIRFs in Section 5.

## References


Aastveit, K. A. and T. Trovik (2014). Estimating the output gap in real time: A factor model approach. *The Quarterly Review of Economics and Finance 54*, 180–193.

Ahn, H. J. and M. Luciani (2024). Common and idiosyncratic inflation. FEDS 2020-024r1, Board of Governors of the Federal Reserve System.

Aruoba, S. B., F. X. Diebold, J. Nalewaik, F. Schorfheide, and D. Song (2016). Improving GDP measurement: A measurement-error perspective. *Journal of Econometrics 191*, 384–397.

Ascari, G., P. Bonomolo, M. Hoeberichts, and R. Trezzi (2023). The euro area great inflation surge. Policy Brief 548, SUERF.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica 70*, 191–221.

Bai, J. and S. Ng (2004). A PANIC attack on unit roots and cointegration. *Econometrica 72*, 1127–1177.

Bańbura, M. and E. Bobeica (2023). Does the Phillips curve help to forecast euro area inflation? *International Journal of Forecasting 39*, 364–390.

Bańbura, M., D. Giannone, and M. Lenza (2015). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. *International Journal of Forecasting 31*(3), 739–756.

Barigozzi, M., M. Lippi, and M. Luciani (2021). Large-dimensional dynamic factor models: Estimation of impulse-response functions with $I(1)$ cointegrated factors. *Journal of Econometrics 221*, 455–482.

Barigozzi, M. and M. Luciani (2023). Measuring the Output Gap using Large Datasets. *The Review of Economics and Statistics 105*, 1500–1514.

Barigozzi, M. and M. Luciani (2024). Quasi maximum likelihood estimation and inference of large approximate dynamic factor models via the EM algorithm. Finance and Economics Discussion Series 2024-086, Board of Governors of the Federal Reserve System.

Benati, L. and T. A. Lubik (2021). Searching for hysteresis. Working Paper 21-03, Federal Reserve Bank of Richmond.

Berger, T., J. Richter, and B. Wong (2022). A unified approach for jointly estimating the business and financial cycle, and the role of financial factors. *Journal of Economic Dynamics and Control 136*, 104315.

Bergholt, D., F. Canova, F. Furlanetto, N. Maffei-Faccioli, and P. Ulvedal (2025). What drives the recent surge in inflation? the historical decomposition roller coaster. *American Economic Journal: Macroeconomics*, *forthcoming*

Berson, C., V. Botelho, A. D. da Silva, C. Foroni, M. Mohr, C. Schroeder, and M. Weissler (2024). Explaining the resilience of the euro area labour market between 2022 and 2024. Economic Bulletin 8/2024, European Central Bank.

Bianchi, F., G. Nicoló, and D. Song (2023). Inflation and real activity over the business cycle. Finance and Economics Discussion Series 2023-038, Board of Governors of the Federal Reserve System.

Blanchard, O. J. and D. Quah (1989). The dynamic effects of aggregate demand and supply disturbance. *The American Economic Review 79*, 655–673.

Boivin, J. and S. Ng (2006). Are more data always better for factor analysis? *Journal of Econometrics 132*, 169–194.

Borio, C., P. Disyatat, and M. Juselius (2017). Rethinking potential output: embedding information about the financial cycle. *Oxford Economic Papers 69*, 655–677.

Buncic, D. and A. Pagan, and T. Robinson (2023). Recovering stars in macroeconomics. SSRN working paper 4562801.

Burlon, L. and P. D'Imperio (2020). Reliable real-time estimates of the euro-area output gap. *Journal of Macroeconomics 64*, 103191.

Canova, F. (2025). FAQ: How do I estimate the output gap? *The Economic Journal 135*, 59–80.

Carriero, A., T. E. Clark, M. Marcellino, and E. Mertens (2024). Addressing COVID-19 outliers in BVARs with stochastic volatility. *The Review of Economics and Statistics 106*, 1403–1417.

Cette, G., J. Fernald, and B. Mojon (2016). The pre-Great Recession slowdown in productivity. *European Economic Review 88*, 3–20.

Ciccarelli, M. and C. Osbat (2017). Low inflation in the euro area: Causes and consequences. Occasional Paper Series 181, European Central Bank.

Claessens, S., M. A. Kose, and M. E. Terrones (2012). How do business and financial cycles interact? *Journal of International Economics 87*, 178–190.

Conti, A. M. (2021). Resurrecting the Phillips curve in low-inflation times. *Economic Modelling 96*, 172–195.

Corsello, F., S. Neri, and A. Tagliabracci (2021). Anchored or de-anchored? that is the question. *European Journal of Political Economy 69*, 102031.

Crump, R. K., S. Eusepi, D. Giannone, E. Qian, and A. Sbordone (351–409). A large bayesian var of the united states economy. *International Journal of Central Bankingt 21*.

De Masi, P. (1997). IMF estimates of potential output: Theory and practice. IMF Working Paper 177.

Del Negro, M., D. Giannone, M. P. Giannoni, and A. Tambalotti (2017). Safety, liquidity, and the natural rate of interest. *Brookings Papers on Economic Activity Spring 2017*, 235–316.

Del Negro, M., F. Schorfheide, F. Smets, and R. Wouters (2007). On the fit of new Keynesian models. *Journal of Business & Economic Statistics 25*, 123–143.

Doz, C., D. Giannone, and L. Reichlin (2012). A quasi-maximum likelihood approach for large, approximate dynamic factor models. *The Review of Economics and Statistics 94*, 1014–1024.

Elfsbacka Schmöller, M. and M. Spitzer (2021). Deep recessions, slowing productivity and missing (dis-) inflation in the euro area. *European Economic Review 134*, 103708.

European Commission (2018). Staff working document on the review of the flexibility under the Stability and Growth Pact. COM(2018) 335.

Forni, M., L. Gambetti, A. Granese, L. Sala, and S. Soccorsi (2025). An American macroeconomic picture: Supply and demand shocks in the frequency domain. *American Economic Journal: Macroeconomics*. forthcoming.

Furlanetto, F., P. Gelain, and M. T. Sanjani (2021). Output gap, monetary policy trade-offs, and financial frictions. *Review of Economic Dynamics 41*, 52–70.

Gambetti, L. and A. Musso (2017). Loan supply shocks and the business cycle. *Journal of Applied Econometrics 32*, 764–782.

Giannone, D. and G. Primiceri (2024). The drivers of post-pandemic inflation. Working Paper 32859, National Bureau of Economic Research.

González-Astudillo, M. (2019). An output gap measure for the euro area: Exploiting country-level and cross-sectional data heterogeneity. *European Economic Review 120*, 103301.

Hallin, M. and R. Liška (2007). Determining the number of factors in the general dynamic factor model. *Journal of the American Statistical Association 102*, 603–617.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *The Review of Economics and Statistics 100*, 831–843.

Hartl, T., R. Tschernig, and E. Weber (2022). Solving the unobserved components puzzle: A fractional approach to measuring the business cycle. mimeo.

Hasenzagl, T., F. Pellegrino, L. Reichlin, and G. Ricco (2019). The inflation puzzle in the euro area. VoxEU 16 October 2019, CEPR.

Hasenzagl, T., F. Pellegrino, L. Reichlin, and G. Ricco (2022). A Model of the Fed's View on Inflation. *The Review of Economics and Statistics 104*, 686–704.

Havik, K., K. Mc Morrow, F. Orlandi, C. Planas, R. Raciborski, W. Röger, A. Rossi, A. Thum-Thysen, V. Vandermeulen, et al. (2014). The production function methodology for calculating potential growth rates & output gaps. Economic Papers 535, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Jarociński, M. and M. Lenza (2018). An inflation-predicting measure of the output gap in the euro area. *Journal of Money, Credit and Banking 50*, 1189–1224.

Justiniano, A., G. Primiceri, and A. Tambalotti (2013). Is there a trade-off between inflation and output stabilization? *American Economic Journal: Macroeconomics 5*, 1–31.

Kamber, G., J. Morley, and B. Wong (2018). Intuitive and reliable estimates of the output gap from a Beveridge-Nelson filter. *The Review of Economics and Statistics 100*, 550–566.

Kiley, M. T. (2013). Output gaps. *Journal of Macroeconomics 37*, 1–18.

Kim, C.-J. and J. Kim (2022). Trend-cycle decompositions of real GDP revisited: Classical and Bayesian perspectives on an unsolved puzzle. *Macroeconomic Dynamics 26*, 394–418.

Lane, P. R. (2024). The 2021-2022 inflation surges and the monetary policy response through the lens of macroeconomic models. Speech by Philip R. Lane, Member of the Executive Board of the ECB, at the SUERF Marjolin Lecture hosted by the Banca d'Italia Rome, 18 November 2024.

Lenza, M. and G. E. Primiceri (2022). How to estimate a vector autoregression after March 2020. *Journal of Applied Econometrics 37*, 688–699.

Luciani, M. (2014). Forecasting with approximate dynamic factor models: The role of non-pervasive shocks. *International Journal of Forecasting 30*, 20–29.

McCracken, M. and S. Ng (2020). FRED-QD: A quarterly database for macroeconomic research. NBER working paper 26872.

McCracken, M. W. and S. Ng (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics 34*, 574–589.

Mian, A. and A. Sufi (2018). Finance and business cycles: The credit-driven household demand channel. *Journal of Economic Perspectives 32*, 31–58.

Mian, A., A. Sufi, and E. Verner (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics 132(4)*, 1755–1817.

Morley, J., C. R. Nelson, and E. Zivot (2003). Why are the Beveridge-Nelson and unobserved-components decompositions of GDP so different? *The Review of Economics and Statistics 85*, 235–243.

Morley, J., D. Rodríguez-Palenzuela, Y. Sun, and B. Wong (2023). Estimating the euro area output gap using multivariate information and addressing the COVID-19 pandemic. *European Economic Review 153*, 104385.

Morley, J., T. D. Tran, and B. Wong (2024). A simple correction for misspecification in trend-cycle decompositions with an application to estimating $r$. *Journal of Business & Economic Statistics 42*, 665–680.

Morley, J. and B. Wong (2020). Estimating and accounting for the output gap with large Bayesian vector autoregressions. *Journal of Applied Econometrics 35*, 1–18.

Ng, S. (2018). Comments on the cyclical sensitivity in estimates of potential output. *Brookings Papers on Economic Activity 49*, 412–423.

Ng, S. (2021). Modeling macroeconomic variations after COVID-19. NBER working paper 29060.

Onatski, A. and C. Wang (2021). Spurious factor analysis. *Econometrica 89*, 591–614.

Phillips, P. C. and S. Jin (2021). Business cycles, trend elimination, and the HP filter. *International Economic Review 62*, 469–520.

Phillips, P. C. and Z. Shi (2021). Boosting: Why you can use the HP filter. *International Economic Review 62*, 521–570.

Plagborg-Møller, M., L. Reichlin, G. Ricco, and T. Hasenzagl (2020). When is growth at risk? *Brookings Papers on Economic Activity Spring 2020*, 167–229.

Reichlin, L., G. Ricco, and T. Hasenzagl (2020). Financial variables as predictors of real growth vulnerability. Deutsche Bundesbank Discussion Papers 05/2020.

Rünstler, G. and M. Vlekke (2018). Business, housing, and credit cycles. *Journal of Applied Econometrics 33*, 212–226.

Stock, J. H. and M. W. Watson (2016, January). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In J. B. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2, pp. 415–525. Elsevier.

Stock, J. H. and M. W. Watson (2025). Recovering from COVID. Brookings Paper on Economic Activity Conference Draft, March 27-28, 2025. link.

Thum-Thysen, A., F. Blondeau, F. d'Auria, B. Döhring, A. Hristov, and K. Mc Morrow (2022). Potential output and output gaps against the backdrop of the COVID-19 pandemic. *Quarterly Report on the Euro Area 21*, 21–30.

Tóth, M. (2021). A multivariate unobserved components model to estimate potential output in the Euro Area: A production function based approach. ECB working paper 2523.

Winter, J. d., S. J. Koopman, and I. Hindrayanto (2022). Joint decomposition of business and financial cycles: Evidence from eight advanced economies. *Oxford Bulletin of Economics and Statistics 84*, 57–79.

*Supplementary material for the paper:*

# Measuring the Euro Area Output Gap

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## Summary

In Appendix A, we provide full details on the dataset. In Appendix B, we formally state all assumptions of our model and provide motivation and comments for each of them. In Appendix C, we provide details of all estimation steps, and Appendix D explains how we compute the confidence bands to measure the uncertainty around our output gap estimate. Appendix E presents the results of various information criteria employed to select the number of common factors. Next, Appendix F compares our estimate of the output gap with the one obtained when identifying the common trend as suggested by Morley et al. (2024). In Appendix G, we show how our measures would change if we did not model the effect of Covid explicitly, and we also compare our measure of the output gap with the ones obtained by using a different estimate of the Covid factor or when modeling the Covid induced volatility as suggested by Lenza and Primiceri (2022). In Appendix H, we show the effect of not allowing some parameters to be time-varying. In Appendix I we compare our output gap estimate with that obtained using alternative methodologies, and Appendix J assesses the reliability of our output gap estimate.

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Disclaimer: the views expressed in this paper are those of the authors and do not necessarily reflect the views and policies of the Board of Governors or the Federal Reserve System.

## A Data Description

Table A2 provides a brief description for each of the 118 series in our dataset. Moreover, for each variable, Table A2 indicates the source, the unit of measure, the seasonal adjustment treatment, the transformation (if any), model for the deterministic component for the idiosyncratic component. Table A1 presents a glossary to proper understand the data description presented in Table A2.

All the series were retrieved in February 2025, with the sample starting in January 2000 and ending in October 2024, the last observation available for all the series. After dropping missing values and transforming the variables, the actual starting point for the analysis is 2001:Q1. Monthly series, which constitute around one-third of the dataset, are aggregated at the quarterly level by simple averages; hence, the sample used for the analysis is 2001:Q1-2024:Q3 ($T = 95$).

Most of the series in the dataset are available already seasonally adjusted from the source, while others, e.g., financial variables and producer price indexes, are only available not seasonality adjusted. In these cases, we deseasonalize the series using a simple dummy variable approach.

