It is All About Demand and Supply: a Dualistic View of the Euro Area Business Cycle*

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Abstract

We study the nature of Euro Area business cycle drivers. We build an extensive dataset of quarterly time series covering EA aggregates and the most important country members. We find that two shocks are enough to explain the majority of EA aggregates variability, and we show that those two cyclical shocks can be interpreted as classic demand-side and supply-side shocks. Additionally, we (i) document a high synchronization in the responses to such shocks across the different EA members, (ii) provide a demand-supply historical decomposition of the EA variables, with a particular focus on the recent inflation surge and (iii) study the reasons behind the flattening of the EA Phillips' Curve. On this topic, results find that the EA Phillips curve is alive, and point to a flattening of the curve to a stricter mandate of the monetary policy stance towards inflation targeting.

Keywords: Business Cycle, Identification, Frequency Domain, Euro Area Economy, Dynamic Factors, Phillips' Curve

JEL codes: C38, E32

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1 Introduction

Macroeconomic analysis often seeks to identify the key forces driving economic fluctuations. Over the past 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, often suggesting a simple demand/supply view of the economy – see, for instance, Shapiro (2024); Eickmeier and Hofmann (2022); Ascari et al. (2023); Bergholt et al. (2023); Forni et al. (2024); Giannone and Primiceri (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 economic fluctuations.

The idea that a limited number of shocks can describe the overall data volatility is not new in the economic literature and dates back to the seminal work of Burns and Mitchell (1946). Currently, this concept is also implicitly embedded in the construction of most of the macroeconomic theoretical models, which typically rely on one or just a few shocks driving the entire system (*e.g.*, Kydland and Prescott, 1982; Christiano et al., 2018).

Recently, Angeletos et al. (2020) (ACD henceforth) studied the main source of US business cycle fluctuations. They adopted an agnostic frequency-domain identification strategy in a Vector Autoregressive (VAR) framework and obtained what they label the *main business cycle shock* (MBC). They find that this shock alone explains the bulk of cyclical fluctuations of real macroeconomic variables. However, its interpretation is rather puzzling. Its disconnection from the long-run excludes supply-side shocks, as the technology shock of Kydland and Prescott (1982). At the same time, it does not affect prices, which rules out standard inflationary demand shocks from the possible candidates. In contrast, Avarucci et al. (2021) and Forni et al. (2024) (FGGSS henceforth) found that one shock is not sufficient to adequately explain US data volatility, supporting instead a two-shocks representation of the economy. These shocks fit well in the standard AD-AS narrative, as they have salient features of textbook demand and supply shocks, a result that is also confirmed by Cubadda and Mazzali (2024).[1]

The present paper extends the study of the business cycle's drivers to the Euro Area (EA) economy. The EA economy forms an interesting case study given the intrinsic level of heterogeneity across the different member countries. Moreover, this analysis is particularly relevant for the EA economy and can provide important policy implications. Despite that, to our knowledge, the matter has not been thoroughly addressed by the literature. Similarly to us, Giannone et al. (2019) (GLR henceforth) identify a cyclical shock and examine its properties using Impulse Response Functions (IRFs). Although some of their results can be used as a reference for our study, GLR primary focus is on the impact of the Great Financial Crisis on the transmission mechanism in EA, particularly in the context of financial variables. Differently from them, we offer a fairly comprehensive treatment of aggregated business cycle fluctuations and the propagation mechanism of common shocks, for which we also provide a structural interpretation.

We find that two shocks are required to account for most of EA cyclical fluctuations and

[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.

that, similarly to US, they can be reconciled with the simple, dualistic view of the economy, where textbook-type demand and supply shocks can successfully capture the salient features of the data. From this starting point, we shed light on the recent inflation surge and on the reasons behind the flattening of EA's Phillips curve over the last few years. Finally, we extend our analysis to EA member countries, checking the level of synchronization across the region.

To reach our goal, we build an extensive dataset of 156 quarterly time series, spanning from Q1-1985 to Q4-2019, encompassing real, financial, and nominal variables, for both EA as a whole and its major member countries.[2] We assume that data follow a large structural Dynamic Factor Model (DFM), as introduced by Stock and Watson (2005); Forni et al. (2009).

DFMs are largely employed for the analysis of large-macroeconomic datasets. Specifically for EA data, they have proven particularly convenient both for nowcasting (*e.g.*, Cascaldi-Garcia et al., 2023; Camacho and Perez-Quiros, 2010) and for analysing the transmission of common shocks, typically focusing on monetary policy (*e.g.*, Barigozzi et al., 2014; Corsetti et al., 2022; Barigozzi et al., 2024).

DFMs assume that a large amount of information can be summarized by fewer number of indicators. From a conceptual point of view, the idea 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 Hansen and Sargent, 1991; Lippi and Reichlin, 1993, 1994; Forni et al., 2019). Structural DFMs also permit to work directly on variables corrected for their idiosyncratic component, which is often interpreted as measurement error and/or regional component. Even if small or in a sufficiently informative system, it may dynamically contaminate the structural shocks estimation (see, for instance, Lippi, 2021). The latter feature is particularly desirable within the EA, where the significant degree of heterogeneity across country members might translate into exceptionally noisy data. Although we remain in this general framework, we slightly depart from the standard Structural DFM and opt for the Common Component Structural VAR (CC-SVAR) model by Forni et al. (2020), which combines the good features of DFMs with VARs flexibility.

Our empirical analysis can be divided into two steps. In the first, we select the shock that explains most EA business cycle fluctuations. To do so, we follow ACD and apply the frequency-domain version of the so-called *max-share* identification proposed by Uhlig (2004), which entails maximizing the variance of a target variable over the business cycle frequency band (see also Francis et al., 2014; Dieppe et al., 2021; Barsky and Sims, 2011; Giannone et al., 2019, among the others). FGGSS show the benefits of jointly targeting the variance of multiple variables at once. Taking inspiration from them, we propose to jointly target the variance of a variable along with those of some factors. The resulting *factor-augmented* max-share procedure is more parsimonious and agnostic than FGGSS's and exploits more information than ACD's. We analyse the variance explained by our MBC and the IRFs of EA variables. Our results show that, although such shock explains a substantial part of the business cycle fluctuations, a significant portion of total volatility remains unexplained.

[2] To the best of our knowledge, besides us, only Giannone et al. (2012) and Barigozzi et al. (2024) have built a large database for EA economy.

Indeed, we find that two shocks are needed to adequately describe cyclical fluctuations, as in FGGSS, Granese (2024) and Avarucci et al. (2021) for the US. Remarkably, they also jointly explain a big portion of long-run variance, a somewhat surprising result given that our focus is solely on business cycle fluctuations. Moreover, our MBC is not disconnected from inflation. Rather, this shock resembles a classic inflationary type shock, with prices and output moving in the same direction. Conversely, the *second main business cycle shock* (SBC) exerts a negative comovement between prices and output, suggesting a supply nature of the shock.

