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Do survey data help identify supply and demand shocks in sign-restricted SVARs?

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Abstract

Sign-restricted SVARs are typically characterized by high identification uncertainty. However, using external proxies can be helpful in this context. In this paper, I use business survey data to inform an SVAR of aggregate supply, demand and monetary policy shocks for the euro area. In the surveys, companies report input factors that limit their business activities. I show that sign-identified model sets are very heterogeneous and produce shocks that are only weakly related to survey-based input shortage indicators. In contrast, combining sign restrictions with information from these shortage indicators narrows the set of admissible impulse response functions and affects policy-related conclusions drawn from the model.

Keywords: Proxy VARs, SVAR, sign restrictions

JEL codes: C32, C52, E30

1. Introduction

Sign-restricted structural VARs are a standard tool in macroeconomic analysis, both for policymakers and in academia (Faust, 1998, Uhlig, 2005,

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Rubio-Ramirez et al., 2010). The identification is achieved by assuming how the endogenous model variables react to an orthogonal innovation qualitatively. For instance, the interest rate increases after a contractionary monetary policy shock. Compared to exclusion restrictions like the Cholesky factorization, a qualitative scheme has the advantage that quantitative responses of endogenous variables are left to the data and not determined ex ante. Additionally, sign restrictions build on a variety of theoretical models. However, sign restrictions have the disadvantage that they allow for a potentially infinite number of models that satisfy the given constraints. Routines to choose a representative model exist¹, but they do not solve the problem of high identification uncertainty.

For that reason, methods for narrowing down the eligible models have become more popular. Kilian and Murphy (2012) find that imposing elasticity constraints on the impact response of macroeconomic variables to oil market shocks dramatically sharpens impulse response functions of SVARs originally identified via traditional sign restrictions. Antolín-Díaz and Rubio-Ramírez (2018) find the same result using narrative sign restrictions, hence assumptions on how structural shocks behave during specific historical episodes. To facilitate the use of external information, proxies or instrumental variables can also be helpful. Cesa-Bianchi and Sokol (2017) propose a strategy in which proxies are used for identifying a specific shock, while the remaining shocks result from sign restrictions. Braun and Brüggemann (2023) combine sign-restricted VARs with external proxies for the same shocks. They apply their method to identify monetary policy shocks, finding that IRFs become more informative.

In this paper, I identify an SVAR featuring aggregate supply, demand and

¹Various methods exist to select from the set of admissible models. Fry et al. (2007) propose choosing the impulse response function (IRF) that minimizes the squared distance from the median IRF. Inoue and Kilian (2013) propose to select the IRF that exhibits the highest posterior density

monetary shocks by combining sign restrictions with external information from business survey data. The survey data is informative for the structural shocks as in the underlying questionnaires, firms report whether a lack of demand or a lack of labor is limiting their production. Since the firms report different production obstacles simultaneously, they implicitly identify supply and demand-sided sources of their business activity.

In a first step, I estimate a VAR using a standard sign restriction scheme and examine the empirical connection between the estimated shocks and survey-based shortage indicators. In the second step, I select from the set of accepted models those showing a pre-defined relationship between shocks and shortage indicators. I assume that an aggregate demand shock is related to the average share of firms reporting demand as a production-limiting factor (relevance condition). Furthermore, the demand shock is assumed to be the most important driver for this indicator among all VAR shocks (rank condition). The analogous conditions apply to the supply shock and a measure for labor shortages. To the best of my knowledge, this is the first work to use survey data as external proxies in an SVAR. The empirical design allows for various extensions that involve types of macroeconomic shocks different from those discussed here.

The method maintains the relative flexibility of the sign restriction approach but allows improving the identification by external information. The proxies are integrated into the analysis using mild inequality constraints on their relationship with the shocks. Comparing this approach to instrumental variables (IV) VARs (Mertens and Ravn, 2012, Stock and Watson, 2012, Gertler and Karadi, 2015), this is an advantage because proxies for a specific shock do not necessarily have to be uncorrelated with the other shocks. Instead, the rank condition only assumes that the relationship between a shock of interest and its corresponding proxy is strongest. In addition, the relevance criterion allows for weak instruments to a certain extent because on the one hand, the relationship between shock and proxy must not fall below

a minimum threshold. On the other hand, the threshold can be arbitrarily low.

The empirical results show that the SVAR shocks identified by sign restrictions have limited explanatory power for the survey indicators. In addition, the decomposition of the indicators into shock contributions does not correspond to their structural interpretation. The share of firms reporting demand as production-limiting is predominantly driven by supply shocks, while labor shortages are mainly driven by monetary policy shocks. The results change if only model draws are considered that meet the stated minimum requirements. In particular, this selection reduces identification uncertainty and alters policy-relevant conclusions drawn from the VAR.

The paper is structured as follows: Section 2 presents the survey data, section 3 the empirical framework and the identification schemes. Section 4 shows the results from the conventional sign-restricted setup and those from additionally integrating the survey data. Section 5 concludes.

2. Survey data and SVARs

The survey data used in this paper contain information on specific production-related shortages in the euro area. In the underlying questionnaires, firms report every quarter if the availability of labor, material, financial resources and/or a lack of demand limits their business activities². The analyzed production inputs are displayed in Table 1. It is obvious that by ticking one or more factors among this list, firm managers define the determinants of their business operations. When a manager selects “orders” as a production-limiting factor, it can be assumed that the firm’s production is significantly restricted by a weak demand for its products. The same applies for input factors.

