Identifying sectoral shocks and their role in business cycles*

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August 29, 2023

Abstract

US business cycles can be empirically characterized as a time-varying mix of different sectoral shocks. Sectoral shocks are distinct from aggregate shocks and better capture business cycle fluctuations. A typical recession (or boom) is interpreted as the combination of a few sectoral shocks, which encompass more diverse origins than the typical narrative prevalent for that recession. Sectoral shocks have aggregate consequences through strong input-output network effects. Identification is based on network-implied heterogeneity restrictions in a FAVAR framework and far less dependent on specific DSGE calibrations compared to previous work.

Keywords: SVAR, Sectoral shocks, Production networks, Business cycles
JEL classifications: C38, C50, E32

*We thank Borağan Aruoba, Guido Ascari, Christiane Baumeister, Fabio Canova, Andrew Foerster, Michal Kobielarz, Vivien Lewis, Francesca Loria, Christian Matthes (discussant), Roland Meeks, Karel Mertens, Haroon Mumtaz, Christian Pröbsting, Morten Ravn, Juan Rubio-Ramírez, Frank Smets, Alireza Tahbaz-Salehi, Joris Tielens, Kerem Tuzcuoglu, Harald Uhlig, Raf Wouters, and participants of the 27th international conference on Computing in Economics and Finance (CEF), the 2021 annual conference of the International Association for Applied Econometrics (IAAE), the SCE Session of the Allied Social Science Associations (ASSA) 2022 Annual Meeting, and the Bundesbank Research Seminar for helpful discussions and comments. Jan David Schneider extends thanks to the Research Foundation Flanders (FWO) for funding under the *PhD Fellow fundamental research* grant. The resources and services used in this work were provided by the VSC (Flemish Supercomputer Center), funded by the FWO and the Flemish Government.

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1 Introduction

A lot of macroeconomic research deals with understanding the sources of aggregate fluctuations. In this paper, we are interested in how aggregate business cycles relate to evolutions on the sectoral level of the economy. Breaking down aggregate industrial production into 25 sectoral components, the correlation between monthly sectoral and aggregate growth (year-on-year from 1973 to 2020) is on average 0.6. This signifies a large synchronization in sectors' business cycles. Understanding the source of this sectoral co-movement provides crucial insights into the general understanding of aggregate fluctuations.

While initial explanations of these facts focused on the role of aggregate shocks, Long and Plosser (1983) and Acemoglu et al. (2012), among others, suggest that idiosyncratic shocks can propagate through production networks and thereby cause aggregate fluctuations. Recent structural empirical models with multiple sectors, such as Foerster, Sarte, and Watson (2011), Atalay (2017), and vom Lehn and Winberry (2021), have indeed shown that sector-specific shocks are important drivers of business cycles. However, most of these quantifications on sector contributions rely on a specific calibration of a theoretical model. Ideally, the evidence explaining the source of aggregate fluctuations should not hinge upon that. We therefore propose a new structural econometric framework that can disentangle sectoral shocks from other drivers of aggregate fluctuations without relying on too much economic theory. Our aim is to provide empirical answers that guard against theoretical misspecification concerns, yet still enable causal inference.

Our approach exploits heterogeneity in a cross-section for the identification of a structural time-series model. The main idea behind our identification strategy is as follows: network data (e.g. an input-output table) contains strong information on how idiosyncratic, sector-specific shocks propagate cross-sectionally. The propagation pattern of an idiosyncratic shock differs to those of other shocks depending on the sector where it originates, since every sector connects differently to the network. This heterogeneity distinguishes sector-specific shocks from one another. Aggregate shocks can be seen as a combination of sector-specific shocks. This leads to a mixture of cross-sectional patterns that arise upon individual idiosyncratic shocks. As a consequence, aggregate shocks exhibit cross-sectionally distinct responses to sector-specific shocks. This distinction breaks the observational equivalence between sectoral shocks with aggregate consequences and aggregate shocks.

We implement this identification strategy in a factor-augmented vector autoregressive (FAVAR) model that describes the dynamics of US sectoral industrial production data. We derive cross-sectional rankings from simple network measures, i.e. up- and downstream variations of the production network's Leontief inverse, based on US input-output and capital flow tables. These rankings are largely consistent with the implied rankings of theoretical impulse response functions to sectoral shocks in canonical multi-sectoral models, such as Long and Plosser (1983), Horvath (1998, 2000), and Dupor (1999). Our identification strategy is therefore not reliant on a specific theoretical model but captures network propagation of sectoral shocks more generally. In principle, the method is flexible enough to deal with alternative network measures or alternative model specifications. The identification procedure uses *heterogeneity restrictions* as introduced in De Graeve and Karas (2014). Amir-Ahmadi and Drautzburg (2021) and Matthes and Schwartzman (2021) apply these to sharpen identification of aggregate shocks. We adapt this methodology to identify sector-specific sources of business-cycle fluctuations.

We quantify the contribution of US sectoral shocks to aggregate industrial production growth from the early 1970s until the inception of the COVID-19 pandemic. Aggregate fluctuations can be explained in large part by a combination of sectoral shocks without the need of an aggregate shock.

The identified sectoral shocks and their role in recent US economic history accord well with the typical macro narrative of the time. For instance, our estimates view a large part of the 2001 recession as a tech-related boom gone bust, or we document how idiosyncratic shocks originating in the *oil and gas extraction* sector contribute considerably to most US recessions. Though consistent with such narratives, there are no sectors whose shocks in isolation dictate the aggregate business cycle.

Our results also suggest a particular view of how sectoral shocks generate aggregate consequences. A shock to a single sector is not enough to push the economy into a recession. Recessions are episodes in which several sectors experience negative idiosyncratic shocks. The timing of these shocks is not necessarily synchronized, and can easily be months apart. We also show that without spillovers to other sectors, recessions would be much less severe. This evidence empirically supports the relevance of network propagation in the theoretical production network literature (c.f. Acemoglu et al. 2012).

The importance of sector-specific shocks does not deny the possibility of aggregate shocks in the business cycle. Our estimated sector-specific shocks are uncorrelated with standard proxies for aggregate shocks, granting both types of shocks a role in explaining business cycles. Sectoral shocks however explain a larger part of output fluctuations than aggregate shocks.

1.1 Literature review

The drivers of aggregate output are traditionally considered to also be of aggregate nature, such as productivity, aggregate demand or monetary policy shocks. Most of the literature on economic fluctuations outright disregards the possibility of microeconomic shocks to specific sectors or firms to generate relevant aggregate fluctuations. The argument, famously expressed by Lucas (1977), goes that with a large number of sectors, idiosyncratic shocks average out so that in the aggregate no significant fluctuations occur.

A fast-growing literature has shown that idiosyncratic shocks could indeed explain a more significant share of aggregate fluctuations than traditionally thought. In practice, this is achieved by introducing multiple sectors into standard macroeconomic general equilibrium models used for studying economic fluctuations. Within this "structural/theoretical" branch of the multi-sector literature, there are two main channels through which idiosyncratic shocks translate into aggregate fluctuations: *granularity* and *network linkages*.

Gabaix's (2011) *granularity hypothesis* highlights the potential of shocks to very large firms to cause sizable aggregate fluctuations. For example, in 2011 Walmart's total sales accrued to more than two percent of US GDP. Hence, granularity asserts that shocks to a small amount of very large sectors or firms will not average out. These idiosyncratic shocks then lead to aggregate fluctuations in macroeconomic activity.

The second channel, *network linkages*, is based on the early work of Long and Plosser (1983), who show in a neoclassical multi-sector model with an input-output structure that idiosyncratic shocks can lead to relevant aggregate fluctuations. Dupor (1999) disagrees and asserts that Lucas's (1977) argument on the law of large numbers also applies to models with such input-output linkages. In contrast, Horvath (1998, 2000) argues that Long and Plosser's (1983) hypothesis does hold in the face of the law or large numbers: some more important sectors supply inputs to a large number of other sectors. Small shocks to these important sectors can thus drive aggregate fluctuations and the diversification argument breaks down. Furthermore, Acemoglu et al. (2012) analyze how through higher-order interconnectedness, what the authors refer to as cascade effects, shocks propagate through the economy. Different from granularity, widely-connected sectors do not necessarily need to be large but are of importance due to their exposure to the rest of the economy.[1]

The challenge the multi-sector literature faces is to empirically distinguish idiosyncratic shocks with aggregate consequences from truly aggregate shocks. Such an analysis is especially relevant for policy-makers as the origin of aggregate fluctuations determines the appropriate policy response. Foerster, Sarte, and Watson (2011) provide a first rigorous analysis to address this identification challenge by connecting structural models with reduced-form empirical models. They solve the identification problem that makes disentangling the sources of co-movement difficult. However, their solution depends heavily on DSGE (Dynamic Stochastic General Equilibrium) modeling assumptions as well as calibration.[2] Our approach enables to step away from such tight assumptions. Other recent contributions use sectoral data to distinguish supply and demand drivers during the COVID-19 pandemic, such as Brinca, Duarte, and Faria-e-Castro (2021) and Cesa-Bianchi and Ferrero (2021), but do not solve the identification challenge of disentangling sectoral from aggregate shocks.

Amir-Ahmadi and Drautzburg (2021) also use the cross-section to show how heterogeneity restrictions can help to improve structural identification in VAR-type models. Furthermore in recent work, Matthes and Schwartzman (2021) use input-output data to identify aggregate shocks. However, the focus in these two papers is not on sectoral shocks but rather on how sectoral data can help to identify aggregate shocks.

The remainder of the paper is structured as follows. Section 2 presents the strategy for identifying sector-specific shocks. This motivates the restrictions which we then implement as heterogeneity constraints in Section 3, using a Bayesian FAVAR. In Section 4 we describe the data, its transformations, and the model parameterization. Model results and the analysis of the contribution of sector-specific shocks to aggregate fluctuations is included in Section 5. We provide additional results from simulations using data generated by a typical multi-sector DSGE model in Section 6. Section 7 concludes.

[1] There is a large current interest in embedding multiple sectors into other macroeconomic models, see e.g. Bouakez, Cardia, and Ruge-Murcia (2014), Smets, Tielens, and Van Hove (2019), Baqaee and Farhi (2019, 2020), Bigio and La'O (2020), Pasten, Schoenle, and Weber (2020, 2021), and La'O and Tahbaz-Salehi (2022).

[2] Other papers that identify sectoral origins of business cycles with a strong reliance on specific theory are e.g. Shea (2002), Acemoglu, Akcigit, and Kerr (2016), Atalay (2017), vom Lehn and Winberry (2021), and Foerster et al. (2022).

2 Identification

Given the multitude of static and dynamic models in the multi-sector literature, our goal is to provide a framework that allows identification of sector-specific shocks with a minimum set of assumptions. The general idea is to exploit heterogeneity in a cross-section for the identification of a structural time-series model. More specifically, we use input-output (I-O) data to compile sector-specific rankings that allow us to identify sector-specific shocks and separate them from aggregate shocks. In this section we motivate these identification restrictions.

2.1 Separating individual sectoral shocks from other shocks

We introduce our identification strategy by means of an illustrative hypothetical economic network: Figure 1 represents a stylized five-sector network economy as a weighted directed graph. Sector 1 sells to sector 3, which sells to sector 5. Sector 2 sells to sector 4, which in turn sells to sector 5. Each connection between sectors is weighted which represents the intensity of the ties.

In the left-hand graph, the economy is hit by a shock in sector 1. The shock has a large impact on the origin sector 1, and transmits through the production network, affecting its closest downstream sector 3 more than its farther downstream sector 5. The sectors outside sector 1's network are not affected. The ranking below the directed graph summarizes the cross-sectional impact of this shock.

The middle graph illustrates that this cross-sectional impact is very different from what happens when the economy is hit by a sector-2 shock. Here the sectoral responses are ranked from high to low as: Sector 2 > Sector 4 > Sector 5 > Sectors 1, 3. Comparing the two sectoral shocks exemplifies a first key feature of sectoral shock transmission: sector-specific shocks have utterly different cross-sectional implications due to heterogeneity in production linkages. Our identification strategy exploits this feature by identifying sector-specific shocks as those that accord with the cross-sectional implications of each sector's production linkages.

The right-hand panel in the figure shows what happens when the economy is hit by an aggregate shock. Conceptually, one can think of an aggregate shock as a combination of sector-specific shocks. What is evident from the resulting ranking is that the sector-specific network patterns mix. As a result, the implied cross-sectional ranking does not follow any of the individual sector rankings. These differences in rankings enable us to identify sector-specific shocks as distinct from aggregate shocks (and from one another).

The above example is highly stylized, yet its intuition goes through for different networks. In our main implementation we derive identification restrictions directly from standard input-output tables. We depart from a direct requirements matrix, A, that summarizes the proportion of inputs needed to produce a dollar worth of output, e.g. the input costs of tires, steel, etc. in the production of cars.

Column j of this matrix shows the relative importance of sector j's commodity as an input to the rest of the economy. The largest value in this column for instance indicates the sector that uses sector j's commodity the most, relative to that sector's overall size of production. In order to include network effects we obtain the total requirements matrix H by calculating the Leontief inverse of matrix A: $H = (I - A)^{-1}$.

The columns of H have an interpretation similar to the columns of A but in addition to direct also include all indirect linkages between sectors. We then build our analysis sector by sector. The identification for a shock in sector j, henceforth called the origin sector, is based on vector h_j which corresponds to the j^{th} column of matrix H:

$$h_j = (h_{1j}, h_{2j}, \ldots, h_{Nj})' \ . \tag{1}$$

We then sort h_j from highest to lowest value to obtain the sorted vector γ_j, i.e.

$$\gamma_j = (\gamma_{1j}, \gamma_{2j}, \ldots, \gamma_{Nj})' \ . \tag{2}$$

A ranking γ_j provides information on the degree by which all sectors are connected (downstream) to the origin sector.[3] We exploit this information in our identification strategy: sectors that are ranked higher are expected to respond stronger to a shock in the origin sector than sectors that are ranked lower.

This identification idea also holds in fully-fledged multi-sector DSGE models. Table 1 shows this for a prototype, calibrated RBC model similar to Carvalho's (2008) benchmark model (see Section 6 for

[3] In Section 4.1 we introduce several improvements to the rankings' underlying I-O matrices, such as the distinction between up- and downstream propagation of shocks and the inclusion of investment flow data. However these modifications are not relevant for motivating our core identification idea.

details). The second column of the table ranks sectors as implied by one of the sector's (here sector 13) Leontief inverse. The third column ranks sectors according to their impulse responses (IRF) to a sector-13-specific shock. Comparing both columns highlights that there is a direct correspondence between network measures and theoretical IRFs. The mapping is not perfect but very close. Finally, the last two columns show the ranked theoretical IRFs to an aggregate technology, and to a government spending shock. The table presents a sector-13-specific shock, as the aggregate technology shock has maximal impact on that very sector. This highlights the potential difficulties for identification: identifying a sector-13-specific shock by simply considering IRFs with a maximum effect on sector 13 would lead one to incorrectly identify some aggregate shocks as sector-specific. Looking into the cross-sectional distribution of IRFs however, reveals that aggregate shocks have substantially different cross-sectional implications. The source of that difference is, as in the earlier stylized example, the fact that sector-specific network patterns mix when aggregate shocks hit the economy. The same considerations hold true for the aggregate government spending shock, which has maximal impact in sector 22. Comparing the aggregate shock ranking with that of a sector-22-specific shock (in columns 4 and 5) again reveals stark differences between the aggregate and sectoral shock rankings.

The distinct cross-sectional heterogeneity that follows from different shocks is the key feature that enables us to overcome the fundamental identification problem: separating sectoral shocks from one another and from aggregate shocks. Our strategy can be applied to different shocks (e.g. upstream shocks), to different networks (e.g. accounting for both materials and investment networks) or to different models (e.g. with price frictions).

2.2 Ranking clusters

The *strict* rankings, γ_j, can be used directly for identification of a sector-j shock. One shortcoming of such an approach is that it does not allow for small ranking deviations for sectors that are similarly connected to the sector j. An identification based on strict rankings could be overly dogmatic and would not allow for deviations in sectors' relative responses. Hence, instead of using the strict rankings, we construct looser rankings by distributing sectors with similar requirements values into *clusters*. In this way, we stay agnostic on the exact rankings and rather group sectors according to their connectedness to the origin sector. Intuitively, we sort the strict rankings into four hierarchical clusters: first, the origin sector at the highest rank, a second cluster with highly connected sectors, third, a cluster of somewhat connected sectors, and finally the rest falls into a fourth cluster of only loosely or unconnected sectors.

We define a ranking *cluster*, Γ_j, as

$$\Gamma_j \equiv (\Gamma_{1j}, \Gamma_{2j}, \ldots, \Gamma_{Gj})' \ , \tag{3}$$

where G is the total number of imposed clusters. The individual clusters Γ_{gj} for sector j are composed of the strict rankings γ_{ij}:

$$\begin{aligned} \Gamma_{1j} &\equiv (\gamma_{1j}) \ , \\ \Gamma_{2j} &\equiv (\gamma_{2j}, \ldots, \gamma_{l_2,j}) \ , \\ &\vdots \\ \Gamma_{Gj} &\equiv \left(\gamma_{(l_{(G-1)}+1),j}, \ldots, \gamma_{l_G,j}\right) \ , \end{aligned}$$

where l_g indexes the respective last sector included in cluster g. Note that Γ_{1j} always contains γ_{1j} exclusively, i.e. the index of the origin sector.

An additional advantage of working with clusters is that the resulting cross-sectional implications are more robust to different theoretical models one may have in mind. Alternative theoretical DSGE specifications can imply deviations from the pure Leontief-implied rankings. By allowing deviations from the latter, clusters robustify the cross-sectional implications. At the same time the cross-sectional implications across clusters are still distinct for the different shocks we identify, and thus retain sufficient identification power as our results will show.

3 Model

In this section we lay out the reduced-form Bayesian factor-augmented VAR model framework and then show how sector rankings are used as heterogeneity restrictions to identify structural sectoral shocks.