In the second step, we further rotate the two shocks from the first stage of our analysis to obtain a demand shock and a supply shock. The former is obtained by maximizing the covariance of inflation and output at cyclical frequencies. The latter is automatically identified by the orthogonality condition as the one minimizing the same quantity. We find that the new demand and supply shocks are identical to the MBC and SBC, respectively, suggesting that the EA business cycle is driven by two shocks which are a classic demand and a classic supply shock, pointing at a standard New-Keynesian framework. Our findings are partially at odds with the documented disconnection between the cyclical shock and inflation, *i.e.* GLR for EA and ACD for US, and our demand/supply representation of EA business cycle is coherent with the picture emerging from other US studies, such as Granese (2024) and FGGSS. The demand shock is inflationary, has transitory effects on real activity, and is disconnected to the long-run. Interestingly, the latter aspect is imposed by Blanchard and Quah (1989), whereas in our case it comes from the data. The long-run is manly driven due to supply variations, whereas both shocks contribute to explaining cyclical fluctuations.

To have a clearer picture of EA fluctuations, we compare the propagation of the identified regional-wide shocks across each country. Overall, we observe very similar dynamics, a result that underlines the elevated level of synchronization of country-specific business cycles. To a lesser extent than Cavallo and Ribba (2015), we document a partial disconnection of certain, more peripheral economies, such as Greece and Portugal. In this sense, we contribute also to the literature that investigates business cycle synchronization in EA – see, for instance, Cendejas et al. (2014); Giannone et al. (2008); Agresti and Mojon (2001). However, most of these works do not adopt a (semi-) structural approach and do not focus on IRFs and/or variance decomposition analysis.

Finally, we use our two shocks to address two important recent questions central to policymakers' agendas. First, we extend our dataset over the post-pandemic period and study the factors behind the recent inflation surge. Results suggest that the increase in prices was initially predominantly supply-driven. However, throughout 2022, demand-side pressures grew and remained persistent over 2023, exerting a positive contribution to inflation even at the end of year, offsetting deflationary supply forces (see also Giannone and Primiceri, 2024). Second, inspired by Bergholt et al. (2024), we investigate the causes behind the flattening of the EA Phillips curve. Results reject a flattening of the curve due to a lower slope. Conversely, the stricter mandate of the ECB seems the most plausible explanation, as it inhibits the propagation of cyclical shocks into inflation.

The rest of the paper is structured as follows. Section 2 outlines the methodology adopted. Section 3 describes the dataset and empirical strategy. Section 4 presents the results and Section 5 concludes, summarizing key insights and 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.[3] 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 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.

[3] 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).

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

$$A_\psi(L)Y_t = \varepsilon_t^\psi \quad (5)$$

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 $\mathbb{E}[\varepsilon_t^\psi \varepsilon_t^{\psi\prime}] = \Lambda_\psi \Omega_\varepsilon \Lambda_\psi' = \Omega_\psi$.[4]

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).[5] 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.

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

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

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.

[4]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).

[5]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.

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.[6] 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

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

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 $P_L = E_lw_l$ and $P_K = E_kw_k$, 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

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

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 $g < j$.

[6]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.

3 Empirical application

3.1 Data

We build an extensive dataset of 156 quarterly time series, covering the period from Q1-1985 to Q4-2019. The dataset includes real, financial and nominal variables for EA aggregates, the majority of the EA members plus some global variables. We download most of the Euro Area and country-specific indicators from the OECD datawarehouse, from both the OECD Main Economic Indicator (MEI) and OECD Economic Outlook (EO) datasets.

The Euro Area block consists of 18 variables, including Real GDP and its sub-components, labor market measures (such us unemployment, labor productivity, labor force, capacity utilization rate, compensation to employees), CPI price index, M1, and short and long-term interest rates. On the Euro Area block, we also add the Composite Indicator of Systemic Stress (CISS) from the ECB Data Portal and the Economic and Consumer sentiment index from Eurostat (EIS and CIS, respectively). Major country members' blocks are extensively covered, all including more than twenty-five series each (France 27, Italy 26, Germany 26, and Spain 24). Other countries, such as Netherlands, Belgium and Portugal, have ten and eight variables respectively. We also include Austria, Finland, Greece and Ireland with three series each. Finally, on the global block, we add the Global condition index developed by Baumeister et al. (2022), real Oil price and VIX index from the FRED database and the NFCI from the Chigago Fed.

Most of the variables of interest are available starting from mid-80s. Some of the Euro Area aggregates starts in 1992 and are backdated using the Euro Area Wide model dataset as in Barigozzi et al. (2014).[7] Data are seasonally adjusted and are transformed to reach stationarity. We follow FGGSS and we take the growth rates for real variables and prices while keeping in level the variables already expressed as rates.

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

[7] Euro Area Wide model dataset is available at https://eabcn.org/page/area-wide-model

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 analyze 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.[8] 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.

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.[9] 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.[10]

[8] 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.

[9] 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).

[10] 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.

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, 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. A result 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 analyze a larger set of variables than the one chosen in the baseline specification. We then 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 analyzed 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 analyze 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 analyzed 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 overall data's 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) [11].

While the interpretation of the first two components is straightforward, the latter can be interpreted as anything that moved the variable at time t that is not related to the cycle frequencies, and that can be intended as belonging to the realm of higher or lower frequencies. Results highlight a first clear result that is robust with what we described in the previous section: over the sample analyzed, 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. However, the relative importance of the non-cyclical component increases over the years following the great financial crisis, such as for inflation, unemployment, and consumption.

Moving to 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 up on unemployment. Unsurprisingly, demand shocks are also the main drivers of the great financial crisis for many of the variables. Nevertheless, demand shocks start to lose importance after 2010. This is particularly true for unemployment and inflation, mainly driven by supply-side shocks over 2012-2015, which is likely linked to 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 (Shapiro, 2024; Eickmeier and Hofmann, 2022; Ascari et al., 2023; Giannone and Primiceri, 2024; Bergholt et al., 2023). 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[12].

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

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

[12] 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.

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.

4.4 Why Has the Phillips' Curve Flattened in Euro-Area?

In this section, we use the demand and supply shocks previously identified to investigate the reasons behind the flattening of the aggregate EA Phillips curve. This topic sparked great interest even before the inflation surge after Covid-19, due to the missing disinflation after the Great Financial Crisis and the missing inflation thereafter. A few recent papers analysed the important role of model specification, as Ball and Mazumder (2021) and Moretti et al. (2019). In another study, Bobeica and Jarociński (2019) underlines the importance of accounting for both external and domestic factors. Their results do not point to a flattening of the EA Phillips curve but to a change in the shock decomposition, a theory also supported by Galí and Gambetti (2009) for the US economy.

