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It is all about demand and supply: a dualistic view of the euro area business cycle

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Abstract

What drives business cycle fluctuations in the euro area (EA)? To answer this question, we build a rich, high-dimensional dataset of quarterly time series covering both EA aggregates and its major member countries. We find that just two shocks account for the bulk of the EA's cyclical dynamics, and that they map cleanly onto standard demand and supply disturbances, consistent with textbook macroeconomic theory. Beyond this aggregate result, we uncover a high degree of synchronization in how member states respond to these shocks, highlighting the presence of a shared underlying cycle across the region. We also provide a historical decomposition of key EA macro variables based on the identified demand and supply components, with a particular focus on the recent inflation surge. Our findings show that supply-side factors dominated the initial phase of inflation through mid-2022, while demand-side pressures intensified and became increasingly important from mid-2022 onward.

Key words: Business cycle, identification, frequency domain, euro area economy, dynamic factors, inflation.

JEL classification: C38, E32.

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1 Introduction

Macroeconomic analysis often seeks to identify the key forces driving economic fluctuations. Over the recent years, the policy and academic discussion has shifted back towards a broader and more generic framework that relies on the identification of a restricted number of factors driving macroeconomic fluctuations – typically interpreted within a demand/supply paradigm, (see, e.g., Ascari et al., 2023; Bergholt et al., 2023; Eickmeier and Hofmann, 2022; Forni et al., 2024; Giannone and Primiceri, 2024; Shapiro, 2024). This approach offers policymakers a parsimonious yet effective way to interpret complex dynamics and implement appropriate measures to stabilize the economy accordingly. At the same time, it urges the need for a deeper comprehension of the main drivers of business cycle fluctuations.

In a recent influential study, Angeletos et al. (2020) (ACD henceforth) show that a single *main business cycle shock* (MBC) accounts for most of US business cycle volatility. Their interpretation suggests this shock to be a demand-type shock outside the realm of nominal rigidities, as they find a disconnection from the long-run and inflation dynamics, ruling out both supply-side and standard inflationary demand shocks from the possible candidates. A few contributions followed this seminal study, challenging the one-shock characterization. Notably, Avarucci et al. (2021) and Forni et al. (2024) (FGGSS henceforth) support a two-shocks representation of the economy, as one shock is not sufficient to explain the bulk of the US data volatility. They both find that the two shocks fit well in the standard AD-AS narrative, as they have salient features of textbook aggregate demand and aggregate supply shocks, a view also supported by Cubadda and Mazzali (2024).[1] By contrast, the literature on the main drivers of Euro Area (EA) business cycle fluctuations remains comparatively limited. To our knowledge, the closest study in this regard is Giannone et al. (2019) (GLR henceforth), who identify an EA cyclical shock and examine its properties. However, their primary focus is on the impact of the Great Financial Crisis on the transmission mechanism in EA, and they do not provide a comprehensive treatment of aggregated business cycle fluctuations and the propagation mechanism of common shocks.

Nevertheless, addressing this matter in the context of EA is strongly relevant. The EA is characterized by substantial economic, institutional, and structural heterogeneity, which challenges the presence of a unified propagation mechanism. This forms an ideal setting to test whether a small number of shocks can still explain the bulk of aggregate business cycle volatility. Accordingly, this paper addresses the following questions: Are EA business cycle fluctuations driven by a limited number of shocks and, if so, how many? What are their structural economic interpretations?

The relevance of our study is manyfold. First, we contribute to the ongoing debate on the drivers of business cycle fluctuations by focusing on the EA. While much of the existing literature emphasizes the US, we show that a small number of shocks can still explain the bulk of EA cyclical variability. This finding provides strong evidence that common propagation mechanisms operate even in a more heterogenous economic region. Second, our analysis sheds a new light on the main sources of the EA data volatility and thus carries important policy implications. Identifying the key drivers of EA economic volatility offer crucial insights for

[1] Granese (2024) argues that the differences with ACD are imputable to the fact that the VAR considered by ACD is not *informationally sufficient* – in the sense of Forni and Gambetti (2014) – to recover their baseline MBC shock.

policymakers – particularly the European Central Bank (ECB) – to better assess the sources of economic fluctuations and design more effective responses. In addition, our analysis inform discussions on the synchronization of business cycles across member states – a crucial concern for policymakers seeking to manage divergent economic conditions under a common monetary policy.

We find that two shocks are sufficient to account for most of the EA's cyclical volatility. Impulse response function (IRF) analysis reveals these shocks align with textbook-type demand shock - where inflation and output positively comove - and supply shock - where inflation and output negatively comove. These results confirm that, even in a highly heterogeneous region, a limited number of shocks can effectively capture the essential characteristics of aggregate fluctuations. Moreover, the structural nature of these shocks suggests that the EA economy can be represented within a simple AD-AS framework. Remarkably, this structure holds not only for EA aggregates but also across individual member countries, pointing to a high degree of underlying synchronization. Finally, we show that this framework helps interpret recent inflation dynamics. A historical decomposition suggests that supply-side forces dominated the early phase of the inflation surge, but demand-side pressures became increasingly persistent from mid-2022 onward, remaining influential through the end of 2023. This evolution underscores the importance of distinguishing between shock types for timely and effective policy intervention.

Our strategy involves building an extensive dataset of 156 quarterly time series from Q1:1985 to Q4:2019. The dataset includes real, financial, and nominal variables, covering the EA as an aggregate and its major member countries.[2] We estimate a Common Component Structural VAR (CC-SVAR) model, which was recently proposed by Forni et al. (2020). This model combines the flexibility of VARs and the good features of Dynamic Factor Models (DFMs), allowing to efficiently handle the large cross-sectional information of our dataset.[3] Above all, this model allows us to naturally deal with the idiosyncratic component that can become particularly important when dealing with EA data – as the significant degree of heterogeneity across country members might translate into exceptionally noisy data – and that, as shown by Lippi (2021), may dynamically contaminate the structural shocks estimation.[4]

The study proceeds in two parts. In the first part, we examine how many shocks are required to adequately explain business cycle fluctuations in the EA. Following the approach of ACD and FGGSS, we adopt the *max-share* identification strategy proposed by Uhlig (2004) but applied over the frequency-domain, which involves the maximization of the variance of a targeted variable over the business cycle frequency band.[5] We extend this approach by

[2]To our knowledge, only Barigozzi et al. (2014); Giannone et al. (2012) and Barigozzi et al. (2024) have previously assembled a comparably large dataset for the EA economy.

[3]DFMs have proven particularly convenient in the EA both for both the analysis on the transmission of common shocks (*e.g.*, Barigozzi et al., 2014, 2024; Corsetti et al., 2022) and nowcasting (*e.g.*, Camacho and Perez-Quiros, 2010; Cascaldi-Garcia et al., 2023).

[4]From a conceptual point of view, the idea behind DFMs that a limited number of common shocks primarily drive economic fluctuations fits well with our hypothesis. Moreover, working in a data-rich environment avoids the well-known non-invertibility issue, affecting VARs (as discussed, *i.a.*, in Forni et al., 2019; Hansen and Sargent, 1991; Lippi and Reichlin, 1993, 1994).

[5]Among others, see Barsky and Sims (2011); Francis et al. (2014) for time-domain max-share, and Dieppe et al. (2021); Giannone et al. (2019) for frequency-domain examples.

proposing a *factor-augmented* max-share procedure that jointly targets the variance of a key variable along with selected common factors. Our method incorporates more information than ACD's single-variable strategy while remaining more parsimonious and agnostic than the multi-variable targeting approach of FGGSS. We find that one shock – the main business cycle shock (MBC) – explains a large share of cyclical fluctuations. However, a non-negligible portion of the variance remains unexplained unless a second shock—the second business cycle shock (SBC) – is included. With both shocks, we are able to explain the majority of business cycle volatility in the EA. Notably, we find that both the MBC and SBC are not disconnected from inflation. Moreover, the two shocks also jointly account for a large share of long-run variance, despite our focus is solely on business cycle volatility. Impulse response analysis provides insight into the nature of these shocks. We find that the MBC shock causes a positive comovement between inflation and output, characteristic of a demand-type shock. Conversely, the SBC exerts a negative comovement between prices and output, suggesting a supply-side nature.

In the second part of the analysis, we investigate whether these two shocks can be structurally interpreted as textbook demand and supply shocks. To do this, we rotate the shocks based on a minimal set of economic restrictions: the demand shock is identified by maximizing the covariance of inflation and output at cyclical frequencies, while the supply shock is defined as the orthogonal component that minimizes the same quantity. The resulting shocks closely align with the previously identified MBC and SBC, confirming that EA business cycle dynamics are largely driven by two fundamental shocks that conform to the standard New-Keynesian framework. These findings stand in partial contrast to earlier results from GLR (for the EA) and ACD (for the US), both of which document a disconnection between cyclical shocks and inflation. Our results are instead consistent with more recent US-based contributions, including Avarucci et al. (2021), Granese (2024), and FGGSS.

It is worth stressing that our identification strategy is agnostic on both variables' responses and long run behaviours, as we do not impose any sign restrictions on the impact of the shocks, nor we impose any long-run assumptions. Nevertheless, the identification strategy naturally recovers two well-defined structural shocks. The MBC emerges as a standard demand shock: it has transitory effects on real activity and is disconnected from long-run fluctuations. Interestingly, the long-run neutrality arises endogenously from the data, while for Blanchard and Quah (1989) was an imposed feature. By contrast, the SBC drives long-run dynamics and is consistent with a supply-side interpretation. Together, the two shocks capture the bulk of cyclical volatility in the EA and provide a robust framework for understanding the region's business cycle dynamics.

We complement the picture of EA aggregated fluctuations, and analyze how the identified region-wide shocks propagates across individual member countries. We find broadly similar responses across countries, underscoring a high degree of business cycle synchronization. However, consistent with Cavallo and Ribba (2015), we observe some partial disconnection in more peripheral economies, such as Greece, Ireland and Portugal. In this Regard, our study also contributes to the literature on EA business cycle synchronization – see, for instance, Agresti and Mojon (2001); Cendejas et al. (2014); Giannone et al. (2008). However, most of these works does not rely on (semi-) structural approaches or examine impulse responses and variance decompositions in detail.

Finally, we use our two shocks to study the factors behind the recent surge in inflation. We extend our dataset to include the post-pandemic period and repeat our identification strategy. The results suggest that the initial rise in inflation was predominantly supply-driven. However, demand-side pressures intensified in 2022 and remained persistent throughout 2023. By the end of the year, demand shocks continued to exert upward pressure on inflation, offsetting the effects of deflationary supply forces. These results provide a clear rationale for the restrictive monetary policy stance adopted by the ECB during this period.

The reminder of the paper is structured as follows. Section 2 outlines our econometric framework . Section 3 describes the dataset and the empirical strategy. Section 4 presents the results. Section 5 concludes, summarizing the main insights and policy implications.