3.1 The reduced-form model

The reduced-form is a factor-augmented vector autoregressive model (FAVAR) similar to Bernanke, Boivin, and Eliasz (2005), Boivin, Giannoni, and Mihov (2009), and Stock and Watson (2016):

$$x_t = \lambda^x f_t^x + \lambda^y y_t + \epsilon_t \qquad \text{with } \epsilon_t \sim \mathcal{N}(0, R_\epsilon)\,, \tag{4}$$

$$\begin{pmatrix} f_t^x \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \phi_p \begin{pmatrix} f_{t-p}^x \\ y_{t-p} \end{pmatrix} + u_t \qquad \text{with } u_t \sim \mathcal{N}(0, Q_u)\,, \tag{5}$$

where y_t is an M-by-1 vector of observable factors. In our application y_t contains the origin sector's output growth rate (hence $M = 1$). On the left-hand side of equation (4), x_t is an N_x-by-1 vector including aggregate industrial production growth and all sector output growth rates other than the origin sector. We impose K unobservable factors, f_t^x, that have factor loadings, λ^x, while observable factors have loadings, λ^y. The transition equation follows a VAR process with parameters ϕ_p and P, the number of lags. Reduced-form shocks, u_t, have variance-covariance matrix Q_u and measurement errors, ϵ_t, are distributed according to diagonal variance matrix R_ϵ.

Furthermore, the state-space model (4) and (5) can be rewritten in companion form:

$$X_t = \Lambda F_t + E_t\,, \tag{6}$$

$$F_t = \Phi F_{t-1} + U_t\,, \tag{7}$$

where

$$X_t \equiv (x_t', y_t')'\,, \tag{8}$$

$$f_t \equiv (f_t^{x'}, y_t')'\,, \tag{9}$$

$$\lambda \equiv \begin{bmatrix} \lambda^x & \lambda^y \\ \mathbf{0}_{M\times K} & \mathbf{I}_M \end{bmatrix}, \tag{10}$$

$$F_t \equiv \left(f_t', f_{t-1}', \ldots, f_{t-P+1}'\right)'\,, \tag{11}$$

$$E_t \equiv \left(\epsilon_t', \mathbf{0}_{M\times 1}'\right)'\,, \tag{12}$$

$$U_t \equiv \left(u_t', \mathbf{0}_{(K+M)(P-1)\times 1}\right)'\,, \tag{13}$$

$$\Phi \equiv \begin{bmatrix} \phi_1 & \cdots & \phi_P \\ \mathbf{I}_{KM(P-1)} & & \mathbf{0}_{KM(P-1)\times KM} \end{bmatrix}, \tag{14}$$

$$\Lambda \equiv \left[\lambda\ \mathbf{0}_{(N_x+M)\times(K+M)(P-1)}\right]\,. \tag{15}$$

We apply a joint estimation procedure by likelihood-based Gibbs sampling as in Bernanke, Boivin, and Eliasz (2005). Similar to their approach we solve the standard factor identification problem by setting the upper $K \times K$ block of the loadings matrix λ^x to an identity matrix and the upper $K \times M$ block of λ^y to zero.[4] We impose standard priors for reduced-form parameters as in Koop and Korobilis (2009).

As for identification of structural sectoral shocks, we implement our sector rankings as heterogeneity restrictions using the algorithm of Rubio-Ramírez, Waggoner, and Zha (2010).

We estimate model (4)-(5) for each sector separately. One of the reasons is that we prefer to include the origin sector's growth rate as an observable factor. Including it gives scope to identifying sectoral shocks that would be thrown out if they do not cause enough variance in the unobserved factors. Since we do not identify sectoral shocks jointly, we evaluate their correlation ex-post in Section 5.2.

3.2 Heterogeneity restrictions

The goal of our identification strategy is to isolate idiosyncratic shocks to the respective origin sector. We implement the rankings introduced in Section 2 as heterogeneity restrictions to identify structural shocks in the reduced-form FAVAR model. Contemporaneous impulse responses are defined in the following way:

$$r_a^{(f)} = \mathbf{a}\,, \tag{16}$$

$$r_a^{(X)} = \lambda r_a^{(f)}\,, \tag{17}$$

[4] For more details on estimation see Online Appendix A.

where $\mathbf{a} \in R^{K+M}$ is the impulse vector of a (candidate) structural shock that we check against our restrictions. The vector $r_a^{(f)}$ includes the impulse responses of the unobserved and observed factors. Using the loadings λ we calculate the impulse response vector $r_a^{(X)}$ that contains responses of all sectors as well as aggregate output growth to the candidate structural shock.

We implement the heterogeneity restrictions by comparing the vector elements of $r_a^{(X)}$, i.e. $r_a^{(X)}(i)$, for all $i = 1, \ldots, N$. Since we only impose restrictions on impact and not on later horizons, we only consider impulse responses on impact in the ranking notation below.[5] We first show the implementation for a strict ranking $\gamma_j = (\gamma_{1j}, \gamma_{2j}, \ldots, \gamma_{Nj})'$ and then for a cluster ranking Γ_j. The notation refers to a positive sectoral shock originating in sector j, which implies that $r_a^{(X)}(\gamma_{1j}) > 0$.

The first restriction, referred to as *R1*, ensures that the origin sector has the largest response to the sectoral shock:

$$r_a^{(X)}(\gamma_{1j}) > |r_a^{(X)}(\gamma_{ij})|, \quad \forall i = 2, \ldots, N\,. \tag{18}$$

Note that we additionally require that no sector response can be larger than the negative of the origin sector response.

Given that *R1* is satisfied we check impulse responses against a second type of restriction, referred to as *R2*. For a strict ranking γ_j we require that sector responses compare such that:

$$r_a^{(X)}(\gamma_{ij}) > r_a^{(X)}(\gamma_{(i+1),j}), \quad \forall i = 2, \ldots, (N-1)\,. \tag{19}$$

Figure 2 illustrates the implementation of restrictions *R1* and *R2* for a strict ranking.

In our implementation we use cluster rankings $\Gamma_j = (\Gamma_{1j}, \Gamma_{2j}, \ldots, \Gamma_{Gj})'$ instead of strict rankings γ_j. Hence, we modify *R2* to compare minimum and maximum responses of adjacent clusters:

$$min\left\{r_a^{(X)}(\Gamma_{gj})\right\} > max\left\{r_a^{(X)}(\Gamma_{(g+1),j})\right\}, \quad \forall g = 2, \ldots, (G-1)\,. \tag{20}$$

Restrictions *R1* and *R2* imposed on the impulse responses of sectoral growth rates ensure that we identify shocks that originate from the sectoral level.

Finally, note that we do not identify aggregate shocks explicitly. In principle one could add additional identification restrictions to also disentangle specific aggregate shocks, see e.g. Matthes and Schwartzman (2021) for an approach along those lines.

4 Data and model parameterization

This section first describes cross-sectional sectoral data used for our identification restrictions, introduces sectoral time series data, and parameterization of the empirical model.

4.1 Requirements matrices

Our identification strategy builds on industry-by-industry direct requirements tables that are constructed from input-output (I-O) accounts' make and use tables for the United States. While make tables capture the commodities industries produce, use tables show how industries use commodities as inputs to their production, as well as the final uses of commodities.[6] The Bureau of Economic Analysis (BEA) uses Census data to construct detailed I-O tables every five years for the United States. These tables are based on the North American Industry Classification System (NAICS) and allow a mapping between the components of industrial production and the US I-O accounts. All I-O data are based on 1997 *standard* make and use tables, as well as 1997 capital flow tables.[7]

We now present three modifications to the total requirements matrix H and its rankings introduced initially in Section 2. This will improve their use for identification further.

First, we consider both downstream and upstream propagation of sectoral shocks. Similar to Acemoglu, Akcigit, and Kerr (2016) we use two versions of the standard direct requirements matrices allowing to explicitly track downstream and upstream production linkages between N sectors. The downstream measure, N-by-N matrix A, has elements a_{ij} with the following interpretation:

$$a_{ij} = \frac{\text{Sales of } j \text{ to } i}{\text{Total Sales of } i}\,.$$

[5]Of course it is possible to restrict sectoral impulse responses also at later horizons. However, as De Graeve and Karas (2014) show, the use of heterogeneity restrictions can obfuscate the need for longer horizons.

[6]We use the terms sector and industry interchangeably.

[7]The BEA does not provide capital flow tables more recent than 1997. See the Online Appendix B for additional information on incorporating capital-flow tables.

On the other hand, the upstream measure, matrix $\widetilde{A}$ measures how much of a given input is used in the production of all other commodities:

$$\widetilde{a}_{ij} = \frac{\text{Sales of } i \text{ to } j}{\text{Total Sales of } i} .$$

Its elements $\widetilde{a}_{ij}$ compare to elements a_{ij} of matrix A in the following way: ignoring network effects, column j of matrix A shows the relative importance of sector j's commodity as an input to the economy. The largest value in this column indicates the sector that uses sector j's commodity the most, relative to that sector's overall size of production. On the other hand, column j of matrix $\widetilde{A}$ captures the relative importance of inputs used in production of sector j. The largest value in this column corresponds to the most important input provider for j, relative to that sector's own production.[8]

Similarly, we derive downstream, H, and upstream, $\widetilde{H}$, total requirements matrices as

$$H = (I - A)^{-1} , \tag{21}$$

$$\widetilde{H} = \left(I - \widetilde{A}\right)^{-1} . \tag{22}$$

The respective rankings for downstream and upstream shocks are then

$$\gamma_j = (\gamma_{1j}, \gamma_{2j}, \ldots, \gamma_{Nj})' , \tag{23}$$

$$\widetilde{\gamma}_j = (\widetilde{\gamma}_{1j}, \widetilde{\gamma}_{2j}, \ldots, \widetilde{\gamma}_{Nj})' . \tag{24}$$

This decomposition into downstream and upstream shocks has an analogy to the distinction between sectoral supply and demand shocks. In many theoretical models, such as the one introduced in Section 2, supply shocks can only travel downstream. Demand shocks however, for instance in models with government spending shocks, only travel upstream through the network.[9] Acemoglu, Akcigit, and Kerr (2016) show using four different types of shocks that supply-side (demand-side) shocks do indeed exhibit little upstream (downstream) propagation. Regardless, in our implementation we implicitly allow for the possibility that supply shocks have some upstream and vice versa that demand shocks have some downstream effects. Our only assumption in this regard is that these opposing network effects cannot completely change the respective ranking of sectoral responses.

A second modification of direct and total requirements matrices relates to the inclusion of investment data. Rankings γ (and $\widetilde{\gamma}$) only capture network effects originating from trading materials. Several studies such as Foerster, Sarte, and Watson (2011) or vom Lehn and Winberry (2021) have highlighted the importance of network effects related to investment flows. We therefore extend the rankings above by also including I-O account data of private fixed investment. The resulting downstream and upstream measures, A^c and $\widetilde{A}^c$, combine input-output connections of materials with investment flows between sectors.

To highlight the difference to the "materials-only" direct requirements matrices A and $\widetilde{A}$, we first decompose these as:

$$A = (WB)' , \tag{25}$$

$$\widetilde{A} = \left(W\widetilde{B}\right) , \tag{26}$$

where W is the transformation matrix, used to transform the commodity-by-industry direct input coefficient matrix B (and matrix $\widetilde{B}$) into industry-by-industry direct requirements matrix A and $\widetilde{A}$. Element b_{ij} of matrix B shows the dollar value needed of commodity i to produce one dollar worth of output in industry j, whereas element $\widetilde{b}_{ij}$ of matrix $\widetilde{B}$ shows the dollar value of industry j's output used to produce one dollar worth of commodity i.[10]

Direct requirements measures, A^c and $\widetilde{A}^c$, combine direct coefficient matrices B and $\widetilde{B}$ with capital flow matrices Cap and $\widetilde{Cap}$, respectively:

$$MatCap = B + Cap , \tag{27}$$

[8] This breakdown of the direct requirements tables, A and $\widetilde{A}$, implies that the underlying use and make tables are symmetric. The actual BEA tables are not symmetric and are therefore adjusted. For more details see Online Appendix B.

[9] See for instance Carvalho and Tahbaz-Salehi (2019) for an intuitive theoretical description on supply and demand shocks' different "direction of travel" in a production network.

[10] See Online Appendix B for a derivation of matrices W, B, and $\widetilde{B}$ using *make* and *use* tables.

$$A^c = (WMatCap)' \,, \tag{28}$$

$$\widetilde{MatCap} = \widetilde{B} + \widetilde{Cap} \,, \tag{29}$$

$$\widetilde{A}^c = \left(W\widetilde{MatCap}\right) \,, \tag{30}$$

where matrices *Cap* and $\widetilde{Cap}$ are direct input and output matrices, equivalent to B and $\widetilde{B}$ but for investments in equipment, software, and structures by industries. Analogously to the rankings described above, we then create downstream rankings, (γ_j^c, Γ_j^c), and upstream rankings, $(\widetilde{\gamma}_j^c, \widetilde{\Gamma}_j^c)$, for all $j = 1, \ldots, N$, that capture those combined connections of materials and investments.

The third modification relates to the distinction between the total set of US industries and the subset of industrial production sectors. We disaggregate the private US economy into 64 distinct industries which roughly corresponds to the BEA's aggregation at *summary level*. We modify the BEA's aggregation to allow for a clear separation of 25 sectors that are included in US industrial production indices and 39 non-government sectors that are not. This separation is necessary as a complete set of long output time series data at monthly frequency are only available for NAICS sectors included in industrial production.

The inclusion of non-industrial-production sectors in all I-O matrices requires an additional step in creating all γ-rankings. Before ranking any of the total requirement matrices, we delete all rows and columns that correspond to sectors that are not part of industrial production. The remaining 25-by-25 total requirements matrices can then be used to create the rankings.

4.2 Feasibility

One practical consideration in implementing our identification strategy lies in balancing a trade-off between two opposing issues: first, we need to use sufficient information to rule out that model-identified sector-specific shocks are conflated with aggregate or other sectors' shocks. Second, the feasibility to find structural impulse vectors is directly related to the restrictiveness of the heterogeneity restrictions. In other words, there is a risk of either imposing too few or too many restrictions. For a given sectoral shock, inspecting a ranking's values of the underlying Leontief inverse reveals that there is only a minority of sectors that exhibit high requirements values. We can almost naturally classify sectors into four hierarchical clusters for many rankings: origin sector, highly connected sectors, somewhat connected sectors, and, lastly, loosely/unconnected sectors, which constitutes the majority. As a result we found that a number of four clusters balances the above trade-off well for our application. At the same time, the cross-sectional implications across clusters are still distinct for the different shocks we identify, and thus retain sufficient identification power.[11] Aside from cluster uniqueness, the quality of our identification relies on the heterogeneity within total requirements tables. We therefore only attempt to identify sector-specific shocks that have sufficiently heterogeneous downstream and/or upstream connections.[12]

4.3 Industrial production data

We use monthly growth rates of sectoral output and sectoral shares of industrial production (IP) starting in February 1972. In order to not be affected by the large fluctuations starting in March 2020 induced by the COVID-19 pandemic we run the model through February 2020. The sectoral breakdown of industrial production data is based on NAICS and originates from the Board of Governors of the Federal Reserve.[13]

4.4 Model parameterization

Typical FAVAR models in macro suggest a small number of factors are sufficient to capture aggregate shocks (c.f. Boivin, Giannoni, and Mihov 2009). Because our aim is to identify sectoral shocks, we include many more factors. It is wholly possible that sectoral shocks fully determine aggregate business cycles, but that no single sectoral shock causes more than a small fraction of aggregate volatility. Put differently, a single sectoral shock might not generate enough volatility to be picked up by the first few factors. In a typical two-factor FAVAR that shock would be pushed into the measurement error (and cause correlation across measurement errors, leading to a non-diagonal variance matrix R_ϵ). Onatski

[11] See Online Appendix Figure A.1 for more details on underlying ranking values, as well as Table A.2 that summarizes the cluster composition for all potential sector-specific shocks.

[12] See Online Appendix B.3 for the algorithm we use for clustering and Table A.3 for an overview on which sector-specific shocks are feasible or not to be identified.

[13] See Table A.1 in the Online Appendix for more information on all 25 included sectors. Online Appendix B.4 provides additional details on IP data.

and Ruge-Murcia (2012) and Stock and Watson (2016) also argue that the number of factors should be such that it spans the space of structural shocks of interest.

To allow potentially small contributions to aggregate activity, we determine the number of factors by requiring they explain at least 80 percent of sectoral growth rates in X, on average.[14] In practice, this translates to $K = 15$ unobserved factors for our sample. Given the number of factors, the number of lags is determined by Akaike and Schwartz criteria, both indicating one lag is sufficient.[15]

5 Results

Figure 3 shows that sectoral shocks capture aggregate business cycle fluctuations very well. The red (solid) line is aggregate industrial production (IP) growth. The black (x-marked) line is the median contribution of sectoral shocks to aggregate IP growth, and answers the question: if only sectoral (and no aggregate) shocks were at work, what would aggregate activity be? The black (x-marked) line tracks the red (solid) line closely. The dashed lines depict associated 95-percentile bands and show that the red (solid) line is virtually always within the bands. The figure reveals that a large part of fluctuations in aggregate IP growth is explained by shocks that originate at the sectoral level. Taking the median estimate at face value, the difference between the red (solid) and the black (x-marked) line in Figure 3 captures non-sectoral drivers, i.e. the contribution of aggregate shocks. While substantial at times, the role for aggregate shocks is overall subdued compared to the role of sectoral shocks. We provide a range of robustness analyses in the Online Appendix which includes various alternative versions of Figure 3 that confirm the importance of sectoral shocks in explaining US business cycles.[16]

5.1 How sectoral shocks generate business cycle fluctuations

What causes this predominant role of sectoral shocks for the business cycle? We show it is a combination of two facts. First, recessions and booms are characterized by a number of sectoral shocks occurring around the same time. No single sectoral shock explains the aggregate cycle in full. Moreover, which particular sectors face substantial shocks and which do not varies over time. Second, these sectoral shocks cause large network effects, or spillovers to other sectors.

We now visually detail which sectors quantitatively contribute most during several important episodes in US history. Our discussion focuses on demeaned, median historical contributions.[17] More than the sign of the contributions, it is their dynamics (e.g. peak-to-trough) that shed light on business cycles.

