Persistent and Transitory Inflation in the Euro Area: Insights from Global and Domestic Shocks *

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First draft 10.04.2022

Current version 06.10.2024

Abstract

This paper investigates the drivers behind the post-COVID inflation surge in the euro area by assessing global and domestic shocks from the perspectives of demand and supply. To address this, the paper introduces a novel econometric framework that integrates several key features within a unified setup: (1) the characterization of both long-term trends and business cycle dynamics, including variables such as potential GDP, trend inflation, the output gap, and the inflation gap; (2) the modelling of time-varying volatilities and fat-tailed distributions to account for extreme observations that can significantly affect parameter estimates; and (3) the identification of structural shocks, focusing on their nature—whether transitory or permanent—and their channels, whether global or domestic, demand- or supply-side, or energy-related. The findings provide evidence that both global supply shocks and demand shocks are behind the post-COVID surge in euro area inflation. However, unlike the existing literature, I find that global supply shocks primarily feed into the persistent component of euro area inflation, raising trend inflation to 3% by 2022. In contrast, demand shocks—both domestic and global—manifest primarily in the transitory component (inflation gap), which explains approximately 85% of the total post-COVID increase in inflation.

JEL classification: E32, E44.

Keywords: Inflation Dynamics, Trends and Cycles, Permanent and Transitory Shocks, Stochastic Volatility, Domestic-Global, Demand-Supply.

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†This paper previously circulated under the title "Stable, missing and wild inflation: The case of the euro area". This paper is a revised version of one of the chapters of my Ph.D. dissertation produced at Universidad de Alicante. I am grateful to Prof. Gabriel Pérez-Quirós for his guidance and advice. This paper has also benefited from the insightful comments of Beatriz de Blas, Joan Paredes, Iván Payá, and Marta García-Rodríguez. I thank all the professors at the Alicante Macroeconomic PhD Workshop, and participants at ASSET 2023, 48th Simposio Spanish Economic Association, and IAAE 2024. I acknowledge the financial support from the Universidad de Alicante and the receipt of a full fee waiver for the 48th Simposio SAEe.

1. Introduction

Inflation had remained a relatively minor concern for many years, but since the global economic reopening following the COVID-19 pandemic, inflation has surged to levels not seen in 40 years. This study emerges in the context of a multifaceted economic crisis triggered by the pandemic, with significant shocks originating from both global and domestic factors. The public health crisis initially introduced a supply shock, bringing the global economy to a halt and causing severe economic dislocations. This was soon followed by a demand shock, driven by the reopening of economies, expansive fiscal stimulus, and eventually exacerbated by an energy supply shock following the Russian invasion of Ukraine.

This paper seeks to address two questions: (1) What are the structural channels driving euro area (EA) inflation? By examining both global and domestic shocks from the perspectives of demand and supply. (2) Do these structural channels primarily affect the transitory (inflation gap) or the persistent (trend inflation) components of euro area inflation? In answering these questions, I confront the various demand and supply shocks to uncover their relative contributions to inflation, while distinguishing between their transitory and persistent effects on inflation dynamics.

This paper examines these questions across three distinct periods: (i) the stable period of anchored inflation around 2%, (ii) the period of "missing inflation" from 2012 to 2017, and (iii) the current environment of elevated inflation following the COVID economic reopening. Additionally, the analysis sheds light on the re-emergence of the debate concerning the *'de-anchoring of inflation expectations'*, both from below the 2% target during 2012-2017 and from above the 2% level after 2020.[1]

This paper builds on and integrates two key methodologies commonly employed in the study of inflation fluctuations within a unified framework. The first is to determine the underlying drivers responsible for the observed inflation dynamics. Recently, Ciccarelli and García (2021) highlighted the role of a global inflation channel in transmitting inflation spillovers from the U.S. to the euro area. Ascari et al. (2024) found that global supply shocks were the dominant driver of EA inflation in 2022. Researchers at the ECB, Arce et al. (2024), identified supply shocks, particularly energy supply shocks, as the main driver of EA inflation dynamics after the economic reopening. Conversely, Giannone and Primiceri (2024) indicated that post-pandemic inflation in both the euro area and the U.S. has been predominantly driven by demand-side forces. However, these studies do not distinguish whether these channels primarily affected inflation through its persistent component, its transitory component, or both.

The second approach is the application of an unobserved components trend-cycle model. For example, Jarociński and Lenza (2018) found that trend inflation in the euro area remained

[1] This debate has been ongoing in both academic and policy circles since inflation remained persistently below target after 2012, despite expectations of a rise in inflation due to the ongoing recovery. Notably, the average headline inflation in the euro area from 2012Q1 to 2018Q4 was just 1.28%. In contrast, current inflation dynamics represent a paradigm shift, with EA headline inflation now reaching a 40-year high.

relatively stable at the 2% level from 2000 to 2016. In other words, the missing disinflation was primarily driven by negative transitory developments in inflation (i.e., the inflation gap). However, their analysis did not identify the potential factors driving either the inflation gap or trend inflation.

This paper is built around three core components that guide the analysis: (1) Decomposition of variables as in Del Negro et al. (2017, 2019): The model breaks down macroeconomic variables into their long-term and business-cycle components, such as potential GDP (trend inflation), and the output gap (inflation gap). (2.) Time-varying volatilities and fat-tails as in Jacquier et al. (2004): The inclusion of stochastic volatility and fat-tailed error distributions accommodates extreme observations (such as the COVID-19 outliers), which could otherwise distort parameter estimates. These features are crucial for capturing the heightened uncertainty and volatility in the data.[2] (3.) Structural shock identification: The model diagnoses structural shocks by focusing on their nature (transitory vs. permanent) and their channels (global and domestic, from both the supply and demand sides, as well as energy supply shocks). The identification of shocks relies on sign and magnitude-restrictions, distinguishing supply-side shocks—where output and inflation move in opposite directions—from demand-side shocks, which result in positive comovement. In identifying energy supply shocks, I follow the lessons learned from Kilian (2008, 2009). To differentiate between domestic and global shocks, I follow the methodology of Corsetti, Dedola and Leduc (2014), which assumes that global shocks have a greater effect on global variables than on domestic ones, and vice versa for domestic shocks.[3] In summary, this model allows me to examine the time-varying channels through which shocks affect the economy and to determine whether these shocks have permanent or transitory effects on euro area headline inflation and other macroeconomic variables from the early 1990s to 2024Q1.

I document the following findings: (1) Trend inflation fluctuations: The Euro Area (EA) trend inflation has experienced two significant declines. In the 1990s, trend inflation decreased from 4% to 2%, where it remained anchored for nearly two decades. A second major decline occurred between 2012Q3 and 2016Q1, where trend inflation dropped from 2% to 1%. The decline in trend inflation during 2012-2016 aligns with the demand-side view—both domestic and global—highlighted by Ciccarelli et al. (2017), although I find it to be affecting the persistent component of inflation. While, during the previous period, EA inflation gap is driven by domestic shocks.

(2) Post-COVID EA inflation surge: Following the strong post-COVID economic reopening, trend inflation rose above the 2% level, reaching approximately 3% by 2022Q2.[4] This increase was predominantly driven by global supply shocks, which fed into the persistent component

[2]See Carriero et al. (2021); Lenza and Primiceri (2022); Schorfheide and Song (2021) for similar approaches addressing COVID-19 outliers in VAR models.

[3]To identify global shocks, this paper leverages global measures, consistent with the open-economy perspective on inflation dynamics, as explored in Martínez-García and Wynne (2010), Kabukçuoğlu and Martínez-García (2018), and Duncan and Martínez-García (2023).

[4]The estimated EA trend inflation features similar comovement with inflation swaps of five, ten and twenty years ahead. See Figure 12 within Appendix C.

of inflation. These shocks likely reflect disruptions such as supply chain bottlenecks. Notably, around 85% of the total increase in EA inflation is captured in the inflation gap, primarily explained by demand (domestic and global) shocks. The surge in demand can be attributed to factors such as pent-up consumption, expansive fiscal stimulus measures, and accommodative monetary policy. The rise of trend inflation above 2% suggests that EA inflation is expected to remain persistently above the ECB's target in the medium term. This finding is consistent with the recent analysis by Hilscher et al. (2022), which identifies a high risk of persistent inflation in 2022. Similarly, Reis (2022) explores different channels driving the sudden rise in inflation. Although these trend inflation dynamics are not yet fully documented in the literature, they align with the ECB's evolving disinflation path and its revised monetary policy strategy. By the end of 2022, the ECB adjusted its stance on inflation, shifting from the view that *'the current inflation spike is temporary and driven largely by transitory factors'* in 2021Q4, to *'[...] inflation is expected to decline from an average of 8.4% in 2022, 6.3% in 2023, 3.4% in 2024, and 2.3% in 2025. [...] Headline inflation is expected to fall to the ECB's medium-term inflation target of 2% in the second half of 2025'* by 2022Q4.

(3) Aggregate demand and supply (Phillips) curves: The model suggests that the apparent flatness of the Phillips curve in reduced-form models is primarily due to a flat demand curve, implying a stable supply curve. This finding is consistent with strong credibility of price stability policies. For the flat demand curve to align with one of the paper's key findings—that the EA inflation gap was predominantly driven by demand shocks—shifts in the aggregate demand (AD) curve must be driven by large-magnitude demand shocks. These shocks are reflected with the marked increase in the volatility of the inflation gap.[5] Additionally, the finding of a flat demand curve is consistent with the recent work of Giannone and Primiceri (2024), who argue that an upward shift in the AD curve can be attributed to the ECB's accommodative monetary policy between 2021-22.

(4) Second moments and potential GDP: Excluding stochastic volatility from the model can compromise the accurate decomposition of variables. Specifically, during the COVID-19 period, the sharp decline in real GDP is split between potential GDP and the output gap, leading to an exaggerated reduction in potential GDP. In addition, the model estimates a significant slowdown in EA potential GDP growth, with quarter-on-quarter growth falling from an average of 0.50% during the early 1990s to 2005-06, to just 0.24% from 2006 onwards.[6] This deceleration is primarily driven by global factors, including both demand and supply-side shocks. Furthermore, this result aligns with theories of a permanent shift in globalization, particularly following the synchronized collapse of world trade in late 2008, triggered by a sudden, globally coordinated postponement of purchases, especially of durable consumer goods and investments. These insights are supported by the works of Baldwin (2009), Levchenko et

[5] The methodology used to identify the aggregate demand and supply (Phillips) curves follows Bergholt, Furlanetto and Vaccaro-Grange (2023).

[6] This finding aligns with the documented slowdown in U.S. trend GDP growth by Antolin-Diaz et al. (2017) and Maffei-Faccioli (2021), who attribute the decline in long-run output growth to permanent demand-side shocks.

al. (2010), Alessandria et al. (2010), and Chor and Manova (2012).

Related Literature. The primary contribution of this paper is the introduction of a model that captures within a unified framework: (1) the structural channels driving EA inflation by examining both global and domestic shocks from demand and supply perspectives; (2) the decomposition of variables into trends and cycles, providing a clearer understanding of how and which shocks affect these components; and (3) the incorporation of time-varying second moments, incorporated to handle extreme observations such as the COVID-19 outliers, which could otherwise distort parameter estimates. These features enable the model to comprehensively diagnose the channels of shocks (supply or demand, global or domestic) and assess whether these shocks have permanent or transitory effects on macroeconomic variables.

Given the extensive literature on inflation processes, this paper does not aim to provide an exhaustive survey. Instead, it seeks to position itself within the more relevant literature to highlight its specific contribution, particularly with respect to the euro area.

This work is closely related to the literature investigating the determinants of inflation, both from a historical perspective and in light of recent inflation dynamics. Much of this literature relies on structural models—typically Vector Autoregressive (VAR) models—that do not assess whether macroeconomic shocks affect the persistent or transitory components of macroeconomic variables. Several papers have used these frameworks to explore the historical drivers of inflation before the COVID-19 pandemic. For instance, Ferroni and Mojon (2014) emphasize the role of global demand shocks, which explain much of the inflation rise in 2008 and the subsequent decline in the following years. Similarly, Conti et al. (2017) identify a combination of domestic and global demand shocks in 2008-09, as well as the negative effects of energy supply and domestic demand shocks during the "missing inflation" episode. Ciccarelli et al. (2017) highlight, after 2008, the importance of global shocks, and during the prolonged period of low inflation, distinguishing two stages: a first driven by domestic shocks and a second by global shocks. Bobeica and Jarociński (2019) also point to global demand factors as key drivers of inflation in 2008, while attributing the "missing inflation" episode primarily to domestic shocks.

Regarding more recent inflation dynamics, Ciccarelli and García (2021) explore whether rising U.S. inflation in mid-2021 signaled a return of global inflation. They find that a global inflation channel, operating through inflation compensation markets, reinforces international spillovers from U.S. to euro area inflation. Ascari et al. (2024) identify global supply bottlenecks as the dominant driver of Euro Area inflation in 2022. Similarly, several recent *ECB Economic Bulletin* reports and papers (Arce et al. (2024); Banbura et al. (2023)) share a common finding: current inflation surges are heavily influenced by global supply chain disruptions and energy pressures.[7] In contrast, Giannone and Primiceri (2024) argue that post-pandemic inflation in the euro area has been predominantly driven by demand-side forces. My findings reconcile

[7] Also, see O'Brien et al. (2021); Koester et al. (2021, 2022); ECB (2022).

these results by providing evidence that global supply shocks primarily fed into the persistent component of inflation, pushing it higher. Meanwhile, demand shocks—both domestic and global—explain much of the rise in the transitory component of inflation.

Finally, a recent study of U.S. inflation by Ascari and Fosso (2024) investigates the drivers of U.S. trend inflation and provides evidence supporting the "globalization of inflation" hypothesis. While both their model and mine utilize a trend-cycle BVAR, some notable differences arise. Their identification of shocks and techniques differ between the trend and cycle parts, making it challenging to reconcile the channels affecting the two components. Moreover, their model assumes constant second moments over time, in contrast to the time-varying approach used in this paper.

My model approach builds on the reduced-form decomposition model of Del Negro et al. (2017, 2019).[8] Seminal contributions to this literature began with the univariate models of Beveridge and Nelson (1981), Harvey (1985), Watson (1986), and Clark (1987). In the 2000s, Stock and Watson (2007) extended these models by incorporating stochastic volatility into a univariate unobserved component trend-cycle framework. Within this context, much of the euro area literature has focused on the de-anchoring of inflation expectations, particularly medium- to long-term, or trend inflation. This research primarily seeks to explain the "missing inflation" phase and, more recently, the post-COVID inflation surges.

A key challenge in this area is estimating trend inflation. Various studies have approached this problem differently: for instance, Strohsal and Winkelmann (2015), Gimeno and Ortega (2016), and Hilscher et al. (2022) rely on Euro Area investors' inflation swaps, while Jarociński and Lenza (2018), Corsello et al. (2021), and Dovern et al. (2020) use professional inflation expectations in the Euro Area. Additionally, Łyziak and Paloviita (2017) employ both professional forecasters' and consumers' inflation expectations in their analysis. The resulting findings diverge considerably. For example, while Gimeno and Ortega (2016) detect a slowdown in long-term inflation expectations, falling from 2% since late 2014, Jarociński and Lenza (2018) observe a remarkably stable trend inflation at the 2% level from 2000 to 2016. This paper supports the view of a gradual de-anchoring starting in 2012, consistent with the findings of Gimeno and Ortega (2016), Łyziak and Paloviita (2017), Corsello et al. (2021), and Hilscher et al. (2022). In contrast, my results show evidence against a strong version of anchored inflation expectations during the mid-2010s, contrary to what is suggested by Strohsal and Winkelmann (2015), Jarociński and Lenza (2018), and Dovern et al. (2020). Additionally, my model indicates a rise in trend inflation above 2% post-COVID, aligning with Hilscher et al. (2022), who identify a high risk of persistent inflation in 2022.

Relative to the aforementioned research, this paper introduces several notable econometric features: it does not rely on arbitrary inflation proxies or preliminary de-trending techniques,

[8] My model is essentially an extension of their Vector Autoregressive (VAR) model with common trends taking into account stochastic volatility and fat-tails.

which can introduce distortions.[9] In addition, the model incorporates a rich lag structure to capture dynamic heterogeneity within the cyclical components—capturing multivariate and lagged commonalities in real, nominal (including energy prices), and labor market variables at business cycle frequencies. The cyclical components in the model link the output gap to prices and their expectations via a global Phillips curve relationship, and to unemployment via Okun's law. Furthermore, the model features time-varying second moments. Finally, it allows for detailed decomposition analysis, providing historical decompositions of variables into their permanent and cyclical structural drivers.

The remainder of this paper is structured as follows. In the next section, I introduce the data, detailing its sources and the transformations applied. Section 3 describes the econometric methodology and the shock identification framework. Section 4 presents the empirical decompositions of inflation and real GDP, with Section 4.B focusing on the structural dynamics of trend inflation and the inflation gap, and Section 4.C examining the structural dynamics of potential GDP and the output gap. Section 4.D identifies the aggregate demand and supply (Phillips) curves. Finally, Section 5 concludes the paper.

2. Data: Sources, Transformation and Description

Sources. Data are gathered from two main institutions EuroStat and OECD, and back-dated using the Area Wide Model (AWM) database of Fagan, Henry and Mestre (2005). The frequency of the data are quarterly and spans the period 1970Q1-2024Q1. My dataset consists of two blocks, euro area and whole world. From EuroStat's database, I collect for the euro area the following variables: real GDP, unemployment, consumer confidence indicator, Harmonised Index of Consumer Prices (HICP), price perception of households over the next 12 months, unit labor cost index, and energy price index. From OECD's database, I collect the following variables: OCDE's real GDP and HICP - as proxy of the whole world.[10] Finally, my database is characterized by a 'ragged edge', i.e., it has missing values.

Transformations. The series that are not already available in seasonal adjusted form are seasonally adjusted using JDemetra+ 2.2 - this software uses the following algorithm X-13ARIMA-SEATS. Table 1 reports for each variable the name (column 1), mnemonic (column 2), transformation (column 3), and the data span including the back-dated period. A brief comment is needed for variables y^8 and y^9, that represent the GDP and HICP of the world, respectively. These two variables are defined as the ratio between the analogous euro area variable and OCDE. This transformation becomes relevant, in Section 3, to implement the sign

Variable name	Symbol	Transformation	Data span
Real GDP	y^1	log	1970.Q1 - 2024Q1
Unemployment Rate	y^2	Δ Q-Q	1970.Q1 - 2024Q1
Consumer Confidence	y^3	none	1985.Q1 - 2024Q1
HICP	y^4	Δlog Q-Q	1970.Q1 - 2024Q1
Price Perception HH	y^5	none	1985.Q1 - 2024Q1
Unit Labor Cost Index	y^6	Δlog Q-Q	1970.Q1 - 2023Q4
Energy Price Index	y^7	log	1987.Q4 - 2024Q1
World Real GDP (WRG)	y^8	log(y^1) - log(WRG)	1970.Q1 - 2024Q1
World HICP (WH)	y^9	Δ (log(y^4) - log(WH)) Q-Q	1970.Q1 - 2024Q1

Table 1. Description of the variables

restrictions identification proposed by Corsetti, Dedola and Leduc (2014).

3. Econometric Methodology

The model described in this section is the Vector Autoregressive (VAR) model with common trends of Del Negro, Giannone, Giannoni and Tambalotti (2017, 2019) featuring stochastic volatility (in a similar spirit as Primiceri (2005)) and Student's t-distribution (as in Geweke (1993)). Hence, it is a standard decomposition model of multivariate time series that embeds two hierarchical levels of latent variables. First, series are jointly decomposed into trends - slow-moving variables that are different from typical business cycle fluctuations (e.g potential GDP, trend inflation) - and cycles - fast-moving variables that are the typical business cycle fluctuations (e.g output-gap, energy price cycle, inflation-gap). Second, the variance covariance matrices of both, trends and cycles, are allowed to change over time (adding the second hierarchical level of unobserved components). In addition, the model structure and common identification scheme allows me to easily separate the nature of a set of shocks - energy, global and domestic factors - into permanent and transitory structural shocks, and assess potential changes in terms of volatility overtime. Finally, the underlying structural drivers are identified using sign restrictions.

3.A. The Model: A VAR with Common Trends featuring Stochastic Volatility

The model is given by the measurement equation

$$y_t = \Lambda \bar{y}_t + \tilde{y}_t, \tag{1}$$

[9]For example, some studies account for a trend inflation using exogenous exponentially weighted moving averages of headline inflation, while others apply ad-hoc de-trending filters like the Hodrick-Prescott (HP) filter. See the critique by Hamilton (2018) on the limitations of the HP filter.

[10]The consumer confidence and price perception of households over the next 12 months indicators are qualitative surveys, that are reported as aggregated diffusion time series for the euro area. The frequency of these diffusion series is monthly, so I transform them taking quarterly averages.

where y_t is an n $\times$ 1 vector of observables, $\bar{y}_t$ is a q $\times$ 1 vector of trends, q $\leq$ n, $\Lambda(\lambda)$ is an n $\times$ q matrix of loadings that is restricted and depends on the vector of free parameters λ, and $\tilde{y}_t$ is an n $\times$ 1 vector of stationary components. The rank of Λ, which is equal to q, determines the number of common trends, and the number of cointegrating relationships is therefore n - q. Hence, $\Lambda(\lambda)$ maps the trend component $\bar{y}_t$ to the dependent variable y_t. Both $\bar{y}_t$ and $\tilde{y}_t$ are latent variables and evolve according to the following transition equations, a random walk with drift

$$\bar{y}_t = \bar{c} + \bar{y}_{t-1} + \epsilon_t, \text{ with } \epsilon_t \sim \mathcal{N}(0, \Sigma_t^{\epsilon}), \tag{2}$$

and a VAR

$$\tilde{y}_t = \sum_{j=1}^{P} A_j \tilde{y}_{t-j} + u_t, \text{ with } u_t \sim \mathcal{N}(0, \Sigma_t^{u}) \tag{3}$$

respectively, where the $A_j s$ are n$\times$n matrices.[11]

In this model, the shocks affecting the trend (ϵ_t) and the cycle (u_t) are orthogonal to one another. This implies that my model is a type of "independent trend/cycle decomposition". See Watson (1986), Stock and Watson (1988), and Stock and Watson (2007),for an introduction in standard unobserved component models. This assumption helps introducing in a standard way, time-varying elements in the covariance matrices of the trend and cycle, and a common identification scheme of the structural shocks for the trend and cycle.