2 Econometric Framework

This section presents the CC-SVAR model of Forni et al. (2020) and the frequency domain identification adopted in this work.

2.1 The Common Component SVAR

Let x_t be a N-dimensional vector of weakly stationary time series. Each variable x_{it}, $i = 1, ..., N$, can be rewritten as the sum of two mutually orthogonal unobservable components, $x_{it} = \chi_{it} + \xi_{it}$. The *idiosyncratic* components, ξ_{it}, represent the source of variation affecting a specific variable, and for this, they are usually interpreted as measurement errors or regional/sectoral shocks.[6] The *common* components, χ_{it}, account instead for the bulk of macroeconomic variation. They are assumed to span a finite-dimensional vector space, which implies that there exists a vector F_t, weakly stationary, of dimension $r < N$, such that

$$\chi_{it} = \lambda_{i1}F_{1t} + \lambda_{i2}F_{2t} + ... + \lambda_{ir}F_{rt} \qquad \text{or} \qquad \chi_t = \Lambda F_t \tag{1}$$

where $\chi_t = (\chi_{1t}, ..., \chi_{Nt})$, Λ is a $N \times r$ matrix of *factor loadings* and $F_t = (F_{1t}, \dots, F_{rt})'$ is the r-vector of unobservable *static factors*, which are pervasive and orthogonal to $\xi_t = (\xi_{1t}, \dots, \xi_{Nt})'$.

In representation (1), the static factors are only loaded contemporaneously. One can further assume that F_t follows a VAR(p) law of motion which is driven by a vector of orthonormal white noise $u_t = (u_{1t}, u_{2t}, ..., u_{qt})'$ of dimension $q \leq r$. Formally,

$$D(L)F_t = \varepsilon_t \qquad \text{and} \qquad \varepsilon_t = Ru_t \tag{2}$$

where ε_t is a r-dimensional vector of VAR residuals, with $\mathbb{E}[\varepsilon_t] = 0$ and $\mathbb{E}[\varepsilon_t\varepsilon_t'] = \Omega_\varepsilon$, $D(L)$ is a $r \times r$ stable polynomial matrix of coefficients and R is a $r \times q$ matrix with full-column rank. In finite samples, F_t is not exactly singular. Singularity, which holds only asymptotically, is forced using a rank-reduction (*i.e.*, imposing $q < r$). Forni et al. (2020) show that such a step can be ignored with no consequences on the estimation accuracy of IRFs. By inverting the matrix $D(L)$ in (2), we obtain the MA representation for the static

[6] In our framework, the idiosyncratic components are allowed to be poorly correlated in the cross-sectional dimension. This assumption is milder and more realistic than uncorrelation and is pivotal for ascribing this model to the class of *approximate* factor models. See, for instance, Forni et al. (2009).

factors, $F_t = D(L)^{-1}\varepsilon_t = D(L)^{-1}Ru_t$, which directly implies the following MA representation of the common components

$$\chi_t = \Lambda F_t = \Lambda D(L)^{-1}\varepsilon_t = \Lambda D(L)^{-1}Ru_t \tag{3}$$

Let us, now, define a $n \times (N + r)$ selection matrix ψ, populated by ones and zeros, that selects n variables of interest among $(\chi_t', F_t')'$, say Y_t. We have

$$Y_t = \psi \begin{pmatrix} \chi_t \\ F_t \end{pmatrix} = \left[\Lambda_\psi D(L)^{-1}R\right] u_t = B(L)u_t \tag{4}$$

where $\Lambda_\psi = \psi(\Lambda', I_r')'$ and $B(L)$ is a $n \times q$ matrix polynomial.

If $n > q$, Y_t is a singular stochastic vector, and, if $n \leq r$ its variance-covariance matrix is non-singular for all possible ψ. Generically, if $r \geq n > q$, Y_t also admits a finite VAR representation

$$A_\psi(L)Y_t = \varepsilon_t^\psi \tag{5}$$

where $A_\psi(L)$ is a finite matrix polynomial and $\varepsilon_t^\psi = B(0)u_t = \Lambda_\psi R u_t = R_\psi u_t$ are VAR residuals, with $\mathbb{E}[\varepsilon_t^\psi] = 0$ and $\mathbb{E}[\varepsilon_t^\psi \varepsilon_t^{\psi\prime}] = \Lambda_\psi \Omega_\varepsilon \Lambda_\psi' = \Omega_\psi$.[7]

Following Forni et al. (2020), we ignore the rank-reduction step. This implies that the number of shocks equals the number of variables, *i.e.*, r in (2) and n in (5). As a consequence, R and R_ψ are simply rotation matrices, such that $R'R = \Omega_\varepsilon$ and $R_\psi' R_\psi = \Omega_\psi$, respectively.

Notably, if $r \geq n > q$ the singular VAR in equation (5) can be estimated using a non-singular VAR (Forni et al., 2020). This provides the econometrician with a more flexible framework, but still with some of the desirable characteristics of the Structural DFM. First, the common components of the variables of interest enter directly in the VAR. Secondly, we can add factors to the VAR to increase the information set (as in the FAVAR literature – see Bernanke et al., 2005). Thirdly, it is possible to apply any identification technique used in a standard SVAR directly to the equation (5).[8] Finally, if $n = r$, Y_t spans the same linear space of F_t. This implies that *(i)* imposing the same identification conditions, we get the same estimated structural shocks and *(ii)* the estimated shock(s) of interest and the corresponding IRFs are consistently estimated independently of the choice of ψ. This is a particularly appealing feature that allows the econometrician to study the impact of an identified shock on all the variables of interest without being constrained by the initial choice of ψ.

[7] As a result of Anderson and Deistler (2008a,b), if $B(L)$ is zeroless, then it admits a left-inverse, say $A(L)$, of finite order such that $A(L)B(L) = B(0)$. Thus, $A(L)Y_t = B(0)u_t = \varepsilon_t^\psi$. The fact that $B(L)$ is zeroless is a reasonable assumption, as the coefficients of its entries are free to vary independently to one another (Forni et al., 2020).

[8] Provided that the vector u_t is fundamental for χ_t, the well-known non-fundamentalness issue is also resolved by estimating Y_t through the equation (5). This is always true even if we don't have to directly estimate u_t, which may instead add estimation uncertainty due to possible specifications in the estimation of the dimension q.

2.2 Frequency Domain Identification

Let us consider the linear mapping between VAR residuals and structural shocks, $\varepsilon_t^{\psi} = R_{\psi} u_t = \Lambda_{\psi} R u_t$. Then, let us define $R = SH$, where S is the Cholesky decomposition of Ω_{ε}, such that $SS' = \Omega_{\varepsilon}$, and H is an orthonormal matrix, such that $H^{-1} = H'$ and $HH' = I$. This implies that $RR' = SHH'S' = \Omega_{\varepsilon}$ and $R_{\psi} R_{\psi}' = S_{\psi} HH' S_{\psi}' = \Omega_{\psi}$, where $S_{\psi} = \Lambda_{\psi} S$. We can rewrite (5) as

$$Y_t = A_{\psi}(L)^{-1} \Lambda_{\psi} R u_t = A_{\psi}(L)^{-1} S_{\psi} H u_t = C(L) H u_t \tag{6}$$

where $C(L) = A_{\psi}(L)^{-1} S_{\psi}$ and the structural shocks are $u_t = H' S_{\psi}^{-1} \varepsilon_t^{\psi}$. Since S_{ψ} is the Cholesky factor, identifying the shocks means dealing with H.

The effect of a generic j-th structural shock, $h' S_{\psi}^{-1} \varepsilon_t^{\psi}$, on the k-th variable is given by $e_k' C(L) h$, where e_k is the k-th column of the k-dimensional identity matrix and h is the j-th column of H, such that $h'h = 1$.

Let $[\underline{\omega}, \overline{\omega}]$ be a frequency band, such that $0 < \underline{\omega} \leq \overline{\omega} \leq \pi$. The spectral density matrix of the structural representation of process Y_t in such band is

$$\Sigma(\underline{\omega}, \overline{\omega}) \equiv \int_{\underline{\omega}}^{\overline{\omega}} \Re\left(C(z) HH' C(z^{-1})' \right) d\omega = \int_{\underline{\omega}}^{\overline{\omega}} \Re\left(C(z) C(z^{-1})' \right) d\omega \tag{7}$$

where $z = \exp(-i\omega)$ and $\Re(x)$ is the real part of x.[9] The main-diagonal [off-diagonal] elements of the matrix $\Sigma(\underline{\omega}, \overline{\omega})$ measure the contribution of u_t to the band-specific variance [covariance] of the variables. The variance generated by the j-th column of H is $\Sigma(j, \underline{\omega}, \overline{\omega})$.

Letting $\sigma_{l,k}(\underline{\omega}, \overline{\omega})$ be the element (l, k) of $\Sigma(\underline{\omega}, \overline{\omega})$, the contribution of the j-th shock to such element is

$$\sigma_{l,k}(j, \underline{\omega}, \overline{\omega}) \equiv \int_{\underline{\omega}}^{\overline{\omega}} \Re\left(e_l' C(z) hh' C(z^{-1})' e_k \right) d\omega = h' \left[\int_{\underline{\omega}}^{\overline{\omega}} \Re\left(C(z)' e_l e_k' C(z^{-1}) \right) d\omega \right] h \tag{8}$$

where the integral captures the entire volatility of element (l, k) over the specific frequency band. In the case of single-targeting, equation (8) is the objective function which need to be restricted for identification. For instance, ACD maximize the diagonal element of $\Sigma(j, \underline{\omega}, \overline{\omega})$ corresponding to unemployment in the business cycle frequency band, $[2\pi/32, 2\pi/6]$.

FGGSS show that it is also possible to consider multiple elements of $\Sigma(j, \underline{\omega}, \overline{\omega})$, lying on and off the main diagonal. Suppose we are interested in jointly targeting m entries of $\Sigma(j, \underline{\omega}, \overline{\omega})$, say $(l_1, k_1), (l_2, k_2), \ldots, (l_m, k_m)$. We can easily consider a weighted sum of such entries, with weights equal to the reciprocal of the band-specific standard deviations. In other words, we replace the vectors e_l and e_k in (8) with two $n \times m$ matrices defined as $P_L = E_l w_l$ and $P_K = E_k w_k$, where $E_s = (e_{s_1}, e_{s_2}, \ldots, e_{s_m})$ is $n \times m$ and $w_s = diag\left(\sigma_{s_1,s_1}(\underline{\omega}, \overline{\omega})^{-1/2}, \ldots, \sigma_{s_m,s_m}(\underline{\omega}, \overline{\omega})^{-1/2} \right)$, for $s = (l, k)$, is $m \times m$. We obtain

[9] Main diagonal elements of the spectral density matrix are real, whereas the off-diagonal ones (cross-spectrum) are typically complex and, thus, can be expressed as $a \pm bi$, where a is the real part (co-spectrum) and b is the imaginary part (quadrature-spectrum). As we are (potentially) interested in a measure of covariance over a specific band, and not of the cross-covariance, we consider only the real part of the cross-spectrum.

$$\sigma_{L,K}(j, \underline{\omega}, \overline{\omega}) \equiv h' \left[\int_{\underline{\omega}}^{\overline{\omega}} C(z)' P_L P_K' C(z^{-1}) \quad d\omega \right] h \tag{9}$$

which is the objective function in the case of multi-targeting. Clearly, if $m = 1$, (9) collapses to (8).