[1973–75] Figure 3 shows that IP growth is well explained by sectoral shocks throughout this period. IP growth peaked before the official recession started, which is also true for the contribution of sectoral shocks. The leading character of the idiosyncratic shocks bodes well for the causal interpretation of the shocks. Figure 4a shows that the drop in IP growth is well explained by a combination of several sectors' idiosyncratic shocks. The macro narrative often considers this recession *the* oil recession. Indeed, *Oil-gas* is one of the sectors where shocks originate, but it is not the only one. It is worth recalling that several commodities (e.g. metals, fertilizers, foods, paper, etc.) were subject to steep price increases in the early 70s (c.f. Cooper and Lawrence 1975). The steepest drop in IP growth occurs only mid-recession. The sectoral shock contributions highlight that the timing of that drop is not synchronous: a notable downward acceleration is present already in the summer of 1974 (e.g. *Paper*, *Furniture*), while other sectors experience their steepest drop only from November 1974 onward (e.g. *Chemicals*, *Computers*), and yet others experience a more or less continuous decline throughout the recession (e.g. *Plastics*,

[14]More specifically we calculate for every sector FAVAR the R^2 that capture by how much the observed and unobserved factors explain growth in the sectors included in matrix X. Note that for every separate FAVAR the combination of unobserved and observed factors yields different R^2 because X, the matrix from which unobserved factors are extracted, differs due to the origin sector's growth rate becoming the observed factor. We hence also average across all possible sector-FAVARs with respect to the 80 percent threshold.

[15]Table A.4 in the Online Appendix summarizes all relevant model parameterization.

[16]Specifically, the appendix shows results from a two-step estimation procedure (Figure A.2), sub-sample estimation (Figure A.3), and an estimation based on a finer disaggregation of IP into 88 sectors (Figure A.4). Furthermore, the bands in Figure 3 mix both identification and estimation uncertainty, therefore in Figure A.5 we show similar results for the identified set, as suggested in Baumeister and Hamilton (2018, 2022).

[17]The contributions of sectoral shocks to aggregate growth can be further decomposed into up- and downstream sources. In this paper, we do not focus on this decomposition as our main object of interest is to identify (any) relevant sectoral origins of aggregate fluctuations. Table A.3 in the Online Appendix contains a breakdown of sectors' down- and upstream contributions to IP growth.

Metals).[18] Taken together, Figure 4a suggests there are diverse sectoral shocks contributing to the full depth of the recession. The point in time in which they start contributing differs across sources. The predominant (oil) narrative is one of the sectoral sources, yet in isolation it does not account for the full depth of the recession.

[1980–82] As Figure 3 shows, sectoral shocks do not capture the onset of the 1980 recession well. The breakdown into individual sectoral shock contributions in Figure 4b reveals that while IP growth started to fall early on in the recession, sector-specific shocks pushed up IP growth, if anything. In line with the results in Figure 3, this suggests a significant role for aggregate shocks early on in this recession. Only in its second half, when IP growth fell more strongly, do we see sectoral causes. Each of the highlighted sectors capture roughly one percentage point reduction in the growth rate of IP, which combined account for the full drop in IP growth witnessed from May 1980 onward. The second 80s recession is better captured by sectoral shocks (see Figure 3). Figure 4c shows that the negative contribution of sectoral shocks to IP growth originates mostly in the *Chemicals*, *Oil-gas*, *Wood*, and *Paper* sectors. While some other sectors had milder reductions in their contribution to IP growth (e.g. *Logging*, *Utilities*, *Fabricated metals*), the bulk of remaining sectors (in gray) did not contribute at all, with some even increasing substantially.

[1990–91] The early-90s recession is a relatively minor one in IP growth, by historical standards. This recession, too, is well explained by sectoral shocks. Even more so than any other recession, the sources are diverse. Figure 4d highlights several sectoral shocks that contribute substantially negatively to IP growth's downward trend. *Chemicals* and *Furniture* show the largest reductions in historical decompositions, yet no single sectoral shock contributes massively in its own right. Note also that there are ample sectoral shocks (in gray) that do not contribute at all.

[2001] The early-90s recession was followed by a decade of growth, which ended with the 2001 recession. This period can be understood in large part through just a handful of sector-specific shocks. Figure 5a shows that, first and foremost, *Computers* have the biggest impact on IP growth throughout the decade, a finding that fits neatly with the typical macro narrative of a tech boom-bust cycle. Yet once again, the story is more nuanced. For instance, the key contributing sectors to the 1996–98 run-up in production growth are *Paper*, *Metals* and *Furniture*. The consequent growth slowdown is primarily caused by *Chemicals*. The decade of growth came to an end with the 2001 recession. Yet the key sector-specific contributors to that recession peaked long before its start. The largest downward idiosyncratic shock contributions originate in the *Computers* sector from October 2000 onward. This also aligns well with the commonplace single-shock tech boom-bust narrative. Yet in isolation, it does not tell the whole story: at the median estimates, presented in Figure 5a, it represents only up to a third of the total peak-to-trough reduction in IP growth. The figure reveals that there are at least two other major sector-specific contributors: *Oil-gas* from January 2000 onward and *Metals* starting in the summer of 1999.

[2007–09] The contribution of sectoral shocks to IP growth in Figure 5b drops substantially prior to the start of the recession. This is mainly explained by the negative idiosyncratic shocks to *Oil-gas* (oil prices were on their historically steepest increase from January 2007 to July 2008) and *Wood* (end of the house price and construction boom). The fall in IP growth at the start of the recession (prior to September 2008) is largely captured by negative shocks to *Chemicals*, *Paper* and *Metals*. There is a noticeable downward blip in September 2008 in quite a few of the sectoral shock contributions. It hints at an instance where our approach may pick up something aggregate—the fall of Lehman Brothers. The two sectors where this is most obvious are *Oil-gas* (the biggest drop in oil prices occurred two months earlier) and *Paper* (which was already in free fall since the end of 2007). Nonetheless, another couple of sectors (e.g. *Printing*, *Other Transport*) show contributions that are void of these effects, perhaps reducing the concern that aggregate shocks are what the sectoral shocks are absorbing. We will return to that concern in the next subsection.

[Post Great Recession] In the decade following the Great Recession, *Oil-gas* appears particularly influential (see Figure 5c). The dynamics of its contribution are broadly similar to the unconditional IP growth data. Its contribution in this period is also roughly in line with the evolution of oil prices: following the massive price drop after the Great Recession, it reaches new heights from 2011 and mid-2014, ensued by relatively low oil prices throughout 2015 and bottoming out in January 2016. Does this imply that oil fully determines the business cycle? Not necessarily, as there is an important scale difference. Consider, for instance, the 2016 trough to 2018 peak in IP growth, where total IP growth went up by 8 percentage-points (see Figure 5c, right scale). While the contribution of oil shocks is dynamically

[18] These sector names are mnemonics for NAICS sectors, see Online Appendix Table A.1 for a detailed mapping to NAICS sector names and codes.

similar, quantitatively it accounts for less than half of it (±3.5 percentage-points, left scale).

The above description of several important episodes in US business cycles suggests that recessions can in large part be seen as instances in which several sector-specific shocks combine to create significant fluctuations in aggregate activity. This is effectively the breakdown of the Lucas (1977) "averaging-out" argument. This breakdown occurs because sectors do have connections with one another, which causes shocks to individual sectors to generate substantial macro-effects. This is the central tenet of the literature on input-output networks and is corroborated by our results. First, idiosyncratic sectoral shocks can have a non-negligible impact on aggregate IP growth. They do so by having substantial network effects, as e.g. in Acemoglu, Akcigit, and Kerr (2016). In line with the latter, Figure 6 shows that these network effects are quantitatively large: the magenta (o-marked) line shows what the impact of sector-specific shocks would be if we shut down their effect on other sectors. Second, many historical episodes can be understood as the consequence of just a handful of sectors being hit by idiosyncratic shocks. In other words, these sector-specific shocks do not cancel out, but rather create significant fluctuations in the aggregate.

5.2 Are sectoral shocks really distinct from aggregate shocks?

Since sectoral shocks explain a substantial part of aggregate business cycle fluctuations, it is worth asking if our procedure is not simply picking up aggregate shocks. In addition to the theoretical identification arguments (Section 2) and the DSGE simulation exercises (Section 6), we here document several empirical findings, which suggest that sectoral shocks are distinct from aggregate shocks.

First, we show that sectoral shocks are distinct from one another. If sectoral shocks were capturing aggregate shocks, one would expect sectoral shocks to correlate with one another. The first panel of Figure 7 (*Sectors*) shows that this is not the case. Second, if sectoral shocks were really capturing aggregate shocks, one would expect sectoral shocks to correlate with widely studied measures of aggregate shocks. The remaining panels of Figure 7 show the correlations of all sectoral shocks with 52 proxies for aggregate shocks, as collected by Ramey (2016). Generally, these correlations are small.[19]

A corollary of the absence of significant correlation between sectoral and aggregate shocks is that despite the large contribution of sectoral shocks to business cycles, standard aggregate shocks still have a role to play. Figure 3 already shows how sectoral shocks alone occasionally do not fully trace aggregate fluctuations. The first 1980s recession, as well as the swift recovery of IP growth after the end of the Great Recession are particularly noteworthy examples.

To help quantify the relative role of sectoral and aggregate shocks for the business cycle, Figure 8 contains some illustrative regression statistics. The first three histograms in the top row contain the R^2 of regressing IP growth on each of Ramey's (2016) shock measures, one at a time. Each regression includes both contemporaneous and lagged values of the shocks (up to three years), without additional controls.[20] These histograms capture the well-known fact that while there are many (exogenous) instruments available to plausibly estimate impulse responses, they do not necessarily explain a large part of macroeconomic fluctuations (see e.g. Ramey 2016, for a discussion). The vertical (dashed) line in each panel shows the R^2 of regressing IP growth on all the identified sector-specific shocks, contemporaneously and without lags. The combination of sectoral shocks explains a significant fraction of real volatility, and substantially more so than any single aggregate shock does. Even when combining three types of aggregate shocks (histogram in the last column of Figure 8), the explanatory power of sectoral shocks compares favorably.

The bottom row of Figure 8 presents very similar results for adjusted R^2, and thereby reduces concerns of over-parameterization, due to the many lags in the aggregate shock regressions, and the many shocks in the sectoral shock regressions, respectively. This is especially relevant for the regressions with three types of aggregate shocks, included in the last column of the figure, where over-parameterization is even more of a concern.

[19] The tails of the correlation histogram with *Technology* shocks contain a handful of values of around 0.35 (in absolute value). On the one hand, this may be chance, since we are correlating 26 sectoral shocks with 24 technology shocks. On the other hand, of all the aggregate shocks to correlate with, aggregate technology shocks would be the most natural one to expect perhaps some correlation with our sectoral shocks. After all, our sectoral shocks can capture sector-specific technology shocks, which could seep into measures of aggregate technology.

[20] See e.g. Romer and Romer (2004) for a similar regression. We do not add lagged IP growth or other control variables, because they soak up explanatory power without informing the relative extent to which certain shocks help. The aim here is not to estimate an impulse response, for which lags and other controls would be important.

6 Testing identification using model-generated data

We test our identification method by using simulated data from a standard theoretical multi-sector model. We here present a multi-sector RBC model where sectors use each other's output as inputs in their own production. Online Appendix C shows robustness, including similar tests for a New Keynesian model with sectoral heterogeneity in price stickiness. The model here is similar to Carvalho's (2008) benchmark model, which in turn is close to the Foerster, Sarte, and Watson (2011) model without capital and with log utility in consumption. We also add three additional aggregate shocks, a technology, a government spending and a labor disutility shock. The calibration is largely the same as in Foerster, Sarte, and Watson (2011), including the input-output tables necessary for calibration.[21]

The model can be summarized as:

$$\max \quad \mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t \sum_{j=1}^{N} (\ln C_{jt} - (\Psi + H_t) L_{jt}) \quad \text{s.t.}\,, \tag{31}$$

$$Y_{jt} = C_{jt} + \sum_{i=1}^{N} M_{jit} + G_t \,, \tag{32}$$

$$Y_{jt} = \lambda_{jt} L_{jt}^{1-\sum_{i=1}^{N} b_{ij}} \prod_{i=1}^{N} M_{ijt}^{b_{ij}} \,, \tag{33}$$

$$\ln(\lambda_{jt}) = \rho \ln(\lambda_{jt-1}) + \epsilon_{jt} + \epsilon_t \,, \tag{34}$$

$$G_t = \rho^g G_{t-1} + \epsilon_t^g \,, \tag{35}$$

$$H_t = \rho^h H_{t-1} + \epsilon_t^h \,, \tag{36}$$

where $j = 1, \ldots, N$ is the sector index, $N = 26$ the total number of sectors, β the discount factor and C_{jt} denotes consumption of good j. A disutility of labor weight, composed of a fixed portion, $\Psi = 1$, and a random portion, H_t, multiplies labor input in sector j, L_{jt}. Production of good j, Y_{jt}, uses labor and materials, M_{ijt}, which are produced in sectors $i = 1, \ldots, N$. The share b_{ij} is an element of B, the input-output matrix. Sector-specific technology is described by a productivity index, $\ln(\lambda_{jt})$, that evolves according to an AR process with parameter ρ, and is subject to a sectoral technology shock, $\epsilon_{jt} \sim N(0, \sigma_\epsilon)$, and an aggregate technology shock, ϵ_t. Aggregate government spending and labor disutility also evolve according to AR processes in response to government spending shocks, ϵ_t^g, and labor disutility shocks, ϵ_t^h, respectively.

We set the persistence parameters $\rho = \rho^g = \rho^h = 0.5$ and calibrate the standard deviations of all sectoral shocks to 0.01. The size of the three aggregate shocks is then calibrated accordingly to generate an economy, where roughly 40 percent of the variance in aggregate output is explained by sectoral productivity shocks and 60 percent by the aggregate shocks (20 percent each).

We simulate $T = 600$ observations and then use the simulated data in a FAVAR model, applying the same feasibility and identification procedure as in the main specification with actual data.[22]

Figure 9 shows two of the sectoral shocks as examples: the blue (solid) line corresponds to the theoretical shock series and the black (x-marked) line corresponds to the median recovered series through the FAVAR model and identification. Generally speaking, both series track each other fairly well (while somewhat better for sector 1 than sector 10), especially when taking into account that the figure only shows a small snapshot of the two shocks and that these results stem from a single simulation and subsequent estimation run.[23]

Figure 9 only illustrates the performance of the method for two example shocks. We check the performance for all identified sectoral shocks more generally by calculating the correlation between theoretical and median estimated shocks. The correlation is positive in all cases, and in most cases relatively high considering the small-sample nature of this simulation exercise: it ranges from 17 to 77 percent with an average of 59 percent. Finally, we calculate for each identified shock the frequency by which the

[21] In comparison to the main specification using actual data, our simulated model only includes input-output tables in materials and abstracts from capital flows. Also note that the number of sectors and hence the declaration of sectors differs to the main specification.

[22] In this simulation exercise we do not select VAR lags based on the Akaike or Schwartz information criterion but rather set a fixed $P = 3$. Furthermore, we derive the rankings used for identification directly from the theoretical contemporaneous impulse response functions. However, as illustrated in Section 2.1, the differences to the rankings directly derived from the data are minor.

[23] Additionally, Figure A.8 in the Online Appendix compares the theoretical and empirical impulse responses for identified sector shocks.

theoretical shock lies within the 95-percent confidence interval: this coverage-ratio ranges from 77 to 98 percent with an average of 90 percent.

In the above exercise the data-generating process (DGP) is known, and our restrictions are consistent with it. Yet in reality the DGP is unknown. The fact that our restrictions only rely on cluster-wise relative responses builds in a degree of robustness to misspecification of the DGP.

It is useful to appreciate what type of alternative DGPs our (cluster-wise Leontief-inverse) restrictions can and cannot capture. Let us discuss three variations on the above model.

First, changing the *number of aggregate shocks* in the DGP does not alter the success of our procedure. As per the intuition detailed in Section 2, an aggregate shock will only confound with a sectoral shock if they both affect the same sector maximally (restriction *R1*) and affect the clusters in the same relative order (restriction *R2*). Unless one designs an aggregate shock to do exactly that, there is no obvious reason why this would occur. Moreover, as the number of sectors and/or clusters grows (as e.g. in our 88-sector robustness check), *R2* becomes increasingly binding and hence increasingly unlikely to be also satisfied for an aggregate shock.

Second, adding more *heterogeneity* within the present DGP (e.g. in the shock processes, or in the input-output links), in principle, makes it easier to disentangle shocks, as cross-sectional responses become increasingly different.

Third, *nominal frictions* per se do not change the ranking of sectors conditional on a shock. More specifically, introducing homogeneous price stickiness typically preserves the conditional cross-sectional relative responses. Price stickiness does, however, strongly influence the quantitative response to shocks. But since our restrictions are purely qualitative, it leaves the performance of our procedure unchanged.

So what *is* needed to change the cross-sectional ranking conditional on a shock? Theoretically, DGPs with enough frictions and heterogeneity in them can generate any type of cross-sectional responses. For instance, a model that features input-output networks and heterogeneity in price stickiness could change the cross-sectional ranking conditional on a shock. However, our cluster-wise restrictions hedge against several variations on the DGP. An extended simulation exercise in Online Appendix C shows the resilience of these clusters in the presence of heterogeneity in nominal rigidity. We show that rankings derived from a model without nominal rigidities are still useful for identification when the DGP actually includes heterogeneity in nominal rigidities. The simple reason is that for a majority of feasible sectoral shocks, the corresponding sector clusters are in fact the same (or very close) across the flexible and heterogeneous sticky-price model.[24] While one can specify models where our restrictions are violated, one can equally flexibly adjust the restrictions to whatever concerns that may arise. And importantly, the type of identification assumptions we propose remains far less restrictive than the DSGE calibrations used for empirical quantifications predominant in the literature.

7 Conclusion

Sectoral shocks are an important part of aggregate business cycle fluctuations. Our identification approach allows detecting these shocks through their network links with other sectors. In future work additional information on sectoral prices in conjunction with sectoral output data could further improve the separation of sectoral supply and demand drivers. Moreover, the identification method could easily be applied in different settings, wherever additional cross-sectional information can be exploited for identification, such as financial networks or in an international trade context. Of particular interest is also extending our sample into the COVID-19 episode, where the role of sectoral shocks potentially flared up even more than our results indicate. Doing so may require addressing a number of outlier issues or the use of a more flexible reduced form specification. Yet it can be useful to complement the evidence that thus far relies heftily on calibrated DSGE models.