Inspired by the recent work of Bergholt et al. (2024) on the US economy, we study the reasons behind the recent disconnection between inflation and unemployment in the Euro Area by testing three different hypotheses: whether the Phillips curve has flattened due to *i)* a more active role in monetary policy, i.e. *policy hypothesis*, *ii)* a relatively less importance of demand shock to supply shocks, i.e. *shock hypothesis*, or, finally, *iii)* a decline of the Phillips curve slope, i.e. *slope hypothesis*. The authors set up a simple framework to test these hypotheses. They first identify *generic* demand and supply shocks in a SVAR. Then, they split the sample and they show that the *slope hypothesis* is the only one implying a less positive regression slope between the two samples when data are conditioned on demand shocks, while the *policy hypothesis* assumes a less negative regression slope when data are conditioned on supply shocks. Finally, the *shock hypothesis* is the only option that implies stable regression slopes when we condition either on demand shocks or on supply shocks. Importantly, the authors find evidence for the flatting of the Phillips curve in the US to be mainly attributed to stricter inflation targeting rather than a change in the slope of the Phillips curve.

Our approach is simple. Building on the previous sections, we focus only on the fluctuations of unemployment and inflation explained at business cycle frequency. We then divide the sample before and after the great financial crisis [13], which represents a typical threshold used to analyse the flattening of the Euro Area Phillips curve (see, for instance, Bańbura and Bobeica (2023) and Bobeica and Sokol, 2019), and we regress unemployment over inflation in both the sample cuts. The resulting Phillips curve can be interpreted as an *unconditional*

[13] Specifically before and after 2008Q4.

"business cycle Phillips curve". As shown in the left panel of Figure 8, this exercise depicts a significant flattening of the Phillips curve in the Euro Area, with the post-GFC which depicts a lower slope ($\beta = -0.10$) than the pre-GFC ($\beta = -0.157$).

We then make use of the demand and supply cyclical shocks estimated in section 4.2 to decompose what drove this flattening. Importantly, these shocks are obtained with a minimum set of restrictions as in Bergholt et al. (2024). We build on the historical decomposition analysis presented in 4.3 and we run two different regressions for each sample cut: in the first one, we use only the data of unemployment and inflation conditioned on the demand shock, while in the second we run the same regression but with data conditioned on the supply shock.

Results are shown in the middle and right panels of figure 8. When conditioned on demand shock only (middle panel), the two regressions estimate a very similar slope between the two samples, with a $\beta = -0.16$ in both samples. Conversely, when conditioned on supply-side shock only (right panel), the slopes differ significantly, with a $\beta = -0.17$ in the pre-GFC and $\beta = -0.08$ in the post-GFC, which amounts to approximately a flattening of 60% between the two samples.

These results are in line with what is found by McLeay and Tenreyro (2020) and Bergholt et al. (2024) for the US data and go in favor of the policy hypothesis rather than the slope or shock composition hypotheses. In other words, results suggest that the Phillips curve in the Euro Area is alive, at least over the business cycle frequencies, but the stricter mandate of the central bank to inflation targeting *killed* the propagation of cyclical shocks into inflation.

5 Conclusion

We investigate the sources of EA business cycle fluctuations. To this end, we build an extensive quarterly macroeconomic time series dataset. We provide evidence that EA business cycle fluctuations can be parsimoniously characterized by two shocks, namely a demand and a supply shock. We document an elevated level of synchronization of the EA country members' business cycles. We provide a demand-supply historical decomposition of the EA variables. We use our results to give an economic interpretation of the recent inflation surge. Our findings support the view that prices initially increased due to supply-driven pressures. The demand component, on the other hand, 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. Finally, we investigate the causes behind the flattening of the EA Phillips curve. We find that the curve is alive, with the flattening that is due to the stricter mandate of the monetary policy stance towards inflation targeting, that limited the propagation of cyclical shocks into inflation.

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.

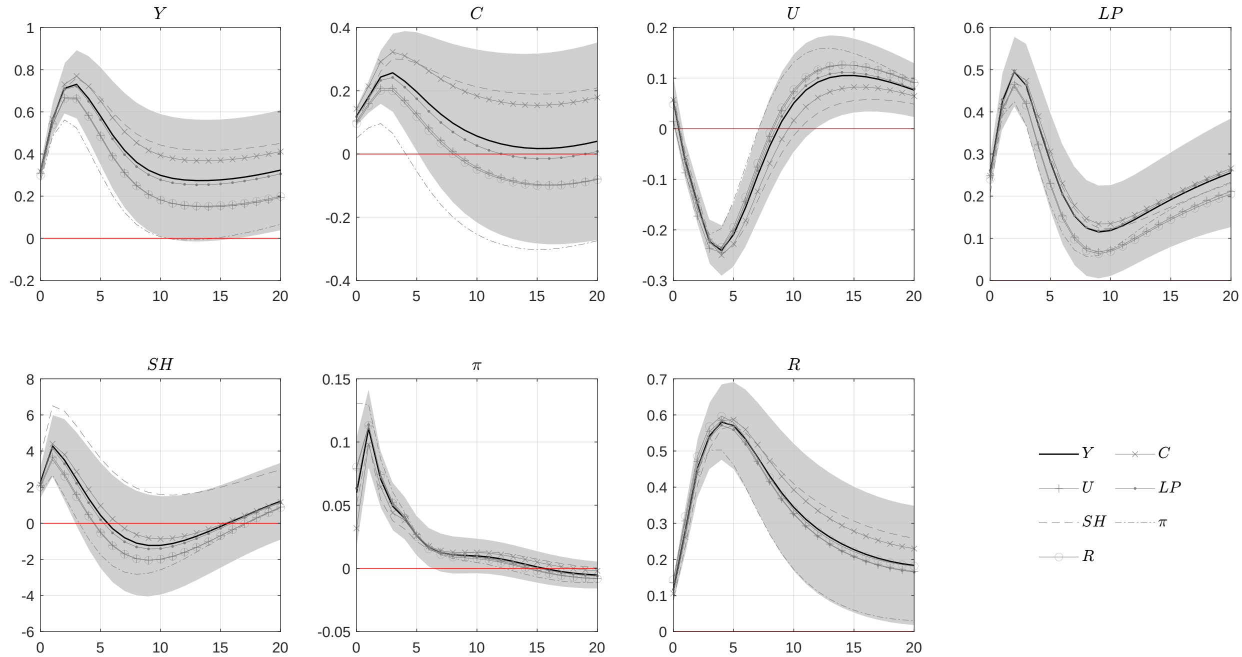

Figure 1: Impulse response functions of the MBC shock obtained by targeting different variables. Baseline is the one targeting GDP (in bold black). The grey areas are the one standard deviation confidence bands, obtained with bootstrap.