The covariance matrices of the error terms ϵ_t and u_t - Σ_t^{ϵ} and Σ_t^{u} - have time-varying elements. The modelization and its core assumptions follow Primiceri (2005), Benati and Mumtaz (2007) and Galí and Gambetti (2009). The structure of the heteroscedastic unobservable shocks is very similar for the permanent and stationary shocks, with two main differences: 1. The dimension of Σ_t^{ϵ} is a q$\times$q matrix, and Σ_t^{u} is of dimension n$\times$n. 2. The innovations of the cycle feature fat-tails and stochastic volatility, while the innovations of the trend only include stochastic volatility.[12] The stochastic volatility helps to capture standard-frequency movements at the cycle's and trend's volatility, see Stock and Watson (2007) for a univariate representation. While, the fat-tails elements capture outliers and extreme realizations over time in the cycle, for example the COVID lockdown.

I consider the following structure for the covariance matrices,

$$\Sigma_t^{\epsilon} = \Phi_{\epsilon,t}^{-1} H_{\epsilon,t} (\Phi_{\epsilon,t}^{-1})', \tag{4}$$

$$\Sigma_t^{u} = \Phi_{u,t}^{-1} H_{u,t} (\Phi_{u,t}^{-1})', \tag{5}$$

where $\Phi_{\epsilon,t}$ and $\Phi_{u,t}$ are lower triangular matrices with elements $\phi_{ij,t}^{\epsilon}$ and $\phi_{ij,t}^{u}$, respectively. $H_{\epsilon,t}$

[11] The drift is incorporated in the trend of variables that enter in levels and contain a time-trend, such as euro area GDP, energy price index, and the ratio between the euro area and world GDP.

[12] The modelling of both fat-tails and stochastic volatility, for the innovations of the cycle, help ease the standard conservative priors (in terms of degrees of freedom) that trend-cycle model usually require to identify the slow and fast-moving latent variables. For example, Del Negro et al. (2017, 2019) impose quite tight and conservative priors on the trend side, by imposing the degrees of freedom equal to a hundred.

is a diagonal matrix with diagonal elements $h^{\epsilon}_{i,t}$, while $H_{u,t}$ is a diagonal matrix with diagonal elements $h^{u}_{i,t}$ and $\delta_{i,t}$ - $diag\left(\frac{h^u_{1,t}}{\delta_{1,t}}, \cdots, \frac{h^u_{i,t}}{\delta_{i,t}}, \cdots, \frac{h^u_{n,t}}{\delta_{n,t}}\right)$.

The structure of Φ^z_t, where z = { ϵ, u}, is

$$\Phi_{z,t} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ \phi^z_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \phi^z_{k1,t} & \dots & \phi^z_{kk-1,t} & 1 \end{pmatrix},$$

where the elements in each row follow

$$\phi^z_{i,t} = \phi^z_{i,t-1} + V^z_{i,t}, \mathrm{Var}\left(V^z_{i,t}\right) = D^z_i, \tag{6}$$

for $i = 1 \cdots k$, where k = { q, n}. I assume that the non-zero and non-one elements of $\Phi_{z,t}$ belonging to different rows evolve independently, with

$$D^z = \begin{bmatrix} D^z_1 & 0_{1\times 2} & \dots & 0_{1\times(k-1)} & 0_{1\times k} \\ 0_{2\times 1} & D^z_2 & \ddots & 0_{2\times k-1} & 0_{2\times k} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0_{(k-1)\times 1} & 0_{k-1\times 2} & \ddots & D^z_{k-1} & 0_{(k-1)\times k} \\ 0_{k\times 1} & 0_{k\times 2} & \ddots & 0_{k\times(k-1)} & D^z_k \end{bmatrix}.$$

In other words, $V^z_{i,t}$ and $V^z_{j,t}$ are uncorrelated for j $\neq$ i.

The structure of H^{ϵ}_t and H^u_t is

$$H_{\epsilon,t} = \begin{bmatrix} h^{\epsilon}_{1,t} & 0 & \dots & 0 \\ 0 & h^{\epsilon}_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & h^{\epsilon}_{q,t} \end{bmatrix}, H_{u,t} = \begin{bmatrix} \frac{h^u_{1,t}}{\delta_{1,t}} & 0 & \dots & 0 \\ 0 & \frac{h^u_{2,t}}{\delta_{2,t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \frac{h^u_{n,t}}{\delta_{n,t}} \end{bmatrix},$$

with

$$\ln h^{\epsilon}_{i,t} = \ln h^{\epsilon}_{i,t-1} + Z^{\epsilon}_{i,t}, \mathrm{Var}\left(Z^{\epsilon}_{i,t}\right) = g^{\epsilon}_i, \tag{7}$$

$$\ln h^{u}_{i,t} = \ln h^{u}_{i,t-1} + Z^{v}_{i,t}, \mathrm{Var}\left(Z^{u}_{i,t}\right) = g^{u}_i, \tag{8}$$

, with slithery abuse of notation, for $i = 1 \cdots$ q / n. I assume that $Z^z_{i,t}$ and $Z^z_{j,t}$ are uncorrelated for j $\neq$ i, with

$$G^z = \begin{bmatrix} g_1^z & 0 & 0 & 0 \\ 0 & g_2^z & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & g_k^z \end{bmatrix}.$$

In line with Geweke (1993), the weights $[\delta_{1,t}, \delta_{2,t}, \cdots, \delta_{n,t}]$ are indexed by time t, since they are meant to capture extreme volatility movements (fat-tails) over time in the cycle, hence potentially providing an effective treatment of outliers and extreme events. $[h_{n,t}^1, h_{n,t}^2, \cdots, h_{n,t}^u]$ captures standard-frequency movements in the cycle's volatility. It is worth noting the following relationships

$$\Phi_{\epsilon,t}(H_{\epsilon,t})^{-1/2}\epsilon_t = w_t^\epsilon, \mathrm{Var}\left(w_t^p\right) = I_q,$$
$$\Phi_{u,t}(H_{u,t})^{-1/2}u_t = w_t^u, \mathrm{Var}\left(w_t^t\right) = I_n.$$

Hence, as shown by Geweke (1993), assuming a Gamma prior for $\delta_{i,t}$ of the form $p(\delta_{i,t}) = \prod_{t=1}^T p(\delta_{i,t}) = \prod_{t=1}^T \tilde{\Gamma}(1, \kappa_{\delta,i})$ leads to a scale mixture of normals for the orthogonal residuals w_t^u, with mean 1 and degrees of freedom $\kappa_{\delta,i}$.[13] This assumption allows the degrees of freedom for the Student's t-distribution to be independent across equations and simplifies the estimation algorithm. To further simplify the estimation of the model, I assume that w_t^ϵ, w_t^u, V_t^ϵ, V_t^u, Z_t^ϵ, Z_t^u are mutually uncorrelated.[14]

As discussed earlier, there are two noteworthy things about this type of trend-cycle model. First, the model decomposes observed variables (y_t) into some slow-moving variables (trends) and fast-moving variables (cycles). Second, this model has two sets of time varying 'coefficients' $\phi_{ij,t}^\epsilon$ and $\phi_{ij,t}^u$ - for the trend and cycle parts -, two stochastic volatility parameters for the diagonal elements of each component, $h_{i,t}^\epsilon$ and $h_{i,t}^u$, and fat-tails ($\delta_{i,t}$) that capture infrequent volatility movements over time in the cycle.

Baseline specification. In the baseline specification, y_t contains nine macroeconomic variables, see table 2. Column two and three describe the macroeconomic trends (five in total - q = 5), and cycles (nine in total - n = 9) characterizing the set of variables in the system. The estimation sample spans the period 1990Q1-2022Q2.[15]

Slow-moving variables: 1. The EA output trend - that I label as EA potential GDP - is restricted to be common across only real EA GDP.[16]

[13]This formulation is equivalent to a specification that assumes Student's t-distribution for w_t^u with $\kappa_{\delta,i}$ degrees of freedom.

[14]These assumptions advocate for a block-diagonal structure for the joint set of innovations in the model. This is convenient for several reasons: First, parsimony, as the model is already quite heavily parameterized. Second, as discussed earlier, it heavily simplifies the estimation algorithm. Third, similar structures are used in other types of model, e.g. TVP-VAR-SV models - see Primiceri (2005, pp. 6-7).

[15]The series used in the baseline specification are available, some of them, from 1970Q1 - see table 1. The period 1970Q1-1989Q4 is used as presample to inform the priors on the initial conditions of the trend and the cycle, which I discuss in the next section.

[16]The drift coefficient in the unit root process, that constantly accumulates over time, can be thought as an

Variable name	Trend	Cycle
Real GDP	Potential GDP	Output Gap
Unemployment Rate	none	Unemployment Cycle
Consumer Confidence	none	Consumer Confidence Cycle
HICP	Trend Inflation	Inflation Gap
Price Trends next 12 m	Trend Inflation	Price Expectation Cycle
Unit Labor Cost Index	Trend Inflation	Labor Cost Cycle
Energy Price Index	Trend Energy	Energy Price Cycle
World GDP	Potential WGDP	World Output Gap
World HICP	Trend W Inflation	World Inflation Gap

Table 2. Description of the variables

2. The persistent component of inflation (trend inflation) is extracted using the information in inflation, households' perceived inflation, and the unit labor cost (a proxy for firms' inflation expectations).[17] Unit labor costs (defined as the growth of nominal wage adjusted per employee) play a role in shaping firms' inflation expectations by influencing future firms' pricing decisions. In theoretical models, the unit labor cost and price inflation are closely interrelated in the medium / long-run. This is due to prices and nominal wages must adjust relative to each other to be consistent with the fact that, in the long-run, the real wage is determined by slow-moving factors such as productivity, wage demands or bargaining power.[18][19]

3. The energy trend which is restricted to be common to EA energy prices. This assumption is standard to be able to estimate an 'energy price cycle', see Hasenzagl et al. (2018). Moreover, Kilian (2008) highlights the important influence of energy prices on economic performance. In particular, Kilian points to the role of energy price fluctuations. In principle, permanent disturbances coming from energy prices should be very low, since the major movements in energy prices should come from the cycle part (which have a temporary influence on the economy).

4. The fourth and fifth trends denote the world potential output and world trend inflation. These two trends are of core use if one seeks to understand the importance of global supply and demand shocks. In particular, to address whether global demand–supply imbalances have potential permanent effects after the pandemic shock.

average effect of technological innovation.

[17] Recently, Candia, Coibion and Gorodnichenko (2021) show that firms' inflation expectations exhibit many of the characteristics of households' inflation expectations and dramatically depart from the inflation expectations of professional forecasters. Moreover, recent empirical evidence for the euro area (e.g. Álvarez and Correa-López (2020)) shows that time series that contain information about households' and firms' perceived inflation are better at predicting inflation than professional forecasters or financial markets - in the context of open economy Phillips curves. In another work, Coibion and Gorodnichenko (2015) present new econometric and survey evidence consistent with firms having similar expectations as households. Moreover, they show evidence that inflation expectation of professional forecasters do not proxy well the expectations of households.

[18] For the case of the euro area, in a recent paper of Bobeica et al. (2019), they find that there is a clear link between the rate of change in labor cost and the rate of change in prices. Moreover, they find that this link becomes stronger when inflation is high. However, in this paper I do not explore that this link could depend on an inflation regime, given that it would make the second part of structural analysis too difficult and cumbersome.

[19] In my model, labor cost inflation and price inflation are cointegrated. Then, gradual changes in the long-run labor cost inflation are mapped to the trend inflation. This assumption implies that in the cost of living enter the dynamics of nominal wages. Hence, I am capturing potential second-round reactions of the labor cost to actual inflation.

The main reason for estimating five trends is to identify the following permanent shocks: domestic demand and supply-side factors, energy supply factors, and global demand and supply-side factors. The identification scheme is presented in the next section.

Fast-moving variables: The macroeconomic cycles are characterized for the same number of variables in the system, nine. Notice that changes in unemployment and the consumer confidence indicator are left trendless.[20] Finally, the information gathered within the interrelation of these macroeconomic cycles - output gap ($\tilde{y}^1$), unemployment cycle ($\tilde{y}^2$), consumer confidence ($\tilde{y}^3$), inflation gap ($\tilde{y}^4$), price expectation cycle ($\tilde{y}^5$), labor cost cycle ($\tilde{y}^6$), energy price cycle ($\tilde{y}^7$), world output gap ($\tilde{y}^8$), and world inflation cycle ($\tilde{y}^9$) - can be compared to a Dynamic Stochastic General Equilibrium (DSGE) model. To be more precise, the cycle VAR structure nests several structural models, for example: (i) a range of Phillips curve models, since inflation can be a purely forward-looking process, driven by expectations on inflation (price expectation cycle) or expectations of future real economic activity (consumer confidence). Moreover, it integrates 'the triangle model of inflation', where potential fluctuations of inflation in response to the temporary influence of movements in energy prices (energy price cycle), the degree of resource utilization in the economy (output-gap and unemployment cycle).[21] To understand inflation dynamics from an open economy perspective, it also takes into account a global Phillips curve part.[22] (ii) From the perspective of the EA output-gap, it features the inverse relation of the Okun's law since output is linked to unemployment fluctuations. Moreover, it captures how slack in real output is affected when potential international political events arise – as is the case for oil price, food and beverages, and the recent global supply bottlenecks. Hence, my model accounts for a wide variety of sources that can modify the interrelation of these macroeconomic cycles.

3.B. Priors and Estimation Procedure

Priors. First, I need to specify a distribution for the initial conditions $\bar{y}_0$ and $\tilde{y}_{0:-p+1} = (\tilde{y}'_0, \cdots, \tilde{y}'_{-p+1})'$ are distributed according to $\bar{y}_0 \sim \mathcal{N}\left(\underline{y_0}, I_q\right)$ and $\tilde{y}_{0:-p+1} \sim \mathcal{N}\left(0, \underline{\Sigma_0^{\mathcal{A}}}\right)$, where $\underline{y_0}$ and $\underline{\Sigma_0^{\mathcal{A}}}$ are computed using pre-sample data.

Starting with the prior for $\Lambda(\lambda)$ is given by $p(\lambda) = N(1, 0.5^2)$, the product of independent Gaussian distributions for each element λ of the matrix $\Lambda(\lambda)$. The drift $\bar{c}$ incorporated in the random walks of the trends is assumed to follow a diffuse normal prior, $\mathcal{N}(\underline{c}_{y,0}, 10)$ with mean $\underline{c}_{y0}$, that represents the average growth rate of the pre-sample variables. The priors for the VAR coefficients $\mathcal{A} = (A_1, \ldots, A_p)$ have a normal posterior distribution with mean $\bar{\mathcal{A}}$ and variance

[20] The inclusion of unemployment and consumer confidence are particularly important for proper estimation of the stationary component of GDP- i.e., the output gap. In fact, core now-casting models, used in many Central Banks, rely on these two core variables. See Laxton and Tetlow (1992); Kamber et al. (2018) and Barbarino et al. (2020), for a more recent view.

[21] See Gordon (1981, 1988). Moreover, it reflects the view of Yellen (2016) which is widely shared by policy makers and central bankers. See also the work of Hasenzagl et al. (2018) that emphasizes the inclusion of an energy price cycle.

[22] The importance of including cyclical global activity measures is suggested in Martínez-García and Wynne (2010); Kabukçuoğlu and Martínez-García (2018); Duncan and Martínez-García (2023).

$\bar{\Sigma}^{\mathcal{A}}$, based on prior mean $\underline{\mathcal{A}}$ and $\underline{\Sigma_0^{\mathcal{A}}}$, where:

$$(\bar{\Sigma}^{\mathcal{A}})^{-1} = (\underline{\Sigma_0^{\mathcal{A}}})^{-1} + \sum_{t=1}^{T} \Big((\Sigma_t^u)^{-1} \otimes \tilde{x}_t \tilde{x}_t' \Big),$$

$$\text{vec}(\bar{\mathcal{A}}) = \bar{\Sigma}^{\mathcal{A}} \left\{ \text{vec}\left(\sum_{t=1}^{T} (\Sigma_t^u)^{-1} \tilde{y}_t \tilde{x}_t' \right) + (\underline{\Sigma_0^{\mathcal{A}}})^{-1} \text{vec}(\underline{\mathcal{A}}) \right\} I(\text{vec}(\underline{\mathcal{A}})),$$

$\tilde{x}_t$ contains the lags of $\tilde{y}_t$ and $I(\text{vec}(\underline{\mathcal{A}})$ is an indicator function that is equal to 0 if the VAR is explosive - some of the eigenvalues of $\mathcal{A}(L)$ are greater than 1 - and to 1 otherwise. Hence, I am enforcing a stationarity constraint on the VAR. Moreover, the prior for the VAR parameters $\text{vec}(\underline{\mathcal{A}})$, describing the components $\tilde{y}_t$, is a standard Minnesota prior with the hyperparameter for the overall tightness equal to the commonly used value of 0.2 (see Giannone, Lenza and Primiceri (2015)), and centered at zero rather than one, since I am dealing with stationary processes. Finally, the VAR uses four lags (p = 4).

The priors for the variance-covariance time-varying elements follows Benati and Mumtaz (2007) and Geweke (1993), with some minor modifications to take into account the important differences between the permanent (Σ_t^{ϵ}) and transitory (Σ_t^u) matrices governing each process. Prior distributions for the time-varying elements in the permanent side are going to be scaled down by a factor of one hundred. Such a choice is clearly arbitrary, but motivated by my goal of informing to the model that the former elements should have much lower volatility than its counter part (the transitory elements). In other words, the elements belonging to the slow-moving variables should resemble two features: (i) low volatility in magnitude and (ii) low expected changed in volatility. This approach helps me to deal with the problem of label switching in mixture models in order to reliably recover the entire posterior distribution.[23]

Following Geweke (1993), I set a hierarchical prior on the parameter controlling the degree of freedom of the Student's t distributions $\kappa_{\delta,i}$ and the weighting vector $\delta_{i,t}$, for $i = 1, \ldots, n$:

$$p(\kappa_{\delta,i}) \sim \tilde{\Gamma}(n_0, 2),$$
$$p(\delta_{i,t}) \sim \tilde{\Gamma}(1, \kappa_{\delta,i}).$$

The prior mean n_0 is assumed to equal 20. This allocates a substantial prior weight to fat-tailed distributions as well as distributions that are approximately Normal. In order to calibrate the prior distributions for $\phi_{ij,0}^z$ and $h_{i,0}^z$, I 'estimate' a time-invariant version of 1 based on an unbalanced dataset, from 1970 Q1 to 1989 Q4.[24] Let Σ_0^z be the estimated variance-covaraince matrices from the time-invariant decomposition model. Let L^z be the lower-triangular Choleski factor of Σ_0^z - i.e., $L^z L^{z'} = \Sigma_0^z$. The initial conditions for the stochastic volatily process, $\ln h_0^u$ and $\ln h_0^{\epsilon}$, are set to follow a $\mathcal{N}(\ln \mu_0^u, 10 \times I_n)$ and $\mathcal{N}(\ln \mu_0^{\epsilon}, 0.1 \times I_q)$, respectively. The prior

[23]See Geweke (2007) and Stephens (2000).

[24]This is not a real estimation. I run just a few iterations MCMC to decompose the pre-sample data into trends and cycles, and obtain the matrices of interest. Notice that this procedure yields 'studpid' elements (i.e., $\phi_{ij,0}^{\epsilon}, \phi_{ij,0}^{u}, h_{i,0}^{\epsilon}$ and $h_{i,0}^{u}$).

means, $\mu_0^z = \{\mu_0^\epsilon, \mu_0^u\}$ is a vector collecting the logarithms of the squared elements on the diagonal of L^z. Then each column of L^z is divided by the corresponding element on its diagonal - i.e., $\tilde{L}^z$ are the rescaled matrices - and set the initial conditions of the elements below the diagonal, $\phi_{ij,0}^u$ and $\phi_{ij,0}^\epsilon$, to follow a $\mathcal{N}(\tilde{\phi}_{ij,0}^u, \tilde{V}(\tilde{\phi}_{ij,0}^u))$ and $\mathcal{N}(\tilde{\phi}_{ij,0}^\epsilon, \tilde{V}(\tilde{\phi}_{ij,0}^\epsilon))$, respectively. The prior means of $\tilde{\phi}_{ij,0}^z$ are the non-zero and non-one elements of $\tilde{L}^z$ (i.e., the elements below the diagonal). The variance-covariance matrices, $\tilde{V}(\tilde{\phi}_{ij,0}^u)$, are postulated to be diagonal with each individual (i,i) element equal to the absolute value of the corresponding $\tilde{\phi}_{ij,0}^z$.

The matrices in D^z are also calibrated following Benati and Mumtaz (2007). D^z follow a diffuse inverse Wishart - $p\left(D_i^z\right) = I\mathcal{W}\left(\kappa_{D,i}, \kappa_{D,i}(\eta_z \underline{D_i^z})\right)$ - with just enough prior degrees of freedom, $\kappa_{D,i}$, set equal to the number of rows in $\underline{D_i^z}$ plus two to have a well-defined prior mode. The mode $\underline{D_i^z}$ is scaled by the number of degrees of freedom and $\eta_{u,\epsilon} = \{10^{-3}, 10^{-5}\}$. Each $\underline{D_i^z}$ is composed of the row elements below the diagonal in $\tilde{L}^z$.

