Online Appendix

CONSUMER PREFERENCES AND INFLATION DIFFUSION

This Online Appendix provides additional details on the following aspects: (i) the theoretical model describing price dependencies arising from value chains of production networks; (ii) the mapping of the input-output (I-O) classification to the COICOP classification, using the concordance matrices from Cai and Vandyck (2020); (iii) the Bayesian VAR model and the prior densities employed in the analysis; (iv) robustness checks related to the identification of the Bayesian VAR model, the inclusion of additional explanatory variables in the panel regressions, and the informational content of alternative network topology measures. Finally, the complete list of subindices for both the COICOP (three-digit) and I-O classifications (two-digit) is provided.

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1. Cross-price effects from a supply side view

This section motivates price-dependencies arising from value chains along production networks. We follow Acemoglu et al. (2012) in this respect. Consider again a static economy with $n \in \mathbb{N}$ goods. We now assume that the demand by consumers for these n goods is perfectly price inelastic. Each good is produced in a distinct industry and can be either purchased by the consumers or used as an intermediate input for the production of other goods. Firms in each industry employ Cobb-Douglas production technologies with constant returns to scale to transform intermediate inputs and labor into final goods. In particular, the output of industry i is given by

$$x_i = \xi_i l_i^{\gamma_i} \prod_{j=1}^{n} x_{ij}^{\gamma_{ij}} \tag{1}$$

where l_i is the amount of labor hired by firms in industry i, $x_{ij} \in \mathbb{R}_+$ is the quantity of good j used for the production of good i, $\gamma_i > 0$ denotes the share of labor in industry i's production technology and ξ_i is an industry specific productivity shock. The exponents $\gamma_{ij} \geq 0$ in equation (1) formalize the idea that firms in an industry may need to rely on the goods produced by other industries as intermediate inputs for production. Note that, in general, $\gamma_{ij} \neq \gamma_{ji}$ and $\gamma_i + \sum_{j=1}^{n} \gamma_{ij} = 1$. Firms in industry i choose their demand for labor and intermediate goods to maximize profits, $\pi_i = P_i x_i - l_i - \sum_{j=1}^{n} P_j x_{ij}$, while taking all prices $(P_1, ..., P_n)$ as given and the wage is normalized to one. The first-order conditions imply that $x_{ij} = \gamma_{ij} P_i x_i / P_j$ and $l_i = \gamma_i P_i x_i$. Plugging these expressions into firm i's production function, equation (1), and taking logarithms implies that

$$\Delta p_i = \sum_{j=1}^{n} \gamma_{ij} \Delta p_j + \varepsilon_i \tag{2}$$

where $\varepsilon_i = -\Delta \log(\xi_i)$ and $p_i = \log(P_i)$. Since the above relationship has to hold for all industries $i = 1, ..., n$, it provides a system of equations to solve for all relative prices in terms of productivity shocks. It can be rewritten in matrix form

$$\Delta \boldsymbol{p} = \boldsymbol{\Gamma} \Delta \boldsymbol{p} + \boldsymbol{\varepsilon} \tag{3}$$

where $\boldsymbol{\Gamma} = [\gamma_{ij}]_{ij=1}^{n}$ is the economy's input–output matrix, $\boldsymbol{p} = [p_i]_{i=1}^{n} \in \mathbb{R}^n$ is again the price vector and $\boldsymbol{\varepsilon} = [\varepsilon_i]_{i=1}^{n} \in \mathbb{R}^n$ is a vector of supply shocks. Since demand is price inelastic, equilibrium prices are set by goods' supplies only according to equation (3). Consequently, the equilibrium CPI inflation rate is given by

$$\pi = \boldsymbol{w}'(I - \boldsymbol{\Gamma})^{-1}\boldsymbol{\varepsilon} \tag{4}$$

where the price level according to the CPI is given by $\log(p) = \boldsymbol{w}'\boldsymbol{p}$ and $\pi = \Delta \log(p) = \boldsymbol{w}'\Delta\boldsymbol{p}$. Equation (4) expresses the inflation rate in terms of industry-level shocks and the economy's production network. The latter captures the input-output (I-O) linkages between various industries, and they are summarized in the matrix $\boldsymbol{\Gamma}$. From an empirical point of view, the I-O matrix of an economy is constructed by the national statistical offices and it is defined in terms of input expenditures as a fraction of sales, that is, $\eta_{ij} = P_j x_{ij}/P_i x_i$. However, in the special case that all technologies are Cobb-Douglas, η_{ij} coincides with the exponent γ_{ij} in equation (1).