Table A1: *Glossary*

| **Source** | **Unit** |
|---|---|
| EUR = Eurostat | CLV= Chain-linked volumes |
| OECD = Organization for Economic Co-operation and Development | 1000-ppl= Thousands of persons |
| ECB = European Central Bank | 1000-U = Thousands of Units |
| FRED = Federal Reserve Economic Data | CP = Current Prices |

| **SA** | **F** | **Trans** | **Trend** | **Idio** |
|---|---|---|---|---|
| NSA = No Seasonal Adjustment | Q = Quarterly | 0 = No Transformation | 0 = No Trend | 0 = I(0) |
| SA = Seasonal Adjustment | M = Monthly | 1 = First Differences | 1 = Deterministic Trend | 1 = I(1) |
| SCA = Seasonal and Calendar Adjustment | | 2 = Log-Transformations | 2 = Time-Varying Trend | |
| MSA = Manual adjustment | | 3 = First-Differences in Logs | 3 = Time-varying Mean | |

TABLE A2: *Data description: Euro Area*

| ID | Ticker | Series | Unit | SA | F | Source | Trans | Trend | Idio |
|---|---|---|---|---|---|---|---|---|---|
| | | (1) **National Accounts** | | | | | | | |
| 1 | GDP | Real Gross Domestic Product | CLV(2015) | SCA | Q | EUR | 2 | 2 | 0 |
| 2 | EXPGS | Real Export Goods and services | CLV(2015) | SCA | Q | EUR | 2 | 1 | 0 |
| 3 | IMPGS | Real Import Goods and services | CLV(2015) | SCA | Q | EUR | 2 | 1 | 0 |
| 4 | GFCE | Real Government Final consumption expenditure | CLV(2015) | SCA | Q | EUR | 2 | 1 | 0 |
| 5 | HFCE | Real Households consumption expenditure | CLV(2015) | SCA | Q | EUR | 2 | 1 | 1 |
| 6 | CONSD | Real Households consumption expenditure: Durable Goods | CLV(2015) | SCA | Q | EUR | 2 | 1 | 1 |
| 7 | CONSND | Real Households consumption expenditure: Non-Durable Goods and Services | CLV(2015) | SCA | Q | EUR | 2 | 1 | 1 |
| 8 | GCF | Real Gross capital formation | CLV(2015) | SCA | Q | EUR | 2 | 0 | 0 |
| 9 | GCFC | Real Gross fixed capital formation | CLV(2015) | SCA | Q | EUR | 2 | 0 | 1 |
| 10 | GFACON | Real Gross Fixed Capital Formation: Construction | CLV(2015) | SCA | Q | EUR | 2 | 0 | 1 |
| 11 | GFAMG | Real Gross Fixed Capital Formation: Machinery and Equipment | CLV(2015) | SCA | Q | EUR | 2 | 0 | 1 |
| 12 | AHRDI | Adjusted Households Real Disposable Income | %change | SCA | Q | EUR | 0 | 0 | 0 |
| 13 | AHFCE | Actual Final Consumption Expenditure of Households | %change | SCA | Q | EUR | 0 | 0 | 0 |
| 14 | GNFCPS | Gross Profit Share of Non-Financial Corporations | Percent | SCA | Q | EUR | 0 | 0 | 0 |
| 15 | GNFCIR | Gross Investment Share of Non-Financial Corporations | Percent | SCA | Q | EUR | 0 | 0 | 0 |
| 16 | GHIR | Gross Investment Rate of Households | Percent | SCA | Q | EUR | 0 | 1 | 0 |
| 17 | GHSR | Gross Households Savings Rate | Percent | SCA | Q | EUR | 0 | 0 | 0 |
| | | (2) **Labor Market Indicators** | | | | | | | |
| 18 | TEMP | Total Employment (domestic concept) | 1000-ppl | SCA | Q | EUR | 2 | 1 | 1 |
| 19 | EMP | Employees (domestic concept) | 1000-ppl | SCA | Q | EUR | 2 | 1 | 1 |
| 20 | SEMP | Self Employment (domestic concept) | 1000-ppl | SCA | Q | EUR | 2 | 0 | 1 |
| 21 | THOURS | Hours Worked: Total | 2015=100 | SCA | Q | EUR | 2 | 0 | 1 |
| 22 | EMPAG | Quarterly Employment: Agriculture, Forestry, Fishing | 1000-ppl | SCA | Q | EUR | 2 | 1 | 0 |
| 23 | EMPIN | Quarterly Employment: Industry | 1000-ppl | SCA | Q | EUR | 2 | 0 | 0 |
| 24 | EMPMN | Quarterly Employment: Manufacturing | 1000-ppl | SCA | Q | EUR | 2 | 0 | 0 |
| 25 | EMPCON | Quarterly Employment: Construction | 1000-ppl | SCA | Q | EUR | 2 | 0 | 1 |
| 26 | EMPRT | Quarterly Employment: Wholesale/Retail trade, transport, food | 1000-ppl | SCA | Q | EUR | 2 | 1 | 1 |
| 27 | EMPIT | Quarterly Employment: Information and Communication | 1000-ppl | SCA | Q | EUR | 2 | 1 | 1 |
| 28 | EMPFC | Quarterly Employment: Financial and Insurance activities | 1000-ppl | SCA | Q | EUR | 2 | 0 | 1 |
| 29 | EMPRE | Quarterly Employment: Real Estate | 1000-ppl | SCA | Q | EUR | 2 | 0 | 0 |
| 30 | EMPPR | Quarterly Employment: Professional, Scientific, Technical activities | 1000-ppl | SCA | Q | EUR | 2 | 1 | 1 |
| 31 | EMPPA | Quarterly Employment: PA, education, health ad social services | 1000-ppl | SCA | Q | EUR | 2 | 1 | 1 |
| 32 | EMPENT | Quarterly Employment: Arts and recreational activities | 1000-ppl | SCA | Q | EUR | 2 | 1 | 0 |
| 33 | UNETOT | Unemployment: Total | %active | SA | M | EUR | 0 | 3 | 0 |
| 34 | UNEO25 | Unemployment: Over 25 years | %active | SA | M | EUR | 0 | 1 | 0 |
| 35 | UNEU25 | Unemployment: Under 25 years | %active | SA | M | EUR | 0 | 1 | 0 |
| 36 | RPRP | Real Labour Productivity (person) | 2015=100 | SCA | Q | EUR | 2 | 1 | 1 |
| 37 | WS | Wages and salaries | CP | SCA | Q | EUR | 2 | 1 | 0 |
| 38 | ESC | Employers' Social Contributions | CP | SCA | Q | EUR | 2 | 1 | 0 |
| | | (3) **Credit Aggregates** | | | | | | | |
| 39 | TAS.SDB | Total Economy - Assets: Short-Term Debt Securities | MLN€ | MSA | Q | EUR | 2 | 0 | 1 |
| 40 | TAS.LDB | Total Economy - Assets: Long-Term Debt Securities | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 41 | TAS.SLN | Total Economy - Assets: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 42 | TAS.LLN | Total Economy - Assets: Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 43 | TLB.SDB | Total Economy - Liabilities: Short-Term Debt Securities | MLN€ | MSA | Q | EUR | 2 | 0 | 1 |
| 44 | TLB.LDB | Total Economy - Liabilities: Long-Term Debt Securities | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 45 | TLB.SLN | Total Economy - Liabilities: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 46 | TLB.LLN | Total Economy - Liabilities: Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 47 | NFCAS | Non-Financial Corporations: Total Financial Assets | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 48 | NFCAS.SLN | Non-Financial Corporations - Assets: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 49 | NFCAS.LLN | Non-Financial Corporations - Assets: Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 50 | NFCLB | Non-Financial Corporations: Total Financial Liabilities | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 51 | NFCLB.SLN | Non-Financial Corporations - Liabilities - Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 52 | NFCLB.LLN | Non-Financial Corporations - Liabilities - Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 53 | GGAS | General Government: Total Financial Assets | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 54 | GGAS.SLN | General Government - Assets: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 55 | GGAS.LLN | General Government - Assets: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 0 | 1 |
| 56 | GGLB | General Government: Total Financial Liabilities | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 57 | GGLB.SLN | General Government - Liabilities: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 58 | GGLB.LLN | General Government - Liabilities: Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 0 | 1 |
| 59 | HHAS | Households: Total Financial Assets | MLN€ | MSA | Q | EUR | 2 | 1 | 1 |
| 60 | HHAS.SLN | Households - Assets: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 61 | HHAS.LLN | Households - Assets: Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 1 | 0 |
| 62 | HHLB | Households: Total Financial Liabilities | MLN€ | MSA | Q | EUR | 2 | 2 | 0 |
| 63 | HHLB.SLN | Households - Liabilities: Short-Term Loans | MLN€ | MSA | Q | EUR | 2 | 0 | 0 |
| 64 | HHLB.LLN | Households - Liabilities: Long-Term Loans | MLN€ | MSA | Q | EUR | 2 | 2 | 0 |

In absence of available data on durable and non-durable goods for the Euro Area, we follow Casalis and Krustev (2022) and build the aggregate series of durable consumption (CONSD) aggregating the data for the 20 individual Euro Area countries. Since data for services and non-durable goods are unavailable for many individual countries as well, we build an aggregate measure of non-durable goods (CONSND) which also includes semi-durable goods and services.

TABLE A2: *Data description: Euro Area*

| ID | Ticker | Series | Unit | SA | F | Source | Trans | Trend | Idio |
|---|---|---|---|---|---|---|---|---|---|
| | | (4) **Labor Costs** | | | | | | | |
| 65 | ULCIN | Nominal Unit Labor Costs: Industry | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 66 | ULCMQ | Nominal Unit Labor Costs: Mining and Quarrying | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 67 | ULCMN | Nominal Unit Labor Costs: Manufacturing | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 68 | ULCCON | Nominal Unit Labor Costs: Construction | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 69 | ULCRT | Nominal Unit Labor Costs: Wholesale/Retail Trade, Transport, Food, IT | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 70 | ULCFC | Nominal Unit Labor Costs: Financial Activities | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 71 | ULCRE | Nominal Unit Labor Costs: Real Estate | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| 72 | ULCPR | Nominal Unit Labor Costs: Professional, Scientific, Technical activities | 2016=100 | SCA | Q | EUR | 2 | 1 | 0 |
| | | (5) **Exchange Rates** | | | | | | | |
| 73 | REER42 | Real Exchange Rate (42 main industrial countries) | 2010=100 | NSA | M | EUR | 2 | 0 | 0 |
| 74 | ERUS | Exchange Rate (US dollar) | 2010=100 | NSA | M | EUR | 2 | 0 | 0 |
| | | (6) **Interest Rates** | | | | | | | |
| 75 | IRT3M | 3-Months Interest Rates | Percent | NSA | M | EUR | 0 | 0 | 1 |
| 76 | IRT6M | 6-Months Interest Rates | Percent | NSA | M | EUR | 0 | 0 | 1 |
| 77 | LTIRT | Long-Term Interest Rates (EMU Criterion) | Percent | NSA | M | EUR | 0 | 0 | 1 |
| | | (7) **Industrial Production and Turnover** | | | | | | | |
| 78 | IPMN | Industrial Production Index: Manufacturing | 2021=100 | SCA | M | EUR | 2 | 0 | 1 |
| 79 | IPCAG | Industrial Production Index: Capital Goods | 2021=100 | SCA | M | EUR | 2 | 0 | 1 |
| 80 | IPCOG | Industrial Production Index: Consumer Goods | 2021=100 | SCA | M | EUR | 2 | 1 | 0 |
| 81 | IPDCOG | Industrial Production Index: Durable Consumer Goods | 2021=100 | SCA | M | EUR | 2 | 1 | 0 |
| 82 | IPNDCOG | Industrial Production Index: Non Durable Consumer Goods | 2021=100 | SCA | M | EUR | 2 | 1 | 0 |
| 83 | IPING | Industrial Production Index: Intermediate Goods | 2021=100 | SCA | M | EUR | 2 | 0 | 1 |
| 84 | IPNRG | Industrial Production Index: Energy | 2021=100 | SCA | M | EUR | 2 | 1 | 0 |
| 85 | TRNMN | Turnover Index: Manufacturing | 2021=100 | SCA | M | EUR | 2 | 1 | 1 |
| 86 | TRNCAG | Turnover Index: Capital Goods | 2021=100 | SCA | M | EUR | 2 | 1 | 1 |
| 87 | TRNDCOG | Turnover Index: Durable Consumer Goods | 2021=100 | SCA | M | EUR | 2 | 0 | 0 |
| 88 | TRNNDCOG | Turnover Index: Non Durable Consumer Goods | 2021=100 | SCA | M | EUR | 2 | 1 | 0 |
| 89 | TRNING | Turnover Index: Intermediate Goods | 2021=100 | SCA | M | EUR | 2 | 0 | 0 |
| 90 | TRNNRG | Turnover Index: Energy | 2021=100 | SCA | M | EUR | 2 | 0 | 0 |
| | | (8) **Prices** | | | | | | | |
| 91 | PPICAG | Producer Price Index: Capital Goods | 2021=100 | MSA | M | EUR | 3 | 0 | 0 |
| 92 | PPIDCOG | Producer Price Index: Durable Consumer Goods | 2021=100 | MSA | M | EUR | 3 | 0 | 0 |
| 93 | PPINDCOG | Producer Price Index: Non Durable Consumer Goods | 2021=100 | MSA | M | EUR | 3 | 0 | 0 |
| 94 | PPIING | Producer Price Index: Intermediate Goods | 2021=100 | MSA | M | EUR | 3 | 0 | 0 |
| 95 | PPIFD | Producer Price Index: Food | 2021=100 | MSA | M | EUR | 3 | 0 | 1 |
| 96 | HICPOV | Harmonized Index of Consumer Prices: Overall Index | 2010=100 | SCA | M | ECB | 3 | 0 | 1 |
| 97 | HICPNEF | Harmonized Index of Consumer Prices: All Items: no Energy & Food | 2010=100 | SCA | M | ECB | 3 | 3 | 0 |
| 98 | HICPG | Harmonized Index of Consumer Prices: Goods | 2010=100 | SCA | M | ECB | 3 | 3 | 0 |
| 99 | HICPSV | Harmonized Index of Consumer Prices: Services | 2010=100 | SCA | M | ECB | 3 | 3 | 0 |
| 100 | HICPNG | Harmonized Index of Consumer Prices: Energy | 2010=100 | MSA | M | EUR | 3 | 3 | 0 |
| 101 | HICPFD | Harmonized Index of Consumer Prices: Food | 2010=100 | MSA | M | EUR | 3 | 3 | 0 |
| 102 | DFGDP | Real Gross Domestic Product Deflator | 2015=100 | SCA | Q | EUR | 3 | 0 | 0 |
| 103 | HPRC | Residential Property Prices (BIS) | MLN€ | SCA | Q | FRED | 3 | 0 | 0 |
| 104 | POIL | Crude Oil Prices: Brent - Europe | €/barrel | MSA | Q | FRED | 3 | 3 | 0 |
| 105 | PNGAS | Global price of Natural gas, EU | €/MMbtu | MSA | Q | FRED | 3 | 3 | 0 |
| | | (9) **Confidence Indicators** | | | | | | | |
| 106 | ICONFIX | Industrial Confidence Indicator | Index | SA | M | EUR | 0 | 0 | 1 |
| 107 | CCONFIX | Consumer Confidence Indicator | Index | SA | M | EUR | 0 | 0 | 0 |
| 108 | ESENTIX | Economic Sentiment Indicator | Index | SA | M | EUR | 0 | 0 | 1 |
| 109 | KCONFIX | Construction Confidence Indicator | Index | SA | M | EUR | 0 | 0 | 1 |
| 110 | RTCONFIX | Retail Confidence Indicator | Index | SA | M | EUR | 0 | 0 | 0 |
| 111 | SCONFIX | Services Confidence Indicator | Index | SA | M | EUR | 0 | 1 | 1 |
| 112 | BCI | Cyclically-Adjusted Business Confidence Index | 2010=100 | SA | M | OECD | 0 | 0 | 1 |
| 113 | CCI | Cyclically-Adjusted Consumer Confidence Index | 2010=100 | SA | M | OECD | 0 | 0 | 0 |
| | | (10) **Monetary Aggregates** | | | | | | | |
| 114 | CURR | Money Stock: Currency | MLN€ | SCA | M | ECB | 2 | 1 | 1 |
| 115 | M1 | Money Stock: M1 | MLN€ | SCA | M | ECB | 2 | 1 | 1 |
| 116 | M2 | Money Stock: M2 | MLN€ | SCA | M | ECB | 2 | 1 | 1 |
| | | (11) **Others** | | | | | | | |
| 117 | SHIX | Share Prices | 2010=100 | SA | M | OECD | 2 | 0 | 1 |
| 118 | CAREG | Passenger's Cars Registrations | 1000-U | SCA | M | ECB | 2 | 0 | 1 |

## B Assumptions

In this section, we state all the formal assumptions underlying the model outlined in Section 3.1, and we provide both econometric and economic justifications for these assumptions. Throughout the text, we let $t_{\text{19Q4}}$, $t_{\text{20Q1}}$ and $t_{\text{21Q4}}$ denote 2019:Q4, 2020:Q1 and 2021:Q4, respectively.