Finally, as for the variances of the stochastic volatility innovations (i.e., the diagonal elements of G^z), I follow Cogley and Sargent (2005). They postulate an inverse-Gamma distribution, $g_j^z \sim I\mathcal{G}\left(\frac{\kappa_G}{2}, \frac{\underline{g_i^z}}{2}\right)$, for the elements of G^z with κ_G degrees of freedom and prior mode $\underline{g_i^z}$. I use different prior modes to take into account the important differences between the permanent (G^u) and transitory (G^ϵ) volatility innovations. In this way, I am informing the model to not mix permanent and transitory volatility processes. For the stochastic volatility innovations from the transitory part, I use the same specifications as Cogley and Sargent (2005), $g_j^u \sim I\mathcal{G}\left(\frac{1}{2}, \frac{10^{-4}}{2}\right)$. The choice of for the stochastic volatility innovations belonging to the permanent part are chosen accordingly to represent specific features. In this sense, I set the mode of diagonal elements of the matrix $\underline{G}^\epsilon = \{\underline{g}_1^\epsilon, \underline{g}_2^\epsilon, \underline{g}_3^\epsilon, \underline{g}_4^\epsilon, \underline{g}_5^\epsilon\}$ to $\underline{G}^\epsilon = \{8.3 * 10^-6, 3.3 * 10^-5, 8.6 * 10^-5, 8.3 * 10^-6, 3.3 * 10^-5\}$. A priori, it implies that the expected change over a period of a hundred years in the volatility of potential GDP, inflation trend, energy trend, potential world GDP, and world inflation trend is 0.33, 1.33, 3.33, 0.33, 1.33 percentage points, respectively.[25] In addition, these priors are a little bit tighter, than previous ones. As I set the degrees of freedom equal to five (i.e., $\kappa_G = 5$). There are two intrinsic reasons for the selection of these priors: (i) to ensure these do not reflect business cycle fluctuations; and (ii) to a priori prevent scenarios such as de-anchoring of long-term inflation trend. Nevertheless, if data spoke loudly in favor of relevant movements in the low-frequency components of the system, it would push away from the prior assumptions.[26]

Estimation. The state-space model, given by equations 1 through 8, is efficiently estimated with Bayesian methods - Gibbs Sampling and Metropolis Hastings algorithm - using Kalman Filter, in conjunction with modern simulation smoothing techniques (Carter and Kohn (1994)) that easily help me to accommodate missing observations, and draw the latent states. All results are based on 250,000 simulations, of which I discard the first 245,000 as burn-in draws

[25] Relative to the ones of the cycle component, the current prior mean values exhibit reductions by factors of 12 for GDP trends, 3 for inflation trends, and 1.2 for energy trends.

[26] While in the baseline specification I specify the same prior on the variance-covariance matrix of the trend components for the euro area and the world, this could be in principle different for the two region components.

and save every 10th draw in order to reduce the autocorrelation across draws.[27] Section A of the appendix describes the Gibbs sampler, which accommodates the hierarchical decomposition model to different modeling choices.

3.C. Shock Identification Strategy

As discussed in the introduction, I identify the shocks that are mostly emphasized in the inflation literature. These structural factors are energy supply, global and domestic from a demand and supply side. All of them are identified from a permanent and transitory perspective to properly understand inflation dynamics.

In order for me to make economically meaningful statements with respect the channels of shocks, I need to impose restrictions on the variance-covariance matrices $(\Sigma_t^{\epsilon}, \Sigma_t^{u})$. These restrictions help me to map the economically meaningful structural shocks from the estimated reduced-form residuals. In this sense, I first introduce the mapping between reduced-form and structural trend residuals be $\epsilon_t = B_t w_t^P$, where B_t is a non-singular matrix such that $B_t B_t' = \Sigma_t^{\epsilon}$ and $w_t^p \sim N(0_{q,1}, I_{q,q})$ are the structural permanent shocks with unit variance. Last, the mapping between reduced-form and transitory structural residuals be $u_t = C_t w_t^T$, where C_t is a non-singular matrix such that $C_t C_t' = \Sigma_t^u$ and $w_t^t \sim N(0_{n,1}, I_{n,n})$ are the structural transitory shocks with unit variance.

Notice that the latent variables - i.e., trends and cycles - in equation 1 can be rewritten as follows,

$$
\begin{aligned}
y_t =& \Lambda\Big(\bar{y}_0 + \sum_{h=1}^{t} h\bar{c} + \sum_{j=0}^{t-1} \epsilon_{t-j}\Big) + \sum_{j=0}^{t-1} \tilde{A}_j u_{t-j} \\
=& \Lambda\Big(\bar{y}_0 + \sum_{h=1}^{t} h\bar{c} + \sum_{j=0}^{t-1} B_{t-j}B_{t-j}^{-1}\epsilon_{t-j}\Big) + \sum_{j=0}^{t-1} \tilde{A}_j C_{t-j} C_{t-j}^{-1} u_{t-j} \\
=& \Lambda\Big(\bar{y}_0 + \sum_{h=1}^{t} h\bar{c}\Big) + \Lambda \underbrace{\sum_{j=0}^{t-1} B_{t-j} w_{t-j}^P}_{\text{Permanent Shocks}} + \underbrace{\sum_{j=0}^{t-1} \tilde{A}_j C_{t-j} w_{t-j}^T}_{\text{Transitory Shocks}}
\end{aligned}
$$

by just applying successive substitution for $\bar{y}_{t-j}$ and $\tilde{y}_{t-j}$, where $\tilde{A}_j$ is the companion form matrix at the power of horizon j, and applying the mapping between reduced-form and structural residuals. Then ΛB_t is interpreted as $\mathrm{d}\bar{y}_t/\mathrm{d}w_t^P$ and $\tilde{A}_j C_{t+j}$ is interpreted as $\mathrm{d}\tilde{y}_{t+j}/\mathrm{d}w_t^T$. Both represent the shock effects on the low and high-frequency components, respectively.

The structural identification relies on sign and magnitude restrictions. First, in order to identify demand-side and supply-side factors, my set of sign restrictions rests on the following argument that supply-side forces move output and inflation in opposite directions, while

[27] I assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distribution's draws. Moreover, I follow the diagnostic for monitoring the convergence of multiple Metropolis Hastings chains of Geweke et al. (1991). The inefficiency factors for all posterior elements are represented in Figure 11 of Appendix B.

demand-side forces imply a positive comovement. Second, to distinguish between domestic and global shocks I follow the comovements proposed by Corsetti et al. (2014), this implies that global shocks affect global variables more than domestic ones, and viceversa for domestic shocks.[28] To satisfactory implement this restriction, world GDP and inflation need to be expressed as the ratio of euro area to world, as described in Section 2. For instance, if a shock results in an increase in real EA GDP, and concurrently leads to an increase in the EA's share of global GDP, it can be inferred that the shock had a greater impact on the domestic economy than on the rest of the world, and thus, can be classified as a domestic shock. Conversely, if the shock results in a decline in the EA economy's share of global GDP, it can be deduced that the shock had a greater impact on the rest of the world, and thus, can be classified as a global shock. For example, a global supply shock would affect positively to EA GDP, negatively to world GDP $(+/(++))$ (i.e., the denominator grows more than the numerator and EA's share of global GDP is reduced), negatively to EA inflation and positively to world inflation $(-/(--))$ (i.e., the EA's share of global inflation increases due to the denominator is more negative than the numerator). Energy supply shocks increase the price of energy, have a negative impact on EA real activity, and rise EA inflation on impact. These restrictions reflect the lessons from the literature that identifies various types of energy-related shocks. See, for example, Kilian (2009) that models the global crude oil market and then, investigates the impact of these shocks on the key macroeconomic variables. Moreover, I assume that energy supply shocks have a greater impact on the euro area, due to its high energy dependence with respect to the world.[29] Finally, negative domestic supply shocks have a lower impact on energy prices compared to positive energy supply shocks, i.e., $e_{ds} < e_{es}$, where e_{ds} and e_{es} represent the response of energy prices to domestic supply and energy supply shocks, respectively. In other words, a contraction in energy supply capacity leads to a greater increase in energy prices than a reduction in domestic economic activity. Furthermore, an expansion in energy supply capacity exerts a stronger downward pressure on energy prices than a comparable expansion in domestic economic activity, such that $e_{ds} > e_{es}$.

Tables 3 and 4 present the set of sign restrictions applied to the permanent and transitory shocks, respectively. The restrictions are consistent across both types of shocks, with a few minor variations. Specifically, for permanent shocks, it is assumed that positive domestic supply-demand shocks have an unrestricted effect on energy price trend. The reason, for not imposing any restriction, is that the euro area is not a energy producer, hence it is very unlikely that the euro area could permanently affect energy prices. Whereas the rest of the world is an energy producer and it can affect it. Finally, on the transitory side four shocks are left unidentified. These shocks could be masking structural shocks such as labor-market shocks, consumption shocks, uncertainty shocks or expectation shocks, among others. Nevertheless, I find that the

	Domestic Supply	Domestic Demand	Energy Supply	Global Supply	Global Demand
EA Potential GDP	+	+	-	+	+
EA Inflation Trend	-	+	+	-	+
Energy Price Trend	e_{ds}<e_{es}	+	+ (e_{es})	-	+
W Potential GDP	+	+	-	-	-
W Inflation Trend	-	+	+	+	-

Table 3. Sign restrictions on trends

	Domestic Supply	Domestic Demand	Energy Supply	Global Supply	Global Demand
Output Gap	+	+	-	+	+
Unemployment Cycle	·	·	·	·	·
Consumer Confidence Cycle	+	·	·	·	·
Inflation Gap	-	+	+	-	+
Price Expectation Cycle	-	+	+	·	·
Labor Cost Cycle	·	·	·	·	·
Energy Price Cycle	e_{ds}<e_{es}	+	+ (e_{es})	-	+
World Output Gap	+	+	-	-	-
World Inflation Gap	-	+	+	+	-

Table 4. Sign restrictions on cycles

total explained share by these four unidentified shocks is around 10% on a historical basis.

The identification algorithm is based on the sign restrictions approach proposed by Canova and De Nicolo (2002) and Uhlig (2005) and refined by Rubio-Ramirez, Waggoner and Zha (2010).[30] This approach is implemented in the same way as for traditional SVARs with sign restrictions. The key difference with respect to standard SVARs is that the structural analysis is not only focus on business cycle fluctuations, but also on low-frequency movements. Since, I focus on the same set of structural shocks that are likely to be relevant for quantifying their role in driving inflation's trend and gap.

4. Results: Dynamics and Drivers of the EA Inflation Trend and Cycle

This section documents my main empirical results obtained from the estimated model. First, I show the dynamics of the hidden states of the model; in other words, I plot the evolution of the potential GDP, inflation trend, output and inflation gap for the euro area since 1990. Second, I quantifying the nature - permanent and transitory - of the structural shocks at play to explain the past and recent dynamics of EA inflation. To do so, I construct a historical decomposition with the effect at time t of each structural shock. Finally, I identify the slope of the aggregate demand and supply curves, following the methodology proposed by Bergholt et al. (2023). This

[28] Other empirical papers that also aim at identifying global and domestic shocks, using similar techniques, are Bobeica and Jarociński (2019) and Conti et al. (2017).

[29] Currently, the euro area has an energy import dependency rate that stands around 60%.

[30] Additional details on the sign and magnitude restrictions algorithm are provided in Appendix A.2

exercise separates the variation in inflation-gap and output-gap into the components driven by demand and supply disturbances.

4.A. Hidden Components, It Is The Trend Not The Cycle

Figures 1 and 2 show the estimated low and high-frequency components of inflation and GDP together with the actual data. Trends components are plotted first, and cycles in the second row. The red solid lines correspond to the actual data, while the thick black lines represent the point-wise median estimates of the trend and cycle components, with the associated 68% credible bands.

The trend-cycle components capture accurately the slow and high-moving behavior with relatively small uncertainty. Focusing on the trend components, there are substantial fluctuations in both, inflation and GDP over the sample, despite the conservative prior modes imposed on the time-varying variance-covariance matrix. Therefore, the data speaks in favor of significant low-frequency variation.

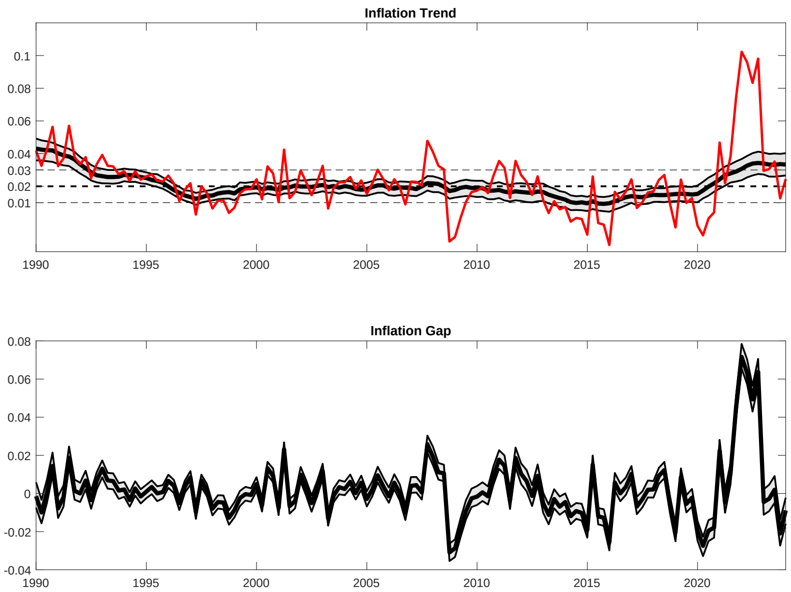


Figure 1. Actual data and estimated trends and cycles of HICP inflation

Note: Point-wise median (solid black line) with 68% credible bands are based on 250000 draws. HICP is defined in annualized quarter-on-quarter terms.

Inflation (Trend Inflation & Inflation-Gap). Figure 1 illustrates significant fluctuations in the estimated point-wise median of trend inflation over the observed period, which can be divided into five distinct phases: (1.) Early 1990s Decline: In the early 1990s, the estimated trend inflation saw a marked decline of over 200 basis points, falling from approximately 4% to 2% by 1995. (2.) Anchored Period (1995–2012Q3): Following this decline, the estimated trend inflation remained anchored around the 2% level for nearly two decades. This period is characterized by low variability in the estimates, reinforcing the notion of well-anchored inflation expectations. (3.) European Sovereign Debt Crisis (2012–2015): During the European sovereign debt crisis, the median estimated trend inflation slowed by more than 100 basis points, reaching an all-time low of 1% in 2015Q1. (4.) Post-Sovereign Debt Crisis Recovery: After the crisis, estimated trend inflation re-anchored near the 2% level. (5.) Post-COVID Economic Reopening: In the aftermath of the economic reopening following the COVID-19 pandemic, estimated trend inflation rose above the 2% threshold, reflecting renewed inflationary pressures.

It is worth mentioning that the estimates of trend inflation exhibit a strong correlation with three medium- to long-term market expectations—euro area inflation swaps for five, ten, and twenty years ahead. These correlations are statistically significant, as detailed in Appendix B, Figure 12.

The first two findings are in line with the prevailing narrative that inflation expectations were firmly anchored around the 2% level, primarily due to the strong credibility of price stability policies (see Altissimo et al. (2006); Bowles et al. (2007); Gorter et al. (2008)). However, the estimated decline in trend inflation between 2012 and 2016 is more contested. Some studies argue that euro area trend inflation showed little evidence of de-anchoring during the mid-2010s (see Strohsal and Winkelmann (2015); Jarociński and Lenza (2018); Dovern et al. (2020)), while this paper supports a gradual de-anchoring process that began in 2012, as documented by Gimeno and Ortega (2016); Łyziak and Paloviita (2017), and more recently by Corsello et al. (2021). Additionally, the more recent dynamics in estimated trend inflation have not yet been documented in the literature. These results suggest that inflation is expected to remain persistently above the ECB's target in the medium term, around 3%. This trend aligns with the recent shift in ECB monetary policy communication. Initially, in 2021Q4, *'the current inflation spike is temporary and driven largely by transitory factors.'*, whereas by 2022Q4, *'[...] inflation is expected to decline from an average of 8.4% in 2022, 6.3% in 2023, 3.4% in 2024 and to 2.3% in 2025. [...] Headline inflation is expected to fall to the ECB's medium-term inflation target of 2% in the second half of 2025'.*[31]

On the other hand, the lower panel, which examines the inflation-gap, shows values around 6-7% during periods of high inflation. This indicates that roughly 85% of the increase in headline inflation can be attributed to transitory factors, which is also reflected in the marked increase in the volatility of the inflation gap, as shown in Figure 27 in Appendix C. Notably, by 2023Q3, the HICP inflation decreased to levels between 2% and 3%, coinciding with a negative inflation-gap. This observation is consistent with the negative output gap currently experienced in the euro area (as reflected in the bottom panel of Figure 2).

[31] See ECB (2021, 2022).

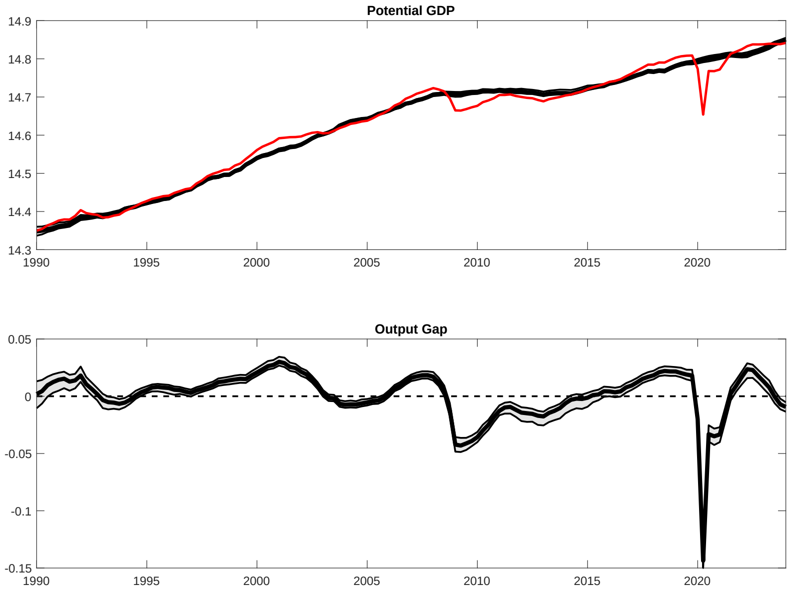


Figure 2. Actual data and estimated trends and cycles of real GDP

Note: Point-wise median (solid black line) with 68% credible bands are based on 250000 draws. Real GDP is defined in log terms.

GDP (Potential GDP & Output-Gap). Figure 2 displays the point-wise median dynamics of potential GDP and the corresponding output-gap over the studied period. Two distinct patterns in potential GDP growth emerge: (1.) Early 1990s to 2005-06: During this period, potential GDP exhibited robust growth, averaging 0.5% quarter-on-quarter (Q-Q). This strong trend reflects the economic expansion phase that characterized much of this period. (2.) Post-2007 Slowdown: From 2007 onwards, the data reflects a significant slowdown in potential GDP growth, consistent with the 'secular stagnation' hypothesis. The trend growth rate declined to an average of 0.24% Q-Q. This deceleration is consistent with the findings of Ball (2014); Fernández-Villaverde et al. (2013); Gordon (2014); Summers (2014); Gordon (2015), who highlighted a persistent reduction in GDP growth for advanced economies after 2006. Even after excluding major crises such as the Great Financial Crisis (GFC), the European Sovereign Debt Crisis, and the COVID-19 pandemic, the potential GDP growth remained low at around 0.34% Q-Q, further reinforcing the view of stagnating growth potential.[32]

During the COVID-19 pandemic, the model suggests that potential GDP remained relatively stable, indicating that the available factors of production were not severely impacted. One likely explanation for the resilience of potential GDP during the pandemic is the rapid implementation of supportive policies aimed at mitigating the economic impact of the lockdowns. Studies such as Bodnár et al. (2020); Blanchard et al. (2020); Bénassy-Quéré et al. (2020) suggest that liquidity policies, which helped to temporarily transfer labor costs from firms to governments, played

[32]Figure 13 in Appendix C presents the average quarterly growth rate of euro area potential GDP (point-wise median) using five-year rolling windows. It is evident that after 2005-06, the growth rate of euro area potential GDP begins to decline and remains consistently lower thereafter. This observed pattern aligns with recent findings in the literature that document a slowdown in U.S. long-term output growth (see Antolin-Diaz et al. (2017) and Maffei-Faccioli (2021)). The latter study specifically attributes this deceleration to permanent demand-side shocks that began affecting GDP growth after 2000.

a key role in preventing widespread financial distress among firms, thus maintaining overall production capacity. In addition, the bottom subfigure in the image depicts the dynamics of the output-gap, showing a sharp negative value of -14.7% during the COVID-19 lockdowns. This substantial output gap indicates that the economy was operating well below its potential, primarily driven by the sudden and severe contraction. This is also reflected in the increased volatility of the output gap, as shown in Figure 27 in Appendix C.[33]

Moreover, Figure 14 in Appendix C provides a decomposition of real GDP into potential GDP and the output-gap using a model that excludes stochastic volatility, on both the permanent and transitory dimensions. This decomposition highlights that, when stochastic volatility is not included, the sharp downturn in real GDP observed during the pandemic is offset between the potential GDP and output-gap components. Further comparisons with estimates from the European Commission, presented in Figure 15 (Appendix C), underscore the importance of including stochastic volatility in GDP decomposition models.

Regarding the dynamics of the output gap in the post-COVID period, the data suggest that the strong economic reopening following the pandemic lockdowns was accompanied by a positive output gap, coinciding with a period of robust real GDP growth. However, as the post-pandemic recovery began to lose momentum, the output gap quickly reversed, turning negative. This reversal appears to have occurred in conjunction with the global monetary tightening cycle, most notably the European Central Bank's (ECB) rate hikes.

4.B. Historical Decomposition of euro area Inflation

This subsection provides a historical analysis of the contribution of various structural channels influencing EA trend inflation, driven by permanent shocks, and the EA inflation-gap, shaped by transitory shocks.

Permanent factors driving trend inflation. Figure 3 presents the estimated historical decomposition for the point-wise median of trend inflation. The colored bars illustrate the cumulative contribution of each structural shock—domestic (both demand- and supply-side), global (demand- and supply-side), and energy supply—from 1990Q2 to 2022Q2, measured as deviations from the baseline period of 1990Q1.[34] The point-wise median of trend inflation is shown alongside these contributions, providing insight into the evolution of inflation dynamics over time.[35]

Over the entire sample period, global and domestic factors account for the majority of the variation in trend inflation, while energy supply shocks play a modest role overall. However, the relative importance of these five factors in explaining trend inflation movements shifts across

[33] For example, the stochastic volatility of the EA output gap effectively captures the turbulent period of the GFC and the spike in volatility during the COVID-19 crisis.

[34] Figure 16 in Appendix C depicts the structural shocks affecting the changes in the point-wise median of trend inflation, without accumulation.

