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Abstract
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SECTORAL AND AGGREGATE EFFECTS OF SUPPLY CHAIN DISRUPTIONS IN A SMALL OPEN ECONOMY

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ABSTRACT. We present a country-specific measure of supply chain disruptions and compare it with a global counterpart. We identify each measure's macroeconomic role and consider a sectoral extension using the two-digit NACE level of disaggregation and a multi-sector general equilibrium model to assess the contribution of each sector to CPI inflation. Our results indicate that supply chain disruptions elicit substantial contractionary effects both at the macroeconomic level and in most sectors, and that country-level disruptions significantly dominate their global counterparts. The manufacturing sector emerges as the main domestic transmitter of shocks, with significant spillovers to private services. Consumer preferences tend to spread supply chain disruptions fairly evenly across COICOP categories as they pass through to CPI inflation.

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1. Introduction

The decades leading up to the COVID-19 pandemic were marked by an increasing trend toward organizing the production of goods through global value chains (Ascari et al., 2024). This shift contributed to greater efficiency in manufacturing, as firms were able to specialize and hence to capitalize on comparative advantages and lower production costs. Concurrently, this trend contributed to the buildup of risk due to an ever-increasing reliance on imported intermediate goods. One instance that brought to the surface the consequences of this very risk materializing was the recovery from the COVID-19 pandemic: As economies began recovering from the recession, a pronounced dispersion in its pace and magnitude became evident across countries.[1] The fact that some countries recovered more swiftly and robustly suggests that domestic factors mattered. The results in Kemp et al. (2023), Ascari et al. (2024) and IMF (2024, Chapter 2) indicate that disruptions in global supply chains particularly slowed the recovery in countries heavily dependent on imported intermediate goods. The resulting supply shortage caused prices to soar up to levels not seen for decades.

Benigno et al. (2022) construct an index measuring supply chain disruptions at the global level and highlight the index's ability to explain a large part of the producer price inflation rate in the US. De Santis (2024) stresses the importance of this index for the euro currency block and Cevik and Gwon (2024) for several other countries. Notwithstanding the capabilities of the global index, however, it faces significant challenges at the country level. Its adequacy depends crucially on country characteristics related to idiosyncratic production structures, trade relations, or the reliance on imported intermediate goods. For example, the impact of supply chain disruptions in a country with a large manufacturing sector that relies heavily on imported components will be very different from that in a country with a predominantly service-based economy or one that imports fewer intermediate goods. A country-specific index would therefore better capture the nuances of local disruptions, such as those related to domestic logistics, border controls or sectoral dependencies, which may not be immediately relevant at the global level.

[1] A similar dispersion is reported as to the severity of the output contraction in the wake of the COVID-19 pandemic (see IMF, 2021; Glocker and Piribauer, 2021, among others).

Our contribution can be outlined as follows. First, we construct a composite index that quantifies the extent of supply chain disruption at the country level, inspired by Benigno et al. (2022). We then examine the implications of this index at the macroeconomic level, assessing its impact on aggregate inflation and real economic activity and compare the results to those of the global index. In order to gain deeper insights into aggregate dynamics, we delve into sectoral dynamics by extending our analysis to the two-digit NACE Rev. 2 level of production, covering 63 sectors. This allows us to examine both the direct and indirect effects of supply chain disruptions on inflation and output dynamics in these sectors. Finally, we introduce the sector-specific results into a multi-sector (static) general equilibrium model to examine the contribution of each sector to the overall CPI inflation rate, taking into account each sector's particular exposure to supply chain disruptions.

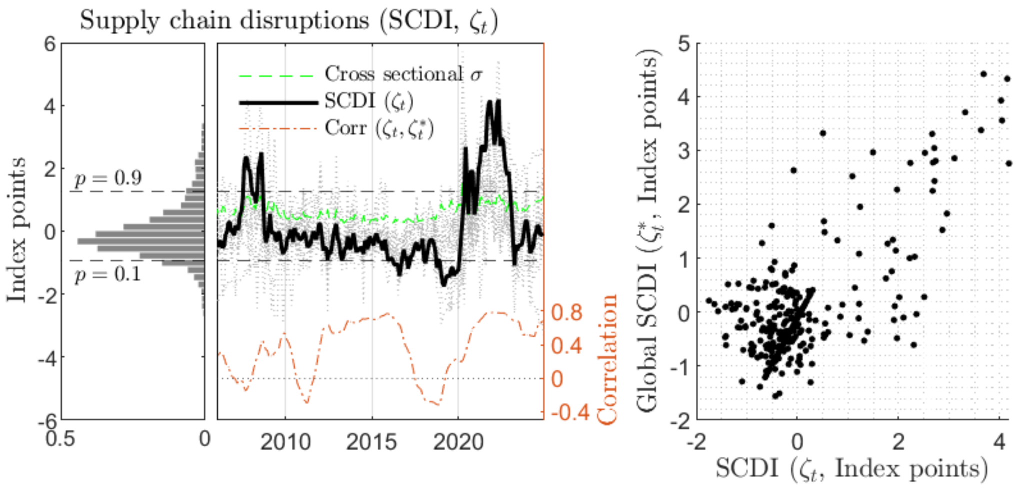
We focus on Austria as a case study for the country-specific analysis, which provides a particularly interesting context due to its (i) large manufacturing sector relative to GDP (Hölzl and Reinstaller, 2011), (ii) high degree of integration into global value chains (Ascari et al., 2024), and (iii) significant reliance on imported intermediate and energy goods (Pichler et al., 2024). All these characteristics suggest that Austria should have experienced significant sectoral and economy-wide effects from supply chain disruptions, rendering it an ideal country setting to explore the broader implications of such shocks. The use of a small open economy addresses concerns about possible endogeneity between economic performance and supply chain disruptions, allowing the results to be interpreted causally. The findings should not be seen as country-specific. The country characteristics are shared by many other European economies, thus extending the applicability of our findings to a broader context.

To preview some results, the structural analysis reveals that supply chain disruptions behave as contractionary supply shocks, reducing real economic activity and increasing inflation. Although they account for a small share of the variation in these variables on average, their impact on inflation and output was particularly pronounced in 2021 and 2022. Moreover, supply chain disruptions at the country level have a stronger explanatory power than the global index in determining inflation and real activity. This highlights the superior information content of the country-specific measure for supply chain disruptions relative to a global counterpart. On the sector level, supply chain disruptions lead to contractionary effects across most sectors, especially in manufacturing, which also experiences the highest inflationary pressures. The sectoral variation in output contraction is largely explained by unit labor costs, while inflationary responses are most significant in sectors reliant on imported inputs. Introducing these effects into a multi-sector general equilibrium model, we identify both the direct and indirect effects of supply chain disruptions on CPI inflation. We find that 78 percent of the inflationary effect of supply chain disruptions emerges from cross-sector dependencies within the production network, with manufacturing subsectors being the primary transmitters of these shocks. Consumer preferences lead to a fairly even distribution of supply chain disruptions across COICOP categories in their transmission to CPI inflation.

The recent literature has extensively examined the macroeconomic and sectoral implications of global supply chain disruptions, particularly following the COVID-19 pandemic. A key focus has been the development of indices to quantify these pressures, such as the Global Supply Chain Pressure Index (see Benigno et al., 2022) and an index based on container ship congestion (see Bai et al., 2024). Empirical analyses using these indices reveal that disruptions have been a significant driver of inflation (Ascari et al., 2024), with shocks to global supply chains exhibiting a persistent and hump-shaped impact on prices. These disruptions can lead to both reduced output and increased unemployment, highlighting stagflationary effects (see Bai et al., 2024). In addition, financial distress can cascade through supply chains, affecting upstream suppliers and thus having contractionary aggregate effects (see Dai et al., 2021). Furthermore, sector-specific analyses, such as those using input-output models to assess energy related shocks (see Pichler et al., 2024), demonstrate the heterogeneous impacts across industries due to supply chain vulnerabilities. This underscores the importance of sector-specific and product-specific factors (Reiter and Stehrer, 2023) in shaping aggregate dynamics as also highlighted in Molnarova and Reiter (2022); Lehmann and Zarges (2025). Overall, the literature emphasizes the significant and widespread economic consequences of disruptions in supply chains.

The paper is structured as follows. Section 2 introduces the country specific supply chain disruptions index and Section 3 motivates the empirical model and provides the results for the macroeconomic analysis. Section 4 extends the model of Section 3 to the sectoral level and provides sector specific findings and

FIGURE 1. Descriptive overview



Note: The (Austrian) supply chain disruptions index is shown in the second subpanel as a black solid line, together with all subindices (gray dotted lines) and the standard deviation across the subindices (green dashed line). The first subpanel shows the histogram of the supply chain disruptions, and the third subpanel shows the supply chain disruptions index relative to its global counterpart as developed in Benigno et al. (2022). The dynamic conditional correlation is computed based on the methodology of Engle and Sheppard (2001).

an explanation for the sectoral heterogeneity. Section 5 introduces the sectoral results into a multi-sector general equilibrium model and examines sector-specific contributions to the CPI inflation rate. Finally, Section 6 concludes.

2. Quantifying supply chain disruptions

We develop a composite index, subsequently denoted by ζ_t, to measure supply chain disruptions at the national (i.e. Austrian) level.[2] This exercise is grounded in the availability of suitable data and draws inspiration from the index of global supply chain disruptions (ζ_t^*) developed by Benigno et al. (2022). Our composite index is constructed using monthly data starting in 2006 and consists of ten subindicators, five of which are derived from national business survey data and the rest from global transport price data. Price data are used as reliable scarcity signals, while the survey data provide a direct measure for the timely availability of input factors to production and, consequently, the extent to which production is constrained by supply chain disruptions. Among the survey data, three cover delivery times, order backlogs and inventories in

[2]The Austrian index is published on the dashboard of the Supply Chain Intelligence Institute Austria as Austrian supply chain pressure Index (`https://ascii.ac.at/dashboard/`).

the manufacturing sector and the remaining two information on shortages of materials and equipment as input factors to production in both the manufacturing and the construction sector. The transport price subindicators include three measures of ocean freight prices (the Baltic Dry (cape-size) index and two container freight price indices) and two global air freight prices, all of which measure price movements on major routes between North America, Asia and Europe.

Following Benigno et al. (2022), we remove the effects of cyclical demand from the subindicators to ensure that the composite index exclusively reflects supply chain disruptions.[3] As the selected indicators also contain information that are not related to supply chain disruptions, we construct the composite index by applying principal component analysis to the ten subindicators. Further details on the construction of the index and the treatment of the subindicators (mixed frequency, etc.) can be found in the Appendix.

The temporal evolution of the resulting Supply Chain Disruptions Index (SCDI, ζ_t) is depicted in the second subpanel of Figure 1. This index successfully captures well-documented historical episodes of supply chain disruptions, including those preceding the global financial crisis[4] of 2008–2009 and disruptions associated with the COVID-19 pandemic and the subsequent global economic recovery. The informational content of the various subindicators remains relatively stable over time, as indicated by the consistent temporal profile of the standard deviation (green line in the second subpanel), underscoring the sustained relevance of each subindicator and, consequently, the robustness of the composite index. Nevertheless, some degree of right-skewness is evident (first subpanel); however, this skewness is not excessive.[5] Moreover, its magnitude is comparable to that of the index proposed by Benigno et al. (2022). Our index exhibits a positive relationship (third subpanel and Table 1) with its global counterpart (ζ_t^*), although the correlations[6] range from -0.3 to 0.8

[3]This approach also makes it possible to separate supply chain disruptions from excessive commodity price fluctuations, which are largely driven by demand-side factors (Jacks and Stuermer, 2020).

[4]An interpretation of the increase in the Austrian supply chain disruptions index during 2008–2009 is Austria's close integration into German-centered manufacturing value chains, which may have transmitted intermediate-input shortages during the sharp contraction in German manufacturing.

[5]The Jarque-Bera test fails to reject the null hypothesis that the data follow a normal distribution.

[6]We use dynamic conditional correlations (DCC), computed based on the methodology of Engle and Sheppard (2001), to examine the temporal (in-)stability of the correlation between the two indices.

Table 1. Cross-correlations and Granger-causality test results

	ζ_t	ζ_t^*	$\hat{y}_t$	π_t
	Cross-correlation			
Global SCDI (ζ_t^*)	0.67			
Output gap ($\hat{y}_t$)	-0.31	-0.20		
Inflation (π_t)	0.66	0.53	0.58	
	Granger-causality test: p-values			
(National) SCDI (ζ_t)	0.00	0.10	0.32	0.87
Global SCDI (ζ_t^*)	0.42	0.00	0.66	0.76
Output gap ($\hat{y}_t$)	0.08	0.65	0.00	0.07
Inflation (π_t)	0.00	0.08	0.00	0.00

Note: The table shows the cross-correlations and the p-values for the Granger-causality test for a set of variables including the (Austrian) supply chain disruptions index (ζ_t), its global counterpart (ζ_t^*) as presented in Benigno et al. (2022), and the output gap ($\hat{y}_t$) and the inflation rate (π_t, based on the GDP deflator, year-over-year relative change).

(orange line in the second subpanel). This variation reflects Austria's substantial reliance on global supply chains, while also highlighting the influence of significant country-specific elements.[7]

The national and global indices correlate negatively with the (Austrian) output gap and positively with inflation (Table 1) with the correlations being noticeably larger in size (in absolute value terms) with the national index. The Granger-causality test results reveal that the national index Granger-causes inflation at the one percent level of statistical significance, while its effect on the output gap is weaker in terms of statistical significance. The global index Granger-causes the national index solely at the ten percent level. Notably, neither the output gap nor inflation Granger-cause any of the supply chain disruption indices. However, the output gap Granger-causes inflation at the one percent level of statistical significance, while inflation, in turn, Granger-causes the output gap only at the ten percent level. These results indicate an interplay between supply chain disruptions, inflation, and output, with some directional relationships being stronger than others.

[7]In the case of Austria, the country-specific elements are probably not primarily due to pure national factors, but are also an expression of Austria's integration into the regional manufacturing value chain, the so-called Central European manufacturing core, which includes Germany, the Czech Republic, Slovakia, Hungary and Poland in addition to Austria.

3. Macroeconomic implications of supply chain disruptions

We now empirically investigate the implications of supply chain disruptions. In doing so, we consider the standard New Keynesian (NK) three-equations model[8] as theoretical basis (Galí, 2008, Chapter 3) and starting point for the analysis

$$(1) \qquad \hat{y}_t = -\frac{1}{\eta}\left(i_t - \pi_{t+1|t}\right) + \hat{y}_{t+1|t} + \nu_t^D, \quad \text{with} \quad \nu_t^D \sim N(0, \sigma^2_{\nu^D})$$

$$(2) \qquad \pi_t = \beta\pi_{t+1|t} + \kappa\hat{y}_t + \nu_t^S, \quad \text{with} \quad \nu_t^S \sim N(0, \sigma^2_{\nu^S})$$

$$(3) \qquad i_t = \phi_\pi\pi_t + \phi_y\hat{y}_t + \nu_t^i, \quad \text{with} \quad \nu_t^i \sim N(0, \sigma^2_{\nu^i})$$

Equation (1) represents the dynamic IS curve, (2) the NK Phillips curve, and (3) the Taylor rule. $\hat{y}_t$ and π_t denote the output gap and inflation, $\hat{y}_{t+1|t}$ and $\pi_{t+1|t}$ their one-step ahead forecasts (or the next period's expected values), and the $\nu_t^{(\cdot)}$-terms are structural shocks. The parameter $\eta \geq 1$ is the coefficient of relative risk aversion, $\beta < 1$ is the discount factor, and $\kappa \geq 0$ reflects the price stickiness. Monetary policy is characterized by $\phi_\pi > 1$ and $\phi_y \in [0, 1]$.

While deriving the rational expectations solution for this model is an option, we adopt a different approach. We solve the model by assuming static expectations for the two forward-looking variables ($\hat{y}_{t+1|t}$ and $\pi_{t+1|t}$), which will subsequently turn out as being sufficient for our purposes and at the same time more convenient than the rational expectations solution.[9] The static expectations assumption states that economic agents expect the value of an economic variable in the next period to be proportional to its current value. Against this background, we assume that a simple first-order difference equation provides a reasonable forecast, as suggested by Doan et al. (1984) for most economic time series. This gives rise to $\hat{y}_{t+1|t} = \rho_y\hat{y}_t$, $\pi_{t+1|t} = \rho_\pi\pi_t$, where $\rho_y \in (-1, 1)$ and $\rho_\pi \in (-1, 1)$. Substituting these expressions, along with the Taylor rule

[8] While the theoretical motivation in the paper is based on the standard closed-economy New Keynesian model, the corresponding small-open-economy framework leads to a closely related representation in terms of the output gap and inflation; see, e.g., Galí (2008) Chapter 7. The main conceptual difference is that, in the open-economy setting, the relevant inflation concept is domestically produced goods inflation, whereas CPI inflation additionally reflects movements in the terms of trade. Since our empirical specification uses the GDP deflator, which refers to prices of final domestically produced goods and services, we do not believe that an open-economy formulation would alter the core identification strategy, though it provides a more natural interpretation for a small open economy such as Austria.

[9] We present the rational expectations solution in the Appendix. The implications for the identification of the empirical model are the same across both assumption of expectations formation (static expectations and rational expectations).

(3) into the IS curve (1) and the Phillips curve (2), we obtain

$$\hat{y}_t = \delta\pi_t + \eta\nu_t^D - \nu_t^i, \tag{4}$$

$$\pi_t = \varsigma\hat{y}_t + \frac{\nu_t^S}{1-\beta\rho_\pi}, \tag{5}$$

where $\delta = -\frac{\phi_\pi-\rho_\pi}{\eta(1-\rho_y)+\phi_y}$ and $\varsigma = \frac{\kappa}{1-\beta\rho_\pi} > 0$. We will refer to these equations as the aggregate demand (AD) and aggregate supply (AS) relations. In the AD curve, δ represents the short-run price elasticity of demand, while the AS curve is expressed in inverse form, with $\varsigma > 0$ denoting the reciprocal of the price elasticity of supply. Under the assumption that the Taylor principle ($\phi_\pi > 1$) holds, we have $\delta < 0$, which we adopt as our baseline assumption. However, under certain conditions (see Bilbiie, 2008, for example), an inverted Taylor principle could result, giving rise to $\delta > 0$. In this case, for an equilibrium to exist, it is sufficient that $\delta < 1/\varsigma$, leading to an AS curve ($d\hat{y}_t/d\pi_t|_{\text{AS}} = 1/\varsigma$) that is steeper (in the $[\pi_t, \hat{y}_t]$-space) than the AD curve ($d\hat{y}_t/d\pi_t|_{\text{AD}} = \delta$). While we discuss this possibility in a robustness check involving a size restriction ($\varsigma > 1/\delta$), we maintain the stronger assumption that $\delta < 0$ for our baseline results, which is consistent with the AS-AD framework presented in Heijdra (2017, Chapter 2). This assumption reflects the positive relationship between inflation and the output gap in the AS curve, and the inverse relationship in the AD curve.