[24]The exercise is based on Pasten, Schoenle, and Weber (2021) who include heterogeneous price stickiness across sectors. They show how shocks that appear relatively subdued in a real model may well become very important as a result. That is, if sector i's shock generates more aggregate volatility than sector j's shock in a real model, that may turn around in the presence of heterogeneity in nominal rigidity. Note that that is a change in sector ranking across different sectoral shocks, whereas what we restrict is a ranking conditional on a single sectoral shock. Schneider (2023) studies this robustness across more elaborate DSGE models with input-output networks for a wide variety of frictions, calibrations, and time variation in I-O tables.

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A Tables

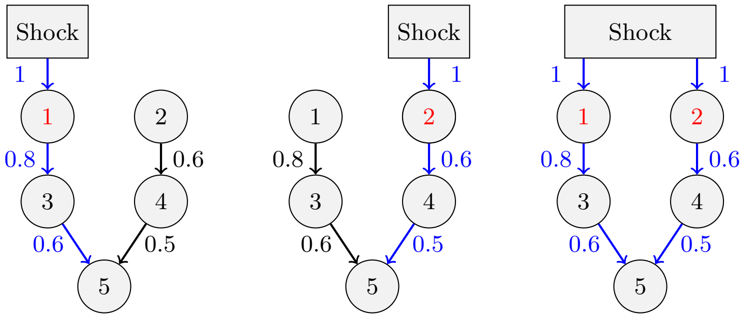
Table 1: Implied rankings of sectoral and aggregate shocks in a theoretical model

	ϵ_{13}		ϵ_{22}		Aggr. tech. (ϵ)	Aggr. gov. (ϵ^g)
Rank	Leontief	$IRF_{t=0}$	Leontief	$IRF_{t=0}$	$IRF_{t=0}$	$IRF_{t=0}$
1.	13	13	22	22	13	22
2.	3	3	19	19	22	6
3.	2	2	1	1	6	9
4.	14	14	2	2	17	17
5.	1	1	3	3	7	7
6.	26	26	10	10	8	13
7.	17	17	13	13	9	10
8.	15	15	18	18	10	19
⋮	⋮	⋮	⋮	⋮	⋮	⋮
20.	9	4	12	12	1	5
21.	4	23	6	6	2	26
22.	23	9	15	15	24	12
23.	24	24	8	8	16	16
24.	5	5	24	24	3	24
25.	25	25	7	7	26	25
26.	20	20	9	9	25	3

Notes: The underlying theoretical model is presented in Section 6. The table shows various sector rankings for four types of shocks: first the ranking for a sector-13 shock, derived from the Leontief inverse of the input-output data used for calibration of the model. The next column shows the ranked theoretical contemporaneous impulse response functions (IRFs) to a sector-13 shock. Analogously, the next two columns show this exercise for a sector-22 shock. Finally, the last two columns show the ranked theoretical IRFs to an aggregate technology and to a government spending shock.

B Figures

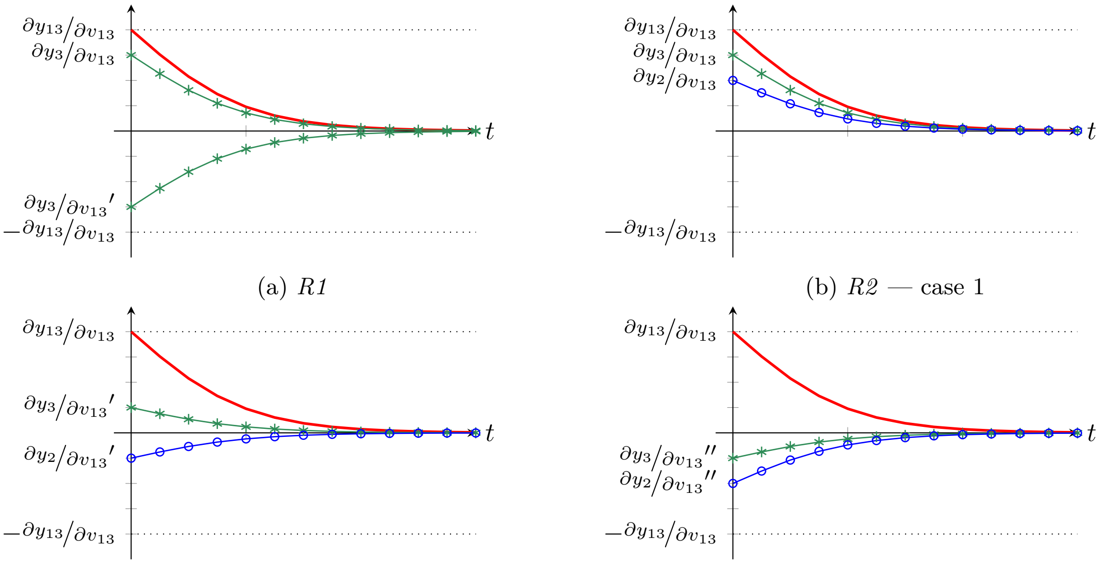
Figure 1: Stylized identification example: 3 shocks, 3 rankings



Ranking (value):	Ranking (value):	Ranking (value):
1 (1)	2 (1)	5 (1.1)
3 (0.8)	4 (0.6)	1 (1)
5 (0.6)	5 (0.5)	2 (1)
2 (0)	1 (0)	3 (0.8)
4 (0)	3 (0)	4 (0.6)

Notes: This is a stylized example illustrating how different shocks, sectoral or aggregate, generally imply different sector rankings. We look at three different shocks and rank the magnitude of the responses: first, a shock originating in sector 1, second, a shock in sector 2, and third, a combination of sector 1 and 2 shocks.

Figure 2: Identification implementation — example for a sector-13 shock

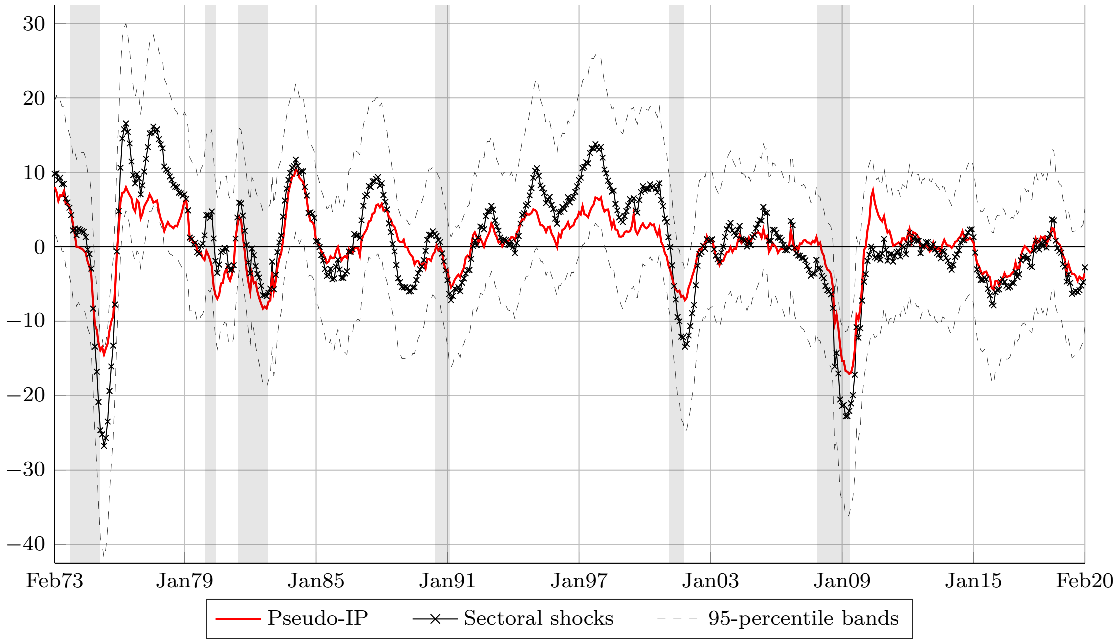


(a) *R1* (b) *R2* — case 1

(c) *R2* — case 2 (d) *R2* — case 3

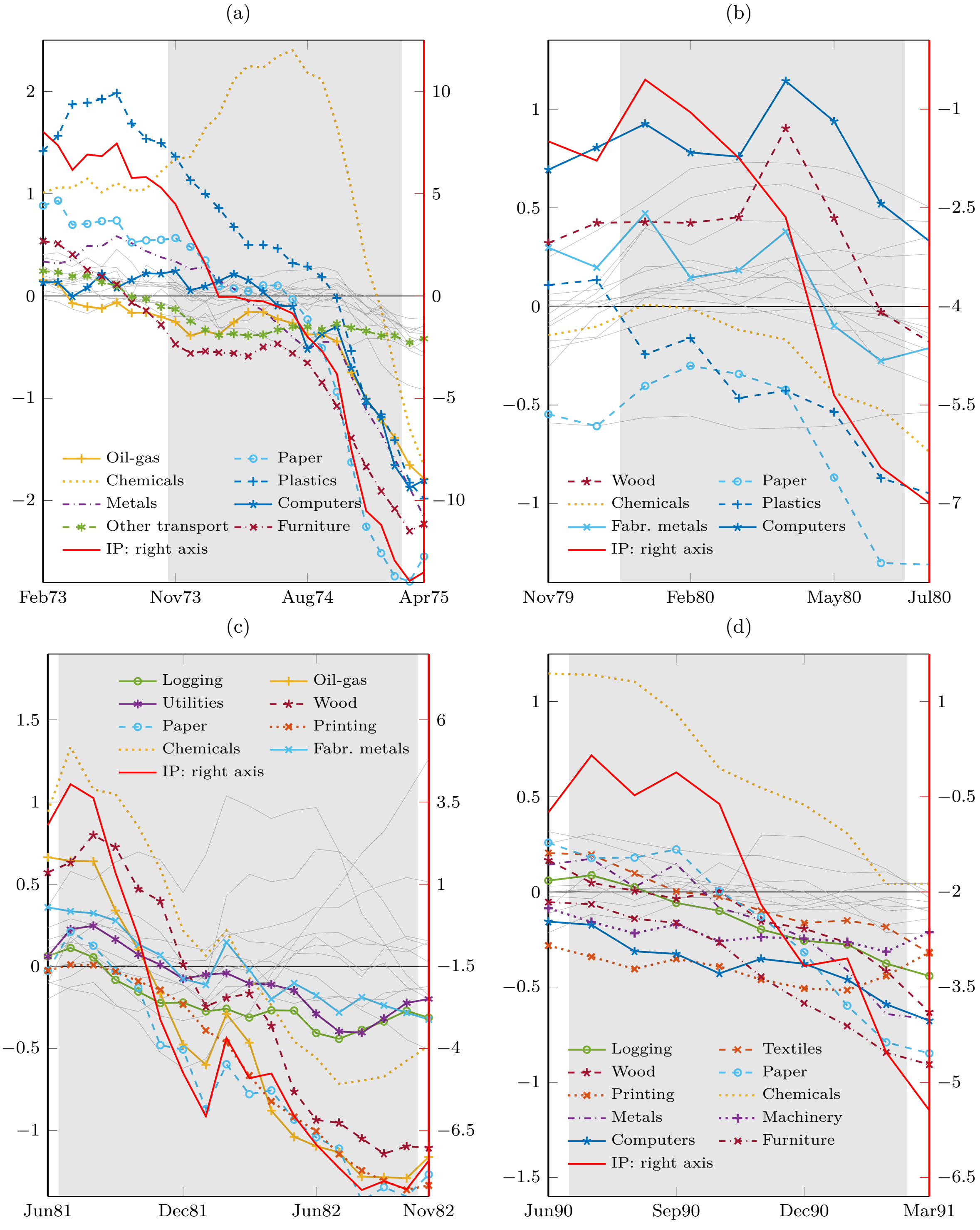
Notes: This figure shows the implications of restrictions *R1* and *R2* on all sectoral impulse response functions in response to an exemplary positive sectoral shock (sector 13). Let the ranking for such a shock be $\gamma_{13} = (\gamma_{1,13}, \gamma_{2,13}, \gamma_{3,13}, \ldots)' = (13, 3, 2, \ldots)'$. The upper left panel illustrates *R1*, i.e. $r_a^{(X)}(\gamma_{1,13}) > |r_a^{(X)}(\gamma_{i,13})|$, $\forall i = 2, \ldots, N$. The remaining three panels show cases permissible under *R2*, i.e. $r_a^{(X)}(\gamma_{i,13}) > r_a^{(X)}(\gamma_{(i+1),13})$, $\forall i = 2, \ldots, (N-1)$.

Figure 3: IP conditional on sectoral shocks (demeaned, y-o-y growth, in percent)



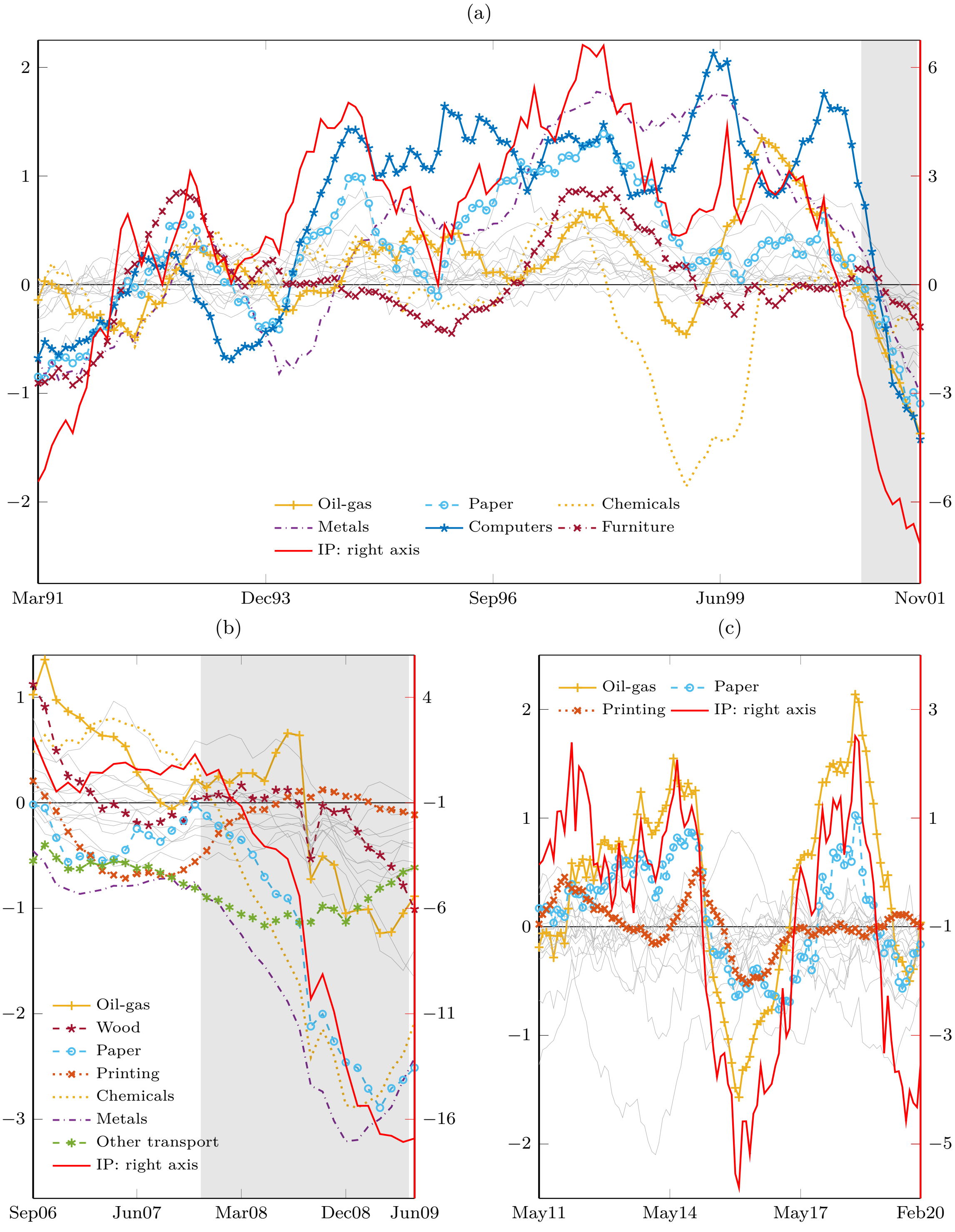
Notes: IP refers to demeaned, year-on-year (y-o-y), aggregate industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on only sectoral shocks. This historical contribution is the sum of all effects that the identified sectoral up- and downstream shocks have on IP growth, reported at the median and a 95%-percentile band.

Figure 4: Sector contributions to IP: 1970s-90s (demeaned, y-o-y growth, in percent)



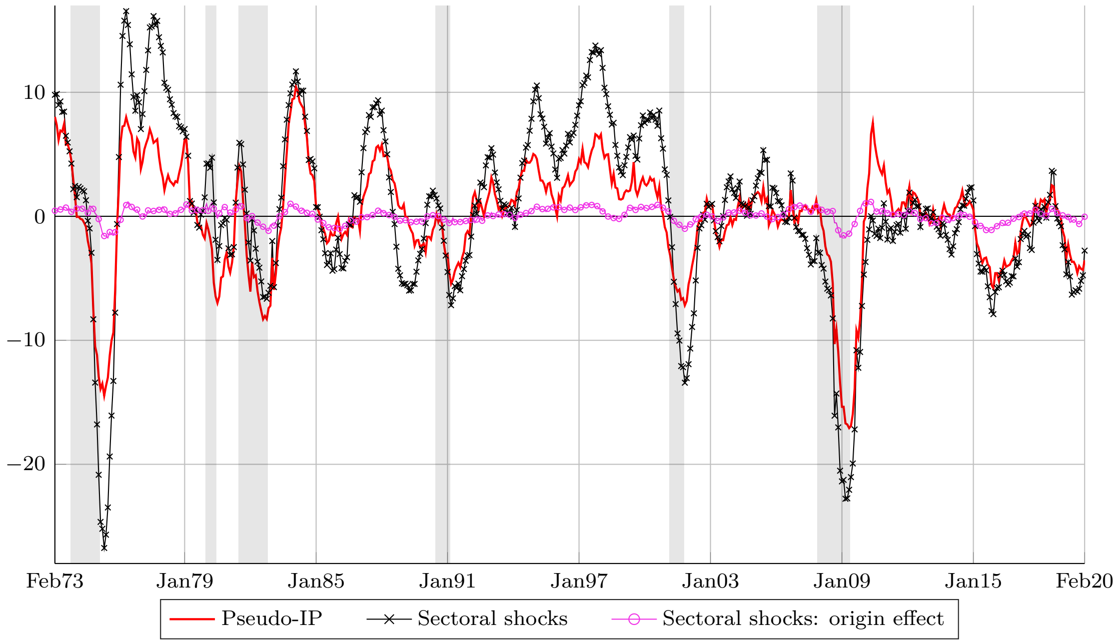
Notes: IP refers to demeaned, year-on-year (y-o-y), aggregate (Pseudo) industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights. For every sub-sample the other series show the contribution of respective sectoral shocks to Pseudo-IP. The sectoral series includes either a sectoral downstream, upstream, or both types of shocks (when identified) originating in the indicated sector, reported at the median.