*Identifying assumptions for the space spanned by the factors.*

(1) The number of factors $q$ is such that $q < n$ and is independent of $n$.

(2) The $q$-dimensional vector $\mathbf{f}_t$ is such that $\mathbb{E}[\Delta\mathbf{f}_t] = \mathbf{0}$ and $\mathbb{E}[\Delta\mathbf{f}_t\Delta\mathbf{f}_t'] = \mathbf{I}$.

(3) The $n \times q$ matrix $\boldsymbol{\Lambda} = (\boldsymbol{\lambda}_1 \cdots \boldsymbol{\lambda}_n)'$, with $\boldsymbol{\lambda}_i = (\lambda_{i1} \cdots \lambda_{iq})'$, $1 \le i \le n$, is such that $\lim_{n\to\infty} n^{-1}\boldsymbol{\Lambda}'\boldsymbol{\Lambda} = \mathbf{H}$ positive definite.

(4) The scalar $g_t$ is such that $\mathbb{E}[\Delta g_t] = 0$ and $\mathbb{E}[(\Delta g_t)^2] = 1$.

(5) The $n$-dimensional vector $\boldsymbol{\gamma} = (\gamma_1 \cdots \gamma_n)'$, is such that $\lim_{n\to\infty} n^{-1}\boldsymbol{\gamma}'\boldsymbol{\gamma} > 0$.

(6) The $q$-dimensional vector $\mathbf{u}_t$ is such that $\mathbb{E}[\mathbf{u}_t] = \mathbf{0}$, $\mathbb{E}[\mathbf{u}_t\mathbf{u}_t'] = \boldsymbol{\Sigma}_u$ is positive definite, and $\mathbb{E}[\mathbf{u}_t\mathbf{u}_{t-k}'] = \mathbf{0}$ for $k \neq 0$. Moreover, $s_t$ is deterministic with $s_t > 0$.

(7) The idiosyncratic innovations $e_{it}$, $1 \le i \le n$, are such that $\mathbb{E}[e_{it}] = 0$, $\mathbb{E}[e_{it}^2] = \sigma_{e_i}^2 > 0$ for all $t$. Moreover, there exist finite constants $M_{ij} > 0$ independent of $t$ and $0 < \rho < 1$ independent of $t$, $i$, and $j$ such that $|\mathbb{E}[e_{it}e_{j,t-k}]| \le M_{ij}\rho^{|k|}$ for all $k \in \mathbb{Z}$, with $\sum_{i=1,i\neq j}^{n} M_{ij} \le M$ and $\sum_{j=1,j\neq i}^{n} M_{ij} \le M$ for some finite constant $M > 0$ independent of $i$, $j$, and $n$.

(8) $\mathbb{E}[e_{it}\mathbf{u}_s] = \mathbf{0}$, for all $i, t, s$.

Assumptions (1)-(3) require the $q$ factors $\mathbf{f}_t$ to be pervasive so that they have a non-negligible effect on the variables of interest (Bai and Ng, 2004; Barigozzi et al., 2021). Following Stock and Watson (2025), these assumptions are extended in parts (4) and (5) to the Covid factor, $g_t$, where pervasiveness stems from the common nature of the Covid shock affecting most of the series included in the dataset. Including both 2020 and 2021 in the Covid period is consistent with the evolution of the pandemic in Europe.

Assumption (6) assumes white noise innovations whose volatility changes over time after the Covid shock—time-varying volatility is not a prominent feature in the pre-2020 sample (Jarociński and Lenza, 2018). Accounting for the change in volatility due to Covid has proven to be fundamental both for estimation and forecasting, and here we adopt an approach similar to Lenza and Primiceri (2022) by introducing a scaling term $s_t$ modeled independently for each period starting from 2020:Q1. Lenza and Primiceri (2022) analyze monthly US data and impose an exponential decay for $s_t$ starting in June 2020. In contrast, we estimate one parameter for each period starting in 2020:Q1 because many series exhibit large variation even after the first half of 2020, which is not surprising given that (i) mobility restriction measures in the EA were much more restrictive than in the US, lasted for longer, and were also implemented in 2021, and (2) the Russia-Ukraine war had a much larger impact on Europe by pushing natural gas prices (and gasoline prices to a lesser extent) to the roof, and in creating a lot of macro-financial uncertainty. Moreover, as Morley et al. (2023) pointed out, quarterly data do not allow for a sharp identification of the decay parameter.

Assumption (7) allows the idiosyncratic innovations to be mildly cross-sectionally correlated and serially correlated with summable autocovariances, thus compatible with stationary ARMA dynamics (Bai and Ng, 2004; Barigozzi et al., 2021). Last, Assumption (8) requires the idiosyncratic and factor innovations to be uncorrelated at all leads and lags, a requirement consistent with the idea of global macroeconomic shocks being unrelated to local dynamics.

*Assumptions on the dynamic specifications on the non-stationary idiosyncratic components and the secular components.*

(9) Let $\mathcal{I}_1$ be the set of indexes such that $\xi_{it} \sim I(1)$ if $i \in \mathcal{I}_1$, then $n_I = \#\{i : i \in \mathcal{I}_1\}$ is such that $0 < n_I < n$.

(10) Let $\mathcal{I}_b$ be the set of indexes such that $b_{it} \neq 0$ if $i \in \mathcal{I}_b$, then $n_B = \#\{i : i \in \mathcal{I}_b\}$ is such that $0 < n_B < n$. Moreover, $\mathrm{D}_{i0} = a_i \neq 0$, for all $i$.

(11) Let $\widehat{\sigma}^2_{\Delta y_i}$ and $\widehat{\sigma}^2_{y_i}$ be the sample variances of $\Delta y_{it}$ and $y_{it}$ respectively, computed for $1 \leq t \leq t_{19Q4}$ and $t_{21Q4} + 1 \leq t \leq T$.

(a) Let $\mathcal{L}_1 :=$ {GDP, HHLB, HHLB.LLN} be the set of indexes such that for $i \in \mathcal{L}_1$ we have $\sigma^2_{\eta_i} \neq 0$, then $\mathbb{E}[\eta_{it}] = 0$ and we set $\sigma^2_{\eta_i} = (1600\widehat{\sigma}^2_{\Delta y_i})^{-1}$.

(b) Let $\mathcal{L}_0 :=$ {UNETOT, HICPOV, HICPNEF, HICPG, HICPSV, HICPFD, POIL, PNGAS} be the set of indexes such that for $i \in \mathcal{L}_0$ we have $\sigma^2_{\epsilon_i} \neq 0$, then $\mathbb{E}[\epsilon_{it}] = 0$ and we set $\sigma^2_{\epsilon_i} = (800\widehat{\sigma}^2_{y_i})^{-1}$.

Assumption (9) allows the idiosyncratic component to be $I(1)$ for some, but not all, of the series. This assumption is crucial when estimating the model on a large dataset. Imposing the assumption of all idiosyncratic components being $I(0)$ would be overly restrictive, as it implies cointegration for any $q$-dimensional vector of series (Barigozzi et al., 2021). While cointegration may hold for certain series, it is highly unlikely to hold for many others. To accommodate potential cointegration, we allow only a limited number $n_I$ of variables to possess a non-stationary idiosyncratic component. Our dataset, where only $n_I = 57$ out of $n = 118$ series exhibit a non-stationary idiosyncratic component, supports this assumption.

Assumption (10) allows for a non-stationary secular component for some, but not all, of the variables in the dataset. This modeling choice is coherent with the properties of a standard macroeconomic dataset.

Specifically, variables related to the real sector of the economy, such as consumption or investments, commonly display a distinct (upward) trend. Conversely, this may not hold for other variables, such as inflation rates or interest rates, for example. This intuition finds support in the empirical data, where only $n_B = 58$ out of $n = 118$ series exhibit a linear trend.

Assumptions (10) and (11a) imply that GDP, households' financial liabilities and long-term loans, have a secular component given by the local linear trend model

$$\mathrm{D}_{it} = a_i + b_{it}t, \qquad b_{it} = b_{i,t-1} + \eta_{it}, \qquad i \in \mathcal{L}_1, \tag{B1}$$

where $a_i = \mathrm{D}_{i0}$.

We introduce a local-linear trend for GDP to capture the gradual drift in the secular decline in long-run output growth documented both for the US and the EA (Cette et al., 2016; Antolin-Diaz et al., 2017; Gordon, 2018). The literature has identified several factors contributing to this slowdown, with particular emphasis on declining productivity growth. This decline has been more pronounced in the EA due to heterogeneity between core and peripheral countries, as peripheral countries are experiencing a larger misallocation of economic resources (Cette et al., 2016). Therefore, it is crucial to accurately account for these features to assess GDP's long-run dynamics. This assessment is essential for estimating potential output, as it avoids spuriously inflating the output gap with unexplained predictable variation (Ng, 2018).

We introduce a local-linear trend for household financial liabilities and long-term loans, which constitute about 85% of total household liabilities, to capture the slowdown in their average growth rates that occurred since the GFC.

Assumptions (10) and Assumption (11b) implies that the unemployment rate, all consumer price inflation indexes, oil and natural gas prices have a secular component given by the local level model

$$\mathrm{D}_{it} = a_{it}, \qquad a_{it} = a_{i,t-1} + \epsilon_{it}, \qquad i \in \mathcal{L}_0, \tag{B2}$$

This specification captures relevant labor and demographic factors that may affect the unemployment rate secular trend, such as, for example, the aging of the population and the misallocation of resources in the labor market due to "soft budget constraints" or stringent labor market policies can lead to a mismatch between employers' needs and the skill-set of the unemployed (Cette et al., 2016). Similarly, this specification also allows us to account for the slowdown in inflation occurred after the GFC.

All the other variables in the dataset have either a deterministic linear trend or a constant mean, i.e, $\mathrm{D}_{it} = a_i + b_i t$ if $i \in \mathcal{I}_b$, or $\mathrm{D}_{it} = a_i$ otherwise. Although it is technically possible to model a time-varying component for all the variables in the dataset, such an approach would introduce complexities in the estimation framework, with the number of latent states increasing linearly with the number of series.

In Assumption (11) we fix the variances of the stochastic secular components following Del Negro et al. (2017) in order to effectively capture the gradual and persistent nature of the secular trends. This specification implies that when $i \in \mathcal{L}_1$, the standard deviation of the secular trend is approximately 1% over 100 years, while when $i \in \mathcal{L}_0$, the standard deviation of the secular trend is approximately 1% over 50 years. This choice consistent with the notion of a slow-moving secular component.

*Assumptions on the dynamics of the factors, trend, and cycles.*

(12) The polynomial $\det(\mathbf{I} - \sum_{j=1}^{p} \mathbf{A}_j z^j) = 0$ has 1 root in $z = 1$ and the remaining $q-1$ roots in $|z| > 1$.

(13) The $q$-dimensional vector $\boldsymbol{\psi}$ is such that $\boldsymbol{\beta}'\boldsymbol{\psi} = \mathbf{0}$, where $\boldsymbol{\beta}$ is the $q \times (q-1)$ matrix having as columns the cointegrating vectors of $\mathbf{f}_t$, i.e., such that $\boldsymbol{\beta}'\mathbf{f}_t$ is weakly stationary.

(14) The $q$-dimensional vector $\boldsymbol{\omega}_t$ is weakly stationary and such that $\mathbb{E}[\boldsymbol{\omega}_t] = \mathbf{0}$ and $\mathbb{E}[\boldsymbol{\omega}_t\boldsymbol{\omega}_t'] = \boldsymbol{\Sigma}_\omega$ is positive definite.

(15) The scalar $\nu_t$ is such that $\mathbb{E}[\nu_t] = 0$ and $\mathbb{E}[\nu_t^2] = \sigma_\nu^2 > 0$.

(16) $\mathbb{E}[\nu_t\boldsymbol{\omega}_t] = \mathbf{0}$ for all $t$.

Assumption (12) imposes that 1 common trend drives the non-stationarity in the common factors, hence, that the factors are cointegrated with $q-1$ cointegrating relations—our data provide strong support for the presence of just one common trend. This is a standard assumption in the literature, which often assumes that common productivity trend is the sole driver of long-run economic growth (see, e.g., Del Negro et al., 2007).

Assumptions (13) and (14) imply that $\boldsymbol{\omega}_t$, defined in (6), belongs to the cointegration space of the common factors. This view is consistent with theoretical models assuming that the output gap represents deviations from long-run equilibria determined by a common productivity trend (Del Negro et al., 2007).

Assumption (15) assumes that $\nu_t$ is a stochastic process—hence $\tau_t$ is a common stochastic trend—but it does not constraint $\nu_t$ to be a white noise—hence $\tau_t$ to be a random walk. Indeed, our estimates suggest that $\nu_t$ is autocorrelated, in line with the theoretical arguments by Lippi and Reichlin (1994).

Finally, Assumption (16) implies contemporaneous orthogonality between potential output and the output gap, which is also assumed in the non-parametric approaches used by Barigozzi and Luciani (2023).

Then, the extended state-space form of the model is given by:

$$y_{it} = \mathrm{D}_{it} + \boldsymbol{\lambda}_i'\mathbf{f}_t + \gamma_i g_t \mathbb{I}_{t_{20Q1} \le t \le t_{21Q4}} + \zeta_{it} + z_{it}, \qquad 1 \le i \le n,\ 1 \le t \le T, \tag{B3a}$$

$$\mathbf{f}_t = \sum_{j=1}^{p} \mathbf{A}_j \mathbf{f}_{t-j} + \{s_t \mathbb{I}_{t \geq t_{20Q1}} + (1 - \mathbb{I}_{t \geq t_{20Q1}})\}\mathbf{u}_t, \qquad \mathbf{u}_t \overset{i.i.d.}{\sim} (\mathbf{0}, \mathbf{\Sigma}_u), \tag{B3b}$$

$$\mathrm{D}_{it} = \begin{cases} a_i + b_i t & \text{if } i \in \mathcal{I}_b, \\ \mathrm{D}_{it-1} + b_{it-1},\ b_{it} = b_{it-1} + \eta_{it} & \text{if } i \in \mathcal{L}_1, \quad \eta_{it} \sim (0, \sigma^2_{\eta_i}), \\ \mathrm{D}_{it-1} + \epsilon_{i,t} & \text{if } i \in \mathcal{L}_0, \quad \epsilon_{it} \sim (0, \sigma^2_{\epsilon_i}), \\ a_i & \text{otherwise,} \end{cases} \tag{B3c}$$

$$\zeta_{it} = \begin{cases} \xi_{it},\ \xi_{it} = \xi_{i,t-1} + e_{it} & \text{if } i \in \mathcal{I}_1, \quad e_{it} \sim (0, \sigma^2_{e_i}), \\ 0 & \text{if } i \notin \mathcal{I}_1, \end{cases} \tag{B3d}$$

$$z_{it} = \begin{cases} z^*_{it} & \text{if } i \in \mathcal{I}_1, \quad z^*_{it} \overset{i.i.d.}{\sim} (0, R_i), \\ e_{it} & \text{if } i \notin \mathcal{I}_1, \quad e_{it} \sim (0, R_i), \end{cases} \tag{B3e}$$

$$R_i = \begin{cases} \sigma^2_z & \text{if } i \in \mathcal{I}_1, \\ \sigma^2_{e_i} & \text{if } i \notin \mathcal{I}_1. \end{cases} \tag{B3f}$$

As defined in Assumption (9), $\mathcal{I}_1$ denotes the set of series with an $I(1)$ idiosyncratic component. As defined in Assumption (10), $\mathcal{I}_b$ denotes the set of series with a deterministic linear trend. Finally, as defined in Assumption (11), $\mathcal{L}_1$ denotes the set of series with a time-varying trend modeled as a local-linear trend, while $\mathcal{L}_0$ denotes the set of series with a time-varying mean modeled as a random walk.