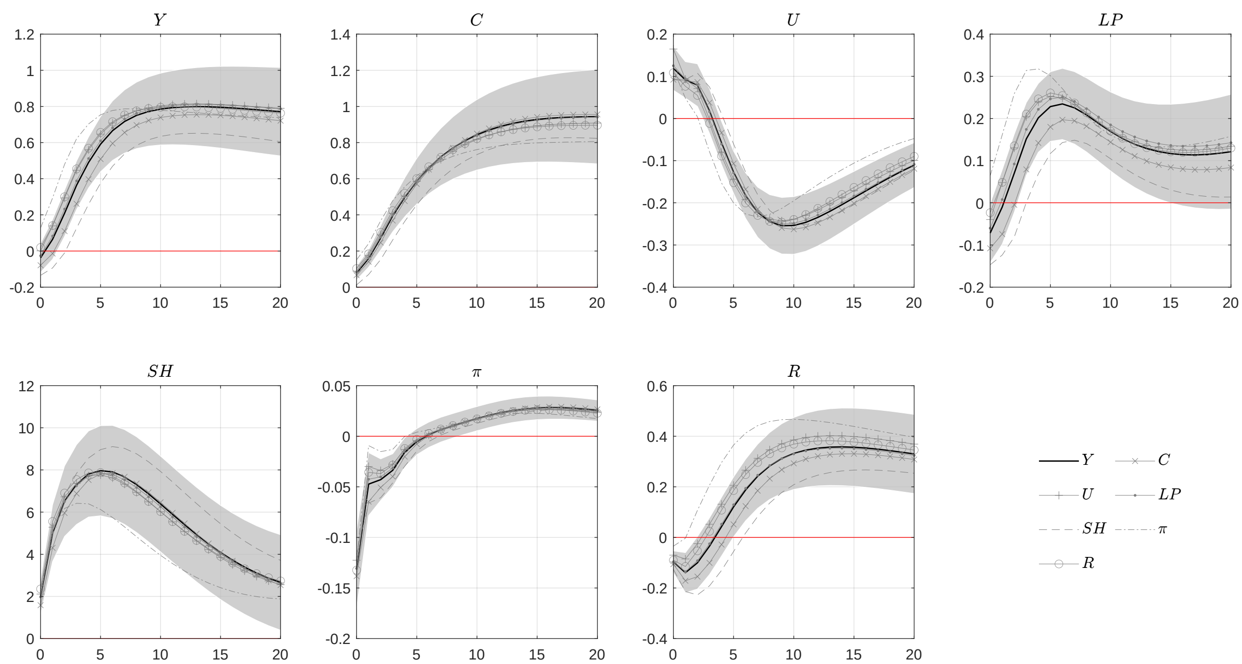

Figure 2: Impulse response functions of the SBC shock obtained by targeting different variables. Baseline is the one targeting GDP (in bold black). The grey areas are the one standard deviation confidence bands, obtained with bootstrap.

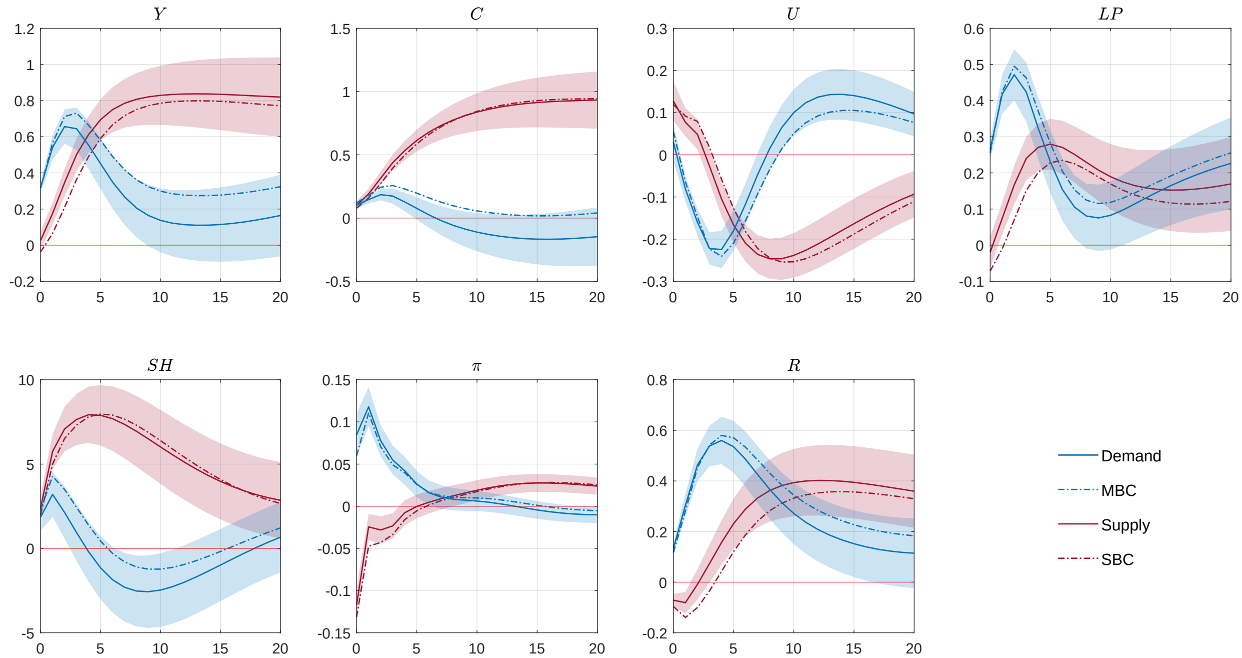

Figure 3: Impulse response functions of the demand (blue) and supply (red) shocks, for key variables. The shaded areas are the one standard deviation confidence bands, obtained with bootstrap. Dotted lines are MBC (blue) and SBC (red).

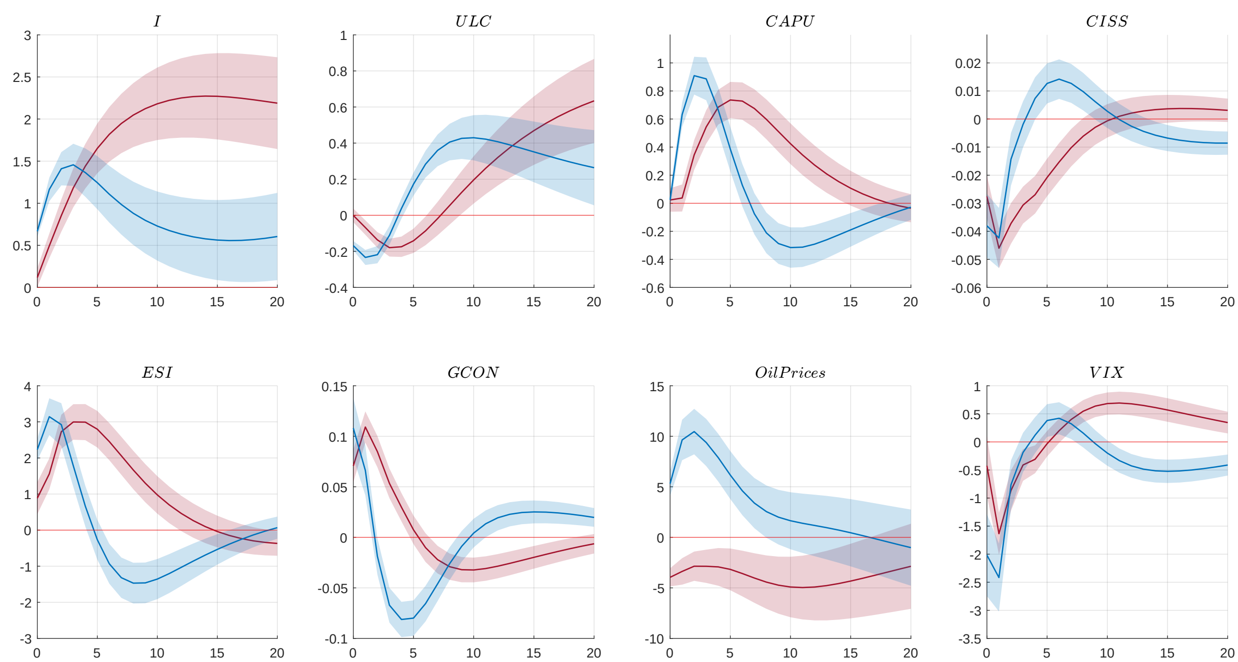

Figure 4: Impulse response functions of the demand (blue) and supply (red) shocks, for a few secondary selected EA variables. The shaded areas are the one standard deviation confidence bands, obtained with bootstrap.