Figure 5: Sector contributions to IP: 1990s-2020s (demeaned, y-o-y growth, in percent)



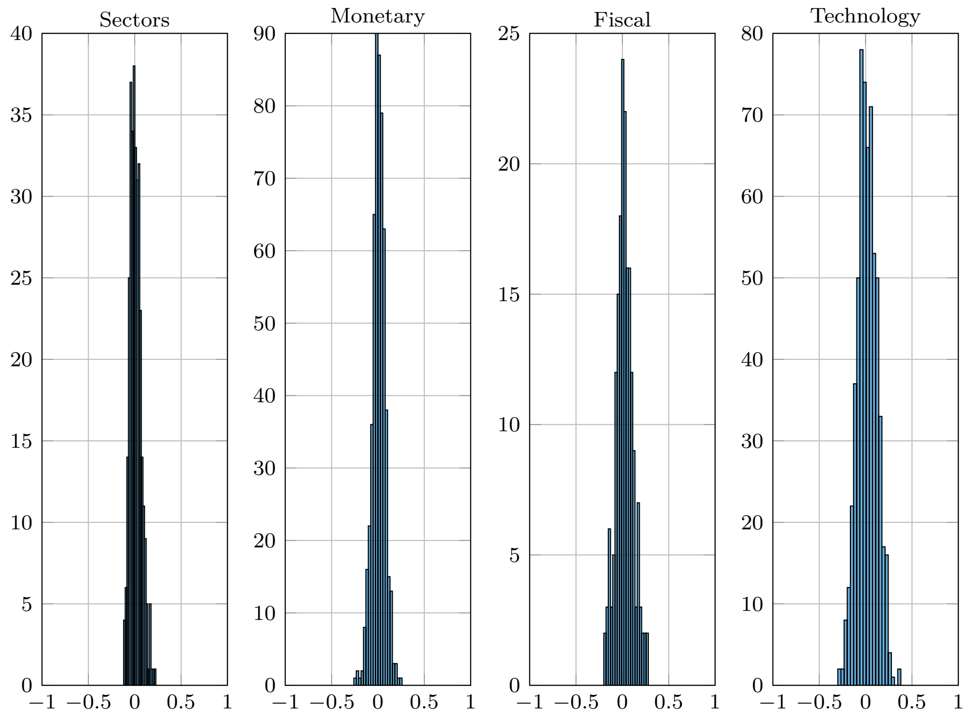
Notes: See notes to Figure 4.

Figure 6: IP conditional on sectoral shocks: origin effect (demeaned, y-o-y growth, in percent)



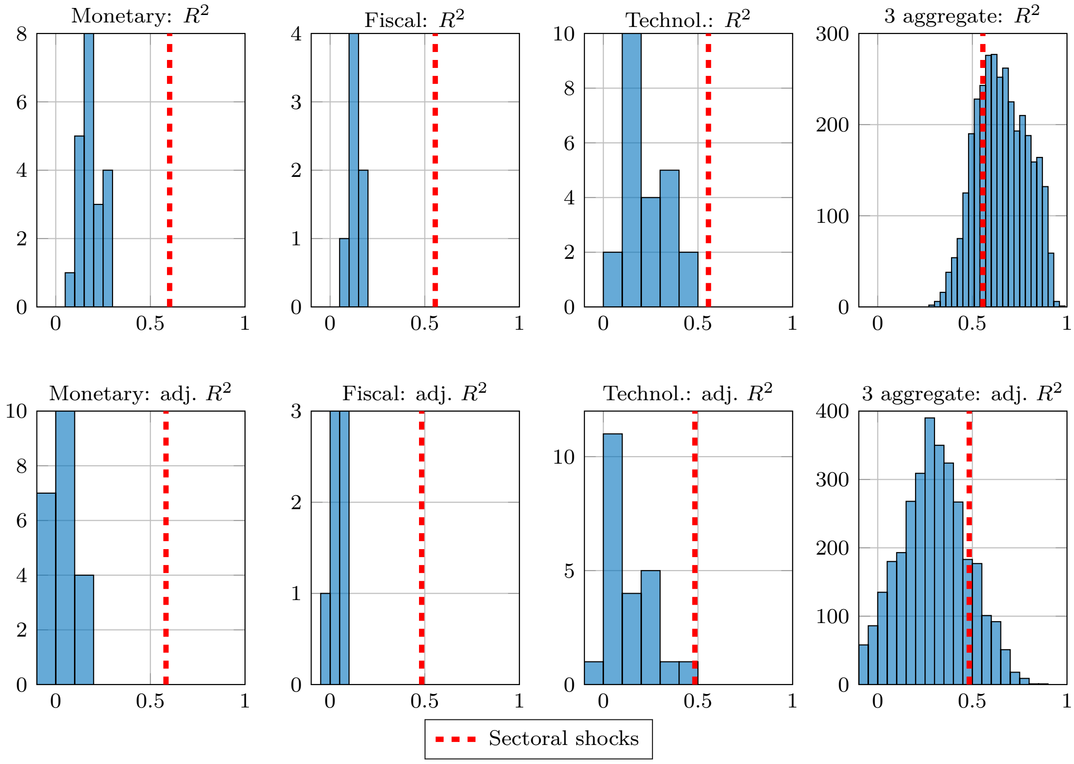
Notes: IP refers to demeaned, year-on-year (y-o-y), aggregate industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on only sectoral shocks. This historical contribution is the sum of all effects that the identified sectoral up- and downstream shocks have on IP growth, reported at the median and a 95%-percentile band. The origin effect (magenta, o-marked series) only includes the effect that sectoral shocks have in their respective origin sector and thereby ignores the effect sectoral shocks have in other sectors.

Figure 7: Correlations of sectoral and aggregate shocks



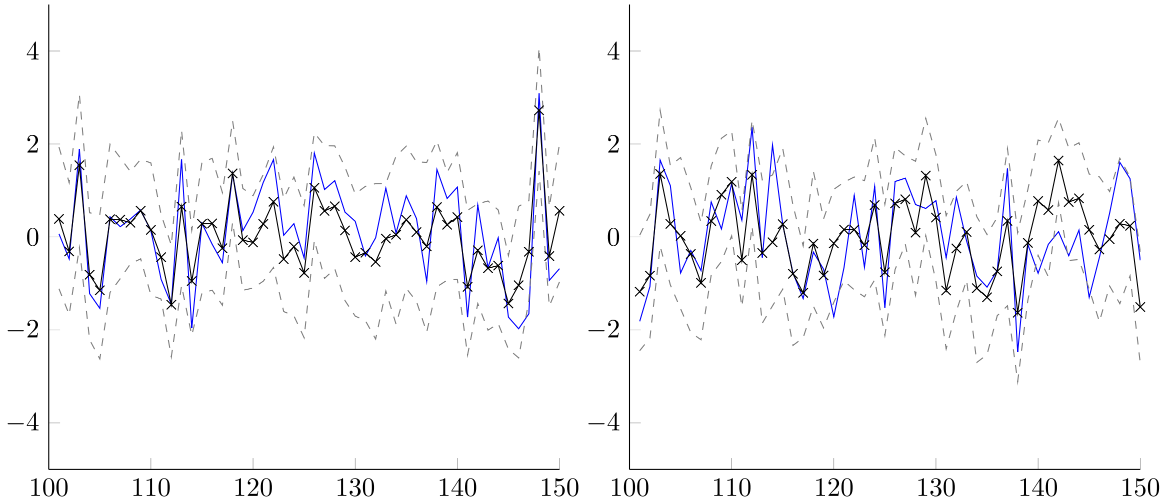
Notes: Panel *Sectors*: median correlations between random draws of different sector's shocks. Panel *Monetary* (respectively *Fiscal*, *Technology*): correlation between the median sectoral shock for each sector and each of the 21 monetary (respectively 7 fiscal, 24 technology) shock proxies studied by Ramey (2016).

Figure 8: Explanatory power of sectoral and aggregate shocks



Notes: In the first three columns, histograms contain the (adjusted) R^2 of regressing IP growth on a single monetary (resp. fiscal, technology) shock from Ramey (2016). Each regression contains the contemporaneous shock and three years of its lags, without additional controls. Monetary shocks and regressions are at monthly frequency, while fiscal and technology regressions are at quarterly frequency. The vertical line shows the (adjusted) R^2 of regressing IP growth on all the contemporaneous sectoral shocks jointly, without lags or additional controls, at the same frequency as the respective aggregate shock. The last column is based on regressions containing a monetary (at quarterly frequency), fiscal, and technology shock, iterating through all possible combinations of available shock proxies. Due to overfitting concerns we repeat this exercise with three aggregate shocks in Online Appendix Figure A.7 for lags covering alternatively one or two years.

Figure 9: Data simulation: theoretical and structural empirical shocks



(a) γ_1 shock

(b) γ_{10} shock

Notes: The figure shows two example sectors for which we compare theoretical and empirical structural shocks: the blue (solid) line corresponds to the theoretical shock series and the black (x-marked) line corresponds to the median recovered series through the FAVAR model and identification. Additionally 95-percentile bands are shown. Note that this figure only reports results for a *single* simulation and subsequent FAVAR estimation run. While the total number of simulated periods is 600 we only show a snapshot for data points 101 to 150, respectively.

Online Appendix to "Identifying sectoral shocks and their role in business cycles"

August 29, 2023

A Model derivations

Recall the reduced-form model of the main text:

$$x_t = \lambda^x f_t^x + \lambda^y y_t + \epsilon_t \qquad \text{with } \epsilon_t \sim \mathcal{N}(0, R_\epsilon)\,, \tag{A.1}$$

$$\begin{pmatrix} f_t^x \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \phi_p \begin{pmatrix} f_{t-p}^x \\ y_{t-p} \end{pmatrix} + u_t \qquad \text{with } u_t \sim \mathcal{N}(0, Q_u)\,, \tag{A.2}$$

where y_t is an M-by-1 vector of the origin sector's output growth rate and is treated as an observable factor. Since we identify every shock separately we set M equal to one for every model. On the left-hand side of equation (A.1), x_t is an N_x-by-1 vector including aggregate output growth and all sector output growth rates other than the origin sector. Unobservable factors f_t^x have factor loadings, λ^x, while observable factors have loadings, λ^y. The transition equation follows a VAR process with parameters, ϕ_p and P numbers of lags. Reduced-form shocks, u_t, have variance-covariance matrix Q_u and measurement errors, ϵ_t, are distributed according to diagonal variance matrix R_ϵ. The measurement equation (A.1) of the main text can be rewritten as:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} \lambda^x & \lambda^y \\ \mathbf{0}_{M\times K} & \mathbf{I}_M \end{bmatrix} \begin{bmatrix} f_t^x \\ y_t \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ 0 \end{bmatrix}. \tag{A.3}$$

Furthermore the state-space model (A.1) and (A.2) can be rewritten in companion form as

$$X_t = \Lambda F_t + E_t\,, \tag{A.4}$$

$$F_t = \Phi F_{t-1} + U_t\,, \tag{A.5}$$

which implies that the parameters and variables of the state-space model are stacked in the following way:

$$X_t \equiv (x_t', y_t')'\,, \tag{A.6}$$

$$f_t \equiv (f_t^{x'}, y_t')'\,, \tag{A.7}$$

$$\lambda \equiv \begin{bmatrix} \lambda^x & \lambda^y \\ \mathbf{0}_{M\times K} & \mathbf{I}_M \end{bmatrix}, \tag{A.8}$$

$$\phi \equiv [\phi_1, \phi_2, \ldots, \phi_P]\,, \tag{A.9}$$

$$F_t \equiv \left(f_t', f_{t-1}', \ldots, f_{t-P+1}'\right)'\,, \tag{A.10}$$

$$E_t \equiv \left(\epsilon_t', \mathbf{0}_{M\times 1}'\right)'\,, \tag{A.11}$$

$$U_t \equiv \left(u_t', \mathbf{0}_{(K+M)(P-1)\times 1}\right)'\,, \tag{A.12}$$

$$\Phi \equiv \begin{bmatrix} \phi_1 & \cdots & \phi_P \\ \mathbf{I}_{KM(P-1)} & & \mathbf{0}_{KM(P-1)\times KM} \end{bmatrix}, \tag{A.13}$$

$$\Sigma \equiv \begin{bmatrix} R_\epsilon & \mathbf{0}_{N_x\times M} \\ \mathbf{0}_{M\times N_x} & \mathbf{0}_{M\times M} \end{bmatrix}, \tag{A.14}$$

$$Q \equiv \begin{bmatrix} Q_u & \mathbf{0}_{(K+M)\times(K+M)(P-1)} \\ \mathbf{0}_{(K+M)(P-1)\times(K+M)} & \mathbf{0}_{(K+M)(P-1)\times(K+M)(P-1)} \end{bmatrix}, \tag{A.15}$$

$$\Lambda \equiv \left[\lambda \ \mathbf{0}_{(N_x+M)\times(K+M)(P-1)}\right]. \tag{A.16}$$

For the derivations below it is also convenient to rewrite the model in matrix form:

$$X = F\lambda' + E\,, \tag{A.17}$$

$$F = F_{(-1)}\phi' + U\,, \tag{A.18}$$

where X is a $(T-P)$-by-(N_x+M) matrix containing all observations, including the observed factor, y_t. F is a $(T-P)$-by-$(K+M)$ and $F_{(-1)}$ a $(T-P)$-by-$(K+M)P$ matrix of the (lagged) unobserved and observed factors. Alternatively the model can be stacked in the following way:

$$x = fl + e \qquad \text{with } e \sim \mathcal{N}(0, I\otimes\Sigma)\,, \tag{A.19}$$

$$f^* = f_{(-1)}^*\phi^* + u \qquad \text{with } u \sim \mathcal{N}(0, I\otimes Q_u)\,, \tag{A.20}$$

with x being a stacked $(T-P)(N_x+M)$-by-1 vector of all observations, including the observed factor. Matrix f has dimensions $[(T-P)(N_x+M)\times(K+M)(N_x+M)]$ and l is a $(K+M)(N_x+M)$-by-1 vector of the loadings. The transition equation uses the following definitions: f^* is a $(T-P)(K+M)$-by-1 vector, $f^*_{(-1)}$ a $(T-P)(K+M)$-by-$(K+M)(K+M)P)$ matrix of the lagged factors, and $\phi^* = vec\,(\phi')$ is a $(K+M)P(K+M))$-by-1 stacked vector of parameters. Note that in all derivations we abstract from the constant included in the VAR equation in order to lighten notation.

In the main specification we apply a joint estimation procedure by likelihood-based Gibbs sampling as in Bernanke, Boivin, and Eliasz (2005). Similar to their approach we solve the standard factor identification problem by setting the upper $K\times K$ block of the loadings matrix λ^x to an identity matrix and the upper $K\times M$ block of λ^y to zero.

Alternatively, we estimate the model using a two-step procedure as in Bernanke, Boivin, and Eliasz (2005) and Boivin, Giannoni, and Mihov (2009). In the first step of this estimation we follow Boivin, Giannoni, and Mihov (2009) to ensure that the unobserved factors do not capture dynamics induced by the observed factor:

(i) Obtain initial estimate of f_t^x as first K principle components of x_t; denote as $f_t^{x,(0)}$.

(ii) Regress x_t on $f_t^{x,(0)}$ and y_t; obtain coefficients on y_t and denote as $\lambda^{y,(0)}$.

(iii) Compute $\widetilde{x}_t^{(0)} = x_t - \lambda^{y,(0)} y_t$.

(iv) Estimate $f_t^{x,(1)}$ as first K principle components of $\widetilde{x}_t^{(0)}$.

(v) Repeat steps (ii)-(iv) multiple times.