# C Estimation in detail

In this section, we provide details on the estimation procedure described in Section 3.2.

## Estimating the dynamic factor model

### *Initialization*

In order to apply the Kalman filter and smoother, we need initial estimates of all the quantities described in Equations (B3a)-(B3f), with the exception of $\sigma^2_{\eta_i}$, $\sigma^2_{\epsilon_i}$, both set as in Assumption 11, and $\sigma^2_z$ set to $10^{-2}$, as suggested by Opschoor and van Dijk (2023) who show that smaller values might be detrimental for the performance of the algorithm.

We denote with the superscript "19" all quantities computed with data up to 2019. Let $\breve{y}^{19}_{it} = (y^{19}_t - \breve{a}^{(0),19}_i - \breve{b}^{(0),19}_i \cdot t)/\widehat{\sigma}^2_{\Delta y^{19}_i}$, where $\widehat{\sigma}^2_{\Delta y^{19}_i}$ is the sample variance of $\Delta y^{19}_{it}$, and $\breve{a}^{(0),19}_i$ and $\breve{b}^{(0),19}_i$ are estimated by regressing $y^{19}_{it}$ on a constant and a time trend, whenever $i \in \mathcal{I}_b$ or $i \in \mathcal{L}_1$. If $i \in \mathcal{I}_a$ or $i \in \mathcal{L}_0$ we let $\breve{y}_{it} = y^{19}_{it} - \breve{a}^{(0),19}_i$, where $\breve{a}^{(0),19}_i$ is the sample average of $y_{it}$. The standardized slopes are denoted as $\widehat{b}^{(0),19}_i = \breve{b}^{(0),19}_i / \widehat{\sigma}^2_{\Delta y^{19}_i}$. We initialize the loadings using the estimator of Barigozzi et al. (2021): the $n \times q$ matrix of estimated loadings $\widehat{\mathbf{\Lambda}}^{(0),19} = (\widehat{\boldsymbol{\lambda}}^{(0),19}_1, \ldots, \widehat{\boldsymbol{\lambda}}^{(0),19}_q)'$ is obtained by principal components on the standardized first differences of the data, i.e. $(\Delta y^{19}_{it} - \overline{\Delta y^{19}_i})/\widehat{\sigma}^2_{\Delta y^{19}_i}$, where $\overline{\Delta y^{19}_i}$ is the sample mean of $\Delta y^{19}_{it}$. Given the loadings, we also obtain a first estimate of the $q$ common factors, $\widehat{\mathbf{f}}^{(0),19}_t = n^{-1} \widehat{\mathbf{\Lambda}}^{(0),19\prime} \breve{\mathbf{y}}^{19}_t$ and of the idiosyncratic components, $\widehat{\xi}^{(0),19}_{it} = \breve{y}^{19}_{it} - \widehat{\boldsymbol{\lambda}}^{(0),19\prime}_i \widehat{\mathbf{f}}^{(0),19}_t$. Furthermore, we obtain $\widehat{\mathbf{A}}^{(0),19}_j$, $j = 1, \ldots, p$, by fitting a VAR($p$) on $\widehat{\mathbf{f}}^{(0),19}_t$. Given the residuals $\widehat{\mathbf{u}}_t^{(0),19} = \widehat{\mathbf{f}}_t^{(0),19} - \widehat{\mathbf{A}}^{(0),19}\widehat{\mathbf{f}}_{t-1}^{(0),19}$, where $\widehat{\mathbf{A}}^{(0),19}$ is the companion form representation of the autoregressive matrices $\widehat{\mathbf{A}}_1^{(0),19}, \dots, \widehat{\mathbf{A}}_p^{(0),19}$, an estimate of the latent covariance is given by $\widehat{\boldsymbol{\Sigma}}_u^{(0),19} = \widehat{\text{Cov}}(\widehat{\mathbf{u}}_t^{(0),19})$, where $\widehat{\text{Cov}}$ is the sample covariance matrix. Finally, when $i \notin \mathcal{I}_1$ we set $\widehat{R}_i^{(0),19} = (\widehat{\sigma}_{e_i}^{(0),19})^2 = \widehat{\text{Var}}(\widehat{\xi}_{it}^{(0),19})$, where $\widehat{\text{Var}}$ is the sample variance. And when $i \in \mathcal{I}_1$ we set $(\widehat{\sigma}_{e_i}^{(0),19})^2 = \widehat{\text{Var}}(\Delta\widehat{\xi}_{it}^{(0),19})$.

TABLE C1: *Initialization of states for the Kalman filter*

| | |
|---|---|
| $\mathbf{f}_{0\|0}^{19} = \widehat{\mathbf{f}}_0^{(0),19}$ | |
| $\text{vec}\left(\mathbf{P}_{0\|0}^{19}\right) = \left(\mathbf{I}_{pq^2} - \widehat{\mathbf{A}}^{(0),19} \otimes \widehat{\mathbf{A}}^{(0),19}\right)^{-1} \text{vec}\left(\widehat{\boldsymbol{\Sigma}}_u^{(0),19}\right)$ | |
| $\text{D}_{i,0\|0}^{19} = \widehat{b}_i^{(0),19}$ | if $i \in \{\mathcal{I}_b, \mathcal{L}_1\}$ |
| $\text{D}_{i,0\|0}^{19} = 0$ | if $i \in \mathcal{L}_0$ |
| $\text{D}_{i,0\|0}^{19} = 0$ | if $i \notin \{\mathcal{I}_b, \mathcal{L}_0, \mathcal{L}_1\}$ |
| $b_{i,0\|0}^{19} = \widehat{b}_i^{(0),19}$ | if $i \in \{\mathcal{I}_b, \mathcal{L}_1\}$ |
| $P_{i,0\|0}^{D(19)} = \frac{1}{(1-0.99)^2}\sigma_{\eta_i}^2$ | if $i \in \mathcal{L}_1$ |
| $P_{i,0\|0}^{D(19)} = \sigma_{\epsilon_i}^2$ | if $i \in \mathcal{L}_0$ |
| $P_{i,0\|0}^{D(19)} = 0$ | if $i \notin \{\mathcal{L}_0, \mathcal{L}_1\}$ |
| $P_{i,0\|0}^{b(19)} = \frac{1}{(1-0.99)^2}\sigma_{\eta_i}^2$ | if $i \in \mathcal{L}_1$ |
| $\zeta_{i,0\|0}^{19} = \widehat{\xi}_{i1}^{(0),19}$ | if $i \in \mathcal{I}_1$ |
| $P_{i,0\|0}^{\zeta(19)} = \frac{1}{(1-0.99)^2}\widehat{\text{Var}}\left(\Delta\widehat{\xi}_{it}^{(0),19}\right)$ | if $i \in \mathcal{I}_1$ |

Table C1 provides an overview of the initial values of the states for the Kalman filter.

*Step 1: Estimate the model up to 2019:Q4 (pre-Covid step)*

Given the initial values of the parameters and the states, we run the Kalman filter and smoother using a standardized version of the data in levels, up to 2019, that is:

$$\tilde{y}_{it}^{19} = \begin{cases} \frac{y_{it}^{19} - \check{a}_i^{19}}{\widehat{\sigma}^2_{\Delta y_i^{19}}} & \text{if } i \in \{\mathcal{I}_b, \mathcal{L}_1\} \\ \frac{y_{it}^{19} - \bar{y}_i^{19}}{\widehat{\sigma}^2_{\Delta y_i^{19}}} & \text{otherwise} \end{cases}$$

Given $\tilde{\mathbf{y}}_t^{19} = (\tilde{y}_{1,t}, \dots, \tilde{y}_{n,t})'$, we obtain a new estimate of the states, namely the factors $\mathbf{f}_{t|T}^{19}$, the time-varying secular components $\mathbf{D}_{t|T}^{19}$ and slopes $\mathbf{b}_{t|t}^{19}$, and the non-stationary idiosyncratic components $\boldsymbol{\zeta}_{t|T}^{19}$ , along with the corresponding conditional covariances.

Given the smoothed states, we estimate all the parameters as follows:

- FACTOR LOADINGS:

$$\widehat{\boldsymbol{\lambda}}_i^{19'} = \left(\sum_{t=1}^{T}\left(\tilde{y}_{it}^{19} - \text{D}_{i,t|T}^{19} - \zeta_{i,t|T}^{19}\right)\mathbf{f}_{t|T}^{19'}\right)\left(\sum_{t=1}^{T}\mathbf{f}_{t|T}^{19}\mathbf{f}_{t|T}^{19'} + \mathbf{P}_{t|T}^{19}\right)^{-1}$$

- Parameters of the law of motion of the common factors:

$$\widehat{\mathbf{A}}^{19} = \left(\sum_{t=2}^{T} \mathbf{f}_{t|T}^{19}\mathbf{f}_{t-1|T}^{19\prime} + \mathbf{P}_{t,t-1\,|\,T}^{19}\right)\left(\sum_{t=2}^{T} \mathbf{f}_{t-1|T}^{19}\mathbf{f}_{t-1|T}^{19\prime} + \mathbf{P}_{t-1\,|\,T}^{19}\right)^{-1}$$

$$\widehat{\boldsymbol{\Sigma}}_u^{19} = \frac{1}{T}\left(\sum_{t=2}^{T}\left(\mathbf{f}_{t|T}^{19}\mathbf{f}_{t|T}^{19\prime} + \mathbf{P}_{t\,|\,T}^{19}\right) - \widehat{\mathbf{A}}^{19}\sum_{t=2}^{T}\left(\mathbf{f}_{t|T}^{19}\mathbf{f}_{t-1|T}^{19\prime} + \mathbf{P}_{t,t-1\,|\,T}^{19}\right)\right)$$

- Slopes of secular trend:

$$\widehat{b}_i^{19} = \left(\sum_{t=1}^{T}\left(\tilde{y}_{it}^{19} - \widehat{\boldsymbol{\lambda}}_i^{19\prime}\mathbf{f}_{t|T}^{19} - \zeta_{i,t|T}^{19}\right)t\right)\left(\sum_{t=1}^{T} t^2\right)^{-1}$$

- Variance of $I(1)$ idiosyncratic components:

$$\widehat{\sigma}_{e_i}^{2,19} = \frac{1}{T}\sum_{t=2}^{T}\left(\zeta_{i,t|T}^{19}\zeta_{i,t|T}^{19\prime} + P_{i,t\,|\,T}^{\zeta(19)}\right) + \frac{1}{T}\sum_{t=2}^{T}\left(\zeta_{it-1|T}^{19}\zeta_{it-1|T}^{19\prime} + P_{i,t-1\,|\,T}^{\zeta(19)}\right) -$$
$$- \frac{2}{T}\sum_{t=2}^{T}\left(\zeta_{it|T}^{19}\zeta_{it-1|T}^{19\prime} + P_{i,t,t-1\,|\,T}^{\zeta(19)}\right)$$

- Covariance prediction error:

$$\widehat{R}_i^{19} = \frac{1}{T}\sum_{t=1}^{T}\left\{\left(\tilde{y}_{i,t}^{19} - \widehat{\boldsymbol{\lambda}}_i^{19\prime}\mathbf{f}_{t|T}^{19} - \mathbb{I}_{i\in\mathcal{I}_b}\mathrm{D}_{i,t|T}^{19} - \mathbb{I}_{i\in\mathcal{I}_1}\zeta_{i,t|T}^{19}\right)^2 + \widehat{\boldsymbol{\lambda}}_i^{19\prime}\mathbf{P}_{t,T\,|\,T}^{19}\widehat{\boldsymbol{\lambda}}_i^{19} +\right.$$
$$\left. + \mathbb{I}_{i\in\mathcal{I}_b}P_{i,t\,|\,T}^{\mathrm{D}(19)} + \mathbb{I}_{i\in\mathcal{I}_1}P_{i,t\,|\,T}^{\zeta(19)}\right\}$$

*Step 2: Estimate the Covid factor and volatility (Covid step)*

Given the estimated parameters up to 2019:Q4, we run the Kalman filter and smoother using standardized data in levels for the entire sample, that is:

$$\tilde{y}_{it} = \begin{cases} \frac{y_{it} - \breve{a}_i}{\widehat{\sigma}^2_{\Delta y_i}} & \text{if } i \in \{\mathcal{I}_b, \mathcal{L}_1\} \\ \frac{y_{it} - \bar{y}_i}{\widehat{\sigma}^2_{\Delta y_i}} & \text{otherwise} \end{cases}$$

In computing $\bar{y}_i$, $\widehat{\sigma}^2_{\Delta y_i}$ and $\breve{a}_i$, we treat Covid outliers as missing values. Given $\tilde{\mathbf{y}}_t = (\tilde{y}_{1,t}, \dots, \tilde{y}_{n,t})'$, we obtain the estimated states given the pre-Covid parameters. In doing so, we truncate the Kalman smoother in correspondence of 2020:Q1, to avoid spurious backward effects from the presence of Covid outliers. The estimated states are denoted as $\mathbf{f}_{t\,|\,T}^{(0)}$, $\mathbf{D}_{t\,|\,T}^{(0)}$, $\mathbf{b}_{t\,|\,T}^{(0)}$ and $\boldsymbol{\zeta}_{t\,|\,T}^{(0)}$.

Given the smoothed states, let:

$$\widehat{\boldsymbol{\xi}}_t = \tilde{\mathbf{y}}_t - \widehat{\boldsymbol{\Lambda}}^{19}\mathbf{f}_{t|T}^{(0)} - \mathbf{D}_{t|T}^{(0)}$$

and denote as $\widehat{\boldsymbol{\Xi}} = (\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_t)'$ the $T \times n$ matrix of idiosyncratic components. Then we estimate the Covid factor by estimating the first principal component using the $n \times n$ variance-covariance matrix of the estimated idiosyncratic components from 2020:Q1 to 2021:Q4, denoted as $\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{\Xi}^C}$. This is the procedure proposed by Stock and Watson (2025) that we modify to account for non-stationarity in the idiosyncratic component. This done by partitioning the matrix of idiosyncratic components during the Covid period as $\widehat{\boldsymbol{\Xi}}^C = (\widehat{\boldsymbol{\Xi}}^{C,1} | \widehat{\boldsymbol{\Xi}}^{C,0})$, where $\widehat{\boldsymbol{\Xi}}^{C,1}$ and $\widehat{\boldsymbol{\Xi}}^{C,1}$ are the matrices of estimated idiosyncratic components in the period 2020:Q1 to 2021:Q4 for $i \in \mathcal{I}_1$ and $i \in \mathcal{I}_0$, respectively. Then, we estimate $\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{\Xi}^C}$ (Hamilton, 2020, Chapter 17; Bai, 2004):

$$\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{\Xi}^C} = \begin{bmatrix} \frac{1}{(T^C)^2} \widehat{\boldsymbol{\Xi}}^{C,1\prime} \widehat{\boldsymbol{\Xi}}^{C,1} & \frac{1}{(T^C)^{3/2}} \widehat{\boldsymbol{\Xi}}^{C,1\prime} \widehat{\boldsymbol{\Xi}}^{C,0} \\ \frac{1}{(T^C)^{3/2}} \widehat{\boldsymbol{\Xi}}^{C,0\prime} \widehat{\boldsymbol{\Xi}}^{C,1} & \frac{1}{T^C} \widehat{\boldsymbol{\Xi}}^{C,0\prime} \widehat{\boldsymbol{\Xi}}^{C,0} \end{bmatrix}$$

where $T^c = 8$ denotes the time-periods between 2020:Q1 and 2021:Q4.