²The surveys are conducted in the manufacturing, the construction and the service sector and for all member countries of the European Union.

Table 1: Firm questionnaire

Our production activity is currently limited:

Yes No

If yes, through the lack of:

Orders Workers Financial resources

Material or commodities Other factors

The causal linkage between these factors and production is further strengthened by the fact that a variety of production factors is queried and simultaneously considered by the firm manager when filling in the questionnaire. If only a single production factor would be analyzed, the survey results would likely be different from those presented here. This is the case because production factors are not independent from each other. A reduction of orders should affect the procurement market through a lower demand for inputs. Therefore, if firms were only asked about labor shortages, the corresponding indicator might be driven more by a change in orders than by changes in labor supply. The same applies to different production inputs that are complements, e.g., material and labor supply.

Of course, reporting multiple production-limiting factors instead of just one does not rule out the possibility that the labor shortage is influenced by the order situation. This is clear from Figure 1, which shows the share of firms over time that reports a specific production-limiting factor. It clearly shows that the Great Recession, the Euro debt crisis and the Covid-19 recession were shaped by a changing assessment of production factors. Each of these events is characterized by a significant increase in the demand indicator, implying that a lack of demand increasingly limited production. At the same time, the labor supply indicator decreased, hence the labor shortage was less of a constraint on business activity. However, there are also periods when the labor supply moved idiosyncratically. This was especially the case between

2021 and 2023, when labor shortages became more significant. Hence, the fact that there are indicators for supply and demand enables measuring both dimensions independently. For instance, the labor supply indicator could be isolated from demand influences by regressing it on the demand indicator and computing the residuals.

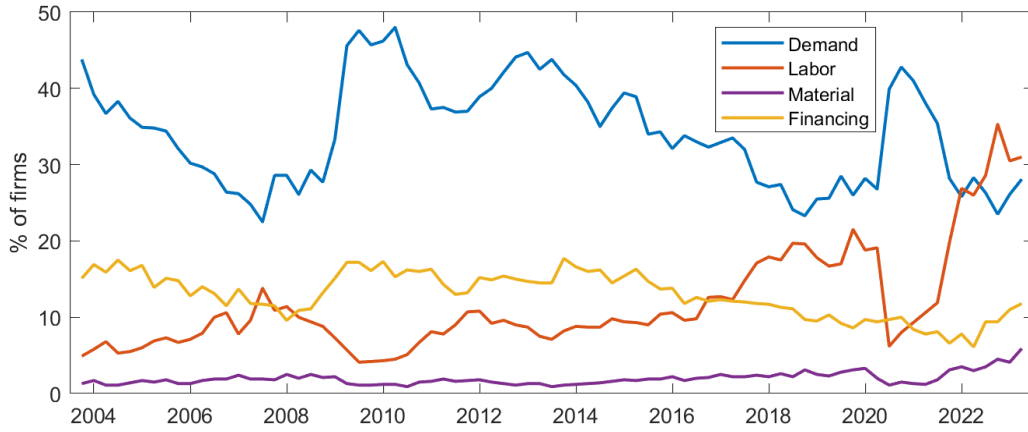


Figure 1: Production-limiting factors in the service sector in the Euro Area

Notes: The figure shows the share of firms reporting demand (blue), labor supply (red), financial resources (yellow) and material (purple) as production-limiting factors.

As a result, the survey indicators have a natural relationship to standard macro SVARs of (orthogonal) supply and demand shocks. Ideally, the empirical results of a corresponding SVAR should reflect the firms' judgment and vice versa, and thus lead to similar conclusions. For instance, the marked increase in labor shortages following the Covid-19 pandemic should have been due to an adverse labor supply shock because the assessment of other production inputs changed disproportionately.

However, a full match is not likely. The conclusions drawn from an estimated structural VAR depend on model and identifying assumptions and national accounts data. In contrast, the survey-based decomposition of macroeconomic drivers results from the firms' observation of production conditions,

e.g. the selling and the procurement market, and potentially the macroeconomic environment. On the one hand, this is a advantage over an analysis based on estimated shock series as the surveys lead to time series indicators that can in principle be treated as observable variables (not considering measurement error). On the other hand, the survey data has the disadvantage that firms are only asked about production obstacles, ignoring price and wage adjustments related to these obstacles. While this implies a physical perspective on production inputs, including prices and quantities as endogenous variables in macro VARs allows for a more comprehensive analysis. Another drawback is that private households do not take part in the surveys. Hence, the consumer side is only indirectly taken into account. In contrast, standard macro VARs consider both households and firms because they mimic a general equilibrium setup.

Due to the different characteristics of survey and model-based analyses, it might make sense to augment the SVAR by the survey data and profit from a richer information set. In the analysis described in section 3, I use the demand indicator from Figure 1 as a proxy variable for the aggregate demand shock. The conditions on the procurement market are asked in more detail in the questionnaires, distinguishing between labor and commodities. I use the labor shortage indicator as a proxy for the aggregate supply shock instead of the commodity shortage indicator because labor is an important production input in all sectors of the economy and because it is a domestic input factor. Disruptions in other procurement markets are taken into account by the fact that the sign restrictions allow for all types of supply-side shocks that lead to diverging production and prices movements. Using the labor supply indicator as proxy for the aggregate supply shock does not rule out this property because the set-identification allows mild inequality constraints on the relationship between shock and proxy.