[35] Figure 17 in Appendix C also plots the historical decomposition of structural shocks and the point-wise median of trend inflation, with all values expressed as deviations from 1990Q1.

different time periods.

In the early and late 1990s, domestic factors (both demand- and supply-driven) and global supply-side forces play a key role in driving trend inflation downward. Domestic demand shocks and domestic supply shocks, alongside global supply shocks, contributed to reducing trend inflation during this period. This corresponds with the prevailing view that strong potential GDP growth—both in the euro area and globally—was supported by substantial increases in supply-side capacity. Additionally, the accumulation of negative domestic demand shocks aligns with the brief economic downturns experienced in the early to mid-1990s.

In the early 2000s, the negative contributions from domestic and global supply-side factors were counterbalanced by an increasing contribution from domestic demand shocks and a diminishing negative contribution from global demand shocks (due to a sequence of positive shocks) - see Figure 16 in Appendix C. By 2006-07, global demand shocks even began to make a positive contribution to trend inflation. The interplay of these forces led to a decade of stability in trend inflation around the 2% level.[36]

After the 2008 financial crisis, the figure shows a series of negative shocks from both domestic and global sources. Domestic and global demand shocks began to unwind, exerting downward pressure on trend inflation. These pressures were partially offset by a series of negative supply shocks, which tended to raise trend inflation. During this time, energy supply shocks also began to exert upward pressure, particularly following the sharp rise in oil prices during 2007-08. Nevertheless, the de-anchoring of trend inflation from 2% to 1% was primarily driven by a series of negative demand-side shocks, as explored further in Figure 4.

In the post-2019 period, the onset of the COVID-19 pandemic triggered an increase in trend inflation, primarily driven by supply-side factors (global, energy and domestic) and to some extent by demand-side factors. The contribution of global supply shocks rapidly declined due to a series of negative shocks, while energy supply shocks sharply increased, particularly starting in 2021Q1 with growing energy pressures. Additionally, the negative contribution from global demand shocks, which had accumulated during the Sovereign Debt Crisis, began to reverse as a result of positive shocks. These dynamics are explored in greater detail in Figure 5.

[36] As noted by Borio and Filardo (2007) and Bianchi and Civelli (2015), globalization reduced inflationary pressures before the GFC in many countries, including the euro area.

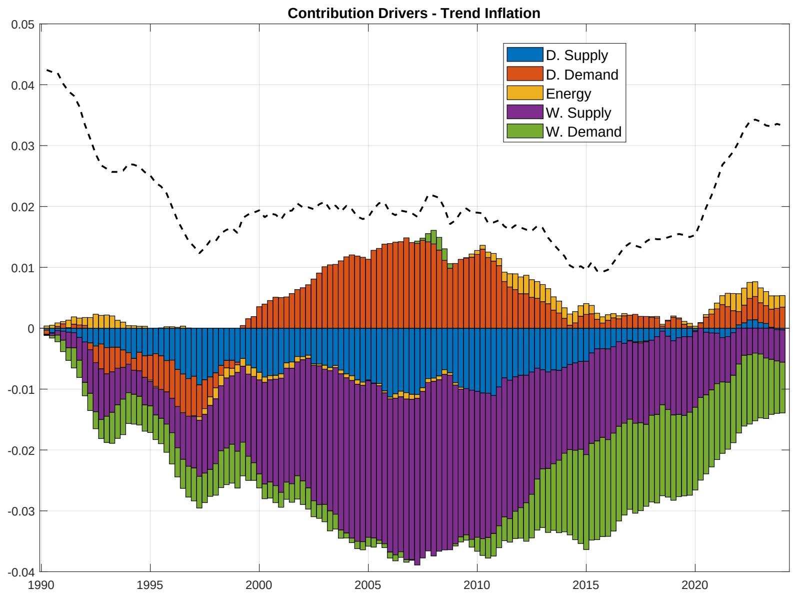


Figure 3. Estimated historical decomposition of the point-wise median of trend inflation from 1990Q2 to 2022Q2

Note: The black line represents the point-wise median of trend inflation, while the colored bars depict the cumulative contribution of each structural shock—domestic (demand- and supply-side), global (demand- and supply-side), and energy supply—at time t, measured as deviations from the baseline period of 1990Q1.

The episode of missing inflation in the Euro Area appears to support explanations that are largely related to the demand side of the economy, both domestic and global.[37] To gain a clearer understanding of the role that demand shocks played in the missing inflation, Figure 4 presents the cumulative contribution of structural shocks starting in 2008.[38]

Trend inflation begins to gradually decrease from the 2% level after 2010, largely due to the increasing impact of negative demand shocks (both domestic and global). However, this downward trend accelerates significantly after 2013. Although a series of negative supply shocks exerted upward pressure on trend inflation in the aftermath of the GFC, the cumulative negative contribution of demand shocks—amounting to -0.03—outweighed these supply-side pressures. The upward pressure on trend inflation from supply shocks can be attributed to higher trade costs, the fragmentation, and disruptions in global value chains following the GFC. These factors diminished the ability of firms to maintain low costs by sourcing goods from the most cost-effective global suppliers. The breakdown of these supply chains resulted in higher input costs for many Euro Area firms, which ultimately translated into higher consumer prices. This effect reversed some of the disinflationary trends that had been attributed to globalization (see Bianchi and Civelli (2015); Auer et al. (2017); Forbes (2019); Ha et al. (2019)).

According to the right panel of Figure 18 in Appendix C, demand shocks explain approxi-

[37]See IMF (2016, 2017).

[38]Figure 18 in Appendix C shows, on the left, the historical decomposition of structural shocks and the point-wise median of trend inflation, with all values expressed as deviations from 2008Q1. The right panel displays the variance decomposition of each shock over the period from 2008 to 2017.

mately 60% of the fluctuations in trend inflation during this period. Notably, around 60% of the total demand-side impact is attributed to global demand shocks. Therefore, the drivers identified in this study to explain the period of missing inflation are consistent with narratives presented in the existing literature (Ferroni and Mojon (2014, 2017); Conti et al. (2017); Ciccarelli et al. (2017); Bobeica et al. (2019)). However, my findings highlight the more persistent nature of these shocks, contrasting with the transitory effects suggested in much of the literature.

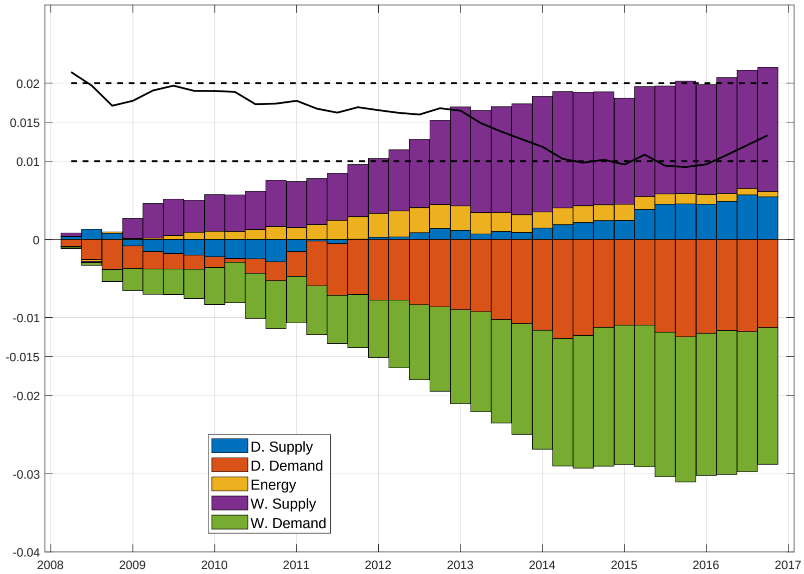


Figure 4. Estimated historical decomposition of median trend inflation from 2008 to 2017

Note: The black line represents the point-wise median of trend inflation, while the colored bars depict the cumulative contribution of each structural shock—domestic (demand- and supply-side), global (demand- and supply-side), and energy supply—at time t, measured as deviations from the baseline period of 2008Q1.

The recent period of the "COVID economic reopening" is characterized by a significant surge in trend inflation, largely driven by a combination of supply shocks: global, domestic, and energy-related. Figure 5 illustrates the cumulative contribution of structural shocks starting from 2019Q4.[39]

The predominance of supply shocks is clear, particularly global supply shocks. These can be traced back to widespread global and domestic supply chain disruptions. The economic disruptions caused by the pandemic have resulted in a disequilibrium between supply and demand, likely stemming from a reduction in the world economy's overall supply capacity. Additionally, the influence of energy supply shocks increases markedly from 2021 onwards, which is closely tied to the rise in wholesale energy prices globally in the aftermath of the COVID-19 pandemic. However, the exacerbating effect of the Russian invasion of Ukraine appears not to have significantly impacted the persistent component of inflation, but rather the transitory one.

[39] Figure 19 in Appendix C provides, on the left, the historical decomposition of structural shocks and the point-wise median of trend inflation, with all values expressed as deviations from 2019Q3. The right panel shows the variance decomposition of each shock over the period from 2020 to 2024.

These results suggest that supply shocks—particularly global supply shocks—have significantly influenced the persistent component of inflation, pushing trend inflation up by nearly 200 basis points. Toward the end of the period, the impact of demand-side shocks (domestic and global) begins to intensify, particularly after 2023.

These findings are consistent with recent studies that highlight the role of persistent global supply chain disruptions, bottlenecks in industrial goods, and shortages of critical inputs like semiconductors in driving inflation in the Euro Area (see Ascari et al. (2024) and Arce et al. (2024)). The primary distinction in my findings is the observation that supply shocks feed directly into the persistent component of inflation (i.e., trend inflation).

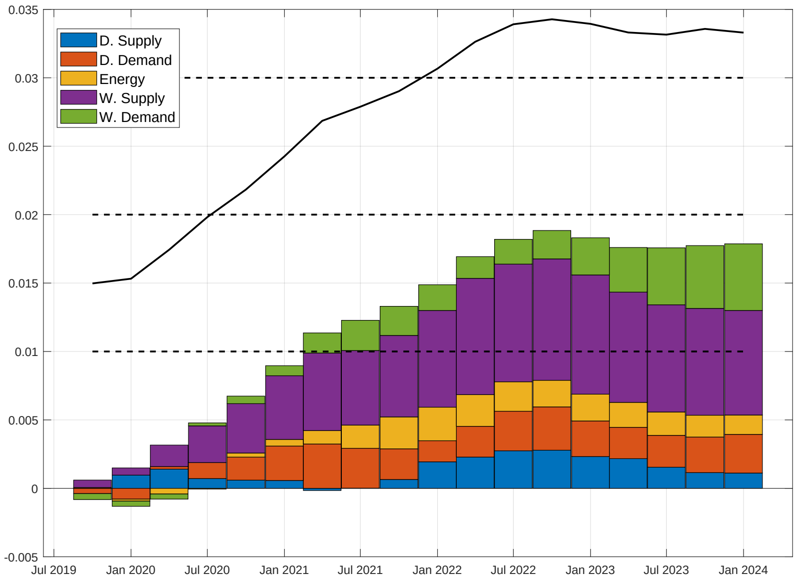


Figure 5. Estimated historical decomposition of median trend inflation from 2019 to 2022

Note: The black line is the point-wise median of trend inflation. The colored bars (areas) represent the contribution (share of the variance decomposition) of each structural shock - domestic (demand and supply-side), global (demand and supply-side) and energy supply - at time t.

Transitory factors driving inflation-gap. Figure 6 illustrates the estimated historical decomposition for the point-wise median of the inflation-gap. The colored bars represent the estimated contribution of each structural shock at each point in time, including domestic shocks (both demand- and supply-side), global shocks (demand- and supply-side), energy supply shocks, and a residual shock (which aggregates the contribution of the four unidentified shocks) over the period from 1990Q2 to 2022Q2.[40]

Starting from the GFC onward, the observed deflation, characterized by a negative inflation gap, was predominantly influenced by demand-side factors. In particular, global demand shocks played a critical role in exerting downward pressure on inflation, as consumers and businesses worldwide significantly reduced their spending in response to heightened financial instability and constrained credit conditions. Several studies support this view; for instance, Ciccarelli

[40]The sum of the four unidentified shocks may encompass structural shocks such as labor supply shocks, consumption shocks, uncertainty shocks, or expectation shocks, among others.

and Mojon (2010), Mumtaz and Surico (2012), Henriksen et al. (2013), and Ferroni and Mojon (2017) emphasize that weakened global demand was a primary contributor to the disinflationary environment during the GFC, mirroring the global decline in both investment and consumption. The relative importance of each shock, over time, is illustrated in Figure 21 in Appendix C.

The low inflation period, from the European Sovereign Debt Crisis through 2015, can be attributed largely to domestic shocks, initially from demand-side and subsequently from supply-side factors, which began to have a more pronounced effect on the inflation gap. This period reflects the influence of austerity policies and fiscal tightening measures across Euro Area economies. Furthermore, from 2013 to 2015, the significance of domestic supply shocks increased markedly, accounting for nearly 40% of the inflation gap variation, as shown in Figure 21 in Appendix C. This likely reflects constraints in productive capacity and reduced public and private sector spending due to fiscal consolidations within the Euro Area. The prominent role of domestic factors during this period is also noted by Bobeica and Jarociński (2019).

The COVID-19 pandemic and its aftermath, introduced a notable shift in inflation dynamics. Model estimates suggest that recent inflationary episodes have primarily been driven by transitory factors, which account for approximately 85% of the inflation surge. In particular, domestic and global demand shocks are the principal contributors to fluctuations in the inflation gap, while energy supply shocks play a modest role, accounting for around 10 to 15% of the upward pressures. These findings align with recent research by Giannone and Primiceri (2024), which also indicates that post-pandemic inflation in both the Euro Area and the U.S. has been predominantly demand-driven. The main distinction in my analysis lies in that demand shocks are captured within the model's transitory inflation component, whereas supply shocks are incorporated into the persistent component (as we saw previously).

This demand-driven surge arose as economies reopened and pandemic-related restrictions were relaxed (beginning in 2021Q2), resulting in a sharp increase in consumer spending that exceeded the pace of supply chain recovery. The surge in domestic demand can be attributed to factors such as pent-up consumption, expansive fiscal stimulus measures (including job retention schemes), and accommodative monetary policy. Additionally, savings accumulated significantly during lockdowns, reaching 25% of disposable income by the second quarter of 2020. As the economy reopened, the savings ratio has since receded from its peak. On a global level, demand-side pressures were further amplified as the United States and other economies experienced substantial increases in imports, particularly of consumer goods—U.S. import activities, for example, rose by 24% compared to 2019 levels.[41] During this period, demand shocks (domestic and global) account for roughly 60% of the total variance observed in the inflation gap, as illustrated in Figure 21 in Appendix C. Moreover, as we will see in the subsection, these strong temporary effects in domestic demand are also supported by a positive output gap, which is mainly driven by domestic demand.

[41] See Higgins et al. (2021).

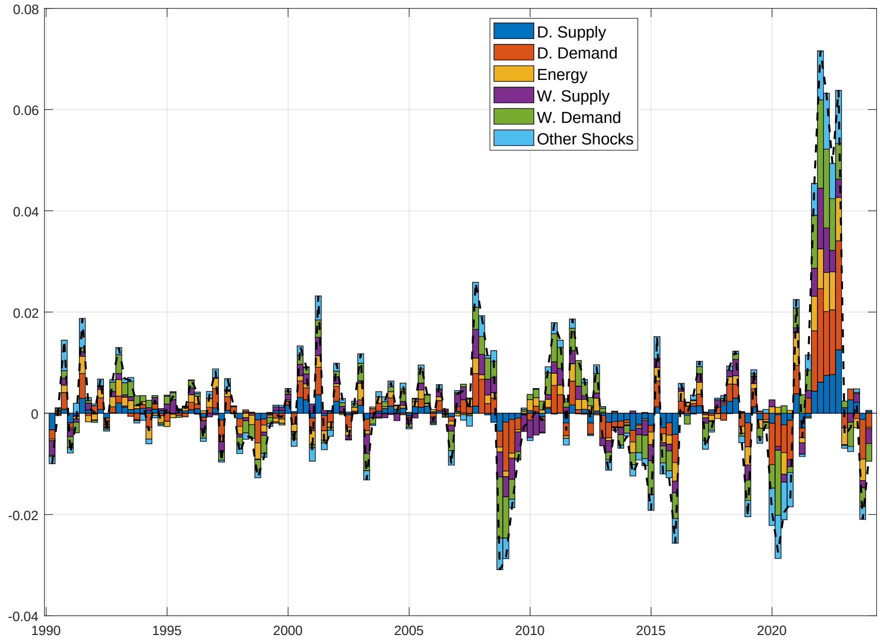


Figure 6. Estimated historical decomposition of the point-wise median of inflation-gap from 1990Q2 to 2022Q2

Note: The black line is the point-wise median of inflation-gap. The colored bars represent the contribution of each structural shock - domestic (demand and supply-side), global (demand and supply-side), energy supply and the residual is the sum of the four unidentified shocks - at time t.

Finally, from a long-term historical perspective, Figure 22 in Appendix C presents the asymptotic variance decomposition of the inflation gap. Over the entire sample period, from both domestic and global perspectives, domestic shocks explain approximately 40% of the historical variance in the inflation gap. Global shocks contribute an additional 35-40%, while energy supply shocks account for 10-15% of the variance. An unexplained 10% remains, which is attributed to unidentified shocks. From a demand and supply perspective, demand shocks are found to account for around 60% of the historical variance in the inflation gap.

4.C. Historical Decomposition of euro area GDP

This subsection provides a historical analysis of the contribution of various structural channels influencing EA potential GDP, driven by permanent shocks, and the EA output-gap, shaped by transitory shocks.

Permanent factors driving potential GDP. Figure 7 presents the estimated historical decomposition for the point-wise median of potential GDP, excluding the drift term $\bar{c}$. The colored bars illustrate the cumulative contribution of each structural shock—domestic (both demand- and supply-side), global (demand- and supply-side), and energy supply—over the period from 1990Q2 to 2022Q2, expressed as deviations from the baseline period of 1990Q1.[42]

It is crucial to note that in the absence of shocks, potential GDP grows at a constant rate

[42]Figure 20 in Appendix C depicts the structural shocks affecting changes in the point-wise median of potential GDP, excluding the drift $\bar{c}$, and without accumulation.

$\bar{c}$ (see Equation 2). Therefore, in the absence of any structural shocks, the point-wise median of potential GDP should follow a linear trajectory. Any deviation from this behavior indicates the influence of permanent shocks, which in turn generate either positive or negative hysteresis effects. In other words, the constant growth of potential GDP driven by $\bar{c}$ can be accelerated or decelerated at time t by these shocks.[43]

In the first part of the sample (pre-GFC), shocks positively contribute to potential GDP growth, with global supply factors playing a major role in explaining the long-run fluctuations of potential GDP, followed by domestic demand shocks, up to 2007. Additionally, global demand factors also played an important role, transitioning from a considerable negative contribution in the late 1990s to achieving a positive contribution by 2006-07, due to a continuous sequence of positive shocks—see Figure 20 in Appendix C.

After the 2008 financial crisis, there is a surprising de-accumulation of the contribution of shocks. Indeed, from 2008 onwards, potential GDP growth appears to be holding up entirely due to the cumulative effect of the drift coefficient $\bar{c}$, until 2022Q4, when the net contribution of shocks once again turns positive, similar to the pre-GFC period. This result helps explain why potential GDP growth was stronger between 1990-2007 (0.50% Q-Q growth) compared to the period after 2008 (0.34% Q-Q growth, excluding the events of the GFC, the European Sovereign Debt Crisis, and the COVID pandemic).

These findings suggest a structural shift after the 2008 financial crisis, with respect to the underlying forces driving potential GDP in the Euro Area. The pre-GFC period is characterized by positive hysteresis, where potential GDP is driven primarily by global supply factors, along with the cumulative effect of the drift coefficient. In contrast, the post-GFC period is characterized by negative hysteresis, as the contribution of global shocks begins to de-accumulate, putting downward pressure on potential GDP growth. However, domestic shocks maintain their total contribution until the Sovereign Debt Crisis. Furthermore, the positive contribution of global demand shocks quickly turns negative, signaling a persistent change in globalization. This result aligns with the theory of the 'great trade collapse', which suggests that the synchronized global trade collapse in late 2008—driven by the postponement of purchases, especially of durable consumer and investment goods—created permanent losses globally.[44]

Another factor driving potential GDP growth downward is the negative impact of energy supply shocks after the GFC, which begins to converge toward zero from 2013 onwards. This coincides with the major expansion of oil and gas fracking between 2012 and 2014, during which oil prices dropped significantly between 2014-2015 due to the surge in U.S. shale oil production.[45]

[43] For instance, Bluedorn and Leigh (2019) provide evidence of positive hysteresis in 34 advanced economies, where permanent reductions in unemployment are associated with prolonged periods of economic expansion. Conversely, Furlanetto et al. (2021) find evidence of negative hysteresis, showing that negative permanent demand shocks significantly affect the U.S. economy, leading to permanent declines in employment and investment.

[44] For evidence on the collapse being driven primarily by a drop in global demand, see Baldwin (2009), Levchenko et al. (2010), Abiad et al. (2014), and Chen et al. (2019). Other studies suggest that global supply-side disruptions also played a significant role, in conjunction with global demand factors—see Alessandria et al. (2010), Chor and Manova (2012), Bems et al. (2013), and Eaton et al. (2016).

[45] Between June 2013 and January 2016, global oil prices dropped by approximately 70%. Brent crude oil,

After 2021, the influence of energy supply shocks rises markedly, which is closely tied to the global surge in wholesale energy prices following the COVID-19 pandemic. The onset of the Russian invasion of Ukraine also appears to contribute negatively—see the big negative shocks in 2022Q1-Q2 in Figure 20 in Appendix C—though this negative contribution begins to fade.

In addition, with the onset of the COVID-19 pandemic, the contribution of global shocks declines dramatically (with global supply becoming less influential and global demand more negative), while domestic demand shocks remain stable. After 2022, the contribution of global shocks starts to increase again, particularly with global demand shrinking due to a sequence of positive shocks.