Given $\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{\Xi}^C}$, we obtain the Covid factor and the corresponding loadings as:

$$\widehat{\boldsymbol{\gamma}} = \sqrt{n} \cdot \widehat{\mathbf{V}}_{\bar{\boldsymbol{\Xi}}^C}$$

$$\widehat{\mathbf{g}} = \frac{1}{\sqrt{n}} \cdot (\widehat{\boldsymbol{\Xi}}^C \widehat{\mathbf{V}}_{\bar{\boldsymbol{\Xi}}^C})$$

where $\widehat{\mathbf{g}}$ is the $T^C \times 1$ vector with entries $\widehat{g}_t$ and $\widehat{\mathbf{V}}_{\boldsymbol{\Xi}^C}$ is the $n \times 1$ eigenvector corresponding to the largest eigenvalue of $\widehat{\boldsymbol{\Sigma}}_{\widehat{\boldsymbol{\Xi}}^C}$. Given $\widehat{\mathbf{g}}$, the associated loadings are $\widehat{\boldsymbol{\gamma}} = (\widehat{\gamma}_1, \ldots, \widehat{\gamma}_n)'$.

Next, give the estimate of states and the Covid factor, we account for the presence of changes in the volatility after the Covid shock by modifying the Lenza and Primiceri (2022) procedure to accommodate for quarterly data. Let $s_t^* = s_t \mathbb{I}_{t \geq t_{20\text{Q}1}} + (1 - \mathbb{I}_{t \geq t_{20\text{Q}1}})$, the likelihood writes as:

$$\begin{aligned} \mathcal{L}(\mathbf{f}^{(0)} \,|\, \mathbf{A}, \boldsymbol{\Sigma}_u, s_1^*, \ldots, s_T^*) &\propto \prod_{t=2}^{T} \left| (s_t^*)^2 \boldsymbol{\Sigma}_u \right|^{-\frac{1}{2}} \cdot \exp\left\{ -\frac{1}{2} \sum_{t=2}^{T} \left( \mathbf{f}_{t|T}^{(0)} - \mathbf{A}\mathbf{f}_{t-1|T}^{(0)} \right)' \left( s_t^2 \boldsymbol{\Sigma}_u \right)^{-1} \left( \mathbf{f}_{t|T}^{(0)} - \mathbf{A}\mathbf{f}_{t-1|T}^{(0)} \right) \right\} \\ &\propto \left( \prod_{t=2}^{T} (s_t^*)^{-n} \right) |\boldsymbol{\Sigma}_u|^{-\frac{T-1}{2}} \cdot \exp\left\{ -\frac{1}{2} \sum_{t=2}^{T} \left( \mathbf{f}_{t|T}^{*(0)} - \mathbf{A}\mathbf{f}_{t-1|T}^{*(0)} \right)' (\boldsymbol{\Sigma}_u)^{-1} \left( \mathbf{f}_{t|T}^{*(0)} - \mathbf{A}\mathbf{f}_{t-1|T}^{*(0)} \right) \right\} \end{aligned}$$

where $\mathbf{f}_{t\,|\,T}^{*(0)} = \mathbf{f}_{t\,|\,T}^{(0)} / s_t^*$, with corresponding variance-covariance matrix $\mathbf{P}_{t\,|\,T}^{*(0)}$.

The maximum-likelihood estimators of $\mathbf{A}$ and $\boldsymbol{\Sigma}_u$ given the factors are:

$$\check{\mathbf{A}} = \left( \sum_{t=2}^{T} \mathbf{f}_{t|T}^{*(0)} \mathbf{f}_{t-1|T}^{*(0)\prime} + \mathbf{P}_{t,t-1\,|\,T}^{*(0)} \right) \left( \sum_{t=1}^{T} \mathbf{f}_{t-1|T}^{*(0)} \mathbf{f}_{t-1|T}^{*(0)\prime} + \mathbf{P}_{t-1\,|\,T}^{*(0)} \right)^{-1}$$

$$\check{\boldsymbol{\Sigma}}_u = \frac{1}{T} \left( \sum_{t=2}^{T} \left( \mathbf{f}_{t|T}^{*(0)} \mathbf{f}_{t|T}^{*(0)\prime} + \mathbf{P}_{t\,|\,T}^{*(0)} \right) - \check{\mathbf{A}} \sum_{t=2}^{T} \left( \mathbf{f}_{t|T}^{*(0)} \mathbf{f}_{t-1|T}^{*(0)\prime} + \mathbf{P}_{t,t-1\,|\,T}^{*(0)} \right) \right)$$

Substituting $\check{\mathbf{A}}$ and $\check{\boldsymbol{\Sigma}}_u$ in the likelihood, we obtain the concentrated likelihood:

$$\mathcal{L}(\mathbf{f}^{(0)} \,|\, \check{\mathbf{A}}, \check{\boldsymbol{\Sigma}}_u, s_1^*, \ldots, s_T^*) \;=\; \prod_{t=2}^{T} (s_t^*)^{-n} \cdot \left|\check{\boldsymbol{\Sigma}}_u\right|^{-\frac{T}{2}}$$

By numerically maximizing the concentrated likelihood we obtain the volatility parameters $\widehat{s}_t$.

*Step 3: Full sample estimation*

Given the Covid factor estimated in Step 2, we obtain all the other parameters in the model:

- Factor loadings:

$$\widehat{\boldsymbol{\lambda}}_i' \;=\; \left(\sum_{t=1}^{T}\left(\tilde{y}_{it} - \mathrm{D}^{(0)}_{i,t\,|\,T} - \zeta^{(0)}_{i,t\,|\,T}\right)\mathbf{f}^{(0)'}_{t\,|\,T} - \widehat{\gamma}_i\widehat{g}_t\right)\left(\sum_{t=1}^{T}\mathbf{f}^{(0)}_{t\,|\,T}\mathbf{f}^{(0)'}_{t\,|\,T} + \mathbf{P}^{(0)}_{t\,|\,T}\right)^{-1}$$

- Slopes of secular trend:

$$\widehat{b}_i \;=\; \left(\sum_{t=1}^{T}\left(\tilde{y}_{it} - \widehat{\boldsymbol{\lambda}}_i'\mathbf{f}^{(0)}_{t|T} - \zeta^{(0)}_{i,t|T} - \widehat{\gamma}_i\widehat{g}_t\right)t\right)\left(\sum_{t=1}^{T}t^2\right)^{-1}$$

- Variance of $I(1)$ idiosyncratic components:

$$\begin{aligned}\widehat{\sigma}^2_{e_i} \;=& \frac{1}{T}\sum_{t=2}^{T}\left(\zeta^{(0)}_{i,t|T}\zeta^{(0)'}_{i,t|T} + P^{\zeta(0)}_{i,t\,|\,T}\right) + \frac{1}{T}\sum_{t=2}^{T}\left(\zeta^{(0)}_{it-1|T}\zeta^{(0)'}_{it-1|T} + P^{\zeta(0)}_{i,t-1\,|\,T}\right) - \\ &- \frac{2}{T}\sum_{t=2}^{T}\left(\zeta^{(0)}_{it|T}\zeta^{(0)'}_{it-1|T} + P^{\zeta(0)}_{i,t,t-1\,|\,T}\right)\end{aligned}$$

- Covariance prediction error:

$$\begin{aligned}\widehat{R}_i \;=& \frac{1}{T}\left\{\sum_{t=1}^{T}\left(\tilde{y}^{(0)}_{i,t} - \widehat{\boldsymbol{\lambda}}_i^{(0)'}\mathbf{f}^{(0)}_{t|T} - \mathbb{I}_{i\in\mathcal{I}_b}\mathrm{D}^{(0)}_{i,t|T} - \mathbb{I}_{i\in\mathcal{I}_1}\zeta^{(0)}_{i,t|T} - \widehat{\gamma}_i\widehat{g}_t\right)^2 + \widehat{\boldsymbol{\lambda}}_i'\mathbf{P}^{(0)}_{t,T\,|\,T}\widehat{\boldsymbol{\lambda}}_i + \right.\\ &\left. + \;\mathbb{I}_{i\in\mathcal{I}_b}P^{\mathrm{D}(0)}_{i,t\,|\,T} + \mathbb{I}_{i\in\mathcal{I}_1}P^{\zeta(0)}_{i,t\,|\,T}\right\}\end{aligned}$$

Given the estimated parameters, using data net of the Covid component, i.e. $\tilde{\mathbf{y}}_t - \widehat{\boldsymbol{\gamma}}\widehat{g}_t$, we obtain a final estimates of all the states, $\mathbf{f}_{t\,|\,T}$, $\mathbf{D}_{t\,|\,T}$, $\mathbf{b}_{t\,|\,T}$, $\boldsymbol{\zeta}_{t\,|\,T}$ and their conditional covariances with the Kalman filter and smoother. Note that, for this final run, the Kalman filter and smoother do not need to be truncated in 2019:Q4 because we have already controlled for the Covid pandemic.

## Estimating the common trend

With the estimated factors, $\mathbf{f}_{t\,|\,T}$, we obtain an estimate of the trend and cyclical component by means of the EM algorithm. To run the algorithm, we need an initial estimate of the parameters $\boldsymbol{\psi}$, $\boldsymbol{\Sigma}_\omega$, and $\sigma^2_\nu$.

(a) Let $\widehat{\tau}_t^{(0)}$ be the initial estimate of the common trend. We set $\widehat{\tau}_t^{(0)} = f_{j,t\,|\,T}$, where $f_{j,t\,|\,T}$ is the factor explaining the largest share of long-run dynamics. Specifically, let $\widehat{S}_j(\omega)$ denote the estimated spectral density of $\Delta f_{j,t\,|\,T}$ for frequency $\omega$, and $\widehat{s}_j(\omega)$ be the corresponding standardized spectral density. Let $\bar{s}_j$ be the integral of $\widehat{s}_j(\omega)$ over frequencies $\geq 8$ years. The common trend is initialized as the factor $f_{j,t\,|\,T}$ with the highest value of $\bar{s}_j$. This corresponds to an initial value of $\boldsymbol{\psi}$, denoted as $\widehat{\boldsymbol{\psi}}^{(0)}$, such that $\widehat{\psi}_j^{(0)} = 1$ and $\widehat{\psi}_{-j}^{(0)} = 0$.

(b) Given $\widehat{\boldsymbol{\psi}}^{(0)}$ and $\widehat{\tau}_t^{(0)}$, we obtain an initial estimate of the cyclical component $\widehat{\boldsymbol{\omega}}_t^{(0)} = \mathbf{f}_{t\,|\,T}^{(0)} - \widehat{\boldsymbol{\psi}}^{(0)}\widehat{\tau}_t^{(0)}$

(c) We initialize $\sigma_\nu^2$ following Del Negro et al. (2017), so that $\widehat{\sigma}_\nu^{2,(0)} = (400\widehat{\sigma}^2_{\Delta\tau})^{-1}$, where $\widehat{\sigma}^2_{\Delta\tau}$ is the sample variance of $\Delta\widehat{\tau}_t^{(0)}$. We chose a very small value for the variance of $\widehat{\sigma}_\nu^{2,(0)}$ to incorporate our prior assumption of a slow-moving trend.

(d) Lastly, since by construction $\widehat{\boldsymbol{\omega}}_t^{(0)}$ has a sample covariance matrix of reduced rank $(q-1)$, in order to run the EM algorithm we initialize this covariance as $\widehat{\boldsymbol{\Sigma}}_\omega^{(0)} = T^{-1}\sum_{t=1}^T \widehat{\boldsymbol{\omega}}_t^{(0)}\widehat{\boldsymbol{\omega}}_t^{(0)\prime} + \kappa\mathbf{I}_q$, where we set $\kappa = 10^{-2}$, in agreement with the recommendations by Opschoor and van Dijk (2023).

Once the initial estimates for the algorithm have been computed, in the E-step we run the Kalman filter and smoother to obtain a new estimate of the trend, namely $\tau_{t\,|\,T}^{(1)}$, along with an estimate of its conditional variance and covariance, $P_{t\,|\,T}^{(1)}$ and $P_{t,t-1\,|\,T}^{(1)}$, respectively. The smoothed trend is then used to estimate the parameters in the M-step. This procedure is repeated iteratively until convergence.

For a generic iteration $k$ of the algorithm, we estimate the parameters as follow:

- Trend loadings:

$$\widehat{\boldsymbol{\psi}}^{(k)} = \left(\sum_{t=1}^{T}\mathbf{f}_{t\,|\,T}\tau_{t\,|\,T}^{(k)}\right)\left(\sum_{t=1}^{T}\tau_{t\,|\,T}^{2(k)} + P_{t\,|\,T}^{\tau(k)}\right)^{-1}$$

- Variance of common trend:

$$\widehat{\sigma}_\nu^{2(k)} = \frac{1}{T}\sum_{t=2}^{T}\left(\tau_{t|T}^{2(k)} + P_{t\,|\,T}^{\tau(k)}\right) + \frac{1}{T}\sum_{t=2}^{T}\left(\tau_{t-1|T}^{2(k)} + P_{t-1\,|\,T}^{\tau(k)}\right) -$$
$$- \frac{2}{T}\sum_{t=2}^{T}\left(\tau_{t|T}^{(k)}\tau_{t-1|T}^{(k)} + P_{t,t-1\,|\,T}^{\tau(k)}\right)$$

- Covariance of transitory component

$$\widehat{\boldsymbol{\Sigma}}_\omega^{(k)} = \frac{1}{T}\sum_{t=1}^{T}\left\{\left(\mathbf{f}_{t\,|\,T} - \widehat{\boldsymbol{\psi}}^{(k)}\tau_{t\,|\,T}^{(k)}\right)\left(\mathbf{f}_{t\,|\,T} - \widehat{\boldsymbol{\psi}}^{(k)}\tau_{t\,|\,T}^{(k)}\right)' + \widehat{\boldsymbol{\psi}}^{(k)}P_{t\,|\,T}^{\tau(k)}\widehat{\boldsymbol{\psi}}^{(k)\prime}\right\}$$

The algorithm is stopped using the likelihood-based criterion of Doz et al. (2012), with a threshold of $10^{-3}$. At convergence, we obtain an estimate of the trend and transitory components, $\tau_{t\,|\,T}$ and $\boldsymbol{\omega}_{t\,|\,T}$, respectively, along with the estimated parameters $\widehat{\boldsymbol{\psi}}$, $\widehat{\sigma}_\nu^2$ and $\widehat{\boldsymbol{\Sigma}}_\omega$.

