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ARTICLE

Consumer preferences and inflation diffusion

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Abstract

We study how consumer preferences affect the transmission of microeconomic price shocks to consumer price index (CPI) inflation. These preferences give rise to complementarities and substitutions between goods, generating demand-driven cross-price dependencies that either amplify or mitigate the impact of price shocks. Our results demonstrate that while both effects are present, positive spillovers due to complementarities dominate. The magnitude of these cross-price effects is significant, demonstrating their importance in shaping CPI inflation dynamics. Most importantly, demand-driven price linkages decisively shape the impact of producer prices on CPI inflation. These findings underscore the need to take into account demand-driven price dependencies when assessing the impact of price shocks on CPI inflation, rather than relying solely on supply-related ones.

Keywords: inflation; consumer behavior; cross price dependencies; network analysis

JEL classifications: C11; C53; D85; E31

1. Introduction

We analyze the role of microeconomic price shocks in shaping fluctuations in aggregate price measures such as the consumer price index (CPI). Our focus is on the links between prices and whether they can act as a channel for the propagation and amplification of shocks. Links between prices can arise for several reasons. First, from a (firm) supply side view, distinct goods (and services) may contain the same intermediate goods, resulting in cross-price dependencies that reflect value chains along production networks. Second, from a (consumer) demand side view, individual goods' price shocks may spill over to other goods' prices due to the complementarity or substitutability of goods reflecting consumer preferences. For example, a high demand for restaurant visits ("catering services") might not only raise prices in this subcomponent but also in those which are closely related ("food," "beverages," "transport services," etc.). Acemoglu et al. (2012) construct a theoretical model of a production network in which links between prices emerge from intra-industry relationships. In this setting, any additional link exacerbates microeconomic shocks. However, this is unlikely to be the case when considering the consumer demand side view, since the effect of an additional link depends on whether it arises from a complementary or substitutive relationship between goods. Consequently, microeconomic price shocks could either be exacerbated or mitigated.

Our contribution is threefold. First, we establish a theoretical model to capture the role of demand-driven links between prices for the CPI inflation rate. This serves to highlight that microeconomic price shocks diffuse through the demand system and hence may not remain confined to where they originate. Second, we estimate these links for a large set of countries and compare them to those from the supply side. This allows us to compare the size and sign of the spillover effects of microeconomic price shocks from demand- and supply-driven cross-price dependencies. Third, we examine the role of the structure of the demand-driven cross-price

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dependencies for the CPI inflation rate. This serves to empirically assess their role in the propagation and amplification of microeconomic price shocks to the CPI inflation rate through the demand system.

Assessing the transmission of microeconomic price shocks to a headline measure of inflation is currently an active area of research. However, the focus in this context has so far been limited to the supply side. Bilgin and Yılmaz (2018) consider a production network to examine how shocks to prices, rather than quantities, are transmitted across industries. They show that the input-output (I-O) linkages across industries form a network through which the price shocks are transmitted. Moreover, they cannot reject the hypothesis that their system-wide measure of the underlying network Granger-causes the system-wide measure of inflation linkages. As an extension, Bilgin (2022) shows how the underlying I-O linkages are responsible for the transmission of inflation. A common feature of these studies is their focus on the supply side. While it is clear that the effect of microeconomic price shocks can be amplified as they propagate through the production network, the same shocks can also propagate through the demand side. The extent of shock diffusion, in turn, shapes the overall inflation dynamics.

We therefore employ a simple theoretical general equilibrium model in which links between prices emerge from consumers' cross-demand, hence reflecting consumer preferences. Cross-demand captures the extent to which goods are related from a demand side view. This in turn creates links between the prices of goods which we will henceforth refer to as demand-driven cross-price dependencies. As cross-demands lead to complements or substitutes, the corresponding links between prices can be assigned negative or positive values. The model serves to examine the consequence of the demand-driven cross-price dependencies for shaping the spillover effects of microeconomic price shocks on the CPI inflation rate. The spillover effects reflect the degree of connectedness of the network of cross-price dependencies which can be decomposed into (i) a *strength* effect and (ii) a *diffusion* effect. While the former is determined by the size and sign of the links (edges) between prices (nodes), the latter is determined by the structure of the demand-driven cross-price dependencies. We use distinct network topology measures to capture the spillover effects arising from the strength and diffusion effect. We then estimate the key equation of the theoretical model to examine the empirical evidence for demand-driven cross-price dependencies. We apply a Bayesian vector-autoregressive econometric framework and use the three-digit price subindices of the CPI for 28 countries (UK and the current EU member states) to compare the resulting links between prices with those emerging from a production network. The latter is based on the I-O tables which are converted into the CPI's Classification of Individual Consumption by Purpose (COICOP) using the concordance matrices of Cai and Vandyck (2020). Finally, the estimated price network is used to examine the first-order and second-order effects of the demand-driven cross-price dependencies (proxied by the network topology measures) on the CPI inflation rate.

To preview some results, we find empirical support for the existence of demand-driven cross-price dependencies which render the overall effect of microeconomic price shocks on the CPI inflation rate distinct to their mere direct effect (DE). Most importantly in the context of consumer demand, the presence of substitutes and complements leads to an exacerbation or mitigation of microeconomic price shocks. In particular, we find, first, that positive valued links dominate, which highlights the relative importance of the complementarity property among goods. Second, spillover effects of the price subindices on the CPI inflation rate are both negative and positive and their quantitative size outweighs the DEs in most of the cases. This emerges from the high number of cycles among prices. Third, demand-driven links among prices show remarkable differences to a supply side counterpart and they tend to change over time, reflecting changes in consumer preferences. Most importantly, we find that the demand-driven cross-price dependencies explain a major part of the CPI inflation rate. We do so by proxying the corresponding spillover effects with distinct network topology measures and regressing them on the CPI inflation rate. We find

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that, while they explain significant variation in the CPI inflation rate by themselves, they critically shape the effects of other variables (e.g., producer prices, PPI) on the CPI inflation rate. This empirical result is consistent with the theoretical model and highlights the importance of the demand system for the diffusion of microeconomic price shocks to the CPI inflation rate.

Related literature

Our contribution is related to various strands of the literature, of which we already mentioned the ones on the inflation linkages from the production (I-O) network. This literature extends to cross-border I-O linkages for explaining inflation synchronization Neely and Rapach, 2011; Auer and Mehrotra, 2014; Ahmad and Staveley-O'Carroll, 2017, cross-country differences Hall et al. 2023; Choi et al. 2018, the propagation of tax changes through the production network (Fu and Wang, 2023) and network spillovers arising from technological-knowledge bias (Afonso and Magalhães, 2020). Our study is also related to the literature analyzing consumer demand and cross-price demand effects. Work by Mulhern and Leone (1991); Regmi and Seale (2010); Mehta and Ma (2012) highlight the dominance of substitutes, while others (van Oest, 2005) that of complements. Using 7,264 estimates from 115 studies, Auer and Papies (2020) find that the mean cross-price demand elasticity is 0.26 (median: 0.10), with high-stockpiling groceries having the highest cross-price elasticities. With a view to the composite price indices for goods categories, Regmi and Seale (2010) highlight that among their nine categories of goods,[1] non-zero cross-price dependencies hold in 97 percent of all possible combinations. They stress the dominance of complements.

The paper is structured as follows. Section 2 presents the theoretical model and introduces the network topology measures to capture the spillover effects that emanate from the demand-driven cross-price dependencies. Section 3 motivates the econometric model to estimate the demand-driven cross-price dependencies and compares the resulting spillover effects with those from a supply side set-up. Section 4 extends the analysis by examining as to whether the structure of the cross-price dependencies matters for explaining the variation of the inflation rate. Finally, Section 5 concludes.

2. Consumer preferences and inflation dynamics

The aim of this section is to illustrate the influence of cross-price effects on inflation dynamics. The focus of this analysis is on demand-driven cross-price effects. In accordance with the tenets of classical demand theory,[2] cross-price effects emerge as a consequence of consumer preferences, thereby giving rise to the substitutability or complementarity of goods. We analyze their role in shaping the impact of microeconomic price shocks on the CPI inflation rate.

2.1 Cross-price effects and the inflation rate

Consider a static economy with $n \in \mathbb{N}$ goods produced by a unit mass of firms. The total quantity of each of the n goods produced is given by $x_i^s \geq 0 \; \forall \; i = 1, \ldots, n$, which in turn is supplied in perfectly competitive markets at market prices $p_i \in \mathbb{R} \; \forall \; i = 1, \ldots, n$. We take a short term view and assume that the supply of each good x_i^s is perfectly inelastic with respect to its price p_i. Consumers in turn buy these goods. We consider a unit mass of representative consumers out of which consumer j's consumption of the n different types of goods is given by the Walrasian (Marshallian) demand function[3] $x_i^{j,d} = x_i^{j,d}(p_i, \boldsymbol{p}_{-i}, m^j) \; \forall \; i = 1, \ldots, n$, with $x_i^{j,d}$ being the quantity demanded of good i, m^j denotes the consumer's available budget and $\boldsymbol{p}_{-i} = \left[p_k\right]_{k=1}^{n \setminus \{i\}} \in \mathbb{R}^{n-1}$ is a vector of prices excluding the price of good i. Summation over the mass of consumers establishes the total demand for good i, which is given by the total demand function $x_i^d = \sum_j x_i^{j,d} = x_i^d(p_i, \boldsymbol{p}_{-i}, \sum_j m_j)$, where

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the last step follows from the assumption of representative consumers. In equilibrium $x_i^s = x_i^d = x_i$, which gives rise to the following equilibrium quantity

$$x_i = x_i(p_i, \boldsymbol{p}_{-i}, m) \tag{1}$$

where $m = \sum_j m_j$ is consumers' total income. With the assumption of a perfectly price-inelastic supply, equilibrium prices are shaped by demand shocks only. This implies that, whenever a demand shock occurs, the equilibrium quantity x_i will be left unchanged and only the price p_i will be affected. The latter, though, is likely to shape the demand for yet other goods $x_j \, \forall \, j \neq i$, which emerges from the circumstance that goods may be substitutes or complements to each other, reflecting consumer preferences. This, in turn, will then also shape the prices of these goods ($p_j \, \forall \, j \neq i$), which establishes links across prices in equilibrium. In what follows, we use this set-up to elaborate on the role of cross-price dependencies for an aggregate price measure and its rate of change. It is useful to this purpose to express the demand function for good i as of equation (1) by means of its inverse demand function $p_i = p_i(x_i, \boldsymbol{p}_{-i})$. Collecting all goods' (inverse) total demand functions in the price vector function $\boldsymbol{p}^f(\cdot)$ gives the following vector of equilibrium prices

$$\boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) = \begin{bmatrix} p_1(x_1, \boldsymbol{p}_{-1}) \\ \vdots \\ p_n(x_n, \boldsymbol{p}_{-n}) \end{bmatrix} \tag{2}$$

where all arguments beyond prices p_i are omitted in $p_i(\,\cdot\,)$ for simplicity. Letting $\boldsymbol{w} = \left[w_i\right]_{i=1}^n$ with $w_i \in [0, 1] \, \forall \, i = 1, \ldots, n$ and $\sum_{i=1}^n w_i = 1$ be the vector of expenditure shares (that is, the weights) of the goods, then the consumer price index p (CPI), as an aggregate price measure, is given by $p = \boldsymbol{w}' \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x})$ and its change is

$$\Delta p = \boldsymbol{w}' \cdot \Delta \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) \tag{3}$$

where $\boldsymbol{p} = \left[p_i\right]_{i=1}^n \in \mathbb{R}^n$ and the geometric mean, as used for constructing the CPI (IMF, 2022a), is approximated with the arithmetic mean. Observe that the price vector $\boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x})$ is a function $\boldsymbol{p}^f : \mathbb{R}^n \to \mathbb{R}^n$ that takes a vector as input and produces a vector as output. We can identify the cross-price effects from this vector of inverse demand functions by computing the total differential which yields

$$\Delta \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) = \mathcal{A} \cdot \Delta \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) + \tilde{\boldsymbol{u}} \tag{4}$$

where $\mathcal{A} = \nabla_{\boldsymbol{p}} \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x})$ is a $n \times n$ Jacobian matrix of partial derivatives and given by

$$\mathcal{A} = \begin{bmatrix} 0 & \cdots & \frac{\partial p_1(x_1, \boldsymbol{p}_{-1})}{\partial p_n} \\ & \ddots & \\ \frac{\partial p_n(x_n, \boldsymbol{p}_{-n})}{\partial p_1} & \cdots & 0 \end{bmatrix} \tag{5}$$