As ACD, we are interested in maximizing an objective function over a specific band. Thus, we need to find the h_1 that maximizes (8), or (9), such that $h_1' h_1 = 1$.

Interestingly, if one is interested in identifying more than one shock, say q, the procedure can be extended to identify multiple shocks sequentially (Forni et al., 2024). Once h_1 is obtained, we can retrieve h_j, with $1 < j \leq q$, maximizing (8), or (9), such that $h_j' h_j = 1$ and $h_j' h_g = 0$, with $g < j$.

3 Empirical application

3.1 Data

We construct a comprehensive dataset of 156 quarterly time series, covering the period from 1985:Q1 to 2019:Q4. The dataset includes a wide range of real, nominal, and financial variables, covering both Euro Area aggregates and most of its major member countries, as well as selected global indicators. The majority of the Euro Area and country-level data are retrieved from the OECD Data Warehouse, specifically from the Main Economic Indicators (MEI) and Economic Outlook (EO) databases.

The Euro Area aggregate block consists of 18 variables, including Real Gross Domestic Product (GDP) and its sub-components, labor market measures, Consumper Price Index (CPI), money aggregates (M1 and M2), an index of stock prices and the interest rates.Additionally, we include the Composite Indicator of Systemic Stress (CISS) from the ECB Data Portal and the Economic Sentiment Index (ESI) from Eurostat. For the country-level dimension, we include 23 series for both Italy and France, 22 for Germany, and 20 for Spain. Variables for these countries include GDP and its expenditure components, interest rates, real effective exchange rate, stock market indeces, labor market indicators, GDP deflator, Producer Price Index (PPI), CPI, Industrial and Consumer Confidence Indicators and an housing price index. We further include 11 variables for Belgium and the Netherlands, 10 for Portugal and 5 for Austria, including GDP and its expenditure components, CPI, interest rates and some key labor market indicators. Finally, only GDP, CPI and short-term interest rates for Finland, Greece and Ireland. We complement the dataset with a set of global variables: the Global Condition Index (GCON) developed by Baumeister et al. (2022), the Brent Crude Oil Spot Price and the VIX index (from FRED), and the National Financial Conditions Index (NFCI) provided by the Chicago Fed.

Some further notes on data coverage are in order. While most of the variables of interest are available starting from mid-1980s, a few indicators start later. In these cases, they are backdated using the Area Wide Model dataset (Fagan et al., 2005), MEI growth rates, or Barigozzi et al. (2014)'s dataset. Data are seasonally adjusted and are transformed to achieve stationarity. Following FGGSS, we express real variables and price indices in growth rates, while variables already expressed in percentage terms (such as interest rates and unemployment) are kept in levels. A complete list of variables, data sources and the transformations is provided in Appendix A.

3.2 Estimation and Model Specification

We estimate the CC-SVAR as suggested by Forni et al. (2020). First, we determine the number of static factors following Alessi et al. (2010), which build on the test of Bai and Ng (2002). The test suggests $\hat{r} = 9$. Subsequently, we estimate the loading matrix $\hat{\Lambda}$ as $\sqrt{N}$ times the normalized eigenvectors corresponding to the largest $\hat{r}$ eigenvalues of the sample covariance matrix of the standardized x_t. Then, we obtain the static factors F_t projecting the estimated loadings onto the (standardized) data. The common component is finally $\hat{\chi}_t = \hat{\Lambda}\hat{F}_t$.

For the construction of Y_t, we set $n = \hat{r}$ following the suggestions in Forni et al. (2020). As previously discussed, with a $n > \hat{r}$, we would face a singular variance-covariance matrix of the Y_t. Thus, we choose the largest value for n. Since we do not apply rank-reduction techniques, estimation of q is not strictly necessary. Our baseline specification includes 7 key Euro Area series: Real GDP growth (Y), Real Private Consumption growth (C), Unemployment (U), Labor productivity growth (LPr), Real Stock Prices (SH), CPI inflation (π) and Short-term rate (R), along with two factors, which are crucial for our identification strategy. Table 1 provides the common and idiosyncratic shares for the selected series and underlines that most of the fluctuations are considered as common.Finally, we estimate the VAR in (5) over the selected Y_t, with lag order $p = 2$, and retrieve $\hat{A}_\psi(L)$ and $\hat{\varepsilon}_t^\psi$.

The variable choice is motivated by the goal of our analysis, which aims to investigate the existence of a shared propagation mechanism at the aggregate regional level. However, thanks to the intrinsic properties of the model, we can also analyse the impact of the identified shocks on other variables included in our dataset in a standard DFM manner. As previously explained, when $n = r$, results are robust on the choice of ψ.[10] Therefore, we repeat the estimation procedure of Y_t with a different selection matrix ψ, re-estimating our CC-SVAR with different variables of interest at each time and analyzing other EA aggregate series and individual country-specific variables.

3.3 The Identification Procedure

We divide the identification procedure into two distinct steps. First, we ask whether the MBC shock concept can be extended to the EA economy and how many shocks are needed to explain the bulk of EA economic fluctuations at the business cycle frequency. Secondly, we delve into the structural economic interpretation of the shocks.

Our strategy bridges the ACD's single-targeting and FGGSS's multi-targeting. Similarly to FGGSS, we opt for targeting multiple variables at once. However, rather than jointly targeting an *ad hoc* set of variables, we exploit the information incorporated in the factors. The resulting procedure is more parsimonious and general than FGGSS's.

[10]This allows the econometrician to study the responses of all the variables of the dataset to the identified shocks without affecting the original results of baseline specification. As explained in Section 2, this feature is true by construction and it distinguishes the CC-SVAR from both standard SVAR and FAVAR models.

We first identify q shocks that jointly maximize the variance of a specific variable along with the variance of the two factors included in the VAR over the business cycle frequency band, *i.e.*, the band that corresponds to $[6, 32]$ quarters.[11] We choose GDP for our baseline specification. We repeat the same procedure varying the target variable, for a total of $n-2$ times. Each time, we solve the sequential maximization problem in (9) until we obtain q shocks, *i.e.*, $h^* = [h_1, h_2, ..., h_q]$, as explained in Section 2.2. We show below that $q = 2$ shocks are enough to explain most of the cycle fluctuations. In what follows, we will refer to the shock identified by h_2 as the *second main business cycle shock* (SBC).

The max-share identification offers the advantage of being agnostic. However, this comes with a cost: the shocks are statistically identified, thus with no economic interpretation *per se*. Therefore, we add a second step and adopt the methodology suggested by FGGSS, applying a second rotation that imposes economic restrictions. The new rotation matrix imposes that the first shock minimizes the covariance of GDP growth and the inflation rate at business cycle frequencies, whereas the second shock is obtained by orthogonality condition, as the one maximizing the same quantity. In so doing, we identify a supply and a demand shock, respectively.[12]

4 Results

4.1 Euro-Area Business Cycle fluctuations: a tale of two shocks

Table 2 reports the results obtained in the first step. Let us focus on the left part of the table, where we report the portion of the variance of the variables explained by the MBC over the business cycle (upper panel) and the long run (lower panel). The first column shows the variance explained by the shock obtained multi-targeting the variance of GDP, jointly with the two factors, over business cycle frequency bands. The shock accounts for a substantial part of fluctuations in the business cycle frequency of all the variables, with share variances above 45% for GDP, Unemployment, Interest rate, and Labour Productivity. Consumption, Inflation and stock prices display slightly lower values, but still around 30%. On the other hand, as evident from the lower panel, the shock appears partially unrelated to long-term economic fluctuations, with the long-run variance explained for GDP, Consumption, and Unemployment which is lower than 12%. Notably, these findings are robust across different shocks, reported in the other columns, supporting the existence of a shared underlying dynamic that influences the business cycle fluctuations across the region. While the disconnection between the shock and the long run is consistent with results obtained by ACD for the US economy, the connection between inflation and the MBC is a significant departure from GLR and ACD, where the shock targeting Unemployment has only a limited explanatory power on prices in EA and US, with our results being closer to Bianchi et al. (2023). Granese (2024) have similar results both for inflation and the long-run, but they are not robust to the variable choice, whereas we find a strong interchangeability among shocks,

[11] This coincides with a frequency band equal to $[2\pi/32, 2\pi/6]$, a rather common band to defined the business cycle in the literature. See, for instance, Beaudry et al. (2020).

[12] As underlined by FGGSS, this identification scheme, does not impose any restrictions on the timing effect of the demand shock, which in principle could also affect output in the long run.

showing comparable share variances.

Figure 1 completes the analysis and compares the IRFs of all the identified shocks. The responses to the shock targeting GDP are presented as a solid black line and are plotted against all the point estimates of the remaining shocks. There is a large synchronization in the propagation mechanism across all the shocks, reinforcing previous results and confirming the existence of an MBC shock in the Euro Area. This shock elicits positive hump-shaped responses in GDP and Consumption, alongside a counter-cyclical response for Unemployment. The IRFs peak around the first year after the shock before either returning to (GDP and Unemployment) or below the initial level (Consumption). Interestingly, the shock also causes a positive and permanent response to Labour Productivity, while stock prices initially increase before rebounding after one year. Concerning the remaining variables, interest rate positively reacts at impact, peaking at around the fifth quarter before gradually reverting. Inflation responses are particularly noteworthy: we observe a significant and persistent inflation increase, taking about four years to return to pre-shock levels. Again, this is at odds with the results of ACD for the US data and with what is found in GLR in the EA data, where price responses were mainly flat. Conversely, our MBC shock shows an inflationary nature and, might be akin to a classic demand shock. This aspect will be better analysed later in the paper.

Although the MBC accounts for a substantial part of business cycle fluctuations, a significant portion of the total volatility remains unexplained. Table 3 reports the cumulative variance of the first three shocks obtained sequentially maximizing the variance of GDP. Some observations are in order. Most notably, two shocks ($q = 2$) adequately - and parsimoniously - explain the majority of EA business cycle fluctuations. They collectively account for 96% of the variance in GDP, 92% of Labour Productivity, and over 80% for Consumption, Unemployment and interest rate. Inflation and stock prices are also well explained with a share variance above 65%. Conversely, the third shock plays only a marginal role in business cycle frequency. This finding closely aligns with what is found in FGGSS, Granese (2024) and Avarucci et al. (2021) for the US data, who also indicate $q = 2$. Interestingly, two shocks together account for a significant share of the long-run variance of the variables. This is a non-trivial result, as the shocks are identified by only targeting the business cycle frequency. Thus, the cyclical fluctuations and the long-run trend might share a common driver, that must be strongly linked to the second shock, as the MBC has a significant long-term disconnection.