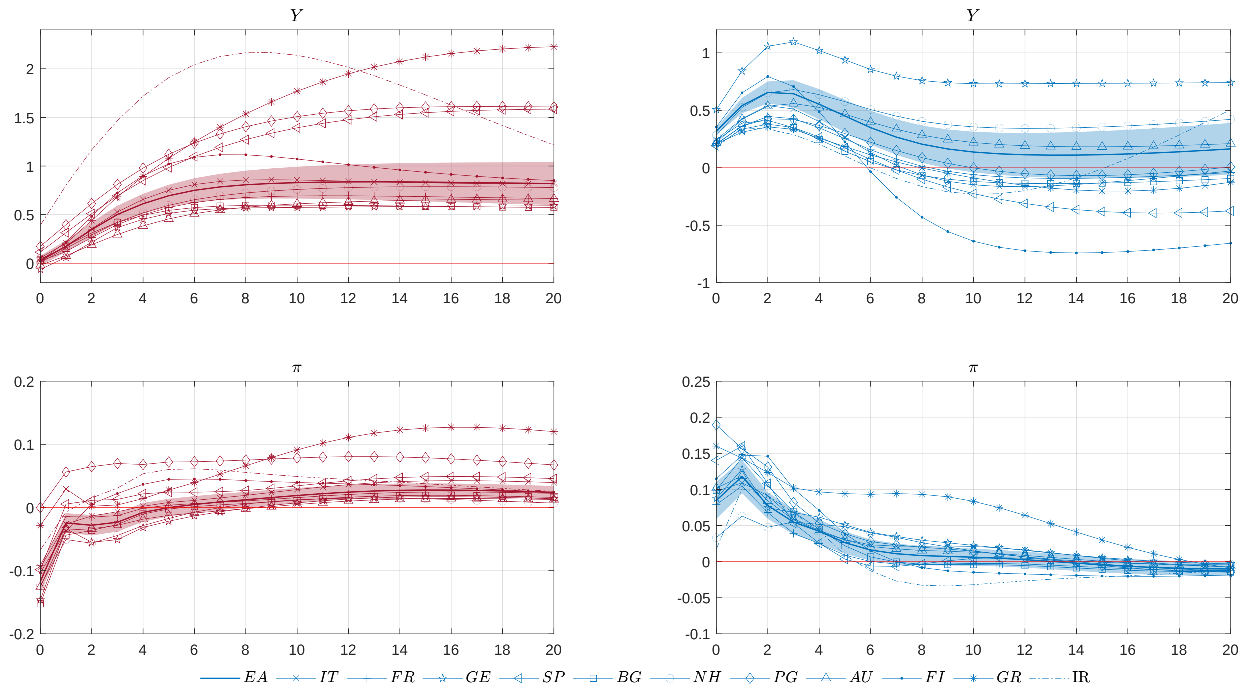

Figure 5: Impulse response functions of the demand (blue) and supply (red) shocks, of country-specific GDP and Inflation. The shaded areas are the one standard deviation confidence bands, obtained with bootstrap.