Some remarks on the matrix $\boldsymbol{\Gamma}$ are in order. First, note that the assumption that $\gamma_i + \sum_{j=1}^{n} \gamma_{ij} = 1$ with $\gamma_i > 0$ implies that for all rows $i = 1, ..., n$ in $\boldsymbol{\Gamma}$ we have that $\sum_{j=1}^{n} \gamma_{ij} < 1$. Following Werner (2009), this implies that the matrix $\boldsymbol{\Gamma}$ has a spectral radius $\varrho(\boldsymbol{\Gamma})$ that satisfies $0 < \varrho(\boldsymbol{\Gamma}) < 1$, which in turn guarantees that $I - \boldsymbol{\Gamma}$ is invertible and, moreover, the economy's Leontief inverse $\tilde{\mathcal{L}} = (I - \boldsymbol{\Gamma})^{-1}$ can be decomposed in form of a Neumann-series: $\tilde{\mathcal{L}} = (I - \boldsymbol{\Gamma})^{-1} = \sum_{k=0}^{\infty} \boldsymbol{\Gamma}^k$. This implies that $\tilde{l}_{ij} = \gamma_{ij} + \sum_{h=1}^{n} \gamma_{ih}\gamma_{hj} + [...]$, where $\tilde{l}_{ij} \in \tilde{\mathcal{L}}$, with the first term in this expression accounting for industry j's role as a direct intermediate goods' supplier to industry i, the second term accounting for j's role as a supplier to i's suppliers, and so on. Interpreted in terms of the production network representation of the economy, $\tilde{l}_{ij}$ accounts for all possible directed walks (of various lengths) that connect industry j to industry i over the network. The latter in turn shapes the transmission of price shocks originating in specific industries on the CPI inflation rate.

1.1. **From the I-O to the COICOP (CPI) classification.** In what follows, we examine the conversion of the production network $\boldsymbol{\Gamma}$ based on the I-O classification into the COICOP classification on which the CPI is based upon. This serves to enable a direct comparison of the two price networks given by $\mathcal{A}$ and $\boldsymbol{\Gamma}$. We use the input-output (I-O) tables to this purpose. I-O tables can be product-by-product or industry-by-industry matrices combining both supply and use tables into a single matrix. We use the latter for our purposes. These tables depict inter-industry relationships within an economy, showing how output from one industry may become an input to another industry. They quantify the inter-industry relationships by means of a matrix. Their column entries capture inputs to an industry, while row entries represent outputs from a given industry. This arrangement, therefore, shows the extent of dependency of one industry on another, both as a customer of outputs from other industries and as a supplier of inputs. Industries may also depend on their own output, that is, on a portion of their own production; this is delineated by the entries of the main diagonal. Each column of the I-O matrix shows the monetary value of inputs to each sector and each row represents the value of each sector's outputs.

We convert the I-O classification into the COICOP classification on which the CPI is based upon by using the concordance matrices $\boldsymbol{B}$ of Cai and Vandyck (2020). This gives rise to a production network expressed in terms of the COICOP classification, which we denote by $\tilde{\boldsymbol{\Gamma}}$, and it is given by

$$\tilde{\boldsymbol{\Gamma}} = \boldsymbol{B}'\boldsymbol{\Gamma}\boldsymbol{B} \tag{5}$$

Equation (5) maps the production network based on the I-O classification into a new production network based on the COICOP classification. Moreover, the transformation in equation (5) makes sure that both matrices ($\mathcal{A}$ from the demand (consumer) side and $\tilde{\boldsymbol{\Gamma}}$ from the supply (firm) side) have the same dimension ($n \times n$). This implies that the two price-Jacobian matrices can now be compared directly to each other.

1.2. **Price dependencies from the supply side.** We collect the I-O tables ($\boldsymbol{\Gamma}$) for the UK and the current EU member countries for the year 2015 which allows for the highest data coverage across countries; no I-O tables are available for Bulgaria and Luxembourg. The classification which these tables are based upon is outlined in Table 4 below. We re-classify the tables by using the concordance matrices of Cai and Vandyck (2020) which map the I-O tables ($\boldsymbol{\Gamma}$) based on the I-O classification (Table 4) into the COICOP classification (Table 3) by using equation (5). This yields $\tilde{\boldsymbol{\Gamma}}$. We re-classify the matrix $\tilde{\boldsymbol{\Gamma}}$ in line with the assumptions of equation (1) and the constraint that $\gamma_i + \sum_{j=1}^{n} \gamma_{ij} = 1$, where we set the labor share γ_i equal to 0.45 for each sector $i = 1, ..., n$ (Acemoglu et al., 2012). This implies that the elements $\tilde{\gamma}_{ij} \in \tilde{\boldsymbol{\Gamma}}$ satisfy $0 \leq \tilde{\gamma}_{ij} < 1 \ \forall \ i, j = 1, ..., n$. We then compute the average of $\tilde{\boldsymbol{\Gamma}}$ across all countries in our sample and show the corresponding production network in Figure 3 of the main text. We omit self-loops and use size-thresholding to enable a better visual inspection. The size-thresholding applies to the value of the edges $\tilde{\gamma}_{ij}$ and we omit all those edges which are less than 0.01 in value. This gives rise to a link density equal to 33 percent, see Table 2 of the main text. Note that the price network $\mathbf{\Gamma}$ as of the production network does not need to be estimated as it was the case for the price network $\mathcal{A}$ as of the consumer demand side. This is due to the fact that the I-O tables identify the links (edges) of the network (compare Bilgin and Yılmaz, 2018).