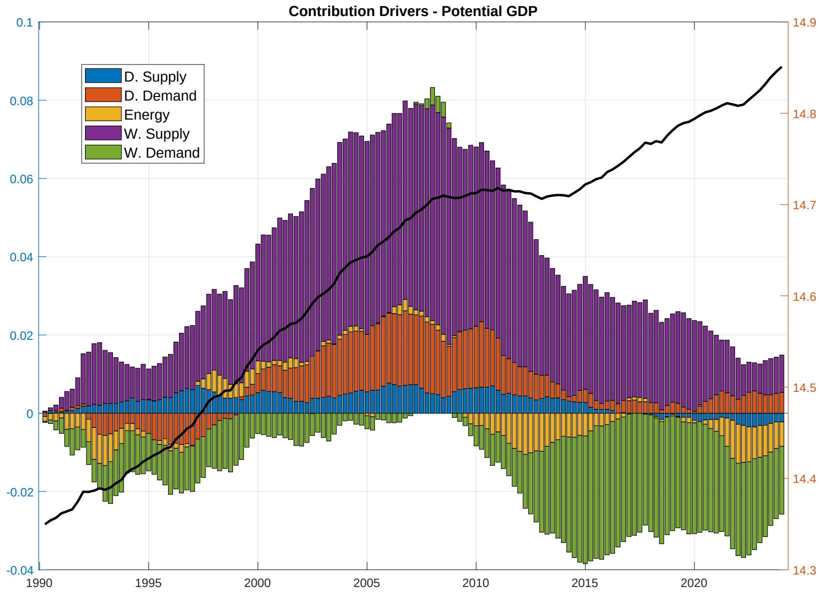


Figure 7. Estimated historical decomposition of the point-wise median of potential GDP, discounting the drift $\bar{c}$, from 1990.Q2 to 2022.Q2

Note: The black line is the point-wise median of potential GDP. The colored bars represent the contribution of each structural shock - domestic (demand and supply-side), global (demand and supply-side) and energy supply - at time t.

Transitory factors driving output-gap. Figure 8 represents the estimated historical decomposition for the point-wise median of the output-gap. The colored bars illustrate the estimated contribution of each structural shock at each point in time, including domestic shocks (both demand- and supply-side), global shocks (demand- and supply-side), energy supply shocks, and a residual shock (which aggregates the contribution of the four unidentified shocks) over the period from 1990Q2 to 2022Q2.

The Financial Crisis and the European Sovereign Debt Crisis are characterized by distinct factors driving economic activity during these periods. The sharp contraction in economic activity between 2008-09 is predominantly explained by global factors, accounting for approximately 70% of the output gap fluctuations (with global demand contributing 45% and global supply

which was trading at around \$115 per barrel in mid-2014, fell to about \$30 per barrel by early 2016. For more on the effects of fracking on economic growth, see Hausman and Kellogg (2015) and Gilje et al. (2016).

25%). In contrast, the downturn between 2012-15 is driven more by domestic factors, with around 50% of the output gap variation explained by domestic supply and demand shocks (30% and 20%, respectively). See Figure 23 in Appendix C, which plots the relative importance of each shock from a historical perspective.

The COVID-19 lockdown resulted in a significant negative output gap, as reflected in my model estimates. It is challenging to provide a definitive economic interpretation for the magnitude of this drop; however, a tentative explanation can be drawn based on the historical decomposition results. These results suggest that the COVID-19 (lockdown) shock was multifaceted, with sources from both global and domestic factors.[46]

The subsequent economic rebound after reopening is predominantly driven by domestic demand factors, accounting for nearly 90% of the recovery. This supports the earlier inflation-gap findings and highlights that, following the reopening, demand for goods and services surged, further supported by robust fiscal and monetary policies. These results align with the narratives in the Economic Bulletin Articles, such as De Santis and Stoevsky (2023), where they emphasize that demand-side forces played a crucial role in driving the post-pandemic recovery in economic activity. Higher household consumption and increased business investment spurred growth across various sectors, although supply-side disruptions, such as supply chain bottlenecks and labor shortages, continued to affect industrial production. The primary driver of the recovery was driven by demand.

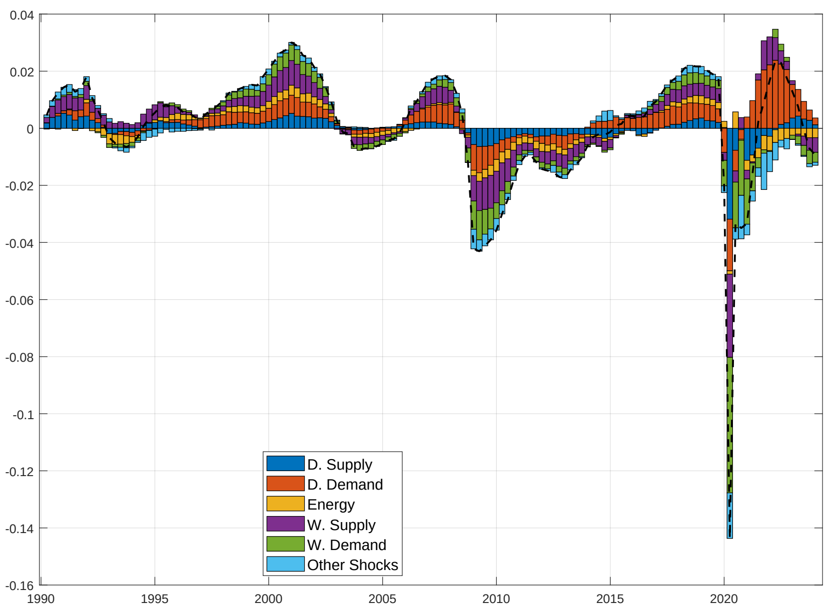


Figure 8. Estimated historical decomposition of the point-wise median of output-gap from 1990.Q2 to 2022.Q2

Note: The black line is the point-wise median of output-gap. The colored bars represent the contribution of each structural shock - domestic (demand and supply-side), global (demand and supply-side), energy supply and the sum of the four unidentified shocks - at time t.

[46]Similar conclusions are drawn by reports from the ECB and St. Louis Federal Reserve; see Croitorov et al. (2021), Martin et al. (2022), and Muggenthaler et al. (2021).

Finally, Figure 22 in Appendix C provides a long-term historical perspective of the output gap, illustrating the asymptotic variance decomposition. Over the entire period, the asymptotic shares of each shock explaining the Euro Area output gap closely resemble those explaining the Euro Area inflation gap. From both domestic and global perspectives, domestic and global shocks each account for approximately 40% of the historical variance in the output gap. The key difference arises in the asymptotic contribution of global supply shocks, which historically constituted 30%, but following the aftermath of the COVID-19 pandemic, this share decreases to 20%, with a corresponding increase in the share of global demand shocks from 10% to 20%.

4.D. Identification of the Aggregate Demand and Aggregate Supply (Phillips) Curves

In this analysis, I draw upon the methodology proposed by Bergholt et al. (2023) to address two important issues. The first is to corroborate one of the main findings of this section: that the euro area inflation gap was predominantly driven by demand shocks. The second issue pertains to the large and growing body of literature that suggests a notable disconnect between the inflation gap and the output gap, particularly since the 1990s. My objective is to explore this disconnect by examining the cyclical structural dynamics of aggregate supply and demand disturbances. This methodology is particularly intuitive, as Bergholt et al. (2023) emphasize, "*All that is needed is a way to purge demand from supply in the observable, unconditional data*" to derive aggregate demand and supply curves.

Starting with the aggregate supply (Phillips) curve—traditionally viewed as upward-sloping—it is identified when the data are purged of demand-side shocks. A low positive regression slope implies a flattened aggregate supply curve, assuming constant demand dynamics. Conversely, the aggregate demand curve, typically downward-sloping, is identified after adjusting the data for supply-side shocks. A less pronounced negative regression slope reflects a stricter central bank commitment to inflation stability, resulting in subdued inflationary fluctuations and a flatter demand curve, while maintaining constant supply dynamics.

Making use the cycle decompositions, I isolate historical data variations attributable to both supply and demand shocks. Based on these decompositions, I focus on the median contribution of each shock to fluctuations in the inflation gap and output gap. Supply shocks encompass domestic, global, and energy supply dynamics, while demand shocks aggregate domestic and global demand variations.

Figure 9 presents the results conditioned on identified demand shocks (i.e., purging the data from demand disturbances), revealing a positive correlation between output and inflation. The slope is notably steep at 0.40 and is statistically significant. These findings suggest a consistent supply curve, contrasting with a notably flat demand curve. Such observations challenge the widely accepted narrative of a declining Phillips curve.[47]

[47] These results align with the conclusions of Bergholt et al. (2023) regarding the U.S. economic landscape.

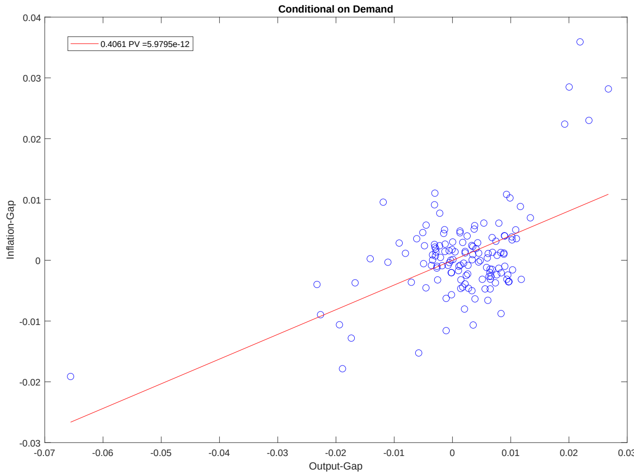


Figure 9. Conditional on demand

Note: Conditional data on demand disturbances obtained from the estimated cycle model part (i.e cleaning the data from demand disturbances). Corresponding slope estimate is 0.40 with a P-value of 0.

In contrast, Figure 10, conditioned on supply shocks (i.e., after purging the data of supply disturbances), reveals a negative correlation between output and inflation, with a notably flat slope. This flatness can be attributed to the European Central Bank's "historically" strong reputation as an inflation-targeting institution, bolstered by the legacy left by Mario Draghi's leadership and his famous "whatever it takes" commitment during the Eurozone Sovereign Debt Crisis. A flat AD curve implies that supply shocks significantly depress economic output without generating equivalent inflationary pressures, a pattern observed during the early stages of the pandemic. However, inflation seems to have surged due to an upward shift in the AD curve, driven by large-magnitude demand shocks, which are reflected in the marked increase in the volatility of the inflation gap, as shown in Figure 27 in Appendix C.

This finding aligns with the reasoning of Giannone and Primiceri (2024) regarding the role of demand shocks in the Euro Area. Domenico Giannone and Giorgio Primiceri argue that the upward shift in the AD curve can be attributed to the ECB's accommodative monetary policy, which enabled demand shocks to exert a strong inflationary impact. They also suggest that had the ECB strictly adhered to its inflation-targeting regime, inflation might have been lower, but the economy would have experienced significant output losses. Consequently, demand-side disturbances were central to explaining the inflationary pressures during this period.

Furthermore, the findings of Bergholt et al. (2023) related to the aggregate demand curve reveal a similarly flat slope for the most recent period in the U.S. economy.

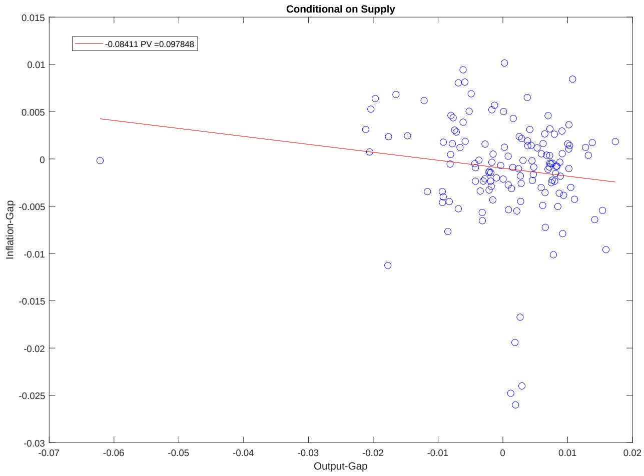


Figure 10. Conditional on supply

Note: Conditional data on supply disturbances obtained from the estimated cycle model part (i.e cleaning the data from supply disturbances). Corresponding slope estimate is -0.08 with a P-value of 0.097.

5. Conclusions

Since the COVID economic reopening, euro area inflation has surged to a 40-year high, raising significant concerns. This paper addresses two questions: (1) What are the structural channels driving euro area inflation? By examining both global and domestic shocks from the perspectives of demand and supply. (2) Do these structural channels primarily affect the transitory (inflation gap) or the persistent (trend inflation) components of euro area inflation? To answer these questions, I use a novel econometric model that integrates decomposition of variables into trends and cycles, models time-varying second moments, and identifies structural shock. By confronting various domestic and global (demand and supply) shocks, I am able to assess their relative contributions and distinguish between their transitory and persistent effects on inflation and other macroeconomic variables.

The findings provide evidence that both global supply shocks and demand shocks (domestic and global) have been the primary drivers of the post-COVID inflation surge. However, unlike the existing literature, I find that global supply shocks primarily feed into the persistent component of euro area inflation, raising trend inflation to 3% by 2022. In contrast, demand shocks—both domestic and global—manifest primarily in the transitory component (inflation gap), which explains approximately 85% of the total post-COVID increase in inflation. Nonetheless, the rise in trend inflation above 2% indicates that EA inflation is likely to remain persistently above the ECB's target in the medium term.

Furthermore, this paper highlights the importance of modeling time-varying second moments. Excluding time-varying second moments can compromise the accurate decomposition of variables. For instance, during the COVID-19 period, the sharp decline in real GDP was incorrectly absorbed between potential GDP and the output gap, leading to an exaggerated reduction in potential GDP. In addition, the model estimates a significant slowdown in EA potential GDP growth, with quarter-on-quarter growth falling from an average of 0.50% during the early 1990s to 2005-06, to just 0.24% from 2006 onwards. This deceleration is largely driven by global factors, aligning with theories suggesting a permanent shift in globalization.

While this paper offers a novel benchmark, I acknowledge that this is done at the cost of imposing an independent trend/cycle decomposition. This assumption may limit its flexibility in capturing the joint interactions between transitory and permanent shocks. Hence, more work needs to be done on the econometric framework of the model decomposition and its shock identification scheme. In fact, allowing for the transmission of transitory shocks to the permanent side while retaining time-varying second moments, seems a fruitful area for future research. For example, allowing a transitory shock to become more persistent or even permanent, if it triggers specific mechanisms in the model that allow to create persistent sources of economic disruption.

A A Gibbs Sampler for a VAR with Common Trends featuring Stochastic Volatility

The VAR with Common Trends and SV with fat-tails specified in equations 1 through 8 is estimated using a Gibbs sampler and Metropolis hasting, which involves the following blocks:

1. The first step requires to set up starting values, $\phi^{\epsilon}_{ij,t}, \phi^{u}_{ij,t}, h^{\epsilon}_{i,t}, h^{u}_{i,t}, \delta_{i,t}$, to form the history of $\Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}$. Draws from the joint distribution $\bar{y}_{0:T}, \tilde{y}_{-p+1:T}, \lambda \mid \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})$, are obtained, which is given by the product of the marginal posterior of $\lambda \mid \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})$ times the distribution of the initial observations $\bar{y}_{0:T}, \tilde{y}_{-p+1:T} \mid \lambda, \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})$. Where, $\text{vec}(\mathcal{V}) = \text{vec}(D^u, D^{\epsilon}, G^u, G^{\epsilon}, \kappa_{\delta})$. The marginal posterior of $\lambda \mid \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})$ is given by:

$$p\left(\lambda \mid \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})\right) \propto \mathcal{L}\left(y_{1:T} \mid \lambda, \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, \text{vec}(\mathcal{V})\right) p(\lambda)$$

where $\mathcal{L}\left(y_{1:T} \mid \lambda, \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, \text{vec}(\mathcal{V})\right)$ is the likelihood obtained by using the Kalman Filter in the state-space model specified in equation (1). Since $p\left(\lambda \mid \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})\right)$ could feature an unknown form, this step involves a Metropolis-Hastings algorithm. Finally, in step 1, I use Carter and Kohn (1994)'s simulation smoother to obtain draws for the trend and cycle components $\bar{y}_{0:T}, \tilde{y}_{-p+1:T}$, for given $\lambda, \bar{c}$ and $\text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, \Sigma^{u}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})$.

2. The second step is standard to the time-series literature because $\bar{y}_{0:T}, \tilde{y}_{-p+1:T}$ are given. Starting with the transitory component equation, the posterior distribution of $\text{vec}(\bar{\mathcal{A}})$ is given by

$$\begin{aligned}
(\bar{\Sigma}^{\mathcal{A}})^{-1} &= (\underline{\Sigma_0^{\mathcal{A}}})^{-1} + \sum_{t=1}^{T} \left((\Sigma^u_t)^{-1} \otimes \tilde{x}_t \tilde{x}'_t \right), \\
\text{vec}(\bar{\mathcal{A}}) &= \bar{\Sigma}^{\mathcal{A}} \left\{ \text{vec}\left(\sum_{t=1}^{T} (\Sigma^u_t)^{-1} \tilde{y}_t \tilde{x}'_t \right) + (\underline{\Sigma_0^{\mathcal{A}}})^{-1} \text{vec}(\underline{\mathcal{A}}) \right\} I(\text{vec}(\underline{\mathcal{A}})),
\end{aligned}$$

where $\tilde{x}_t = (\tilde{y}'_1, \ldots, \tilde{y}'_T)'$.

3. To obtain the time-varying elements of $\Sigma^u_{1:T}$, $p\left(\Sigma^u_{1:T} \mid \tilde{y}_{1:T}, \bar{y}_{1:T}, \lambda, \bar{c}, \text{vec}(\mathcal{A}), \Sigma^{\epsilon}_{1:T}, y_{1:T}, \text{vec}(\mathcal{V})\right)$, I follow the algorithm described in Primiceri (2005) and Benati and Mumtaz (2007). (i) Compute the VAR residuals, $\hat{u}_t = \tilde{y}_t - \bar{\mathcal{A}}' \tilde{x}_t$. Draw the time-varying, $\phi^u_{ij,t}$, elements of Φ^u_t using the Carter and Kohn algorithm (conditional on $\bar{\mathcal{A}}, H^u_t, D^u_{1:n}$). Then the state space formulation for $\phi^u_{ij,t}$ is derived from the following relationship

$$\begin{pmatrix} 1 & 0 & \cdots & 0 \\ \phi^u_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \phi^u_{k1,t} & \cdots & \phi^u_{kk-1,t} & 1 \end{pmatrix} \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{k,t} \end{pmatrix} = \begin{pmatrix} o_{1,t} \\ o_{2,t} \\ \vdots \\ o_{k,t} \end{pmatrix},$$

where, $\text{VAR}(o_t) = H_t^u$. The state space formulation for $\phi_{21,t}^u$ is

$$u_{2,t}^u = -a_{21,t}^u u_{1,t} + o_{2,t},\ VAR\left(o_{2,t}\right) = h_{2,t}^u$$
$$a_{21,t}^u = a_{21,t-1}^u + V_{1t},\ VAR\left(V_{1t}\right) = D_1^u.$$

The state space formulation for $a_{31,t}^u$ and $a_{32,t}^u$ is

$$u_{3,t} = -a_{31,t}^u u_{1,t} - a_{32,t}^u u_{2,t} + o_{3,t}, VAR\left(o_{3,t}\right) = h_{3,t}^u$$
$$\begin{pmatrix} a_{31,t}^u \\ a_{32,t}^u \end{pmatrix} = \begin{pmatrix} a_{31,t-1}^u \\ a_{32,t-1}^u \end{pmatrix} + \begin{pmatrix} V_{2t} \\ V_{3t} \end{pmatrix}, VAR\begin{pmatrix} V_{2t} \\ V_{3t} \end{pmatrix} = D_2^u.$$

The same procedure is applied to obtain the rest of the state space formulations. (ii) Conditional on a draw for $(a_{21,t}), (a_{31,t}$ and $a_{32,t}), \ldots, (a_{81,t}, \ldots,$ and $a_{87,t})$ calculate the residuals $(V_{1,t}^u, V_{2,t}^u, \ldots, V_{8,t}^u)$. Draw each of D_i^u from the inverse Wishart distribution with scale matrix $V_{i,t}^{\prime,u} V_{i,t}^u + (\kappa + i + 1) D_{i,0}^u$ and degrees of freedom $T + \kappa_{V,u}$, where i = 1, $\cdots$, (n-1). (iii) Using the draw of Φ_t^u calculate $o_t = \Phi_t^u u_t$. Notice that, o_t are contemporaneously uncorrelated then drawing $h_{i,t}^u$ and $\delta_{i,t}$ can be done separately by simply applying the independence Metropolis-Hastings algorithm. (iii-A) As in Geweke (1993) I use the Random Walk Metropolis Hastings Algorithm to draw from the following conditional distribution:

$$G(\kappa_{\delta,i}|\Psi) \propto \left(\frac{\kappa_{\delta,i}}{2}\right)^{\frac{T\kappa_{\delta,i}}{2}} \Gamma\left(\frac{\kappa_{\delta,i}}{2}\right)^{-T} \exp\left(-\left(\frac{1}{n_0} + 0.5\sum_{t=1}^{T}\left[\ln\left(\delta_{t,k}^{-1}\right) + \delta_{t,k}\right]\kappa_{\delta,i}\right)\right)$$

. More specifically, for each of the n equations of the VAR, I draw $\kappa_{\delta,i}^{\text{new}} = \kappa_{\delta,i}^{\text{old}} + \tilde{c}^{1/2}\tilde{u}$ with $\tilde{u} \sim N(0,1)$. The draw is accepted with probability $\min\left(1, \frac{G(\kappa_{\delta,i}^{\text{new}}|\bar{\delta}_k)}{G(\kappa_{\delta,i}^{\text{old}}|\bar{\delta}_i)}\right)$, where $\bar{\delta}_i = [\delta_1, \delta_2, \ldots, \delta_T]$, with $\tilde{c}$ chosen to keep the acceptance rate around 20-40%. (iii-B) $h_{i,t}^u$ can be done separately by simply applying the independence Metropolis-Hastings algorithm conditional on a draw for g_i^u. This is done using the univariate algorithm by Jacquier et al. (2004). Finally, as discussed in Cogley and Sargent (2005) draw g_i^u (each diagonal element of G^u), conditional on $h_{i,t}^u$, from inverse Gamma distribution with scale parameter

$$\frac{\left(\ln h_{i,t}^u - \ln h_{i,t-1}^u\right)'\left(\ln h_{i,t}^u - \ln h_{i,t-1}^u\right) + g_{i,0}^u}{2}$$

and degrees of freedom $\frac{T+v_0}{2}$.