Using the above theoretical framework, we consider an extension to the following empirical model

$$\hat{y}_t = \delta\pi_t + \mathbf{b}_1'\mathbf{x}_{t-1} + u_t^D, \quad \delta < 0 \tag{6}$$

$$\pi_t = \varsigma\hat{y}_t + \mathbf{b}_2'\mathbf{x}_{t-1} + u_t^S, \quad \varsigma > 0 \tag{7}$$

where $\mathbf{y}_t = [\hat{y}_t,\ \pi_t]'$ is the vector of endogenous variables, and the vector $\mathbf{x}_{t-1} = \left[\mathbf{y}_{t-1}', \ldots,\ \mathbf{y}_{t-m}'\right]'$ is of dimension $(k \times 1)$, with $k = 2m$ and m being the lag length, and finally, $\mathbf{b}_1$ and $\mathbf{b}_2$ are $(k \times 1)$ vectors of coefficients. The composite structural demand and supply shocks are given by $u_t^D = \eta\nu_t^D - \nu_t^i$ and $u_t^S = \frac{\nu_t^S}{1-\beta\rho_\pi}$, with variances $\sigma_{u^D}^2 = \eta^2\sigma_{\nu^D}^2 + \sigma_{\nu^i}^2$ and $\sigma_{u^S}^2 = \frac{\sigma_{\nu^S}^2}{(1-\beta\rho_\pi)^2}$.

Equations (6) and (7) can now be cast into the following multivariate system

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{u}_t, \quad \text{with} \quad \mathbf{u}_t \sim N(\mathbf{0}, \mathbf{D}) \tag{8}$$

where $\mathbf{u}_t = \left[u_t^D,\ u_t^S\right]'$ is a (2×1) vector of structural shocks with variance-covariance matrix given by the matrix $\mathbf{D} = \text{diag}(\sigma_{u^D}^2, \sigma_{u^S}^2)$, $\mathbf{B} = [\mathbf{b}_1,\ \mathbf{b}_2]'$, and the matrix $\mathbf{A}$ is given by

$$\mathbf{A} = \begin{bmatrix} 1 & -\delta \\ -\varsigma & 1 \end{bmatrix} \tag{9}$$

Equation (8) represents a structural vector-autoregressive (SVAR) model. A key focus of this model is on the structural shocks u_t^D and u_t^S, both of which are composites of various underlying demand and supply shocks. For example, the composite demand shock $u_t^D = \eta\nu_t^D - \nu_t^i$ encompasses the monetary policy shock (ν_t^i), while ν_t^D can be decomposed into further granular demand shocks that include fiscal policy shocks, household preference shocks, household uncertainty shocks, foreign demand shocks, and the like. To the extent that u_t^D is a composite of various underlying demand shocks, the same is true for the supply shock u_t^S, which can also be viewed as a combination of various underlying supply shocks, such as cost-push shocks related to input prices, technology shocks, business uncertainty shocks, and other related disturbances. Our primary interest is in the supply shock u_t^S, specifically its subcomponent related to supply chain disruptions. The supply chain disruptions index ζ_t serves as a measure of frictions in supply chains across production networks. This index captures a particular type of supply shock, one that reflects shortages caused by adverse supply side developments specific to disruptions in the supply chain. Given the small open economy framework and the fact that the supply chain disruptions are not affected (Granger-caused) by the output gap ($\hat{y}_t$) and inflation (π_t), we treat ζ_t as exogenous to domestic variables. Since ζ_t represents supply side shocks arising from supply chain disruptions, while u_t^S represents a broader, composite supply shock, we decompose u_t^S into two orthogonal elements: $\tilde{u}_t^S$ and ζ_t, as follows

$$u_t^S = \tilde{u}_t^S + \vartheta\zeta_t, \tag{10}$$

where $\tilde{u}_t^S$ reflects the set of (structural) residual supply shocks[10] not directly attributable to ζ_t. Given that $\tilde{u}_t^S \perp \zeta_t$, we then get for $E(u_t^S)^2 = \sigma_{u^S}^2 \in \mathbf{D}$ the

[10]The term "residual" is used here to refer to the set of supply shocks that remain after ζ_t has been removed, and it should not be confused with its meaning in a regression analysis.

following

$$\sigma_{u^S} = \sqrt{\sigma^2_{\tilde{u}^S} + \vartheta^2 E(\zeta_t)^2} \tag{11}$$

and ϑ is a parameter. Defining $\tilde{\mathbf{u}}_t = \left[u_t^D,\ \tilde{u}_t^S\right]'$, the vector of structural shocks can be re-written as

$$\mathbf{u}_t = \tilde{\mathbf{u}}_t + \boldsymbol{\vartheta}\zeta_t, \quad \text{with} \quad \boldsymbol{\vartheta} = [0,\ \vartheta]' \tag{12}$$

Finally, using equation (12) in equation (8) implies that the SVAR can be re-written as an SVAR with an exogenous variable (SVARX)

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \boldsymbol{\vartheta}\zeta_t + \tilde{\mathbf{u}}_t, \quad \text{with} \quad \tilde{\mathbf{u}}_t \sim N(\mathbf{0}, \tilde{\mathbf{D}}) \tag{13}$$

where $\tilde{\mathbf{D}} = \text{diag}(\sigma^2_{u^D}, \sigma^2_{\tilde{u}^S})$, and we have the following association between the variance-covariance matrices $\mathbf{D}$ and $\tilde{\mathbf{D}}$

$$\mathbf{D} = \tilde{\mathbf{D}} + \boldsymbol{\vartheta}\boldsymbol{\vartheta}' E(\zeta_t)^2 \tag{14}$$

where the (1,1)-element in $\mathbf{D}$ is given by $\sigma^2_{u^D}$ (same as in $\tilde{\mathbf{D}}$) and the (2,2)-element by $\sigma^2_{u^S}$ as of equation (11), with $\sigma^2_{u^S} \geq \sigma^2_{\tilde{u}^S}$.

The SVAR model in equation (13) has the following reduced-form representation

$$\mathbf{y}_t = \boldsymbol{\Phi}\mathbf{x}_{t-1} + \boldsymbol{\chi}\zeta_t + \tilde{\boldsymbol{\epsilon}}_t \tag{15}$$

$$\tilde{\boldsymbol{\epsilon}}_t = \mathbf{H}\tilde{\mathbf{u}}_t, \quad \text{with} \quad E(\tilde{\boldsymbol{\epsilon}}_t\tilde{\boldsymbol{\epsilon}}_t') = \tilde{\boldsymbol{\Sigma}} \tag{16}$$

where $\mathbf{H} = \mathbf{A}^{-1}$, $\boldsymbol{\Phi} = \mathbf{HB}$, $\boldsymbol{\chi} = \mathbf{H}\boldsymbol{\vartheta}$ and $\tilde{\boldsymbol{\Sigma}} = \mathbf{H}\tilde{\mathbf{D}}\mathbf{H}'$, with $\tilde{\boldsymbol{\epsilon}}_t$ being the (2×1) reduced-form error term. The reduced-form representation is given by a VARX model, i.e., a VAR with an exogenous variable (in our case, ζ_t). The findings presented in Section 2 lend strong support to the validity of treating the supply chain disruptions index as an exogenous variable within the VAR framework.

Most importantly, noting that the vector $\mathbf{u}_t$ contains the composite structural shocks, the corresponding composite reduced-form error term $\boldsymbol{\epsilon}_t$ is given by

$$\boldsymbol{\epsilon}_t = \tilde{\boldsymbol{\epsilon}}_t + \boldsymbol{\chi}\zeta_t, \quad \text{with} \quad E(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') = \boldsymbol{\Sigma}, \tag{17}$$

$$\boldsymbol{\Sigma} = \tilde{\boldsymbol{\Sigma}} + \boldsymbol{\chi}\boldsymbol{\chi}' E(\zeta_t)^2. \tag{18}$$

where equations (12) and (16) were used. It is important to distinguish between $\mathbf{\Sigma}$ and $\tilde{\mathbf{\Sigma}}$. These two matrices differ with respect to one important element, which is the ζ_t-part of the composite supply shock u_t^S. The matrix $\mathbf{\Sigma}$ is the reduced-form variance-covariance containing the variances of both the composite demand shock (u_t^D) and the composite supply shock (u_t^S). More specifically, the elements of $\mathbf{\Sigma}$ are given by a linear combination of the variances of u_t^D and u_t^S. In contrast, while the matrix $\tilde{\mathbf{\Sigma}}$ still contains the composite demand shock (u_t^D) in full, it, however, only contains a portion of the supply shock. Since it only contains $\tilde{u}_t^S$, it hence omits those elements of the supply shock that are akin to supply chain disruptions, captured in ζ_t (consider equation (10)). In view of the structural equations system put forth by equations (6)-(7), the identification of the elements in the matrix $\mathbf{A}$ requires the composite supply shock u_t^S, rather than just its subcomponent $\tilde{u}_t^S$. Therefore, $\mathbf{\Sigma}$ is considered the appropriate reduced-form variance-covariance matrix for the subsequent identification of $\mathbf{A}$ and hence the SVAR model. We will show below the consequences for the estimated price elasticities when using $\tilde{\mathbf{\Sigma}}$ in the identification instead of $\mathbf{\Sigma}$.

Relation to literature. We consider this approach as being related to the external instruments approach in VAR analysis (see Stock and Watson, 2018, among others). By incorporating an external instrument directly as an exogenous variable in a VARX model, we implicitly assume that the instrument fully captures the structural shock of interest and affects the endogenous variables solely through the channel of that specific shock. This contrasts with the traditional external instruments approach, where the instrument serves as a proxy for an unobserved structural shock. Notably, simply including the instrument as an additional variable in a VAR model does not necessarily establish a direct link to a specific structural shock. In our case, this connection is explicitly established through equation (12), where ζ_t is directly related to the supply shock u_t^S. However, if the instrument contains measurement error or is only imperfectly correlated with the true shock, treating it as exogenous in a VARX framework may introduce attenuation bias.

3.1. **Identification.** An important element of our empirical approach concerns the identification of the structural equations system (6)-(7), that is, the transformation of the reduced-form VAR model (15) into the structural form (13). We already discussed the role of the reduced-form variance-covariance matrices $\mathbf{\Sigma}$ and $\tilde{\mathbf{\Sigma}}$ in this context. We now discuss the particular approach that we chose for the identification.

We employ sign restrictions. However, in contrast to the literature (see Baumeister and Hamilton, 2015, among others), we do not consider sign restrictions on the impulse response functions,[11] but on the elements in the matrix $\mathbf{A}$. In view of the structural equations system (6)-(7), we expect the following signs of the elements in the matrix $\mathbf{A}$

$$\text{sgn}(\mathbf{A}) = \begin{bmatrix} + & + \\ - & + \end{bmatrix} \tag{19}$$

where the "+" and "−" symbols refer to the sign restrictions that we impose. The first row identifies the AD relation, equation (6), and the second row the AS relation, equation (7).

We use the eigenvector-eigenvalue decomposition of the variance-covariance matrix $\mathbf{\Sigma}$ given in equation (18) and define $\mathbf{V} = \mathbf{E_\Sigma}\mathbf{\Lambda}_{\mathbf{\Sigma}}^{1/2}$, where $\mathbf{E_\Sigma}$ is the (orthogonal) matrix of eigenvectors and $\mathbf{\Lambda_\Sigma}$ 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 $\mathbf{E_\Sigma}$ 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 (19), 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.

[11] While we also consider shocks to supply chains as in Bai et al. (2024), we regard our identification approach as both more intuitive and by far simpler, since our methodology relies solely on assumptions regarding the coefficients of price elasticities within a classical (aggregate) demand and supply framework. In contrast, the approach proposed by Bai et al. (2024) necessitates a theoretical model to motivate the sign restrictions on the impulse response functions and hence the matrix $\mathbf{H}$.

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. The matrices $\mathbf{A}$ and $\mathbf{H}$ are related by the following: $\mathbf{H} = \mathbf{A}^{-1}$, as highlighted previously.

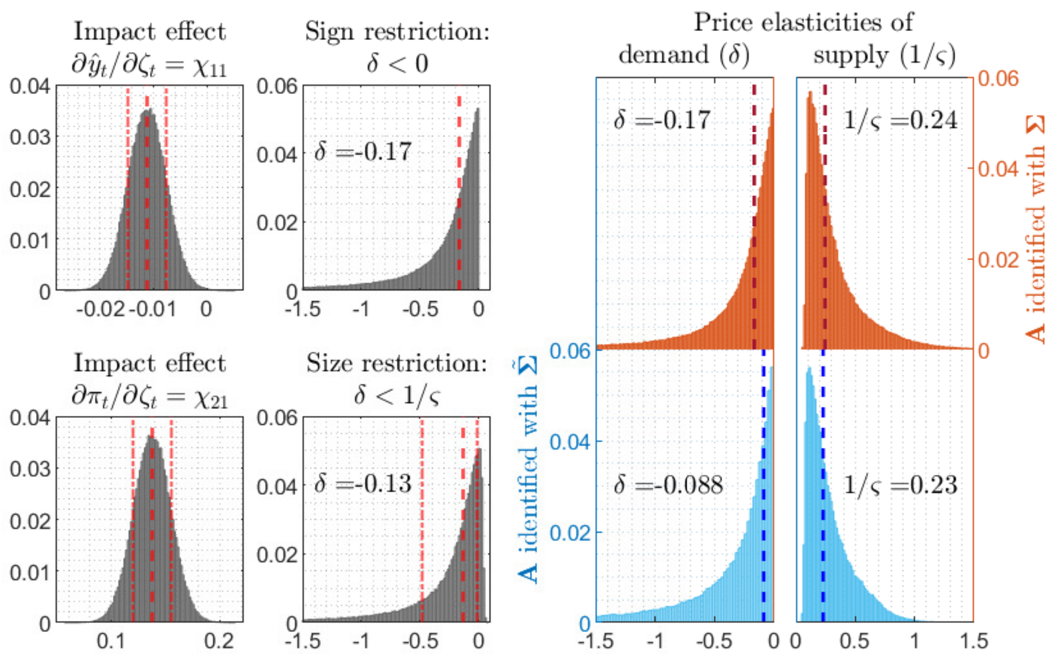
3.2. **Data and model specification.** We estimate the reduced-form model using Bayesian methods (for further technical details, see the Appendix) and employ the Schwarz (Bayesian) information criterion to select the appropriate lag length m. The variables π_t and $\hat{y}_t$ represent the inflation rate (measured as the year-over-year relative change of the GDP deflator, expressed in percent) and the output gap (measured as the ratio of gross domestic product to potential output, also expressed in percent). We use the Hamilton filter (Hamilton, 2018) to compute the potential output and in turn the output gap. We use the GDP deflator as our central price measure because it refers only to prices of (final) domestic goods and services. The supply chain disruptions index, as described in Section 2, is used for ζ_t.

To transform the quarterly data for π_t and $\hat{y}_t$ into a monthly frequency, we apply the temporal disaggregation methodology of Chow and Lin (1971). For the inflation rate (π_t), we use monthly data from (i) the consumer price index, (ii) the producer price index, and (iii) the wholesale price index. To disaggregate the output gap ($\hat{y}_t$), we employ monthly data from (i) the industrial production index, (ii) the retail trade index, and (iii) the European sentiment index for Austria, a composite index that captures sentiment in the (1) manufacturing, (2) construction, (3) services, (4) retail trade sectors, and (5) consumer sentiment. The monthly dataset spans the period from January 2006 to December 2024.

Additionally, we include a constant term and two dummy variables: one for the COVID-19 pandemic and another for the post-pandemic period.[12] The

[12]The two dummy variables were specified and incorporated to ensure that the resulting residuals of the (reduced-form) VAR model satisfy the assumptions of normality and lack of autocorrelation. Specifically, their inclusion prevents the residuals from failing the Jaque-Bera test for normality and the test for no-autocorrelation as proposed in Lütkepohl (1991).

FIGURE 2. Coefficient estimates



Note: The two subpanels in the first column display the histograms for the impact effect of supply chain disruptions on the output gap and the inflation rate. The two subpanels in the second column display the estimated price elasticity of demand (δ) based on the sign restriction approach ($\delta < 0$ used in the identification, upper subpanel) and on the size restriction approach ($\delta < 1/\varsigma$ used in the identification, lower subpanel). The red-solid line is the median estimate and red-dashed lines indicate the 68 percent credible intervals (only for the lower subpanel). The two right-hand side subpanels present the histograms for the price elasticities of demand and supply, estimated using two distinct variance-covariance matrices–$\mathbf{\Sigma}$ and $\tilde{\mathbf{\Sigma}}$–which represent two different information sets used for the identification.

time series for the three variables (supply chain disruptions index, the output gap and the inflation rate) are provided in Figures 1 (supply chain index) and 4 (output gap and inflation, solid red lines).

3.3. **The price elasticities: Estimation and discussion.** The third and fourth subpanels in Figure 2 display the histograms for the price elasticity of demand (δ) and the price elasticity of supply ($1/\varsigma$), respectively. Focusing first on the upper (orange) histograms, in each case, the dashed red line indicates the median of the posterior distribution, with the median estimate for the

We considered various additional dummy variables for particular events, including military conflicts (e.g., Lebanon in 2006, Libya in 2011, Yemen/Syria 2014, and Ukraine in 2022), other geopolitical or significant national events (e.g., the Arab Spring, the "Gilets Jaunes" movement), as well as major economic events such as the Global Financial Crisis and the European Debt Crisis. However, in all cases, we observed that the relevant dummy variables were not statistically significantly different from zero at the 10 percent level of statistical significance.

price elasticity of demand being -0.17 and for the price elasticity of supply being 0.24. These estimates suggest that both demand and supply exhibit inelastic, yet non-zero, short-run reactions of the output gap to price changes.

Our estimates for the price elasticity of aggregate demand and aggregate supply are in line with those in the literature. Niemira (2023) provide estimates of -0.14 and 0.60 for the (short-run) price elasticities of aggregate demand and supply for the US economy and report a long-run price elasticity of aggregate supply above unity.

The histograms provide valuable insights into the effects of the zero restrictions imposed during the identification process. This impact is particularly evident for the price elasticity of demand, where the peak of the histogram is concentrated near zero, indicating a strong influence of the sign restriction. In contrast, the histogram for the price elasticity of supply shows a peak that is distinctly shifted to the right of zero, reflecting the fact that the sign restrictions are less binding for the supply elasticity than for the demand elasticity.