It is worth noticing that the third shock is also an important driver of the long run. As it is not the object of the current analysis, we leave the study of long-run dynamics to future research.

Figure 2 reveals another significant result: the SBC propagates differently than the MBC. Notably, the SBC induces a small effect at impact, which later becomes positive and permanent for both GDP and Consumption. On the other hand, the Interest Rate negatively reacts at impact. Similarly, Inflation significantly decreases before swiftly reverting to its steady state, a dynamic that may suggest a classical deflationary-type supply nature for the SBC shock.

4.2 A Demand and Supply Story

The previous section points to the EA business cycle to be almost entirely driven by two shocks which are akin to demand and supply shocks. As our identification of MBC and SBC is fundamentally agnostic, no structural interpretation is possible. Thus, we add a second step which imposes some economic restrictions by rotating the non-structural shocks obtained in the previous section. Details on the procedure are described in Section 3.

We focus only on the first two shocks that maximize the variance of GDP, along with the factors, as prior results have shown variable choice to be non-influential. Following FGGSS, we choose a rotation matrix such that the first shock maximizes the co-spectrum of GDP and Inflation over business cycle frequency, while the second shock, by orthogonality condition, is automatically identified as the one minimizing the same quantity. In such a way, we identify a demand and supply shock, respectively, that are economically meaningful and a linear combination of the previous shocks.

Figure 3 depicts the IRFs of both the demand (solid blue line) and the supply (solid red line) shocks. The two shocks are plotted against the MBC (dashed blue line) and SBC (dashed red line) shocks to facilitate the comparison. Remarkably, the shocks are almost identical. This is an important result, highlighting that with our purely agnostic first step identification, we retrieve a classic inflationary demand shock as the main and a supply shock as the second driver of the business cycle. These findings are at odds with ACD for the US, who instead interpreted the MBC shock as a demand shock outside the realm of nominal price rigidities.

Table 4 completes the picture and confirms that the demand shock is the primary driver of the EA cycle fluctuation, although the supply shock also plays a significant role. In this sense, we can cast EA in a standard New-Keynesian framework, where both demand and supply shocks are important to explain the cyclical fluctuations. Moreover, the disconnection of the MBC/demand shock aligns with Blanchard and Quah (1989), who proposed a transitory, long-run neutral demand shock. Notably, our results are also particularly similar to FGGSS and Avarucci et al. (2021) for the US data, suggesting similar business cycle dynamics and characteristics between the US and the Euro Area economy, as also underlined, for instance, in Agresti and Mojon (2001).

Although we do not find evidence of the hysteresis effect, we find that a demand shock has a sizeable and persistent impact on Labour Productivity, aresult that is in line with Jordà et al. (2024) and Bachmann and Sims (2012), who both found that different types of demand shocks could induce a significant and long-lasting response in productivity.

Interestingly, the demand shock exerts a positive co-movement of the Interest Rate and GDP, excluding the monetary policy shock as the main driver of business cycle fluctuations. Consumption is explained by the more persistent supply shock in a larger measure than the rest of the variables analysed, a result explainable by the permanent income theory (Quah, 1990). Finally, the two shocks have a similar initial positive impact on stock prices, which however decline almost immediately and turn negative after a year when hit by a demand shock, while the response is larger and more persistent when hit by the supply shock. This behavior is consistent with the literature related to news shock, with the anticipation of future productivity increases raises expected corporate earnings, leading to persistently higher stock prices.

4.2.1 What about other variables?

As described in Section 3, the model framework where we operate permits us to analyse a larger set of variables than the one chosen in the baseline specification. We briefly study some extra variables not included in the main specification. In Figure 4 we report the response of global variables (global economic condition index, VIX, real oil prices) and EA variables (economic sentiment index, CISS, private investment, capacity utilization, unit labor costs).

The IRFs confirm the demand and supply nature of the two shocks, with all the variables that depict larger initial responses to the demand shock that, however, tend to dissipate quicker than the supply shock. In particular, the demand shock has a sizable effect on private investment at impact, which could at least partially explain the response of labor productivity. On the other hand, the supply shock has a persistent effect on investment, in line with what is predicted by a technology shock. The responses of wages follow with those of a supply and demand shock: unit labor costs increase following a demand shock, which could point to firms competing for workers over periods of economic boom, but the effect is only transitory and goes back to its steady state around the fourth year.

The nature of the analysed shocks is further corroborated by the response of real oil prices, which increase significantly to a demand shock and decrease substantially to a supply shock. Interestingly, both the responses are very persistent.

A demand shock exerts a temporary increase in the global economic and economic sentiment indices, but the effect reverts quickly around the second year and becomes negative. This compounds with the response of the CISS and ESI and points to a shock that creates a boom in the economy and is subsequently followed by a burst over the following years, which may suggest a link between the demand shock and a shock originating in the financial markets. It is worth noting that the significant reaction of the global variables highlights the global nature of both shocks, which are therefore not to be intended as solely Euro Area domestic shocks.

4.2.2 Responses at Country levels

Our dataset includes country-specific indicators. We extend the analysis to these variables, studying how the regional-wide demand and supply shocks identified in the previous section propagate through the economies of the country members. We focus on GDP and CPI inflation and we analyse the degree of heterogeneity of each country's responses by focusing on both the IRFs and the variance explained by the two shocks.

In the first step, we check the portion of variance explained by the common and the idiosyncratic components for both GDP and inflation. Table 5 shows that most countries are well synchronized, with the common component accounting for at least 50% of the total variation for all countries except Greece and Ireland, which are mostly driven by country-specific dynamics. CPI inflation, on the other hand, is even more synchronized among the country members, which may suggest the important role played by the monetary union in the Euro Area.

Let us move now to the analysis of the IRFs in Figure 5. Overall, we find a surprisingly high level of synchronization in the response of both GDP growth and Inflation to the euro-area demand and supply shock, with a very similar dynamic compared to the Euro Area aggregate variable analysed in the previous section. This is an important result that shows how the Euro-Area economies share similar dynamics. However, we find a few exceptions. Greece, Ireland, Spain, and Portugal show an elasticity to the supply shock that is particularly high compared to the rest of the countries, while Germany is the least responsive. Conversely, Germany has a larger elasticity to a demand shock. The panel below shows the response of inflation to the two shocks. Again, there is a very high level of synchronization, even higher than that of Real GDP, which could be explained by the common monetary policy stance toward the same inflation target.

Table 6 shows the variance explained by both the two shocks at business cycle frequencies. By analyzing the overall sum of the variance, it is evident that, at least for what concerns the common components, each country is well explained by two shocks. This confirms what we previously found for the Euro Area aggregate variables, and tells us that two shocks are enough to explain most country-specific common economic fluctuations. The demand shock is the main driver of GDP fluctuations for most of the countries, with a share that ranges between 53% and 70%, except for Greece, Ireland and Portugal, where the supply shock is equally or more important when compared to the demand shock. Inflation provides a similar picture, with demand-side shocks that are relatively more important to explain the fluctuations of price growth. Nevertheless, the supply shocks still play an important role, accounting for more than 20% for the majority of countries, except for, again, Portugal, Spain, and Greece.

4.3 An Historical Perspective of the Identified Shocks

One could now ask how much of the data's overall volatility is explained by the identified *cyclical* demand and supply shocks over time. The results of this exercise - akin to a pure historical decomposition procedure - are reported in Figure 6. Here, we decompose the common components of the variables included in our baseline model into the relative role of the demand shock (blue bars), supply shocks (red bars), and residual (grey bars).[13]

While the interpretation of the first two components is straightforward, the grey bars can be insetad interpreted as a) the residual component in the cycle frequencies and b) any driver that falls into the realm of higher or lower frequencies. In this sense, Figure 6 highlights a first clear result that is robust with what we described in the previous sections: over the sample analysed, a big portion of the variables' volatility is driven by business cycle forces, as testified by the relatively low magnitude of the grey bars, at least up to 2010, while the relative importance of the non-cyclical component increases over the years following the great financial crisis, such as for inflation, unemployment, and consumption. Figure 6 also implicitly underscores the importance to account for both the first two cyclical shocks to fully grasp the dynamics of these variables. Neglecting either of the two could leave a substantial portion of volatility unexplained, potentially leading to policy misjudgments.

Moving to the relative importance of the supply-side and demand-side shocks, the 90s were mainly driven by demand shocks. This is particularly evident with the recession of 1992-1993, with demand shocks pushing down on Real GDP growth and consumption growth and

[13]In principle, it would be enough to add the idiosyncratic component into the residual component to obtain the decomposition of the overall data

up on unemployment. Unsurprisingly, demand shocks were also the main drivers of the great financial crisis for many of the variables, although supply shocks played also a significant role in the years preceding the GFC, probably capturing the commodities price boom in 2006-2007. Demand shocks started to lose importance after 2010, particularly for unemployment and inflation, which are instead mainly driven by supply-side shocks over 2012-2015 following the sequence of oil shocks experienced over that period.

4.3.1 On the recent inflation surge

At this point, it seems natural to check what our model suggests to be the main drivers of the post-pandemic inflation surge, a question still highly relevant in both the academic and policy debate, as testified by the many recent contributions to this question (Ascari et al., 2023; Bergholt et al., 2023; Eickmeier and Hofmann, 2022; Giannone and Primiceri, 2024; Shapiro, 2024). In our framework, we can check how much of the inflation over the recent years was to be addressed to the *cyclical* component, and, naturally, what is the relative importance of the demand and supply factors. To answer this question, we extend the data and estimate the model up to 2023Q4, replicating the identification strategy described in Section 2.2 and decomposing inflation as explained in this paragraph.[14]

Results for inflation are reported in Figure 7. Overall, our model predicts that most of the inflation increase is linked to business cycle fluctuations, with the two components explaining almost all of the inflation volatility over the analysed period. Moreover, the initial inflation spike was driven totally by supply forces, with demand that started to pick up only around the beginning of 2021, before becoming the main driver around the beginning of 2022. This is consistent with the view that the initial inflationary forces were mainly due to supply bottlenecks that arose over the pandemic, with the imbalance between supply and demand that became more extreme as consumers' spending behavior went gradually back to the pre-pandemic level. Interestingly, the model predicts that over 2023, inflation was still elevated mainly due to inflationary demand forces, while the supply shock was already pushing down on price growth. This may suggest that both the supply bottlenecks and the energy shock were already, at least partially, reabsorbed by the end of 2023. At the same time, it justifies the need for a restrictive monetary policy stance as demand pressure was still elevated.