3. Empirical framework

The analysis is based on a standard VAR framework with sign restrictions. The structural model of lag order p is given by:

$$Y_t = \nu + \sum_{k=1}^p B_k Y_{t-k} + u_t \quad (1)$$

$$u_t = P_j \epsilon_t \quad (2)$$

where Y_t is an $n \times 1$ vector of endogenous variables. $u_t \sim N(0, \Sigma)$ denotes the vector of reduced-form residuals and $\epsilon_t \sim N(0, I_n)$ are the structural shocks. The matrix P_j with property $P_j P_j' = \Sigma$ describes the contemporaneous relationship between the reduced-form residuals and the structural shocks. To find an economically interpretable decomposition (2), identifying restrictions are necessary. I focus on identifying an aggregate supply shock ϵ_t^s , an aggregate demand shock ϵ_t^d and a monetary policy shock ϵ_t^m in a small-scale VAR of $n = 3$ variables, namely quarter-on-quarter GDP growth, quarter-on-quarter percentage changes in the GDP deflator and the shadow short rate by Krippner (2013)³. I use the shadow short rate instead of the MRO rate to take unconventional monetary policy measures into account. The selection of variables rests on the New-Keynesian DSGE model setup incorporating a dynamic IS curve, a Phillips curve and a monetary policy rule.

3.1. Baseline identification

To find the structural decomposition of u_t in (2), I impose the sign restriction scheme on the IRFs proposed by Fry et al. (2007)⁴. The restrictions

³I estimate the reduced-form VAR by standard methods using Euro Area data from 1995Q1 until 2023Q2. To prevent my results from being driven by large outliers, I trim any growth rate or inflation rate that is further than five times the interquartile range away from its median to the respective threshold. Details on the estimation can be found in the appendix.

⁴Fry et al. (2007) assume a positive reaction of interest rates to an adverse supply shock. Instead, I leave the reaction unrestricted to account for the tradeoff central banks

are outlined in Table 2. Candidates for P_j are randomly drawn using the method by Rubio-Ramirez et al. (2010) and stored if the resulting IRFs meet the given assumptions. I repeat this procedure until M models are found, $P = \{P_1, \dots, P_M\}^5$.

Table 2: Sign restrictions

	Demand shock	Supply shock	Monetary policy shock
GDP	+	-	-
GDP deflator	+	+	-
Interest rate	+	•	+

Notes: The table shows the sign restrictions imposed upon the IRFs following a structural VAR shock. The IRFs are restricted for 3 quarters. A "•" signifies an unrestricted IRF.

By applying this restrictions scheme, the VAR is fully identified and can be used for analyses such as IRFs. However, the set of accepted models is heterogenous, as Figure 3 shows. In the combined identification described in the following, I select from the set of accepted models those having a specified relationship with the survey indicators. Hence, the combined identification is included in the baseline identification.

3.2. Combined identification

The linkage between the survey indicators and the SVAR can be established using the estimated structural shocks ϵ_t (Braun and Brüggemann, 2023). To this end, I regress each of the survey indicators on a constant and p lags of each estimated shock series, as defined by the following regression equation:

face between reducing inflation or supporting output. However, restricting the interest rate reaction to a supply shock does not change the results significantly.

⁵I apply a rotation scheme to the impact matrix $P_j = \text{chol}(\Sigma)Q'$ with a randomly drawn candidate rotation matrix Q . Q is $n \times n$ -dimensional and has the property $Q'Q = Q^{-1}Q = I_n$.

$$s_t^i = c^i + \sum_{k=1}^p \beta_k^i \hat{\epsilon}_{t-k} + \varepsilon_t^i \quad (3)$$

where the $n \times 1$ - dimensional vector $\hat{\epsilon}_t$ contains the estimated shocks⁶ and s_t^i , $\{i = d, s\}$ denote proxies for aggregate demand and labor supply. Due to the correlation between the demand indicator and the labor supply indicator shown in Figure 1, I orthogonalize these by regressing the labor supply indicator on the demand indicator and taking the residuals for s_t^s in regression (3). This regression isolates the component of the labor supply that is not correlated with the demand indicator and imitates a Cholesky ordering with the demand indicator ordered first.

The regressions of equations (3) are similar to augmenting the VAR by the survey indicators and inverting the model. I refrain from including the survey indicators into the set of endogenous variables to keep it parsimonious and to isolate the impact of the additional information. Braun and Brüggemann (2023), Carstensen and Salzmann (2017) and Kilian (2009) use similar approaches.

After estimating the regressions (3) for each of the M model draws, I select the draws which meet the following inequality constraints. The relevance condition requires that a survey indicator s_t^i needs to be related to its corresponding shock $\hat{\epsilon}_t^i$. Specifically, the variance share of the demand indicator explained by the demand shock must not fall below a defined threshold c . The same is assumed for the relationship between the labor supply indicator and the supply shock. Both conditions are based on the assumption that the structural VAR shocks at least partially reflect the firms' assessment on production factors.

⁶I only include one structural shock at a time as regressor, which is a valid approach as the shocks are orthogonal.

The rank condition requires that the relationship between a survey indicator s_t^i and a related VAR shock $\hat{\epsilon}_t^i$ has to be stronger than the relationship with all other shocks $\hat{\epsilon}_t^j, i \neq j$. For instance, the variance of the labor supply indicator should be mainly due to the supply shock. This condition is justified if firms observe the shocks and assign them to the related factors offered in the questionnaires.