We will henceforth refer to $\mathcal{A}$ as the *price-Jacobian* matrix. It tells us the relationship between changes in the input and changes in the output, for instance, considering the i, j element, the corresponding entry in $\mathcal{A}$ identifies the effect of a change in p_j on p_i which is given by $\Delta p_i = \frac{\partial p_i(x_i, \boldsymbol{p}_{-i})}{\partial p_j} \cdot \Delta p_j$. This can be generalized in matrix notation as $\Delta \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) = \mathcal{A} \cdot \Delta \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x})$. The vector $\tilde{\boldsymbol{u}} = [\tilde{u}_1, \ldots, \tilde{u}_n]'$ captures demand effects in shaping prices, as for instance, in form of a change in income ($\nabla_m \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) \cdot \Delta m$) and alike. In particular, $\tilde{u}_i = \frac{\partial p_i}{\partial m} \Delta m = \frac{\partial p_i}{\partial x_i} \frac{\partial x_i}{\partial m} \Delta m$, where $\partial p_i / \partial x_i$ determines the slope of the demand curve for good i and $\partial x_i / \partial m$ the slope of the Engel curve. We will henceforth refer to $\tilde{u}_i \in \tilde{\boldsymbol{u}}$ as an exogenous demand shock in the form of a disturbance to the price of good i, so that the own price effect is given by $\Delta p_i = \sum_{j=1}^n \alpha_{ij} \Delta p_j + \tilde{u}_i$ with

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$\partial p_i(x_i, \boldsymbol{p}_{-i})/\partial p_j \equiv \alpha_{ij} \in \mathcal{A}$ and the effect on other goods' prices by $\Delta p_k = \sum_{j=1}^{n} \alpha_{kj} \Delta p_j \, \forall \, k \neq i$. Since this relationship has to hold for all prices, it provides a system of equations to solve for all prices in terms of demand shocks $\tilde{\boldsymbol{u}}$.

Equation (4) solves for the change in the price vector as follows: $\Delta \boldsymbol{p}^f(\boldsymbol{p}, \boldsymbol{x}) = (I - \mathcal{A})^{-1} \tilde{\boldsymbol{u}}$, provided that the inverse of $I - \mathcal{A}$ exists (more on this in Section 2.2). From this equation we can then determine the effect on the CPI inflation rate by using equation (3), which implies

$$\pi = \boldsymbol{w}'(I - \mathcal{A})^{-1} \boldsymbol{u} \tag{6}$$

where the CPI inflation rate π is given by $\pi = \frac{\Delta p}{p}$ and $\boldsymbol{u} = \tilde{\boldsymbol{u}}/p$. As equation (6) illustrates, the CPI inflation rate is shaped by cross-price effects captured in the price-Jacobian matrix $\mathcal{A}$. If the price-Jacobian matrix is equal to the null matrix, then we have that $\partial \pi / \partial u_i = w_i$, which implies that the effect of a shock to an individual price on the CPI inflation rate equals this price's weight w_i times the size of the shock. When cross-price dependencies are present, the price-Jacobian matrix is then distinct to the null matrix and a shock to an individual price may affect the CPI inflation rate not only directly, but also via spillover effects arising from the cross-price dependencies. What matters in this context are (i) the sign of the off-diagonal elements in the price-Jacobian matrix $\mathcal{A}$ reflecting the substitution and complementarity relationships among goods, and (ii) the structure that emerges from the cross-price dependencies. In what follows, we discuss this in more detail using graph theory.

2.2 On the price-Jacobian matrix

The price-Jacobian matrix $\mathcal{A}$ in equation (4) is derived under the assumption of inelastic supply. It therefore only captures price effects of demand shocks. We establish equivalent relations to equations (4) and (6) from a supply side approach discussed in the Online Appendix. It is useful to take a closer look at the properties of the price-Jacobian matrix $\mathcal{A}$ and the matrix $\mathcal{L} = (I - \mathcal{A})^{-1}$. In the context of a production network the latter is commonly referred to as the economy's Leontief inverse (see the Online Appendix). There economic theory imposes certain restrictions on $(I - \mathcal{A})$, which guarantee the invertibility of $\mathcal{L}$ and its representation as an infinite sum. While this also applies in our case, the presence of negatively valued edges (due to a substitution relationship among goods) results in a more complex presentation.

First of all, the elements $\alpha_{ij} \in \mathcal{A}$ can have both positive and negative entries. This results from the substitution and complementarity of the goods, reflecting consumer preferences. Consider goods i and j and their prices: a demand shock, for instance, in the form of a change in income m by dm, gives rise to $dx_i = 0 \, \forall i = 1, .., n$ due to the assumption on supply and hence only prices will react: $dp_i/dm = -\frac{dx_i/dm}{dx_i/dp_i} \, \forall i = 1, \ldots, n$. Since $dp_i/dp_j = \frac{dp_i/dm}{dp_j/dm}$, we obtain the following expression for the cross-price dependencies by means of the total differential of equation (1)

$$\frac{\partial p_j}{\partial p_i} = \frac{dx_j/dp_i}{dx_j/dp_j} \lessgtr 0 \tag{7}$$

Ruling out Giffen goods implies that $dx_j/dp_j < 0 \, \forall \, j = 1, \ldots, n$. With regard to cross-price effects, whenever good i and j are complements ($dx_j/dp_i < 0$), we have that $\frac{\partial p_j}{\partial p_i} > 0$. Conversely, $\frac{\partial p_j}{\partial p_i} < 0$ when they are substitutes. In other words, the demand shock (dm) leads to a positive co-movement among prices of those goods that are complements, while the opposite applies to prices of goods that are substitutes.

Second, $\alpha_{ij} \neq \alpha_{ji}$ since in general $\frac{dx_i}{dp_j} \neq \frac{dx_j}{dp_i}$. This is found in existing empirical studies,[4] moreover, Sethuraman et al. (1999) highlight the importance of two effects in this context: the asymmetric price effect and the neighborhood price effect. The asymmetric price effect states that cross-price elasticities are larger when the price changing good has a higher price than the demand

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changing good. Under the neighborhood price effect, cross-price elasticities are larger when the two competing goods are closer in price.

Third, the price-Jacobian matrix $\mathcal{A}$ captures both own- and cross-price elasticities. Defining by $\varepsilon_i = \frac{dx_i/x_i}{dp_i/p_i}$ the (uncompensated) own-price elasticity and by $\varepsilon_{ij} = \frac{dx_i/x_i}{dp_j/p_j}$ the cross-price elasticity of demand, the elements α_{ij} are given by $\alpha_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_i}\frac{p_i}{p_j}$, and the price-Jacobian matrix can then be decomposed in the following form

$$\mathcal{A} = -\boldsymbol{E}^{-1}\bar{\boldsymbol{H}} \tag{8}$$

where $\boldsymbol{E} = \text{diag}\,(|\varepsilon_i|, \ldots, |\varepsilon_n|)$ and $\bar{\boldsymbol{H}} = [\eta_{ij}]_{ij=1}^{n}$ with $\eta_{ij} = \varepsilon_{ij}\frac{p_i}{p_j} \lessgtr 0 \; \forall \, i \neq j$ and $\eta_{ij} = 0 \; \forall \, i = j$. The matrix $\boldsymbol{E}$ captures the own-price effects while $\bar{\boldsymbol{H}}$ the cross-price demand effects. In what follows, we assume that $\sum_{j=1}^{n} \varepsilon_{ij}\frac{p_i}{p_j} < |\varepsilon_i| \; \forall \, i = 1, \ldots, n$. Under this assumption, all column-sums of the price-Jacobian matrix $\mathcal{A}$ are less than unity. This motivates the following Lemma.

Lemma 1. *If* $\sum_{j=1}^{n} \varepsilon_{ij}\frac{p_i}{p_j} < |\varepsilon_i| \; \forall \, i = 1, \ldots, n$, *then the matrix* $\mathcal{L}$ *can be expressed as an infinite sum of the price-Jacobian matrix* $\mathcal{A}$, *that is*

$$\mathcal{L} = (I - \mathcal{A})^{-1} = \sum_{k=0}^{\infty} \mathcal{A}^k \tag{9}$$

The proof of Lemma 1 follows directly from the relation between any matrix norm and the spectral radius.[5] Important for our context, Lemma 1 illustrates that the (i, j) element of the matrix $\mathcal{L}$, denoted by l_{ij}, captures the importance of price j as a direct and indirect shock transmitter to price i. To see this, note that, for any $i \neq j$, Lemma 1 implies that $l_{ij} = \alpha_{ij} + \sum_{h=1}^{n} \alpha_{ih}\alpha_{hj} + [\,\ldots\,]$, with the first term in this expression accounting for price j's role as a direct shock transmitter to price i, the second term accounting for price j's role as a transmitter to the recipients of price i, and so on. Interpreted in terms of a network, l_{ij} accounts for all possible directed walks that connect price j to price i over the network.

Fourth, in general, most non-zero entries in $\mathcal{A}$ are small in amount as found in existing empirical studies.[6] Moreover, cross-price elasticities enter $\alpha_{ij} \in \mathcal{A}$ only relative to a good's own price elasticity, which is likely to be larger in amount.

2.3 The price-Jacobian matrix as a graph

The price-Jacobian matrix $\mathcal{A}$ can be considered as a directed weighted graph $\mathcal{G} = (\mathcal{N}, \mathcal{E}, \mathcal{A})$, where the $n > 1$ nodes in $\mathcal{N} = \{v_1, \ldots, v_n\}$ represent the goods' prices $\Delta p_i \; \forall \, i = 1, \ldots n$, which are related to each other via the edges $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{N}$, and the weight matrix $\mathcal{A} \in \mathbb{R}^{n \times n}$ determines the size (and sign) of the edges. Hence, the elements $\frac{\partial p_i(x_i, \boldsymbol{p}_{-i})}{\partial p_h} \; \forall \, i, h = 1, \ldots, n$ with $i \neq h$ quantify the strength of the network's edges across nodes i and h, that is, $v_i v_h \in \mathcal{E} \iff \frac{\partial p_i(x_i, \boldsymbol{p}_{-i})}{\partial p_h} \neq 0$ with $\frac{\partial p_i(x_i, \boldsymbol{p}_{-i})}{\partial p_h} \in \mathcal{A}$.

In order to illustrate the role of the network structure for the effects of the cross-price dependencies on the CPI inflation rate, we assume that all non-zero edges have the same weight $\alpha_{ij} = \alpha$. We further simplify the exposition by considering a graph with three prices ($n = 3$), each represented by a node in the network (both assumptions are relaxed in the empirical part). The focus is explicitly on the network's structure in order to assess its consequence for the inflation rate π. To this purpose, we assume that each price has the same weight w in the CPI.