The resulting network shown in Figure 3 of the main text has some interesting characteristics. First of all, the prices associated with the nodes 1, 3, 7, 10 and 39 act as the central sources of shocks in the network. In each case, the out-degree clearly predominates over the in-degree (nodes in red). While the interaction among themselves is limited, they in turn shape the dynamics of a series of other prices (nodes) which are connected to these five central prices. This particular network structure gives rise to a disassortative network (negative degree-correlation, see Table 2 of the main text). Secondly, the network is characterized by rich dynamics, since a cycle applies twice involving on the one hand prices No. 1 and 3 and prices No. 7 and 39 on the other hand. This can also be seen by the high value of the graph energy (GE) measures as provided in Table 2 of the main text. Third, the network gives rise to three blocks and can hence be considered as a *stochastic block model* (Holland et al., 1983; Karrer and Newman, 2011). The first involves the prices in the upper-left corner of Figure 3 of the main text with prices No. 7 and 39 as the central ones; the second block is given by the prices in the right part of the figure involving price No. 10 as the central one, and finally, the third block is comprised by the prices in the lower-left corner involving prices No. 1 and 3 as the central ones.

2. Bayesian estimation and prior densities

Our benchmark BVAR model can be re-arranged to the following expression:

$$Y = Xb + E, \tag{6}$$

where X now includes all regressors of equation (22) of the main part (that is, lagged endogenous and exogenous variables), and E has a variance-covariance matrix Σ.

We use a rather diffuse version of the conjugate prior densities. To this purpose, we utilize the Normal-Wishart prior density for b and Σ^{-1}: $p(b, \Sigma^{-1}) = p(b)p(\Sigma^{-1})$, where $b \sim N(\underline{b}, \underline{V})$ and $\Sigma^{-1} \sim W(\underline{H}, \underline{v})$. The rather agnostic setup of the prior densities is then obtained by using $\underline{v} = 0$ and $\underline{H}^{-1} = I$, where I is the identity matrix of conformable size. For the slope parameters we set $\underline{b} = 0$ and $\underline{V} = 100I$. Given this particular specification for the prior densities, we obtain the following conditional posterior densities for $p(b|Y, \Sigma^{-1})$ and $p(\Sigma^{-1}|Y, b)$:

$$b|Y, \Sigma^{-1} \sim N\left(\bar{b}, \bar{V}\right) \qquad \Sigma^{-1}|Y, b \sim W\left(\bar{H}, \bar{v}\right), \tag{7}$$

with $\bar{V} = \left(\underline{V}^{-1} + \sum_{t=1}^{T} X'\Sigma^{-1}X\right)^{-1}$, $\bar{b} = \bar{V}\left(\underline{V}^{-1}\underline{b} + \sum_{t=1}^{T} X'\Sigma^{-1}Y\right)$, $\bar{v} = T - \underline{v}$ and $\bar{H} = \left(\underline{H}^{-1} + \sum_{t=1}^{T} X'\Sigma^{-1}(Y - Xb)(Y - Xb)'\right)^{-1}$.

We employ a Gibbs sampler to draw from the multivariate Normal $p(b|Y, \Sigma^{-1})$ and the Wishart $p(\Sigma^{-1}|Y, b)$ distribution.

We sample 6,000 draws from the posterior distribution. After discarding the first 1,000, we are left with 5,000 draws for each parameter. As is common in the literature for Bayesian estimation of VARs, we use rejection sampling to impose stability on the BVAR coefficients and only keep stable draws. Our results are qualitatively not affected by this choice of the sampling.

3. Robustness and extensions

We consider various robustness checks which concern both the estimation of the demand-driven cross-price dependencies, the role of additional explanatory variables for the results and finally additional network topology measures to capture the spillover effects that emanate from the network structure. In what follows we address each aspect.

3.1. Alternative identification: sign restrictions on the impulse response functions.

The baseline results presented in Sections 3 and 4 rely on the identification of the matrix $\mathbf{A}$, which governs the contemporaneous interactions among the endogenous variables in $\mathbf{y}_t^{ij}$. This identification captures only the demand-driven cross-price dependencies that arise from contemporaneous effects, while ignoring any delayed effects. In the following, we explore an alternative approach that accounts for demand-driven cross-price dependencies that may arise with a delay. Specifically, we adopt the traditional method of sign restrictions, which imposes constraints on the columns of the matrix $\mathbf{H}$ of equation (23) of the main part to identify the sign of the impact response of structural shocks on the endogenous variables in $\mathbf{y}_t^{ij}$.

We maintain the sign restrictions derived from the structural system of equations (16)-(19) of the main part, but now apply them to the impact responses of the endogenous variables to the structural shocks, consisting of two supply and two demand shocks. According to this system, supply shocks induce opposite movements in prices and quantities, whereas demand shocks cause prices and quantities to move in the same direction. Thus, we assume that the signs of the elements in $\mathbf{H} = \mathbf{A}^{-1}$ are characterized as follows:

$$\text{sign}(\mathbf{H}) = \begin{bmatrix} + & \cdot & + & \cdot \\ \cdot & + & \cdot & + \\ - & \cdot & + & \cdot \\ \cdot & - & \cdot & + \end{bmatrix} \tag{8}$$

where again a dot refers to unrestricted elements. The first two columns identify the supply shock to good i and to good j, while the latter two identify the demand shock to good i and to good j.

We employ the same procedure for implementing sign restrictions as previously described, which involves the eigenvalue-eigenvector decomposition of the reduced-form variance-covariance matrix, along with the extension using orthonormal $\mathbf{Q}$-matrices from the QR decomposition.