I impose the relevance and rank condition on the variance shares of the survey indicators⁷. In summary, the selection of model draws is based on the following inequality constraints:

$$R_{i,i}^2 > c \quad (\text{relevance condition}) \quad (4)$$

$$R_{i,i}^2 > R_{i,j}^2 \quad i \neq j \quad (\text{rank condition}) \quad (5)$$

where $R_{i,j}^2$ denotes the share of the forecast error variance of the survey indicator $i = \{s, d\}$ explained by the VAR shock $j = \{s, d, m\}$. The empirical variance shares result from the estimated regressions (3). c is a threshold value chosen by the researcher. For the results described below I choose $c = 20\%$, but other values do not affect the main conclusions of the paper. As $n = 3$ shocks are identified but only $k = 2$ proxies are used, each of the M model draws of the baseline identification is tested with respect to $n + k(n - 1) = 6$ inequality constraints, n relevance conditions and $k(n - 1)$ rank conditions. The accepted draws are assigned to the combined identification set, while the remaining ones continue belonging only to the baseline identification set.

The relevance and rank criterion are similar to those needed in IV-VARs for valid instruments but slightly less restrictive. This is because the instruments (proxies in this case) are included using inequality constraints on the relationship with the shock. Compared to the exogeneity assumption in IV-

⁷Correlation constraints are generally also possible but are not invariant to normalizations of the VAR shocks. For instance, it might be the case that the $\text{corr}(s_i, \epsilon_i) = 0.1 > \text{corr}(s_i, \epsilon_j) = 0$. However, the relationship reverses if ϵ_i is multiplied by -1.

VARs, the rank condition does not require the relationship between a shock of interest and a non-related proxy to be zero. Instead, it only has to be weaker than the relationship between the shock and its corresponding proxy. Exogeneity cannot be assumed anyway because demand shocks might also change the firms' assessment of supply conditions. This case is not excluded in the rank condition. Furthermore, numerical selection based on the relevance criterion allows for weak instruments because the relationship between shock and proxy only needs to meet some minimum requirements. However, if the proxy has no explanatory power at all for the shock, the selection routine indicates this by discarding all candidate draws.

4. Results

I estimate the model using Bayesian techniques but with uninformative priors⁸. Details are described in the appendix. In the following I discuss the empirical relationship between the VAR shocks and the external survey data. Subsequently, I show how IRFs and historical decompositions depend on the identification.

4.1. Relationship between survey indicators and SVAR shocks

Table 3 shows the shares of the forecast error variance of the survey indicators accounted for by the demand (AD), supply (AS) and monetary policy (MP) shocks (R^2 s). The R^2 s are based on the regression equations (3) for all retained model draws. Hence, they are the relevant statistics for the inequality constraints. Table 3 shows only the medians of the R^2 s, while the distributions can be found in Figure 6 in the appendix.

⁸I randomly draw from the reduced-form VAR and rotate each of the decompositions in equation (2) 1,000 times. I stop the routine once $N = 1,000$ draws of the combined model are stored. The ratio between the number of accepted models under the combined identification to the number of accepted models under the baseline model is approximately 10%.

Table 3: Variance shares of survey indicators explained by SVAR shocks

Proxy	Identif. + shocks	Baseline identif.				Combined identif.			
		AD	AS	MP	Σ	AD	AS	MP	Σ
Demand indicator		0.15	0.22	0.05	0.42	0.27	0.09	0.06	0.41
Labor supply indicator		0.02	0.08	0.11	0.21	0.01	0.25	0.07	0.33

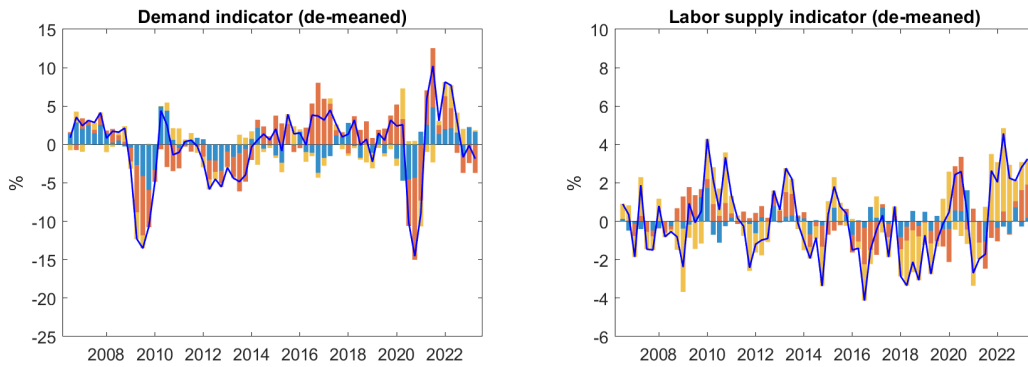
Notes: The table shows the median shares of the forecast error variance of the survey indicators accounted for by SVAR shocks.

At the median across all draws of the baseline model, the VAR shocks explain 42 % of the fluctuations of the demand indicator and 21 % in the labor supply indicator. The composition of shocks also differs between the indicators. The supply shocks explain about half of the explained variance of the demand indicator. This share is larger than the share of the demand shock, which is only one third. The fitted part of the labor supply indicator is predominantly determined by monetary policy shocks.