Figure 1 shows several simple network structures (first column) and their consequences for the CPI inflation rate in response to a shock in the first price (u_1). We establish the adjacency matrix $\mathcal{A}$ for the five cases, (a)–(e), and compute the CPI inflation rate π using equation (6). In

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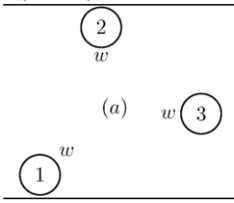
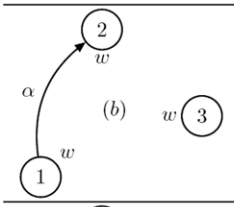
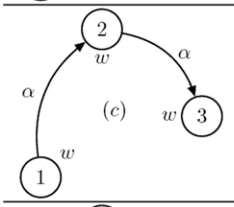
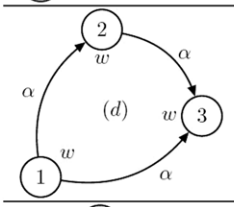
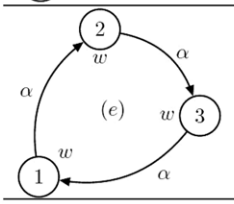
Network topology (cases)	Spillover effect of shock $u_1 = 1$	Link density	Network density	Graph energy
	$\varsigma^{(a)} = 0$	0	0	0
	$\varsigma^{(b)} = w\alpha$	$\frac{1}{6}$	$\frac{\alpha}{6}$	0
	$\varsigma^{(c)} = \varsigma^{(b)} + w\alpha^2 = w\alpha(1+\alpha)$	$\frac{1}{3}$	$\frac{\alpha}{3}$	0
	$\varsigma^{(d)} = \varsigma^{(c)} + w\alpha = w\alpha(2+\alpha)$	$\frac{1}{2}$	$\frac{\alpha}{2}$	0
	$\varsigma^{(e)} = \frac{w\alpha}{1-\alpha}$	$\frac{1}{2}$	$\frac{\alpha}{2}$	$2\lvert\alpha\rvert$

Figure 1. Examples of network structures.
Note: The table shows distinct network structures and their implications for the spillover effects ς from a shock to the first price by $u_1 = 1$. The table also displays the values of three distinct network topology measures (link density (LD), network density (ND) and graph energy ($GE_{\mathbb{R}}$)) for each network structure. For $\alpha = 1$, we have that $GE_{\mathbb{R}} = GE_{\mathbb{Z}_2}$.

the absence of links, the effect of a unit-shock to the first price ($u_1 = 1$) on the CPI inflation rate equals $\pi^{(a)} = w$ (the superscript "(a)" refers to the case considered). Hence the effect of the shock (u_1) on the CPI inflation rate equals the weight w of the first price times the size of the shock. We refer to this case as the "zero-link" case and it is given by $\pi^{(a)} = \boldsymbol{w}'\boldsymbol{u}$ in a more general form. The introduction of links between the prices extends the zero-link effects by spillover effects (ς), that is, the effects relative to those emanating from the zero-link case (a):

$$\begin{aligned}\varsigma^{(i)} &= \pi^{(i)} - \pi^{(a)} \\ &= \boldsymbol{w}'(I - \mathcal{A})^{-1}\boldsymbol{u} - \boldsymbol{w}'\boldsymbol{u} \\ &= \boldsymbol{w}'\left((I - \mathcal{A})^{-1} - I\right)\boldsymbol{u} \end{aligned} \tag{10}$$

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Importantly, the spillover effects (second column in Figure 1) emerge from the cross-price dependencies, and they reflect the degree of connectedness in the network. The degree of connectedness is in turn shaped by (i) a *strength* effect and (ii) a *diffusion* effect. When no links are present, the price-Jacobian matrix is equal to the null matrix. Hence, the spillover effects are equal to zero as neither a strength nor a diffusion effect applies. When the goods are complements to each other ($\alpha > 0$), then the strength effect implies that the degree of connectedness (and hence the spillover effects) increases with α, as can be seen in case (b): $\partial \varsigma^{(b)}/\partial \alpha = w > 0$. Conversely, the diffusion effect implies that the degree of connectedness (and hence the spillover effects) is determined by the number of links ($\varsigma^{(b)} < \varsigma^{(c)} < \varsigma^{(d)}$) and by the structure of the links in directed networks[7] (acyclic or cyclic network structures: $\varsigma^{(d)} < \varsigma^{(e)}$ when $\alpha \in (0, 1)$).

A complication arises from the fact that goods may be substitutes to each other ($\alpha < 0$). Considering case (c), we then have that $\partial \varsigma^{(c)}/\partial \alpha = w + 2w\alpha \gtreqless 0$, which implies that for certain network structures, the strength (and diffusion) effect can go either way.

The network structure is typically captured by so called network topology measures. The challenge in this respect is to establish network topology measures that adequately capture the variation in the spillover effects due to distinct network structures and edge weights α. In what follows, we introduce three distinct network topology measures to capture the spillover effects.

2.4 Network topology measures and spillover effects

We use network topology measures to capture the size and the sign of the spillover effects, paying attention to strength and diffusion effect. The former concerns the quantitative size of the link between two connected nodes, while the latter concerns the amount of links and the overall arrangement of the links. We consider the following network topology measures:

1. Link density (LD): This measures how many links exist between nodes relative to the maximum possible number of links (Newman, 2010). Link density is thus a measure for the diffusion effect. For a directed graph with an $N \times N$ adjacency matrix $B = [\beta_{ij}]_{ij=1,\ldots,N}$ with $B \neq B'$, the link density is given by the scalar $\text{LD}(B) = \frac{\sum_i^N \sum_{j \neq i}^N \mathbb{1}_{\{|\beta_{ij}|>0\}}}{N(N-1)} \in [0, 1]$, where N is the number of nodes[8] and $\mathbb{1}_{\{|\beta_{ij}|>0\}}$ is the indicator function, which takes on a value of one if the condition $|\beta_{ij}| > 0$ is satisfied.
2. Network density (ND): For the same directed graph as before, the network density (Horvath, 2011) is given by the scalar $\text{ND}(B) = \frac{\sum_i^N \sum_{j \neq i}^N \beta_{ij}}{N(N-1)} \in \mathbb{R}$. It extends the link density by taking into account the weight of each edge $\beta_{ij} \in B$. Thus, for a given link density, the network density measures the strength effect.
3. Graph energy (GE): For the same graph as before, the graph energy is defined by the scalar $\text{GE}(B) = \sum_{i=1}^N |\Re(z_i)|$, where $\Re(z_i)$ is the real part of the complex number z_i, and the $z_i \, \forall \, i = 1, \ldots, N$ are the eigenvalues of the adjacency matrix B (Gutman, 1978; Peña and Rada, 2008). $GE(B) = 0$ means that a network has a perfect tree-like structure in which no loop is formed. Thus, the higher the graph energy,[9] the more cyclic is the architecture of the network. We consider two versions of graph energy: the first is given by $\text{GE}_{\mathbb{Z}_2} \geq 0$ (henceforth binary GE) and is based on $\beta_{ij} \in B$ with $\beta_{ij} \in \{0, 1\} \, \forall \, i, j = 1, \ldots, N$ and $i \neq j$, and the second is given by $\text{GE}_{\mathbb{R}} \geq 0$ (henceforth non-binary GE) and is based on $\beta_{ij} \in B$ with $\beta_{ij} \in \mathbb{R} \, \forall \, i, j = 1, \ldots, N$ and $i \neq j$. The first measure ($\text{GE}_{\mathbb{Z}_2}$) captures the diffusion effect solely, while the second ($\text{GE}_{\mathbb{R}}$) captures both the diffusion and the strength effect.

We show the values of the three network topology measures for each of the five cases (a)–(e) in the third to fifth columns of Figure 1. Their adequacy for our analysis is determined by their ability to capture the size and sign of the spillover effects.

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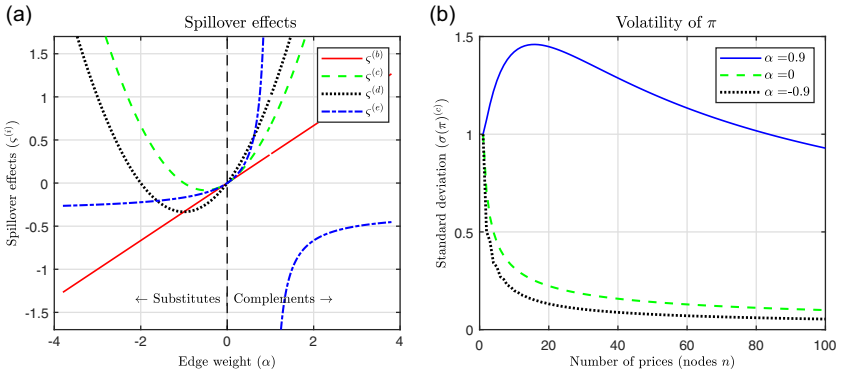


Figure 2. Spillover effects and inflation.
Note: Panel (a) shows the spillover effects of a unit-shock to the first node ($u_1 = 1$) for varying values of the edge weight α for a given node weight $w = 1/3$. Panel (b) shows the volatility of the CPI inflation rate as a function of the number of prices (nodes, n) in the network (each price i has a weight $w_i = 1/n$ in the CPI) for three distinct values of the edge weight α.

Considering Figure 1, in the absence of links, no spillover effects arise ($\varsigma^{(a)} = 0$) and the three topology measures (LD, ND, and GE) are all equal to zero. When links are present, spillover effects occur. Whenever the goods are complements ($\alpha > 0$), increasing the number of links leads to yet larger spillover effects (second column) due to the diffusion effect. This is captured by the link density (third column) and applies to the cases (b)–(d). However, for the same cases, the presence of substitutes ($\alpha < 0$) renders the spillover effects negative, thus mitigating the effects of the shock. While the link density fails to capture this, the network density in turn does (fourth column), as it captures the strength effect, which in turn is affected by the sign of the edges. Importantly, though, a positive spillover effect can also occur in the case of substitutes. This is indicated by cases (c) and (d) and is shown in Figure 2, which illustrates the spillover effects for varying edge weights α.

Finally, case (e) comprises an interesting alternative network structure. It shares similarities with cases (c) and (d). The similarity with case (c) emerges from the fact that the CPI inflation rate for the network structure in case (c) is given by

$$\pi^{(c)} = \frac{w}{1-\alpha} \tag{11}$$

and the spillover effect by $\varsigma^{(c)} = \frac{w\alpha}{1-\alpha}$ once the number of nodes n becomes large and each node (except the first and the last) has exactly one in-degree and one out-degree,[10] and $|\alpha| < 1$. In this case, the two networks have the same spillover effects despite their distinct structures. In contrast, as regards cases (d) and (e), while the link and network densities are the same for these two cases, the graph energy is not. In particular, the spillover effect arising from case (e) can indeed be sizeable, especially in the case of complements[11] (see Figure 2). Hence, the link and network density fail to capture this effect adequately from a quantitative point of view. Importantly, the effect emerges from a cyclical feature: Cases (b)–(d) represent *acyclic* networks, each with a nilpotent adjacency matrix. Case (e), on the other hand, is a *cyclic* network, which differs from the previous ones in that once a shock hits this network, a series of knock-on effects arise from the fact that the shock is continuously transmitted through the nodes forming the cycle (Boccaletti et al. 2006). From a technical point of view, the adjacency matrix has non-zero eigenvalues (Newman, 2010). While the number of non-zero eigenvalues depends on the number of cycles present in the network, we hence use an overall eigenvalue measure, which is given by the graph energy.[12] This measure captures spillover effects emerging from cycles.

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2.5 Individual price shocks and inflation dynamics

While the previous section illustrated the extent to which cross-price dependencies can act as a mechanism for propagating shocks from one good's price to the CPI inflation rate, we now examine whether they play a role for the inflation volatility.