Our focus extends beyond the entries $h_{34} \in \mathbf{H}$ and $h_{43} \in \mathbf{H}$, as we now consider demand-driven cross-price effects that occur beyond contemporaneous interactions. To this end, we compute the impulse responses, which are given by

$$\mathbf{H}_s = \frac{\partial \mathbf{y}_{t+s}}{\partial \mathbf{u}_t'} = \mathbf{\Psi}_s \mathbf{H} \tag{9}$$

with $\mathbf{\Psi}_0 = \mathbf{I}$, and $\mathbf{\Psi}_s$ is found from the first 4 rows and columns of $\mathbf{F}^s$, which is the companion matrix of the reduced form model as put forth in equation (22) of the main part.

We compute impulse response functions over a horizon s of up to three months and use the average from the first to the third month as a quantitative measure for the a_{ij} elements of the price-Jacobian matrix $\mathcal{A}$. This pertains to the elements $h_{34,1} \in \mathbf{H}_1$

Table 1. Network topology statistics

	Demand ($h = 3$)		Demand (contemporaneous)	
	Mean	Standard deviation	Mean	Standard deviation
Positive edges ratio[1]	0.75	0.09	0.74	0.09
Link (degree) density (LD)	0.25	0.06	0.19	0.06
Network density (ND)	0.06	0.08	0.03	0.05
Graph energy (binary, $GE_{\mathbb{Z}_2}$)	47.95	3.61	43.14	5.60
Graph energy (non-binary, $GE_{\mathbb{R}}$)	11.24	4.83	6.55	2.72
(Dis-)Assortativity[2]	0.06	0.03	0.03	0.07

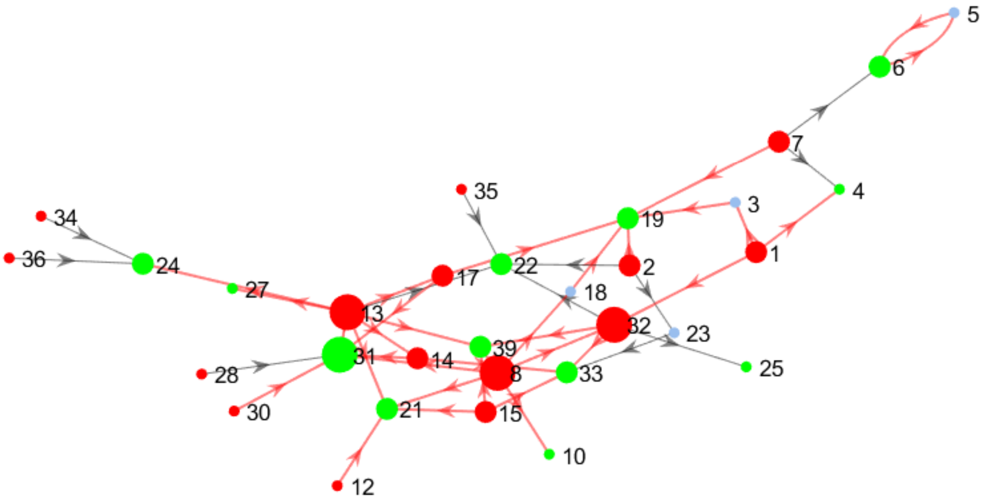
Notes: The moments (*Mean* and *Standard deviation*) are computed for each network topology measure across the countries. The figures shown are the mean and the standard deviation across the countries. [1] *Positive edges ratio* denotes the number of edges with a positive value relative to the total number of non-zero edges. [2] Assortativity (Dis-assortativity if negative) is a measure of the preference of nodes in a network to attach to others that are (dis-)similar in terms of their degree. It is operationalized as the correlation between two nodes.

through $h_{34,3} \in \mathbf{H}_3$, and $h_{43,1} \in \mathbf{H}_1$ through $h_{43,3} \in \mathbf{H}_3$. Thus, $a_{ij} = \frac{1}{3}\sum_{s=1}^{3} h_{34,s}$ and $a_{ji} = \frac{1}{3}\sum_{s=1}^{3} h_{43,s}$, respectively. Given that we have a posterior distribution for the elements in $\mathbf{H}_s$, we also obtain a posterior distribution for the a_{ij} terms, enabling inference and the exclusion of insignificant responses, as discussed and done in Section 3.1 of the main part.

We subsequently carry out the same exercises as in Sections 3 and 4. Table 1 compares the network topology statistics across the price-Jacobian matrices which emerge from the different approaches. As can be seen, there is a similar positive edges ratio, however, the number of links tends to be higher when a larger horizon is considered (link density rises to 0.25 from 0.19). At the same time, also the network density increases slightly. The larger number of links is also reflected in the binary graph energy measure which now has a higher value, but also the non-binary graph energy measure rises. Finally, the extent of assortativity is now higher (0.06 instead of 0.03), with a now smaller standard deviation across countries. The higher assortativity is shaped by three nodes solely, which are the ones capturing (i) catering services (No. 32), (ii) maintenance and repair of dwelling (No. 8), and (iii) household appliances (No. 13).

The network is depicted graphically in Figure 1. As observed, its shape and structure align with those presented in Figure 2 of the main part; however, the increased number of links renders the network denser. This larger number of links

Figure 1. Demand-driven cross-price dependencies (long horizon)



Note: The figure shows the cross-price dependencies as a network. We only show the edges that are present in 50 percent of the countries. Nodes in red indicate out-degree dominance, while those in green indicate in-degree dominance; nodes in blue indicate equality between out- and in-degree. Edges in red refer to positive valued links (complements) and those in black to negative ones (substitutes). The identification is based on sign restrictions on the impulse response functions (**H** matrix).