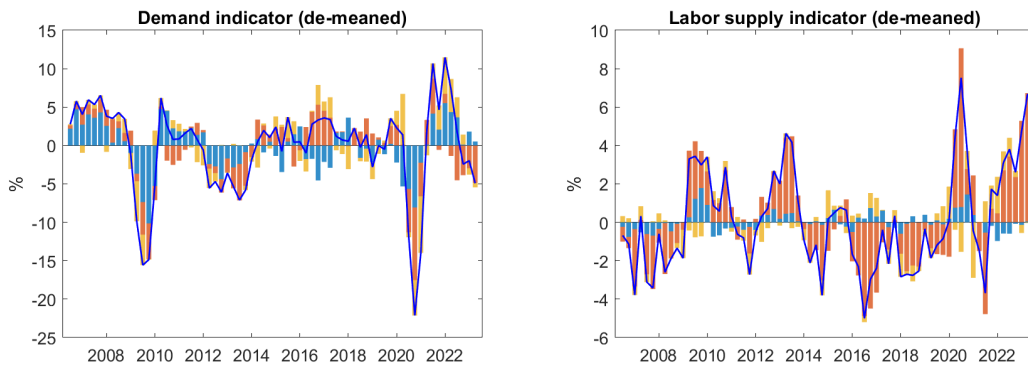
These results are reflected in Figure 2, which shows the historical decomposition of the survey indicators⁹. Slight differences from the results of Table 3 can be explained by the fact that the historical decomposition is based on the model draw with the highest posterior density.

These results show that the VAR shocks under the baseline identification only partly reflect the firms' perceptions of macroeconomic drivers and vice versa. This is particularly true for the supply shock, which meets neither the rank condition nor the relevance condition at the median. The demand shock appears to be relevant to the demand indicator, but contributes less to it than the supply shock and thus violates the rank condition. In the combined identification, these conditions are satisfied by assumption. As expected, the decomposition of the labor supply indicator is particularly affected by

⁹The residuals of the regression equations (3) are displayed in Figure 7.



(a) Baseline identification



(b) Combined identification

Figure 2: Decomposition of the survey indicators into VAR shocks

Notes: The blue graphs depict the survey indicators explained by all VAR shocks. The bars in blue, red and yellow are the growth contributions accounted for by demand, supply and monetary policy shocks, respectively. The results are based on regressions 3 and the VAR model with highest posterior density. The demand indicator is inverted.

the additional restrictions. In addition, the additional restrictions lead to a higher overall fit of the labor supply indicator as the fit increases from 21 % to 33 %. Hence, the higher contribution of supply shocks is only partially compensated by lower contributions of the other shocks.

In the next section, I discuss IRFs and historical decompositions under the different identification schemes.

4.2. Impulse response functions

Figure 3 shows 68% of the IRFs with highest posterior density (HPD) under the baseline identification (in blue) and the combined identification (in red). The highlighted graphs represent the IRF with the highest posterior density. The set of accepted IRFs represents both model and estimation uncertainty, as discussed by Inoue and Kilian (2013).

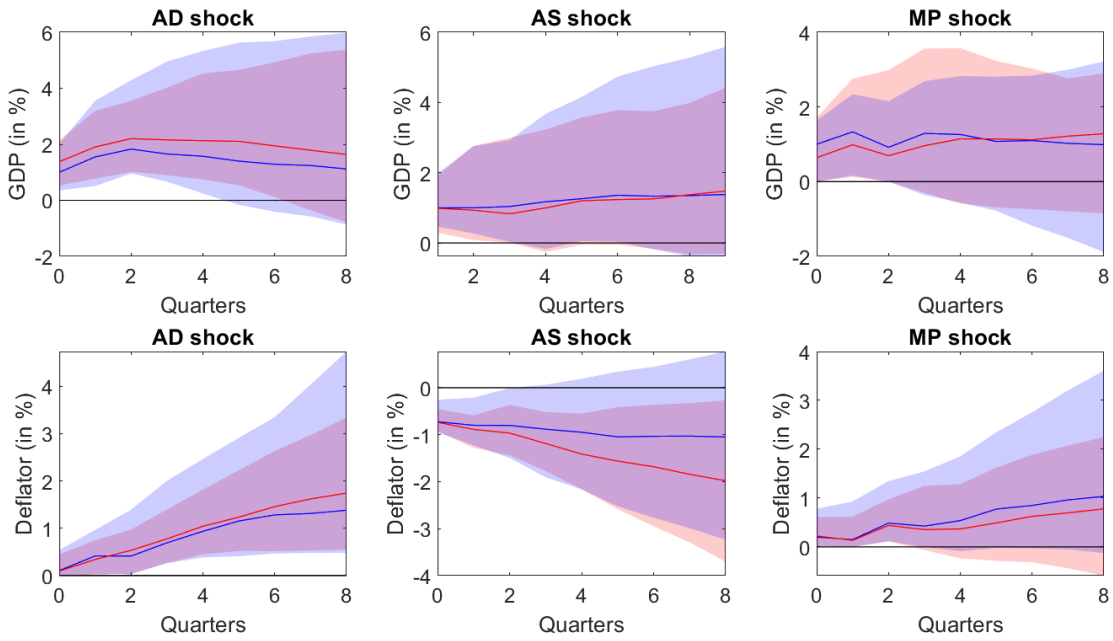


Figure 3: Impulse response functions of GDP and prices

Notes: The IRFs of the baseline identification are depicted in blue and those of the combined identification in red. The shaded areas are 68% HPD regions. The highlighted graphs are the IRFs with the highest posterior density. The shocks are re-scaled such that GDP increases on impact by 1% in the baseline identification using the model with highest posterior density.