4. To obtain the time-varying elements of $\Sigma_{1:T}^{\epsilon}$, $p\left(\Sigma_{1:T}^{\epsilon} \mid \bar{y}_{1:T}, \tilde{y}_{1:T}, \lambda, \bar{c}, \text{vec}(\mathcal{A}), \Sigma_{1:T}^u, y_{1:T}, \text{vec}(\mathcal{V})\right)$, of the trend component equation, where the coefficients ($\bar{c}$) and latent trends ($\bar{y}_t$) are known. Now the number of variables is q instead of n. Compute the residuals, $\hat{\epsilon}_t = \bar{y}_t - c - \bar{y}_{t-1}$. Repeat sub-steps (i), (ii), and (iii-B) to obtain the time-varying elements of $\Sigma_{1:T}^{\epsilon}$. Repeat steps 1 and 4 M times. The last L draws provide an approximation to the marginal posterior distributions of the model parameters.

Identification procedure. The identification procedure described in subsection $3.C$ is performed using the algorithm of Rubio-Ramirez et al. (2010), which consists of the following steps, for each given draw from the posterior of the reduced-form parameters (permanent side):

Step one. Draw a q x q matrix W from $N(0_n, I_q)$ and perform a QR decomposition of W, with the diagonal of R normalized to be positive and $Q^{\epsilon}Q^{\epsilon\prime} = I_q$.

Step two. Let S_t^{ϵ} be the lower triangular Cholesky decomposition of Σ_t^{ϵ} and define $B_t = S_t^{\epsilon}Q^{\epsilon\prime}$. Compute the candidate (permanent) responses are given by B_t. Check the set of permanent responses, if it satisfies all the sign restrictions, store them. If not, discard them and go back to the first step.

Step three. Repeat steps 1 and 2 until M impulse responses that satisfy the sign restrictions are obtained. The resulting set characterizes the set of structural VAR models that satisfy the sign restrictions.

The identification procedure for the transitory side is as follows:

Step one. Draw a n x n matrix W from $N(0_n, I_n)$ and perform a QR decomposition of W, with the diagonal of R normalized to be positive and $Q^{u}Q^{u\prime} = I_n$.

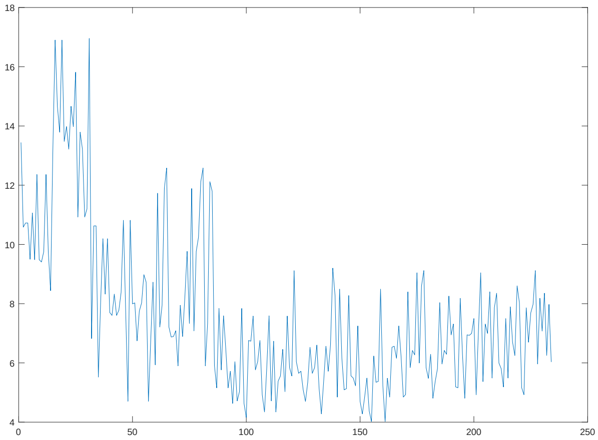
Step two. Let S_t^{u} be the lower triangular Cholesky decomposition of Σ_t^{u} and define $C_t^{u} = S_t^{u}Q^{u\prime}$. Compute the candidate impulse responses as $IRF_{j,t} = A_jC_t^{u}$, where A_j are the reduced form impulse responses from the Wold representation, for $j = 0, \ldots, J$. If the set of impulse responses satisfies all the sign restrictions, store them. If not, discard them and go back to the first step.

Step three. Repeat steps 1 and 2 until M impulse responses that satisfy the sign restrictions are obtained. The resulting set characterizes the set of structural VAR models that satisfy the sign restrictions.

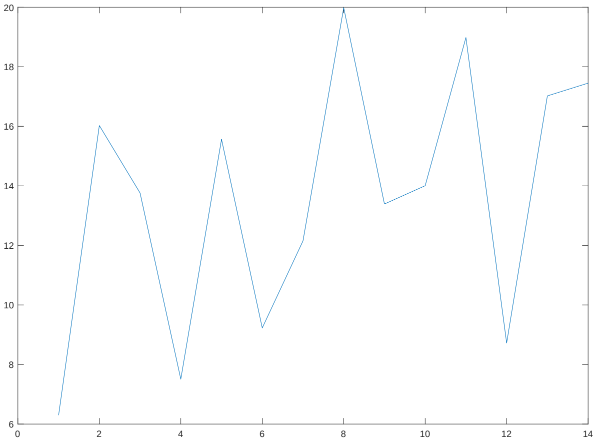
B Convergence of the Markov chain Monte Carlo algorithm

This appendix assesses convergence of the Markov chain Monte Carlo algorithm in the baseline application to the euro area data. Following Primiceri (2005), I assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distribution's draws. In order to judge how well the chain mixes, common practice is to look at the draws' inefficiency factors (IF) for the posterior estimates of the parameters. Specifically, that is the inverse of the relative numerical efficiency measure of Geweke et al. (1991), i.e., the IF is an estimate of $(1 + 2\sum_{i=1}^{\infty} \rho_i)$, where ρ_i is the i-th autocorrelation of the chain. In this application the estimate is performed using a Parzen window.[48] Values of the IFs below or around 20 are regarded as satisfactory, as stressed by Primiceri (2005). Figure 11 plots a complete description of the characteristics of the chain for the different sets of parameters. All the IFs are around or even below 20. $D^\epsilon, D^u, G^\epsilon, G^u$: elements of the covariance matrix of the model's innovations; $H_{\epsilon,t}, H_{u,t}$: time varying volatilities from the permanent and transitory side; $\Phi_{\epsilon,t}, \Phi_{u,t}$: time varying simultaneous relations; κ_δ: degrees of freedom for the Student's t-distribution; $\mathcal{A}$: time-invariant autoregressive coefficients; Λ: time-invariant cointegrating coefficients; $\bar{c}$: time-invariant drifts.

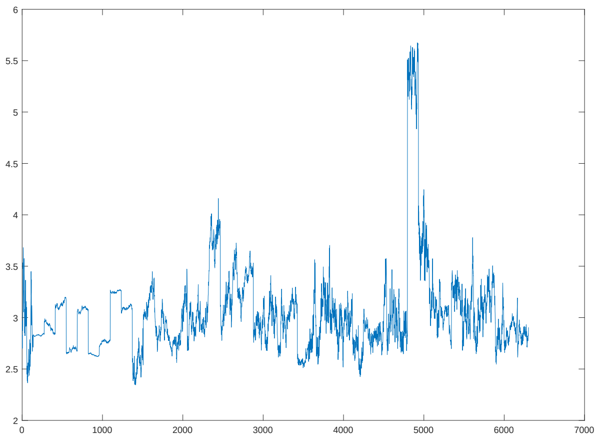
[48]For inefficiency factors, see Section 6.1 of Giordani et al. (2011).



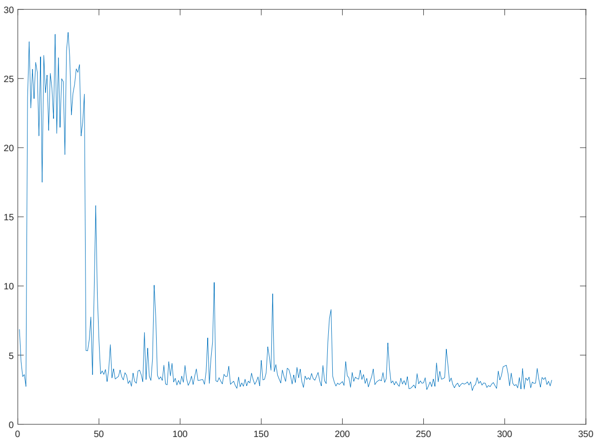
Elements of D^{ϵ}, D^{u}



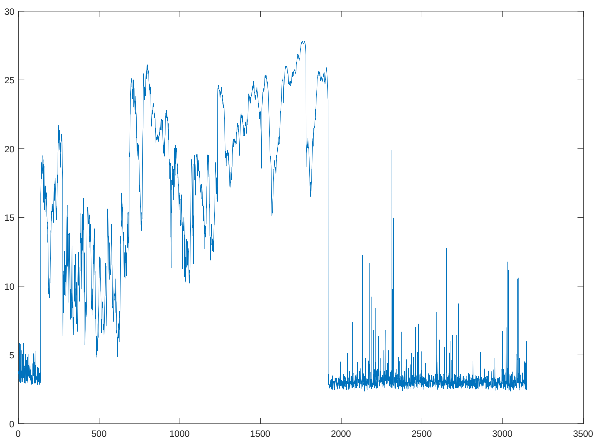
Elements of G^{ϵ}, G^{u}



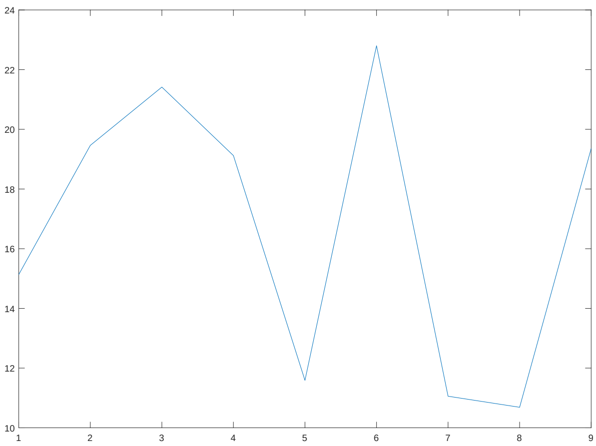
Elements of $\Phi_{\epsilon,t}, \Phi_{u,t}$



Elements of Λ, $\bar{c}$, $\mathcal{A}$



Elements of $H_{\epsilon,t}, H_{u,t}$



Elements of κ_{δ}

Figure 11. Summary of the distribution of the Inefficiency Factors for different sets of parameters

C Figures

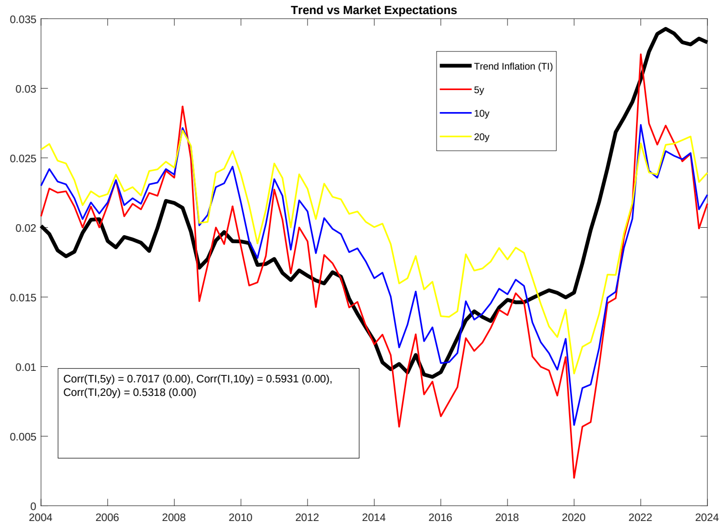


Figure 12. Market inflation swaps: 5, 10 and 20 year and median trend inflation

Note: Source of inflation swaps: Refinitiv. Table in the graph shows the correlation between each market inflation swap and the median trend inflation. In parenthesis, it is shown the p-value significance of each correlation.

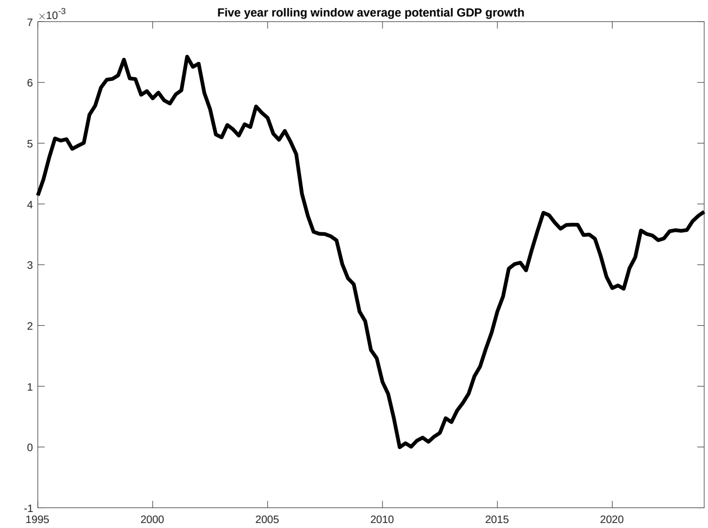


Figure 13. Average quarterly growth rate over five-year rolling windows

Note: Average quarterly growth rate of EA Potential GDP Point-wise median over five-year rolling windows.

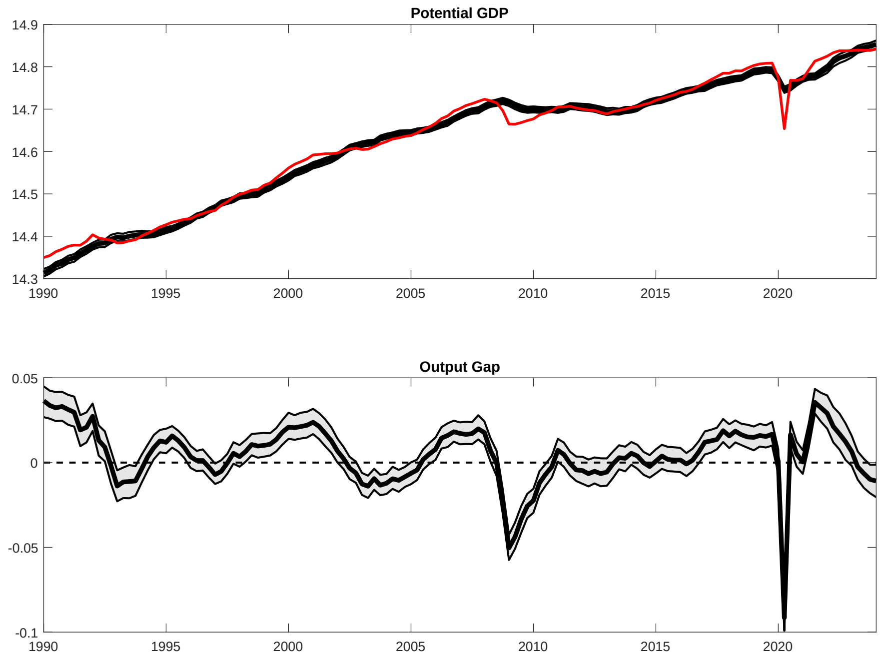


Figure 14. Actual data and estimated trends and cycles of real GDP in a model without Stochastic Volatility

Note: Point-wise median (solid black line) with 68% credible bands. Real GDP is defined in log terms. The model is estimated using the same priors but without the feature of Stochastic Volatility in both the permanent and transitory sides.

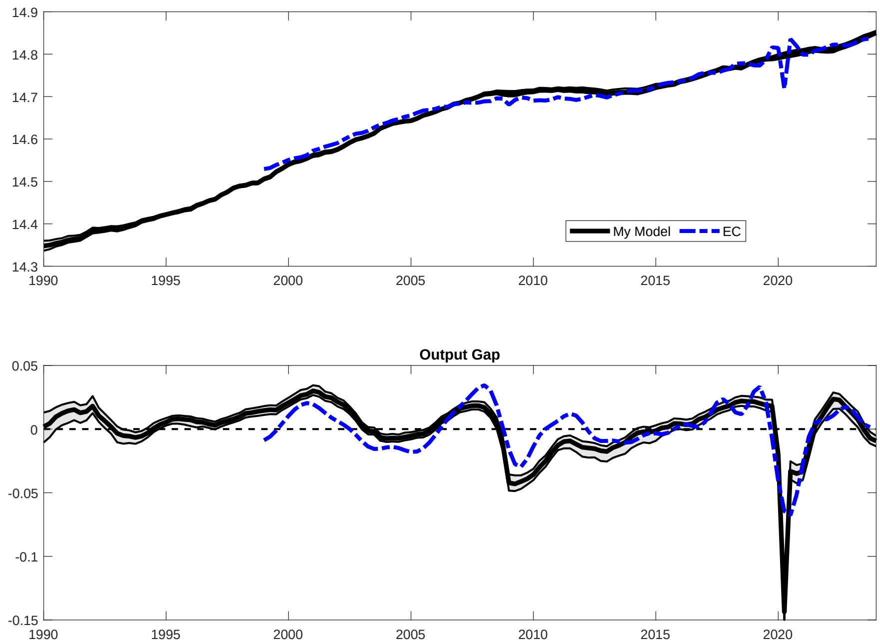


Figure 15. EA Potential GDP and Output-gap from the European Commission compared to the estimated trends and cycles of real GDP in the baseline model.

Note: The dash-dotted blue line represents the official estimates of EA Potential GDP and Output-gap from the European Commission. The model estimates of EA Potential GDP and Output-gap are represented by the point-wise median (solid black line) with 68% credible bands.

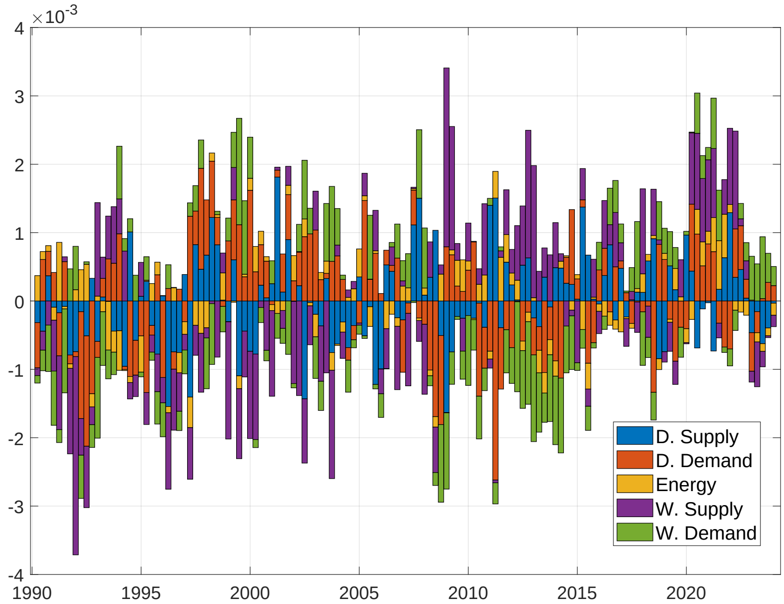


Figure 16. Estimated structural shocks of the point-wise median change of trend inflation from 1990Q2 to 2022Q2

Note: Colored bars depict the structural shocks —domestic (demand- and supply-side), global (demand- and supply-side), and energy supply— affecting the changes in the point-wise median of trend inflation, at time t.

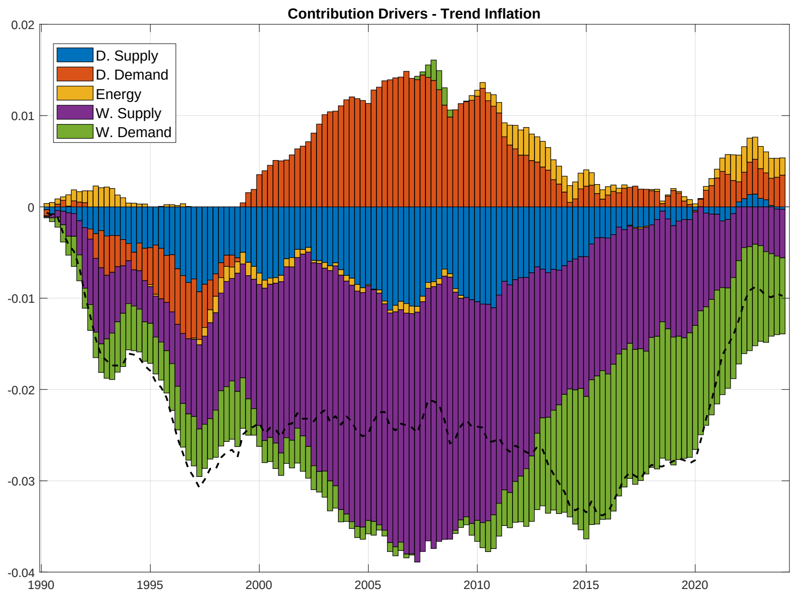


Figure 17. Estimated historical decomposition of the point-wise median of trend inflation from 1990Q2 to 2022Q2

Note: Both the black line, representing the point-wise median of trend inflation, and the colored bars, depicting the cumulative contribution of each structural shock—domestic (demand- and supply-side), global (demand- and supply-side), and energy supply—at time t, are expressed as deviations from the baseline period of 1990Q1.

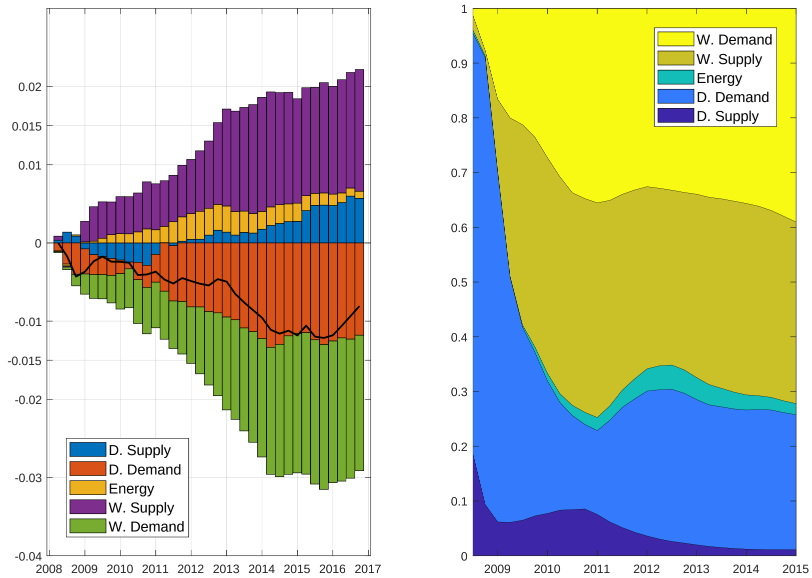


Figure 18. Estimated historical decomposition of the point-wise median of trend inflation from 2018 to 2017

Note: Both the black line, representing the point-wise median of trend inflation, and the colored bars, depicting the cumulative contribution of each structural shock—domestic (demand- and supply-side), global (demand- and supply-side), and energy supply—at time t, are expressed as deviations from the baseline period of 2008Q1.