A key feature highlighted by these subpanels concerns the role of the variance-covariance matrix used in the identification process ($\tilde{\mathbf{\Sigma}}$ versus $\mathbf{\Sigma}$). The lower (blue) histograms represent elasticities derived using a partial set of supply shocks and $\tilde{\mathbf{\Sigma}}$ as their variance-covariance matrix for identifying $\mathbf{A}$. In contrast, the upper (orange) histograms rely on the full set of supply shocks and $\mathbf{\Sigma}$ as their variance-covariance matrix. A comparison allows for an assessment of the differing informational content of the two matrices and, consequently, the distinct sets of structural shocks they capture. From a theoretical perspective (see Hamilton, 1994, Chapter 9), identifying the slope of the demand curve requires shifting the supply curve through a sufficient set of supply shocks. Conceptually, omitting a particular source of supply shocks–such as those associated with ζ_t–should directly affect the estimate of the slope of the demand curve and, therefore, the price elasticity of demand (δ). If an inadequate set of supply shocks is considered, the resulting supply curve shifts may be insufficient for accurately recovering δ. Consequently, using $\tilde{\mathbf{\Sigma}}$ instead of $\mathbf{\Sigma}$ can significantly influence the identification process. This becomes evident when comparing the orange and blue histograms for the price elasticity of demand. Notably, the blue histogram derived from $\tilde{\mathbf{\Sigma}}$ exhibits a pronounced shift toward zero, resulting in a smaller median point estimate of $\delta = -0.09$. This illustrates the differing informational content in $\tilde{\mathbf{\Sigma}}$ and $\mathbf{\Sigma}$ and its implications for estimating the price elasticity of demand.

Finally, Figure 2 presents a comparison of the implications for δ when applying a size restriction ($\delta < 1/\varsigma$, lower panel in second column) instead of a sign restriction ($\delta < 0$, upper panel in second column). Under the sign restriction, the distribution of δ is confined to values less than zero. When the size restriction is applied, the overall pattern remains similar, although a few positive values are observed. As a result, the median value of δ under the size restriction approach is slightly higher at -0.14, compared to -0.17 under the sign restriction. Despite the presence of a few positive values, their frequency is low, and the 68 percent credible interval (indicated by the red dashed-dotted lines) excludes zero. This provides strong support for our baseline approach, which imposes direct sign restrictions on the price elasticity of aggregate demand, ensuring that $\delta < 0$.

3.4. **Supply chain disruptions: The contemporaneous effects.** The contemporaneous effects are encapsulated in the vector $\boldsymbol{\chi} = [\chi_{11},\ \chi_{21}]'$ with $\chi_{11} = d\hat{y}_t/d\zeta_t$ and $\chi_{21} = d\pi_t/d\zeta_t$. Figure 2 (first and second subpanels) presents the histograms of the posterior distributions of these parameters. Since we have that $\boldsymbol{\chi} = \mathbf{A}^{-1}\boldsymbol{\vartheta}$, this highlights the critical dependence of these impact responses on the price elasticities of aggregate demand and supply, underscoring their central role in understanding the transmission of supply chain disruptions.

This relationship is evident in equation (13). Consider, for instance, the impact of supply chain disruptions on inflation. As shown in equation (13), this impact consists of both a direct contemporaneous effect ($\zeta_t \rightarrow \pi_t$), captured in the first row, and an indirect contemporaneous effect ($\zeta_t \rightarrow \hat{y}_t \rightarrow \pi_t$), captured in the second row. Together, these effects constitute the total impact, which is given by

$$\frac{d\pi_t}{d\zeta_t} = \frac{\vartheta}{1 - \delta\varsigma}, \tag{20}$$

while the impact on the output gap is

$$\frac{d\hat{y}_t}{d\zeta_t} = \frac{\delta\vartheta}{1 - \delta\varsigma} = \delta\frac{d\pi_t}{d\zeta_t} \tag{21}$$

In view of Figure 2, an increase in the supply chain disruptions index by one index point (ζ_t ranges from -2 as the minimum to 4 as the maximum, and has an average value of zero) causes a drop in the output gap by 0.012 percentage points and an increase in the inflation rate by 0.15 percentage points. These values are the medians of the respective posterior distributions, both of which are statistically different from zero, as indicated by the 68 percent credible intervals (indicated by the red dashed lines). These results highlight that supply chain disruptions induce significant contemporaneous effects on real economic activity and inflation. Any lagged effects are discussed in the next section.

3.5. **Supply chain disruptions: The dynamic effects.** We now examine the dynamic implications of shocks arising from supply chain disruptions ζ_t and compare them to those of demand shocks (u_t^D) and the residual supply shocks ($\tilde{u}_t^S$). To this purpose, it is convenient to re-write the SVAR model put forth in equation (13) in the following form

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \boldsymbol{\Theta} \begin{bmatrix} \tilde{\mathbf{u}}_t \\ \zeta_t \end{bmatrix} \quad \text{with} \quad \boldsymbol{\Theta} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & \vartheta \end{bmatrix} \tag{22}$$

The corresponding vector moving average (VMA) representation is given by

$$\mathbf{y}_t = \sum_{i=0}^{\infty} \boldsymbol{\Psi}_i \tilde{\mathbf{H}} \begin{bmatrix} \tilde{\mathbf{u}}_{t-i} \\ \zeta_{t-i} \end{bmatrix} \tag{23}$$

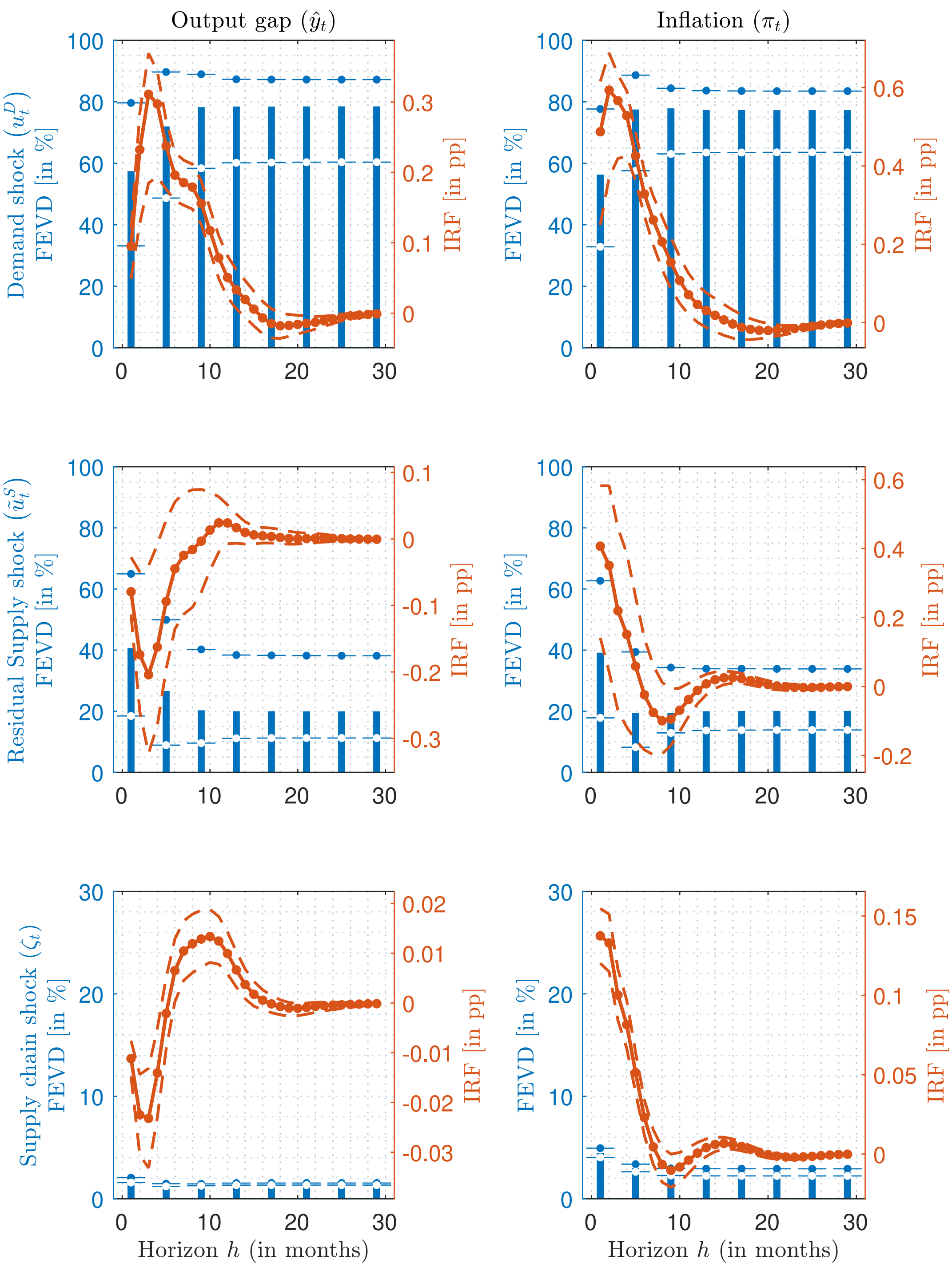
with $\tilde{\mathbf{H}}$ being the (2×3) matrix determining the contemporaneous impact response of the vector of structural shocks and it is given by

$$\tilde{\mathbf{H}} = \mathbf{H}\boldsymbol{\Theta} = \begin{bmatrix} \mathbf{H} & \boldsymbol{\chi} \end{bmatrix}_{(2\times 3)} \tag{24}$$

where the last equality is due to $\boldsymbol{\chi} = \mathbf{H}\boldsymbol{\vartheta}$ as of equation (15). As highlighted by equation (24), the inclusion of ζ_t as shock in the system extends the traditional impact response matrix $\mathbf{H}$ by a column which is the impact response vector $\boldsymbol{\chi}$. Moreover, we have that $\left(\mathbf{I} - \sum_{i=1}^{m} \boldsymbol{\Phi}_i L^i\right)^{-1} = \sum_{i=0}^{\infty} \boldsymbol{\Psi}_i L^i$ with $\boldsymbol{\Phi}_i \in \boldsymbol{\Phi}\ \forall\ i = 1, ..., m$, and finally, $\boldsymbol{\Psi}_0 = \mathbf{I}$. From equation (23), we can then compute the (structural) impulse response functions (IRF) at horizon h as follows

$$\frac{\partial \mathbf{y}_{t+h}}{\partial \hat{\mathbf{u}}_t'} = \boldsymbol{\Psi}_h \tilde{\mathbf{H}} \tag{25}$$

Figure 3. Dynamic implications of the shocks



Note: The figure displays impulse response functions by orange solid lines (median) and dashed lines (68 percent credible interval), alongside forecast error variance decompositions represented by blue bars (median) and blue/white dots for the 68 percent credible interval. Both statistics are shown for the three shocks (demand shock u_t^D, residual supply shock $\tilde{u}_t^S$, and supply chain disruptions ζ_t) and for the two endogenous variables (output gap $\hat{y}_t$, and inflation rate π_t).

where $\hat{\mathbf{u}}_t = [\tilde{\mathbf{u}}_t', \ \zeta_t]'$. Finally, based on the VMA representation of equation (23), we derive the expressions for the forecast error variance decomposition

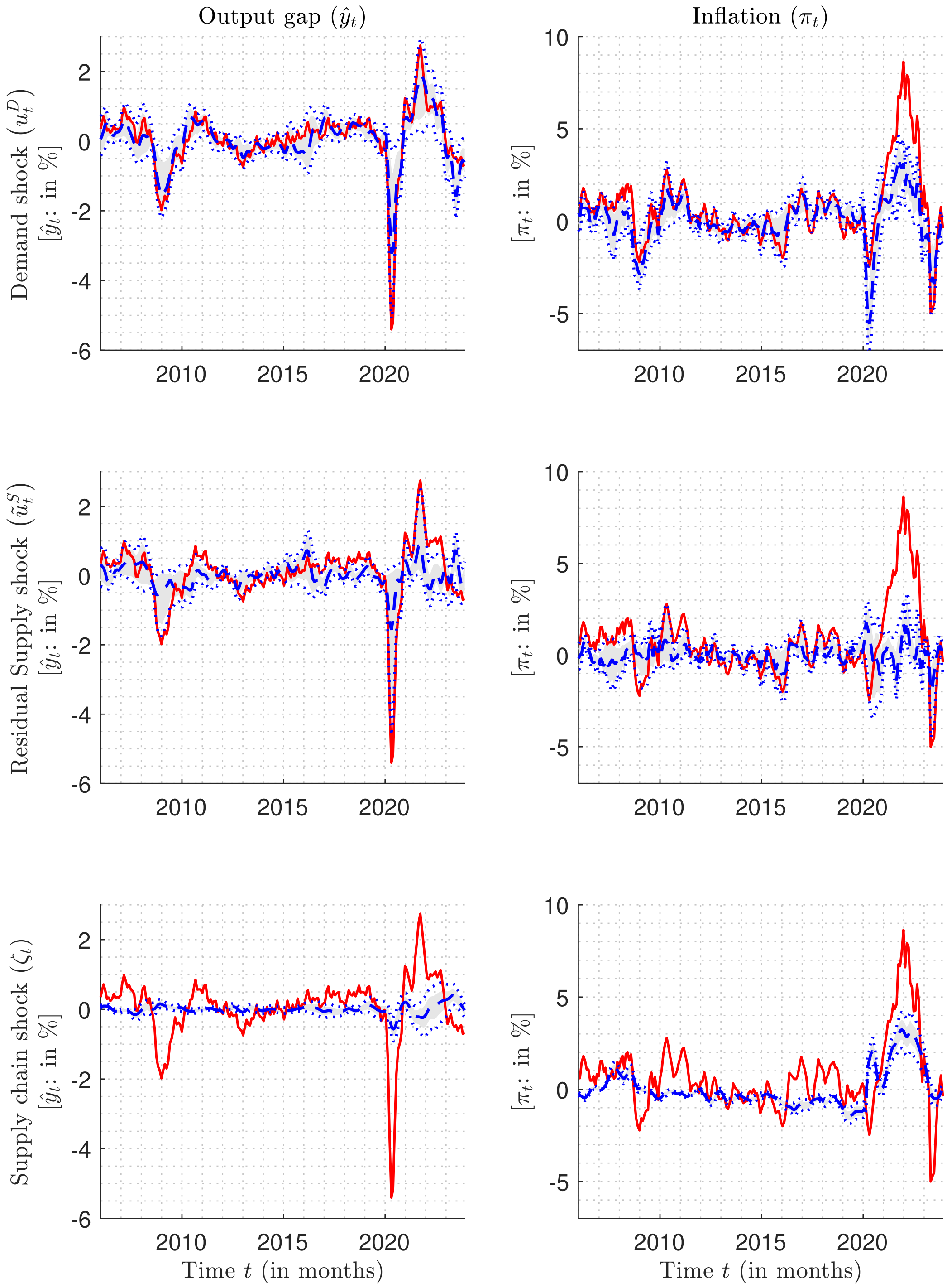
(FEVD) and the historical decomposition, following the approach outlined in Hamilton (1994), but utilizing the non-quadratic matrix $\tilde{\mathbf{H}}$.

The results for the impulse response functions (IRFs) and forecast error variance decompositions (FEVD) are presented in Figure 3. The orange solid lines represent the IRFs over a 30-month horizon, accompanied by 68 percent credible intervals (indicated by the orange dashed lines). The blue bars display the FEVD for selected months, with 68 percent credible intervals marked by the blue and white dots above and below the bars. The point estimates for both the IRFs and FEVD are the medians of the respective posterior distributions.

The subpanels in the first row show the responses to the (expansionary) demand shock, while the second row presents the (contractionary) residual supply shock. As expected, the demand shock induces a positive co-movement of the output gap and inflation, whereas the supply shock generates the opposite. In both cases, the IRFs indicate that the responses are statistically significantly different from zero, with a particularly strong inertia in case of the demand shock. The FEVD further reveals that demand shocks account for up to 75 percent of the fluctuations in both the output gap and inflation, although this contribution is lower at shorter horizons. In contrast, the residual supply shock explains a smaller portion of the fluctuations, ranging from 40 percent at short horizons to 20 percent at longer horizons. Molnarova and Reiter (2022) also find evidence in favor that the bulk of the aggregate fluctuations is explained by aggregate demand shocks.

The subpanels in the third row present the effects of supply chain disruptions. This shock is contractionary, meaning that an unexpected increase in ζ_t causes a drop in the output gap while simultaneously increasing inflation. The impact responses replicate those found in the first two subpanels of Figure 2. The significant contemporaneous reactions in the output gap and inflation persist over time. Although the peak response for inflation occurs immediately, the output gap reaches its maximum response with a one-quarter lag. While supply chain disruptions induce statistically significant changes in both the output gap and inflation, they explain a relatively small proportion of fluctuations in these variables—less than 5 percent in both cases. However, this value represents the time average, and obscures the fact that supply chain disruptions can lead to considerable fluctuations at specific points in time. This is further explored in the next section.

FIGURE 4. Historical decomposition of the shocks



Note: The figure shows the historical decomposition for the output gap ($\hat{y}_t$) and inflation rate (π_t) across the three shocks. Red lines represent the actual time series of $\hat{y}_t$ and π_t and the blue dashed lines their hypothetical path if only (i) the demand shock (u_t^D, first row), (ii) the residual supply shock ($\tilde{u}_t^S$, second row), or (iii) supply chain disruptions (ζ_t, third row) were present. Blue dotted lines and gray shaded areas show 95 percent and 68 percent credible intervals.

3.6. Supply chain disruptions: A historical view.

Historical decomposition is a technique used to break down the observed time series of a variable into the contributions of different structural shocks over time. Its primary purpose is to quantify how much each shock has influenced the movements of a variable over a specified period. By isolating the impact of each shock, this method enables us to trace the historical trajectory of a variable and identify the key drivers behind its fluctuations.

Figure 4 illustrates how various structural shocks–the demand shock, the residual supply shock, and supply chain disruptions–have affected the paths of the output gap and inflation. Each subplot displays the actual trajectories of the output gap (left-hand columns) and inflation (right-hand columns) indicated by the red solid lines. The blue dashed lines are the historical decompositions (median value jointly with 68 and 95 percent credible intervals) of the SVAR model. They represent the hypothetical path of these variables given only one particular shock. For instance, the historical decomposition of the demand shock (subpanels in the first row) shows that during the global financial crisis (2008/2009), the red and blue lines largely overlap, suggesting that demand shocks were the predominant drivers of fluctuations in the output gap and inflation during this period. A similar pattern is observed for the post-pandemic period: the sizable positive output gap after 2021 is primarily attributed to demand shocks (the blue and red lines overlap to a large extent again), while post-pandemic inflation dynamics are largely driven by both demand shocks and supply chain disruptions. Notably, in 2021 and 2022, supply chain disruptions account for a significant portion of inflationary pressures, although their influence wanes after the third quarter of 2022. A similar but smaller role is observed in the output gap, though the contribution is quantitatively less important.