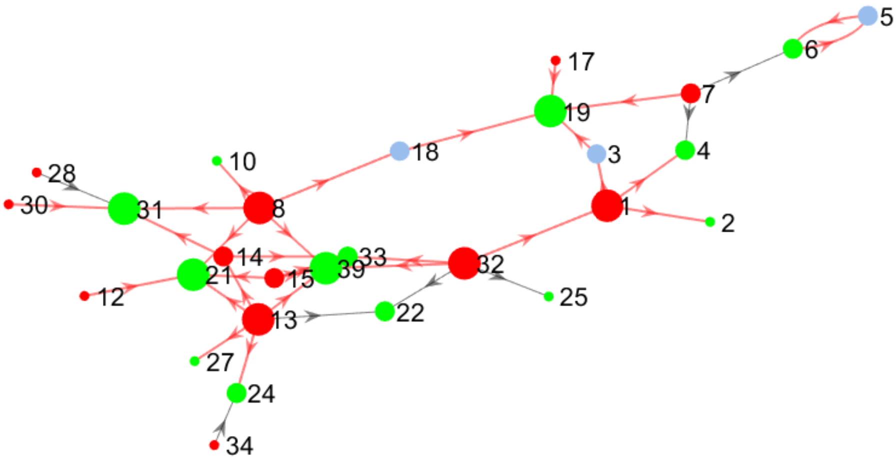
The key nodes are: (8) "Maintenance and Repair of the Dwelling", (13) "Household Appliances", (19) "Hospital Services", (21) "Operation of Personal Transport Equipment", (31) "Package Holidays", (32) "Catering Services", and (39) "Other services".

underscores the importance of delayed effects in shaping demand-driven interactions among prices (and quantities).

Finally, we also carry out the regression analysis as put forth in Section 4 of the main part. We observe that with the higher horizon of the impulse responses, the statistical significance level of the network topology measures in the first-order type regressions (Reg. 2 – Reg. 6) declines. However, the high level of statistical significance of the interaction terms in the second-order type regressions (Reg. 8 – Reg. 11) is preserved. We interpret this in favor of the overall robustness of the baseline results.

3.2. **Alternative identification: using a combination of sign and size restrictions.** We consider yet another identification strategy. It differs from the one of the previous section by again applying sign restrictions on the (rows of the) **A** matrix of the SVAR model, as was done in the main part, however, it is distinct to the identification strategy carried out in the main part as we now consider an identification that relies on a combination of sign and size restrictions.

FIGURE 2. Demand driven cross-price dependencies



Note: The figure shows the cross-price dependencies as a network. We only show the edges that are present in 50 percent of the countries. Nodes in red indicate out-degree dominance, while those in green indicate in-degree dominance; nodes in blue indicate equality between out- and in-degree. Edges in red refer to positive valued links (complements) and those in black to negative ones (substitutes). The network shown is the average over all countries (the UK and the current EU member countries). The identification is based on a combination of sign and size restrictions on the **A** matrix.

The key nodes are: (8) "Maintenance and Repair of the Dwelling", (13) "Household Appliances", (19) "Hospital Services", (21) "Operation of Personal Transport Equipment", (31) "Package Holidays", (32) "Catering Services", and (39) "Other services".

The core of this new identification strategy retains the individual good-specific sign restrictions for both the demand and supply curves, as originally specified, that is, the supply curve for each good is upward sloping, while the demand curve for each good is downward sloping. However, we dismiss the restrictions concerning the simultaneity of supply and demand shocks, i.e., the occurrence of aggregate shocks. Instead of these aggregate restrictions, we introduce size restrictions that require the demand (supply) elasticity for a good with respect to its own price to be larger (in absolute value) than that with respect to other goods' prices. The size restriction is motivated by Lemma 1, which discusses the stability and invertibility of the price-Jacobian matrix (in the case for the demand elasticities). While the size restriction we impose is slightly distinct from the one in Lemma 1, they are still closely related, since in both cases the own-price elasticity is set relative to the cross-price elasticity.

We use this alternative identification strategy and carry out the same analysis as in the main part. Figure 2 illustrates the resulting demand-driven cross-price dependencies, again displayed as a network. By comparing this network with the one shown in Figure 2 of the main part, it becomes clear that all links from the previous identification scheme are preserved in the new one. Furthermore, the new identification introduces an additional link between good 1 ("food") and good 2 ("non-alcoholic beverages"), which was absent in the old identification. We consider this as a fairly similar set of demand-driven cross-price dependencies, which, in our view, strengthens the validity of the results obtained from both identification strategies.

Additionally, we extend our analysis by conducting the temporal investigation, as described in Section 4 of the main part, in which we examine the time variation next to the variation across countries by means of panel data regressions. Specifically, we again estimate the BVAR models over different time windows (nine windows) and compute the three network topology measures (such as link density, network density, and graph energy) accordingly. We then repeat the panel data regressions from Section 4 of the main part using these new estimates. The results are presented in Table 2. We observe that, while there are some quantitative changes in the parameter estimates, overall the results remain unchanged qualitatively. Notably, the statistical significance of the parameters related to the network topology measures is still consistent across both identification schemes (sign restrictions as carried out in Section 4 in the main part and the sign & size restrictions approach carried out here).