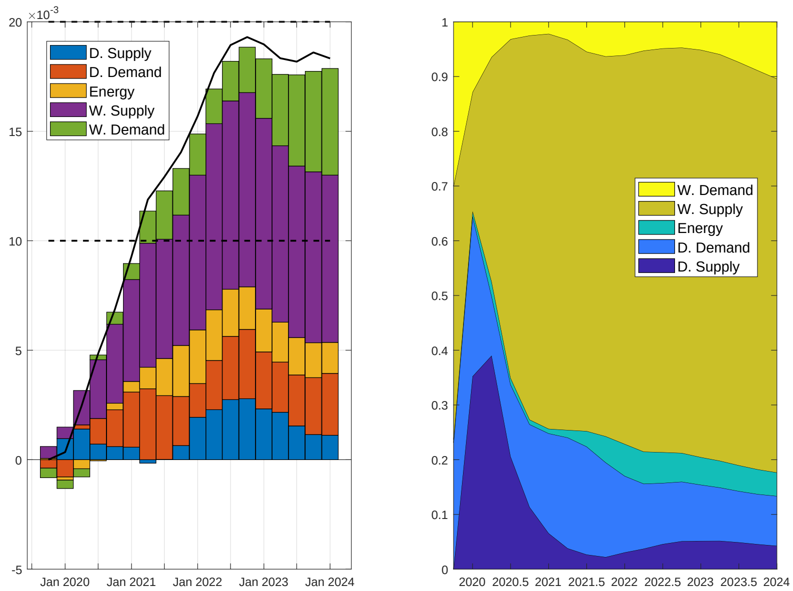


Figure 19. Estimated historical decomposition of the point-wise median of trend inflation from 2020 to 2024

Note: Both the black line, representing the point-wise median of trend inflation, and the colored bars, depicting the cumulative contribution of each structural shock—domestic (demand- and supply-side), global (demand- and supply-side), and energy supply—at time t, are expressed as deviations from the baseline period of 2019Q3.

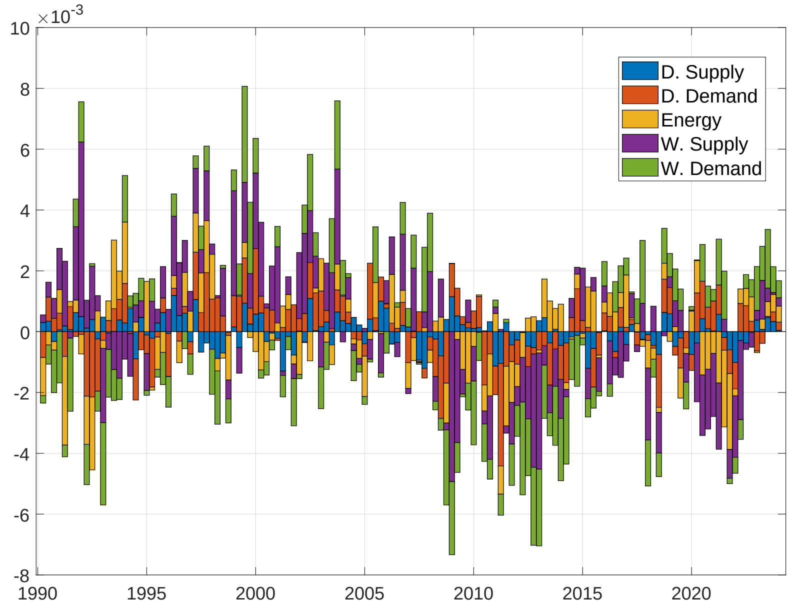


Figure 20. Estimated structural shocks of the point-wise median change of potential GDP, discounting the drift $\bar{c}$, from 1990Q2 to 2022Q2

Note: Colored bars depict the structural shocks —domestic (demand- and supply-side), global (demand- and supply-side), and energy supply— affecting the changes in the point-wise median of potential GDP, discounting the drift $\bar{c}$, at time t.

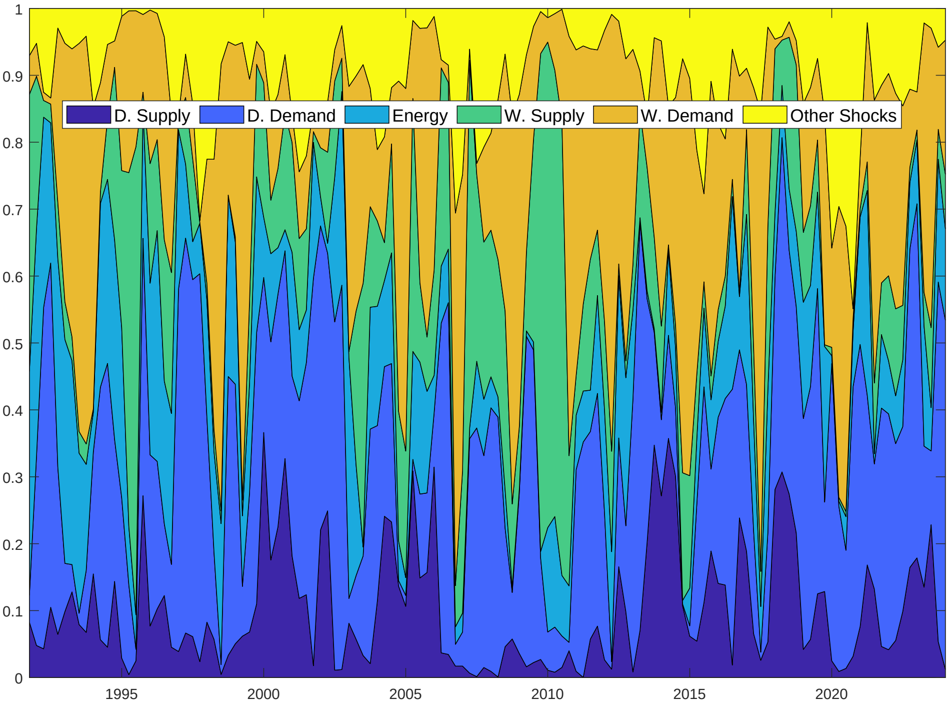


Figure 21. Estimated variance decomposition for the historical decomposition of inflation-gap (point-wise median) from 1990Q2 to 2022Q2. Short term horizon of 1 year

Note: The colored areas represent the share of the variance decomposition of each structural shock - domestic (demand and supply-side), global (demand and supply-side) and energy supply. The variance decomposition is computed over a one year rolling window, allowing the researcher to represent the explained share of each structural shock over a short horizon. The shorter the horizon the more variability there would be in the variance decomposition for the historical decomposition.

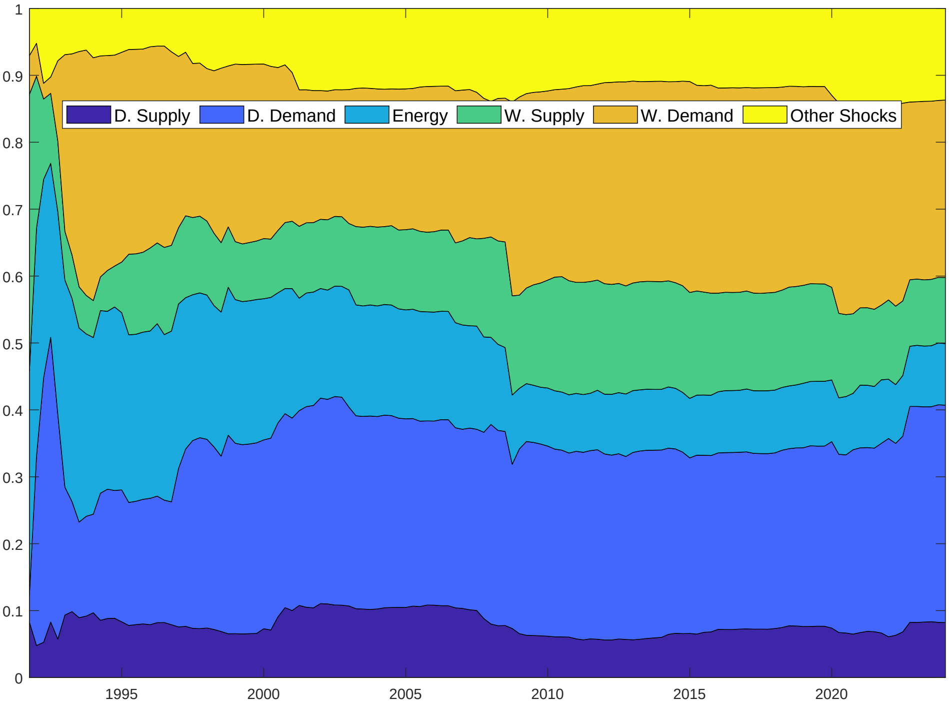


Figure 22. Estimated variance decomposition for the historical decomposition of inflation-gap (point-wise median) from 1990Q2 to 2022Q2. Long term horizon

Note: The colored areas represent the share of the variance decomposition of each structural shock - domestic (demand and supply-side), global (demand and supply-side) and energy supply. The variance decomposition is computed over a long horizon accumulating the shocks over the entire sample. This allows the researcher to represent the asymptotic explained share of each structural shock. The longer the horizon the less variability there would be in the variance decomposition for the historical decomposition.

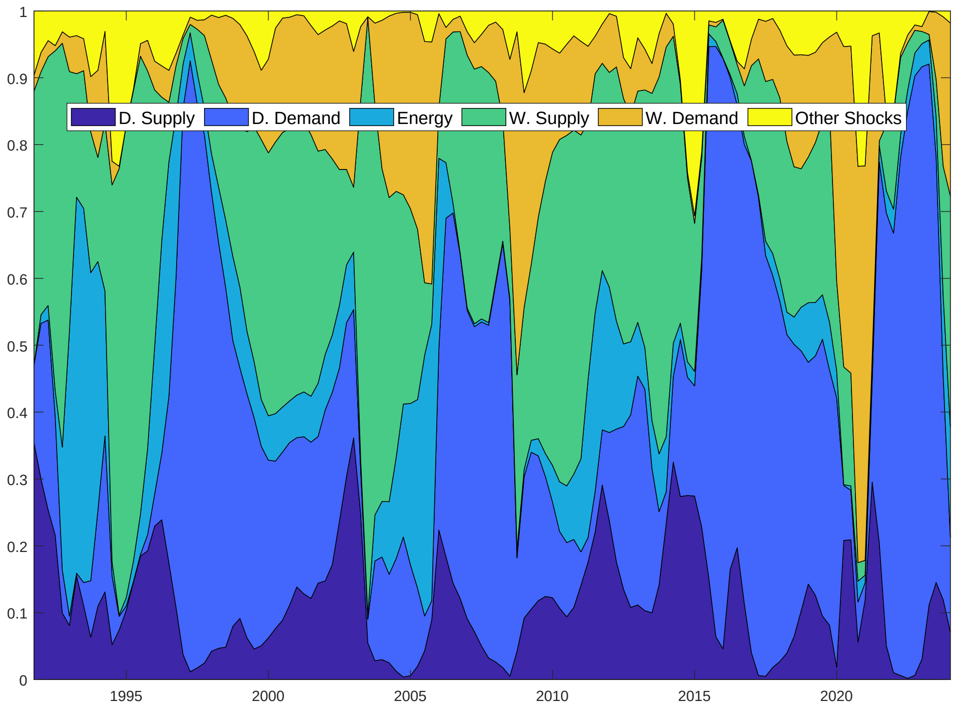


Figure 23. Estimated variance decomposition for the historical decomposition of output-gap (point-wise median) from 1990Q2 to 2022Q2. Short term horizon of 1 year

Note: The colored areas represent the share of the variance decomposition of each structural shock - domestic (demand and supply-side), global (demand and supply-side) and energy supply. The variance decomposition is computed over a one year rolling window, allowing the researcher to represent the explained share of each structural shock over a short horizon. The shorter the horizon the more variability there would be in the variance decomposition for the historical decomposition.

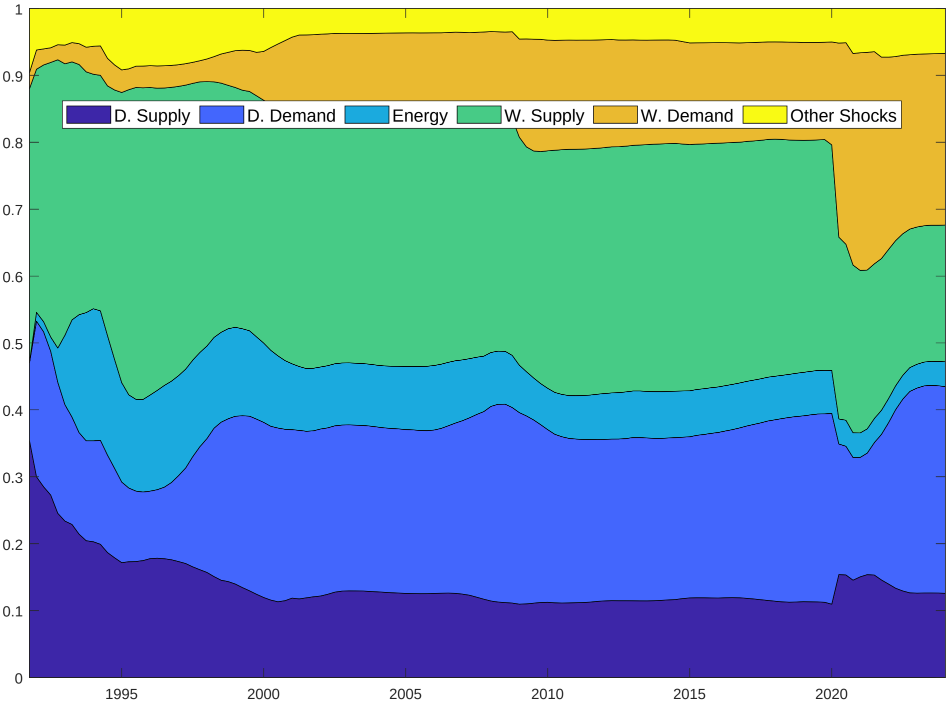


Figure 24. Estimated variance decompostion for the historical decomposition of inflation-gap (point-wise median) from 1990Q2 to 2022Q2. Long term horizon

Note: The colored areas represent the share of the variance decomposition of each structural shock - domestic (demand and supply-side), global (demand and supply-side) and energy supply. The variance decomposition is computed over a long horizon accumulating the shocks over the entire sample. This allows the researcher to represent the asymptotic explained share of each structural shock. The longer the horizon the less variability there would be in the variance decomposition for the historical decomposition.

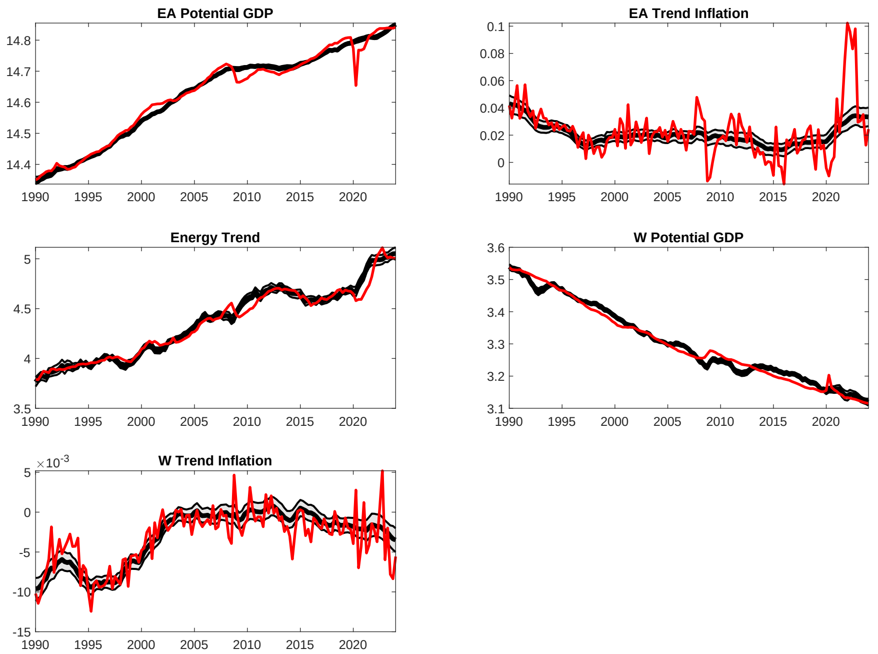


Figure 25. Actual data and estimated trends

Note: Point-wise median (solid black line) with 68% credible bands are based on 250000 draws. Variables are defined as in Table 1 and 2.

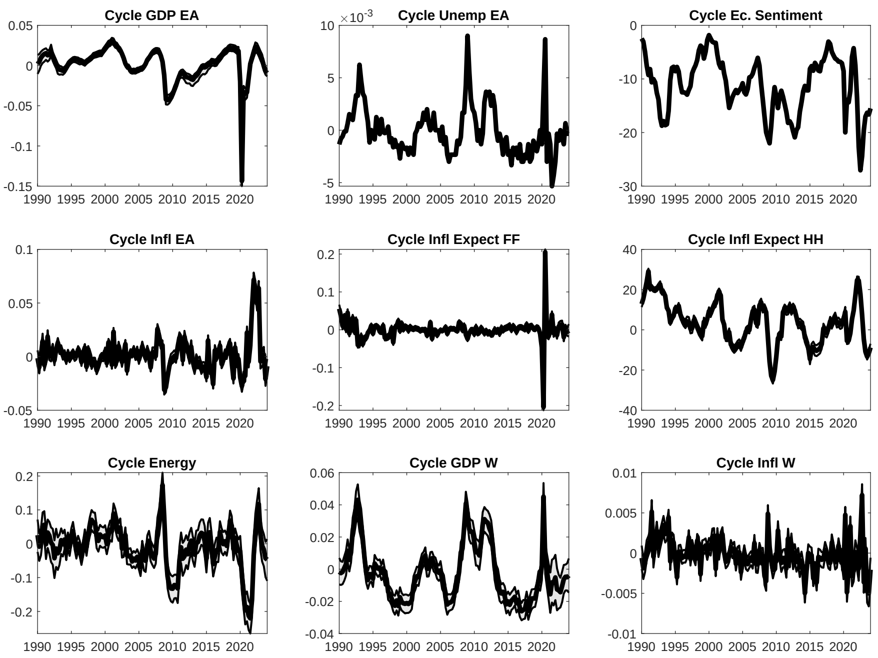


Figure 26. Actual data and estimated cycles

Note: Point-wise median (solid black line) with 68% credible bands are based on 250000 draws. Variables are defined as in Table 1 and 2.