Using equation (6) and setting the price-Jacobian matrix $\mathcal{A}$ equal to the null matrix (case (a) of Figure 1) implies that the volatility of the CPI inflation rate π that is due to idiosyncratic microeconomic price shocks is given by

$$\sigma(\pi)^{(a)} = ||\boldsymbol{w}|| \tag{12}$$

where $\sigma(\cdot)$ denotes the standard deviation and the demand shocks' variance is given by $E[\boldsymbol{u}\boldsymbol{u}'] = I$. Since $||\boldsymbol{w}|| = (\sum_{i=1}^{n} w_i^2)^{1/2}$, equation (12) highlights that more dispersion in the weights $\boldsymbol{w}$ can result in higher levels of volatility emerging from purely idiosyncratic shocks. In this regards, Gelos and Ustyugova (2017) highlight that countries with a higher weight of food in the CPI experience more persistent inflationary effects from commodity price shocks. In the absence of dispersion in the weights ($w_i = w \; \forall \; i = 1, \ldots, n$), we have that

$$\sigma(\pi)^{(a)} = \frac{1}{\sqrt{n}} \tag{13}$$

since the weights $\boldsymbol{w}$ satisfy $\sum_{i=1}^{n} w_i = 1 = nw$. This equation implies that when the weights of all prices are identical, the volatility of the inflation rate is proportional to $1/\sqrt{n}$, which is consistent with the diversification argument put forth in the context of production networks[13] (Acemoglu et al. 2012; Fadinger et al. 2022) and financial networks (Teteryatnikova, 2014; Glasserman and Young, 2016; Das et al. 2022; Balcilar et al. 2023). However, the presence of cross-price dependencies can render the effects of a shock from any individual price large, irrespective of the dispersion of the weights. In this case, the prices of goods would be correlated, and thus individual price shocks may not disappear when aggregated, even if the shocks themselves are independent. Consider case (c) of Figure 1, where $|\alpha| < 1$ and n is large; the effect of a shock to u_1 on the CPI inflation rate is given in equation (11); generalizing this result to the vector of shocks $\boldsymbol{u}$, we then obtain the following

$$\sigma(\pi)^{(c)} = \frac{1}{(1-\alpha)\sqrt{n}} \tag{14}$$

which implies that $\sigma(\pi)^{(c)} > \sigma(\pi)^{(a)}$ whenever $\alpha > 0$ due to network spillover effects. The above equation highlights that there is a tradeoff between the network and the volatility of the CPI inflation rate: A higher degree of connectedness–either via the strength effect (higher value of $|\alpha|$) and/or the diffusion effect (larger number of connections)–exacerbates the effect of microeconomic price shocks on the CPI inflation rate. The effect rises with a low number of nodes n, but then quickly gets attenuated by the degree of diversification, that is, a high n. This argument, however, only holds when cross-price dependencies emerge in the wake of complements ($\alpha > 0$), as illustrated in panel (b) of Figure 2. When dependencies arise from substitutes, then both the network effect (higher or lower degree of connectedness) and the diversification effect operate in the same direction rendering the mitigation of microeconomic shocks especially strong. In other words, each shock dissipates quickly and exerts an effect on the CPI inflation rate that is smaller than its pure DE.

3. Estimating the price-jacobian matrix

If the equilibrium conditions $x_i(p_i, \boldsymbol{p}_{-i}, m) \; \forall \; i = 1, \ldots, n$ set out in Section 2.1 are based on homothetic consumer preferences,[14] then the rate at which a consumer is willing to substitute one good for another is independent of his income level. This, in turn, implies homogeneity of expenditure

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patterns across consumers with different income levels, that is, consumers spend the same share of their total expenditure on particular goods regardless of differences in income (Jehle and Reny, 2011). Since the assumption of homothetic preferences is at the core of the CPI (see among others Diewert 2009; IMF 2022b), we estimate the price-Jacobian matrix $\mathcal{A}$ by proxying the elements in the price vector of equation (2) by subcomponents of the CPI.

The goods and services in the CPI basket are classified by purpose into consumption groups (COICOP) at various levels of (dis-)aggregation, which are referred to as *structure levels*. We use the three digit COICOP structure of the CPI, which consists of 44 distinct monthly price subindices $P_{i,t}$. We collect these data for 28 countries (the UK and the current EU member states). From these we exclude all those subindices for which the sample does not date back until (at least) 2004. This involves the price subindices related to educational goods and services (cp_101 to cp_105), leaving a total of $n = 39$ subindices and their respective basket weights.[15] The details of the subindices are provided in the Online Appendix.

Our choice of the three-digit COICOP level is motivated by our ambition to compare demand- with supply-driven cross-price dependencies for which we rely on the work of Cai and Vandyck (2020). They establish concordance matrices that map the statistical classification of the input-output (I-O) tables to the COICOP classification. These matrices are limited to the three-digit COICOP level, so we only consider the price subindices of this level of disaggregation (consider the Online Appendix for further details). This then allows the cross-price dependencies of the supply side ($\tilde{\Gamma}$) to be directly compared with those of the demand side ($\mathcal{A}$).

3.1 The econometric methodology

Our objective is to estimate demand-driven cross-price dependencies in a setting where, unlike the theoretical model presented in Section 2, supply is not perfectly price inelastic. To achieve this, we employ a vector autoregressive (VAR) model and sequentially estimate the components of the price-Jacobian matrix $\mathcal{A}$, as defined in equation (4).

We define the vector of endogenous variables as $\mathbf{y}_t^{ij} = \left[x_t^i, x_t^j, p_t^i, p_t^j\right]'$, where x_t^i, x_t^j denote the (equilibrium) quantities and p_t^i, p_t^j the (equilibrium) prices of goods i and j, while $\mathbf{x}_{t-1}$ represents a $(k \times 1)$ vector (with $k = 4m + 1$), comprising a constant and m lags of $\mathbf{y}$, denoted as $\mathbf{x}_{t-1} = \left[(\mathbf{y}_{t-1}^{ij})', \ldots, (\mathbf{y}_{t-m}^{ij})', \mathbf{1}'\right]'$. Furthermore, $\mathbf{u}_t$ is a (4×1) vector of structural disturbances with a diagonal variance-covariance matrix denoted by $\mathbf{I}$ (idenity matrix). The structural VAR model is thus expressed as (for clarity and brevity, the *ij* superscript is omitted from all elements except $\mathbf{y}_t^{ij}$)

$$\mathbf{A}\mathbf{y}_t^{ij} = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{u}_t \tag{15}$$

To quantify demand-driven cross-price dependencies, we proceed by considering the following structural model, which is comprised by a system of supply (S) and demand (D) equations for goods i and j

$$\mathrm{S}_i: \quad x_t^i = \gamma_i p_t^i + \gamma_{ij} p_t^j + \zeta_{ij} x_t^j + \mathbf{b}_1' \mathbf{x}_{t-1} + u_{S,t}^i \quad \text{with } \gamma_i > 0 \tag{16}$$

$$\mathrm{S}_j: \quad x_t^j = \gamma_j p_t^j + \gamma_{ji} p_t^i + \zeta_{ji} x_t^i + \mathbf{b}_2' \mathbf{x}_{t-1} + u_{S,t}^j \quad \text{with } \gamma_j > 0 \tag{17}$$

$$\mathrm{D}_i: \quad p_t^i = a_i x_t^i + a_{ij} p_t^j + \xi_{ij} x_t^j + \mathbf{b}_3' \mathbf{x}_{t-1} + u_{D,t}^i \quad \text{with } a_i < 0 \tag{18}$$

$$\mathrm{D}_j: \quad p_t^j = a_j x_t^j + a_{ji} p_t^i + \xi_{ji} x_t^i + \mathbf{b}_4' \mathbf{x}_{t-1} + u_{D,t}^j \quad \text{with } a_j < 0 \tag{19}$$

In the two supply curves, $\gamma_i > 0$ and $\gamma_j > 0$ are the short-run price elasticities of supply. The two demand curves are written in inverse form, so that $a_i < 0$ and $a_j < 0$ (we rule out Giffen goods) are hence the reciprocal of the price elasticities of demand. Our focus is on the cross-price elasticities

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a_{ij} and a_{ji}, which we intend to estimate. In view of equation (7) and the two (inverse) demand equations (18) and (19), we have that the demand-driven cross-price dependencies are given by

$$\frac{\partial p_t^j}{\partial p_t^i} = \frac{dx_t^j/dp_t^i}{dx_t^j/dp_t^j} = \frac{-a_{ji}/a_j}{1/a_j} = -a_{ji} \tag{20}$$

so that $-a_{ji} < 0$ implies substitutes and $-a_{ji} > 0$ complements. We use these estimates to populate the price-Jacobian matrix $-a_{ji} \in \mathcal{A}$ sequentially.[16] To this purpose, we reformulate the above system of equations (16)–(19) into the structural VAR model (15), where the matrix $\mathbf{A}$, governing the contemporaneous interactions among the endogenous variables, is given by

$$\mathbf{A} = \begin{bmatrix} 1 & \cdot & -\gamma_i & \cdot \\ \cdot & 1 & \cdot & -\gamma_j \\ -a_i & \cdot & 1 & -a_{ij} \\ \cdot & -a_j & -a_{ji} & 1 \end{bmatrix} \tag{21}$$

All parameters of the contemporaneous relationship beyond interest were substituted with a dot. The structural model (15) has the following reduced form representation

$$\mathbf{y}_t^{ij} = \mathbf{\Phi}\mathbf{x}_{t-1} + \boldsymbol{\epsilon}_t \tag{22}$$

$$\boldsymbol{\epsilon}_t = \mathbf{H}\mathbf{u}_t \tag{23}$$

where $\mathbf{H} = \mathbf{A}^{-1}$, $\mathbf{\Phi} = \mathbf{A}^{-1}\mathbf{B}$ and $E(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') = \mathbf{\Sigma}$, with $\boldsymbol{\epsilon}_t$ being the reduced form error term. We estimate the reduced form model using Bayesian techniques (consider the Online Appendix for further technical details) and we use the Schwarz (Bayesian) information criterion to select the lag length. The variables p_t^i and $p_t^j \; \forall \, i, j = 1, \ldots, n$ refer to the three-digit level subindices of the CPI and they enter the vector $\mathbf{y}_t^{ij}$ in annual percentage changes. The quantities (x_t^i and x_t^j) are taken from national account consumption data and they also enter in annual percentage changes. Importantly, they have the same COICOP classification as the CPI, and hence correspond directly to the respective prices (p_t^i and p_t^j).[17] Additionally we use two dummy variables, one of which for the Covid-19 episode and the second for the post-pandemic episode. These variables are used for each country. The monthly dataset spans from January 2000 to December 2023,[18] yielding a total of $T = 288$ observations. We estimate equation (22) for each pairing i, j of prices and quantities and for each country individually, so that each individual VAR provides estimates for two entries in the price-Jacobian matrix $\mathcal{A}$. With $n = 39$, this requires to estimate $n(n-1)/2 = 741$ models in total for each of the 28 countries.

3.1.1 Identification

An important element of our empirical approach concerns the identification of the structural equation system (16)–(19), that is, the transformation of the reduced form VAR model (22) into the structural form (15). To this purpose, we employ sign restrictions. However, in contrast to the literature (see among others Canova and De Nicolo 2002; Uhlig, 2005; Baumeister and Peersman, 2013; Glocker and Towbin, 2015), we do not consider sign restrictions on the impulse response functions, but on the elements in the matrix $\mathbf{A}$. In view of the structural equation system (16)–(19), we expect the following signs of the elements in the matrix $\mathbf{A}$

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$$\text{sign}(\mathbf{A}) = \begin{bmatrix} + & \cdot & - & \cdot \\ \cdot & + & \cdot & - \\ + & \cdot & + & \cdot \\ \cdot & + & \cdot & + \end{bmatrix} \tag{24}$$

where a dot refers to an unrestricted element. The "+" and "−" symbols refer to the sign restrictions that we impose. Importantly, we leave the two demand-driven cross-price elasticities a_{ji} (the [3,4]-element) and a_{ij} (the [4,3]-element) unrestricted as we intend to be agnostic about their sign (and size).

We use the eigenvector-eigenvalue decomposition of the variance-covariance matrix $\mathbf{\Sigma}$ and define $\mathbf{V} = \mathbf{E}_{\mathbf{\Sigma}} \mathbf{\Lambda}_{\mathbf{\Sigma}}^{1/2}$, where $\mathbf{E}_{\mathbf{\Sigma}}$ is the (orthogonal) matrix of eigenvectors and $\mathbf{\Lambda}_{\mathbf{\Sigma}}$ is the (diagonal) matrix of eigenvalues. In view of the properties of this decomposition in case of symmetric matrices ($\mathbf{E}'_{\mathbf{\Sigma}} = \mathbf{E}_{\mathbf{\Sigma}}^{-1}$, since $\mathbf{E}_{\mathbf{\Sigma}}$ is an orthogonal matrix), we have that $\mathbf{\Sigma} = \mathbf{V}\mathbf{V}'$. We then multiply $\mathbf{V}$ with an orthonormal matrix $\mathbf{Q}$ to obtain $\mathbf{H} = \mathbf{V}\mathbf{Q}$, from which we can compute a candidate for $\mathbf{A} = \mathbf{H}^{-1}$. The matrix $\mathbf{Q}$ is a random orthonormal matrix of the same dimension as $\mathbf{\Sigma}$. We follow Rubio-Ramírez et al. (2010) and compute $\mathbf{Q}$ by drawing an independent standard normal matrix $\mathbf{X}$ (of the same size as $\mathbf{\Sigma}$) and apply the QR decomposition $\mathbf{X} = \mathbf{Q}\mathbf{R}$ to get $\mathbf{Q}$.