In the baseline model, the set is very heterogenous. An expansionary demand shock raises GDP by magnitudes between 0.3% and 4.2% after four quarters. The uncertainty regarding the supply and the monetary policy shock is similarly high. Due to the wide ranges, the effects of the shocks are

sometimes not statistically significant. For example, the price reaction to a supply shock becomes insignificant after three quarters at the 68% confidence level.

The range of possible effects shrinks significantly in the combined identification. This is particularly true for the reaction of prices. The impact of the demand shock on the GDP deflator tend to become smaller, now ranging between 0.5 % and 1.5 % after four quarters (relative to an interval of 0.5 % and 2.4 % in the baseline model). This is due to the fact that draws with large and in some cases pathological candidates are discarded. In contrast, the IRFs of the GDP deflator following a supply shock are now larger in absolute value and statistically significant. This result is also reflected in the posterior modes, which differ substantially between the identification schemes.

4.3. Historical decompositions

The impulse response analysis shows how standardized shocks affect the economy. Historical decompositions of the endogenous variables allow studying specific historic events like the Covid-19 pandemic. They do not only reflect the impact of shocks but also take the actual evolution of shocks into account.

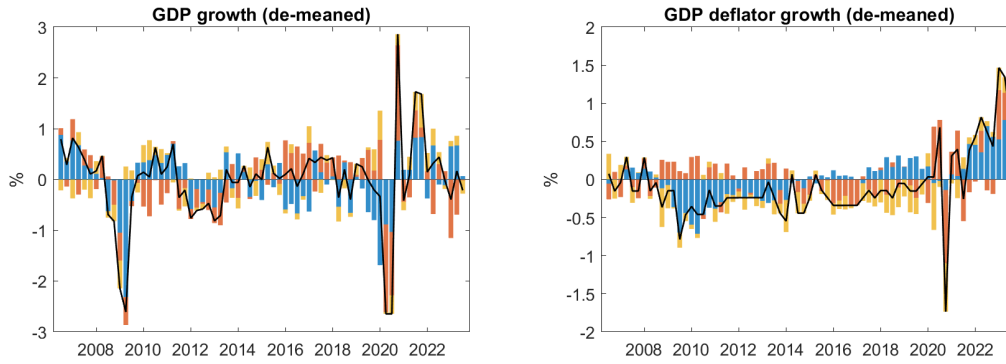
Figure 4 shows historical decompositions of GDP growth and inflation in the euro area since 2006. The comparison between the identification schemes reveals substantial differences. Under the baseline approach, demand shocks tend to be important determinants of GDP and inflation. In the period after the Covid-19 pandemic from 2021 to 2023, positive demand shocks accounted for at least half of macroeconomic fluctuations. This finding is consistent with contributions finding a significant weight of expansionary demand shocks during this period (Celasun et al., 2022, Alonso et al., 2021, Gonçalves et al., 2022). The baseline identification also finds supply shocks to be inflationary and contractionary after 2021, reflecting disruptions on the production side such as material and labor shortages. However, supply

shocks appear to have had a much smaller impact on inflation than demand shocks.

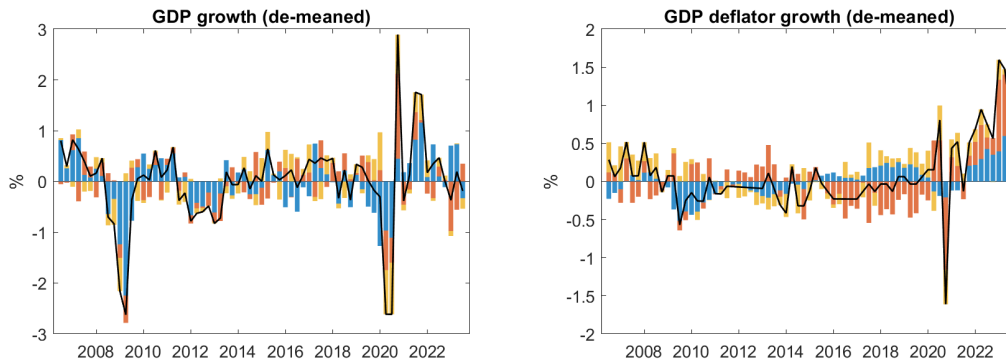
Under the combined identification supply shocks generally contribute more to inflation. This can be partly explained by the fact that supply shocks are more closely linked to labor shortages, which tightened after the Covid-19 pandemic in parallel with the rise in inflation. As a result, only VAR draws implying inflationary and labor-related supply shocks are considered in the combined identification. To control for the influence of the observations on the results, I repeat the analysis using a restricted sample until 2019. Compared to the full sample estimation, this slightly reduces the median impact of supply shocks on inflation, as measured by IRFs. The main conclusions of this paper, however, remain intact.

5. Conclusion

Sign-identified SVARs are typically characterized by high identification uncertainty. However, it has been shown that using external proxies can be helpful in this context. In this paper, I use business survey data to inform the model setup. The data is helpful because firms are simultaneously asked about different supply and demand-sided factors that limit their production. I incorporate the survey data in the empirical analysis by making assumptions about their relationship with the structural VAR shocks. I find that this approach significantly increases the identification accuracy and also alters the IRF posterior mode. If the survey data are not considered in the estimation, the SVAR generates structural shocks which are inconsistent with the survey data. Compared to narrative approaches, the use of survey data in Proxs-SVARs is easy to implement and can be applied to a variety of empirical questions involving macroeconomic shocks different from those discussed in this paper.