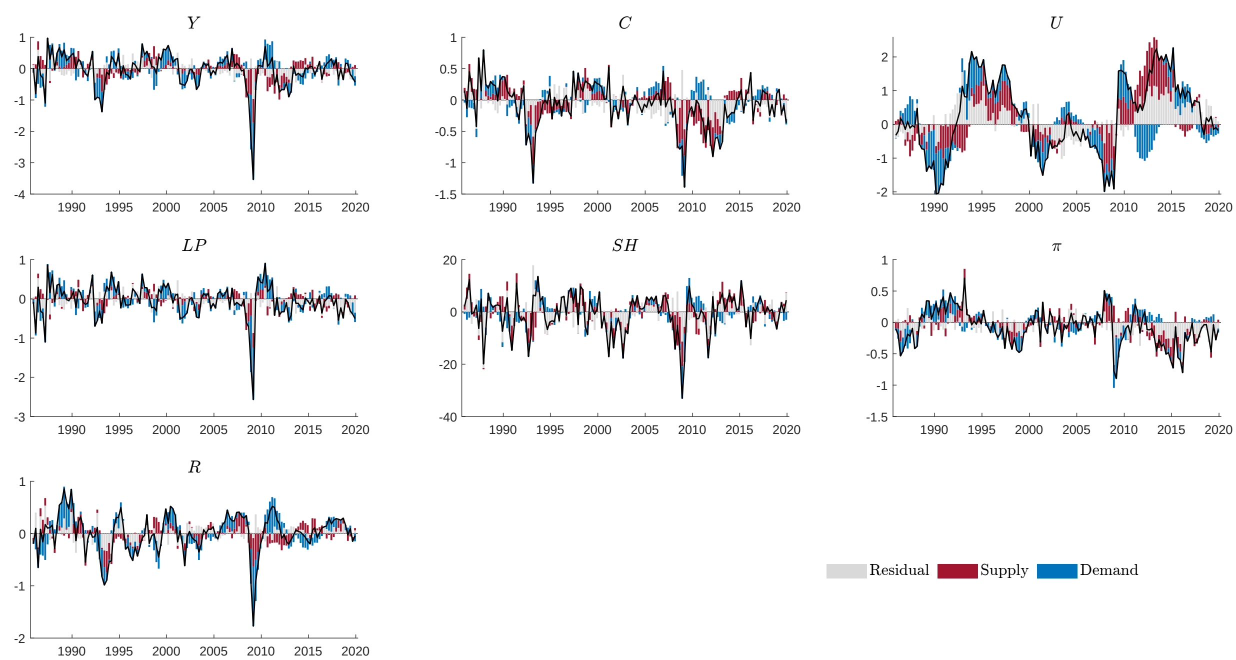

Figure 6: Historical decomposition for a few selected EA variables

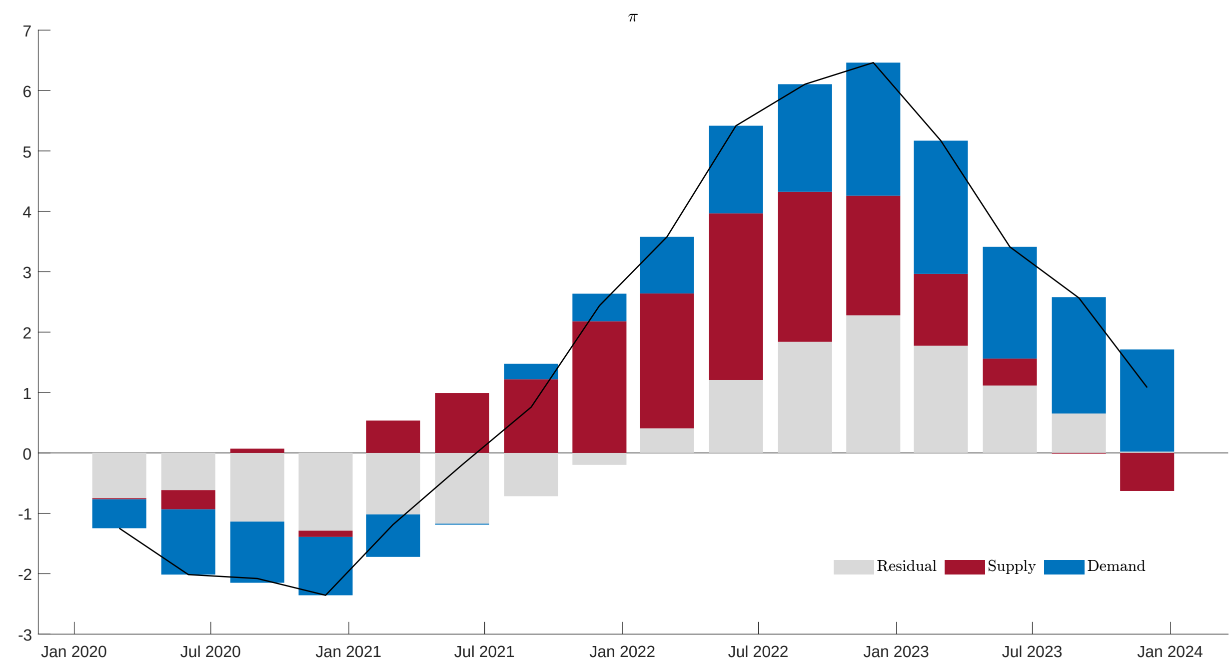

Figure 7: Historical decomposition of EA Inflation

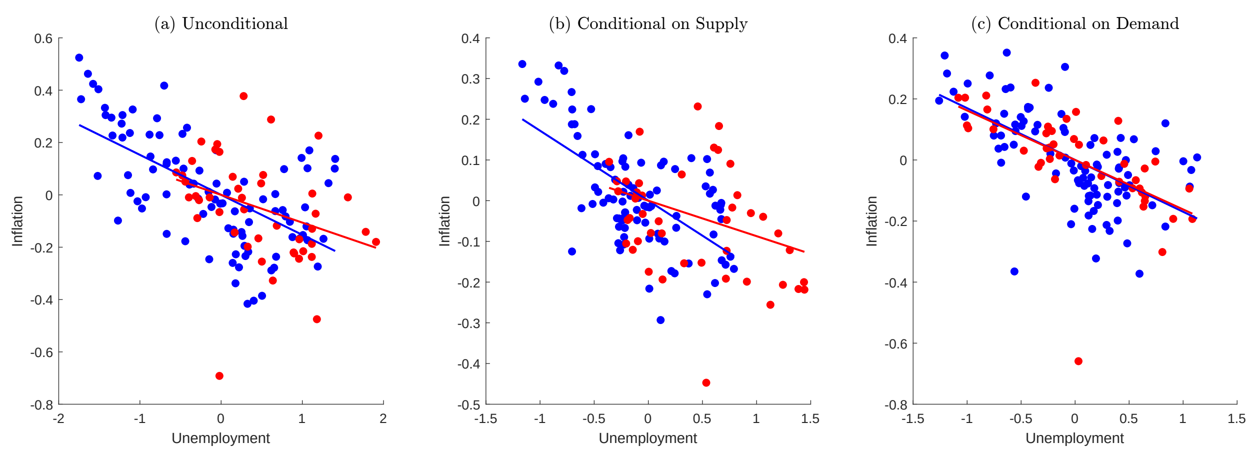

Figure 8: Empirical scatterplots. Unconditional data (a) against conditional data on supply (b) and on demand (c) obtained from the estimated CC-SVAR model. In blue data before Q4-2008, in red data after Q4-2008.

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A Robustness

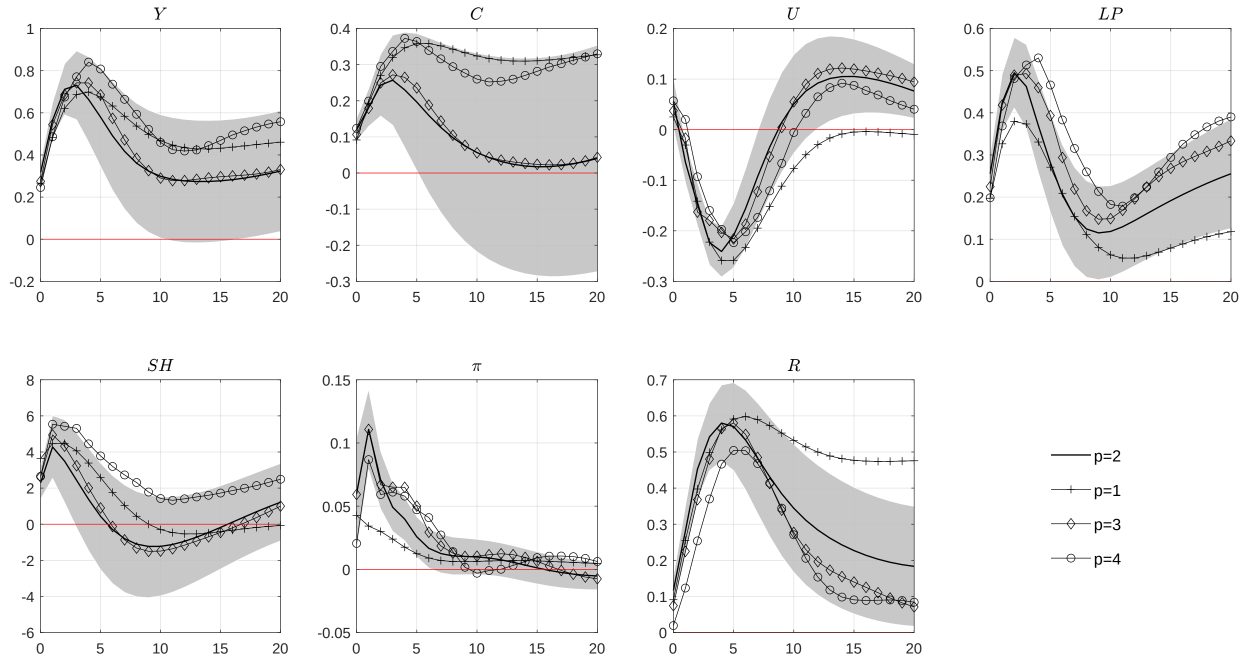

Figure 9: Impulse Response Functions of a MBC shock. Robustness on p.