Regarding the sign restrictions, if the corresponding entries in a candidate matrix $\mathbf{A}$ are consistent with the sign restrictions outlined in (24), we retain the candidate draw and proceed to the next draw until a total of 5,000 accepted draws is obtained. Otherwise, a new $\mathbf{Q}$ matrix is drawn until the sign restrictions are satisfied.

Notably, we impose two additional constraints: (i) simultaneous supply shocks are prohibited, which excludes rows of the form [+, +, −, −] in the first and second rows of $\mathbf{A}$; and (ii) simultaneous demand shocks are also prohibited, excluding rows of the form [+, +, +, +] in the third and fourth rows of $\mathbf{A}$. These additional restrictions ensure that neither aggregate supply nor aggregate demand shocks influence the individual good-specific relationships.

We emphasize that while the estimation and inference of the reduced-form model are based on a fairly non-informative prior for all coefficients, an informative prior arises in the structural model due to the QR decomposition (Baumeister and Hamilton, 2015). Additionally, it is important to note that in our case, the sign restrictions are applied row-wise to the matrix $\mathbf{A}$. This differs from the column-wise procedure used for the matrix $\mathbf{H}$ when applying sign restrictions to impulse response functions following structural shocks (see for example Baumeister & Hamilton, 2015, 2019).

We consider two alternative approaches to identification, both of which are described in detail in the Online Appendix and serve as robustness checks. The first approach involves sign restrictions on the impulse response functions and hence on the columns of the matrix $\mathbf{H}$. The advantage of this alternative approach is that it allows for the inclusion of lags in the effects associated with demand-driven cross-price dependencies. The second approach considers a combination of sign and size restrictions, applied on the rows of the matrix $\mathbf{A}$. The size restrictions set the elasticity for a good with respect to its own price relative to that of another price. This introduces Lemma 1 into the empirical model. While the size restrictions we impose are slightly different 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.[19]

3.1.2 In-significant entries

We use the posterior median for the a_{ij} elements. In many cases, the estimated values of a_{ij} are small and statistically indistinguishable from zero. To address this, we introduce an additional step involving statistical inference. We transform the estimated matrix $\mathcal{A}$ that emerges from

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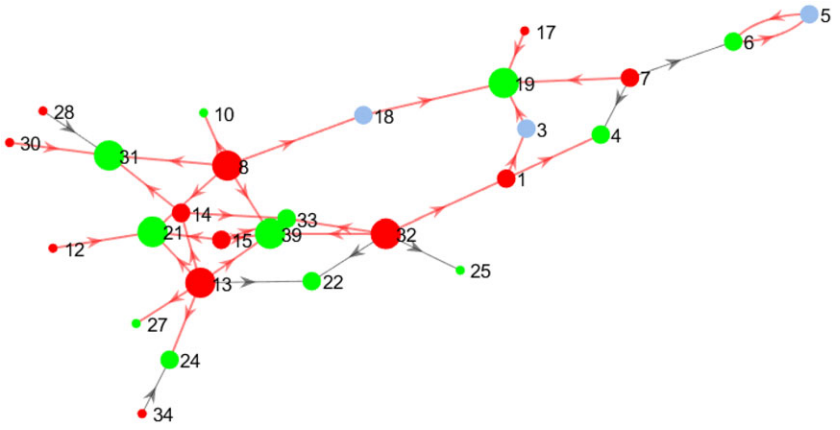


Figure 3. Demand driven cross-price dependencies.
Note: The figure shows the cross-price dependencies as a network. We only show the edges that are present in 50 percent of the countries. Nodes in red indicate out-degree dominance, while those in green indicate in-degree dominance; nodes in blue indicate 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 key nodes are: (1) "Food," (3) "Alcoholic Beverages," (4) "Tobacco," (5) "Clothing," (6) "Footwear," (7) "Actual Rentals for Housing," (8) "Maintenance and Repair of the Dwelling," (13) "Household Appliances," (14) "Glassware, Tableware and Household Utensils," (15) "Tools and Equipment for House and Garden," (19) "Hospital Services," (21) "Operation of Personal Transport Equipment," (22) "Transport Services," (25) "Telephone and Telefax Equipment," (31) "Package Holidays," (32) "Catering Services," (33) "Accommodation Services," and (39) "Other services."

the repeated estimation of equation (15) into an adjacency matrix $\tilde{\mathcal{A}}$ by applying the following statistical thresholding

$$\tilde{\alpha}_{ij} = \begin{cases} a_{ij} & \text{if } \forall\, i \neq j\text{: } \Pr(a_{ij} \neq 0) \geq 1 - \bar{p} \\ 0 & \text{else} \end{cases} \tag{25}$$

where $-a_{ij} \in \mathcal{A}$ and $-\tilde{\alpha}_{ij} \in \tilde{\mathcal{A}}$, and we use a significance value of $\bar{p}$ equal to one percent. In other words, all elements in the price-Jacobian matrix ($\tilde{\alpha}_{ij}$), for which the corresponding values of the a_{ij} elements are not statistically different from zero, are set to zero. The $\tilde{\alpha}_{ij}$ elements then define the edges of the weighted directed network of empirical cross-price dependencies. Since we have a posterior distribution for $\mathcal{A}$, the same then applies to the adjacency matrix $\tilde{\mathcal{A}}$ (in particular, its non-zero elements). Moreover, we keep all those posterior draws of $\tilde{\mathcal{A}}$ that satisfy Lemma 1. On average (across countries), three percent of the draws are discarded as a consequence.[20]

3.2 The empirical demand-driven cross-price dependencies

Figure 3 shows the empirical cross-price dependencies given by the matrix $\tilde{\mathcal{A}}$ across all countries. We display only those edges that are present in 50 percent of the countries, in order to allow for a reasonable inspection of the most relevant links. Edges in red refer to positive entries (complements) and those in black to negative ones (substitutes).

The estimated cross-price dependencies imply, for instance, that an increase in demand for food (node 1) leads to higher prices in this group and to price changes in two closely related groups, that is, alcoholic beverages (node 3) and tobacco (node 4), both of which are affected positively, highlighting complementary effects. Food prices are connected with the prices of catering services (node 32), which also affect the prices of other goods.

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Table 1. Network topology statistics

	Demand ($\tilde{\mathcal{A}}$)		Supply ($\tilde{\mathbf{\Gamma}}$)	
	Mean	Standard deviation	Mean	Standard deviation
Positive edges ratio[(1)]	0.74	0.09	1	0
Link (degree) density (LD)	0.19	0.06	0.33	0.02
Network density (ND)	0.03	0.05	0.15	0.00
Graph energy (binary, $GE_{\mathbb{Z}_2}$)	43.14	5.60	25.18	3.36
Graph energy (non-binary, $GE_{\mathbb{R}}$)	6.55	2.72	2.64	0.56
(Dis-)Assortativity[(2)]	0.03	0.07	−0.27	0.07
	Sensitivity	Specificity	Accuracy	Cosine-similarity
Similarity of $\tilde{\mathcal{A}}$ to $\tilde{\mathbf{\Gamma}}$ [(3)]	0.06	0.48	0.32	0.04
	(0.03)	(0.08)	(0.10)	(0.03)

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 (in parenthesis in the lower part of the Table) 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.
[(3)] $\tilde{\mathcal{A}}$ refers to the demand-driven and $\tilde{\mathbf{\Gamma}}$ to the supply-driven network of cross-price dependencies.

As a second example, consider an increase in rental prices for housing (node 7), which triggers substitution effects for tobacco (node 4) and clothing (node 6). The latter, in turn, forms a cycle with footwear (node 5), that is, higher demand for clothing raises demand for footwear with price increases in both groups; higher demand for footwear in turn stimulates demand for clothing with another round of price increases in both groups. The interaction is shaped by positive-valued edges resulting in goods being complementary to each other. Table 1 highlights that the complementarity property of goods dominates. The mean (across countries) of the ratio of positive-valued edges to the total number of non-zero edges equals 74 percent, which is well in line with the 67 percent estimate in Regmi and Seale (2010). A cross-country mean value of 19 percent for the link (degree) density contrasts a fairly low value for the network density due to negative-valued edges.

3.3 Demand and supply-driven cross-price dependencies: a comparison

The cross-price dependencies as shown in Figure 3 emerge from demand shocks. This naturally raises the question as to what extent they differ to the supply side cross-price dependencies. We show the supply-driven cross-price dependencies in Figure 4, with all details provided in the Online Appendix. They are based on a simple supply side model, which is a version of the model considered in Acemoglu et al. (2012). The model is calibrated using, among others, the I-O tables. Most importantly for our purposes, the statistical classification of the I-O tables was mapped to the COICOP classification by using the concordance matrices of Cai and Vandyck (2020). A direct visual comparison of the two networks of cross-price dependencies reveals notable differences, as do the network statistics provided in Table 1. First, the supply side network has a high level of dis-assortativity (negative degree correlation), but also a high extent of assortative hubs (nodes 1, 3, 10 and 39). Colizza et al. (2006) point out that most real-world (scale-free) networks have this feature. A closer look reveals that these hubs have a significant out-degree dominance. The implication for the network is that a small set of nodes shapes the network's overall dynamics. In contrast to that, the demand-driven cross-price dependencies show a lower extent of dis-assortativity with a more balanced distribution of the nodes with out-degree dominance. Second,

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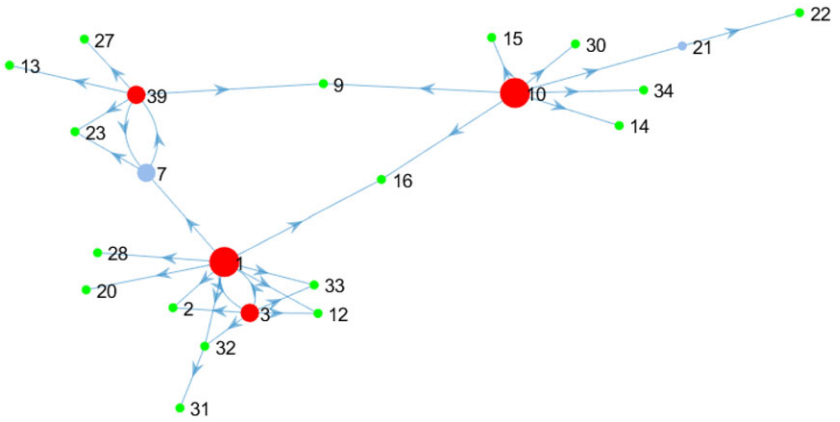


Figure 4. Supply driven cross-price dependencies.
Note: The figure shows the production network given by the I-O tables mapped into the COICOP classification for which the concordance matrices of Cai and Vandyck (2020) were used. The network shown is the average over all countries (the UK and the current EU member countries). We only show the edges that are greater than 0.01. Nodes in red indicate out-degree dominance while those in green in-degree dominance; nodes in blue indicate equality between out- and in-degree. The key nodes are: (1) "Food," (3) "Alcoholic Beverages," (10) "Electricity, Gas and Other Fuels," (39) "Other Services N.E.C.".

the supply-driven network displays a high clustering tendency, which is manifested in the form of nodes being divided into three blocks. The network aligns with a so called *stochastic block model* (Frank and Harary, 1982; Holland et al. 1983; Karrer and Newman, 2011). The implication is that the network's dynamics are determined by the interaction of the nodes in these blocks, which in turn are shaped by the hubs in these blocks. Such block clustering is absent in the demand-driven network of cross-price dependencies. Third, both networks share a high degree of cyclicality. Both have individual cycles.[21] In each case this gives rise to a high overall extent of network dynamics, as indicated by the high values of the graph energy (see Table 1).