A.1 Gibbs sampler, priors, and posterior distributions

This section lays out the estimation steps of the Gibbs sampler. We first use the Carter and Kohn (1994) algorithm to sample latent factors. Second, we sample factor loadings and the variance-covariance matrix Σ. Since this matrix is diagonal we can estimate the factor loadings and error variances equation-by-equation. This means that for every equation we estimate an l_i that is a $(K+M)$-by-1 sub-vector of the stacked loadings l from observation $(i-1)(K+M)+1$ to $i(K+M)$ for all $i=1,\dots,N_x$. Priors are denominated with lower bars and posteriors with upper bars. We impose an independent Normal-Gamma prior for the loadings and measurement errors' variance-covariance matrix:

$$l_i \sim \mathcal{N}\left(\underline{l_i}, \underline{V_{l_i}}\right)\,, \tag{A.21}$$

$$\sigma_i^{-2} \sim \mathcal{G}\left(\underline{s}^{-1}, \underline{v}\right)\,. \tag{A.22}$$

The derivation of the conditional posterior distributions is standard. They are of the following form:

$$l_i \mid X, \Sigma^{-1} \sim \mathcal{N}\left(\overline{l_i}, \overline{V_{l_i}}\right)\,, \tag{A.23}$$

$$\sigma_i^{-2} \mid X, l_i \sim \mathcal{G}\left(\overline{s}^{-1}, \overline{v}\right)\,, \tag{A.24}$$

for all $i=1,\dots,N_x$, where

$$\overline{V_{l_i}} = \left(\underline{V_{l_i}^{-1}} + \sigma_i^{-2} F'F\right)^{-1}\,, \tag{A.25}$$

$$\overline{l_i} = \overline{V_{l_i}}\left(\underline{V_{l_i} l_i} + \sigma_i^{-2} F'X_i\right)\,, \tag{A.26}$$

$$\overline{v} = \underline{v} + T\,, \tag{A.27}$$

$$\underline{S_i} = \underline{v s_i}\,, \tag{A.28}$$

$$\overline{S_i} = \overline{v s_i}\,, \tag{A.29}$$

$$\underline{S_i} = \underline{S_i} + (X_i - F\lambda_i')'(X_i - F\lambda_i')\,. \tag{A.30}$$

Since we are proceeding equation-by-equation, we define for the i^{th} variable a vector X_i as the i^{th} column of X and S_i as the corresponding sum of squared residuals. The latter is a function of the degrees of freedoms v and the variance s_i. Vector λ_i corresponds to the i^{th} row of λ. We impose uninformative priors using the following hyperparameters for all $i=1,\dots,N_x$:

$$\underline{V_{l_i}} = cI \text{ with } c = 4\,,$$

$$
\begin{aligned}
\underline{l_i} &= 0\,, \\
\underline{v} &= 0.01\,, \\
\underline{s_i}^{-1} &= 1000\,.
\end{aligned}
$$

In the next step we estimate the VAR parameters ϕ^* and the corresponding variance-covariance matrix Q_u using a diffuse (Jeffrey's) prior:

$$\phi^*, Q_u \propto |Q_u|^{-\frac{K+M}{2}}\,, \tag{A.31}$$

which implies the following posterior distribution:

$$\phi^* \mid Q_u, f^* \sim \mathcal{N}\left(\widehat{\phi}^*, Q_u \otimes (F'F)^{-1}\right)\,, \tag{A.32}$$

$$Q_u \mid f^* \sim \mathcal{W}^{-1}\left(\widehat{S}, T - P - (K+M)P - 1\right)\,, \tag{A.33}$$

where Q_u is sampled from an inverse Wishart distribution. The vector $\widehat{\phi}^*$ refers to the OLS estimate and $\widehat{S}$ to the sum of squared residuals of the VAR equation.

Finally, for every model run we check at least 3 million replications, where for every replication we check 100 impulse vectors against our heterogeneity restrictions. We stop the estimation once we have reached 500 successful draws. Every model uses a burn-in period of 20,000 replications.

B Data sources and transformations

B.1 Make, use, and capital-flow tables

We follow the BEA's (2009) procedure for constructing the industry-by-industry direct and total requirements matrices of the main text. These matrices derive from the 1997 input-output (I-O) account's *standard* make and use tables.

Make tables are industry-by-commodity tables that show the production of commodities by industries. Rows correspond to the dollar value of commodities produced in a given industry. Columns correspond to the dollar value of industries' production of a given commodity. Row sums amount to total industry outputs and column sums to total commodity outputs. Use tables are commodity-by-industry tables that show industries' intermediate as well as final uses of commodities. Rows correspond to the dollar value of given commodities used by all industries and the commodities' values in final demand. Columns correspond to the dollar value of commodities used by a given industry as well as the value added realized in that industry. Row sums amount to total commodity outputs and column sums to total industry outputs. The BEA derives make and use tables from Census data which are compiled every five years.

Our network rankings of the main text are augmented by the 1997 capital flow table. This table provides detailed information on investments in equipment, software, and structures by industries. In the use table, capital flows are accounted for in the private fixed investment (PFI) column. The capital flow table expands the PFI column to show detailed flows of commodities and industries similarly to the intermediate portion of the use table. While PFI includes purchases of new and used assets, the capital-flow table only accounts for purchases of new assets.[1]

B.2 Industry-by-industry direct & total requirements matrices

In this subsection we describe the construction of the commodity-by-industry direct input coefficient matrix B (as well as matrix $\widetilde{B}$) needed to derive the downstream and upstream measures, A and $\widetilde{A}$, of Section 4.

We start from the make table V and the intermediate use table U, i.e. omitting the columns of the use matrix that include final demand uses and follow the BEA's (ibid.) procedure to derive an industry-by-industry direct requirements matrix WB. This matrix is a product of the direct input coefficient matrix B and transformation matrix W, which in turn is a function of the market share matrix D:

$$B = U\left(diag(g)\right)^{-1} , \tag{A.34}$$

$$D = V\left(diag(q)\right)^{-1} , \tag{A.35}$$

$$W = \left(I - diag(p)\right)^{-1} D , \tag{A.36}$$

where $diag(x)$ refers to a square matrix where the elements of vector x are on the diagonal and zeros elsewhere. The vector g includes total industry output, q is a vector of total commodity outputs, and p is vector of the ratio of scrap production to total industry output. The transformation procedure for direct requirements tables needs to explicitly take into account the production of scrap materials which is a commodity produced as a by-product.[2]

The upstream measure $\widetilde{A}$ of the main text uses a variation of this procedure and is based on matrix $\widetilde{B}$:

$$\widetilde{B} = \left(diag(q)\right)^{-1} U . \tag{A.37}$$

Furthermore, the measures A^c and $\widetilde{A}^c$ in the main text also include direct coefficient matrices Cap and $\widetilde{Cap}$ for investments, which are defined similarly to matrices B and $\widetilde{B}$:

$$Cap = F\left(diag(g)\right)^{-1} , \tag{A.38}$$

$$\widetilde{Cap} = \left(diag(q)\right)^{-1} F , \tag{A.39}$$

where F is the commodity-by-industry capital flow table.

[1] For more information see BEA (2009, pp. 12.4-12.5).

[2] For more details on the need for accounting for scrap materials see BEA (ibid., pp. 12.21–12.24).

B.3 Feasibility criterion

Every sector shock is identified using four ranking clusters. For some sector shocks there is not enough variation in the respective total requirements vector. We label these types of shocks infeasible and do not attempt to identify them.

We determine whether a sector ranking is feasible using the following rule: for every sectoral shock we take the sorted total requirements values and assess the variation in that ranking. Specifically, we calculate the differences between adjacent ranking values and define a minimum cut-off value of 0.01 that separates the clusters. This implies that we need at least 3 cut-offs in each ranking that are larger than 0.01 so that we can obtain four well-defined clusters. We experimented with many different feasibility criteria but this one seemed to be the most reasonable both in terms of simplicity and for eliminating sectoral shocks that are difficult to identify.

In the set of infeasible sectoral shocks we also include the special case of the upstream ranking for *Petroleum and coal products*, i.e. ranking $\widetilde{\gamma}_{12}^{c}$. For this ranking the restriction *R1* that the origin sector has the largest total requirements value is violated, as the total requirement values for both sector 2, *Oil and gas extraction* as well as sector 4, *Support activities for mining*, are in fact larger than for sector 12. We therefore do not identify upstream sector-12 shocks.

B.4 Industrial production data

Data on seasonally-adjusted industrial production (IP) originate from the Board of Governors of the Federal Reserve. We use monthly data from January 1972 until February 2020.[3] We match the sector disaggregation of industrial production data to the NAICS (North American Industry Classification System) sector definition of I-O account data.

For some sectors industrial production data is not directly available but can be approximated according to the board's suggested aggregation procedure. The approximation of missing sector data falls into either of two cases. First, for a sector a that is the composite of a sector b and c the industrial production growth rate of a is approximated by:

$$\frac{I_{at}}{I_{a,t-1}} = \left(\frac{\frac{I_{bt}}{I_{b,t-1}}w_{b,t-1} + \frac{I_{ct}}{I_{c,t-1}}w_{c,t-1}}{w_{b,t-1} + w_{c,t-1}}\right)^{0.5} \times \left(\frac{w_{bt} + w_{ct}}{\frac{I_{b,t-1}}{I_{bt}}w_{bt} + \frac{I_{c,t-1}}{I_{ct}}w_{ct}}\right)^{0.5}, \tag{A.40}$$

where I_{it} refers to industrial production of sector i and ω_{it} is the relative importance weight of that sector. The approximation for sector a's relative importance weight in aggregate industrial production is $w_{at} = w_{bt} + w_{ct}$. Alternatively, if we wanted to approximate sector b as the difference between a sector a and a sector c, we calculate the growth rate of b as:

$$\frac{I_{bt}}{I_{b,t-1}} = \left(\frac{\frac{I_{at}}{I_{a,t-1}}w_{a,t-1} - \frac{I_{ct}}{I_{c,t-1}}w_{c,t-1}}{w_{a,t-1} - w_{c,t-1}}\right)^{0.5} \times \left(\frac{w_{at} - w_{ct}}{\frac{I_{a,t-1}}{I_{at}}w_{at} - \frac{I_{c,t-1}}{I_{ct}}w_{ct}}\right)^{0.5}, \tag{A.41}$$

with the approximation for sector b's weight in aggregate IP being $w_{bt} = w_{at} - w_{ct}$.

[3]The industrial production data from the Board of Governors of the Federal Reserve was downloaded on 13 June 2022.

C Additional exercises using model-generated data

The data-generating process (DGP) used in Section 6 derives from a simple flexible-price model. Theoretically, DGPs with enough frictions and heterogeneity in them can generate any type of cross-sectional responses. As a consequence there is a concern that our cross-sectional rankings may be invalid for other such DGPs with additional frictions. Hence in this appendix, we show that rankings derived from a model without nominal rigidities (*Flex. ranking*) are still useful for identification when the actual DGP includes heterogeneity in nominal rigidities (*Het. DGP*). The reason is that our cluster-wise restrictions (derived from a flexible price model) have a sufficient degree of robustness built in.

Table A.5 compares the identification results across the different model exercises. Details on the underlying models of the DGPs are referred to the next sub-section. The first three columns of the table report different combinations of model-generated data and the rankings used for the identification exercise. *Flex. DGP* refers to data generated from the flexible price model (Equation A.42) and *Het. DGP* to the heterogeneous price-stickiness model (Equation A.43). Similarly, *Flex. ranking* refers to sector rankings derived from the flexible price, and *Het. ranking* from the heterogeneous price-stickiness model. We report for each combination of model-generated data and theory-implied rankings the performance for all identified sectoral shocks by calculating the correlation between theoretical and median estimated shocks. Similarly, we calculate per combination of data and ranking the frequency by which theoretical shocks lie within the 95-percent confidence interval.

For ease of reference the last column of Table A.5 includes the correlations and coverage ratios for the DGP of the main text. Inspecting the results of the first three columns reveals that both correlations and coverage ratios are in same ballpark of the DGP exercise presented in the main text. Column *Flex. DGP/ Flex. Ranking* shows the success of our procedure is very comparable for an alternative flexible price DGP (the DGP in the main text differs in some details). If instead the true DGP features heterogeneity in price stickiness, an econometrician who implements our method based on that belief is as successful in detecting the theoretical sectoral shocks (see column *Het. DGP/ Het. Ranking*).

Of course the econometrician does not know the DGP in reality which implies there is scope for misspecification. Column *Het. DGP/ Flex. Ranking* shows the results of this experiment. Suppose the econometrician would only use rankings derived from a flexible price economy (without incorporating information on heterogeneous price stickiness), while the true DGP features heterogeneity in price stickiness. Even in this case where there is a mismatch between DGP and empirical approach, the econometrician would still be similarly successful in retrieving the true sectoral shocks.

C.1 Model setup

The solutions used to simulate the two DGPs are taken from Schneider (2023), which in turn are based on Pasten, Schoenle, and Weber's (2021) New Keynesian model. In this exercise we simulate sectoral technology shocks as well as an aggregate technology shock.

Note that the input-output network is different to the one in Section 6 and uses a breakdown of the full US economy into $J = 33$ sectors. The model version of the main text uses a different sector decompositions and only captures the industrial-production portion of the US economy. Furthermore, the two models of this appendix are not based on gross output (such as industrial production indices) but on GDP which in absence of capital production is just equal to consumption expenditure in these types of models.

For a full model setup see Schneider (2023). Here we just introduce the key equations for the sectoral rankings. The first of the two models is a flexible price version and the solution is based on the following multiplier matrix:

$$\widehat{\mathbf{X}}^{im} \equiv [\mathbf{I} - \delta\mathbf{\Omega}]^{-1} , \tag{A.42}$$

where $\mathbf{I}$ is the identify matrix, $\mathbf{\Omega}$ is the J-by-J I-O matrix, and $\delta = 0.53$ is the intermediate input share in production. The second model is a New Keynesian variant using a simple information friction to model price rigidity. The model explicitly allows for sector heterogeneity in price stickiness:

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im}) , \tag{A.43}$$

where $\mathbf{\Lambda}^{im}$ is a diagonal J-by-J matrix including sectoral price-rigidity probabilities, λ_j. The diagonal elements λ_j measure the probability by which a firm needs to set its price before it can observe the shocks.[4] The J-by-1 vector of sectoral consumption expenditures (in log deviations from steady state), $\mathbf{c}_t$, is given by:

$$\mathbf{c}_t = \widehat{\mathbf{X}}^c \mathbf{a}_t \,, \tag{A.44}$$

where $\mathbf{c}_t$ is expressed in response to J sectoral productivity processes, $\mathbf{a}_t$. The consumption multiplier matrix, $\widehat{\mathbf{X}}^c$, is a function of multiplier matrix, $\widehat{\mathbf{X}}^{im}$:

$$\widehat{\mathbf{X}}^c = [\eta \mathbf{I} + (1-\eta)\iota \boldsymbol{\Omega}_c'] \, \widehat{\mathbf{X}}^{im} \,. \tag{A.45}$$

Here, $\eta = 0.5$ is the elasticity of substitution across sectors, ι is a column vector of ones of the appropriate dimension, and $\boldsymbol{\Omega}_{\mathbf{c}}$ is a vector of sectoral consumption shares.[5] The corresponding sector rankings (and clusters) used as identification restrictions for sectoral shocks are then based on $\widehat{\mathbf{X}}^c$, similarly to the main text. We apply the feasibility criterion of the main text to the flexible-price model solution and use the resulting set of feasible sectors for both the flexible and heterogeneous price-stickiness model to ensure comparability.[6]

As in Section 6, we assume a sectoral technology process (the vector elements of $\mathbf{a}_t$):

$$a_{jt} = \rho a_{jt-1} + \epsilon_{jt} + \epsilon_t \,, \tag{A.46}$$

where $\epsilon_{jt} \sim N(0, \sigma_\epsilon)$ is a sectoral technology shock, and ϵ_t is the aggregate technology shock. We set the persistence parameters $\rho = 0.5$ and calibrate the standard deviations of all sectoral shocks to 0.01. The standard deviation of the aggregate technology shock targets roughly 60 percent of the variance in aggregate output with the remaining 40 percent being explained by sectoral technology shocks.

We simulate $T = 600$ observations and then use the simulated data in a FAVAR model, applying the same identification procedure as in the main specification with actual data.[7]

[4] Monthly frequencies of producer prices are based on older Standard Industrial Classification (SIC) estimates from Peneva (2011) and are converted to current NAICS definitions.

[5] Note that in contrast to Schneider (2023), we only consider NAICS sectors and do not map the model to US Personal Consumption Expenditure categories. Hence, the solution for consumption $\mathbf{c}_t$ used in this appendix assumes that (in notation of Schneider 2023): $\mathbf{K} = \mathbf{I}$, $\boldsymbol{\Omega}_{\mathbf{c}} = \boldsymbol{\Omega}_{\mathbf{c}}^{\mathbf{im}}$, and $\boldsymbol{\Lambda}^{pce} = \mathbf{0}$.

[6] To be more precise, feasibility is derived from $\widehat{\mathbf{X}}^{im}$ of the flexible price model, as this object is closest to the total requirements values used in the main text.

[7] In this simulation exercise we do not select VAR lags based on the Akaike or Schwartz information criterion but rather set a fixed $P = 3$.

D Additional tables

Table A.1: Industrial production sectors: fact sheet

No.	Name	Mnemonic	NAICS	Weight	SDev
1.	Logging	Logging	1133	0.24	8.76
2.	Oil and gas extraction	Oil-gas	211	6.95	5.48
3.	Mining excl. oil and gas	Mining	212	2.37	8.44
4.	Support activities for mining	Support Mining	213	1.55	19.56
5.	Electric and gas utilities	Utilities	221	9.47	3.75
6.	Food, beverage and tobacco products	Food	311_2	10.09	2.26
7.	Textile mills and textile product mills	Textiles	313_4	1.5	7.5
8.	Apparel and leather and allied products	Apparel	315_6	1.61	7.57
9.	Wood products	Wood	321	1.39	8.39
10.	Paper and paper products	Paper	322	2.98	5.13
11.	Printing and related support activities	Printing	323	2.11	4.88
12.	Petroleum and coal products	Petroleum-coal	324	2.31	4.99
13.	Chemicals	Chemicals	325	9.91	5.39
14.	Plastics and rubber products	Plastics	326	3.14	7.68
15.	Nonmetallic mineral products	Non-metals	327	2.15	6.71
16.	Primary metals	Metals	331	3.22	11.32
17.	Fabricated metal products	Fabr. metals	332	5.77	6.68
18.	Machinery	Machinery	333	6.23	9.02
19.	Computer and electronic products	Computers	334	7.48	10.8
20.	Electrical equipment, appliances, and components	Electronics	335	2.37	7.44
21.	Motor vehicles, bodies and trailers, and parts	Vehicles	3361_3	5.71	14.75
22.	Other transportation equipment	Other transport	3364_6,9	4.23	8.69
23.	Furniture and related products	Furniture	337	1.41	8.11
24.	Miscellaneous manufacturing	Misc	339	2.63	4.68
25.	Newspaper, periodical, book, and database publishers	Publishing	5111	3.2	5.2

Notes: The table shows for every industrial production sector the average sector *Weight* (in percent) and standard deviation (*SDev*) of the sector year-on-year growth rates (in percent). A more detailed description of these NAICS sectors can be found at naics.com.