The historical decomposition highlights that supply chain disruptions played a substantial role in driving fluctuations in both inflation and the output gap during 2021 and 2022, but had a negligible impact outside this period. This finding helps explain why the FEVD, shown in Figure 3, attributes a relatively small contribution to supply chain disruptions: their influence is limited to specific periods, primarily 2021 and 2022. During these years, supply chain disruptions were a major source of shocks, while playing a subdued role otherwise.

3.7. **Supply chain disruptions: country-specific versus global factors.** The results of using the global index of supply chain disruptions are presented in the Appendix. When comparing the results of the country-specific index with those for its global counterpart, the main conclusion is that the former has a superior information content. While the results are qualitatively the same, there are significant quantitative differences that are also statistically significantly different from zero. Hence, disruptions at the country level prove to be significantly more influential than their global counterparts.

4. Sector-specific implications of supply chain disruptions

We now extend the macroeconomic analysis conducted in Section 3 by introducing a more granular examination of supply chain disruptions, focusing specifically on the consequences at the sectoral level. In this analysis, we consider the two-digit NACE sector decomposition, the structure of which is provided in Table 6 in the Appendix, along with the corresponding sector acronyms. In total, we examine 63 sectors.

To carry out this sectoral analysis, we continue to rely on the SVAR model (henceforth referred to as baseline model) introduced in Section 3. However, we now extend the (2×1) vector of endogenous variables, $\mathbf{y}_t = [\hat{y}_t,\ \pi_t]'$, to a (4×1) vector, $\mathbf{y}_t^i = [\mathbf{y}_t',\ y_t^i,\ \pi_t^i]'$, where y_t^i and π_t^i denote the output (real value added) and inflation rate (deflator of value added) of sector i. The analysis is conducted for each of the 63 production (i.e. supply) sectors by sequentially estimating the reduced-form VARX model given by equation (15). Following the extension of the vector of endogenous variables ($\mathbf{y}_t \rightarrow \mathbf{y}_t^i$), we adjust all other elements in the VARX model with an i superscript to indicate the change in the dimension due to the introduction of sector-specific variables for output and inflation (notably, ζ_t remains the same across all specifications, though $\boldsymbol{\chi}$, of dimension 2×1, is also extended to $\boldsymbol{\chi}^i$, of dimension 4×1). The extended model hence reads

$$\mathbf{y}_t^i = \boldsymbol{\Phi}^i \mathbf{x}_{t-1}^i + \boldsymbol{\chi}^i \zeta_t + \tilde{\boldsymbol{\epsilon}}_t^i \quad \text{with} \quad \mathrm{Var}(\tilde{\boldsymbol{\epsilon}}_t^i) = \tilde{\boldsymbol{\Sigma}}^i \tag{26}$$

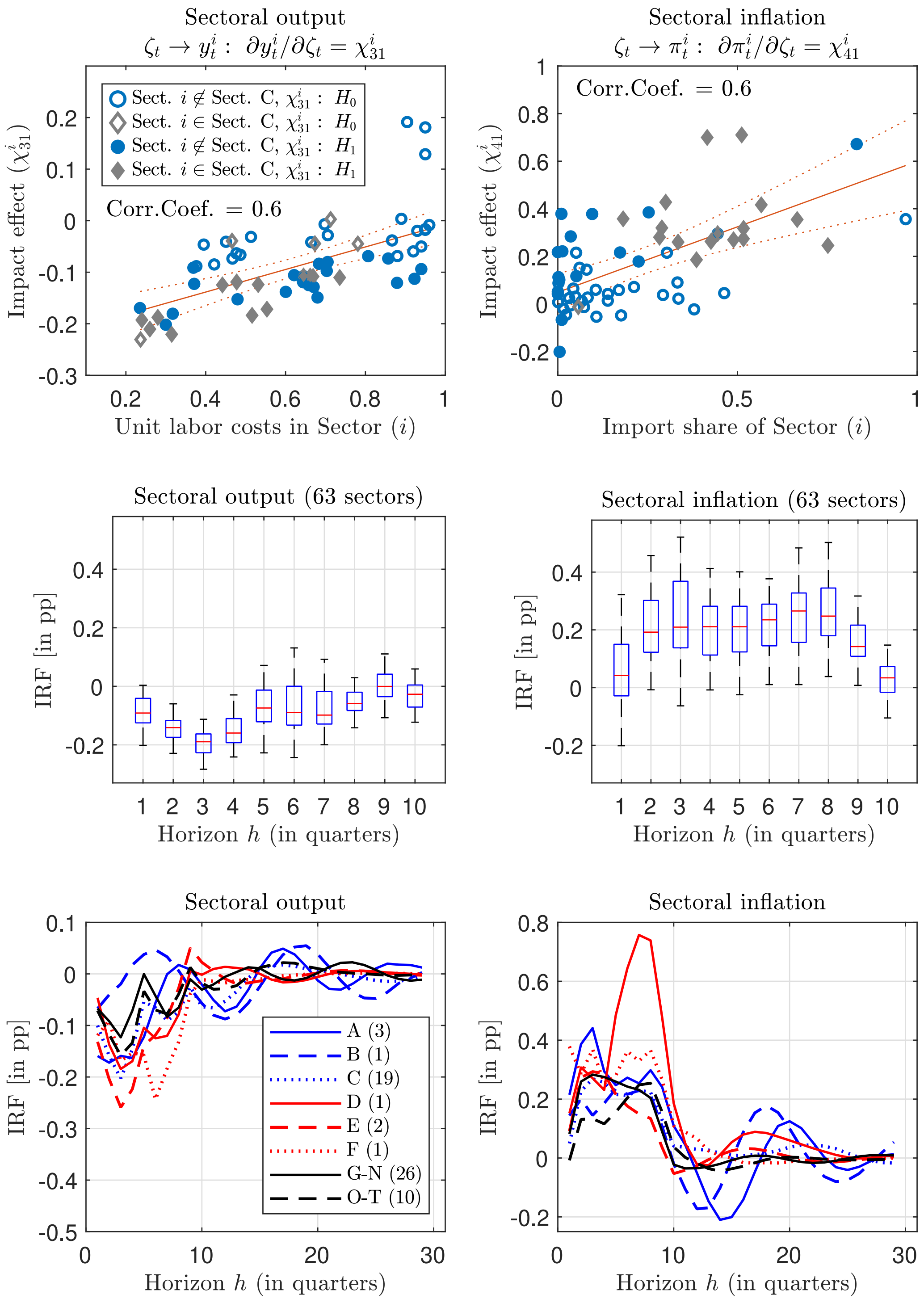
Equation (15) is now estimated using quarterly data. The necessity of this frequency adjustment arises since the sector-specific variables for output and inflation are only available at an annual frequency, while the supply chain disruptions index, ζ_t, is available at a monthly frequency. We chose a quarterly frequency to strike a balance between the available data frequencies. Aggregating the monthly series of ζ_t to a quarterly frequency is done by computing the three-month average to obtain quarterly values. For the sector-specific data, we use the value added (year-over-year changes in percent) and the corresponding deflator (year-over-year changes in percent) of sector i as output and inflation measure. We employ the method of Chow and Lin (1971) for the temporal disaggregation of output and inflation of the 63 sectors and various higher-frequency indicators.[13]

We proceed with the same analysis as in the baseline model, focusing on the coefficients that capture the effects of supply chain disruptions on sectoral output and inflation. These coefficients are contained in the vector $\boldsymbol{\chi}^i$ and given by $\partial y_t^i / \partial \zeta_t = \chi_{31}^i$ and $\partial \pi_t^i / \partial \zeta_t = \chi_{41}^i$, compare equation (23). The estimates of these coefficients for all 63 sectors are displayed in Figure 5. The upper-left subpanel presents the output coefficient χ_{31}^i for all sectors, with the vertical axis serving as the reference axis for the coefficients. The upper-right subpanel displays the inflation coefficients χ_{41}^i. In both subpanels, gray diamonds represent subsectors of the manufacturing sector (NACE section C), while blue circles/dots indicate the remaining sectors. A filled diamond or circle denotes a coefficient estimate that is statistically different from zero at the 95 percent credible interval, while unfilled diamonds or circles represent estimates that are statistically indistinguishable from zero.

Regarding the output coefficient χ_{31}^i, we observe that most coefficients are negative, indicating that supply chain disruptions generally have a contractionary effect on most sectors. Although a few positive coefficients are found, they are not statistically significant. The mean value of χ_{31}^i across all sectors is approximately -0.1, suggesting that a one index point increase in the supply chain disruptions index leads to a 0.1 percentage point decrease in the sector-average output growth rate. As indicated by the gray diamonds in the figure, the effect on subsectors of the manufacturing sector is more negative, reaching

[13] To disaggregate sectoral output and inflation from an annual to a quarterly frequency, we employ the following quarterly indicators (i) sector specific business survey indicators (if available at a monthly frequency, we consider the quarterly average), (ii) sector specific data on retail and wholesale trade and the two-digit disaggregation of the industrial production index, and (iii) the one-digit disaggregation of the NACE production classification, which consists of 21 sectors (consider the Appendix for a detailed overview for the classifications). At the two-digit level, the disaggregation includes 88 divisions identified by two-digit numerical codes (01 to 99), of which 63 sectors are included in our analysis, all of which are available at an annual frequency. The output and inflation data at the one-digit level are available at a quarterly frequency.

FIGURE 5. Supply chain disruptions: A sectoral decomposition



Note: The figure shows the point estimates for the sectoral output and inflationary effects of supply chain disruptions at the two-digit NACE level (63 sectors). The subpanels in the second and the third row show the sectoral distribution of the impulse response functions (IRFs) of the two-digit NACE level via boxplots (based on the median value for each sector), and as line plots where the two-digit IRFs (median values) were aggregated to the one-digit NACE level. The numbers in parenthesis next to the sector acronyms in the lower subpanel of the first column indicate the number of aggregated two-digit subsectors.

up to −0.2. Furthermore, the figure also relates the estimated output coefficients (χ^i_{31}) to the sector specific unit labor costs, according to which higher unit labor costs align with a weaker output contraction.

Turning to the upper-right subpanel, which shows the inflation coefficients (χ^i_{41}), we observe that the estimated values are predominantly positive, suggesting that supply chain disruptions generally exert upward inflationary pressure. Notably, the inflationary effects are most pronounced for subsectors of the manufacturing sector, all of which are statistically significantly different from zero (indicated by filled gray diamonds). The mean value of χ^i_{41} across all sectors is approximately 0.35, implying that a one index point increase in the supply chain disruptions index leads to a 0.35 percentage point increase in the sector-average inflation rate. Additionally, when we relate the inflation coefficients to the import share of each sector, we observe a strong positive relationship: sectors with higher import shares tend to have larger estimated inflation coefficients. This effect is particularly pronounced for manufacturing subsectors and for sector B (mining and quarrying), while the relationship is less pronounced for other sectors.

4.1. **Explaining the sectoral heterogeneity.** The point estimates from equation (26) for the contemporaneous response of output and inflation to supply chain disruptions exhibit substantial heterogeneity across the 63 sectors considered. This raises an important question regarding the underlying factors driving this variation. Figure 5 has already highlighted the role of the sectoral import share as a possible explanatory factor for the inflationary response, and of unit labor costs for output. In what follows, we delve deeper and identify additional factors that may explain these differences. We focus on five variables: (i) sectoral unit labor costs, (ii) the sectoral import share, (iii) the share of sectoral output used as an input in other sectors, (iv) sectoral labor productivity, and (v) whether the sector is public or private.

Sectoral unit labor costs are measured as the ratio of the compensation of employees to gross value added (W^iN^i/P^iY^i), with both variables expressed in nominal terms, and sectoral labor productivity is measured as the ratio of gross value added to employment. The sectoral import share captures the proportion of inputs sourced from abroad relative to the total input usage in a given sector. This share is relatively high in sectors such as mining and quarrying (Sector B) and various manufacturing subsectors (Sector C), whereas it is considerably

Table 2. Cross-sectional parameter heterogeneity

	Coefficient for sectoral	
	Output	Inflation
Dependent variable[(1)] →	$\chi_{31}^{i,(d)}$	$\chi_{41}^{i,(d)}$
Unit labor cost	0.07*	−0.15*
Import share	0.08	0.62*
Intermediate share	0.14	0.09
Productivity	0.18*	−0.08
Public sector	0.05*	−0.05
Constant term	−0.24*	0.11
N	63	63
R^2	0.30	0.39

Notes: The number of observations is given by the number of production sectors N_S. A * indicates a level of statistical significance equal to 68 percent credible interval. The regressions account for the estimation uncertainty of the dependent variables by carrying out the regressions for each draw d of the dependent variables.
[(1)] The values of the dependent variables are displayed in the first and second subpanels in Figure 5 (y-axis).
[(2)] The R^2 is the normal (i.e. non-adjusted) goodness-of-fit measure.

lower in most service-related sectors. The third variable reflects the share of a sector's output used as an input in the production processes of other sectors. This share is particularly high in agriculture-related subsectors (Sector A) and lower in other sectors, resulting in significant cross-sectoral variation. Finally, the public sector variable is a dummy variable that takes the value of one for sectors associated with primarily public or general government activities (sectors O–T) and zero otherwise.

We use these five variables to explain the cross-sectional variation in the estimated coefficients for output (χ_{31}^{i}) and inflation (χ_{41}^{i}) by running the following regression:

$$\chi_{(\cdot)1}^{i,(d)} = \boldsymbol{\beta}'\boldsymbol{x}_i + e_i, \quad \text{with} \quad e_i \sim N(0, \sigma_e^2), \tag{27}$$

where $i = 1, \ldots, N_S$, with $N_S = 63$ representing the sectoral dimension, $\boldsymbol{x}_i$ is a vector of independent variables containing the five aforementioned explanatory variables and a constant term, e_i is the error term, and $\chi_{(\cdot)1}^{i,(d)}$ denotes the dependent variable, which can either be $\chi_{31}^{i,(d)}$ (the sectoral output coefficient) or $\chi_{41}^{i,(d)}$ (the sectoral inflation coefficient). The superscript (d) indicates that the dependent variable is an estimated parameter with a posterior distribution.

Equation (27) is estimated using Bayesian methods. Given that we have 5,000 posterior draws for $\chi_{(\cdot)1}^{i,(d)}$, we estimate this regression 5,000 times. At each iteration, we draw 200 draws for σ_e^2 and $\boldsymbol{\beta}$ from their respective posterior distributions, assuming a natural conjugate prior that is weakly informative. This results in one million draws for $\boldsymbol{\beta}$ in total. This procedure takes into account both, the estimation uncertainty inherent to equation (27), and the estimation uncertainty in the dependent variables ($\chi_{31}^{i,(d)}$ and $\chi_{41}^{i,(d)}$). We report the median estimate (across the draws) of $\boldsymbol{\beta}$ in Table 2.

The most notable finding in Table 2 concerns the coefficient for unit labor costs. The estimated coefficient is positive for output (0.07) and negative for inflation (-0.15), suggesting that high unit labor costs mitigate the impact of supply chain disruptions. The intuition behind this result is that high unit labor costs in a sector imply a large share of wages in gross value added, reflecting the dominance of labor as the primary input factor in production. Since supply chain disruptions conceptually relate to the scarcity of certain goods as input factors, sectors where labor constitutes the predominant input are relatively less dependent on other inputs. Consequently, sectors with high unit labor costs are more insulated from the direct effects of supply chain disruptions. This results in a more moderate contraction in output and a dampened inflationary response. This applies primarily to service related sectors.

The results also underscore the significant role of the import share, though its relevance is confined to the inflation coefficient ($\chi_{41}^{i,(d)}$). The point estimate indicates that the inflationary response is more pronounced in sectors where inputs are predominantly sourced from abroad. This finding aligns with the notion that supply chain disruptions exert greater pressure on prices when the affected sectors rely heavily on imported inputs.

For the remaining variables, we find that the parameter estimates for productivity and the public sector dummy variable are significant for output. This suggests that higher productivity and a sector characterized by public activities can mitigate the output contraction. However, the share of sectoral output used as input in other sectors is found to be statistically insignificant. While the regressions explain a reasonable share of the variation in $\chi_{31}^{i,(d)}$ and $\chi_{41}^{i,(d)}$, it is important to note that the sample size ($N_S = 63$) is relatively small. This suggests that the results should be interpreted with caution and viewed as indicative rather than definitive.

4.2. **Dynamic effects at the sectoral level.** The subpanels in the second row of Figure 5 present the IRFs of sectoral output and inflation over a ten quarter horizon to a one index point increase ζ_t. Since we have IRFs for 63 sectors, we focus on the median value of each sector's IRF at each horizon and display the resulting trajectories of the 63 sectors as boxplots. The width of each box reflects the variation of the IRFs across sectors at a particular horizon. As shown in the figure, the negative output effect at impact becomes more pronounced in the subsequent quarters before gradually converging back to zero. The width of the boxes is narrow, indicating strong co-movement–both qualitatively and quantitatively–across sectors. In contrast, the inflationary effects show a positive contemporaneous effect across most sectors, which intensifies in subsequent quarters, resulting in an inflationary peak around the third quarter. Unlike the output effects, the boxes for inflation are wider, indicating greater heterogeneity in the inflationary effects of supply chain disruptions across sectors. This heterogeneity is most pronounced at the three-quarter horizon, but it diminishes in later quarters.

The subpanels in the third row in Figure 5 show the IRFs for output and inflation from the two-digit level, though aggregated up to the one-digit level (sectors G-N and O-T are aggregated to even broader sectors). The results highlight a negative output response across all eight sector. The contraction is largest in size in case of sectors C (manufacturing), E (water supply, sewerage, waste management and remediation activities) and F (construction). The negative response lasts for several quarters. The inflationary response is positive through the eight sectors, with the responses being largest in size in case of sectors A (agriculture, forestry and fishing), D (electricity, gas, steam and air conditioning supply) and F (construction).

Overall, this analysis highlights two key findings: (i) supply chain disruptions have a substantial effect on both output and inflation at the sectoral level, and (ii) there is significant heterogeneity in the effects across sectors. In the following section, we further investigate the sector-specific implications of supply chain disruptions by examining each sector's contribution to CPI inflation.

5. CPI-specific implications of supply chain disruptions

In this section, we analyze the implications of supply chain disruptions on the Consumer Price Index (CPI) based inflation rate. While one could extend the baseline model to directly incorporate the CPI inflation rate (we do so in the Appendix in the context of a robustness check), we instead adopt a more nuanced approach. Our objective is not only to quantify the effects of supply chain disruptions on CPI inflation, but also to identify which production sectors play the most significant role in this process. Identifying these critical sectors, however, is a complex task, as the importance of a production sector in shaping CPI inflation is determined by two dimensions. First, the direct effect of supply chain disruptions on a particular production sector. Second, the extent to which the output of a sector is used as an input by other sectors, captured through input linkages. Frictions in one particular sector due to, for instance supply chain disruptions, will affect connected production sectors as a consequence. According to these two dimensions of influence, it is possible that a sector might not be directly affected by supply chain disruptions, but could still experience sizable consequences through indirect effects as disruptions propagate through the production network.