Although the previous analysis already indicated significant differences between the price dependencies of the demand side and the supply side, we now formalize this using statistical criteria. The accuracy of the estimated demand-driven price dependencies (and hence the quality of the estimation of the matrix $\boldsymbol{A}$, which emerges from the repeated estimation of equation (15)) can be assessed by comparing them with their supply side counterpart. In this context, a high degree of similarity indicates an insufficient coverage of demand factors to explain the price dependencies. To this purpose, we use the cross-price adjacency matrices of the demand side ($\tilde{\mathcal{A}}$) and the supply side ($\tilde{\Gamma}$) and evaluate their similarities. We do this following Gandy and Veraart (2019) and consider the following standard criteria

$$\text{Sensitivity} = \frac{1}{\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}\mathbb{1}_{\{\tilde{\alpha}_{ij}\neq 0\}}\cdot\mathbb{1}_{\{\tilde{\gamma}_{ij}>0\}} \tag{26}$$

$$\text{Specificity} = \frac{1}{n^2-\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}\mathbb{1}_{\{\tilde{\alpha}_{ij}=0\}}\cdot\mathbb{1}_{\{\tilde{\gamma}_{ij}=0\}} \tag{27}$$

$$\text{Accuracy} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\mathbb{1}_{\{\tilde{\alpha}_{ij}=0\,\wedge\,\tilde{\gamma}_{ij}=0\}}+\mathbb{1}_{\{\tilde{\alpha}_{ij}\neq 0\,\wedge\,\tilde{\gamma}_{ij}>0\}}\right) \tag{28}$$

$$\text{Cosine-Similarity} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{\alpha}_{ij}\tilde{\gamma}_{ij}}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{\alpha}_{ij}^2}\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{\gamma}_{ij}^2}} \tag{29}$$

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where, as before, $\mathbb{1}_{\{\cdot\}}$ is the indicator function and $\mu = \sum_{i=1}^{n} \sum_{j=1}^{n} \mathbb{1}_{\{\tilde{\gamma}_{ij}>0\}}$. The first three criteria are in the range [0, 1], and higher values indicate a greater extent of similarity, while the fourth is in the range $[-1, 1]$, with a higher value (in amount) indicating a higher extent of similarity. The results are provided in Table 1. The low value of the sensitivity measure indicates a markedly low congruence between the two adjacency matrices ($\tilde{\mathcal{A}}$ for the demand-driven and $\tilde{\Gamma}$ for the supply-driven cross-price networks) with respect to the non-zero entries. This shows, on the one hand, that sufficient supply variables have been included in the estimation to separate the demand- and supply-driven influences on the cross-price dependencies, and, on the other hand, that the cross-price dependencies from the estimation of the matrix $\tilde{\mathcal{A}}$ using equation (15) repeatedly, can indeed be interpreted as the result of demand-specific influences. The moderate value of the specificity measure is due to the fact that both cross-price networks are rather sparse, giving rise to only a small number of non-zero edges (consider the link density in Table 1). The accuracy measure, as a combination of the previous two, confirms the low congruence of the two adjacency matrices. Finally, the cosine-similarity measure again has a markedly low value, which is due to the low overall congruence of the two adjacency matrices with respect to their non-zero edges on the one hand, and on the other hand, to the fact that once a non-zero edge applies to the same element *ij* in the two adjacency matrices, the sign of these entries can be different, which augments their dis-similarities even further.

3.4 The empirical spillover effects

The network representations in Figure 3 and 4 show the links, their signs and the corresponding node connections, but do not allow a quantitative assessment of individual price shocks on the CPI inflation rate. Moreover, given the differences between the demand- and supply-driven cross-price dependencies, the question arises as to what extent the resulting spillover effects of microeconomic price shocks on the CPI inflation rate differ. A quantification of the spillover effects and a comparison between the demand- and supply-driven network of cross-price dependencies is the focus of what follows.

In line with the second column of Figure 1, we compute the spillover effects of the individual price subindices on the CPI inflation rate. Technically, this is done by again using equation (10), where we set each element in the vector of shocks $\boldsymbol{u}$ equal to zero except its i's element which has a unit entry ($u_i = 1$). This allows us to calculate the spillover effect of a shock to the price subindex i on the CPI inflation rate. We do this for each price subindex. The results for the demand side are provided in the first panel of Figure 5 in the form of box-plots showing the variation across countries. The figure highlights a few noteworthy things.

First, there is a remarkable cross-country variation in the sign and quantitative magnitude of the spillover effects. Consider, for instance, the price subindex No. 1 (food) in the left-hand panel. The median value of the spillover effect of this subindex is 0.17 implying that a one percentage point increase of this subindex raises the CPI inflation rate by 0.17 percentage points; the values for the boxes (25th and 75th percentiles) are 0.12 and 0.21, respectively, which underscores the large cross-country differences. The finding of a significant extent of heterogeneity in the spillover effects across countries aligns with the results put forth in Abdallah and Kpodar (2023); Glocker and Wegmüller (2024), who focus on the role of retail energy prices for the CPI.[22]

Second, the spillover effects from the supply-driven network (second panel of Figure 5) are always non-negative because of the solely positive valued edges while those from the demand-driven counterpart can be either negative or positive. Thus, while microeconomic price shocks can only be exacerbated by supply-driven cross-price dependencies, demand-driven cross-price dependencies can lead to an attenuation or exacerbation of the same shocks. This is particularly evident in the case of the price subindex No. 39 (other services n.e.c.), where a large positive (median) value of the supply-driven network of cross-price dependencies contrasts with a negative

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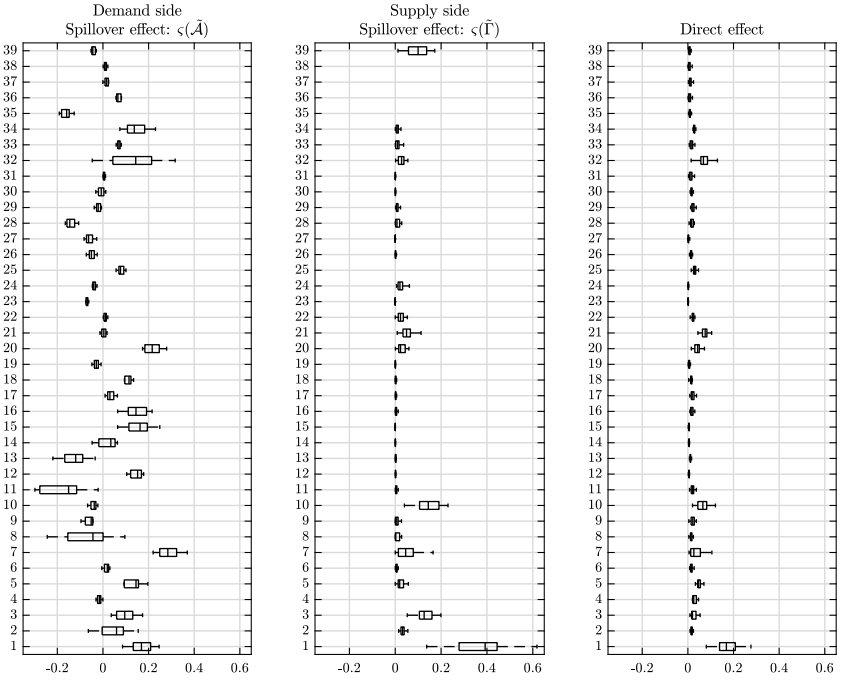


Figure 5. Individual price shocks: direct and spillover effects.
Note: The box-plots show the variation across countries of (i) the spillover effects, and (ii) the DEs of a shock to an individual price subindex to the CPI inflation rate. The DEs are given by $\pi^{\mathrm{DE}} = \boldsymbol{w}'\boldsymbol{u}$ (this just reflects the weights of the price subindices in the CPI) and the spillover effects by equation (10). In each box, the central marker indicates the median, and the lower and upper edges of the box indicate the 25th and 75th percentiles of the cross-country variation, respectively. The whiskers extend to the most extreme non-outlying data points.

value of the demand-driven counterpart. In a similar vein, the extent of shock exacerbation is likely to be especially pronounced in the case of the price subindices No. 1 (food), 20 (purchase of vehicles) and 32 (catering), as in each case positive valued spillover effects result from both the demand- and supply-driven cross-price dependencies.

Third, on average, the size of the spillover effect of the price subindices exceeds their DE (right-hand panel in Figure 5, reflecting the weights of the price subindices in the CPI) on the CPI inflation rate. This is the case for both the demand- and the supply-driven cross-price networks. For the latter, the extent of asymmetry is especially pronounced for the price subindices No. 1 (food), 3 (alcoholic beverages), 10 (electricity, gas and other fuels) and 39 (other services n.e.c.). This highlights the importance of the spillover effects relative to the DEs in explaining the impact of microeconomic price shocks on the CPI inflation rate.

4. The role of cross-price dependencies for inflation dynamics

The previous section has highlighted the role of the cross-price dependencies for the size and sign of the spillover effects of microeconomic price shocks on the CPI inflation rate. This raises the question of whether they also matter for the overall inflationary dynamics.

With a view to equation (6), the inflation rate is determined by two elements. On the one hand, there are the exogenous shocks $\boldsymbol{u}$. In the theoretical model in Section 2, supply was assumed to be inelastic with respect to the price, so that demand shocks were the only element shaping prices and hence the CPI inflation rate. In a more general setting, however, the vector $\boldsymbol{u}$ can contain

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any exogenous shock. On the other hand, the inflation rate in equation (6) depends on the extent of cross-price dependencies, which are governed by the price-Jacobian matrix $\mathcal{A}$. The cross-price dependencies determine the size and sign of the spillover effects. For a given vector of shocks $\boldsymbol{u}$, changes in the price-Jacobian matrix alter the spillover effects and hence the inflation rate. This motivates considering the CPI inflation rate π as a function $f(\cdot)$ of (i) the exogenous shock elements in $\boldsymbol{u}$ and (ii) the spillover effects $\varsigma_{\mathcal{A}} \in \mathbb{R}$ that emerge from the price-Jacobian matrix $\mathcal{A}$

$$\pi = f(\varsigma_{\mathcal{A}}, u) \tag{30}$$

where the vector of shocks $\boldsymbol{u}$ has been reduced to the scalar u for simplicity. Importantly, the spillover effects $\varsigma_{\mathcal{A}}$ are determined by the strength and the diffusion effect, both of which were discussed in Section 2.3. To get a better insight into the role of the spillover effects on the CPI inflation rate, we consider a second-order Taylor approximation of equation (30) around $u_0 = 0$, which yields the following

$$\pi = f_{\varsigma_{\mathcal{A}}} \cdot \tilde{\varsigma}_{\mathcal{A}} + f_u \cdot u + \frac{1}{2}\left(f_{\varsigma_{\mathcal{A}}\varsigma_{\mathcal{A}}} \cdot (\tilde{\varsigma}_{\mathcal{A}})^2 + f_{uu} \cdot (u)^2\right) + f_{\varsigma_{\mathcal{A}}u} \cdot \tilde{\varsigma}_{\mathcal{A}} u \tag{31}$$

where $\tilde{\varsigma}_{\mathcal{A}} = \varsigma_{\mathcal{A}} - \varsigma_{\mathcal{A},0}$ and $f(\varsigma_{\mathcal{A}}, 0) = 0$. We explicitly consider non-linearities through the inclusion of second-order terms, between the spillover effects $\varsigma_{\mathcal{A}}$ and the CPI inflation rate π. Importantly, this non-linear relationship is implied and motivated by equation (6).