We interpret these findings as supporting the stability of our baseline results with respect to distinct identification approaches, indicating that the results are not sensitive to the specific choice of identification approach.

3.3. **Additional explanatory variables.** The estimation of the cross-price dependencies ($\boldsymbol{A}$) in equation (22) of the main part does not use exogenous variables. This specification is motivated for reasons specific to parsimoniousness, however, it is still important to examine whether controlling for exogenous influences shapes the baseline results. In what follows, we check for the stability of the estimates of the adjacency matrix $\tilde{\mathcal{A}}$ that emerges from the baseline estimation. To this purpose, we consider various exogenous variables, which are: the 10-year government bond rate, a measure of administered prices, global measures such as shipping costs (Carrière-Swallow et al., 2023), the oil price (Brent), a price measure for natural gas (Dutch TTF), the global supply chain impairment measure of Benigno et al. (2022). We

Table 2. Network topology measures and the CPI inflation rate

	First-order Taylor approximation						Second-order Taylor approximation				
	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5	Reg. 6	Reg. 7	Reg. 8	Reg. 9	Reg. 10	Reg. 11
	Dependent variable: CPI inflation rate[a]										
LD	–	0.07**	–	–	–	0.10*	–	0.11*	–	–	–
ND	–	–	0.17**	–	–	0.17**	–	–	0.13**	–	–
$GE_{\mathbb{Z}_2}$	–	–	–	0.0002**	–	0.0001*	–	–	–	0.0002**	–
$GE_{\mathbb{R}}$	–	–	–	–	0.002***	0.001**	–	–	–	–	0.002**
PPI[a]	0.59***	0.54***	0.54***	0.60***	0.58***	0.51***	0.29***	0.21*	0.32***	0.79***	0.00
U-Gap[b]	−0.73***	−0.75***	−0.70***	−0.70***	−0.73***	−0.67***	−0.50***	−0.52***	−0.51***	−0.45***	−0.51***
int. rate[a]	0.39***	0.38***	0.39***	0.37***	0.35***	0.35***	0.39***	0.37***	0.38***	0.41***	0.38***
LD · PPI	–	–	–	–	–	–	–	0.34*	–	–	–
ND · PPI	–	–	–	–	–	–	–	–	3.03**	–	–
$GE_{\mathbb{Z}_2}$ · PPI	–	–	–	–	–	–	–	–	–	−0.02**	–
$GE_{\mathbb{R}}$ · PPI	–	–	–	–	–	–	–	–	–	–	0.06***
$(LD)^2$	–	–	–	–	–	–	–	−0.32	–	–	–
$(ND)^2$	–	–	–	–	–	–	–	–	−1.51**	–	–
$(GE_{\mathbb{Z}_2})^2$	–	–	–	–	–	–	–	–	–	0.00	–
$(GE_{\mathbb{R}})^2$	–	–	–	–	–	–	–	–	–	–	0.001*
$(PPI)^2$	–	–	–	–	–	–	3.35***	3.18**	1.06	5.23***	−0.42
R^2	0.63	0.63	0.67	0.62	0.64	0.68	0.68	0.70	0.72	0.71	0.74
$\bar{R}^2$	0.58	0.58	0.62	0.59	0.61	0.64	0.64	0.65	0.67	0.65	0.70

Notes: The table reports the results from a panel data fixed effects regression model. The acronyms refer to link density (LD), network density (ND) and graph energy (GE) for the network topology measures and producer price index (PPI), unemployment gap (U-Gap) and 10-year government bond rate (GBR) for the remaining explanatory variables. For each regression, the number of observations is $N \cdot T = 252$ with $T = 9$ and $N = 28$. The asterisks refer to the following levels of statistical significance: *** for 1 percent, ** for 5 percent and * for 10 percent. $\bar{R}^2$ refers to the adjusted R^2.
[a] The inflation rates of the CPI, PPI, the unemployment gap and the government bond rate are calculated as monthly averages for each of the nine windows.
[b] The unemployment gap (U-Gap) is measured by the cyclical component of the year-over-year change in unemployment, extracted using the Hodrick-Prescott filter with a smoothing parameter of 14,400.

employ each of these listed exogenous variables once at a time and put them into the VAR model given by its reduced form representation in equation (22) of the main part as truly exogenous variables. We consider this specification as appropriate as none of these variables is likely to be affected by the dynamics of the three-digit level goods quantities and prices in a particular country in our sample.

We subsequently re-estimate $\tilde{\mathcal{A}}$ and the network topology measures for each country, to then re-run the panel data regression models as of equation (32) of the main part. We find that the results put forth in Table 3 of the main part hold qualitatively and conclude that our results are robust to extensions in the form of exogenous variables.

In a second extension in this context, we employ our baseline results for the estimated price-Jacobian matrix $\mathcal{A}$ and the corresponding adjacency matrix $\tilde{\mathcal{A}}$ and consider additional exogenous variables in the panel data regression model. We consider the country-specific nominal effective exchange rate, unit labor costs, GDP, the money supply (M1), and labor market conditions such as the labor force participation rate and the number of job vacancies. Each of these variables is used in annual growth rates (except the labor force participation rate) and a temporal disaggregation to a monthly frequency is implemented, if necessary, using the method of Chow-Lin. We examine these variables solely in the first-order set-up in equation (32) of the main part to assess the differences in the parameter estimates of the network topology measures relative to those of the baseline results. We find that there are no qualitative changes to the results of the panel data regression models, provided in Table 3 of the main part. Most importantly, also the significance pattern of the estimated parameters remains unchanged. It has to be noted, though, at this point that the comparison is impaired to some extent by the fact that the country coverage is limited in some cases since not all countries provide (long) time series on vacancies, and alike.