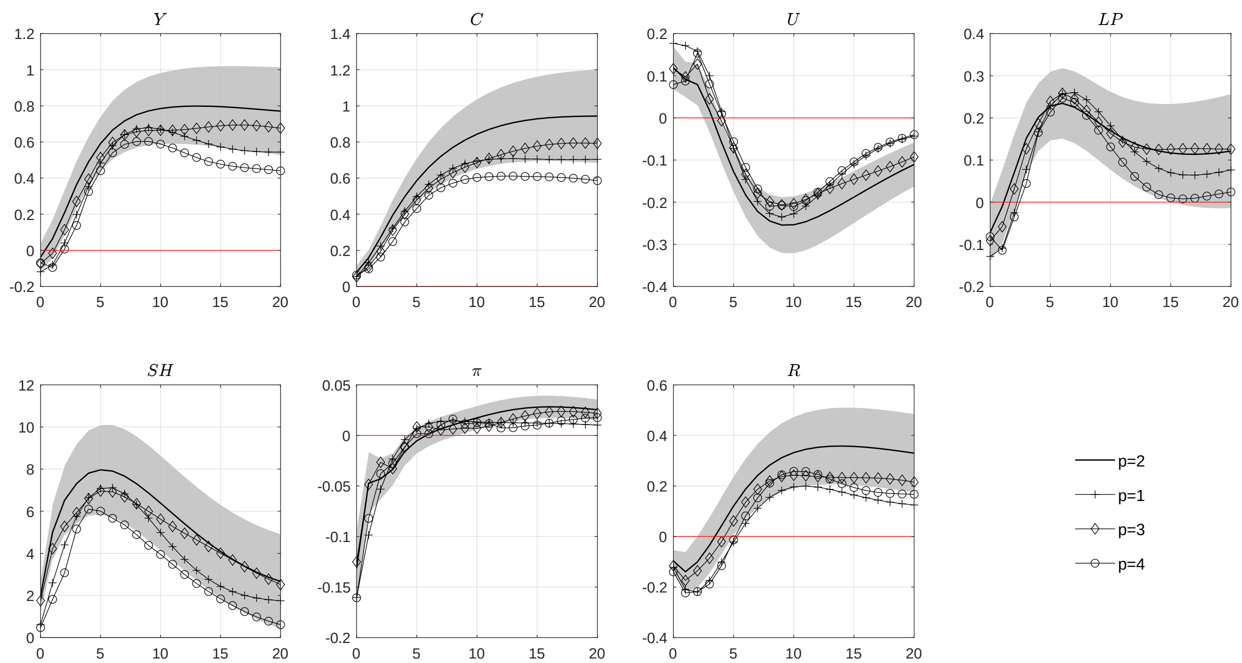

Figure 10: Impulse Response Functions of a SBC shock. Robustness on p.

B Extra

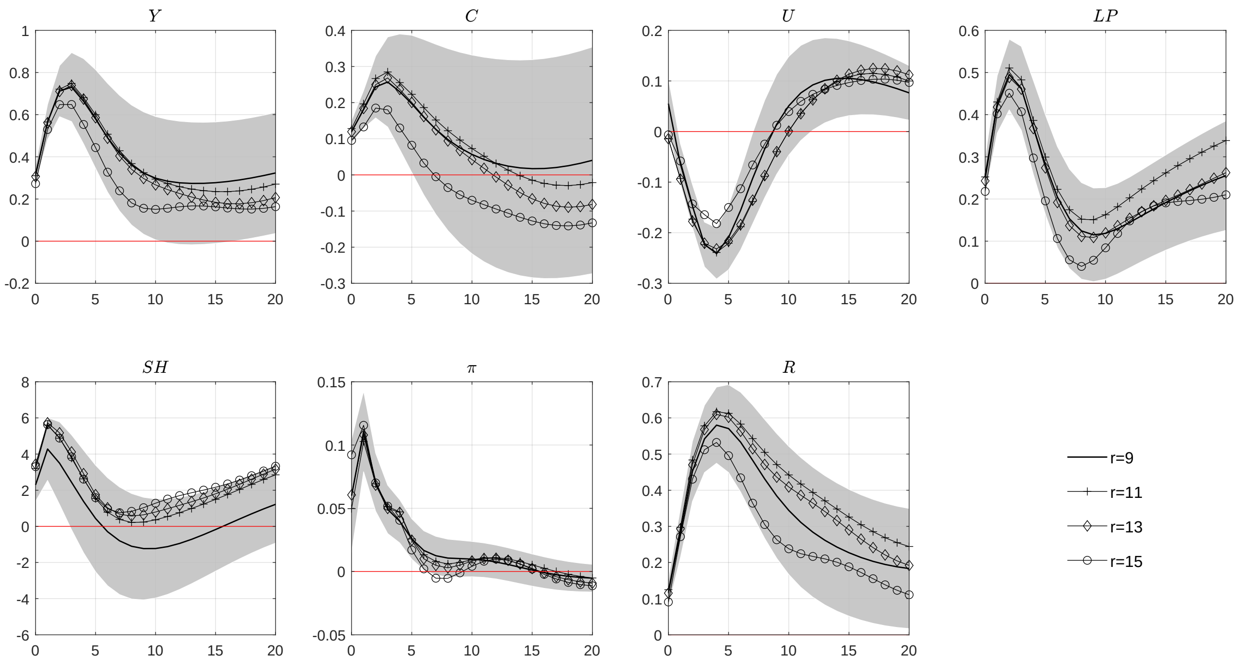

Figure 11: Impulse Response Functions of a MBC shock. Robustness on r.