The spillover effects $\varsigma_{\mathcal{A}}$ thus shape the inflation rate along two dimensions. The first of these comes from the first-order terms and holds whenever $f_{\varsigma_{\mathcal{A}}} = \partial\pi/\partial\varsigma_{\mathcal{A}} \neq 0$. The effects of this term can be considered as an extension of the weights $\boldsymbol{w}$ of the individual price subindices for the CPI. For given values of u, changes in it will affect the CPI inflation rate. The second dimension is comparatively more important and emerges from the second-order terms. The main focus here is on the term $f_{\varsigma_{\mathcal{A}}u}$. It determines the propagation mechanism of the exogenous shocks u. It applies whenever $f_{\varsigma_{\mathcal{A}}u} = \partial^2\pi/\partial u\partial\varsigma_{\mathcal{A}} \neq 0$, given that $f_u = \partial\pi/\partial u \neq 0$. Intuitively, changes in consumer preferences are likely to alter the structure of the cross-price dependencies, which in turn causes changes to the propagation mechanism of microeconomic price shocks to the CPI inflation rate.[23] In what follows, we examine both dimensions. To do so, we approximate the spillover effects $\varsigma_{\mathcal{A}}$ by the network topology measures put forth in Section 2.4.

4.1 First-order terms

We put the first-order terms of equation (31) into a panel data regression model in which we explain the CPI inflation rate by the spillover effects $\varsigma_{\mathcal{A}}$ and the shocks $\boldsymbol{u}$. We proxy the spillover effects by the network topology (NT($\tilde{\mathcal{A}}$)) measures (link density, network density and graph energy) as motivated in Section 2.4. For the shock elements $\boldsymbol{u}$, we use the variables of a classical Phillips curve specification, namely: the producer price index (PPI), the cyclical unemployment gap (U-Gap)[24] and in addition to this, a long-term interest rate (10-year government bond rate, GBR) (see and the references there in Aguiar and Martins 2005; Hazell et al. 2022). We create an appropriate time variation of the network (compare Holme and Saramäki 2012) by estimating equation (15) over different time windows of 60 months each, with an overlap to obtain estimates for a total of nine windows.[25] We use the adjacency matrix $\tilde{\mathcal{A}}_{c,t}$ of each window $t = 1, \ldots, 9$ to compute the network topology measures[26] and we do this for each country $c = 1, \ldots, 28$. Importantly, we use the median across the draws of the posterior distribution of $\tilde{\mathcal{A}}_{c,t}$ for each country and time-window. Figure 6 illustrates the variation in the four network topology measures and the CPI inflation rate (median and 68-percentile across countries) over time and across countries. The width of the boxes indicates the variation across countries. The median estimate demonstrates the variation over time.

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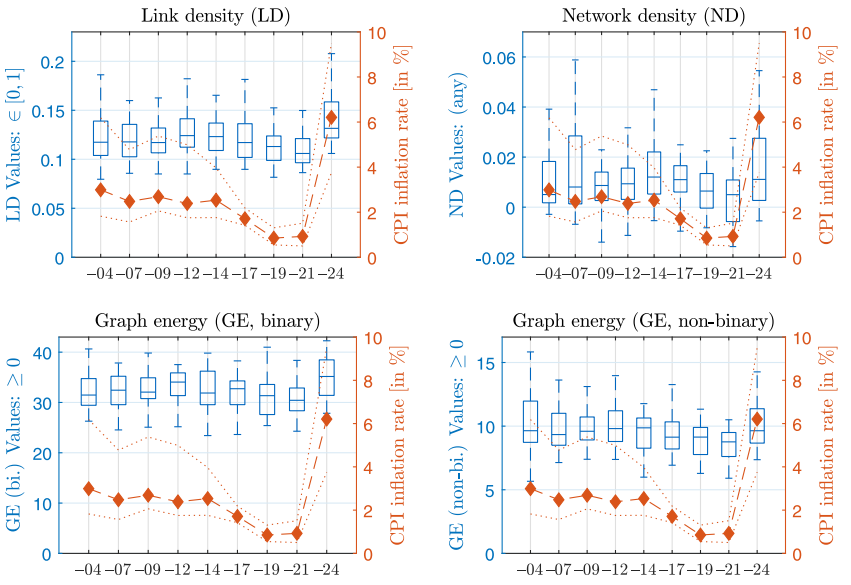


Figure 6. Network topology measures: country and time variation.
Note: The box-plots show the variation across countries and time of the network topology measures. They are based on a window estimation of equation (15), with each window having a length of 60 months.

We estimate a panel data regression model of the form

$$\pi_{c,t} = \beta_{\text{NT}} \cdot \text{NT}\left(\tilde{\mathcal{A}}_{c,t}\right) + \sum_{i\geq 1}^{K} \beta_i x_{c,t,i} + e_{c,t} \tag{32}$$

to explain the CPI inflation rate $\pi_{c,t}$. As regards equation (32), the $K = 3$ explanatory variables ($x_{c,t,i}$) next to the network topology measure $\text{NT}\left(\tilde{\mathcal{A}}_{c,t}\right)$ are given by the PPI, the unemployment gap (U-Gap) and the GBR, $e_{c,t}$ is the error term, c denotes the country and t the time variation. The temporal variation t is limited to the nine time windows. All variables are based on a monthly frequency. The price variables (CPI, PPI) are expressed as relative changes (year-over-year changes). The value of all variables within the nine windows is calculated as the mean value of the corresponding months.

We use the fixed effects (FEs) estimator as it is considered to be the adequate approach for a situation where there are unobservable country effects and unobservable time effects. The results are provided in Table 2, where we report the estimates of distinct specifications of equation (32) (Reg. 1 to Reg. 6). The first regression (Reg. 1) does not include any of the network topology measures and the estimates for the partial effects of the remaining explanatory variables (PPI, U-Gap, GBR) are in each case statistically significantly different from zero at least at the one percent level and all parameter estimates have their expected signs. For example, the estimates indicate, that a one percentage point increase in the producer price inflation rate leads to an increase in the CPI inflation rate of 0.6 percentage points; this partial effect turns out higher in the case of the unemployment gap (−0.73). Finally, while the positive estimate for the GBR aligns with the Fisher-effect, the estimated value, however, clearly subceeds unity as would be expected from theory (see Wickens, 2012 Chapter 14.2).

In a sequential extension of the basic regression model (Reg. 1) to include the network topology measures, we find that, first, link density (Reg. 2) is statistically significant in explaining the CPI inflation rate. This confirms the importance of cross-price dependencies for the CPI inflation rate

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Table 2. Network topology measures and the consumer price index (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	–	0.06 **	–	–	–	0.14 **	–	0.12 *	–	–	–
ND	–	–	0.18 ***	–	–	0.23 ***	–	–	0.15 **	–	–
$GE_{\mathbb{Z}_2}$	–	–	–	0.0001 *	–	0.0001 *	–	–	–	0.0002 **	–
$GE_{\mathbb{R}}$	–	–	–	–	0.001 ***	0.001 *	–	–	–	–	0.001 *
PPI[(a)]	0.59 ***	0.56 ***	0.52 ***	0.58 ***	0.56 ***	0.53 ***	0.29 ***	0.24 *	0.33 ***	0.78 ***	0.00
U-Gap[(b)]	−0.73 ***	−0.73 ***	−0.71 ***	−0.72 ***	−0.72 ***	−0.69 ***	−0.50 ***	−0.51 ***	−0.53 ***	−0.46 ***	−0.49 ***
GBR[(a)]	0.39 ***	0.39 ***	0.37 ***	0.40 ***	0.37 ***	0.33 ***	0.39 ***	0.39 ***	0.36 ***	0.40 ***	0.36 ***
LD · PPI	–	–	–	–	–	–	–	0.32 *	–	–	–
ND · PPI	–	–	–	–	–	–	–	–	3.02 **	–	–
$GE_{\mathbb{Z}_2}$ · PPI	–	–	–	–	–	–	–	–	–	0.02 **	–
$GE_{\mathbb{R}}$ · PPI	–	–	–	–	–	–	–	–	–	–	0.05 ***
$(LD)^2$	–	–	–	–	–	–	–	−0.30	–	–	–
$(ND)^2$	–	–	–	–	–	–	–	–	−1.56 **	–	–
$(GE_{\mathbb{Z}_2})^2$	–	–	–	–	–	–	–	–	–	0.00	–
$(GE_{\mathbb{R}})^2$	–	–	–	–	–	–	–	–	–	–	0.001**
$(PPI)^2$	–	–	–	–	–	–	3.35 ***	3.20 **	1.02	5.25 *	−0.44
R^2	0.63	0.63	0.66	0.63	0.64	0.67	0.67	0.70	0.71	0.71	0.73
$\bar{R}^2$	0.58	0.58	0.62	0.58	0.59	0.62	0.63	0.65	0.67	0.66	0.69

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. 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. 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.

in general. The point estimate implies that an increase in the number of links by one percent raises the inflation by 0.06 percentage points. While this concerns only the diffusion effect, we also find evidence in favor of the strength effect: the network density (Reg. 3) has a high statistical support for explaining the variation in the CPI inflation rate. Its point estimate implies that an increase in the network density by one percent raises the inflation rate by 0.18 percentage points. While link density has indicated the significant role of the diffusion effect, network density implies that the strength effect is of even higher importance. This can be seen by both the significantly higher partial effect, and by the increase in the goodness-of-fit measures (normal R^2 and adjusted R^2, the latter being denoted as $\bar{R}^2$) of Reg. 3 relative to Reg. 2.

Finally, the graph energy (Reg. 4 and Reg. 5) has a high explanatory power for the CPI inflation rate. This is the case for both measures ($GE_{\mathbb{Z}_2}$ and $GE_{\mathbb{R}}$). Although the coefficient estimate of the binary graph energy measure ($GE_{\mathbb{Z}_2}$) is small, this should not obscure the importance of this variable, especially as its values are high (see Figure 6). The fact that the graph energy measures have a statistically significant impact on the inflation rate highlights the role of cyclical interdependencies between the price sub-indices (see Figure 1). Cyclical interdependencies imply that the effects of microeconomic price shocks are slow to dissipate, resulting in long-lasting effects of microeconomic price shocks on the CPI inflation rate, hence shaping its inertia.

The simultaneous utilization of all four network topology measures in the regression model (Reg. 6) yields statistically significant results at least at the 10% level. This corroborates the important role of both the diffusion and strength effects.

4.2 Second-order terms

We now extend the panel data regression model given by equation (32) to include the second-order terms of equation (31). We estimate the extended model again using the FEs estimator and provide the results in the last five columns (Reg. 7 to Reg. 11) of Table 2. We present results involving the interaction terms only between the PPI and the four network topology measures; this is because in all other cases (this includes also the second-order terms of the unemployment gap and the GBR) the results are not statistically significant.

The results highlight that in all cases (Reg. 7 to 11) the unemployment gap (U-Gap) and the GBR keep their high level of statistical significance. As regards the PPI, both the first-order terms and the quadratic terms are statistically significant (consider Reg. 7) and the partial effect is given by $\frac{\partial \pi}{\partial \text{PPI}} = 0.45$ (the mean value of the PPI was used: $\overline{\text{PPI}} = 0.03$), which subceeds that of the first-order terms model.

When the network topology measures (Reg. 8 to Reg. 11) are added, the quadratic term of the PPI loses its high level of statistical significance in some cases. The partial effect of the PPI $\partial \pi / \partial \text{PPI}$ is now given by 0.43 for Reg. 8, 0.42 for Reg. 9, 0.47 for Reg. 10 and 0.44 for Reg. 11, when using the mean values for the relative change in the PPI ($\overline{\text{PPI}} = 0.03$), the link density ($\overline{\text{LD}} = 0.12$), the network density ($\overline{\text{ND}} = 0.01$) and the graph energy measures ($\overline{\text{GE}}_{\mathbb{Z}_2} = 32.2$ and $\overline{\text{GE}}_{\mathbb{R}} = 9.8$).

We find the following partial effects of the network topology measures on the CPI inflation (noting the interaction and second-order terms): $\frac{\partial \pi}{\partial \text{LD}} = 0.05$, $\frac{\partial \pi}{\partial \text{ND}} = 0.18$, $\frac{\partial \pi}{\partial \text{GE}_{\mathbb{Z}_2}} = 0.0001$, and $\frac{\partial \pi}{\partial \text{GE}_{\mathbb{R}}} = 0.001$. They all align well in size with the corresponding estimates of the first-order regressions (Reg. 2 to Reg. 5).