5 Conclusion

We investigate the sources of EA business cycle fluctuations. To this end, we build an extensive quarterly macroeconomic time series dataset, and we provide evidence that EA business cycle fluctuations can be parsimoniously characterized by two shocks. These shocks can be seen as an inflationary-type demand - although not *fully* monetary policy - shock and a deflationary-type supply shock. Our findings are in line with some recent studies in

[14] To deal with the huge volatility over covid, we set all the data except for the nominal variables as unobserved over 2020 and 2021. We then estimate the factors and the factors and the common components via the EM algorithm proposed by McCracken and Ng (2020) which can deal with missing data. The idea is to use the information carried by the nominal variables which do not show any huge volatility to interpolate the missing data of the remaining "real" variables.

the US, and confirm the idea that the drivers of the business cycle fluctuations can fit into a classic AD-AS narrative.

Finally, we provide a demand-supply historical decomposition of the EA variables, and analyse the drivers behind the recent inflation surge. Our conclusions support the view that prices initially increased due to supply-driven pressures, while the demand component grew over 2022 and remained persistent over 2023, exerting a positive contribution to inflation even at the end of 2023, more than compensating for the reabsorption of negative supply side shocks.

Although our work shows a clear link between business cycle and long run fluctuations, we do not fully explore the main drivers of the low frequencies, which we leave to future research. Moreover, we believe that the demand and supply shocks we identify in this work could help answer other important macroeconomic questions. For instance, recent studies utilize demand and supply shocks identified with a minimum set of restrictions as instruments to retrieve the slope of the supply and demand curve respectively. In this sense, our shocks may fit well in this empirical framework, as they are identified by using generic economic restrictions.

Tables

	χ	ξ
Y	94.50	5.50
C	67.40	32.60
U	78.20	21.80
LP	88.00	12.00
SH	83.50	16.50
π	88.90	11.10
R	76.90	23.10

Table 1: Percentage of the variance explained by the estimated common and idiosyncratic components for a few selected variables. Baseline specification: $r = 9$ static factors

	Business Cycle													
	MBC							SUM						
	Y	C	U	LP	SH	π	R	Y	C	U	LP	SH	π	R
Y	73.76	72.86	70.46	73.84	67.13	60.34	69.66	96.61	96.39	93.46	96.74	91.28	91.73	93.16
C	35.35	41.32	32.66	34.51	32.57	23.51	31.26	81.48	86.68	77.71	80.18	70.65	76.39	78.70
U	45.56	44.29	50.44	45.25	39.88	46.31	47.68	83.10	82.68	87.84	82.32	79.24	77.03	81.38
LP	77.92	74.80	74.16	78.88	68.08	66.19	73.48	92.44	91.17	88.22	93.61	87.03	88.00	87.91
SH	27.72	27.24	24.89	26.84	46.80	20.40	23.50	64.32	59.99	62.88	63.06	85.72	54.14	63.43
π	34.24	23.39	40.49	36.87	22.43	67.55	41.00	67.81	66.53	64.81	68.03	62.32	84.58	69.95
R	66.31	62.60	69.59	66.12	55.24	66.24	72.16	88.64	88.81	87.71	87.79	87.05	88.28	93.82
	Long-run													
	MBC							SUM						
	Y	C	U	LP	SH	π	R	Y	C	U	LP	SH	π	R
Y	12.11	18.10	5.60	11.05	20.57	1.91	5.80	59.80	59.15	56.35	60.96	48.64	48.46	53.35
C	1.50	4.62	0.98	1.14	5.26	4.72	0.96	62.74	66.92	58.14	62.22	50.16	51.37	56.63
U	1.97	1.77	3.88	2.26	2.80	7.88	3.97	55.13	57.90	51.01	54.02	51.20	37.87	49.54
LP	15.47	17.62	10.35	15.85	14.04	11.25	9.67	23.44	23.83	18.63	25.28	16.14	20.82	17.53
SH	4.05	3.68	5.04	3.83	12.06	4.74	4.55	25.13	23.52	25.05	24.57	42.74	14.39	24.20
π	16.25	15.64	17.05	16.23	17.18	21.58	15.89	39.92	40.57	38.15	39.88	36.52	35.19	35.12
R	25.47	31.63	23.73	23.11	34.01	11.78	25.45	55.45	57.34	62.12	52.16	51.66	60.22	59.24

Table 2: Percentage of variance explained by the MBC shock and the SUM of the two main shocks for a few selected variables, by frequency bands. The columns correspond to different targets in the construction of the shock.

	Business Cycle			Long-run		
	q = 1	q = 2	q = 3	q = 1	q = 2	q = 3
Y	73.76	96.61	97.17	12.11	59.80	64.93
C	35.35	81.48	84.85	1.50	62.74	77.27
U	45.56	83.10	90.07	1.97	55.13	68.96
LP	77.92	92.44	93.29	15.47	23.44	39.67
SH	27.72	64.32	64.63	4.05	25.13	27.75
π	34.24	67.81	69.24	16.25	39.92	63.96
R	66.31	88.64	88.83	25.47	55.45	56.45

Table 3: Cumulative percentage of variance explained by the three main shocks for a few selected variables, by frequency band.

	Business Cycle			Long-run		
	Demand	Supply	SUM	Demand	Supply	SUM
Y	71.04	25.57	96.61	4.53	55.27	59.80
C	32.07	49.41	81.48	1.53	61.21	62.74
U	48.66	34.45	83.10	5.85	49.28	55.13
LP	76.46	15.98	92.44	11.41	12.03	23.44
SH	22.80	41.52	64.32	4.48	20.64	25.13
π	46.32	21.49	67.81	16.25	23.68	39.92
R	69.27	19.37	88.64	18.12	37.33	55.45

Table 4: Percentage of variance explained, individual and cumulative, by the supply and demand shocks for a few selected variables, by frequency bands.

	Y		π	
	χ	ξ	χ	ξ
EA	94.51	5.49	88.87	11.13
IT	72.74	27.26	88.05	11.95
FR	79.91	20.09	70.19	29.81
GE	80.55	19.45	74.45	25.55
SP	59.18	40.82	78.25	21.75
BG	66.01	33.99	63.47	36.53
NH	58.75	41.25	55.49	44.51
PG	60.37	39.63	84.15	15.85
AU	56.16	43.84	61.52	38.48
FI	51.52	48.48	68.62	31.38
GR	22.76	77.24	87.97	12.03
IR	23.90	76.10	64.70	35.30

Table 5: Percentage of the variance explained by the estimated common and idiosyncratic components of country-specific GDP and Inflation. Baseline specification: r = 11 static factors

	Y			π		
	Demand	Supply	SUM	Demand	Supply	SUM
IT	63.59	29.76	93.35	43.21	16.33	59.54
FR	66.82	29.41	96.23	51.03	14.91	65.93
GE	78.36	11.78	90.14	36.78	27.06	63.84
SP	47.23	45.45	92.68	53.93	7.02	60.95
BG	68.48	27.97	96.45	55.24	23.30	78.54
NH	70.18	21.39	91.57	27.36	45.92	73.28
PG	39.80	53.96	93.76	50.42	6.65	57.07
AU	74.67	20.25	94.91	57.77	25.47	83.24
FI	66.67	23.92	90.59	70.61	17.89	88.49
GR	18.62	30.14	48.76	18.23	4.57	22.80
IR	17.50	64.94	82.44	44.70	18.82	63.52

Table 6: Percentage of variance explained, individual and cumulative, by the supply and demand shocks for country-specific GDP and Inflation, over the business cycle.

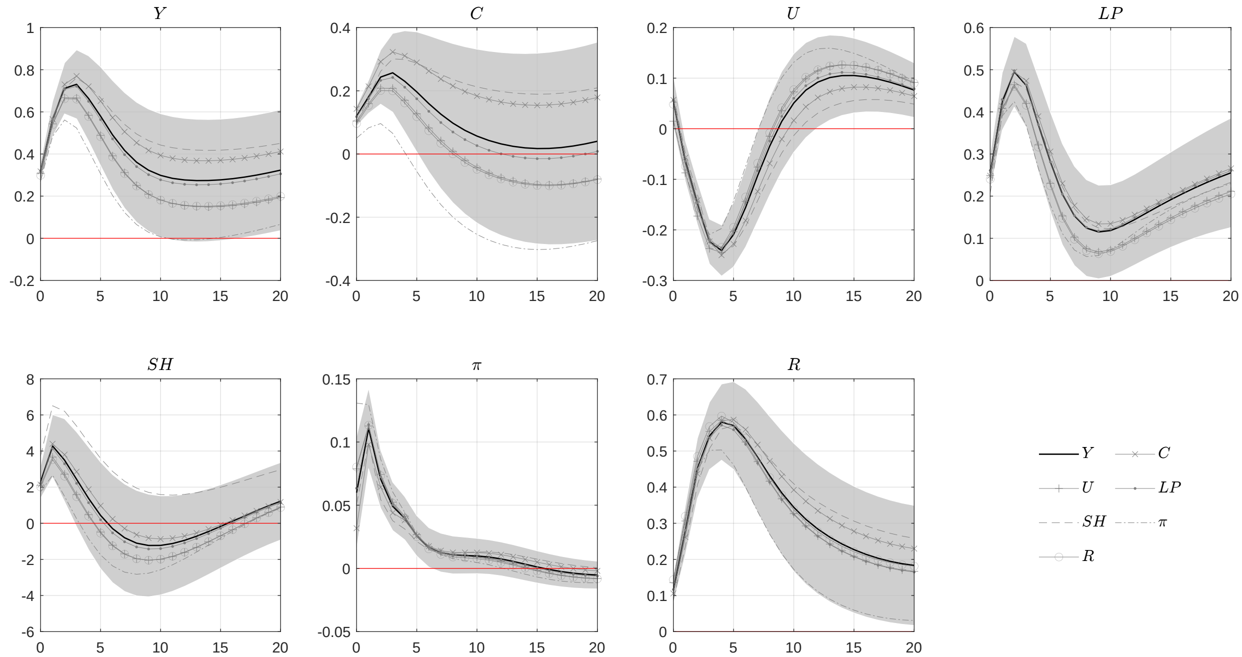

Figure 1: Impulse response functions of the MBC shock obtained by targeting different variables. Baseline is the one targeting GDP (in bold black). The grey areas are the one standard deviation confidence bands, obtained with bootstrap.