3.4. **Additional network topology measures.** We challenge the baseline results with various additional network topology measures. This is important in our context since we utilize network topology measures to proxy for the spillover effects that emerge from the extent of network connectedness. To this purpose we consider the following additional measures: (i) transitivity, (ii) rich-club metric, and (iii) assortativity.

With a view to the network structure as provided in Figure 2 in the main part, Xu et al. (2010) stress the importance of high-degree nodes for the structure of a complex system. This is commonly referred to as transitivity ("rich-club" phenomenon) and has been discussed in several instances in both social and computer sciences and refers to the tendency of high-degree nodes–the hubs of the network–to be very well connected to each other. For example, the clustering coefficient (Watts and Strogatz, 1998) is used to measure the transitivity property of a network. If a social network has a high clustering coefficient, it means that the "friends" of someone are also likely to be "friends" themselves (Newman and Park, 2003). It is calculated by the ratio between the observed number of closed triplets and the maximum possible number of closed triplets in the graph. However, the clustering coefficient ignores the extent of interaction among high-degree nodes. To this purpose, Opsahl et al. (2008) extended the rich-club metric (Colizza et al., 2006) to take the tightness among connected nodes into account. Finally, the (dis-)assortativity is yet another measure in this context (Newman, 2003). It captures the preference for a network's nodes to attach to others that are (dis-)similar in some way.

We use each of these alternative network topology measures at a time instead of the ones in Table 3 of the main part. We find that all of these three measures have a statistically significant first-order effect on the CPI inflation rate. The level of statistical significance is particularly high in case of the rich-club metric (<0.005). This highlights the role of the high-degree nodes in shaping the network structure, the overall network connectedness and hence the size (and sign) of the spillover effects of microeconomic price shocks on the CPI inflation rate.

4. Additional tables

Table 3. The three-digit subindices of the CPI (COICOP classification)

	ID	Description
1	cp_011	Food
2	cp_012	Non-Alcoholic Beverages
3	cp_021	Alcoholic Beverages
4	cp_022	Tobacco
5	cp_031	Clothing
6	cp_032	Footwear
7	cp_041	Actual Rentals for Housing
8	cp_043	Maintenance and Repair of the Dwelling
9	cp_044	Water Supply and Miscellaneous Services Relating to the Dwelling
10	cp_045	Electricity, Gas and Other Fuels
11	cp_051	Furniture and Furnishings, Carpets and Other Floor Coverings
12	cp_052	Household Textiles
13	cp_053	Household Appliances
14	cp_054	Glassware, Tableware and Household Utensils
15	cp_055	Tools and Equipment for House and Garden
16	cp_056	Goods and Services for Routine Household Maintenance
17	cp_061	Medical Products, Appliances and Equipment
18	cp_062	Out-Patient Services
19	cp_063	Hospital Services
20	cp_071	Purchase of Vehicles
21	cp_072	Operation of Personal Transport Equipment
22	cp_073	Transport Services
23	cp_081	Postal Services
24	cp_082	Telephone and Telefax Equipment
25	cp_083	Telephone and Telefax Services
26	cp_091	Audio-Visual, Photographic and Information Processing Equipment
27	cp_092	Other Major Durables for Recreation and Culture
28	cp_093	Other Recreational Items and Equipment, Gardens and Pets
29	cp_094	Recreational and Cultural Services
30	cp_095	Newspapers, Books and Stationery
31	cp_096	Package Holidays
32	cp_111	Catering Services

Table 3. The three-digit subindices of the CPI (COICOP classification)

	ID	Description
33	cp_112	Accommodation Services
34	cp_121	Personal Care
35	cp_123	Personal Effects N.E.C.
36	cp_124	Social Protection
37	cp_125	Insurance
38	cp_126	Financial Services N.E.C.
39	cp_127	Other Services N.E.C.
Not used:		
–	cp_101	Pre-Primary and Primary Education
–	cp_102	Secondary Education
–	cp_103	Post-Secondary Non-Tertiary Education
–	cp_104	Tertiary Education
–	cp_105	Education Not Definable by Level

TABLE 4. The I-O tables: Classification

	ID	Description
1	CPA_A01	Products of agriculture, hunting and related services
2	CPA_A02	Products of forestry, logging and related services
3	CPA_A03	Fish and other fishing products; aquaculture products; support services to fishing
4	CPA_B	Mining and quarrying
5	CPA_C10-12	Food, beverages and tobacco products
6	CPA_C13-15	Textiles, wearing apparel, leather and related products
7	CPA_C16	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials
8	CPA_C17	Paper and paper products
9	CPA_C18	Printing and recording services
10	CPA_C19	Coke and refined petroleum products
11	CPA_C20	Chemicals and chemical products
12	CPA_C21	Basic pharmaceutical products and pharmaceutical preparations
13	CPA_C22	Rubber and plastic products
14	CPA_C23	Other non-metallic mineral products
15	CPA_C24	Basic metals
16	CPA_C25	Fabricated metal products, except machinery and equipment
17	CPA_C26	Computer, electronic and optical products
18	CPA_C27	Electrical equipment
19	CPA_C28	Machinery and equipment n.e.c.
20	CPA_C29	Motor vehicles, trailers and semi-trailers
21	CPA_C30	Other transport equipment
22	CPA_C31_32	Furniture and other manufactured goods
23	CPA_C33	Repair and installation services of machinery and equipment
24	CPA_D	Electricity, gas, steam and air conditioning
25	CPA_E36	Natural water; water treatment and supply services
26	CPA_E37-39	Sewerage services; sewage sludge; waste collection, treatment and disposal services; materials recovery services; remediation services and others
27	CPA_F	Constructions and construction works
28	CPA_G45	Wholesale and retail trade and repair services of motor vehicles and motorcycles
29	CPA_G46	Wholesale trade services, except of motor vehicles and motorcycles