(a) Baseline identification



(b) Combined identification

Figure 4: Historical decomposition of quarterly GDP growth and inflation

Notes: The bars in blue, red and yellow are the growth contributions accounted for by demand, supply and monetary policy shocks, respectively. The black graphs are the sum of all shock contributions. The decomposition is based on the model yielding the highest posterior density.

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Appendix

The reduced-form VAR is estimated by Bayesian methods. To implement the priors, I write the VAR in matrix form as

$$Y = ZB + U$$

where $Y = (Y_1, \dots, Y_T)'$, $Z = (Z_1, \dots, Z_T)'$ with $Z_t = (1 \ Y'_{t-1}, \dots, Y'_{t-p})$, $U = (u_1, \dots, u_T)'$, and $B = (c \ B_1, \dots, B_p)'$. I follow Kadiyala and Karlsson (1997) and Inoue and Kilian (2013) in imposing a Normal inverse-Wishart prior

$$\text{vec}(B)|\Sigma \sim N(\text{vec}(\underline{B}), \Sigma \otimes \underline{V}^{-1}) \quad \text{and} \quad \Sigma \sim IW(\underline{\nu}\underline{S}, \underline{\nu})$$

where the prior parameters \underline{B} , \underline{S} , \underline{V} , and $\underline{\nu}$ are chosen by the researcher. I choose flat priors, i.e., $\underline{B} = \mathbf{0}_{np+1 \times n}$, $\underline{S} = \mathbf{0}_{n \times n}$, $\underline{V} = \mathbf{0}_{np+1 \times np+1}$, and $\underline{\nu} = 0$. The conditional posterior distribution of the VAR parameters is given by

$$\text{vec}(B)|\Sigma, Y \sim N\left(\text{vec}(\bar{B}), \Sigma \otimes \bar{V}^{-1}\right) \quad \text{and} \quad \Sigma|Y \sim IW(\bar{\nu}\bar{S}, \bar{\nu})$$

where

$$\begin{aligned} \bar{B} &= \bar{V}^{-1} \left(\underline{V}\underline{B} + Z'Z\tilde{B} \right) \\ \bar{S} &= \frac{1}{\bar{\nu}} \left(T\tilde{\Sigma} + \underline{\nu}\underline{S} + (\tilde{B} - \underline{B})'\underline{V}\bar{V}^{-1}Z'Z(\tilde{B} - \underline{B}) \right) \\ \bar{\nu} &= T + \underline{\nu} \\ \bar{V} &= \underline{V} + Z'Z \end{aligned}$$

and $\tilde{\Sigma}$ and \tilde{B} are least squares estimates. In this paper, the prior parameters \underline{B} , \underline{S} , \underline{V} , and $\underline{\nu}$ are matrices of zeros such that the posterior means equal the least squares estimates.

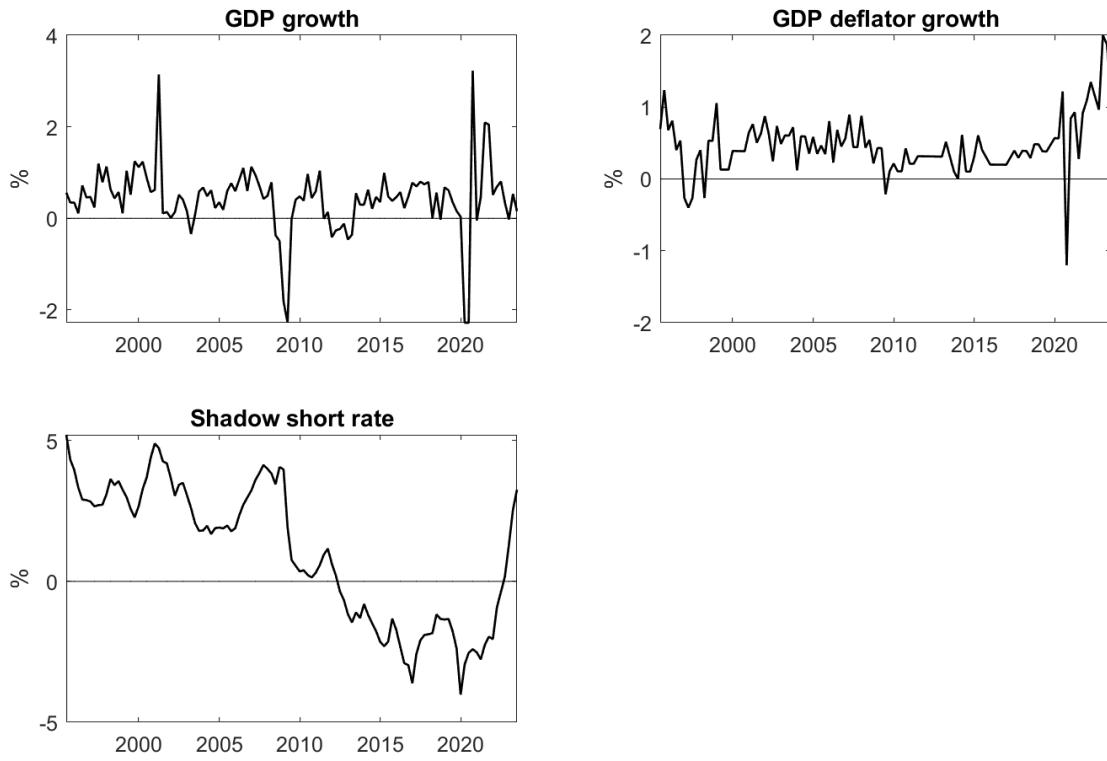
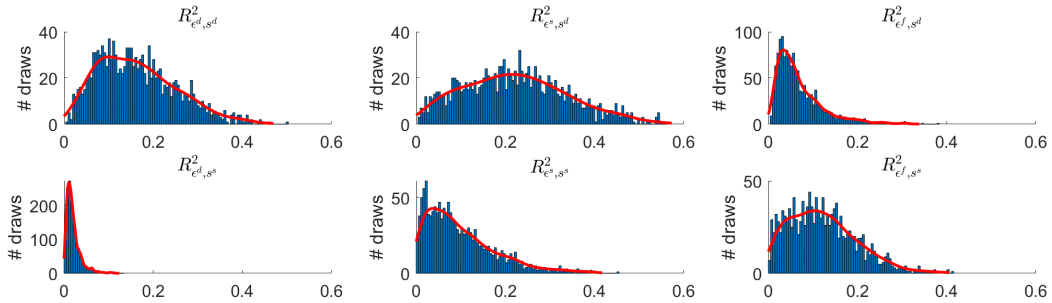
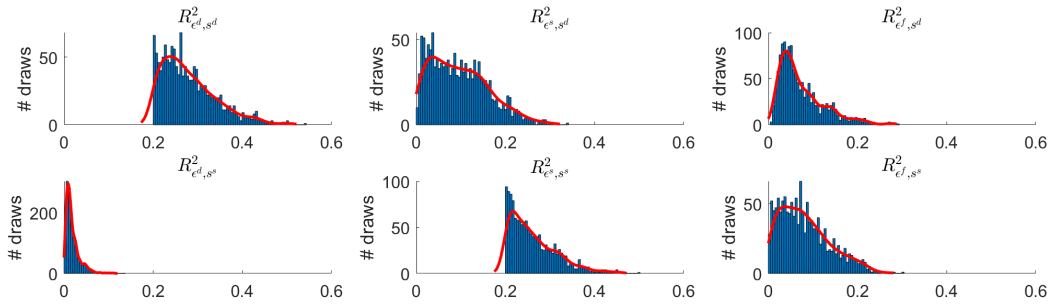