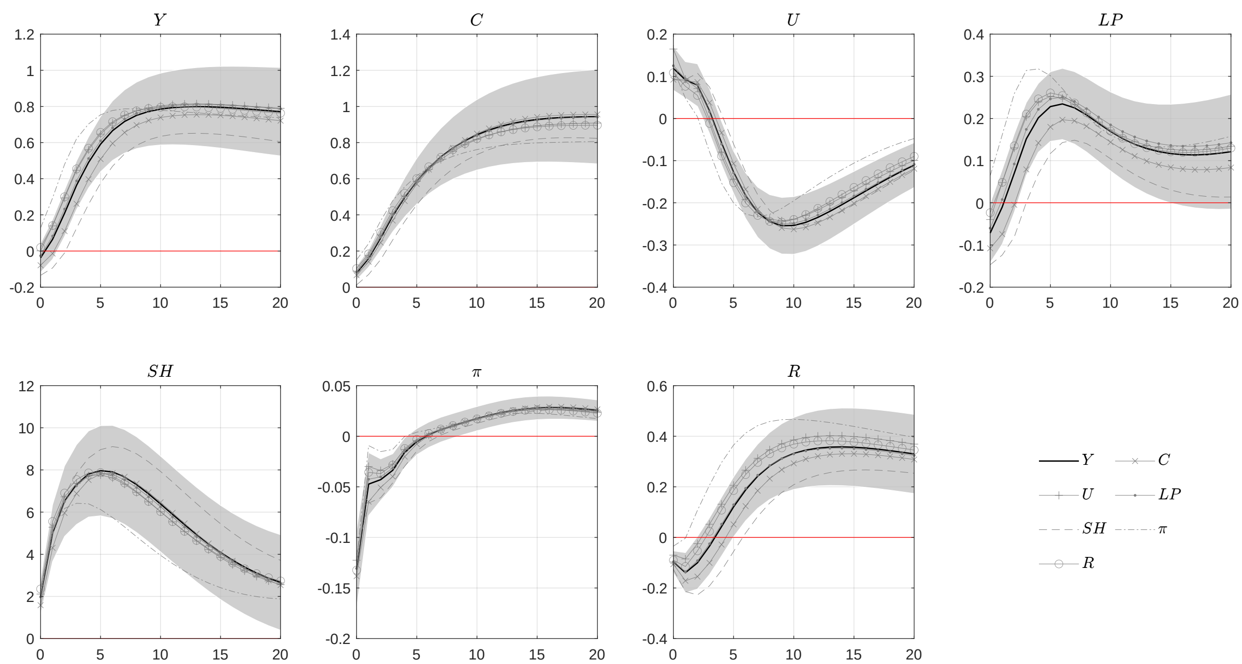

Figure 2: Impulse response functions of the SBC shock obtained by targeting different variables. Baseline is the one targeting GDP (in bold black). The grey areas are the one standard deviation confidence bands, obtained with bootstrap.

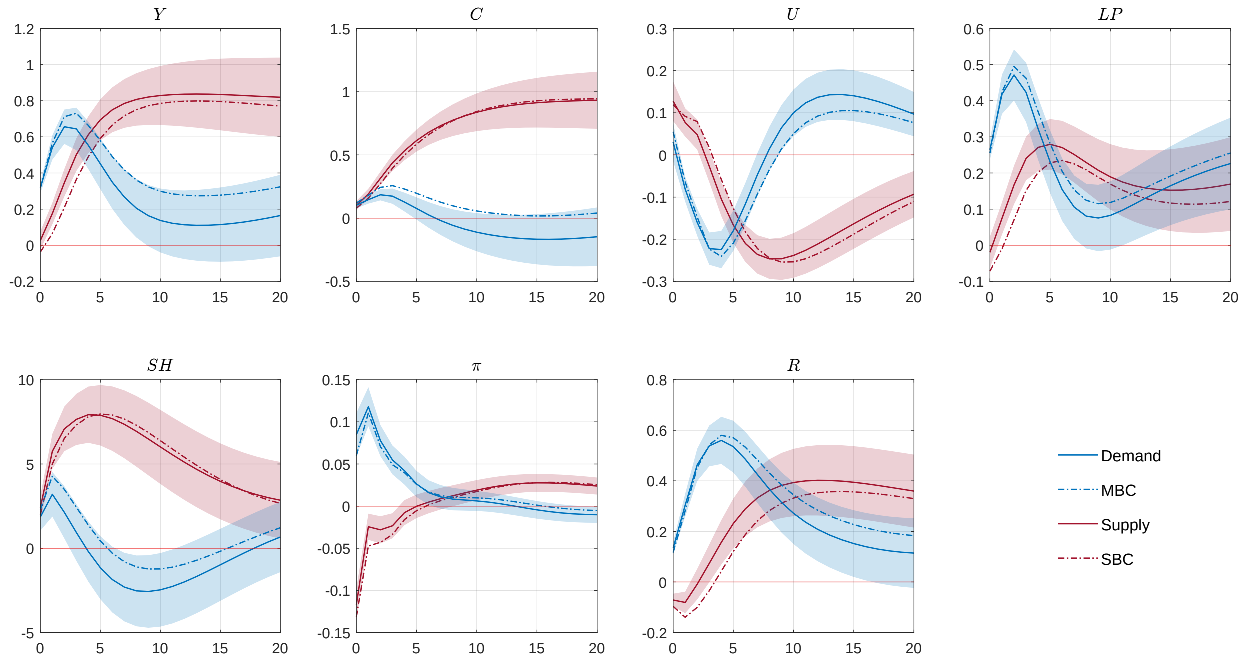

Figure 3: Impulse response functions of the demand (blue) and supply (red) shocks, for key variables. The shaded areas are the one standard deviation confidence bands, obtained with bootstrap. Dotted lines are MBC (blue) and SBC (red).

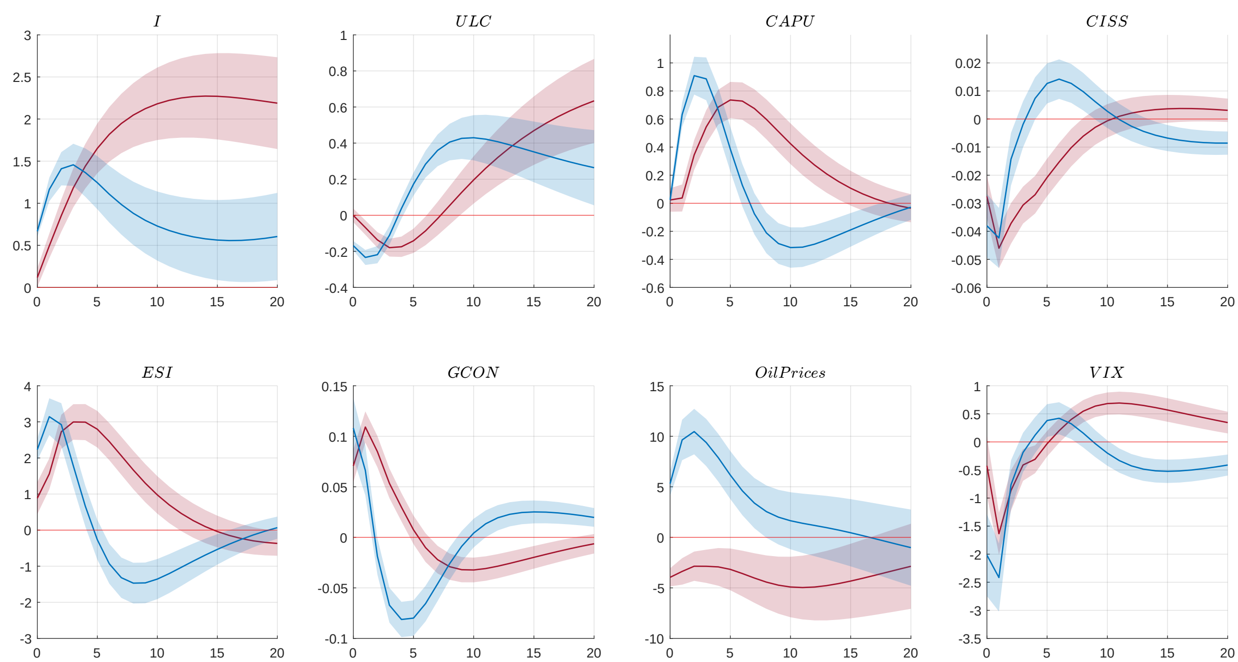

Figure 4: Impulse response functions of the demand (blue) and supply (red) shocks, for a few secondary selected EA variables. The shaded areas are the one standard deviation confidence bands, obtained with bootstrap.

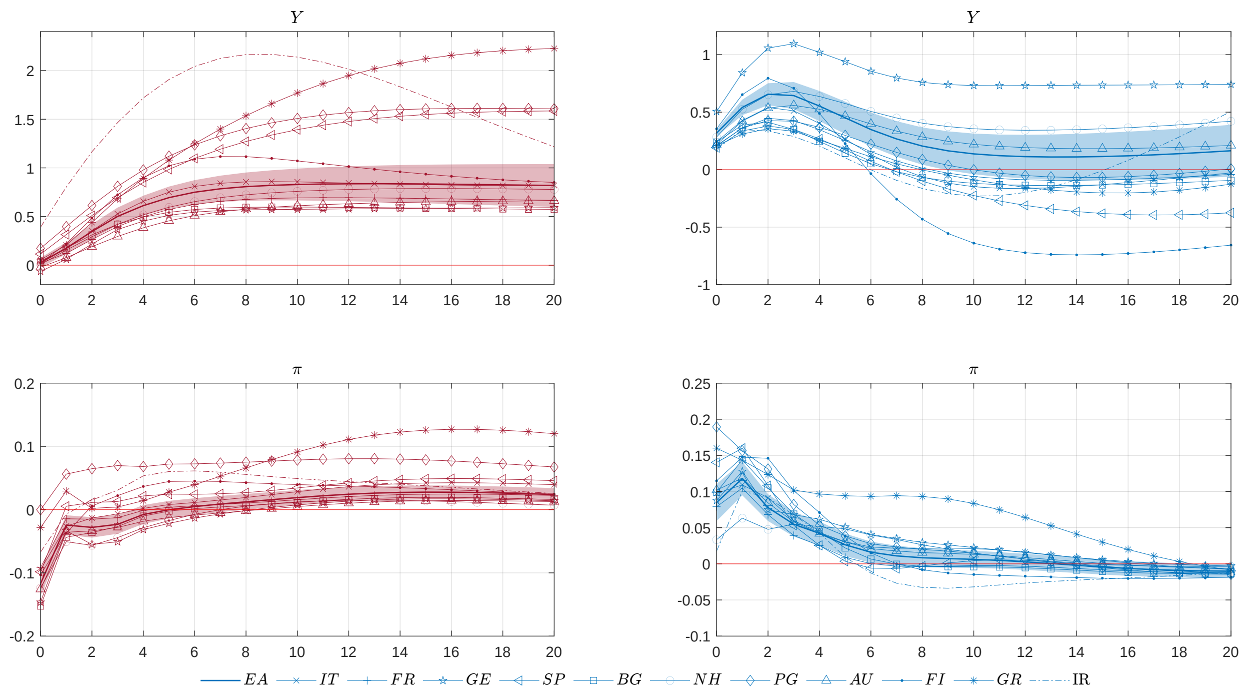

Figure 5: Impulse response functions of the demand (blue) and supply (red) shocks, of country-specific GDP and Inflation. The shaded areas are the one standard deviation confidence bands, obtained with bootstrap.