To investigate these dimensions, we adopt a multi-sector (static) general equilibrium model. The model is outlined in detail in the Appendix. We once again consider the producer price based inflation rates of production sectors at the two-digit level, collected in the vector (subsequently, the time t subscript is omitted in order to maintain simplicity in the notation) $\boldsymbol{\pi}_S = \left[\pi^1, \ldots, \pi^{N_S}\right]$, where $N_S = 63$ represents the number of production sectors as introduced in Section 4. This model allows us to establish a relationship that links the inflation rates based on the sectoral producer prices across these N_S sectors to a vector of exogenous supply shocks $\boldsymbol{\xi}$ and the inter-sectoral linkages, represented by the input-output (IO) matrix $\boldsymbol{\Gamma}$, as follows

$$\boldsymbol{\pi}_S = \boldsymbol{\Gamma}\boldsymbol{\pi}_S + \Delta\boldsymbol{\xi} \tag{28}$$

where Δ is the difference operator. In this framework, we assume inelastic demand, meaning that price changes in each sector arise solely from the supply side shocks ($\boldsymbol{\xi}$). Consequently, $\boldsymbol{\pi}_S = (\boldsymbol{I} - \boldsymbol{\Gamma})^{-1}\Delta\boldsymbol{\xi}$ represents the vector of equilibrium producer price inflation rates.

The next step is to introduce the supply chain disruptions index, ζ, and relate the resulting vector of equilibrium producer price inflation rates to CPI inflation, which is a scalar. This process unfolds in two stages.

The first stage involves extending the vector of sector-specific supply shocks, $\boldsymbol{\xi}$, with the supply chain disruptions index, ζ. In other words, we again introduce a step, as already done in equation (10), in which a general supply shock was rendered into a more specific one. We decompose $\boldsymbol{\xi}$ into two orthogonal elements, the first of which captures supply chain disruptions (ζ), while the second is a residual element ($\tilde{\boldsymbol{\xi}}$). We note, however, that the vector $\boldsymbol{\xi}$ is of dimension ($N_S \times 1$), while ζ is a scalar. To reconcile this dimensionality problem, we use the estimated coefficients χ_{41}^{i} from the reduced-form VARX model as of equation (26) and shown in the upper-right subpanel in Figure 5, which we collect in the vector $\boldsymbol{\chi}_{\pi_i} = \left[\chi_{41}^{1}, \ldots, \chi_{41}^{N_S}\right]$. This allows us to express the vector of structural supply shocks as

$$\boldsymbol{\xi} = \tilde{\boldsymbol{\xi}} + \boldsymbol{\chi}_{\pi_i}^{(d)} \zeta \tag{29}$$

The coefficients in the vector $\boldsymbol{\chi}_{\pi_i}^{(d)}$ capture the sensitivity of each sector's inflation rate ($\pi^i \ \forall \ i = 1, ..., N_S$) to supply chain disruptions (ζ). Note that we have a posterior distribution for each element in $\boldsymbol{\chi}_{\pi_i}^{(d)}$, and hence the overall vector itself too, which is indicated by the (d) superscript. The residual supply shock $\tilde{\boldsymbol{\xi}}$ involves both aggregate and sector specific supply shock elements. Since we will subsequently not use it any further, we shall simply assume that no shock emerges from it, that is, $\Delta\tilde{\boldsymbol{\xi}} = \mathbf{0}$ without loss of generality, so that $\Delta\boldsymbol{\xi} = \boldsymbol{\chi}_{\pi_i}^{(d)} \Delta\zeta$.

The second stage involves relating the producer price inflation rates ($\boldsymbol{\pi}_S$) to the CPI inflation rate (π^{CPI}). The CPI inflation rate is defined as a weighted average of the inflation rates of its subindices, with weights based on the COICOP (Classification of Individual Consumption by Purpose) classification. Specifically, the CPI can be expressed as

$$P^{\text{CPI}} = \prod_{i=1}^{N_C} P_{C,i}^{\omega_i} \quad \text{with} \quad \sum_{i=1}^{N_C} \omega_i = 1, \tag{30}$$

where the $P_{C,i} \ \forall \ i = 1, \ldots, N_C$ elements represent the prices of the N_C (consumption) subindices of the CPI, and $\omega_i \ \forall \ i = 1, \ldots, N_C$ reflect consumer preferences (or the CPI weights).[14] For the purposes of this analysis, we consider a three-digit level of disaggregation, implying $N_C = 35$ subindices. A list of these subindices is provided in the Appendix.

Taking the logarithm of the CPI and the first difference leads to the following expression for the CPI inflation rate:

$$\pi^{\text{CPI}} = \boldsymbol{\omega}'\boldsymbol{\pi}_C \tag{31}$$

where $\pi^{\text{CPI}} = \Delta \log(P^{\text{CPI}})$ represents the CPI inflation rate, while $\boldsymbol{\omega} = [\omega_1, \dots, \omega_{N_C}]$ and $\boldsymbol{\pi}_C = [\pi_{C,1}, \dots, \pi_{C,N_C}]$ are vectors of consumer preferences and inflation rates for the subindices ($\pi_{C,i} = \Delta \log(P_{C,i}) \; \forall \; i = 1, \dots, N_C$) of the CPI.

The final stage in our approach involves mapping the N_S production sectors (which are classified according to the NACE classification) to the N_C CPI subindices (which are classified according to the COICOP classification). This mapping is achieved through the bridge matrix $\boldsymbol{\Theta}$, which has dimension $(N_C \times N_S)$ and transforms the NACE into the COICOP classification. The matrix $\boldsymbol{\Theta}$ is introduced and established in Cai et al. (2019); Cai and Vandyck (2020) and described in detail in the Appendix. Using this mapping, we can relate the equilibrium producer price inflation rates, given by $\boldsymbol{\pi}_S = (\boldsymbol{I} - \boldsymbol{\Gamma})^{-1} \boldsymbol{\xi}$ where $\boldsymbol{I}$ is the identity matrix, to the corresponding equilibrium consumer price inflation rates $\boldsymbol{\pi}_C$, which gives $\boldsymbol{\pi}_C = \boldsymbol{\Theta}\boldsymbol{\pi}_S$. Using this expression in equation (31), the CPI inflation rate can then be expressed as

$$\pi^{\text{CPI}} = \boldsymbol{\omega}'\boldsymbol{\Theta}\boldsymbol{\pi}_S. \tag{32}$$

By combining equations (28) and (29), we obtain the following supply side driven relationship between supply chain disruptions and the CPI inflation rate

$$\pi^{\text{CPI}} = \boldsymbol{\omega}'\boldsymbol{\Theta} (\boldsymbol{I} - \boldsymbol{\Gamma})^{-1} \boldsymbol{\chi}^{(d)}_{\pi_i} \Delta\zeta \tag{33}$$

[14]The assumption of homothetic preferences is at the core of the CPI. 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. As a consequence, the weights ω_i represent the elasticity of the utility function u with respect to good i, hence clearly identifying and representing *consumer preferences*. Concurrently, ω_i measures the spending share on good i and this share is independent of the budget level. Not least, the assumption of homothetic preferences also implies that all income elasticities of demand are unity.

This equation encapsulates the impact of supply chain disruptions on the CPI inflation rate.[15] Specifically, it decomposes the overall effect into four elements, the first of which is $\boldsymbol{\chi}_{\pi_i}^{(d)}$ which captures the sensitivity of sectoral producer prices (all expressed in relative terms) to supply chain disruptions. The second element concerns the term $(\boldsymbol{I} - \boldsymbol{\Gamma})^{-1}$ which captures the effect of the sectoral production linkages. The third element is the bridge matrix $\boldsymbol{\Theta}$, which maps the N_S equilibrium producer prices of the NACE classification into an equivalent COICOP classification. This is a pure mechanic step involving a mapping from one to another data classification at the sectoral level. Finally, the fourth step involves the CPI weights $\boldsymbol{\omega}$, which reflect consumer preferences. This vector maps equilibrium producer prices now based on the COICOP classification into the CPI inflation rate. In what follows, we analyse each element in more detail.

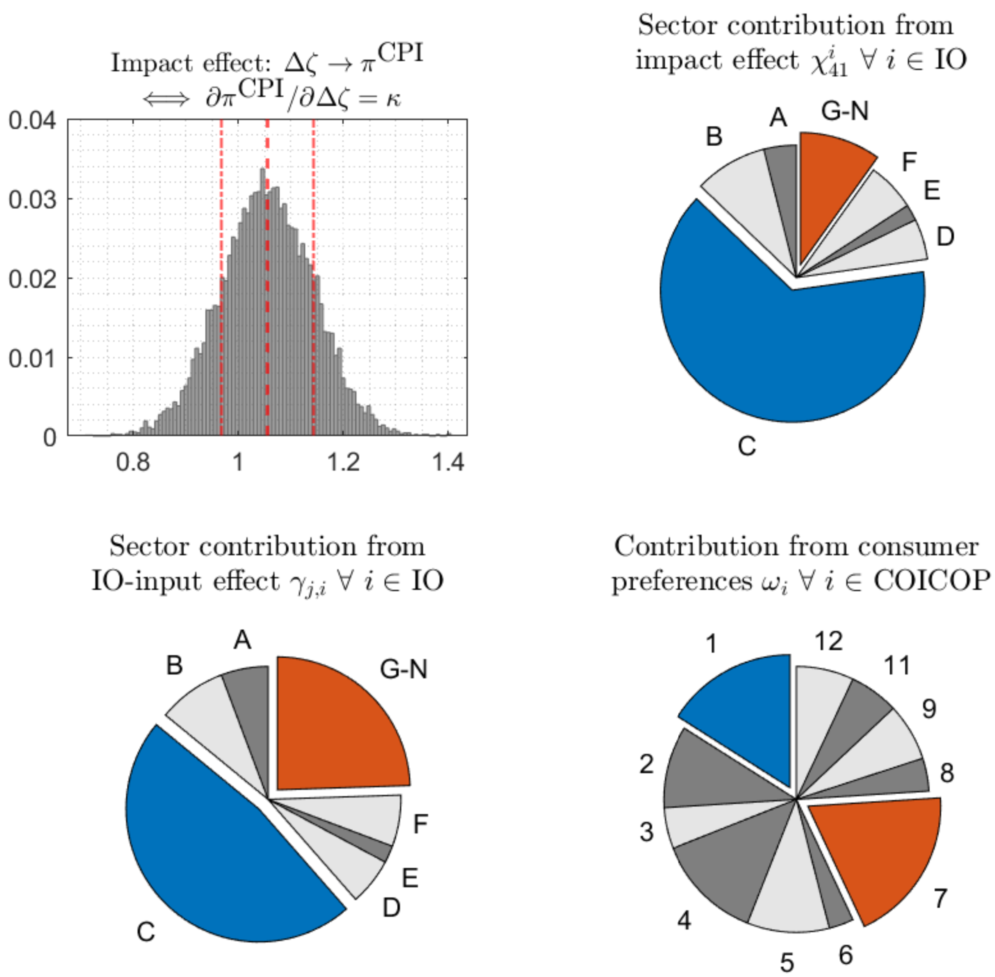
5.1. **Direct effects.** Equation (33) gives rise to a linear relationship between the CPI inflation rate π^{CPI} and supply chain disruptions ζ with the slope coefficient $\kappa^{(d)}$ given by

$$\kappa^{(d)} = \frac{\partial \pi^{\text{CPI}}}{\partial \Delta\zeta} = \boldsymbol{\omega}'\boldsymbol{\Theta}\left(\boldsymbol{I} - \boldsymbol{\Gamma}\right)^{-1}\boldsymbol{\chi}_{\pi_i}^{(d)} \tag{34}$$

While most of the elements in (34) are given, those in $\boldsymbol{\chi}_{\pi_i}^{(d)}$ are estimated instead. Hence, the uncertainty surrounding κ is uniquely defined by $\boldsymbol{\chi}_{\pi_i}^{(d)}$ since all other elements are deterministic. Given a posterior distribution for the elements in $\boldsymbol{\chi}_{\pi_i}^{(d)}$ as established by the VAR model as of equation (26) we can hence establish the posterior distribution for $\kappa^{(d)}$ by using equation (34). The distribution of $\kappa^{(d)}$ is provided in Figure 6 in the upper-left subpanel. The median estimate for $\kappa^{(d)}$ is 1.05 with a 68 percent credible interval ranging from 0.96 up to 1.14. This implies that a rise in the supply chain disruptions index ζ by one index point ($\Delta\zeta = 1$) causes the CPI inflation rate to be equal to 1.05 percent ($\Delta\zeta = 1 \;\rightarrow\; \Delta \log(P^{\text{CPI}}) = \pi^{\text{CPI}} = 1.05$). While this seems to be a rather strong price reaction, it has to be kept in mind that the present model's implications for CPI inflation clearly are on the upper edge, since demand has been assumed to be perfectly price inelastic. Hence, there is no mitigation in

[15] While equation (33) captures cross-price dependencies that arise from the (firm) supply side, Glocker and Piribauer (2025) derive an equivalent expression for the cross-price dependencies that arise from the (consumer) demand side.

FIGURE 6. Supply chain disruptions: Effect on CPI inflation



Note: The first subpanel shows the posterior density of the effect of supply chain disruptions on the CPI inflation rate based on the multi-sector general equilibrium model which uses estimates for χ^i_{41} as shown in the second subpanel in Figure 5. The second to third-subpanels show the contributions of the various production sectors (one-digit NACE classification) and consumption good categories (two-digit COICOP classification) of supply chain disruptions for the CPI inflation rate.

the form of a counterbalancing demand reaction to the price surge triggered by supply chain disruptions.

Equation (34) also implies that the slope coefficient $\kappa^{(d)}$ rises with the sensitivity $\chi^i_{41} \in \boldsymbol{\chi}^{(d)}_{\pi_i}$ of the sectoral inflation coefficients to supply chain disruptions. To see this, note that we have the following

$$\frac{\partial}{\partial \chi^i_{41}} \left(\frac{\partial \pi^{\text{CPI}}}{\partial \Delta\zeta} \right) = \boldsymbol{\omega}' \boldsymbol{\lambda}_i \geq 0 \qquad (35)$$

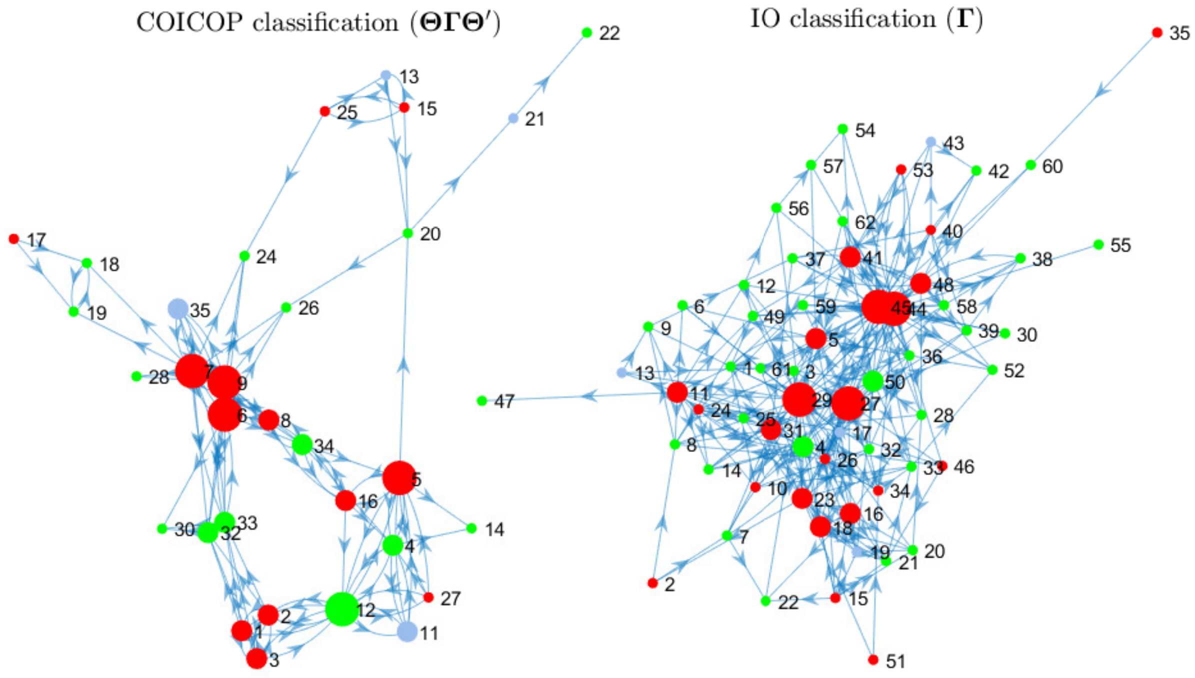
where $\boldsymbol{\lambda}_i$ of dimension $(N_C \times 1)$ is the i'th column-vector of $\boldsymbol{\Theta}\left(\boldsymbol{I} - \boldsymbol{\Gamma}\right)^{-1} = [\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_{N_S}]_{(N_C \times N_S)}$. Since all elements in $\boldsymbol{\Theta}$ and $\boldsymbol{\Gamma}$ are non-negative, it follows that $\partial^2 \pi^{\text{CPI}} / \partial\Delta\zeta \partial\chi^i_{41} \geq 0$.

While it is intuitive that a higher value of any χ_{41}^i raises the effect of ζ on CPI inflation, the enormous heterogeneity of the estimates for χ_{41}^i across production sectors as outlined in the upper-right subpanel in Figure 5, raises the question as to which extent the various production sectors contribute to the transmission channel of supply chain disruptions. To this purpose, we now examine the contribution of each of the N_S production sectors by analyzing each of the N_S elements in the vector $\boldsymbol{\chi}_{\pi_i}^{(d)}$ given by $\chi_{41}^i \ \forall \ i = 1, \ldots, , N_S$. In order to identify the contribution of the i'th production sector, we set $\chi_{41}^i = 0$, while at the same time using the median value of all the remaining elements in $\boldsymbol{\chi}_{\pi_i}^{(d)}$. We then compute the implied CPI inflation rate denoted by π_{-i}^{CPI} (the $-i$ subscript highlights that sector i was omitted) and determine the contribution by computing $1 - \pi_{-i}^{\text{CPI}}/\pi^{\text{CPI}}$, where π^{CPI} is given by equation (33) based on the median value for each element in $\boldsymbol{\chi}_{\pi_i}^{(d)}$. The results are provided in the upper-right subpanel in Figure 6. This exercise is done for all $N_S = 63$ sectors ($i = 1, \ldots, N_S$), but we provide the results solely at the one-digit level of disaggregation to enable a better visual inspection (the mapping from the two-digit to the one-digit level of disaggregation is done by simple aggregation). The sectors G to N, all of which comprise market-based service sectors, were aggregated to one overall sector (sectors G-N), while the remaining ones (O to T) are omitted since their joint contribution is less than one percent to the CPI inflation rate.