Ultimately, given the estimated trend and transitory components, the estimated output gap and potential output are defined as:

$$\widehat{\text{PO}}_t = \text{D}_{\text{GDP},t\,|\,T} + \widehat{\boldsymbol{\lambda}}'_{\text{GDP}}\widehat{\boldsymbol{\psi}}\tau_{t\,|\,T},$$
$$\widehat{\text{OG}}_t = \widehat{\boldsymbol{\lambda}}'_{\text{GDP}}\boldsymbol{\omega}_{t\,|\,T}$$

## D Confidence bands

To obtain confidence bands for our quantities of interest, we follow the procedure outlined in Barigozzi and Luciani (2023). In particular, we simulate all the states in the model using the simulation smoother of Durbin and Koopman (2002), and we generate all the stationary residuals of the model using a stationary block bootstrap procedure (Politis and Romano, 1994). In practice, we have an estimate of all the states, namely $\mathbf{f}_{t\,|\,T}$, $\mathbf{D}_{t\,|\,T}$, $\mathbf{b}_{t\,|\,T}$ and $\boldsymbol{\zeta}_{t\,|\,T}$ , an estimate of the Covid factor $\widehat{g}_t$ and the estimated volatility parameters $\widehat{s}_t$, $t \geq t_{\text{20Q1}}$. Then, the algorithm is structured as follows:

1. Simulate the states by the simulation smoother (Durbin and Koopman, 2002)

   (a) Common factors:

      i. simulate $\tilde{\mathbf{f}}_1^{(b)} \sim N\left(\mathbf{f}_{1\,|\,T}, \mathbf{P}_{1|T}\right)$;

      ii. simulate $\tilde{\mathbf{u}}_t^{(b)} \sim N\left(\mathbf{0}_q, \check{\boldsymbol{\Sigma}}_u\right)$;

      iii. for $t = 2, \dots, T$ generate $\tilde{\mathbf{f}}_t^{(b)} = \sum_{k=1}^p \check{\mathbf{A}}_k \tilde{\mathbf{f}}_{t-k}^{(b)} + \{s_t \mathbb{I}_{t\,\geq\,t_{\text{20Q1}}} + (1 - \mathbb{I}_{t\,\geq\,t_{\text{20Q1}}})\}\tilde{\mathbf{u}}_t^{(b)}$.

   (b) $I(1)$ idiosyncratic components. For each $i \in \mathcal{I}_1$:

      i. simulate $\tilde{\xi}_{i1}^{(b)} \sim N\left(\xi_{i,1\,|\,T}, P^{\zeta}_{i,1|T}\right)$;

      ii. simulate $\tilde{e}_{it}^{(b)} \sim N\left(0, \widehat{\sigma}^2_{e_i}\right)$;

      iii. for $t = 2, \dots, T$ generate $\tilde{\zeta}_{it}^{(b)} = \tilde{\xi}_{it}^{(b)}$; $\tilde{\xi}_{it}^{(b)} = \tilde{\xi}_{it-1}^{(b)} + \tilde{e}_{it}^{(b)}$.

   (c) Time-varying secular components:

      - $i \in \mathcal{L}_1$:

         i. simulate $\tilde{b}_{i,1}^{(b)} \sim N\left(b_{i,1\,|\,T}, P^{b}_{i,1|T}\right)$, and set $\tilde{\text{D}}_{i,1}^{(b)} = \tilde{b}_{i,1}^{(b)}$;

         ii. simulate $\tilde{\eta}_t^{(b)} \sim N\left(0, \sigma^2_{\eta_i}\right)$;

         iii. for $t = 2, \dots, T$ generate $\tilde{b}_{i,t}^{(b)} = \tilde{b}_{i,t-1}^{(b)} + \tilde{\eta}_t^{(b)}$;

         iv. for $t = 2, \dots, T$ generate $\tilde{\text{D}}_{i,t}^{(b)} = \tilde{\text{D}}_{i,t-1}^{(b)} + \tilde{b}_{i,t}^{(b)}$.

      - $i \in \mathcal{L}_0$:

         i. simulate $\tilde{\text{D}}_{i,1}^{(b)} \sim N\left(b_{i,1\,|\,T}, P^{\text{D}}_{i,1|T}\right)$

         ii. simulate $\tilde{\epsilon}_t^{(b)} \sim N\left(0, \sigma^2_{\epsilon_i}\right)$;

   iii. for $t = 2, \dots, T$ generate $\tilde{\mathrm{D}}_{i,t}^{(b)} = \tilde{\mathrm{D}}_{i,t-1} + \tilde{\epsilon}_t^{(b)}$.

2. Simulate the stationary residuals of the model, $\mathbf{z}_t = (z_{1,t}, \dots, z_{n,t})'$, using a stationary block-bootstrap (Politis and Romano, 1994) with an average block length of four quarters. Denote the resulting simulated residuals as $\tilde{\mathbf{z}}_t^{(b)} = (\tilde{z}_{1,t}^{(b)}, \dots, \tilde{z}_{n,t}^{(b)})'$.

3. Generate the data. For $t = 1, \dots, T$, generate:

   (a) $\tilde{y}_{it}^{(b)} = \tilde{\mathrm{D}}_{it}^{(b)} + \widehat{\boldsymbol{\lambda}}_i' \tilde{\mathbf{f}}_t^{(b)} + \widehat{\gamma}_i \widehat{g}_t + \tilde{\zeta}_{it}^{(b)} + \tilde{z}_{it}^{(b)}$, for $i \in \{\mathcal{L}_0, \mathcal{L}_1\}$.

   (b) $\tilde{y}_{it}^{(b)} = \mathrm{D}_{i,t|T} + \widehat{\boldsymbol{\lambda}}_i' \tilde{\mathbf{f}}_t^{(b)} + \widehat{\gamma}_i \widehat{g}_t + \tilde{\zeta}_{it}^{(b)} + \tilde{z}_{it}^{(b)}$, for all other variables.

   where $\tilde{\zeta}_{it}^{(b)} = 0 \ \forall t = 1, \dots, T$ if $i \notin \mathcal{I}_1$

4. Using $\tilde{\mathbf{y}}_t^{(b)} = (\tilde{y}_{1,t}^{(b)}, \dots, \tilde{y}_{n,t}^{(b)})'$, estimate the model as described in Appendix C to get a new estimate of the loadings, $\widehat{\boldsymbol{\Lambda}}^{(b)} = (\widehat{\boldsymbol{\lambda}}_1^{(b)\prime}, \dots, \widehat{\boldsymbol{\lambda}}_N^{(b)\prime})'$, and all the other parameters in the model, as well as a new estimate of the states $\mathbf{f}_{t|T}^{(b)}, \mathbf{D}_{t|T}^{(b)}, \mathbf{b}_{t|T}^{(b)}$ and $\boldsymbol{\zeta}_{t|T}^{(b)}$.

5. Center the estimated states: $\bar{\mathbf{f}}_{t|T}^{(b)} = \mathbf{f}_{t|T} - \tilde{\mathbf{f}}_t^{(b)}$, $\bar{\mathbf{D}}_{t|T}^{(b)} = \mathbf{D}_{t|T} - \tilde{\mathbf{D}}_t^{(b)} + \mathbf{D}_{t|T}^{(b)}$, $\bar{\mathbf{b}}_{t|T}^{(b)} = \mathbf{b}_{t|T} - \tilde{\mathbf{b}}_t^{(b)} + \mathbf{b}_{t|T}^{(b)}$ and $\bar{\boldsymbol{\zeta}}_t^{(b)} = \boldsymbol{\zeta}_{t|T} - \tilde{\boldsymbol{\zeta}}_t^{(b)} + \boldsymbol{\zeta}_{t|T}^{(b)}$.

6. Run the trend cycle decomposition on the estimated factors $\bar{\mathbf{f}}_t^{(b)}$ to get a new estimate of the common trend $\tau_{t|T}^{(b)}$, the transitory component $\boldsymbol{\omega}_{t|T}^{(b)}$, and the parameter $\widehat{\boldsymbol{\psi}}^{(b)}$.

7. Estimate potential output as $\widehat{\mathrm{PO}}_t^{(b)} = \bar{\mathrm{D}}_{\mathrm{GDP},t|T}^{(b)} + \widehat{\boldsymbol{\lambda}}_{\mathrm{GDP}}^{(b)\prime} \widehat{\boldsymbol{\psi}}^{(b)} \tau_{t|T}^{(b)}$, and the output gap as $\widehat{\mathrm{OG}}_t^{(b)} = \widehat{\boldsymbol{\lambda}}_{\mathrm{GDP}}^{(b)\prime} \boldsymbol{\omega}_{t|T}^{(b)}$.

Repeating this procedure $B$ times, we obtain a distribution of the output gap: $\{\widehat{\mathrm{OG}}_t^{(b)}, b = 1, \dots, B\}$. Then, we construct the $(1-\alpha)$ confidence interval as $[\widehat{\mathrm{OG}}_t + z_{\alpha/2} \widehat{\sigma}_t^{\mathrm{OG}}, \widehat{\mathrm{OG}}_t + z_{1-\alpha/2} \widehat{\sigma}_t^{\mathrm{OG}}]$, where $\widehat{\sigma}_t^{\mathrm{OG}}$ is the sample standard deviation of $\{\widehat{\mathrm{OG}}_t^{(b)} - \widehat{\mathrm{OG}}_t\}$ and $z_{\alpha/2} = -z_{1-\alpha/2}$ is the $\alpha/2$-th quantile of a standard normal distribution.

## E Number of Common Factors

In this section, we present the results of various information criteria employed to select the number of common factors.

Assumptions (1)-(3), and (7) imply that the covariance and spectral density matrix of the differenced data $\Delta \mathbf{y}_t = (\Delta y_{1t} \cdots \Delta y_{nt})'$ has at most $q$ eigenvalues diverging as $n \to \infty$, with all the others staying bounded. This allows us to consistently recover the numbers of common factors and common trends via the log-information criteria *IC* of Bai and Ng (2002), Hallin and Liška (2007), and Alessi et al. (2010), as well at the eigenvalue-ratio criterion by Ahn and Horenstein (2013), and the test proposed by Onatski (2009). In order to avoid spurious effects from the Covid period, we employ standardized and de-meaned first-differenced data up to 2019:Q4.

Table E1: *Number of common factors*

| *Criteria* | $q$ |
|---|---|
| Alessi et al. (2010) | 4 |
| Ahn and Horenstein (2013) | 1 |
| Bai and Ng (2002) | 4 |
| Hallin and Liška (2007) | 4 |
| Onatski (2009) | 1 |

As shown in Table E1, the ABC, BN, and HL criteria suggest $q = 4$, while the AH criteria and the ON test suggest $q = 1$. We picked $q = 4$ because it is well documented that (i) the criteria of Ahn and Horenstein (2013) may underperform if there is a significant difference in the explanatory power of the different factors, which is the case in our dataset where the first factor has a much larger explanatory power than the others; and (ii) the Onatski (2009) may not perform well when $T$ is small compared to $n$.

## F Identification à la Morley et al. (2023)

Morley et al. (2024), henceforth MTW, propose an alternative trend smoothing approach to correct the estimated trend whenever it displays some serial correlation in first differences despite being assumed to be a random walk. We can apply the MTW approach in our setting by estimating an ARMA(1,1) model on the first difference of the estimated common trend $\Delta\widehat{\tau}_t^{(0)}$. The trend estimate corrected as in MTW is given by

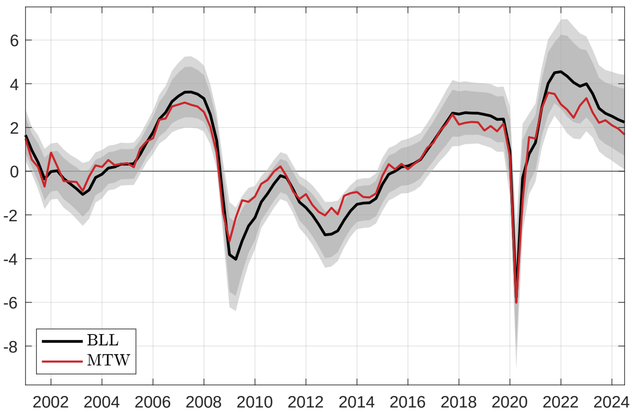
$$\Delta\widetilde{\tau}_t = \left(\frac{1+\widehat{\theta}}{1-\widehat{\phi}}\right)\widehat{\varepsilon}_t, \tag{F1}$$

where $\widehat{\phi}$ and $\widehat{\theta}$ are the estimated ARMA parameters, and $\widehat{\varepsilon}_t$ are the ARMA residuals. By cumulating $\Delta\tilde{\tau}_t$, we obtain the corrected estimate of the common trend, $\tilde{\tau}_t$.

In practice, smoothing as in (F1) seems to be less efficient than our proposal of using the Kalman smoother due to the presence of some residual Covid volatility in the estimated factors that affects the ARMA estimation. In particular, $\widehat{\mathrm{Var}}(\Delta\widehat{\tau}_t) = \widehat{\sigma}_\nu^2 = 0.092$ (computed by excluding observation in 2020 and 2021 from the calculation) when estimating the model with our method, and $\widehat{\mathrm{Var}}(\Delta\widetilde{\tau}_t) = (1+\widehat{\theta})(1-\widehat{\phi})^{-1}\widehat{\sigma}_\varepsilon^2 = 0.17$, when estimating the model as in (F1), using MTW's method, where $\widehat{\sigma}_\varepsilon^2$ is the sample variance of $\widehat{\varepsilon}_t$. Although these values are quite similar, they become very different if we compute them using the whole sample; indeed, they increase to 0.095 and 0.52, respectively. This difference is essentially due to anomalous fluctuations in the ARMA residuals $\widehat{\varepsilon}_t$ during 2020-2021.

Figure F1 compares our output gap estimate with the one obtained by applying the correction proposed by Morley et al. (2024). As expected, the two approaches yield very similar estimates, but in 2021 and 2022, when the MTW corrections reduce the estimate of the output gap from +4% to +3%.

Figure F1: *Output gap estimate with identification à la Morley et al. (2024)*




Notes: The black bold line is our estimate of the output gap. The grey shaded areas are the 68% and 84% confidence bands. The light red line is the estimated output gap obtained applying the correction of the preliminary estimated trend proposed by Morley et al. (2024) (MTW).

# G Accounting for Covid

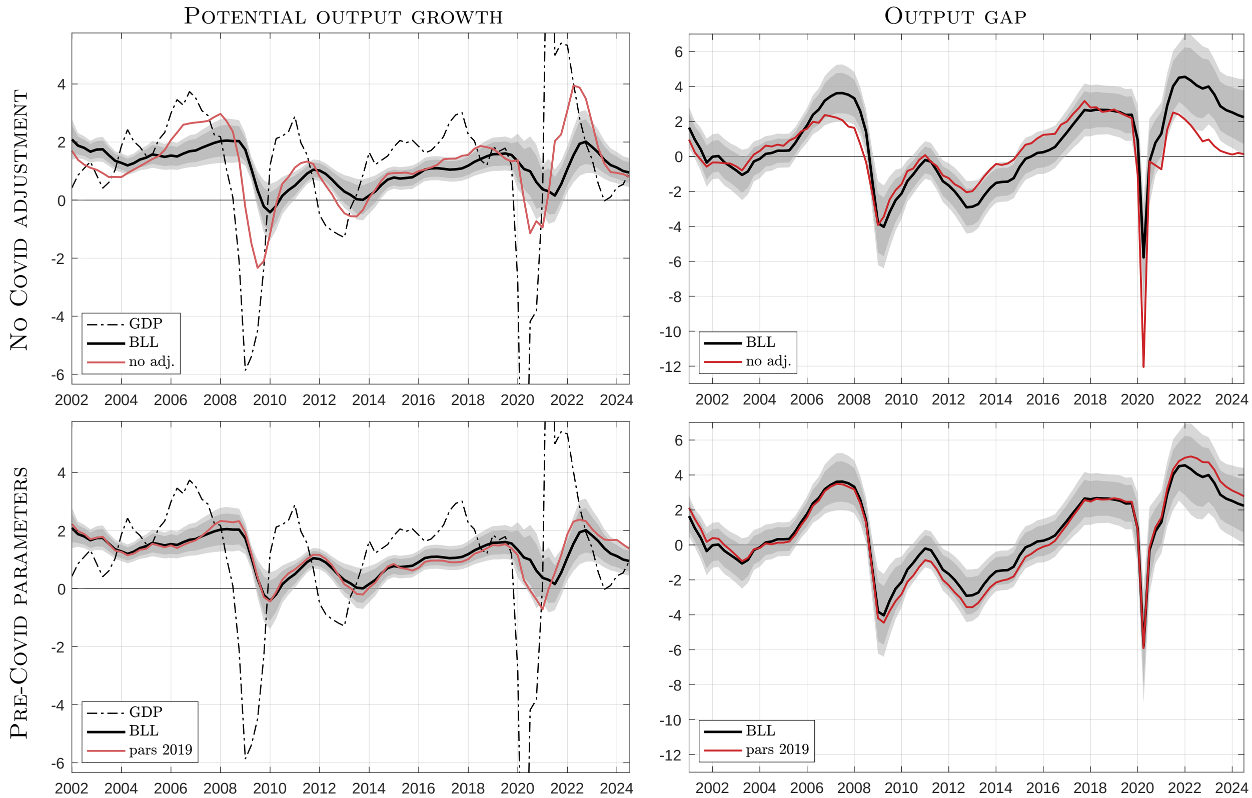
## G.1 Why adjusting for the Covid shock matters

Section 3.2 explained how we accounted for the Covid shock when estimating the model. The upper plots in Figure G1 compare our benchmark estimates with the one we would have obtained if we had estimated the model over the full sample without applying any adjustment for the Covid shock ("no adj."). As can be seen, ignoring the Covid shock affects the estimates of potential output and the output gap throughout the sample, which is undesirable; moreover, ignoring the Covid shock distorts the estimate of common dynamics in 2020 and 2021.