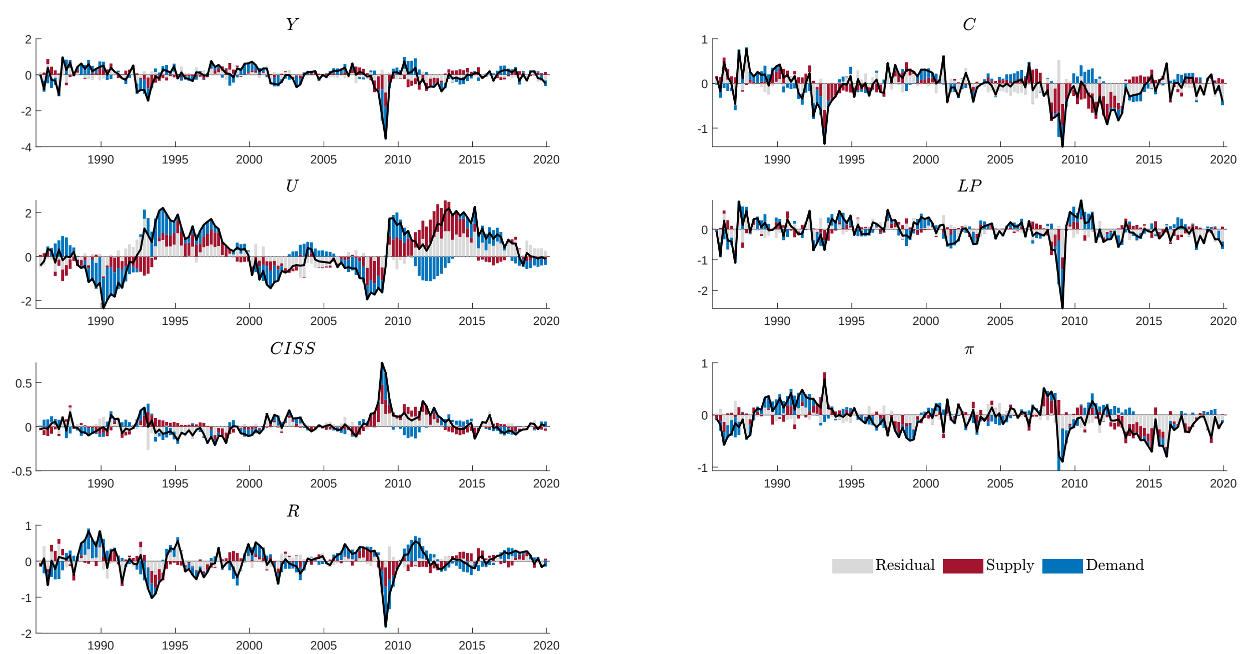

Figure 6: Historical decomposition for a few selected EA variables

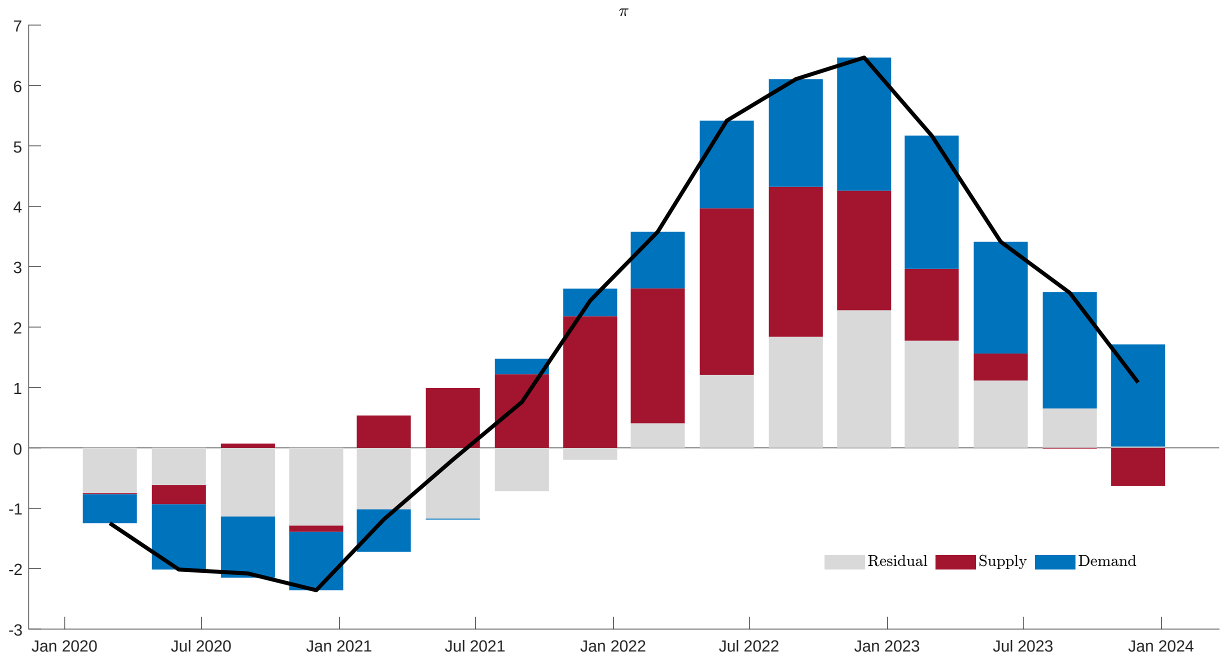

Figure 7: Historical decomposition of EA Inflation

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A Data

ID	Ticker	Source	Description	Backasting	Tcode
1	EA.Y	OEO	Euro Area: Gross domestic product, volume, market prices (Euro, 2015)	AWM	5
2	EA.I	OEO	Euro Area: Gross fixed capital formation, total, volume (Euro, 2015)	AWM	5
3	EA.C	OEO	Euro Area: Private final consumption expenditure, volume (Euro, 2015)	AWM	5
4	EA.G	OEO	Euro Area: Government final consumption expenditure, volume (Euro, 2015)	AWM	5
5	EA.CPI	OEO	Euro Area: Consumer price index, harmonised (Index, 2015)	AWM	5
6	EA.U	OEO	Euro Area: Unemployment rate (%)	AWM	1
7	EA.LPr	OEO	Euro Area: Labour productivity, total economy (Index, 2015)	AWM	5
8	EA.ULC	OEO	Euro Area: Unit labour cost in total economy (Index, 2015)	AWM	5
9	EA.LF	OEO	Euro Area: Labour force (Persons)	AWM	5
10	EA.CAPU	OMEI	Euro Area: Rate of Capacity Utilisation (Manufactoring, %)		1
11	EA.CMP	OEO	Euro Area: Compensation to Employees, total economy (2015=100)	AWM	5
12	EA.M1	OMEI	Euro Area: Narrow Money (M1) Index, SA (2015=100)		5
13	EA.M2	OMEI	Euro Area: M2 Index, SA (2015=100)		5
14	EA.SR	OEO	Euro Area: Short-term interest rate (%)	AWM	2
15	EA.LR	OEO	Euro Area: Long-term interest rate on government bonds (%)	AWM	2
16	EA.SHARE	FRED	Euro Area: Share Prices for Euro Area (19 Countries)		5
17	EA.CISS	ECB	Euro Area: Composite Indicator of Systemic Stress		1
18	EA.ESI	Eurostat	Euro Area: Economic Sentiment Index		1
19	GL.NFCI	CFED	Global: National Financial Conditions Index		1
20	GL.VIX	FRED	Global: VIX, Index		1
21	GL.GCON	BKL	Global: Global Economic Condition Index		1
22	GL.OIL	OEO	Global: Brent crude oil spot price		5
23	IT.Y	OEO	Italy: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)		5
24	IT.C	OEO	Italy: Private Final Consumption Expend, Volume (SAAR,Mil.Chn.2015.Euro)		5
25	IT.G	OEO	Italy: Government Final Consumption Expenditure, Volume (SAAR,Mil.2015.Euro)		5
26	IT.I	OEO	Italy: GFCF, Total, Volume (SAAR,Mil.Ch.2015.Euro)		5
27	IT.X	OEO	Italy: Exports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2015.Euro)		5
28	IT.M	OEO	Italy: Imports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2015.Euro)		5
29	IT.IP	OMEI	Italy: Industrial Production ex Construction (SA, 2015=100)		5
30	IT.U	OEO	Italy: Unemployment Rate (%)		1
31	IT.H	OEO	Italy: Hours Worked Per Employee, Total Economy (Hours)		5
32	IT.LPr	OEO	Italy: Labor Productivity of the Total Economy (2015=100)		5
33	IT.CAPU	OMEI	Italy: Mfg Survey: Rate of Capacity Utilization (SA, %)		1
34	IT.ULC	OEO	Italy: Unit Labor Cost In Total Economy (SWDA, 2015=100)		5
35	IT.DEF	OEO	Italy: Gross Domestic Product, Deflator, Market Prices (2015=100)		5
36	IT.CPI	OMEI	Italy: Consumer Price Index (NSA, 2015=100)		5
37	IT.CORE	OMEI	Italy: CPI: All Items excl Food and Energy [OECD Group] (NSA, 2015=100)		5
38	IT.PPI	OMEI	Italy: Producer Price Index (SA, 2015=100)		5
39	IT.HOUSE	OMEI	Italy: Real House Price Index (SA, 2015=100)		5
40	IT.SR	OEO	Italy: Short-term Interest Rate (%)		2
41	IT.LR	OEO	Italy: Long-term Interest Rate on Government Bonds (%)		2
42	IT.REER	OMEI	Italy: Real Effective Exchange Rates (2015=100)		5
43	IT.SHARE	OMEI	Italy: ISA MIB Storico Share Price Index (2015=100)		5
44	IT.CONFC	OMEI	Italy: Consumer Confidence Indicator (SA, % Bal.)		1
45	IT.CONFI	OMEI	Italy: OECD Mfg Industrial Confidence Indicator [Amp.Adj.] (SA, Norm=100)		1
46	FR.Y	OEO	France: GDP, Volume, Market Prices (SAAR,Mil.Chn.2014.Euro)		5
47	FR.C	OEO	France: Private Final Consumption Expend, Volume (SAAR,Mil.Chn.2014.Euro)		5
48	FR.I	OEO	France: GFCF, Total, Volume (SAAR,Mil.Chn.2014.Euro)		5
49	FR.G	OEO	France: Government Final Consumption Expend, Vol (SAAR,Mil.Chn.2014.Euro)		5
50	FR.X	OEO	France: Exports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2014.Euro)		5
51	FR.M	OEO	France: Imports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2014.Euro)		5
52	FR.IP	OMEI	France: Industrial Production ex Construction (SA, 2015=100)		5
53	FR.U	OEO	France: Unemployment Rate (%)		1
54	FR.H	OEO	France: Hours Worked Per Employee, Total Economy (Hours)		5
55	FR.LPr	OEO	France: Labor Productivity of the Total Economy (2015=100)		5
56	FR.ULC	OEO	France: Unit Labor Cost In Total Economy (SWDA, 2015=100)		5
57	FR.CAPU	OMEI	France: Capacity Utilization: Total Industry (SA, %)		1
58	FR.DEF	OEO	France: Gross Domestic Product, Deflator, Market Prices (2014=100)		5
59	FR.CPI	OEO	France: Consumer Price Index (SA/H, 2015=100)		5
60	FR.CORE	OMEI	France: CPI: All Items excl Food and Energy [OECD Group] (NSA, 2015=100)		5
61	FR.PPI	OMEI	France: PPI: Total Industry excluding Construction (SA, 2015=100)		5
62	FR.HOUSE	OMEI	France: Real House Price Index (SA, 2015=100)		5
63	FR.SR	OEO	France: Short-Term Interest Rate (%)		2
64	FR.LR	OEO	France: Long-Term Interest Rate On Government Bonds (%)		2
65	FR.REER	OMEI	France: Real Effective Exchange Rate (2015=100)		5
66	FR.SHARE	OMEI	France: Paris Stock Exchange: SBF 250 (2015=100)		5
67	FR.CONFC	OMEI	France: Consumer Confidence OECD Indicator [Amp. Adj.] (SA, Norm=100)		1
68	FR.CONFI	OMEI	France: OECD Mfg Industrial Confidence Indicator [Amp.Adj.] (SA, Norm=100)		1
69	GE.Y	OEO	Germany: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)	MEI	5
70	GE.C	OEO	Germany: Private Final Consumption Expend, Volume (SAAR,Mil.Chn.2015.Euro)	MEI	5
71	GE.I	OEO	Germany: GFCF, Total, Volume (SAAR,Mil.Chn.2015.Euro)	MEI	5
72	GE.G	OEO	Germany: GDP: Government Consumption (SWDA, Bil.Chn.2015.Euros)		5
73	GE.M	OEO	Germany: Exports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2015.Euro)	MEI	5
74	GE.X	OEO	Germany: Imports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2015.Euro)	MEI	5
75	GE.IP	OMEI	Germany: Industrial Production ex Construction (SA, 2015=100)		5
76	GE.U	OEO	Germany: Registered Civilian Unemployment Rate (SA, %)		1
77	GE.LPr	OEO	Germany: Productivity: Output per Employed Person (SA, 2010=100)		5
78	GE.ULC	OEO	Germany: Unit Labor Cost: Total Economy [calculated by Haver](SA, 2010=100)		5
79	GE.CAPU	OMEI	Germany: Capacity Utilization: Manufacturing (SA, %)		1
80	GE.DEF	OMEI	Germany: GDP: Deflator Index (SA/WDA, 2015=100)		5
81	GE.CPI	OMEI	Germany: Consumer Price Index (NSA, 2015=100)		5
82	GE.CORE	OMEI	Germany: CPI: All Items excl Food and Energy [OECD Group] (NSA, 2015=100)		5