Figure 5: Variables in the SVAR



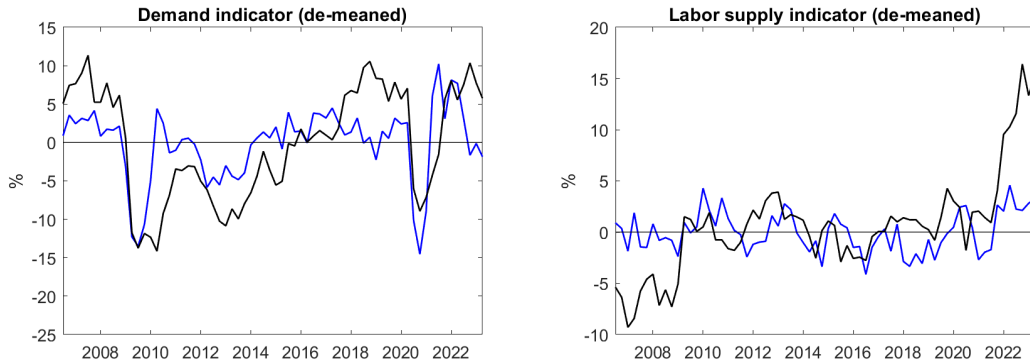
(a) Baseline identification



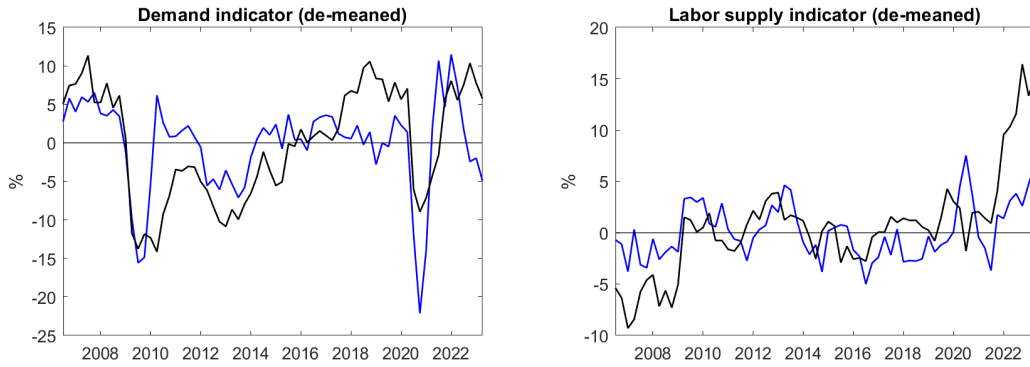
(b) Combined identification

Figure 6: Variance shares of the survey indicators explained by VAR shocks

Notes: The figure shows the variance shares of the survey indicators (from the regression equations 3) accounted for by the shocks. The shocks are implied by all accepted model draws. From the baseline model draws, only a random subset is considered such that the number of draws are identical between the identification schemes.



(a) Baseline identification



(b) Combined identification

Figure 7: Component of the survey indicators explained by VAR shocks

Notes: The black graph depicts the survey indicators used in regressions 3. The blue graphs are the part of the survey indicators explained by the SVAR shocks (using the model with highest posterior density). The demand indicator is inverted.