Having shown that accounting for the Covid shock is necessary, the question is whether a strategy different from the one we adopted would have been desirable. For example, what if we had estimated all parameters up to 2019:Q4 and then extracted the states by simply truncating the Kalman smoother? Despite being effective, this strategy is sub-optimal because estimating the parameters up to 2019 becomes less and less justifiable as new data come in. Moreover, if the increase in volatility induced by the Covid shock turns out to be very persistent, confidence intervals would be underestimated because they only account for the pre-Covid volatility regime. By accounting for the Covid shock, we avoid both these issues.

The lower plots in Figure G1 compare our benchmark estimate with the one obtained by estimating the parameters up to the last quarter of 2019 ("pars 2019"). The two estimates are very similar up to the pandemic, after which the estimate using the up-to-2019 parameters points towards much larger fluctuations

Figure G1: *Output gap when using pre-Covid parameters or without Covid adjustment*




Notes: The black solid line is our benchmark estimate and the grey shaded areas are the 68% and 84% confidence bands, the black dashed line is GDP YoY growth rate, the red lines are the estimates obtained with two alternative estimation strategies: 1. (left) fixing parameters estimated up to 2019:Q4 (pars 2019); 2. (right) estimating the model with no adjustment for Covid (no adj.).

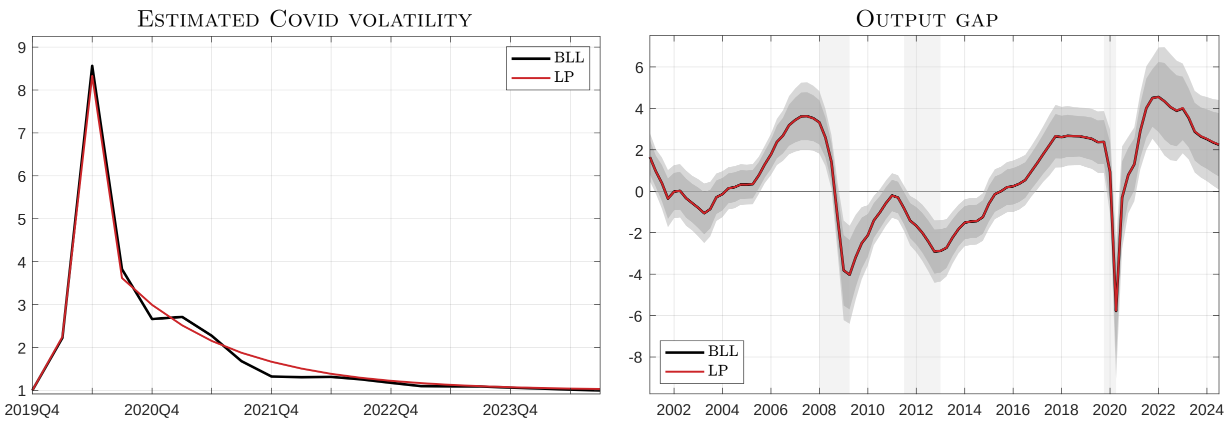
in potential output growth and a much larger output gap, which, if taken at face value, signals a very tight economy.

## G.2 Covid volatiliy

Section 3.2 explained how we accounted for the effect of the Covid shock on the volatility of the common factors. Specifically, we follow Lenza and Primiceri (2022) and introduce a factor $s_t$ that scales the volatility of the common factors from the beginning of the pandemic onward. Lenza and Primiceri (2022) analyzed monthly US data and impose an exponential decay for $s_t$ starting in June 2020. In contrast, we estimate one parameter for each period starting in 2020:Q1. This choice is motivated by both the different impact and policy response of the Covid pandemic in Europe and by the fact that, as Morley et al. (2023) pointed out, quarterly data do not allow for a sharp identification of the decay parameter.

The left plot in Figure G2 shows the estimated scaling factor $s_t$ obtained under both our parametrization (black line) and under the exponential decay parametrization proposed by Lenza and Primiceri (2022) (red line). Our estimate of the volatility closely tracks the evolution of the pandemic, as it spikes in the first two quarters of 2020 when mobility restrictions were most stringent in Europe, and pick-up again in 2021:Q1 when the spread of the Delta variant reached its peak. Moreover, we estimate that the volatility is very persistent—the decay we get is very close to 1 ($\approx 0.98$)—much more persistent than estimated by Lenza and Primiceri (2022), who estimated their model on monthly US data. This difference is likely due to the evolution of the pandemic in Europe, where mobility restriction measures were much more restrictive than in the US, lasted for longer, and were also implemented in 2021. Moreover, the Russia-Ukraine war had a much larger impact on Europe by pushing natural gas (and gasoline prices to a lesser extent) to the roof and creating a lot of macro-financial uncertainty. This result motivates the need to allow for time variation in the factor volatility until the end of the sample.

Figure G2: *Output gap estimate with alternative Covid volatility*




Notes: In the left plot, the black line is our estimate of Covid volatility ($s_t$), the red line is the estimate obtained by assuming the exponential decay parametrization of the Covid volatility as in Lenza and Primiceri (2022). In the right plot, the black line is our benchmark estimate and the grey shaded areas are the 68% and 84% confidence bands, the red line is the estimate obtained with the exponential decay parametrization of the Covid volatility.

As shown in the right plot in Figure G2, the two parametrizations lead to virtually identical results.

## G.3 Alternative estimator for the Covid factor

The approach we described in Appendix C to estimate the Covid factor has the benefit of retaining all the information in $\widehat{\boldsymbol{\xi}}_t$, but it has the problem of relying only on eight data points. That said, since we are only interested in the first eigenvector of $\widehat{\boldsymbol{\Sigma}}_{\widehat{\boldsymbol{\Xi}}^C}$, and given the extent to which the series co-moved during the Covid period, even a few data points should be informative. However, the estimates could be imprecise, thereby motivating an alternative estimation strategy.

As an alternative approach, we estimate the Covid factor by estimating the first principal component using the $T^C \times T^C$ variance-covariance matrix of the estimated idiosyncratic components from 2020:Q1 to 2021:Q4, denoted as $\tilde{\boldsymbol{\Sigma}}_{\boldsymbol{\Xi}^C}$. In order to estimate $\tilde{\boldsymbol{\Sigma}}_{\boldsymbol{\Xi}^C}$, we consider $\widehat{\xi}_{it}$ if $i \in \mathcal{I}_0$ and $\Delta\widehat{\xi}_{it}$ if $i \in \mathcal{I}_1$, i.e. we take first-differences of all non-stationary idiosyncratic components.[viii] We obtain the Covid factor and the

[viii] In this case $\widehat{\boldsymbol{\xi}}_i$ will be a $T-1$ vector denoting at time $t$ the level of the idiosyncratic component for $i \in \mathcal{I}_0$ and the growth rate of the idiosyncratic component for $i \in \mathcal{I}_1$.

corresponding loadings as:

$$\tilde{\mathbf{g}} = \sqrt{T^C} \cdot \tilde{\mathbf{V}}_{\tilde{\Xi}^C}$$

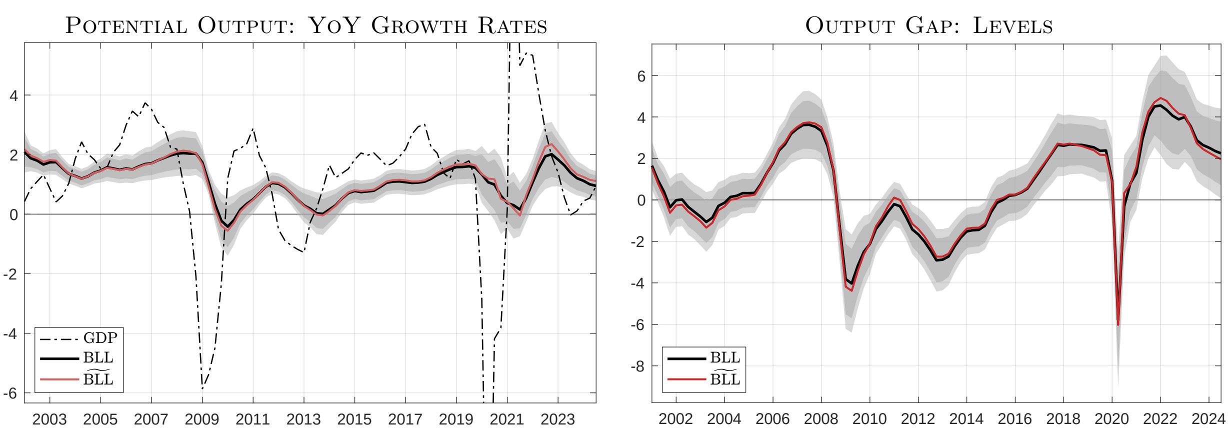
$$\tilde{\gamma} = \frac{1}{\sqrt{T^C}} \cdot (\widehat{\Xi}^C \tilde{\mathbf{V}}_{\tilde{\Xi}^C})$$

where $\tilde{\mathbf{g}}$ is the $T^C \times 1$ vector with entries $\tilde{g}_t$ and $\tilde{\mathbf{V}}_{\Xi^C}$ is the $T^C \times 1$ eigenvector corresponding to the largest eigenvalue of $\tilde{\boldsymbol{\Sigma}}_{\widehat{\Xi}^C}$. Given $\tilde{\mathbf{g}}$, the associated loadings are $\tilde{\boldsymbol{\gamma}} = (\tilde{\gamma}_1, \ldots, \tilde{\gamma}_n)'$.

This second strategy allows us to estimate $\tilde{\boldsymbol{\Sigma}}_{\widehat{\Xi}^C}$ with $N$ data points, thereby yielding a more precise estimate. However, this comes at the cost of missing important information due to differencing of the non-stationary idiosyncratic component. Which one of the two approaches is better?

As a robustness exercise, in this Appendix we look at what would have been the output gap estimate, had we adopted the second strategy to estimate the Covid factor that we just laid out. As shown in Figure G3, the results obtained with the alternative Covid factor are almost identical to those obtained in the benchmark specification. This is not surprising, since the co-movoments observed in most of the series during the Covid period are so large to be easily identified even with a limited range of observations.

Figure G3: *Output gap estimate with the alternative Covid factor*

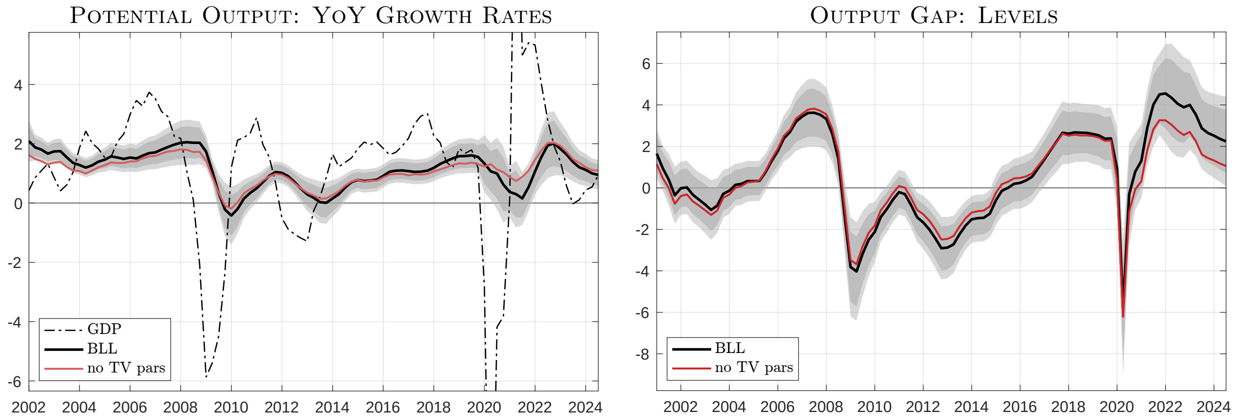



Notes: The black solid line is our benchmark estimate and the grey shaded areas are the 68% and 84% confidence bands. The red solid lines are the estimates obtained with the alternative Covid factor ($\widetilde{\text{BLL}}$). The level of the output gap is the percentage deviation from potential.

## H No time-varying parameters

Figure H1 compares the benchmark estimates of the output gap (right plot) and YoY potential output growth (left plot) with those obtained without allowing for a local linear trend for GDP, household liabilities, and long-term loans and no time-varying mean for the unemployment rate and inflation indicators. Removing the time variation in the secular trends leads to a flatter estimate of potential output growth—hence, a lower output gap—in the post-pandemic periods. This result shows that allowing for a time-varying trend for GDP is crucial to properly capture the slowdown in potential output in the latter part of the sample.

Figure H1: *Output gap estimate when imposing no time-varying parameters*




Notes: The black solid line is our benchmark estimate, the grey shaded areas are the 68% and 84% confidence bands, the black dashed line is GDP YoY growth rate, the red line is the estimate obtained without time-varying parameters (no TV pars). The level of the output gap is the percentage deviation from potential.

## I Comparison with alternative measures

In this section, we compare our estimates of potential output and the output gap with those obtained using four different univariate filters and one multivariate approach:

1) The Hodrick and Prescott (1997) filter (HP), with two different values for the smoothing parameter $\lambda$: (i) $\lambda = 1600$, commonly used for quarterly data, (ii) $\lambda = 51200$, as proposed by Borio (2014) to capture variability at lower frequencies.

2) The Hamilton (2018) filter (Ham), where the trend is the $8-$step ahead forecast of quarterly GDP growth, obtained using the 4 most recent values of quarterly GDP for each time $t$, and the cycle is the residual obtained from this regression.

3) The boosted HP filter (bHP) of Phillips and Shi (2021), which improves on the standard HP filter by applying the filter recursively on the residuals extracted from previous iterations. The number of iterations $m$ is a tuning parameter that controls the intensity of the updating, and it is chosen to minimize the information criterion proposed by the authors.