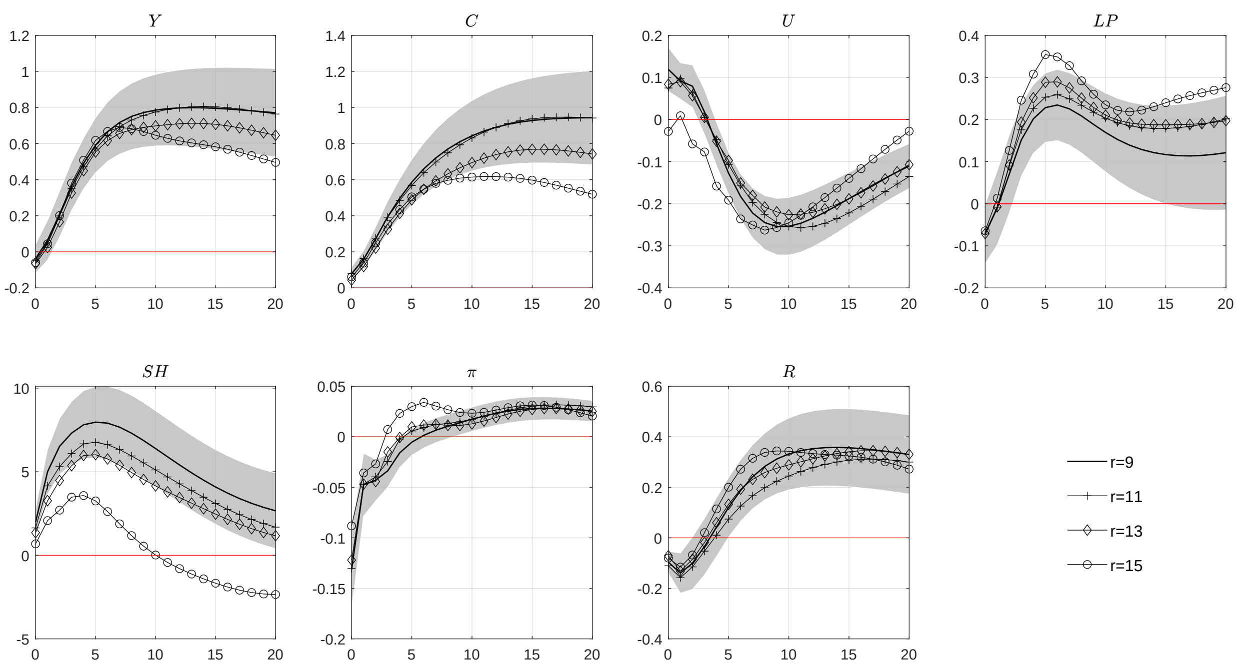

Figure 12: Impulse Response Functions of a SBC shock. Robustness on r.

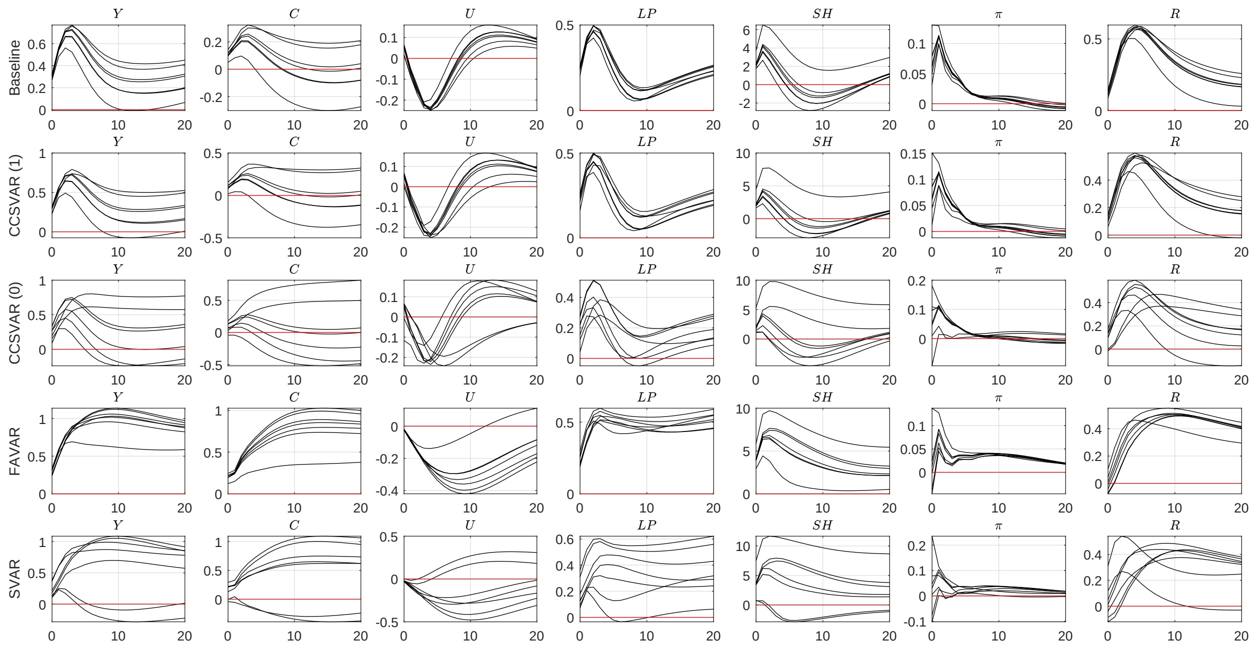

Figure 13: Impulse Response Functions of a MBC shock. Comparison of different specifications.

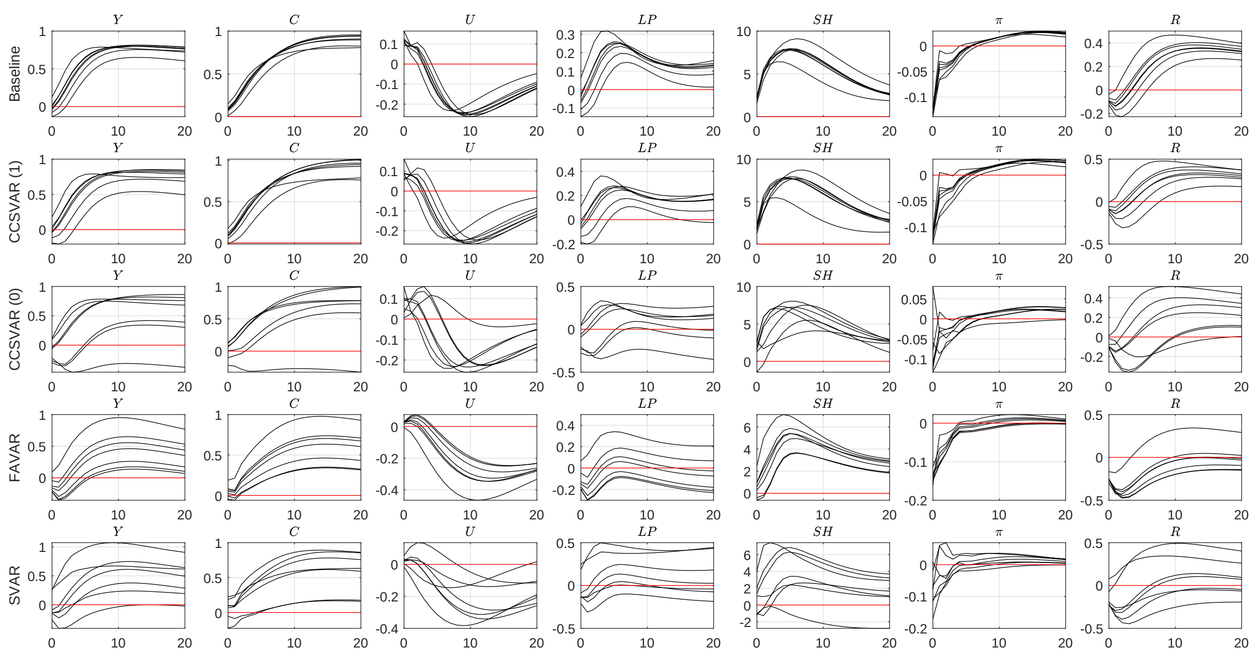

Figure 14: Impulse Response Functions of a SBC shock. Comparison of different specifications.