Most importantly, however, we find that the terms for $f_{\mathcal{S}\mathcal{A}u}$ in equation (31), given by $\frac{\partial^2 \pi}{\partial \text{PPI} \cdot \partial LD} = 0.32$, $\frac{\partial^2 \pi}{\partial \text{PPI} \cdot \partial ND} = 3.02$, $\frac{\partial^2 \pi}{\partial \text{PPI} \cdot \partial GE_{\mathbb{Z}_2}} \approx 0.02$ and $\frac{\partial^2 \pi}{\partial \text{PPI} \cdot \partial GE_{\mathbb{R}}} = 0.05$ from the panel data regression results are all positive. Moreover, these parameter values are all statistically different from zero. This implies that the transmission mechanism of changes in the producer prices to the CPI inflation rate are shaped by the demand-driven cross-price dependencies. More specifically, the demand-driven cross-price dependencies exacerbate any change in the producer prices

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on the CPI inflation rate. With a view to the link density and the binary graph energy, the extent of shock exacerbation occurs due to the diffusion effect. As the results of the network density and the non-binary graph energy highlight, the strength effect is also important alongside to the diffusion effect. Most importantly, the strength effect exacerbates the diffusion effect—this can again be seen by the increase in the goodness-of-fit measures (normal R^2 and adjusted R^2) of Reg. 9 and 11 relative to Reg. 8 and 10.

4.3 Further remarks

The results presented here are robust to various extensions in the form of additional variables used in the VAR model, alternative approaches to identifying the VAR models, additional explanatory variables in the panel data regression model, and the use of robust standard errors. In addition, we examined the sensitivity of the panel data regression to the time span of the Covid-19 pandemic, the subsequent global recovery and significant geopolitical turmoil (military invasions of Iraq, Lebanon, Libya, Ukraine, etc.). Our baseline results remain qualitatively robust to these changes and extensions. Additional robustness checks are discussed in the Online Appendix.

It is important to note that our regression analysis may suffer from the "generated regressor" problem, which occurs when the regressors themselves are estimated rather than directly observed. This can lead to biased standard errors and thus invalid inference. To mitigate this problem, an alternative approach would be to estimate the first- and second-order regression equations repeatedly over all draws from the posterior distribution of the network topology measures. This method would ensure that the variability and uncertainty in the network measures are adequately captured, resulting in more robust and reliable estimates.

Finally, we attempted to estimate the (32) equation using the network topology measures based on the supply-driven cross-price dependencies ($\tilde{\Gamma}$). However, significant data limitations hamper the implementation. On the one hand, calibration is not possible for some countries because I-O tables are not available. On the other hand, for many other countries, I-O tables are only available for a limited number of recent years. This limits both the time span and the country coverage, rendering impossible a proper estimation of equation (32).

5. Conclusion

We assess the role of demand-driven links between prices for the CPI inflation rate. Since the links arise from the complementary and substitutive properties of goods, they can be either negative or positive. Based on a simple theoretical model, we highlight the role of the structure and sign of these links in shaping the spillover effects of microeconomic price shocks on the CPI inflation rate, giving rise to a strength and a diffusion effect. The former is determined by the size and sign of the cross-price dependencies, with spillover effects increasing with the size of positive valued links, while negative links can give rise to both mitigating and exacerbating effects. With regards to the diffusion effect, when goods are complements, the spillover effects increase with the number of links; moreover, the presence of a link structure in the form of a cycle renders the amplification particularly pronounced.

We test the theoretical findings empirically by estimating demand-driven cross-price dependencies using the three-digit subindices of the CPI for 28 countries (UK and current EU member states). Our results can be summarized as follows

- Positive valued links dominate, highlighting the relative importance of the complementarity property between goods.
- The spillover effects of the price subindices on the CPI inflation rate are both negative and positive and their quantitative magnitude outweighs their weight in the CPI.

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- Demand-driven links between prices show remarkable differences to a supply side counterpart and tend to change over time, reflecting changes in consumer preferences.
- While demand-driven cross-price dependencies themselves have a statistically significant impact on the CPI inflation rate, more importantly, they shape the impact of producer prices on the CPI inflation rate.

These results highlight the role of the demand system in the transmission of microeconomic price shocks to the CPI inflation rate. By this, they shed light on the role of consumer preferences in the demand-driven diffusion of inflation. The complementary or substitutive nature of goods is key in this respect, leading to a mitigation or exacerbation of microeconomic price shocks on the CPI inflation rate.

The policy relevance of our findings stems from the goal of mitigating inflationary pressures arising from specific goods. Demand-driven links between prices can either amplify or attenuate price shocks, depending on the nature of these relationships. Therefore, policy effectiveness critically depends on a thorough understanding of these interactions. For instance, interventions aimed at stabilizing the prices of key complementary goods could have broader inflation-stabilizing effects. Conversely, measures that lower the prices of substitute goods may help reduce inflationary pressures by providing consumers with alternative options. Thus, our results underscore the importance for policymakers of considering both demand- and supply-side interactions to avoid incomplete assessments and enhance the effectiveness of policy interventions.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/S1365100525000070.

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Competing interests. The authors declare none.

Notes

1 The nine goods categories are: food, beverage and tobacco; clothing and footwear; gross rent, fuel and power; house operations; medical care; education; transport and communication; recreation; other items.

2 Consider for instance (Chapters 7–10 Varian 1992), (Chapter 2 Mas-Colell et al., 1995) and (Chapters 1–2 Jehle and Reny 2011) for further details.

3 What Varian (1992); Jehle and Reny (2011) call "Marshallian demand" is called "Walrasian demand" by Mas-Colell et al. (1995).

4 Consider Mulhern and Leone (1991); Regmi and Seale (2010); Auer and Papies (2020), among others.

5 Werner (2009) shows that for any real matrix $\mathcal{M}$ we have that $\varrho(\mathcal{M}) \leq ||\mathcal{M}||$, where $||\cdot||$ denotes any natural norm and $\varrho(\mathcal{M})$ is the spectral radius which is defined as the maximum of the absolute values of the eigenvalues of $\mathcal{M}$. Then it follows that $\varrho(\mathcal{M}) \leq ||\mathcal{M}||_\infty$, the maximum absolute row sum, and $\varrho(\mathcal{M}) \leq ||\mathcal{M}||_1$, the maximum absolute column sum. So, if the row sum or the column sum of the matrix $\mathcal{M}$ is less than unity, then these results verify the spectral radius condition. In this case, $I - \mathcal{A}$ is invertible and can be written as the Neumann-series $\sum_{k=0}^{\infty} \mathcal{A}^k = (I - \mathcal{A})^{-1}$.

6 Auer and Papies (2020) find an overall mean cross-price elasticity of 0.26 with 70 percent of all observations being below the mean, and a median of 0.10; similar values (in amount) are provided in Regmi and Seale (2010).

7 More precisely, the network in case (d) constitutes an *acyclic* graph (commonly referred to as *directed acyclic graph*, DAG) and the network in case (e) is a *cyclic* graph.

8 In a directed graph, the maximum number of links (excluding self-loops) is equal to $N(N-1)$.

9 There are various alternatives, as for instance, the *R-measure* of Kim and Kim (2005). They propose a cycle coefficient R that represents the cyclic characteristics of complex networks. Another interesting network topology measure in this context is given by the *cycle ratio* as proposed by Fan et al. (2021), or the cycle nodes ratio, which describes the ratio of the number of nodes belonging to cycles to the number of total nodes (Zhang et al. 2021).

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10 In particular, the network is given by: (Node 1)$\frown$(Node 2)$\frown$(. . .)$\frown$(Node n). In this case, $\varsigma^{(c)} = w\alpha \sum_{i=0}^{n-1} \alpha^i = \frac{w\alpha}{1-\alpha}$ if $|\alpha| < 1$, which is the same as in case (e).
11 If the cycle involves only two nodes: $(\text{Node } 1)\circlearrowright(\text{Node } 2)$, then $\pi = \frac{w}{1-\alpha}$ and $\varsigma = \frac{w\alpha}{1-\alpha}$, which is the same as in case (e), where the cycle involves three nodes.
12 With a view to Figure 1, for $\alpha = 1$ we have that $\text{GE}_{\mathbb{R}} = \text{GE}_{\mathbb{Z}_2}$.
13 The extent of shock mitigation within the network is the core of the *diversification channel* as outlined in Lucas (1977). He argues that idiosyncratic shocks wash out in the aggregate if one focuses on a sufficiently high degree of dis-aggregation; or stating it differently, absent some form of granularity such as fatness in the firm size distribution or the different out-degrees, idiosyncratic shocks are irrelevant in the aggregate.
14 Homothetic preferences apply when the utility function $u(\boldsymbol{x})$ has a linear homogeneity property, which means that u satisfies the following condition: $u(\lambda \boldsymbol{x}) = \lambda u(\boldsymbol{x})$ for all $\lambda > 0$ and all $\boldsymbol{x} \in \mathbb{R}_+$. This assumption implies that each indifference curve is a radial projection of the unit utility indifference curve. It also implies that all income elasticities of demand are unity.
15 The weights were re-adjusted to account for the omission of five subindices.
16 An alternative approach that allows to simultaneously rather than sequentially estimate all parameters is to adopt a spatial econometric framework, as demonstrated in a cross-country setting by Piribauer et al. (2023), among others. However, the limited set of instruments available to us renders this approach less reliable for identifying demand-driven cross-price dependencies.
17 We carry out a temporal disaggregation of the quantity variables (x_t^i and x_t^j) to a *monthly* frequency using the monthly retail trade indices and the methodology of Chow and Lin (1971).
18 For some countries, the sample of the CPI data starts later than January 2000. In these cases, we use the earliest available data.
19 It is worth noting that the use of our four-variable VAR models to estimate cross-price dependencies is based on the assumption that the dynamics for prices and quantities of two goods are fully explained by the two goods-specific demand and supply shocks. While this approach allows us to isolate the demand and supply interactions between two specific goods, it does not take into account potential influences from other shocks. A promising approach for future research may therefore be to consider a much larger set of interactions.
20 Note that we use the approach in equation (25) for sparsifying the adjacency matrix using a post-inference operation. We thereby follow the idea of Hahn and Carvalho (2015), who decouple shrinkage and selection. In their framework, a decision problem is formulated to determine which (shrunk) coefficients are sufficiently close to zero to be treated as exactly zero.
21 The demand-driven network has cycles involving nodes 5 and 6, among others. The supply-driven network has individual cycles involving nodes 1 and 3, and nodes 7 and 39.
22 A similar extent of heterogeneity is identified in Friesenbichler and Glocker (2019); Crespo Cuaresma and Glocker (2023) in the context of tradable and nontradable goods' prices.
23 The structure of cross-price interdependencies could also change with different sources of purchase, given unchanged consumer preferences: Glocker and Piribauer (2021) highlight that price rigidities are lower in online retail markets. The different degree of rigidities in turn shapes the overall price structure of cross-price dependencies.
24 The unemployment gap (U-Gap) is measured by the cyclical component of the monthly year-over-year change in unemployment, extracted using the Hodrick-Prescott filter with a smoothing parameter of 14,400 (Ravn and Uhlig, 2002).
25 The time framework of the windows are specified as follows: Window 1 (−04): M1.2000-M12.2004; Window 2 (−07): M6.2002-M5.2007; Window 3 (−09): M11.2004-M10.2009; Window 4 (−12): M4.2007-M3.2012; Window 5 (−14): M9.2009-M8.2014; Window 6 (−17): M2.2012-M1.2017; Window 7 (−19): M7.2014-M6.2019; Window 8 (−21): M1.2017-M11.2021; Window 9 (−24): M6.2019-M1.2024. Hence, each window contains around 30 months of new data and around 30 months of a previous window's data ("overlap").
26 The selection of nine windows over a period of 60 months presents a challenging tradeoff. On the one hand, there is a need for a sufficient number of observations to enable an accurate estimation of the BVAR models for the price-Jacobian matrix. On the other hand, there is a requirement for a sufficient number of "windows," or time observations, to ensure the adequacy of the panel regression models. After careful consideration, we concluded that nine windows represent an appropriate compromise, providing both reliable estimation of the BVAR models and sufficient amount of temporal-data for the panel regressions.

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