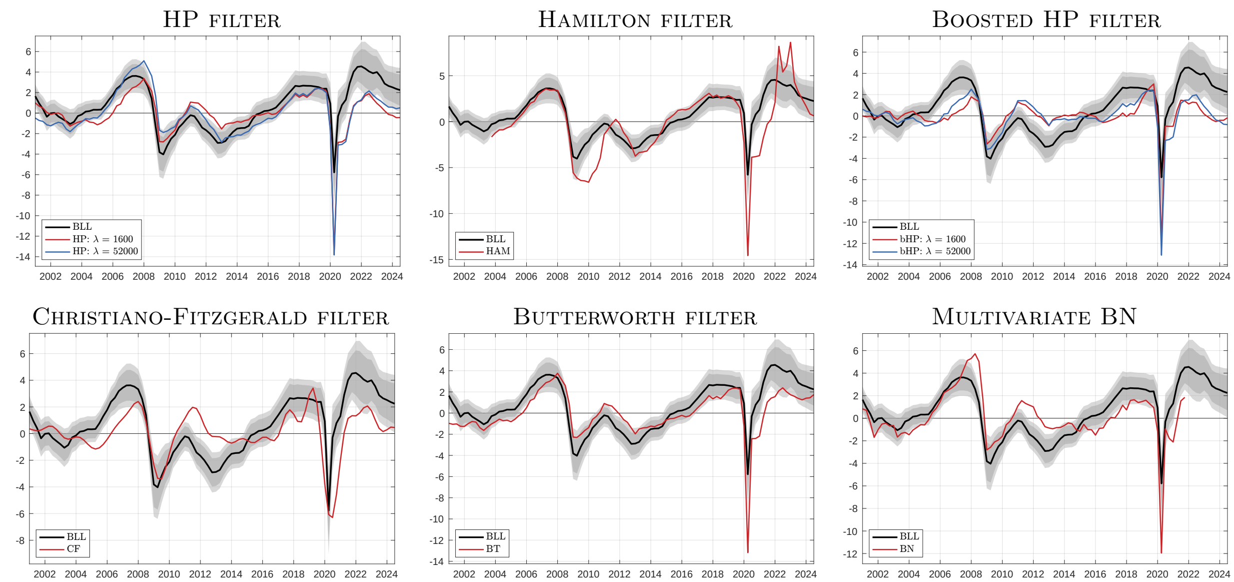
4) The Christiano and Fitzgerald (2003) filter (CF), with cutoff frequencies for the transitory component between 8 and 32 quarters.

5) A Butterworth filter (BT) for the transitory component, as proposed by Canova (2025). This filter can be cast in state-space form, and its squared-gain function defines the frequencies attributed to the cycles. Here, we employ a first-order polynomial $n = 1$, with a cutoff point for the frequency set at $\omega = 0.04$ and scale $G_0 = 1$.

6) The multivariate Beveridge-Nelson (BN) decomposition based on a large Bayesian VAR, as proposed by Morley et al. (2023). The authors estimate the Euro Area output gap from 1999:Q1 to 2021:Q3. Here, due to the lack of availability of their data, we keep their original estimates, truncating the figure in correspondence with our starting point, i.e. 2001:Q1.

Figure I1 presents the results of this exercise. Overall, the output gap obtained with our methodology aligns with those estimated with univariate models in terms of peaks and troughs. However, there are several differences in terms of shape and amplitude.

Figure I1: *Output gap estimates with alternative methods*




Notes: The black line is our benchmark estimate and the grey shaded areas are the 68% and 84% confidence bands, the red and blue lines are alternative estimates.

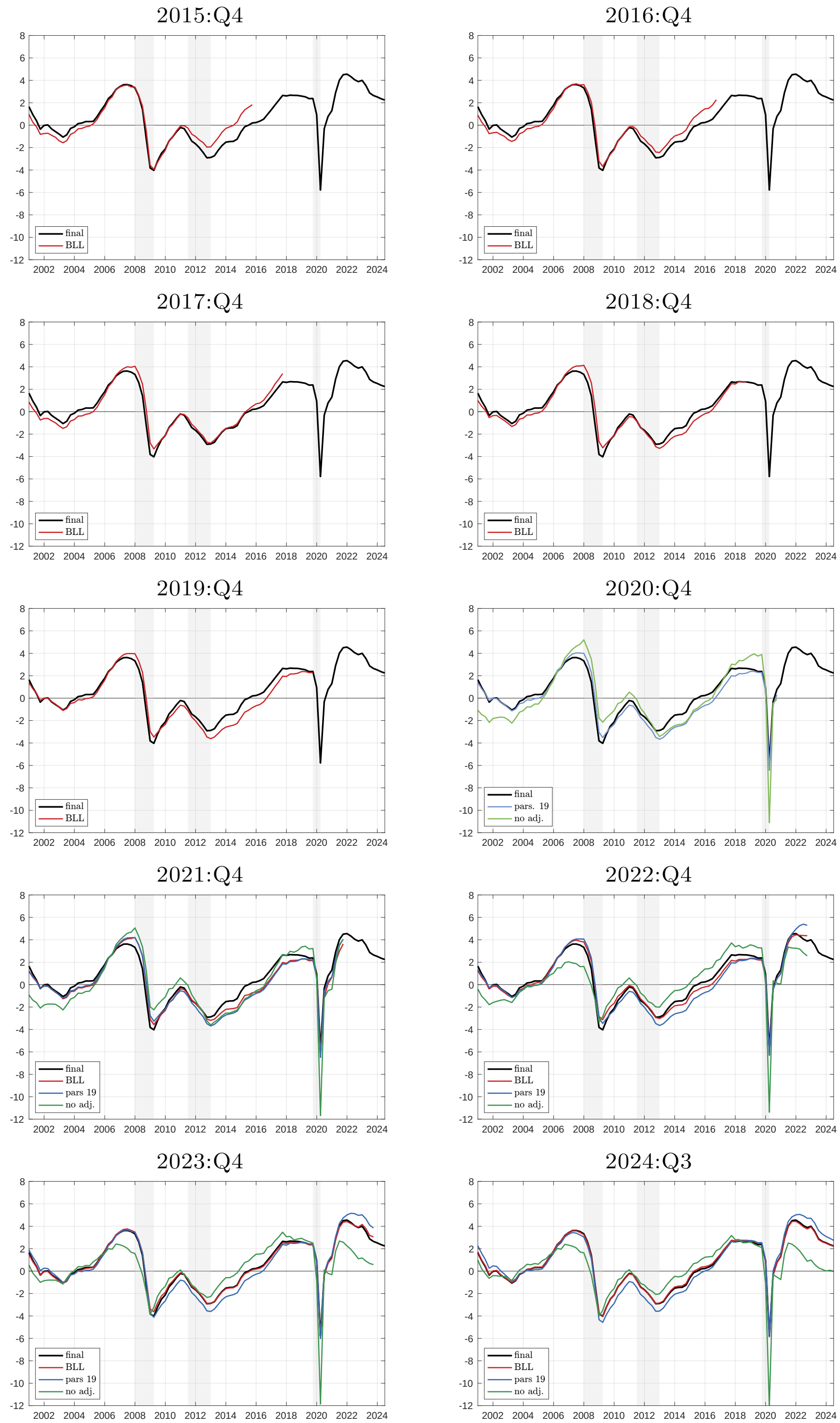
## J Real-time reliability

There is skepticism in the literature on the reliability of model-based output gap estimates in real time because of the size of end-of-sample revisions (Orphanides and van Norden, 2002). Model-based estimates of the output gap are subject to revisions in real time because new information leads to changes in both the estimates of the model parameters and the latent states. In this section, we assess the reliability of our output gap estimate through a *quasi*-real-time exercise on expanding windows, where the first window begins in 2000:Q1 ends in 2015:Q1 ($T = 57$).

Looking at the upper charts in Figure J1, it is clear that the model is slow in recognizing how deep the 2012 Sovereign debt crisis is, only doing so once data for 2016 becomes available. Inasmuch as this result is disappointing, we cannot help but notice that 60 observations are probably too few to pin down the output gap accurately. As more information becomes available, the model's estimate of the output gap stabilizes, so much so that from 2017 onward, the *quasi*-real-time estimate is very close to the final estimate.

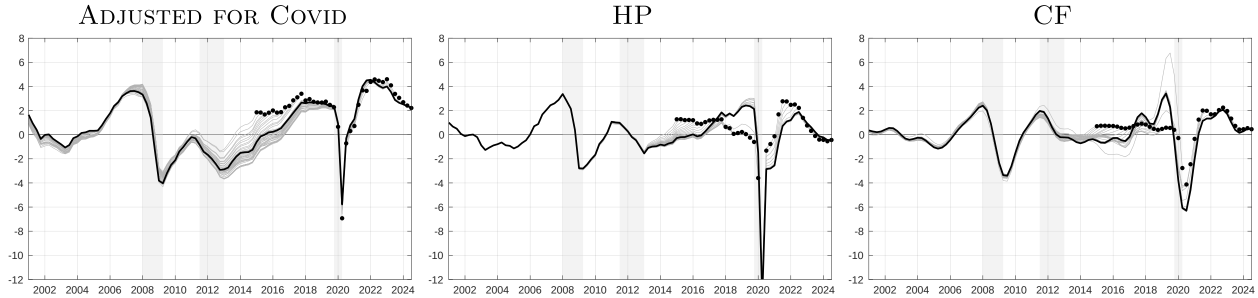
Moving to the Covid pandemic and its aftermath, it is evident that our strategy for adapting to the COVID shock was viable only starting from the second half of 2020 or even 2021. Moreover, it is reasonable to assume that anybody would have understood that doing nothing and allowing the Covid shock to affect the estimates was a huge mistake. Thus, we consider the *quasi*-real-time performance of the simple strategy of freezing the parameters to pre-Covid data. As shown by the green line, if we had followed this approach, we would have had very reliable output gap estimates, as opposed to extreme estimates, had we chosen to do nothing. Finally, by comparing the red and the green lines, we can appreciate the impact of the adjustment we implemented to account for the Covid shock.

FIGURE J1: *Output Gap: quasi-real time, expanding window*




NOTES: The black line is the estimate of the output gap obtained using the final sample of data, up to 2024:Q3. The red line in Figure J1 displays the evolution of our *quasi*-real-time estimate of the output gap obtained using the procedure outlined in Section 3. The blue line shows the estimate we would have obtained without any adjustment for the Covid shock. Lastly, the green line is the estimate we would have obtained if we had frozen the parameter estimate at the value in 2019:Q4.

Figure J2: *Output gap: quasi-real time results*




Notes: the black line is the estimate of the output gap obtained over the full sample, and the thin grey lines are the estimate obtained on all the other subsamples. Each black dots represent the estimate of the output gap for quarter $Q$ and year $Y$ obtained on the sample ending at quarter $Q$ and year $Y$.

Figure J2 compares the *quasi*-real-time estimate of the output gap from our model with those obtained from an HP filter and a Christiano-Fitzgerald band-pass filter. As mentioned earlier, our estimate's weakness is that the one obtained on the sample ending in 2015 is quite different from the final estimate. However, its strength is that from 2017 onward, the *quasi*-real-time estimates converge to the final and are very robust. In contrast, the HP filter and the Christiano-Fitzgerald filter yield *quasi*-real-time estimates that are never to far from the final estimate. However, they converge to the final estimate very late, making them unreliable for real-time analysis.

## References

Ahn, S. C. and A. R. Horenstein (2013). Eigenvalue ratio test for the number of factors. *Econometrica 81*, 1203–1227.

Alessi, L., M. Barigozzi, and M. Capasso (2010). Improved penalization for determining the number of factors in approximate factor models. *Statistics & Probability Letters 80*(23-24), 1806–1813.

Antolin-Diaz, J., T. Drechsel, and I. Petrella (2017). Tracking the slowdown in long-run GDP growth. *The Review of Economics and Statistics 99*, 343–356.

Bai, J. (2004). Estimating cross-section common stochastic trends in nonstationary panel data. *Journal of Econometrics 122*, 137–183.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica 70*, 191–221.

Bai, J. and S. Ng (2004). A PANIC attack on unit roots and cointegration. *Econometrica 72*, 1127–1177.

Barigozzi, M., M. Lippi, and M. Luciani (2021). Large-dimensional dynamic factor models: Estimation of impulse-response functions with $I(1)$ cointegrated factors. *Journal of Econometrics 221*, 455–482.

Barigozzi, M. and M. Luciani (2023). Measuring the Output Gap using Large Datasets. *The Review of*

*Economics and Statistics 105*, 1500–1514.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance 45*, 182–198.

Canova, F. (2025). FAQ: How do I estimate the output gap? *The Economic Journal 135*, 59–80.

Casalis, A. and G. Krustev (2022). Cyclical drivers of euro area consumption: What can we learn from durable goods? *Journal of International Money and Finance 120*, 102241.

Cette, G., J. Fernald, and B. Mojon (2016). The pre-Great Recession slowdown in productivity. *European Economic Review 88*, 3–20.

Christiano, L. J. and T. J. Fitzgerald (2003). The bandpass filter. *International Economic Review 44*, 435–465.

Del Negro, M., D. Giannone, M. P. Giannoni, and A. Tambalotti (2017). Safety, liquidity, and the natural rate of interest. *Brookings Papers on Economic Activity Spring 2017*, 235–316.

Del Negro, M., F. Schorfheide, F. Smets, and R. Wouters (2007). On the fit of new Keynesian models. *Journal of Business & Economic Statistics 25*, 123–143.

Doz, C., D. Giannone, and L. Reichlin (2012). A quasi-maximum likelihood approach for large, approximate dynamic factor models. *The Review of Economics and Statistics 94*, 1014–1024.

Durbin, J. and S. J. Koopman (2002). A simple and efficient simulation smoother for state space time series analysis. *Biometrika 89*, 603–616.

Gordon, R. J. (2018). Declining American economic growth despite ongoing innovation. *Explorations in Economic History 69*, 1–12.

Hallin, M. and R. Liška (2007). Determining the number of factors in the general dynamic factor model. *Journal of the American Statistical Association 102*, 603–617.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *The Review of Economics and Statistics 100*, 831–843.

Hamilton, J. D. (2020). *Time series analysis*. Princeton university press.

Hodrick, R. J. and E. C. Prescott (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking 29*, 1–16.

Jarociński, M. and M. Lenza (2018). An inflation-predicting measure of the output gap in the euro area. *Journal of Money, Credit and Banking 50*, 1189–1224.

Lenza, M. and G. E. Primiceri (2022). How to estimate a vector autoregression after March 2020. *Journal of Applied Econometrics 37*, 688–699.

Lippi, M. and L. Reichlin (1994). Diffusion of technical change and the decomposition of output into trend and cycle. *The Review of Economic Studies 61*, 19–30.

Morley, J., D. Rodríguez-Palenzuela, Y. Sun, and B. Wong (2023). Estimating the euro area output gap using multivariate information and addressing the COVID-19 pandemic. *European Economic Review 153*, 104385.

Morley, J., T. D. Tran, and B. Wong (2024). A simple correction for misspecification in trend-cycle decompositions with an application to estimating $r$. *Journal of Business & Economic Statistics 42*, 665–680.

Ng, S. (2018). Comments on the cyclical sensitivity in estimates of potential output. *Brookings Papers on Economic Activity 49*, 412–423.

Onatski, A. (2009). Testing hypotheses about the number of factors in large factor models. *Econometrica 77*, 1447–1479.

Opschoor, D. and D. J. van Dijk (2023). Slow Expectation-Maximization convergence in low-noise dynamic factor models. SSRN working paper 4408065.

Orphanides, A. and S. van Norden (2002). The unreliability of output-gap estimates in real time. *The Review of Economics and Statistics 84*, 569–583.

Phillips, P. C. and Z. Shi (2021). Boosting: Why you can use the HP filter. *International Economic Review 62*, 521–570.

Politis, D. N. and J. P. Romano (1994). The stationary bootstrap. *Journal of the American Statistical Association 89*, 1303–1313.

Stock, J. H. and M. W. Watson (2025). Recovering from COVID. Brookings Paper on Economic Activity Conference Draft, March 27-28, 2025. link.