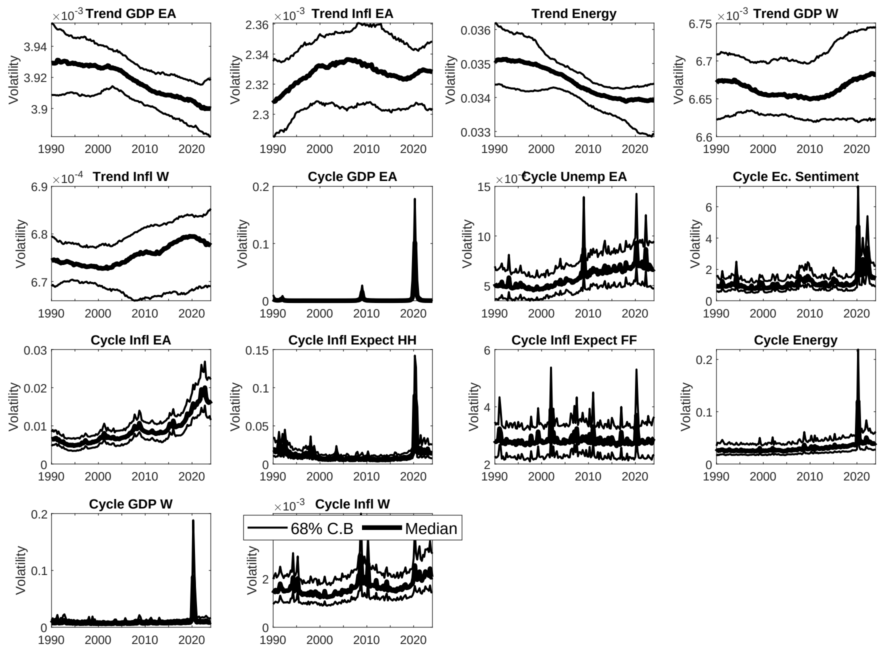


Figure 27. Stochastic volatility. The solid black lines are the posterior medians of the residual time-varing variances permanent (first five) and transitory (last nine), with 68% credible bands

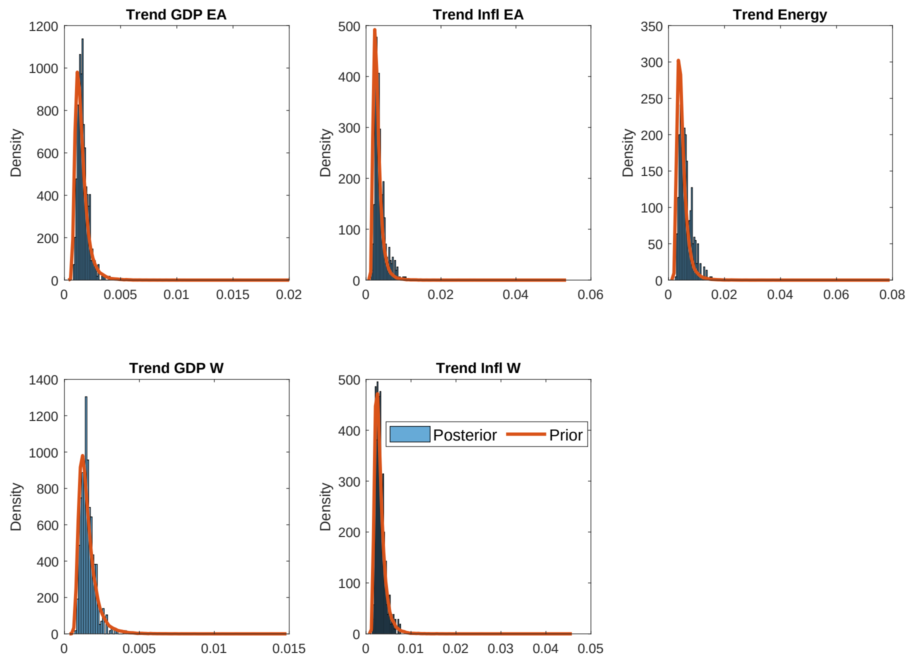


Figure 28. Prior and Posterior Densities of the Coefficients of G^{ϵ}

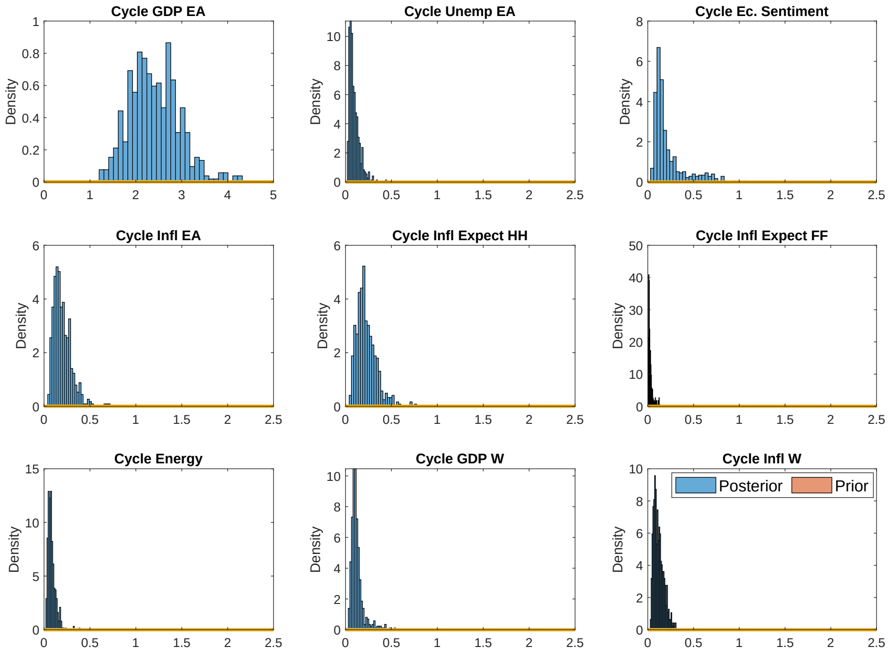


Figure 29. Prior and Posterior Densities of the Coefficients of G^u

References

Abiad, Abdul, Prachi Mishra, and Petia Topalova, "How does trade evolve in the aftermath of financial crises?," *IMF Economic Review*, 2014, *62* (2), 213–247.

Alessandria, George, Joseph P Kaboski, and Virgiliu Midrigan, "Inventories, lumpy trade, and large devaluations," *American Economic Review*, 2010, *100* (5), 2304–2339.

Altissimo, Filippo, Michael Ehrmann, and Frank Smets, "Inflation persistence and price-setting behaviour in the Euro Area-a summary of the IPN evidence," *ECB Occasional paper*, 2006, (46).

Álvarez, Luis J and Mónica Correa-López, "Inflation expectations in euro area Phillips curves," *Economics Letters*, 2020, *195*, 109449.

Antolin-Diaz, Juan, Thomas Drechsel, and Ivan Petrella, "Tracking the slowdown in long-run GDP growth," *Review of Economics and Statistics*, 2017, *99* (2), 343–356.

Arce, Oscar, Matteo Ciccarelli, Antoine Kornprobst, and Carlos Montes-Galdón, "What caused the euro area post-pandemic inflation?," *ECB Occasional Paper*, 2024, (2024/343).

Ascari, Guido and Argia M Sbordone, "The macroeconomics of trend inflation," *Journal of Economic Literature*, 2014, *52* (3), 679–739.

_ **and Luca Fosso**, "The international dimension of trend inflation," *Journal of International Economics*, 2024, *148*, 103896.

_ **, Dennis Bonam, and Andra Smadu**, "Global supply chain pressures, inflation, and implications for monetary policy," *Journal of International Money and Finance*, 2024, *142*, 103029.

Auer, Raphael, Claudio EV Borio, and Andrew J Filardo, "The globalisation of inflation: the growing importance of global value chains," 2017.

Baldwin, Richard E, *The great trade collapse: Causes, consequences and prospects*, Cepr, 2009.

Ball, Laurence, "Long-term damage from the Great Recession in OECD countries," *European Journal of Economics and Economic Policies*, 2014, *11* (2), 149–160.

_ **, N Gregory Mankiw, David Romer, George A Akerlof, Andrew Rose, Janet Yellen, and Christopher A Sims**, "The new Keynesian economics and the output-inflation trade-off," *Brookings papers on economic activity*, 1988, *1988* (1), 1–82.

Banbura, Marta, Elena Bobeica, and Catalina Martínez Hernández, "What drives core inflation? The role of supply shocks," 2023.

Barbarino, Alessandro, Travis J Berge, Han Chen, and Andrea Stella, "Which output gap estimates are stable in real time and why?," 2020.

Bems, Rudolfs, Robert C Johnson, and Kei-Mu Yi, "The great trade collapse," *Annu. Rev. Econ.*, 2013, *5* (1), 375–400.

Bénassy-Quéré, Agnes, Giancarlo Corsetti, Antonio Fatás, Gabriel J FELBERMAYR, Marcel Fratzscher, Clemens Fuest, Francesco Giavazzi, Ramon Marimon, Philippe Martin, Jean Pisani-Ferry et al., "COVID-19 economic crisis: Europe needs more than one instrument," 2020.

Benati, Luca and Haroon Mumtaz, "US evolving macroeconomic dynamics: a structural investigation," 2007.

Bergholt, Drago, Francesco Furlanetto, and Etienne Vaccaro-Grange, *Did monetary policy kill the Phillips curve? Some simple arithmetics*, Norges Bank, 2023.

Beveridge, Stephen and Charles R Nelson, "A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'," *Journal of Monetary economics*, 1981, *7* (2), 151–174.

Bianchi, Francesco and Andrea Civelli, "Globalization and inflation: Evidence from a time-varying VAR," *Review of Economic Dynamics*, 2015, *18* (2), 406–433.

Blanchard, Olivier, Thomas Philippon, Jean Pisani-Ferry et al., *A new policy toolkit is needed as countries exit COVID-19 lockdowns*, JSTOR, 2020.

Bluedorn, Mr John C and Mr Daniel Leigh, *Hysteresis in labor Markets? Evidence from professional long-term forecasts*, International Monetary Fund, 2019.

Bobeica, Elena and Marek Jarociński, "Missing disinflation and missing inflation: A VAR perspective," *57th issue (March 2019) of the International Journal of Central Banking*, 2019.

_ **, Matteo Ciccarelli, and Isabel Vansteenkiste**, "The link between labor cost and price inflation in the euro area," 2019.

Bodnár, Katalin, Julien Le Roux, Paloma Lopez-Garcia, Béla Szörfi et al., "The impact of Covid-19 on potential output in the euro area," *Economic Bulletin Articles*, 2020, *7.*

Borio, Claudio EV and Andrew J Filardo, "Globalisation and inflation: New cross-country evidence on the global determinants of domestic inflation," 2007.

Bowles, Carlos, Roberta Friz, Veronique Genre, Geoff Kenny, Aidan Meyler, and Tuomas Rautanen, "The ECB survey of professional forecasters (SPF)-A review after eight years' experience," *ECB occasional paper*, 2007, (59).

Candia, Bernardo, Olivier Coibion, and Yuriy Gorodnichenko, "The Inflation Expectations of US Firms: Evidence from a new survey," Technical Report, National Bureau of Economic Research 2021.

Canova, Fabio and Gianni De Nicolo, "Monetary disturbances matter for business fluctuations in the G-7," *Journal of Monetary Economics*, 2002, *49* (6), 1131–1159.

Carriero, Andrea, Todd E Clark, Massimiliano Giuseppe Marcellino, and Elmar Mertens, "Addressing COVID-19 outliers in BVARs with stochastic volatility," 2021.

Carter, Chris K and Robert Kohn, "On Gibbs sampling for state space models," *Biometrika*, 1994, *81* (3), 541–553.

Chen, Ms Wenjie, Mr Mico Mrkaic, and Mr Malhar S Nabar, *The global economic recovery 10 years after the 2008 financial crisis*, International Monetary Fund, 2019.

Chor, Davin and Kalina Manova, "Off the cliff and back? Credit conditions and international trade during the global financial crisis," *Journal of international economics*, 2012, *87* (1), 117–133.

Ciccarelli, Matteo and Benoit Mojon, "Global inflation," *The Review of Economics and Statistics*, 2010, *92* (3), 524–535.

_ **and Juan Angel García**, "Expectation spillovers and the return of inflation," *Economics Letters*, 2021, *209*, 110119.

_ **, Chiara Osbat, Elena Bobeica, Caroline Jardet, Marek Jarocinski, Caterina Mendicino, Alessandro Notarpietro, Sergio Santoro, and Arnoud Stevens**, "Low inflation in the euro area: Causes and consequences," *ECB occasional paper*, 2017, (181).

Clark, Peter K, "The cyclical component of US economic activity," *The Quarterly Journal of Economics*, 1987, *102* (4), 797–814.

Clark, Todd E and Troy Davig, "The relationship between inflation and inflation expectations," *memo to the FOMC, November*, 2009, *30*, 2009.

Cogley, Timothy and Thomas J Sargent, "Drifts and volatilities: monetary policies and outcomes in the post WWII US," *Review of Economic dynamics*, 2005, *8* (2), 262–302.

Coibion, Olivier and Yuriy Gorodnichenko, "Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 197–232.

Conti, Antonio Maria, Stefano Neri, and Andrea Nobili, "Low inflation and monetary policy in the euro area," *ECB Working Paper*, 2017.

Corsello, Francesco, Stefano Neri, and Alex Tagliabracci, "Anchored or de-anchored? That is the question," *European Journal of Political Economy*, 2021, *69*, 102031.

Corsetti, Giancarlo, Luca Dedola, and Sylvain Leduc, "The international dimension of productivity and demand shocks in the US economy," *Journal of the European Economic Association*, 2014, *12* (1), 153–176.

Croitorov, Olga, Giulia Filippeschi, Mirko Licchetta, Philipp Pfeiffer, Adriana Reut, Wouter Simons, Anna Thum-Thysen, Anneleen Vandeplas, and Lukas Vogel, "The macroeconomic impact of the COVID-19 pandemic in the euro area," *Q Rep Euro Area*, 2021, *20* (2), 7–16.

Dovern, Jonas, Geoff Kenny et al., "Anchoring inflation expectations in unconventional times: Micro evidence for the euro area," *International Journal of Central Banking*, 2020, *16* (5), 309–347.

Duncan, Roberto and Enrique Martínez-García, "Forecasting inflation in open economies: What can a NOEM model do?," *Journal of Forecasting*, 2023, *42* (3), 481–513.

Eaton, Jonathan, Samuel Kortum, Brent Neiman, and John Romalis, "Trade and the global recession," *American Economic Review*, 2016, *106* (11), 3401–3438.

ECB, Staff, "Annual Report 2021," 2021.

_ , "Economic Bulletin Issue 8, 2022," 2022.

Fagan, Gabriel, Jerome Henry, and Ricardo Mestre, "An area-wide model for the euro area," *Economic Modelling*, 2005, *22* (1), 39–59.

Fernández-Villaverde, Jesús, Luis Garicano, and Tano Santos, "Political credit cycles: the case of the Eurozone," *Journal of Economic perspectives*, 2013, *27* (3), 145–166.

Ferroni, F and B Mojon, "Domestic and global drivers of inflation in the euro area," *ECB Economic Bulletin*, 2017, (4), 72–96.

Ferroni, Filippo and Benoit Mojon, "Domestic and global inflation," *Mimeo. Federal Reserve Bank of Chicago*, 2014.

Forbes, Kristin J, "Has globalization changed the inflation process?," 2019.

Furlanetto, Francesco, Antoine Lepetit, Ørjan Robstad, Juan Rubio Ramírez, and Pål Ulvedal, "Estimating hysteresis effects," 2021.

Galí, Jordi and Luca Gambetti, "On the sources of the great moderation," *American Economic Journal: Macroeconomics*, 2009, *1* (1), 26–57.

Gemma, Yasufumi, Takushi Kurozumi, and Mototsugu Shintani, "Trend Inflation and Evolving Inflation Dynamics: A Bayesian GMM Analysis," *Review of Economic Dynamics*, 2023.

Geweke, John, "Bayesian treatment of the independent Student-t linear model," *Journal of applied econometrics*, 1993, *8* (S1), S19–S40.

_ , "Interpretation and inference in mixture models: Simple MCMC works," *Computational Statistics & Data Analysis*, 2007, *51* (7), 3529–3550.

Geweke, John F et al., "Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments," Technical Report, Federal Reserve Bank of Minneapolis 1991.

Giannone, Domenico and Giorgio Primiceri, "The drivers of post-pandemic inflation," Technical Report, National Bureau of Economic Research 2024.

_ **, Michele Lenza, and Giorgio E Primiceri**, "Prior selection for vector autoregressions," *Review of Economics and Statistics*, 2015, *97* (2), 436–451.

Gilje, Erik, Robert Ready, and Nikolai Roussanov, "Fracking, drilling, and asset pricing: Estimating the economic benefits of the shale revolution," Technical Report, National Bureau of Economic Research Cambridge, MA 2016.

Gimeno, Ricardo and Eva Ortega, "The evolution of inflation expectations in euro area markets," 2016.

Giordani, Paolo, Michael Pitt, and Robert Kohn, "Bayesian inference for time series state space models," 2011.

Gordon, Robert J, "Inflation, flexible exchange rates, and the natural rate of unemployment," Technical Report, National Bureau of Economic Research 1981.

_ , "US inflation, labor's share, and the natural rate of unemployment," 1988.

_ , "The turtle's progress: Secular stagnation meets the headwinds," *Secular stagnation: facts, causes and cures*, 2014, pp. 47–59.

_ , "Secular stagnation: A supply-side view," *American economic review*, 2015, *105* (5), 54–59.

Gorter, Janko, Jan Jacobs, and Jakob De Haan, "Taylor rules for the ECB using expectations data," *Scandinavian Journal of Economics*, 2008, *110* (3), 473–488.

Ha, Jongrim, M Ayhan Kose, and Franziska Ohnsorge, "Global inflation synchronization," 2019.

Hamilton, James D, "Why you should never use the Hodrick-Prescott filter," *Review of Economics and Statistics*, 2018, *100* (5), 831–843.

Harvey, Andrew C, "Trends and cycles in macroeconomic time series," *Journal of Business & Economic Statistics*, 1985, *3* (3), 216–227.

Hasenzagl, Thomas, Filippo Pellegrino, Lucrezia Reichlin, and Giovanni Ricco, "A Model of the Fed's View on Inflation," *The Review of Economics and Statistics*, 2018, pp. 1–45.

Hausman, Catherine and Ryan Kellogg, "Welfare and distributional implications of shale gas," Technical Report, National Bureau of Economic Research 2015.

Henriksen, Espen, Finn E Kydland, and Roman Šustek, "Globally correlated nominal fluctuations," *Journal of Monetary Economics*, 2013, *60* (6), 613–631.

Higgins, Matthew, Thomas Klitgaard et al., "How Much Have Consumers Spent on Imports during the Pandemic?," Technical Report, Federal Reserve Bank of New York 2021.

Hilscher, Jens, Alon Raviv, and Ricardo Reis, "How likely is an inflation disaster?," 2022.

IMF, "Global disinflation in an era of constrained monetary policy," *World Economic Outlook*, 2016.

_ , "Recent wage dynamics in advanced economies: Drivers and implications," *World Economic Outlook, October 2017: Seeking sustainable growth: Short-term recovery, long-term challenges*, 2017, pp. 73–112.

Jacquier, Eric, Nicholas G Polson, and Peter E Rossi, "Bayesian analysis of stochastic volatility models with fat-tails and correlated errors," *Journal of Econometrics*, 2004, *122* (1), 185–212.

Jarociński, Marek and Michele Lenza, "An inflation-predicting measure of the output gap in the euro area," *Journal of Money, Credit and Banking*, 2018, *50* (6), 1189–1224.

Kabukçuoğlu, Ayşe and Enrique Martínez-García, "Inflation as a global phenomenon—Some implications for inflation modeling and forecasting," *Journal of Economic Dynamics and Control*, 2018, *87*, 46–73.

Kamber, Güneş, James Morley, and Benjamin Wong, "Intuitive and reliable estimates of the output gap from a Beveridge-Nelson filter," *Review of Economics and Statistics*, 2018, *100* (3), 550–566.

Kilian, Lutz, "The economic effects of energy price shocks," *Journal of economic literature*, 2008, *46* (4), 871–909.

_ , "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market," *American Economic Review*, 2009, *99* (3), 1053–69.

Koester, Gerrit, Jakob Nordeman, Michel Soudan et al., "Comparing recent inflation developments in the United States and the euro area," *Economic Bulletin Boxes*, 2021, *6.*

__ , **Sofia Cuquerella Ricarte, Ramon Gomez-Salvador et al.**, “Recent inflation developments in the United States and the euro area–an update,” *Economic Bulletin Boxes*, 2022, *1.*

Laxton, Douglas and Robert Tetlow, *A simple multivariate filter for the measurement of potential output*, Vol. 59, Bank of Canada Technical Report No. 59. Ottawa, 1992.

Lenza, Michele and Giorgio E Primiceri, “How to estimate a vector autoregression after march 2020,” *Journal of Applied Econometrics*, 2022.

Levchenko, Andrei A, Logan T Lewis, and Linda L Tesar, “The collapse of international trade during the 2008-2009 crisis: In search of the smoking gun,” Technical Report, National Bureau of Economic Research 2010.

Łyziak, Tomasz and Maritta Paloviita, “Anchoring of inflation expectations in the euro area: recent evidence based on survey data,” *European Journal of Political Economy*, 2017, *46*, 52–73.

Maffei-Faccioli, Nicolò, “Identifying the sources of the slowdown in growth: Demand vs. supply,” Technical Report, Working Paper 2021.

Martin, Fernando M, Juan M Sánchez, and Olivia Wilkinson, “The economic impact of COVID-19 around the world,” *FRB St. Louis Working Paper*, 2022, (2022-30).

Martínez-García, E and MA Wynne, *The global slack hypothesis* number 10, DIANE Publishing, 2010.

Muggenthaler, Philip, Joachim Schroth, and Yiqiao Sun, “The heterogeneous economic impact of the pandemic across euro area countries,” *Economic Bulletin Boxes*, 2021, *5.*

Mumtaz, Haroon and Paolo Surico, “Evolving international inflation dynamics: world and country-specific factors,” *Journal of the European Economic Association*, 2012, *10* (4), 716–734.

Negro, Marco Del, Domenico Giannone, Marc P Giannoni, and Andrea Tambalotti, “Safety, liquidity, and the natural rate of interest,” *Brookings Papers on Economic Activity*, 2017, *2017* (1), 235–316.

__ , __ , __ , **and** __ , “Global trends in interest rates,” *Journal of International Economics*, 2019, *118*, 248–262.

O’Brien, Derry, Clemence Dumoncel, Eduardo Goncalves et al., “The role of demand and supply factors in HICP inflation during the COVID-19 pandemic–a disaggregated perspective,” *Economic Bulletin Articles*, 2021, *1.*

Primiceri, Giorgio E, “Time varying structural vector autoregressions and monetary policy,” *The Review of Economic Studies*, 2005, *72* (3), 821–852.

Reis, Ricardo, "The burst of high inflation in 2021–22: how and why did we get here?," 2022.

Rubio-Ramirez, Juan F, Daniel F Waggoner, and Tao Zha, "Structural vector autoregressions: Theory of identification and algorithms for inference," *The Review of Economic Studies*, 2010, *77* (2), 665–696.

Santis, Roberto A De and Grigor Stoevsky, "The role of supply and demand in the post-pandemic recovery in the euro area," *Economic Bulletin Articles*, 2023, *4*.

Schorfheide, Frank and Dongho Song, "Real-time forecasting with a (standard) mixed-frequency VAR during a pandemic," Technical Report, National Bureau of Economic Research 2021.

Shirota, Toyoichiro, "Flattening of the Phillips curve under low trend inflation," *Economics Letters*, 2015, *132*, 87–90.

Stephens, Matthew, "Dealing with label switching in mixture models," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 2000, *62* (4), 795–809.

Stock, James H and Mark W Watson, "Variable trends in economic time series," *Journal of economic perspectives*, 1988, *2* (3), 147–174.

— **and** — , "Why has US inflation become harder to forecast?," *Journal of Money, Credit and banking*, 2007, *39*, 3–33.

Strohsal, Till and Lars Winkelmann, "Assessing the anchoring of inflation expectations," *Journal of International Money and Finance*, 2015, *50*, 33–48.

Summers, Lawrence H, "U.S. Economic Prospects: Secular Stagnation, Hysteresis, and the Zero Lower Bound," *Business Economics*, 2014, pp. 65–73.

Uhlig, Harald, "What are the effects of monetary policy on output? Results from an agnostic identification procedure," *Journal of Monetary Economics*, 2005, *52* (2), 381–419.

Watson, Mark W, "Univariate detrending methods with stochastic trends," *Journal of monetary economics*, 1986, *18* (1), 49–75.

Yellen, Janet, "Macroeconomic Research After the Crisis: a speech at\" The Elusive'Great'Recovery: Causes and Implications for Future Business Cycle Dynamics\" 60th annual economic conference sponsored by the Federal Reserve Bank of Boston, Boston, Massachusetts, October 14, 2016," Technical Report, Board of Governors of the Federal Reserve System (US) 2016.