Table A.2: Rankings with 4 clusters

Cluster	γ_j	$\widetilde{\gamma}_j$	γ_j^c	$\widetilde{\gamma}_j^c$
1	1	1	1	1
2	9	2	9	2, 4, 18
3	10	13, 12	10	13, 12, 16, 21
4	23, 11, 6, 24, 25, 14, 15, 20, 7, 13, 21, 8, 18, 16, 17, 3, 22, 19, 5, 12, 4, 2	7, 5, 14, 6, 3, 9, 10, 11, 16, 17, 15, 18, 20, 19, 21, 4, 25, 24, 8, 22, 23	23, 11, 6, 24, 25, 14, 15, 7, 20, 13, 21, 5, 3, 8, 18, 12, 16, 22, 2, 17, 19, 4	17, 14, 7, 3, 9, 19, 20, 5, 10, 15, 11, 6, 23, 22, 24, 25, 8
1	2	2	2	2
2	12	4	12	4
3	5	16	5	16, 18
4	13, 3, 4, 14, 7, 10, 16, 15, 6, 1, 9, 20, 8, 11, 21, 17, 23, 22, 24, 18, 19, 25	5, 17, 3, 12, 13, 15, 18, 14, 10, 11, 20, 1, 21, 19, 25, 9, 24, 7, 8, 6, 22, 23	13, 3, 4, 7, 14, 10, 16, 15, 6, 1, 9, 20, 11, 8, 21, 17, 23, 22, 24, 18, 19, 25	17, 3, 21, 15, 19, 12, 5, 20, 14, 13, 22, 10, 11, 1, 9, 23, 7, 24, 25, 8, 6
1	3	3	3	3
2	16, 15	4	16, 15	4
3	5	2	5	18, 2, 16
4	17, 13, 20, 21, 18, 12, 10, 14, 7, 22, 24, 23, 4, 6, 9, 11, 2, 19, 8, 1, 25	12, 18, 16, 5, 17, 14, 15, 13, 1, 20, 10, 9, 11, 21, 25, 19, 7, 24, 22, 8, 6, 23	17, 13, 21, 20, 12, 18, 10, 2, 14, 7, 22, 4, 24, 23, 6, 9, 11, 19, 8, 1, 25	17, 12, 14, 5, 20, 21, 15, 19, 22, 13, 1, 9, 10, 11, 23, 7, 25, 24, 8, 6
1	4	4	4	4
2	2	2	2	18
3	3, 12	16, 15, 12	12	16, 2
4	5, 16, 15, 13, 7, 14, 10, 20, 17, 21, 6, 18, 9, 22, 23, 24, 11, 8, 1, 19, 25	17, 18, 3, 13, 14, 5, 11, 10, 20, 1, 19, 9, 21, 25, 7, 24, 22, 6, 8, 23	3, 5, 13, 16, 15, 7, 14, 10, 6, 20, 9, 21, 1, 17, 11, 8, 22, 18, 23, 24, 19, 25	15, 17, 12, 19, 20, 3, 21, 13, 14, 11, 5, 10, 1, 9, 23, 7, 24, 22, 25, 8, 6
1	5	5	5	5
2	16, 12, 15, 10, 3, 7	2	12, 16, 15, 3, 10	2, 4
3	13, 14	3	7	3
4	17, 2, 9, 6, 8, 11, 20, 21, 23, 18, 24, 22, 4, 19, 1, 25	4, 12, 20, 15, 16, 17, 14, 9, 1, 18, 10, 13, 11, 19, 25, 21, 7, 24, 22, 23, 6, 8	2, 13, 14, 6, 17, 9, 11, 8, 20, 21, 23, 18, 4, 22, 24, 19, 1, 25	20, 16, 18, 15, 17, 19, 12, 21, 9, 14, 1, 13, 10, 11, 23, 22, 7, 24, 25, 8, 6
1	6	6	6	6
2	8	10	8	10
3	10, 7, 13	1, 14, 2	10, 7, 13	1, 18, 14, 17, 2, 4, 16, 15, 13, 21, 3, 11, 20, 12, 5, 19, 9
4	1, 14, 24, 9, 11, 23, 21, 12, 20, 16, 22, 18, 15, 19, 17, 25, 4, 3, 5, 2	13, 17, 15, 11, 12, 3, 5, 16, 9, 20, 7, 18, 19, 25, 24, 21, 4, 8, 22, 23	1, 14, 9, 24, 11, 12, 23, 21, 20, 16, 22, 15, 19, 4, 18, 5, 3, 2, 17, 25	7, 23, 22, 24, 25, 8
1	7	7	7	7
2	8	13	8	13
3	23	8, 2	23	18, 2, 4, 8

Table A.2 — Continued

Cluster	γ_j	$\widetilde{\gamma}_j$	γ_j^c	$\widetilde{\gamma}_j^c$
4	24, 14, 21, 10, 11, 9, 22, 1, 13, 15, 6, 18, 20, 25, 3, 19, 17, 12, 16, 4, 2, 5	11, 10, 5, 3, 14, 15, 12, 1, 17, 19, 16, 9, 20, 18, 6, 25, 24, 4, 21, 22, 23	24, 14, 21, 10, 11, 9, 22, 1, 13, 15, 6, 18, 2, 3, 20, 12, 25, 4, 19, 5, 17, 16	11, 10, 16, 3, 14, 5, 17, 19, 15, 20, 1, 12, 9, 21, 23, 24, 22, 25, 6
1	8	8	8	8
2	7	7	7	7
3	11	13	11	13
4	21, 24, 23, 25, 10, 14, 9, 22, 6, 18, 13, 20, 12, 19, 16, 15, 17, 2, 3, 4, 1, 5	11, 2, 10, 14, 24, 5, 1, 17, 3, 19, 20, 12, 16, 15, 9, 6, 18, 25, 21, 4, 22, 23	21, 24, 23, 25, 10, 14, 2, 12, 9, 22, 6, 3, 4, 13, 18, 20, 16, 19, 15, 5, 17, 1	11, 18, 2, 4, 10, 14, 19, 17, 16, 24, 20, 1, 5, 3, 15, 9, 12, 21, 6, 23, 25, 22
1	9	9	9	9
2	23	1	23	1
3	10	15, 17, 2	10	15, 17, 18, 16, 2, 4, 20, 14, 13, 19, 7, 10, 3, 21, 23, 5, 12
4	24, 11, 15, 20, 21, 6, 16, 14, 7, 18, 22, 5, 8, 17, 25, 13, 3, 19, 4, 1, 12, 2	13, 14, 20, 16, 7, 10, 5, 3, 12, 23, 19, 11, 21, 18, 24, 6, 25, 4, 8, 22	24, 11, 5, 15, 20, 6, 21, 16, 7, 14, 3, 22, 12, 18, 13, 2, 4, 8, 17, 19, 25, 1	11, 24, 22, 6, 25, 8
1	10	10	10	10
2	11	1	11	1
3	25	9	25	9
4	6, 24, 14, 15, 23, 13, 20, 7, 8, 21, 18, 17, 9, 19, 12, 22, 16, 4, 3, 2, 5, 1	13, 2, 14, 3, 7, 5, 17, 12, 16, 11, 19, 15, 20, 18, 6, 25, 24, 4, 8, 21, 23, 22	6, 14, 24, 15, 23, 13, 20, 7, 8, 21, 18, 12, 19, 17, 9, 2, 22, 4, 16, 3, 5, 1	13, 18, 2, 4, 14, 3, 7, 16, 17, 5, 19, 20, 12, 15, 11, 21, 23, 22, 24, 25, 6, 8
1	11	11	11	11
2	25	10	25	10
3	8, 7	1	8, 7, 13, 6, 12, 4, 2, 21, 23, 22, 10, 19, 24, 14, 20, 5, 3, 16, 18, 15, 9, 17	1
4	13, 6, 23, 21, 10, 24, 4, 12, 19, 22, 20, 14, 18, 16, 9, 17, 2, 15, 5, 3, 1	13, 7, 8, 2, 14, 9, 5, 3, 17, 16, 25, 18, 19, 12, 20, 15, 24, 21, 6, 4, 22, 23	1	18, 13, 7, 8, 16, 2, 14, 4, 19, 9, 17, 3, 20, 5, 25, 21, 12, 15, 23, 24, 22, 6
1	12	12	12	12
2	4, 13, 3	2	4, 3, 13	2
3	14, 5, 7, 10, 16, 1, 6, 2, 15, 9, 20, 11, 8, 21, 22, 23, 17, 24, 18	4	5, 2, 14, 7, 10, 16, 6, 1, 15, 9, 20, 11, 21, 8, 22, 23, 17, 18, 24	4
4	19, 25	5, 3, 13, 16, 15, 17, 10, 14, 11, 18, 20, 1, 19, 9, 25, 21, 24, 7, 6, 22, 8, 23	19, 25	5, 3, 18, 16, 17, 15, 13, 19, 21, 20, 14, 10, 11, 1, 22, 9, 23, 7, 24, 25, 8, 6
1	13	13	13	13
2	14, 7	2	14, 7	2, 4
3	10, 8	3, 10, 14, 12	10, 8	3

Table A.2 — Continued

Cluster	γ_j	$\widetilde{\gamma}_j$	γ_j^c	$\widetilde{\gamma}_j^c$
4	24, 11, 20, 23, 6, 15, 12, 21, 9, 1, 22, 4, 17, 18, 3, 19, 2, 16, 25, 5	5, 17, 11, 15, 1, 16, 19, 20, 9, 18, 4, 7, 24, 25, 6, 21, 8, 22, 23	11, 24, 20, 12, 23, 6, 15, 21, 2, 9, 4, 3, 22, 1, 17, 18, 19, 5, 16, 25	14, 10, 12, 18, 17, 16, 19, 5, 15, 20, 11, 1, 21, 9, 23, 7, 24, 22, 25, 6, 8
1	14	14	14	14
2	23	13	23	13
3	21, 24	7, 10, 2	21	7
4	20, 18, 10, 6, 13, 22, 19, 3, 9, 7, 11, 15, 8, 17, 12, 4, 16, 2, 5, 25, 1	1, 15, 16, 3, 17, 5, 12, 20, 19, 11, 9, 18, 24, 25, 4, 6, 8, 21, 22, 23	24, 20, 18, 10, 6, 13, 22, 3, 19, 7, 11, 9, 15, 2, 12, 8, 4, 5, 17, 16, 25, 1	18, 10, 2, 4, 16, 17, 15, 1, 3, 19, 20, 5, 12, 9, 11, 21, 23, 24, 22, 25, 8, 6
1	15	15	15	15
2	16, 20	3	16, 20, 4	3
3	4, 21, 9	10, 2	21, 9, 12, 2, 5, 6, 14, 18, 3, 7, 22, 17, 23, 24, 13, 19, 10, 8, 11	4
4	18, 14, 6, 12, 17, 23, 24, 7, 22, 5, 3, 13, 2, 19, 10, 8, 11, 25, 1	5, 13, 1, 16, 14, 17, 9, 12, 7, 4, 19, 20, 11, 18, 24, 21, 25, 22, 6, 23, 8	1, 25	10, 18, 2, 16, 5, 13, 17, 1, 14, 19, 9, 20, 12, 21, 7, 11, 23, 24, 22, 25, 8, 6
1	16	16	16	16
2	17	3	17	3
3	20, 18, 21	15, 2, 17, 20, 5	20, 18, 21	4, 15, 17, 18, 2, 20
4	22, 24, 23, 4, 19, 3, 2, 12, 14, 15, 9, 5, 10, 6, 13, 11, 7, 8, 25, 1	12, 18, 19, 10, 13, 14, 1, 9, 4, 11, 25, 21, 24, 7, 22, 6, 23, 8	22, 24, 23, 4, 2, 3, 12, 19, 5, 14, 15, 10, 6, 9, 13, 7, 11, 8, 25, 1	5, 19, 12, 14, 9, 10, 13, 1, 21, 11, 22, 23, 25, 7, 24, 6, 8
1	17	17	17	17
2	18, 22	16	22, 18	16
3	21	3	21	3
4	20, 16, 23, 19, 24, 9, 4, 6, 3, 14, 13, 12, 2, 10, 15, 7, 5, 11, 8, 25, 1	2, 15, 20, 10, 13, 5, 14, 18, 19, 1, 12, 11, 9, 7, 21, 24, 25, 4, 22, 23, 6, 8	20, 16, 4, 23, 2, 3, 19, 12, 9, 24, 6, 5, 13, 14, 10, 15, 7, 11, 8, 25, 1	18, 20, 4, 15, 2, 19, 10, 14, 13, 5, 1, 9, 21, 12, 11, 23, 7, 24, 22, 25, 8, 6
1	18	18	18	18
2	3	16	3	16
3	21	17, 20	4	17, 20
4	22, 4, 16, 17, 20, 11, 2, 14, 12, 7, 19, 5, 13, 10, 6, 15, 24, 9, 23, 8, 1, 25	14, 3, 15, 19, 2, 10, 13, 5, 1, 21, 9, 12, 11, 7, 24, 25, 4, 22, 8, 6, 23	21, 2, 12, 22, 16, 14, 7, 10, 11, 6, 17, 15, 19, 20, 5, 13, 9, 24, 23, 8, 1, 25	14, 3, 19, 15, 4, 2, 10, 21, 13, 1, 5, 9, 11, 12, 7, 24, 23, 22, 25, 8, 6
1	19	19	19	19
2	22	16, 20, 17	22	16, 20, 17, 18
3	21, 20	14	21, 20	14
4	18, 24, 14, 16, 7, 10, 11, 17, 8, 9, 23, 13, 15, 4, 12, 6, 25, 3, 2, 5, 1	10, 13, 3, 15, 2, 11, 5, 1, 18, 9, 23, 12, 24, 25, 7, 21, 22, 4, 6, 8	4, 18, 5, 2, 12, 13, 24, 14, 7, 16, 10, 11, 3, 15, 17, 8, 9, 23, 6, 25, 1	10, 15, 3, 13, 2, 4, 23, 1, 11, 9, 21, 5, 24, 12, 7, 25, 22, 8, 6
1	20	20	20	20
2	18	16	18	16

Table A.2 — Continued

Cluster	γ_j	$\widetilde{\gamma}_j$	γ_j^c	$\widetilde{\gamma}_j^c$
3	19, 22, 16, 21	17, 15, 3, 14	5, 19, 16, 22, 21, 4, 3, 9, 17, 12, 2, 14, 10, 13, 7, 24, 15, 6, 8, 23, 11	17
4	9, 17, 5, 14, 24, 8, 23, 3, 7, 10, 13, 4, 15, 12, 6, 11, 2, 25, 1	13, 19, 10, 2, 1, 5, 9, 18, 12, 11, 7, 24, 25, 21, 4, 22, 6, 23, 8	25, 1	15, 3, 14, 19, 18, 13, 10, 4, 2, 1, 9, 5, 12, 21, 11, 7, 23, 24, 22, 25, 6, 8
1	21	21	21	21
2	18	16	2	16
3	9, 22, 3	17	12, 3, 4, 5, 6	17
4	4, 2, 12, 17, 16, 15, 6, 10, 1, 20, 19, 23, 7, 14, 11, 13, 5, 8, 24, 25	14, 3, 7, 15, 19, 18, 20, 13, 2, 10, 8, 5, 1, 9, 11, 12, 24, 25, 4, 22, 6, 23	18, 9, 15, 7, 13, 16, 22, 10, 11, 14, 1, 19, 20, 17, 23, 8, 25, 24	18, 14, 3, 19, 7, 15, 20, 4, 13, 2, 10, 1, 9, 5, 8, 11, 12, 23, 24, 22, 25, 6
1	22	22	22	22
2	21	16, 17	3, 2	16
3	18, 16, 3, 19, 20, 7, 5, 9, 15, 10, 17, 11, 6, 14, 13, 12, 24, 23, 8, 4	19	12	17
4	2, 25, 1	20, 14, 18, 3, 2, 15, 13, 7, 10, 5, 12, 11, 1, 9, 21, 24, 25, 23, 4, 8, 6	5, 16, 21, 15, 4, 13, 10, 6, 7, 9, 14, 18, 11, 20, 19, 17, 23, 24, 8, 1, 25	19, 18, 20, 14, 3, 15, 4, 2, 13, 7, 21, 10, 9, 1, 5, 11, 12, 23, 24, 25, 8, 6
1	23	23	23	23
2	9	9	9	9
3	19, 24	1, 7	19, 24, 4, 22, 2, 5, 12, 3, 11, 21, 10, 13, 15, 7, 6, 25, 20, 16, 18, 14, 8, 17	1, 7
4	22, 21, 10, 20, 16, 5, 18, 7, 15, 17, 8, 14, 13, 11, 6, 12, 4, 3, 25, 2, 1	14, 16, 10, 17, 13, 2, 15, 3, 11, 5, 19, 20, 12, 8, 18, 24, 25, 21, 6, 4, 22	1	14, 16, 17, 10, 18, 13, 15, 2, 3, 4, 19, 20, 11, 5, 21, 12, 8, 24, 22, 25, 6
1	24	24	24	24
2	8	7, 16	8	16, 7
3	18, 22, 21, 13, 20, 19, 9, 15, 10, 11, 14, 7, 23, 17, 16, 12, 6, 2, 4, 25, 3	14, 10	22, 21, 18, 13, 19, 2, 20, 12, 15, 4, 10, 9, 11, 14, 7, 3, 6, 16, 23, 17, 5, 25	14, 10
4	5, 1	1, 13, 9, 17, 3, 15, 2, 19, 11, 20, 5, 8, 12, 18, 23, 25, 6, 21, 4, 22	1	17, 1, 9, 13, 18, 19, 3, 15, 4, 2, 20, 11, 5, 23, 12, 21, 8, 25, 22, 6
1	25	25	25	25
2	11	11	12, 2, 4, 11, 13, 22, 19, 21	11
3	13, 21, 12, 22, 19, 4, 20, 24, 7, 16, 18, 14, 8, 6, 2, 23, 10, 9, 3, 17, 5, 15	10	3, 5, 20, 7, 16, 24, 10, 14, 6, 18, 8, 23, 9, 15, 17	10

Table A.2 — Continued

Cluster	γ_j	$\widetilde{\gamma}_j$	γ_j^c	$\widetilde{\gamma}_j^c$
4	1	1, 13, 2, 17, 9, 14, 7, 5, 16, 3, 12, 19, 8, 15, 20, 18, 24, 21, 6, 4, 22, 23	1	1, 18, 19, 16, 17, 2, 13, 4, 9, 14, 21, 7, 3, 20, 23, 5, 15, 12, 8, 24, 22, 6

Notes: This table shows the clusters for identifying sectoral shocks for four different types of rankings. See Table A.1 for a legend of industry-number codes. In the main text we use rankings derived from both material and capital flows, which correspond to the downstream ranking, γ_j^c, and upstream ranking, $\widetilde{\gamma}_j^c$. We additionally show clusters for rankings γ_j and $\widetilde{\gamma}_j$ that are only derived from material flows, which allows for an assessment of the respective importance of capital flows for a given sectoral shock. The table shows rankings for all 25 industrial production sectors even though we do not identify sectoral shocks for all these sectors due to our feasibility criteria. In this set of infeasible sectoral shocks we also include the special case of the *Petroleum and coal products* sector, i.e. rankings $\widetilde{\gamma}_{12}$ and $\widetilde{\gamma}_{12}^c$. For these two rankings the restriction *R1* that the origin sector has the largest total requirements value is violated, as the total requirement values for sector 2, *Oil and gas extraction*, and sector 4, *Support activities for mining* (just for ranking $\widetilde{\gamma}_{12}^c$), are in fact larger than for sector 12. We therefore do not identify sector-12 upstream shocks, i.e. consider them *infeasible*.