The results highlight that the largest contribution of around 70 percent stems from the manufacturing sector (sector C). It is followed by market-based service sectors (sectors G-N) and the mining and quarrying sector (sector B), each of which contributes around nine percent. The contribution of the remaining ones is less than five percent in each case. The dominance of the manufacturing sector replicates the finding put forth in the upper-right subpanel in Figure 5, which highlighted the comparably large value of the χ_{41}^i coefficients for the manufacturing subsectors. This gives rise to a sizable contribution of the manufacturing sector in shaping the CPI inflation rate in the wake of supply chain disruptions, which we subsequently refer to as the *direct effects* of supply chain disruptions on CPI inflation. In the following section, we extend the analysis to explore the indirect effects of supply chain disruptions.

5.2. **Indirect effects.** We define the indirect effects of supply chain disruptions on CPI inflation as those resulting from their transmission through the

FIGURE 7. Production network: visualization of linkages



Note: The figure shows the production network given by the I-O tables based on the three-digit COICOP classification (left-hand side; 39 nodes) and on the two-digit (NACE) production classification (right hand side; 63 nodes). The mapping from the NACE to COICOP classification uses the concordance matrices of Cai and Vandyck (2020). We only show the edges that are greater than the mean value of all non-zero valued edges. Nodes in red indicate out-degree dominance while those in green in-degree dominance; nodes in blue indicate equality between out- and in-degree.

production network. If a given sector is affected by supply chain disruptions while no other sector is directly affected, the shock can propagate through the production network to the other sectors due to sectoral interdependencies in production. The latter allow shocks to spread beyond the initially affected sector. In what follows, we refer to these effects as *indirect effects* and examine them in detail.

A simple way to examine the overall importance of cross-sector dependencies within the production network for the transmission of supply chain disruptions, is to compare the inflation rate from equation (33) with the case where cross-sector dependencies are omitted. In this case, $\mathbf{\Gamma}$ is equal to the zero matrix and inflation is then given by $\pi_0^{\mathrm{CPI}} = \boldsymbol{\omega}'\mathbf{\Theta}\boldsymbol{\chi}_{\pi_i}^{(d)}\Delta\zeta$. We follow Piribauer et al. (2023); Glocker and Piribauer (2025) and define the (overall) indirect (or spillover) effects (ς) as the effects of equation (33) relative to the zero-link case

(π_0^{CPI}), which gives the following for ς

$$\begin{aligned} \varsigma &= \pi^{\text{CPI}} - \pi_0^{\text{CPI}} \\ &= \boldsymbol{\omega}'\boldsymbol{\Theta}\left[(\boldsymbol{I}-\boldsymbol{\Gamma})^{-1}-\boldsymbol{I}\right]\boldsymbol{\chi}_{\pi_i}^{(d)}\Delta\zeta \end{aligned} \tag{36}$$

Considering a unit shock in $\Delta\zeta$, we find that $\pi^{\text{CPI}} = 1.05$ and $\varsigma = 0.83$. Thus, 78 percent of the CPI inflationary effect is due to cross-sector dependencies within the production network.[16] In the following, we analyze them in detail at the individual level.

The matrix $\boldsymbol{\Gamma}$ is the central element for understanding the indirect effects. Figure 7 illustrates the structure of these dependencies as a network—referred to as the production network. The right-hand subpanel of the figure shows the dependencies based on a two-digit NACE classification, encompassing the 63 production sectors. Only edges with values greater than the mean of all non-zero edges are displayed for clarity. Nodes in red indicate dominance in out-degree, while nodes in green indicate dominance in in-degree; nodes in blue exhibit equal out- and in-degrees. Key sectors with out-degree dominance include sectors 27 (Construction), 29 (Wholesale trade, except for motor vehicles and motorcycles), 44 (Real estate services), and 45 (Legal and accounting activities; activities of head offices; management consultancy activities). Conversely, sectors with in-degree dominance include sectors 4 (Mining and quarrying) and 50 (Rental and leasing activities). These rankings are based on the number of edges, though not on their weight, which could alter the relative importance of the nodes. The network exhibits characteristics of a small-world network (see Newman, 2010, for instance), where most nodes are not direct neighbors but can be reached by a small number of hops, primarily facilitated by hub nodes.

The left-hand subpanel in Figure 7 provides an alternative view of the production network, now based on the COICOP classification. This panel visualizes the entries of $\boldsymbol{\Theta\Gamma\Theta}'$, rather than $\boldsymbol{\Gamma}$ directly. The resulting network structure is notably distinct and aligns with the principles of the stochastic block model (see Holland et al., 1983; Karrer and Newman, 2011, among others). This structure reveals strong clustering within three primary groups: the first group encompasses food and beverage-related items, the second group

[16] This is in line with the results presented in Pichler et al. (2024), who highlight the important role of spillovers in amplifying sectoral shocks to aggregate gross value added.

consists of housing, water, and energy (including electricity, gas, and other fuels), and the third group represents clothing and household textiles. These groups exhibit strong internal connectivity, while also displaying inter-group connections.[17]

To assess the contribution of each of the N_S production sectors to the cross-sector dependency, we proceed as follows: Let $\mathbf{\Gamma} = [\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_{N_S}]$, where column i, denoted as $\boldsymbol{\gamma}_i$, represents the role of sector i's output as an input to the remaining $N_S - 1$ sectors. To isolate the contribution of sector i's output to the remaining production sectors and ultimately to CPI inflation, we set $\boldsymbol{\gamma}_i = \mathbf{0}$ while leaving the other columns of $\mathbf{\Gamma}$ unchanged. The resulting implied CPI inflation rate is then computed and denoted by π_{-i}^{CPI}. The contribution of sector i is calculated as $1 - \pi_{-i}^{\text{CPI}}/\pi^{\text{CPI}}$, where π^{CPI} is the inflation rate obtained using the full matrix $\mathbf{\Gamma}$, as defined in equation (33). The results of this exercise are presented in the lower-left subpanel of Figure 6, where, as before, the exercise is done for all 63 sectors, but we provide the contributions only at the one-digit level of disaggregation for better visual inspection. For clarity, the sectors G to N are aggregated into a single category, and the sectors O to T are omitted from the figure, as their joint contribution is again less than one percent.

The findings reveal that the contributions of sectors A, B, and D to F remain similar in size to their direct contributions, meaning that the direct impact of supply chain disruptions on CPI inflation via these sectors is roughly equal to their indirect impact. However, a different pattern emerges for sector C (manufacturing) and the market-based service sectors G to N. As shown in the upper-right subpanel of Figure 6, the direct contribution of sector C is large, while that of the market-based service sectors is small. When considering the indirect effects, the contribution of sector C diminishes considerably, while the contribution of the market-based service sectors increases significantly. The latter highlights the critical role of the manufacturing sector as a domestic transmitter of supply chain disruptions. Among the market-based service sectors, key subsectors shaping the indirect effects include trade-related

[17] Interestingly, recent evidence suggests that these cross-price dependencies are not static but exhibit significant time variation, with the network structure and strength of linkages changing in response to major economic events such as the recent energy price shock (Iacopini et al., 2026).

sectors (G45-G47), transportation services (H49-H52), and employment activities (N78).

5.3. **The role of consumer preferences.** Finally, we analyze in detail the role of consumer preferences in shaping the transmission of supply chain disruptions to CPI inflation. We consider the contribution of each of the N_C consumption categories by examining the corresponding elements ω_i for $i = 1, \ldots, N_C$ in the vector $\boldsymbol{\omega}$. To isolate the contribution of the ith consumption category, we set $\omega_i = 0$, while keeping the remaining elements of $\boldsymbol{\omega}$ unchanged. The implied CPI inflation rate, denoted as π^{CPI}_{-i}, is then computed, and the contribution of the ith category is then given by $1 - \pi^{\text{CPI}}_{-i}/\pi^{\text{CPI}}$, where π^{CPI} is the CPI inflation rate based on the full vector $\boldsymbol{\omega}$ as defined in equation (33). The results of this exercise are presented in the lower-right subpanel of Figure 6. While this exercise is done for all $N_C = 39$ consumption categories[18] (three digit level), we aggregate the effects to the two-digit level. This gives rise to eleven categories.

The findings indicate that all eleven consumption categories play a significant role in transmitting supply chain disruptions to CPI inflation. Among these, the two categories with the highest contributions are category 1 (Food and non-alcoholic beverages) and category 7 (Transport). The substantial contribution of category 1 can largely be attributed to the high ω-values associated with these items, reflecting their large weight in the CPI basket. In the case of category 7, the main driver is the elevated producer price inflation rates observed in the transport-related production sectors.

When comparing the contribution of consumer preferences to that of the production sectors in explaining CPI inflation resulting from supply chain disruptions, a notable observation emerges. In the case of the production sectors, there are a few sectors–such as manufacturing and market-based services–that clearly dominate the transmission of supply chain disruptions. However, in the case of consumer preferences, the contribution is more evenly distributed across the various consumption categories.

6. Conclusion

We construct a composite index to measure supply chain disruptions and investigate the macroeconomic and sectoral implications, with an application

[18]We omit the categories related education.

to the Austrian economy. The index is built from ten carefully selected constituent indicators, which include business survey data and transport price data. The former provides country-specific information for supply chain disruptions, while the latter adds international elements.

The structural analysis shows that supply chain disruptions are consistent with contractionary supply shocks. They reduce economic activity while raising inflation. Although supply chain disruptions account for a relatively small share of the fluctuations in these two variables on average, they play a significant role in driving inflation and output dynamics in 2021 and 2022. Moreover, supply chain disruptions at the country level clearly dominate their global counterpart in explaining inflation and activity at the country level.

From a sectoral perspective, supply chain disruptions induce contractionary effects across most sectors, with the largest negative impacts observed in manufacturing subsectors. These also experience the most pronounced inflationary pressures. The cross-sectional heterogeneity in output contraction is mainly explained by unit labor costs, while the inflationary response is more pronounced in sectors that rely heavily on imported inputs.

Using a multi-sector general equilibrium model, we identify both the direct and indirect effects of supply chain disruptions on CPI inflation. While cross-sector dependencies within the production network explain 78 percent of the inflationary effect of supply chain disruptions, manufacturing subsectors emerge as the main domestic transmitters of these shocks, with spillovers to market-based service sectors becoming increasingly important as the shock propagates. Finally, consumer preferences lead to a fairly even distribution of supply chain disruptions across consumption groups in their transmission to CPI inflation.

Although this study focuses on a specific country, our findings should not be seen as country-specific. The Austrian economy is characterized by a large manufacturing sector, a high degree of integration in global value chains, and a substantial reliance on imported intermediate goods. The fact that these characteristics are shared by many European countries renders our findings applicable to a broader country context.

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Appendix A. Details on the construction of the supply chain disruption index

This section provides more detail on the construction of the supply chain disruptions index, focusing on the selection of constituent indicators that directly reflect supply chain bottlenecks. Many indicators contain information on supply chain disruptions. However, these indicators are often noisy as they contain also other information that is not related to supply chains. The goal of the construction is to ensure that the composite index exclusively captures supply chain-specific disruptions rather than broader economic fluctuations. The selection process is guided by economic relevance, data availability, timeliness, and the indicators' direct relationship to supply constraints. The composite index is based on monthly data from 2006 onward, incorporating business surveys and price data. To ensure full temporal coverage, missing data are backcasted.[19]

The composite index, denoted as ζ_t, quantifies supply shocks arising from supply chain disruptions while distinguishing them from other supply-side shocks. Our approach follows broadly the construction of the Global Supply Chain Pressure Index (ζ_t^*) developed by Benigno et al. (2022).

Our index comprises ten subindicators: five derived from Austrian business survey data, capturing country-specific supply chain disruptions, and five from international transport price data, incorporating the global dimension. Among the business survey indicators, three cover delivery times, order backlogs, and inventories in the manufacturing sector (source: Austrian purchasing managers' index). Additionally, data on material and equipment shortages in the manufacturing and construction sectors are included (source: WIFO business survey). The quarterly time series of manufacturing were converted to monthly frequency. These indicators measure the availability of key production inputs and the extent to which production is constrained by supply chain disruptions.

Transport price indicators provide additional insights as proxies for logistical supply constraints. The set includes three ocean freight price measures—the

[19]To address data gaps and the absence of vintage data, we use ARIMAX models embedded in a state-space framework, estimated by the Kalman filter. We use primarily indicators used in the construction of the index that supplemented by appropriate auxiliary variables. For example, for backcasting directional air freight prices US inbound and outbound price indices for air freight were used as auxiliary variables. This method, following Chow and Lin (1971), facilitates backcasting, nowcasting, and the conversion of quarterly data to a monthly frequency, ensuring continuous and comprehensive time series.

Baltic Dry (cape-size) index and two container freight indices covering major routes from the Americas to Europe and from Asia to Europe—as well as two global air freight indices tracking price movements across major intercontinental routes (Sources: Drewry container shipping rates and Drewry air freight rates). Price data serve as reliable scarcity signals since prices rise during both demand surges and supply contractions, whereas volume data can be ambiguous under different economic conditions.

During the construction of the index, we also experimented with other indicators. Data on local and regional transport prices (truck price index, rail freight prices) were not used, as they had no relationship (no correlation) with business survey indicators on delivery times or material and equipment shortages. We also tested an index of Suez canal ship transits, as the Huthi attacks on commercial vessels in the Red Sea since 2023 led to a rerouting of supply chains. However, the longer time series almost exclusively captured demand-side influences and had almost no information on supply disruptions.

A crucial step in constructing the composite index involves removing cyclical demand influences to ensure it reflects only supply chain-related shocks. Following Benigno et al. (2022), business survey indicators are regressed on local new orders, using contemporaneous values and two lags, with the residuals retained as demand-adjusted series. A similar approach is applied to transport price indicators, incorporating new orders from Austria, the United States, and China to account for global demand conditions. The demand-adjusted series exhibit greater variance, enhancing the index's ability to capture supply-side disruptions while eliminating cyclical components.

The final composite index ζ_t is constructed using principal component analysis, with the first principal component serving as its basis to extract the common signal across the subindicators. Table 3 presents the factor loadings of the first principal component, which defines the supply chain disruptions index. Higher loadings indicate a stronger contribution to the index, with air cargo rates, ocean container prices, and material shortages in manufacturing playing the most significant roles. In contrast, indicators like backlog of work and stocks of purchases have lower loadings, reflecting weaker associations with overall supply chain disruptions. Notwithstanding the variation in the factor loadings across the subindicators, all are statistically significantly

Table 3. Factor loadings

Aircargo rates Asia-EU	0.84
Aircargo rates America-EU	0.72
Ocean container prices America-EU	0.35
Ocean container prices Asia-EU	0.86
Baltic Dry Index (cape-size)	0.62
Material/equipment shortage construction	0.75
Material/equipment shortage manufacturing	0.84
PMI: Delivery times	0.53
PMI: Stocks of purchases	0.24
PMI: Backlog of work	0.29

Notes: This table presents the factor loadings of the first principal component for the ten subindicators included in the composite supply chain disruptions index. Higher factor loadings indicate a stronger contribution of the respective subindicator to the overall index.

different from zero. Equally important is the stability of the subindicators contribution to the composite index. To this purpose, we consider the temporal path of the standard deviation across the ten subindicators.

The standard deviation across subindicators is provided Figure 1 (green dashed line). The standard deviation remains relatively flat throughout the sample, with a modest increase in early 2020.[20] This profile underscores the stability of informational content across subindicators over time and as a consequence, the robustness of the composite index. Clearly, the index exhibits pronounced peaks, suggesting asymmetric volatility patterns. However, the histogram of its realizations (first subpanel) reveals only moderate right-skewness, comparable to that observed in Benigno et al. (2022).[21]

Appendix B. Rational expectations versus static expectations

This subsection derives the rational-expectations equilibrium of the baseline New Keynesian model and compares its contemporaneous coefficient matrix with that obtained under the static-expectations approximation used in the main text. The purpose is to show that both approaches imply the same sign pattern for the structural matrix A, and therefore support the same sign-identification strategy.

[20]Although the coefficient of variation would typically be preferable for assessing changes in cross-sectional dispersion, its use is impractical here due to instances where the cross-sectional mean is zero.

[21]The Jarque-Bera test fails to reject the null hypothesis that the data follow a normal distribution.