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ID	Ticker	Source	Description	Backasting	Tcode
83	GE.PPI	OMEI	Germany: PPI: Total Industry excluding Construction (SA, 2015=100)		5
84	GE.HOUSE	OMEI	Germany: Real House Price Index (SA, 2015=100)		5
85	GE.LR	OEO	Germany: Fed Govt Securities w/ Residual Maturities of b/w 9-10 Yrs (AVG, %)		2
86	GE.SR	OEO	Germany: Fed Govt Securities w/ Residual Maturities of b/w 1-2 Yrs (%)		2
87	GE.REER	OMEI	Germany: Real Effective Exchange Rate (2015=100)		5
88	GE.SHARE	OMEI	Germany: CDAX Share Price Index (2015=100)		5
89	GE.CONFI	OMEI	Germany: OECD Mfg Industrial Confidence Indicator [Amp.Adj.] (SA, Norm=100)		1
90	GE.CONFC	OMEI	Germany: Consumer Confidence Indicator (SA, % Bal.)		1
91	SP.Y	OEO	Spain: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)		5
92	SP.C	OEO	Spain: Private Final Consumption Expend, Volume (SAAR,Mil.Chn.2015.Euro)		5
93	SP.I	OEO	Spain: GFCF, Total, Volume (SAAR,Mil.Chn.2015.Euro)		5
94	SP.G	OEO	Spain: Government Final Consumption Expend, Vol (SAAR,Mil.Chn.2015.Euro)		5
95	SP.X	OEO	Spain: Exports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2015.Euro)		5
96	SP.M	OEO	Spain: Imports of Goods & Serv, Vol, NA Basis (SAAR,Mil.Chn.2015.Euro)		5
97	SP.IP	OMEI	Spain: Industrial Production ex Construction (SA, 2015=100)		5
98	SP.U	OEO	Spain: Unemployment Rate (%)		1
99	SP.H	OEO	Spain: Hours Worked Per Employee, Total Economy (Hours)		5
100	SP.CAPU	OMEI	Spain: Mfg Survey: Rate of Capacity Utilization (SA, %)		1
101	SP.DEF	OEO	Spain: Gross Domestic Product, Deflator, Market Prices (2015=100)		5
102	SP.CPI	OMEI	Spain: Consumer Price Index (NSA, 2015=100)		5
103	SP.CORE	OMEI	Spain: CPI: All Items excl Food and Energy [OECD Group] (NSA, 2015=100)		5
104	SP.PPI	OMEI	Spain: Industrial Prices: Total Industry (SA, 2015=100)		5
105	SP.HOUSE	OMEI	Spain: Real House Price Index (SA, 2015=100)		5
106	SP.SR	OEO	Spain: Short-Term Interest Rate (%)		2
107	SP.LR	OEO	Spain: Long-Term Interest Rate On Government Bonds (%)		2
108	SP.REER	OMEI	Spain: Real Effective Exchange Rate (2015=100)		5
109	SP.SHARE	OMEI	Spain: MSE General Index (2015=100)		5
110	SP.CONFI	OMEI	Spain: OECD Mfg Industrial Confidence Indicator [Amp.Adj.] (SA, Norm=100)		1
111	BG.Y	OEO	Belgium: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)		5
112	BG.C	OEO	Belgium: Private Final Consumption Expend, Volume (SAAR,Mil.Chn.2015.Euro)		5
113	BG.I	OEO	Belgium: GFCF, Total, Volume (SAAR,Mil.Chn.2015.Euro)		5
114	BG.U	OEO	Belgium: Unemployment Rate (%)		1
115	BG.CAPU	OMEI	Belgium: Mfg Survey: Rate of Capacity Utilization (SA, %)		1
116	BG.ULC	OEO	Belgium: Unit Labor Cost in the Total Economy (SWDA, 2015=100)		5
117	BG.LPr	OEO	Belgium: Labor Productivity of the Total Economy (2015=100)		5
118	BG.DEF	OEO	Belgium: Gross Domestic Product, Deflator, Market Prices (2016=100)		5
119	BG.CPI	OMEI	Belgium: Consumer Price Index (NSA, 2015=100)		5
120	BG.LR	OEO	Belgium: Long-Term Interest Rate On Government Bonds (%)		2
121	BG.SR	OEO	Belgium: Short-Term Interest Rate (%)		2
122	NH.Y	OEO	Netherlands: GDP, Vol, Market Prices (SAAR,Mil.Chn.2015.Euro)		5
123	NH.C	OEO	Netherlands: Private Final Cons Expend, Vol (SAAR,Mil.Chn.2015.Euro)		5
124	NH.I	OEO	Netherlands: GFCF, Total, Vol (SAAR,Mil.Chn.2015.Euro)		5
125	NH.U	OEO	Netherlands: Unemployment Rate (%)		1
126	NH.CAPU	OMEI	Netherlands: Mfg Survey: Rate of Capacity Utilization (SA, %)		1
127	NH.ULC	OEO	Netherlands: Unit Labor Cost In Total Economy (SWDA, 2015=100)		5
128	NH.LPr	OEO	Netherlands: Labor Productivity of the Total Economy (2015=100)		5
129	NH.DEF	OEO	Netherland: Gross Domestic Product, Deflator, Market Prices (2015=100)		5
130	NH.CPI	OMEI	Netherlands: Consumer Price Index (NSA, 2015=100)		5
131	NH.LR	OEO	Netherlands: Long-Term Interest Rate On Government Bonds (%)		2
132	NH.SR	OEO	Netherlands: Short-Term Interest Rate (%)		2
133	PG.Y	OEO	Portugal: GDP, Volume, Market Prices (SAAR,Mil.Chn.2016.Euro)		5
134	PG.C	OEO	Portugal: Private Final Consumption Expend, Vol (SAAR,Mil.Chn.2016.Euro)		5
135	PG.I	OEO	Portugal: GFCF, Total, Volume (SAAR,Mil.Chn.2016.Euro)		5
136	PG.U	OEO	Portugal: Unemployment Rate (%)		1
137	PG.CAPU	OMEI	Portugal: Mfg Survey: Rate of Capacity Utilization (SA, %)		1
138	PG.LPr	OEO	Portugal: Labor Productivity of the Total Economy (2015=100)		5
139	PG.DEF	OEO	Portugal: Gross Domestic Product, Deflator, Market Prices (2016=100)		5
140	PG.CPI	OMEI	Portugal: Consumer Price Index (SA, 2012=100)		5
141	PG.LR	OEO	Portugal: Long-Term Interest Rate On Government Bonds (%)		2
142	PG.SR	OEO	Portugal: Short-Term Interest Rate (%)		2
143	AU.Y	OEO	Austria: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)		5
144	AU.CPI	OMEI	Austria: Consumer Price Index (NSA, 2015=100)		5
145	AU.U	OEO	Austria: Unemployment Rate (%)		1
146	AU.ULC	OEO	Austria: Unit Labor Cost In Total Economy (SWDA, 2015=100)		5
147	AU.SR	OEO	Austria: Short-Term Interest Rate (%)		2
148	FI.Y	OEO	Finland: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)		5
149	FI.CPI	OMEI	Finland: Consumer Price Index (NSA, 2015=100)		5
150	FI.SR	OEO	Finland: Short-Term Interest Rate (%)		2
151	GR.Y	OMEI	Greece: GDP [Index Publication Base] (SA, 2015=100)		5
152	GR.CPI	OMEI	Greece: Consumer Price Index (NSA, 2015=100)		5
153	GR.SR	OEO	Greece: Short-Term Interest Rate (%)		2
154	IR.Y	OMEI	Ireland: GDP, Volume, Market Prices (SAAR,Mil.Chn.2015.Euro)	BCL	5
155	IR.CPI	OMEI	Ireland: Consumer Price Index (NSA, 2015=100)		5
156	IR.SR	OEO	Ireland: Short-Term Interest Rate (%)	BCL	2

Notes: Tcode = 1 stands for level; Tcode = 2 stands for first difference; Tcode = 5 stands for diff(log)