TABLE 4. The I-O tables: Classification

	ID	Description
30	CPA_G47	Retail trade services, except of motor vehicles and motorcycles
31	CPA_H49	Land transport services and transport services via pipelines
32	CPA_H50	Water transport services
33	CPA_H51	Air transport services
34	CPA_H52	Warehousing and support services for transportation
35	CPA_H53	Postal and courier services
36	CPA_I	Accommodation and food services
37	CPA_J58	Publishing services
38	CPA_J59_60	Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services
39	CPA_J61	Telecommunications services
40	CPA_J62_63	Computer programming, consultancy and related services;Information services
41	CPA_K64	Financial services, except insurance and pension funding
42	CPA_K65	Insurance, reinsurance and pension funding services, except compulsory social security
43	CPA_K66	Services auxiliary to financial services and insurance services
44	CPA_L68	Real estate services
45	CPA_M69_70	Legal and accounting services; services of head offices; management consultancy services
46	CPA_M71	Architectural and engineering services; technical testing and analysis services
47	CPA_M72	Scientific research and development services
48	CPA_M73	Advertising and market research services
49	CPA_M74_75	Other professional, scientific and technical services and veterinary services
50	CPA_N77	Rental and leasing services
51	CPA_N78	Employment services
52	CPA_N79	Travel agency, tour operator and other reservation services and related services
53	CPA_N80-82	Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services

Table 4. The I-O tables: Classification

	ID	Description
54	CPA_O	Public administration and defence services; compulsory social security services
55	CPA_P	Education services
56	CPA_Q86	Human health services
57	CPA_Q87_88	Residential care services; social work services without accommodation
58	CPA_R90-92	Creative, arts, entertainment, library, archive, museum, other cultural services; gambling and betting services
59	CPA_R93	Sporting services and amusement and recreation services
60	CPA_S94	Services furnished by membership organisations
61	CPA_S95	Repair services of computers and personal and household goods
62	CPA_S96	Other personal services
63	CPA_T	Services of households as employers; undifferentiated goods and services produced by households for own use

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012) ‘The Network Origins of Aggregate Fluctuations.’ *Econometrica* 80(5), 1977–2016

Benigno, Gianluca, Julian di Giovanni, Jan J. J. Groen, and Adam I. Noble (2022) ‘A new barometer of global supply chain pressures.’ Liberty Street Economics 20220104, Federal Reserve Bank of New York, January

Bilgin, Nuriye Melisa, and Kamil Yılmaz (2018) ‘Producer price inflation connectedness and input-output networks.’ SSRN Working papers 3244645

Cai, Mattia, and Toon Vandyck (2020) ‘Bridging between economy-wide activity and household-level consumption data: Matrices for European countries.’ *Data in Brief* 30, 1–4

Carrière-Swallow, Yan, Pragyan Deb, Davide Furceri, Daniel Jiménez, and Jonathan D. Ostry (2023) ‘Shipping costs and inflation.’ *Journal of International Money and Finance* 130, 102771

Colizza, V., A. Flammini, M. A. Serrano, and A. Vespignani (2006) ‘Detecting rich-club ordering in complex networks.’ *Nature Physics* 2(2), 110–115

Holland, Paul W., Kathryn Blackmond Laskey, and Samuel Leinhardt (1983) ‘Stochastic block models: First steps.’ *Social Networks* 5(2), 109–137

Karrer, Brian, and Mark E. J. Newman (2011) ‘Stochastic block models and community structure in networks.’ *Physical Review E* 83, 016107

Newman, M. E. J. (2003) ‘Mixing patterns in networks.’ *Physical Review E* 67, 026126

Newman, M. E. J., and Juyong Park (2003) ‘Why social networks are different from other types of networks.’ *Physical Review E* 68, 036122

Opsahl, Tore, Vittoria Colizza, Pietro Panzarasa, and José J. Ramasco (2008) ‘Prominence and control: The weighted rich-club effect.’ *Physical Review Letters*

Watts, Duncan J., and Steven H. Strogatz (1998) ‘Collective dynamics of ‘small-world’ networks.’ *Nature* 393(6684), 440–442

Werner, Dirk (2009) ‘Funktionalanalysis.’ In ‘Einführung in die höhere Analysis’ (Berlin, Heidelberg: Springer) pp. 1–88

Xu, Xiao-Ke, Jie Zhang, and Michael Small (2010) ‘Rich-club connectivity dominates assortativity and transitivity of complex networks.’ *Physical Review E*