We start from the baseline theoretical system

$$\hat{y}_t = -\frac{1}{\eta}\left(i_t - E_t\pi_{t+1}\right) + E_t\hat{y}_{t+1} + \nu_t^D, \tag{37}$$

$$\pi_t = \beta E_t\pi_{t+1} + \kappa\hat{y}_t + \nu_t^S, \tag{38}$$

$$i_t = \phi_\pi\pi_t + \phi_y\hat{y}_t + \nu_t^i. \tag{39}$$

The shocks ν_t^D, ν_t^S, and ν_t^i are assumed to be white-noise disturbances. Under rational expectations, this implies

$$E_t\hat{y}_{t+1} = 0, \qquad E_t\pi_{t+1} = 0.$$

Substituting the monetary policy rule into the IS equation gives

$$\hat{y}_t = -\frac{1}{\eta}\left(\phi_\pi\pi_t + \phi_y\hat{y}_t + \nu_t^i\right) + \nu_t^D,$$

while the Phillips curve becomes

$$\pi_t = \kappa\hat{y}_t + \nu_t^S.$$

We now solve the model by means of the method of undetermined coefficients. Conjecture a linear equilibrium of the form

$$\hat{y}_t = a_D\nu_t^D + a_S\nu_t^S + a_i\nu_t^i, \qquad \pi_t = b_D\nu_t^D + b_S\nu_t^S + b_i\nu_t^i.$$

Using the Phillips curve, we obtain

$$b_D = \kappa a_D, \qquad b_S = \kappa a_S + 1, \qquad b_i = \kappa a_i.$$

Substituting these expressions into the IS equation and comparing coefficients on ν_t^D, ν_t^S, and ν_t^i yields

$$a_D = -\frac{1}{\eta}\left(\phi_\pi b_D + \phi_y a_D\right) + 1,$$

$$a_S = -\frac{1}{\eta}\left(\phi_\pi b_S + \phi_y a_S\right),$$

$$a_i = -\frac{1}{\eta}\left(\phi_\pi b_i + \phi_y a_i + 1\right).$$

Defining

$$\Delta \equiv \eta + \phi_y + \kappa\phi_\pi,$$

the solution is

$$a_D = \frac{\eta}{\Delta}, \qquad a_S = -\frac{\phi_\pi}{\Delta}, \qquad a_i = -\frac{1}{\Delta},$$

$$b_D = \frac{\kappa\eta}{\Delta}, \qquad b_S = \frac{\eta + \phi_y}{\Delta}, \qquad b_i = -\frac{\kappa}{\Delta}.$$

Hence, the rational-expectations equilibrium is given by

$$\hat{y}_t = \frac{\eta\nu_t^D - \phi_\pi\nu_t^S - \nu_t^i}{\Delta}, \qquad \pi_t = \frac{\kappa\eta\nu_t^D + (\eta + \phi_y)\nu_t^S - \kappa\nu_t^i}{\Delta}.$$

This solution can be rewritten in the AD-AS form

$$\hat{y}_t = \delta_{RE}\pi_t + u_{t,RE}^D, \qquad \delta_{RE} = -\frac{\phi_\pi}{\eta + \phi_y}, \qquad u_{t,RE}^D = \frac{\eta\nu_t^D - \nu_t^i}{\eta + \phi_y},$$

and

$$\pi_t = \varsigma_{RE}\hat{y}_t + u_{t,RE}^S, \qquad \varsigma_{RE} = \kappa, \qquad u_{t,RE}^S = \nu_t^S.$$

Under the maintained parameter restrictions $\phi_\pi > 1$, $\phi_y \geq 0$, $\eta \geq 1$, and $\kappa \geq 0$, we obtain

$$\delta_{RE} < 0, \qquad \varsigma_{RE} > 0.$$

Accordingly, the contemporaneous structural matrix under rational expectations is

$$A_{RE} = \begin{bmatrix} 1 & -\delta_{RE} \\ -\varsigma_{RE} & 1 \end{bmatrix} = \begin{bmatrix} 1 & \dfrac{\phi_\pi}{\eta + \phi_y} \\ -\kappa & 1 \end{bmatrix},$$

and therefore

$$\text{sgn}(A_{RE}) = \begin{bmatrix} + & + \\ - & + \end{bmatrix}.$$

We now compare this result to the static-expectations approximation used in the main text. Under static expectations,

$$E_t\hat{y}_{t+1} = \rho_y\hat{y}_t, \qquad E_t\pi_{t+1} = \rho_\pi\pi_t,$$

which yields

$$\hat{y}_t = \delta_{SE}\pi_t + u_{t,SE}^D, \qquad \delta_{SE} = -\frac{\phi_\pi - \rho_\pi}{\eta(1 - \rho_y) + \phi_y},$$

and

$$\pi_t = \varsigma_{SE}\hat{y}_t + u_{t,SE}^S, \qquad \varsigma_{SE} = \frac{\kappa}{1 - \beta\rho_\pi}.$$

Since $\rho_y \in (-1, 1)$, $\rho_\pi \in (-1, 1)$, $\phi_\pi > 1$, $\phi_y \geq 0$, $\eta \geq 1$, $\beta < 1$, and $\kappa \geq 0$, we also have

$$\delta_{SE} < 0, \qquad \varsigma_{SE} > 0.$$

Thus,

$$A_{SE} = \begin{bmatrix} 1 & -\delta_{SE} \\ -\varsigma_{SE} & 1 \end{bmatrix}, \qquad \text{sgn}(A_{SE}) = \begin{bmatrix} + & + \\ - & + \end{bmatrix}.$$

The comparison therefore shows that the rational-expectations solution and the static-expectations approximation imply the same sign pattern for the contemporaneous structural matrix A. This is the key object for our identification procedure. Hence, the sign restrictions employed in the empirical model are consistent with both approaches to expectation formation.

For the empirical analysis, we nevertheless retain the static-expectations version in the baseline specification. The reason is not that rational expectations would imply different signs for the contemporaneous structural matrix. Rather, the static-expectations approximation provides a simpler and more transparent mapping from the theoretical model to the estimated SVARX representation, while preserving exactly the same sign implications for A.

Appendix C. Bayesian estimation and prior densities

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

$$Y = Xb + E, \tag{40}$$

where X now includes all regressors of equation (22) of the main part (that is, lagged endogenous and exogenous variables), and E has a variance-covariance matrix Σ. We use a rather diffuse version of the conjugate prior densities. To this purpose, we utilize the Normal-Wishart prior density for b and Σ^{-1}: $p(b, \Sigma^{-1}) = p(b)p(\Sigma^{-1})$, where $b \sim N\left(\underline{b}, \underline{V}\right)$ and $\Sigma^{-1} \sim W\left(\underline{H}, \underline{v}\right)$. The rather agnostic setup of the prior densities is then obtained by using $\underline{v} = 0$ and $\underline{H}^{-1} = I$, where I is the identity matrix of conformable size. For the slope parameters, we set $\underline{b} = 0$ and $\underline{V} = 100I$. Given this particular specification for the prior densities, we obtain the following conditional posterior densities for $p(b|Y, \Sigma^{-1})$ and $p(\Sigma^{-1}|Y, b)$:

$$b|Y, \Sigma^{-1} \sim N\left(\bar{b}, \bar{V}\right) \qquad \Sigma^{-1}|Y, b \sim W\left(\bar{H}, \bar{v}\right), \tag{41}$$

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

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

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

Appendix D. Multi-sector general equilibrium model

This section introduces the multi-sector (static) general equilibrium model. Its key feature is that it allows for price-dependencies arising from value chains along production networks. We follow Acemoglu et al. (2012) in this respect. Consider a static economy with N_S goods.

A representative consumer participating in the market economy devotes all his income to consumption expenditure equal to $\sum_{i=1}^{N_S} P_i C_i$, where C_i and P_i are consumption and the price of good i. We assume that the demand by consumers for these N_S goods is perfectly price inelastic. Moreover, the consumer supplies labor inelastically to firms across sectors equal to L_i for sector i.

Each good i is produced in a distinct sector and can be either purchased by the consumers as final good or used as an intermediate input for the production of other goods. Firms in each sector operate in perfectly competitive input and output markets, and they employ Cobb-Douglas production technologies with constant returns to scale to transform intermediate inputs and labor into output goods. The latter are either sold to the consumer as final goods or to firms in other sectors as intermediate goods. In particular, the output of sector i is given by

$$x_i\left(l_i, x_{i1}, \ldots, x_{iN_S}\right) = \xi_i\, l_i^{\gamma_i} \prod_{j=1}^{N_S} x_{ij}^{\gamma_{ij}} \tag{42}$$

where l_i is the amount of labor hired by firms in sector i, $x_{ij} \in \mathbb{R}_+$ is the quantity of good j used for the production of good i, $\gamma_i > 0$ denotes the share of labor in sector i's production technology and ξ_i is the sector specific total factor productivity. The exponents $\gamma_{ij} \geq 0$ in equation (42) formalize the idea that firms in one sector may need to rely on the goods produced by other industries as intermediate inputs for their own production. Note that, in general, $\gamma_{ij} \neq \gamma_{ji}$ and the assumption of constant returns to scale requires that

$$\gamma_i + \sum_{j=1}^{N_S} \gamma_{ij} = 1 \tag{43}$$

Firms in sector i choose their demand for labor and intermediate goods to maximize profits, $\digamma_i = P_i x_i - l_i - \sum_{j=1}^{N_S} P_j x_{ij}$, while taking all prices (P_1, ...,P_{N_S}) as given and the wage is normalized to one. The first-order conditions imply that $x_{ij} = \gamma_{ij} P_i x_i / P_j$ and $l_i = \gamma_i P_i x_i$. Plugging these expressions into firm i's production function, equation (42), and taking logarithms implies that

$$\pi^i = \sum_{j=1}^{N_S} \gamma_{ij} \pi^j - \Delta \log(\xi_i) \tag{44}$$

where $\pi^i = \Delta \log(P_i)$ is the inflation rate in sector i.

Equation (42) in conjunction with the assumption on consumer demand and labor supply fully specify the environment. The competitive equilibrium of this economy is defined in the usual way: It consists of a collection of prices and quantities such that the representative firm in each sector maximizes its profits, while taking the prices and the wage as given, the representative consumer maximizes its utility (which is simplified by the assumption of price inelastic consumption demand), and all markets clear. Market clearing in the labor market implies that $L_i = l_i \; \forall \; i = 1, \ldots, N_S$, while goods market clearing implies that $x_i = C_i + \sum_{j=1}^{N_S} x_{ij} \; \forall \; i = 1, \ldots, N_S$.

Most importantly for our purposes, since the relationship put forth in equation (44) has to hold for all industries $i = 1, ..., N_S$, it provides a system of equations to solve for all equilibrium relative prices in terms of productivity shocks. It can be rewritten in matrix form as

$$\boldsymbol{\pi}_S = \boldsymbol{\Gamma} \boldsymbol{\pi}_S + \Delta \boldsymbol{\xi} \tag{45}$$

where $\boldsymbol{\Gamma} = [\gamma_{ij}]_{i,j=1}^{N_S}$ is the economy's input–output matrix, $\boldsymbol{\pi}_S = [\Delta \log(P_i)]_{i=1}^{N_S}$ is again the price vector and $\boldsymbol{\xi} = -[\log(\xi_i)]_{i=1}^{N_S} \in \mathbb{R}^{N_S}$ is a vector of supply shocks (made up solely of sectoral shocks to total factor productivity).

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

Appendix E. From the NACE to the COICOP classification

In what follows, we examine the conversion of the production network $\mathbf{\Gamma}$ based on the NACE classification into the COICOP classification on which the CPI is based upon. We use the input-output (IO) tables which can be product-by-product or sector-by-sector matrices combining both supply and use tables into a single matrix. We use the latter based on the NACE classification at the two-digit level for our purposes. These tables depict inter-sector relationships within an economy, showing how output from one sector may become an input to another sector. They quantify the inter-sectoral relationships by means of a matrix. Their column entries capture inputs to an sector, while row entries represent outputs from a given sector. This arrangement, therefore, shows the extent of dependency of one sector on another, both as a customer of outputs from other industries and as a supplier of inputs. Industries may also depend on their own output, that is, on a portion of their own production; this is delineated by the entries of the main diagonal.

We convert the NACE classification of the IO tables into the COICOP classification on which the CPI is based upon by using the bridge (or concordance) matrices $\mathbf{\Theta}$ of Cai and Vandyck (2020). This gives rise to a production network expressed in terms of the COICOP classification, which we denote by $\tilde{\mathbf{\Gamma}}$, and it is given by

$$\tilde{\mathbf{\Gamma}} = \mathbf{\Theta}'\mathbf{\Gamma}\mathbf{\Theta} \tag{46}$$

Since demand is price inelastic, equilibrium prices are set by goods' supplies only according to equation (45). Consequently, the vector of equilibrium producer prices is given by

$$\boldsymbol{\pi}_S = (\boldsymbol{I} - \mathbf{\Gamma})^{-1}\Delta\boldsymbol{\xi} \tag{47}$$

Using bridge matrices of Cai et al. (2019), producer price inflation rates $\boldsymbol{\pi}_S$ can then be mapped into consumer price inflation rates $\boldsymbol{\pi}_C$, as outlined in Section 5. Finally, using the weights of each subcomponent of the CPI, the vector of consumer prices $\boldsymbol{\pi}_C$ can then be reduced to a scalar which is the CPI (inflation rate).

As a final remark, note that equation (47) expresses the vector of equilibrium producer prices (or their inflation rates) in terms of sector-level shocks and the economy's production network. The latter captures the input-output (IO) linkages between various industries, and they are summarized in the matrix $\mathbf{\Gamma}$. From an empirical point of view, the IO matrix of an economy is constructed by the national statistical offices and it is defined in terms of input expenditures as a fraction of sales, that is, $\eta_{ij} = P_j x_{ij}/P_i x_i$. However, in the special case that all technologies are Cobb-Douglas, η_{ij} coincides with the exponent γ_{ij} in equation (42).

Appendix F. Robustness checks

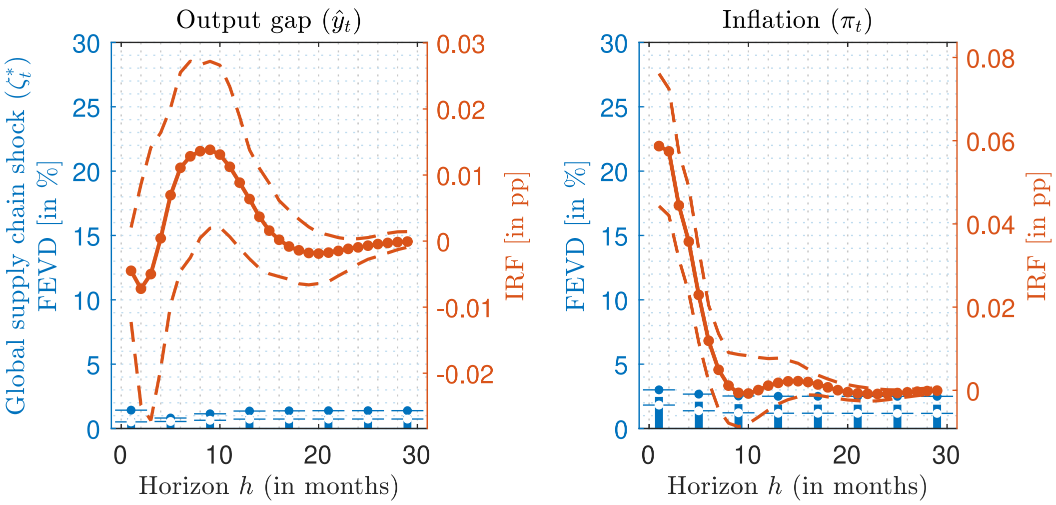
We conduct a series of robustness checks, examining the role of omitted variables, the implications of using alternative measures for inflation and real economic activity, and the potential differences across various subsamples.

F.1. A global versus a local measure for supply chain disruptions.

The main results of this study are based on a country-specific measure for supply chain disruptions. As highlighted, shocks to the index induce a statistically significant response in both the output gap (negatively) and the inflation rate (positively). A key question that arises is whether these shocks represent solely country-specific instances of supply chain disruptions or whether they align in size and sign with those resulting from global supply chain disruptions. The cross-correlation analysis conducted earlier has revealed noticeable differences between the country-specific supply chain disruptions index and its global counterpart. To evaluate these indices more thoroughly, we now carry out the macroeconomic analysis using the global index instead of the country-specific one.

The results of this exercise are presented in Figure 8. As shown, the results when using the global index align qualitatively with those from the country-specific index: the output gap is negatively affected in response to an increase in the supply chain disruptions index, while the inflation rate increases. However, we observe significant quantitative differences. In the case of the country-specific index, the trough of the output gap is around -0.025, and the peak response of the inflation rate is approximately 0.15. When using the global index, the responses are noticeably smaller in size, with a drop in the output gap of only -0.05 and an inflationary response of around 0.06 (in all

Figure 8. Using the global index for supply chain disruptions (ζ_t^*)



Note: The figure displays impulse response functions by orange solid lines (median) and dashed lines (68 percent credible interval), alongside forecast error variance decomposition represented by blue bars (median) and blue/white dots (68 percent credible interval). Both statistics are shown for the shock specific to global supply chain disruptions (ζ_t^*)–across all endogenous variables: output gap ($\hat{y}_t$) and inflation rate (π_t).

cases, these values represent the largest absolute responses). In other words, when using the country-specific index, the response of the output gap to supply chain disruptions is five times as large compared to when the global index is used. Similarly, in the case of the inflation rate, the difference amounts to a factor of three, which is also substantial.

This highlights the superior information content of the country-specific supply chain disruptions index relative to the global index. In this respect, our results emphasize the importance of accounting for country-specific characteristics when examining the implications of supply chain disruptions on economic activity.

F.2. **Omitted variables.** Separate Ljung-Box tests on each residual time series cannot reject the null hypothesis that they follow processes which are uncorrelated over time. However, it is still possible that omitted variables matter for the results. To check whether the two identified shocks (demand shock and supply shock) are correlated with other (omitted) variables, we first compute correlations of the estimated structural disturbances with variables that a large class of general equilibrium models suggests as being jointly generated by various shocks.

We compute correlations of up to six leads and lags between the global demand and supply shock and the growth rate of the domestic stock market indices, employment, consumption, the Brent oil price[22], global industrial production, the price of natural gas (according to Dutch TTF),[23] a financial market stress indicator (Glocker and Kaniovski, 2014; Fortin et al., 2023) and a global stock market index.

The cross-correlations indicate that none of the omitted variables correlates significantly with the structural shocks. The statistical importance of the cross-correlations has been judged by means of the upper and lower limits of an asymptotic 95 percent confidence tunnel for the null hypothesis of no cross-correlation.

We also conduct a more general assessment of the potential effects of omitted variables. To this end, we extend the baseline model by incorporating an additional variable. Specifically, we consider three potential variables in this respect: a financial market stress index, an uncertainty measure related to the manufacturing sector (Sector C), and the Global Supply Chain Pressure Index, as developed by Benigno et al. (2022).

We add each of these additional variables to the baseline model sequentially, thus assessing the role of each in shaping our baseline results individually.

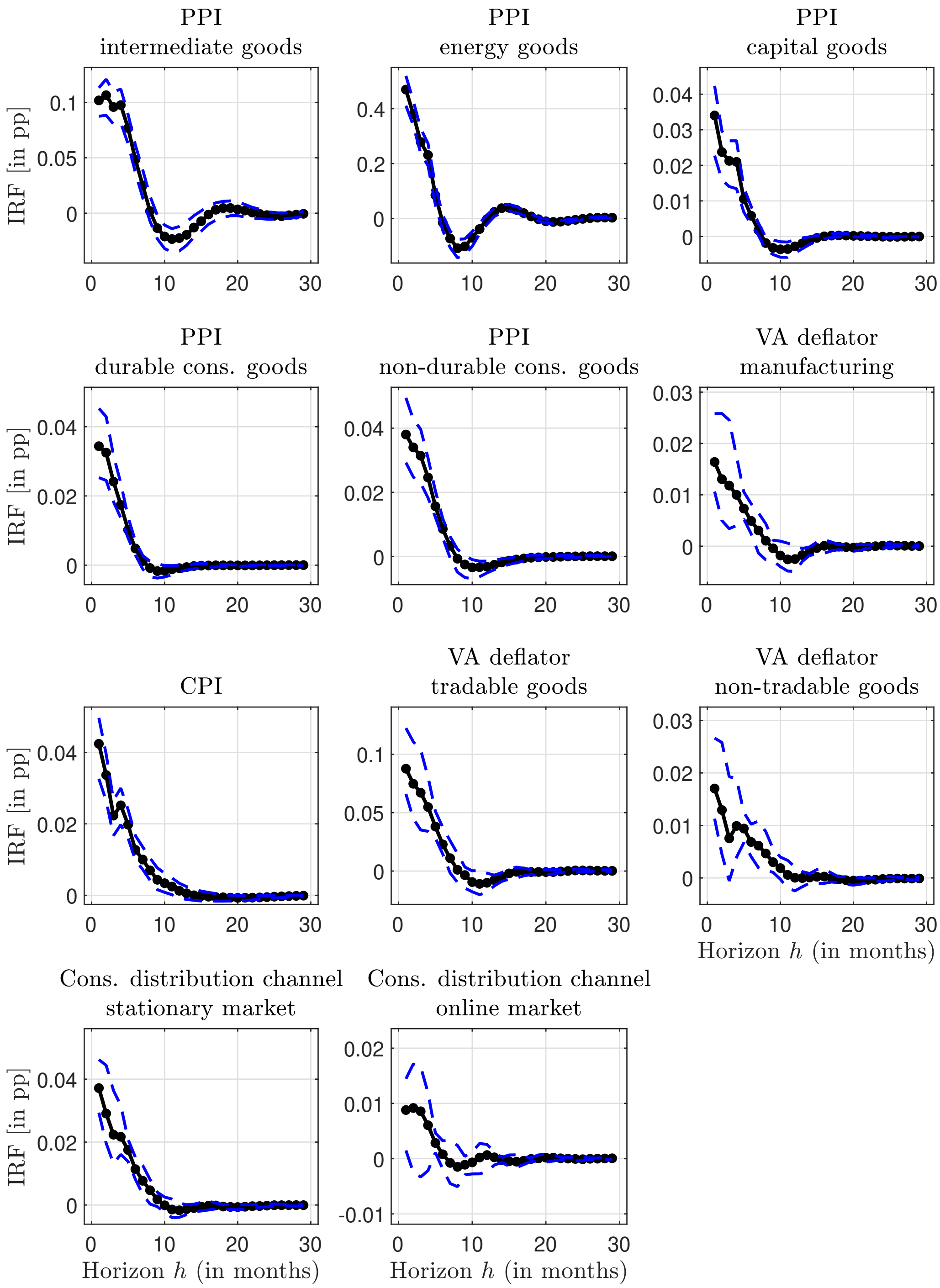
Our findings indicate that the baseline results remain robust to the inclusion of these additional variables. While the qualitative results are confirmed, we observe that the responses of inflation and the output gap remain statistically significantly different from zero in the extended models. Quantitatively, however, the changes are modest and not significantly different from those observed in the baseline specification.

F.3. **Alternative measures for the inflation rate.** To assess the robustness of our findings, we conduct an extensive sensitivity analysis regarding the inflationary measure employed in the baseline model. The baseline results, as

[22]We use the cyclical component of the oil price obtained after applying the Christiano-Fitzgerald filter on the logarithm of the oil price.

[23]As an additional robustness check in this context , we augmented the baseline specification with a range of energy-price measures as exogenous controls, including the Brent crude oil price, the Dutch TTF natural gas price, and the IMF's composite energy price index. While the inclusion of these variables gives rise to some quantitative differences in the estimated impulse responses, the results remain qualitatively unchanged throughout. Most importantly, the corresponding confidence intervals overlap with those of the baseline specification at all horizons, indicating that the differences are not statistically significant and that our main findings are robust to the inclusion of energy-price controls.

Figure 9. Alternative measures for prices



Note: The figure shows the impulse response functions for various alternative measures of inflation, each of which is used instead of the GDP deflator used in the baseline specification. The black solid line indicates the median of the posterior distribution, while the blue dashed lines indicate 68 percent credible intervals.

presented, rely on the GDP deflator as the inflationary measure. In order to evaluate the overall validity of our baseline results, we challenge these findings by substituting the GDP deflator with a series of alternative inflationary measures.

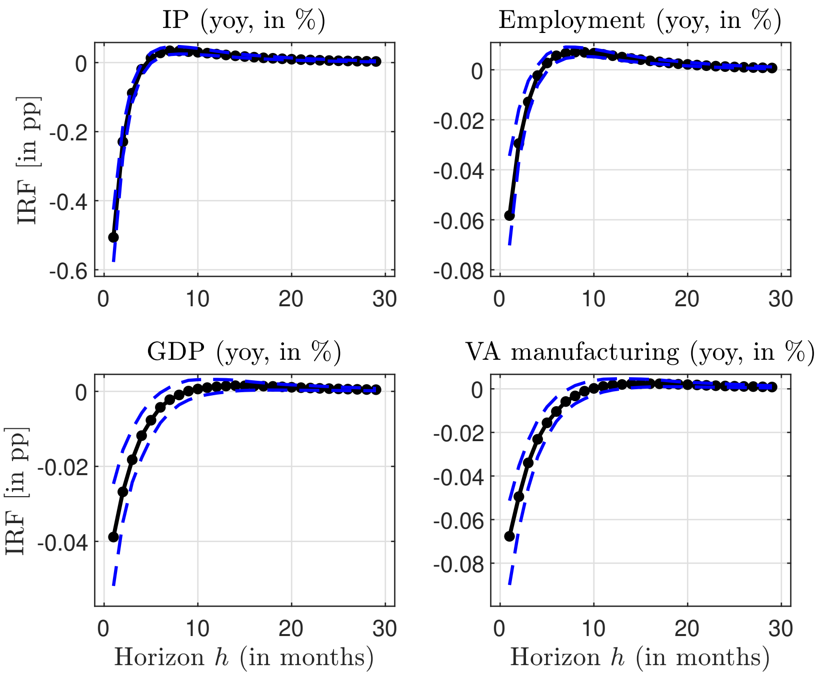
As alternative measures, we consider the five subindices of the producer price index (PPI), which include intermediate goods, energy goods, capital goods, durable consumption goods, and non-durable consumption goods. In addition, we incorporate inflationary measures based on the deflator of the manufacturing sector (Sector C, as outlined in Table 7 for the one-digit level classification), as well as deflators for the tradable and non-tradable goods (and services) sectors, following the classification proposed by Friesenbichler and Glocker (2019); Crespo Cuaresma and Glocker (2023). Finally, we explore inflationary measures based on the consumer price index (CPI) and examine price indices that distinguish different distribution channels of consumer goods to households. In this regard, we consider an inflationary measure based on the price index for goods sold in stationary places (brick-and-mortar stores), and for goods sold via online distribution channels. Each of these alternative price measures (price index and/or deflator) is used in the empirical model in terms of relative year-on-year percentage changes, equivalent to the GDP deflator used in the baseline specification.

For each of these alternative inflationary measures, we estimate the baseline model, substituting the GDP deflator with one of the aforementioned inflationary measures. The results of this exercise are presented in Figure 9. Each subpanel corresponds to an individual model, where the shock in the supply chain disruptions index is specified in the same way as was done for the baseline results, specifically a unit shock in supply chain disruptions ($\zeta_t = 1$) is considered.

Across all alternative inflationary measures, we consistently find that supply chain disruptions lead to upward pressure on inflation. The results are statistically significant in all cases, except for the price index based on the online distribution channel of consumer goods. Notably, the strongest reactions are observed in the various subindices of the producer price index and the inflation rate based on the deflator for tradable goods. The responses tend to be quantitatively smaller for the CPI, the deflator for non-tradable goods, and the price index for goods sold in stationary markets.

Moreover, we observe that for each alternative inflationary measure, the inflationary response is largest in magnitude contemporaneously. While the responses exhibit a significant degree of inertia, the effects tend to dissipate after approximately twelve months.

Figure 10. Alternative measures for real activity



Note: The figure shows the impulse response functions for various alternative measures for real economic activity, each of which is used instead of the output gap used in the baseline specification. The black solid line indicates the median of the posterior distribution, while the blue dashed lines indicate 68 percent credible intervals.

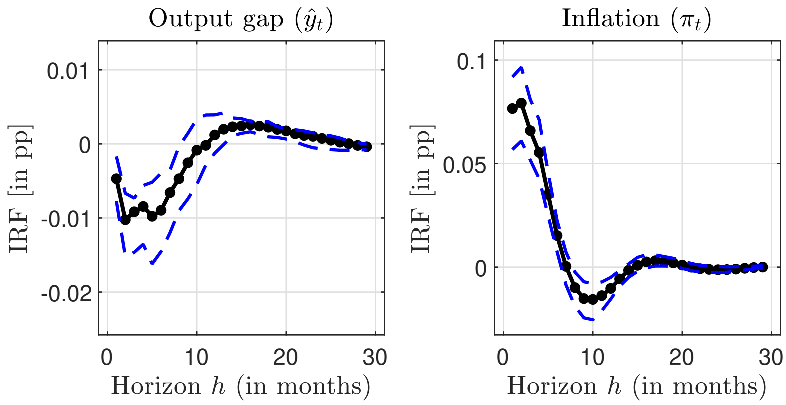
We interpret these findings as supportive of our baseline results, confirming the robustness of the observed relationships. This holds true not only for the production-specific alternative price measures but also for the consumption-specific price measures, particularly those that reflect the distribution channels through which consumer goods are sold.

F.4. **Alternative measures for real activity.** Similar to the approach taken in examining the general validity of the baseline results for inflationary reactions through various distinct inflationary measures, we perform a similar exercise to assess the robustness of our findings with respect to different measures of real economic activity.

In this context, we consider the industrial production index, total employment, real value added in the manufacturing sector, and GDP as alternative measures. Each of these measures is employed in terms of their year-over-year relative change expressed in percent.

We use these alternative measures in the baseline model, substituting the output gap, with each of these new measures. In this way, we estimate the

FIGURE 11. Estimation based on a subsample (2006M1 – 2019M12)



Note: The figure shows the impulse response functions for the inflation rate (based on the GDP deflator) and the output gap, based on a sample from January 2006 to December 2019. The black solid line indicates the median of the posterior distribution, while the blue dashed lines indicate 68 percent credible intervals.

baseline model separately for each alternative measure of real activity. The results of this exercise are presented in Figure 10.

For each of the four alternative measures of real activity, we find that supply chain disruptions exert downward pressure on economic activity. The response of each alternative measure is statistically significantly different from zero.

As in the previous exercise, we consider a unit increase in supply chain disruptions, allowing for direct quantitative comparison with the baseline results. We observe that the response is largest in magnitude when using the industrial production index, while the responses for the remaining three measures are smaller but quantitatively similar to each other. Furthermore, in each of the four alternative measures, we observe that the effects are largest in size contemporaneously. Although the responses show a high degree of inertia, they dissipate after approximately six to eight months. This suggests that the reaction in real activity tends to fade out slightly earlier than the price reaction.

We interpret these results as a confirmation of our baseline findings. Moreover, these results highlight that the effects of supply chain disruptions extend beyond production alone as they also spill over to employment.

F.5. **Subsample stability.** The historical decomposition of our baseline results highlights that the largest share of fluctuations in both inflation and the output gap explained by supply chain disruptions occurs during the period

2021-2022. This period coincides with the largest spikes in the supply chain pressure index. While the index also exhibits sizable changes prior to this period, the question arises as to the extent to which the baseline results are subject to subsample instabilities. In what follows, we examine this possibility.

To assess subsample instabilities, we re-estimate the baseline model in its original specification (utilizing the GDP deflator and the output gap), but now consider a reduced sample period. While the baseline results are derived from a sample spanning January 2006 to December 2024, we now restrict the sample to end in December 2019.

The results of this exercise are presented in Figure 11. As can be seen, the results qualitatively confirm our baseline findings. Specifically, in both cases, we find that the responses in inflation and the output gap are statistically significantly different from zero. However, we observe that the magnitudes of the responses in the reduced sample are somewhat smaller compared to those in the baseline results. In particular, the maximum response (in absolute value terms) of the output gap in the baseline results was -0.020 percentage points, whereas it is reduced to -0.011 percentage points in the shorter sample. Similarly, in the case of inflation, the maximum response in the baseline results was 0.14 percentage points, whereas it drops to 0.08 percentage points in the reduced sample.

We interpret these results as providing general validation of our baseline results across distinct subsamples, particularly in qualitative terms. Quantitatively, however, the reduction in the size of the responses in the reduced sample introduces some uncertainties. This is likely due to the limited frequency of supply chain disruptions during the earlier periods of the sample, which can affect the precision of the estimates.

Appendix G. Additional tables

Table 4: The three-digit subindices of the CPI (COICOP classification)

	ID	Description
1	cp_011	Food
2	cp_012	Non-Alcoholic Beverages
3	cp_021	Alcoholic Beverages
4	cp_022	Tobacco
5	cp_031	Clothing
6	cp_032	Footwear
7	cp_041	Actual Rentals for Housing
8	cp_043	Maintenance and Repair of the Dwelling
9	cp_044	Water Supply and Miscellaneous Services Relating to the Dwelling
10	cp_045	Electricity, Gas and Other Fuels
11	cp_051	Furniture and Furnishings, Carpets and Other Floor Coverings
12	cp_052	Household Textiles
13	cp_053	Household Appliances
14	cp_054	Glassware, Tableware and Household Utensils
15	cp_055	Tools and Equipment for House and Garden
16	cp_056	Goods and Services for Routine Household Maintenance
17	cp_061	Medical Products, Appliances and Equipment
18	cp_062	Out-Patient Services
19	cp_063	Hospital Services
20	cp_071	Purchase of Vehicles
21	cp_072	Operation of Personal Transport Equipment
22	cp_073	Transport Services
23	cp_081	Postal Services
24	cp_082	Telephone and Telefax Equipment
25	cp_083	Telephone and Telefax Services
26	cp_091	Audio-Visual, Photographic and Information Processing Equipment
27	cp_092	Other Major Durables for Recreation and Culture
28	cp_093	Other Recreational Items and Equipment, Gardens and Pets
29	cp_094	Recreational and Cultural Services
30	cp_095	Newspapers, Books and Stationery
31	cp_096	Package Holidays
32	cp_111	Catering Services
33	cp_112	Accommodation Services
34	cp_121	Personal Care
35	cp_123	Personal Effects N.E.C.
36	cp_124	Social Protection
37	cp_125	Insurance
38	cp_126	Financial Services N.E.C.
39	cp_127	Other Services N.E.C.
Not used:		
–	cp_101	Pre-Primary and Primary Education
–	cp_102	Secondary Education
–	cp_103	Post-Secondary Non-Tertiary Education
–	cp_104	Tertiary Education
–	cp_105	Education Not Definable by Level

Table 5: The two-digit subindices of the CPI (COICOP classification)

	ID	Description
1	cp_01	Food and non-alcoholic beverages
2	cp_02	Alcoholic beverages, tobacco and narcotics
3	cp_03	Clothing and footwear
4	cp_04	Housing, water, electricity, gas and other fuels
5	cp_05	Furnishings, household equipment and routine household maintenance
6	cp_06	Health
7	cp_07	Transport
8	cp_08	Information and communication
9	cp_09	Recreation, sport and culture
10	cp_11	Restaurants and accommodation services
11	cp_12	Insurance and financial services, personal care, social protection and miscellaneous goods and services
Not used:		
–	cp_10	Education services

Table 6: The IO tables: NACE (Rev. 2) two-digit Classification of production activity

	ID	Description
1	A01	Crop and animal production, hunting and related service activities
2	A02	Forestry and logging
3	A03	Fishing and aquaculture
4	B	Mining and quarrying
5	C10-12	Manufacture of food products; beverages and tobacco products
6	C13-15	Manufacture of textiles, wearing apparel, leather and related products
7	C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
8	C17	Manufacture of paper and paper products
9	C18	Printing and reproduction of recorded media
10	C19	Manufacture of coke and refined petroleum products
11	C20	Manufacture of chemicals and chemical products
12	C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	C22	Manufacture of rubber and plastic products
14	C23	Manufacture of other non-metallic mineral products
15	C24	Manufacture of basic metals
16	C25	Manufacture of fabricated metal products, except machinery and equipment
17	C26	Manufacture of computer, electronic and optical products
18	C27	Manufacture of electrical equipment
19	C28	Manufacture of machinery and equipment n.e.c.
20	C29	Manufacture of motor vehicles, trailers and semi-trailers
21	C30	Manufacture of other transport equipment
22	C31_32	Manufacture of furniture; other manufacturing
23	C33	Repair and installation of machinery and equipment
24	D	Electricity, gas, steam and air conditioning supply
25	E36	Water collection, treatment and supply
26	E37-39	Sewerage, waste management, remediation activities
27	F	Construction
28	G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
29	G46	Wholesale trade, except of motor vehicles and motorcycles
30	G47	Retail trade, except of motor vehicles and motorcycles
31	H49	Land transport and transport via pipelines
32	H50	Water transport
33	H51	Air transport
34	H52	Warehousing and support activities for transportation
35	H53	Postal and courier activities
36	I	Accommodation and food service activities
37	J58	Publishing activities
38	J59_60	Motion picture, video, television programme production; programming and broadcasting activities
39	J61	Telecommunications
40	J62_63	Computer programming, consultancy, and information service activities
41	K64	Financial service activities, except insurance and pension funding
42	K65	Insurance, reinsurance and pension funding, except compulsory social security
43	K66	Activities auxiliary to financial services and insurance activities
44	L68	Real estate services
45	M69_70	Legal and accounting activities; activities of head offices; management consultancy activities
46	M71	Architectural and engineering activities; technical testing and analysis

Table 6: The IO tables: NACE (Rev. 2) two-digit Classification of production activity

	ID	Description
47	M72	Scientific research and development
48	M73	Advertising and market research
49	M74_75	Other professional, scientific and technical activities; veterinary activities
50	N77	Rental and leasing activities
51	N78	Employment activities
52	N79	Travel agency, tour operator reservation service and related activities
53	N80-82	Security and investigation, service and landscape, office administrative and support activities
54	O	Public administration and defence; compulsory social security
55	P	Education
56	Q86	Human health activities
57	Q87_88	Residential care activities and social work activities without accommodation
58	R90-92	Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities
59	R93	Sports activities and amusement and recreation activities
60	S94	Activities of membership organisations
61	S95	Repair of computers and personal and household goods
62	S96	Other personal service activities
63	T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Table 7: The IO tables: NACE (Rev. 2) one-digit Classification of production activity

	ID	Description
1	A	Agriculture, Forestry and Fishing
2	B	Mining and Quarrying
3	C	Manufacturing
4	D	Electricity, Gas, Steam and Air Conditioning Supply
5	E	Water Supply; Sewerage, Waste Management and Remediation Activities
6	F	Construction
7	G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
8	H	Transportation and Storage
9	I	Accommodation and Food Service Activities
10	J	Information and Communication
11	K	Financial and Insurance Activities
12	L	Real Estate Activities
13	M	Professional, Scientific and Technical Activities
14	N	Administrative and Support Service Activities
15	O	Public Administration and Defence; Compulsory Social Security
16	P	Education
17	Q	Human Health and Social Work Activities
18	R	Arts, Entertainment and Recreation
19	S	Other Service Activities
20	T	Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use