Table A.3: Feasibility and downstream-upstream breakdown

Sectors		Degree		Feasibility		Share SDev(HD)	
		l^c	$\widetilde{l}^c$	γ_j^c (max)	$\widetilde{\gamma}_j^c$ (max)	γ_j^c	$\widetilde{\gamma}_j^c$
1.	Logging	22	24	yes (5)	no	100	–
2.	Oil-gas	7	8	yes (5)	yes (4)	45	55
3.	Mining	20	22	yes (4)	no	100	–
4.	Support Mining	18	25	yes (6)	no	100	–
5.	Utilities	9	3	no	yes (8)	–	100
6.	Food	13	1	no	yes (7)	–	na*
7.	Textiles	12	15	yes (4)	no	100	–
8.	Apparel	25	16	no	no	–	–
9.	Wood	14	7	yes (4)	no	100	–
10.	Paper	8	10	yes (4)	yes (4)	57	43
11.	Printing	17	18	no	yes (4)	–	100
12.	Petroleum-coal	11	2	no	no	–	–
13.	Chemicals	3	5	yes (5)	yes (7)	67	33
14.	Plastics	10	14	no	yes (4)	–	100
15.	Non-metals	19	20	no	no	–	–
16.	Metals	5	11	yes (7)	yes (5)	46	54
17.	Fabr. metals	6	12	yes (5)	yes (5)	51	49
18.	Machinery	4	9	yes (6)	yes (5)	64	36
19.	Computers	1	6	yes (6)	yes (6)	51	49
20.	Electronics	16	17	no	no	–	–
21.	Vehicles	2	4	no	yes (10)	–	100
22.	Other transport	15	13	no	yes (6)	–	100
23.	Furniture	24	23	no	yes (6)	–	100
24.	Misc	23	21	no	no	–	–
25.	Publishing	21	19	no	yes (5)	–	100

Notes: Column l^c corresponds to the (out)degree measure of the total requirements matrix H^c, where for every sector we calculate $l_j^c = \sum_{i=1}^N h_{ij}^c$ and rank the values from highest to lowest. Equivalently $\widetilde{l}^c$ corresponds to the (in)degree measure of the total requirements matrix $\widetilde{H}^c$, based on rankings of $\widetilde{l}_j^c = \sum_{i=1}^N \widetilde{h}_{ij}^c$. The next two columns show whether the sector shock complies with our feasibility criterion and indicate in parentheses the maximum number of clusters that would still comply with the feasibility cut-off of 0.01. The final two columns present for each sector's historical contribution to aggregate Pseudo-IP growth the share of volatility of up- and/or downstream shocks.

* The *na** entry signals that despite being feasible, no upstream *Food* shock was found in the estimation.

Table A.4: Model parameterization: full vs. sub-samples

		Additional sub-samples		
Parameters	Feb73 – Feb20	Feb73 – Dec83	Jan84 – Dec06	Jan07 – Feb20
M	1	1	1	1
K	15	12	15	13
P	1	1	1	1
s	0	0	0	0
r	1	1	1	1

Notes: K is the number of unobserved factors, $M = 1$ indicates that the target sector's growth rate is included as an observed factor, P is the number of VAR lags, s is the first period of impulse responses in which the inequality and sign restrictions are imposed, r is the number of periods for how long inequality and sign restrictions are imposed. We impose a different number of unobserved factors for every sub-sample in order to harmonize the variability covered by the observed and unobserved factors across these sub-samples. As in our main specification our benchmark is to explain on average just more than 80 percent of sector growth.

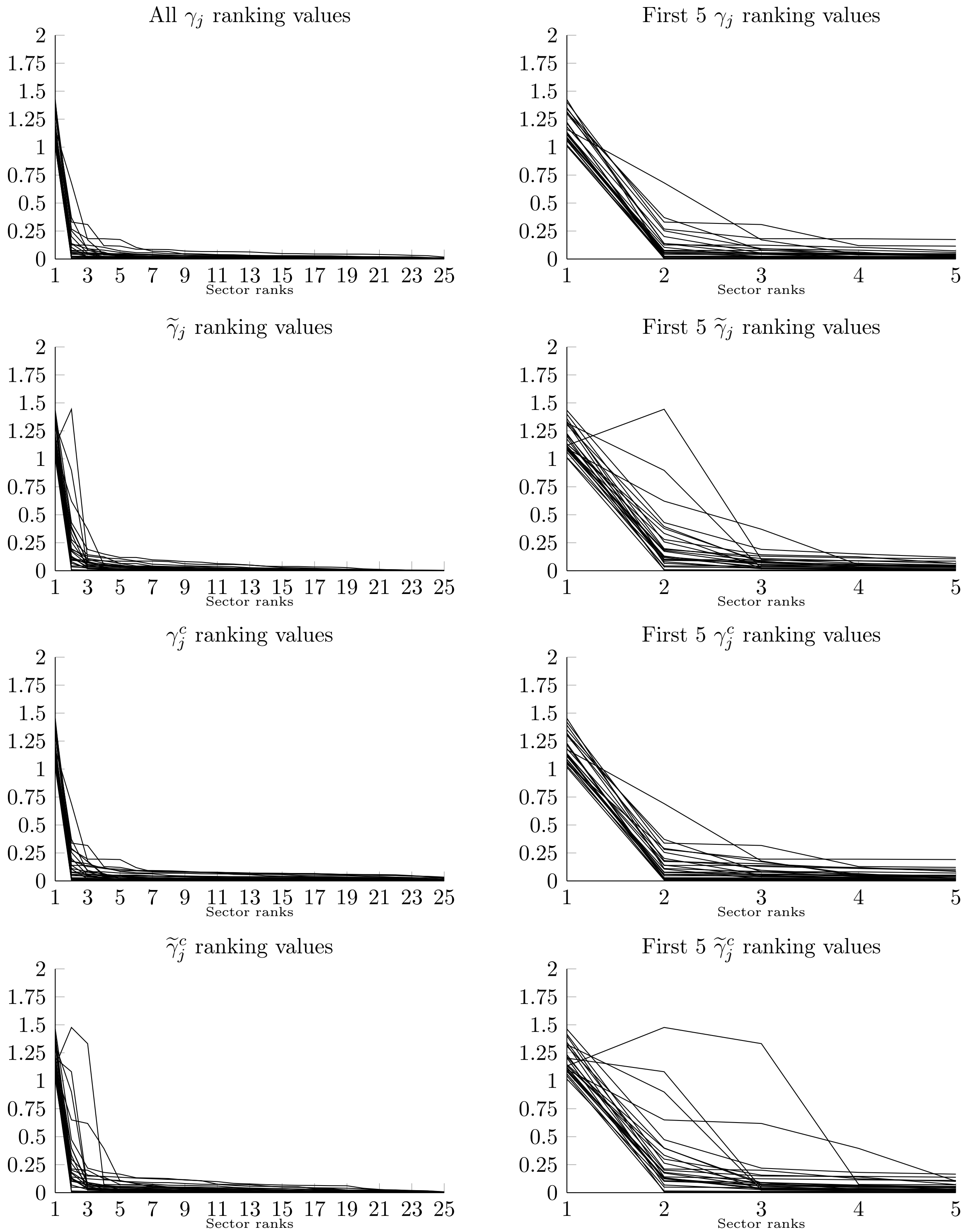
Table A.5: Identification using model-generated data: model comparisons

	Flex. DGP/ Flex. ranking	Het. DGP/ Flex. ranking	Het. DGP/ Het. ranking	Main text
Corr(Theory, FAVAR)				
Mean	0.56	0.63	0.62	0.59
Min	0.48	0.46	0.38	0.17
Max	0.71	0.81	0.81	0.77
FAVAR coverage of Theory				
Mean	0.87	0.87	0.87	0.90
Min	0.75	0.69	0.76	0.77
Max	0.96	0.99	0.99	0.98

Notes: Rows below *Corr(Theory, FAVAR)* report the mean, minimum, and maxium correlation between theoretical and median estimated shocks. Rows below *FAVAR coverage of Theory* report the mean, minimum, and maxium coverage-ratio. We calculate for each identified shock the frequency by which the theoretical shock lies within the 95-percent confidence interval. The first three columns report different combinations of model-generated data and the rankings used for the identification exercise. *Flex. DGP* refers to data generated from the flexible price model of Appendix C and *Het. DGP* to the heterogeneous price-stickiness model. Similarly, *Flex. ranking* refers to sector rankings derived from the flexible price, and *Het. ranking* from the heterogeneous price-stickiness model. Finally, the last column replicates the correlations and coverage ratios from the model exercise of Section 6 for comparison.

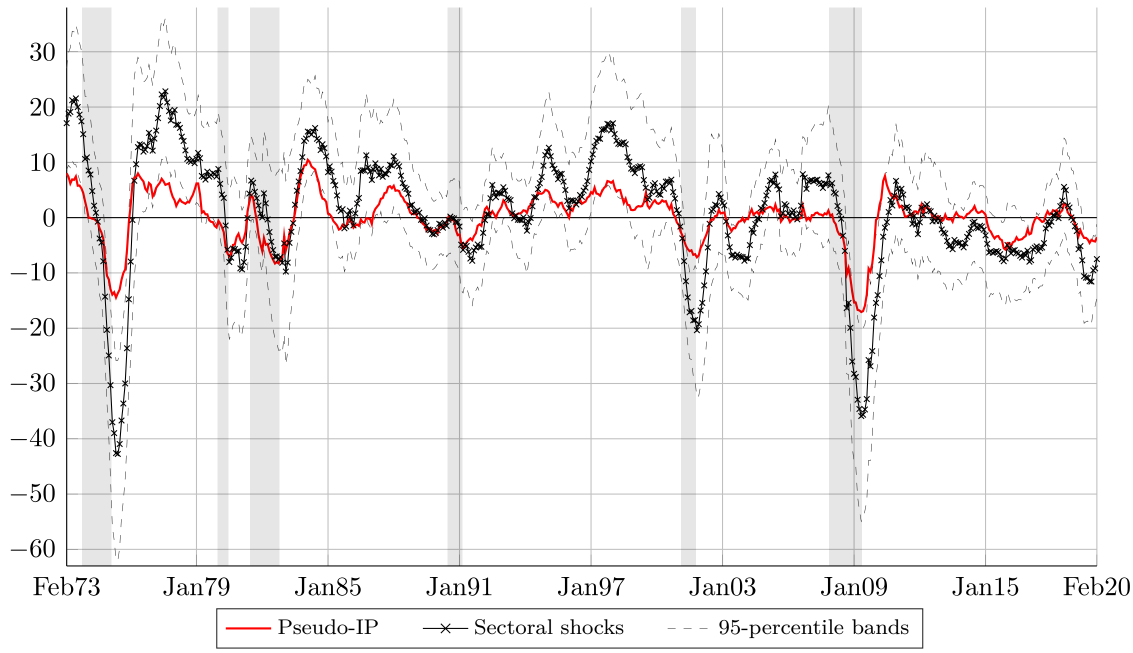
E Additional figures

Figure A.1: Ranking values



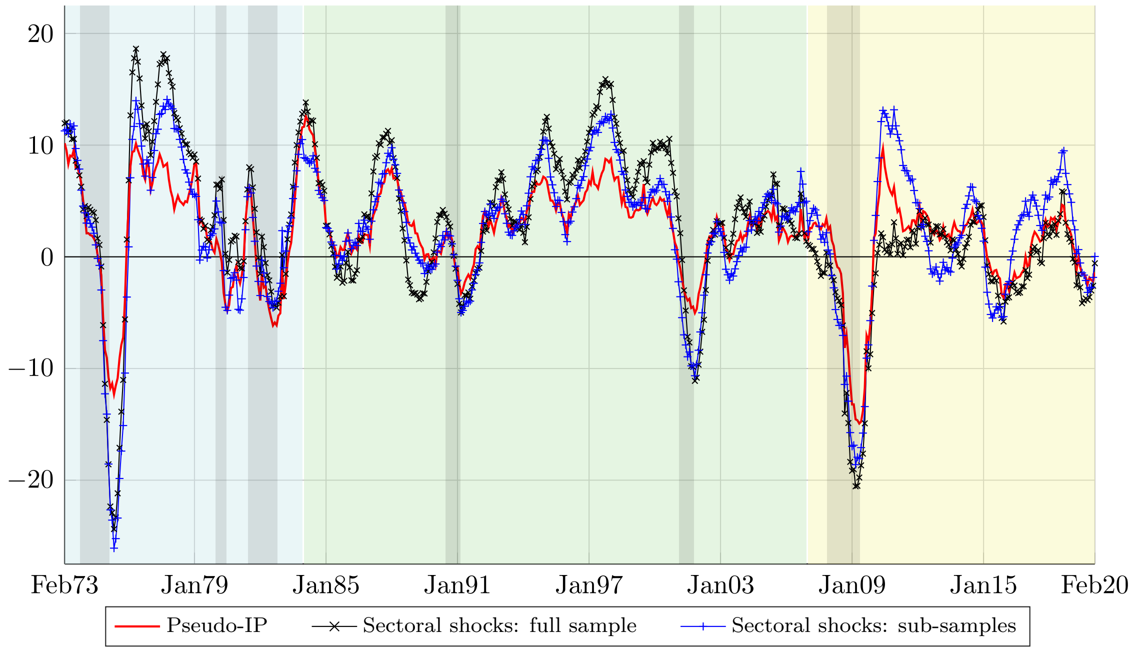
Notes: The figure shows for each respective ranking the values of the underlying Leontief inverses. The first value of each ranking corresponds to the origin sector with the remaining sectors sorted in descending order. The left column shows the rankings for all 25 sectors and the right column illustrates the first five ranks. The first two rows correspond to downstream (γ_j) and upstream ($\widetilde{\gamma}_j$) rankings based only on materials, whereas the rankings in the last two rows are derived using both materials and capital flows (γ_j^c and $\widetilde{\gamma}_j^c$).

Figure A.2: IP conditional on sectoral shocks: 2-step estimator (demeaned, y-o-y growth, in percent)



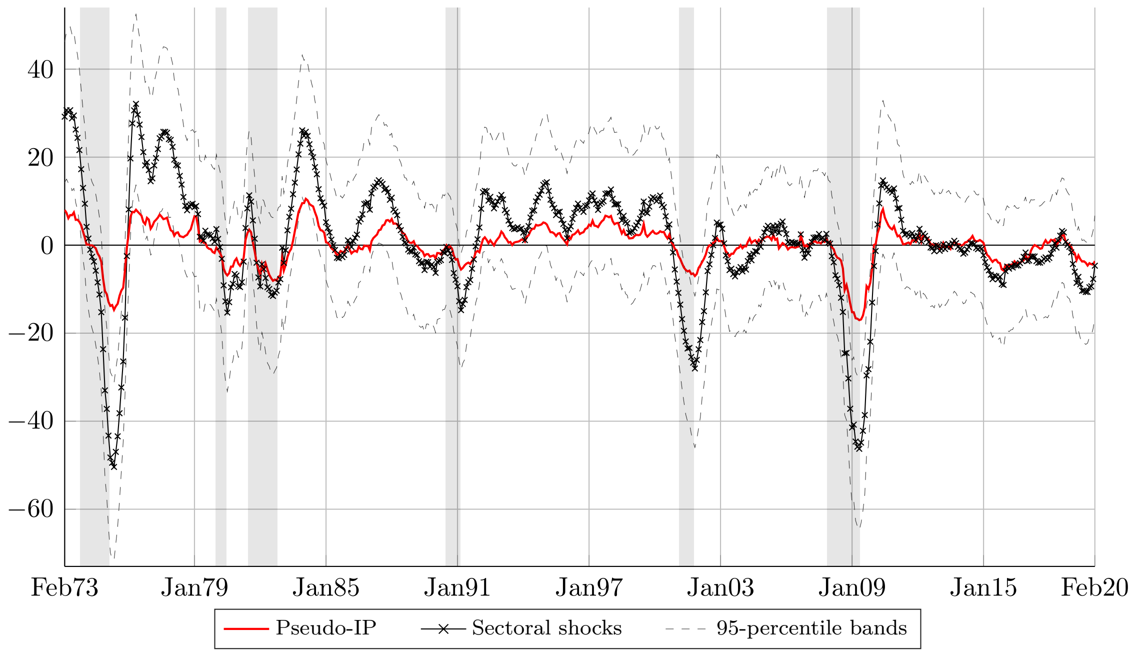
Notes: IP refers to demeaned, year-on-year (y-o-y), aggregate industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on only sectoral shocks. This historical contribution is the sum of all effects that the identified sectoral up- and downstream shocks have on IP growth, reported at the median and a 95%-percentile band. This figure, in contrast to Figure 3 of the main text, is alternatively based on a two-step estimation procedure, as in Bernanke, Boivin, and Eliasz (2005) and Boivin, Giannoni, and Mihov (2009).

Figure A.3: IP conditional on sectoral shocks: sub-samples (y-o-y growth, in percent)



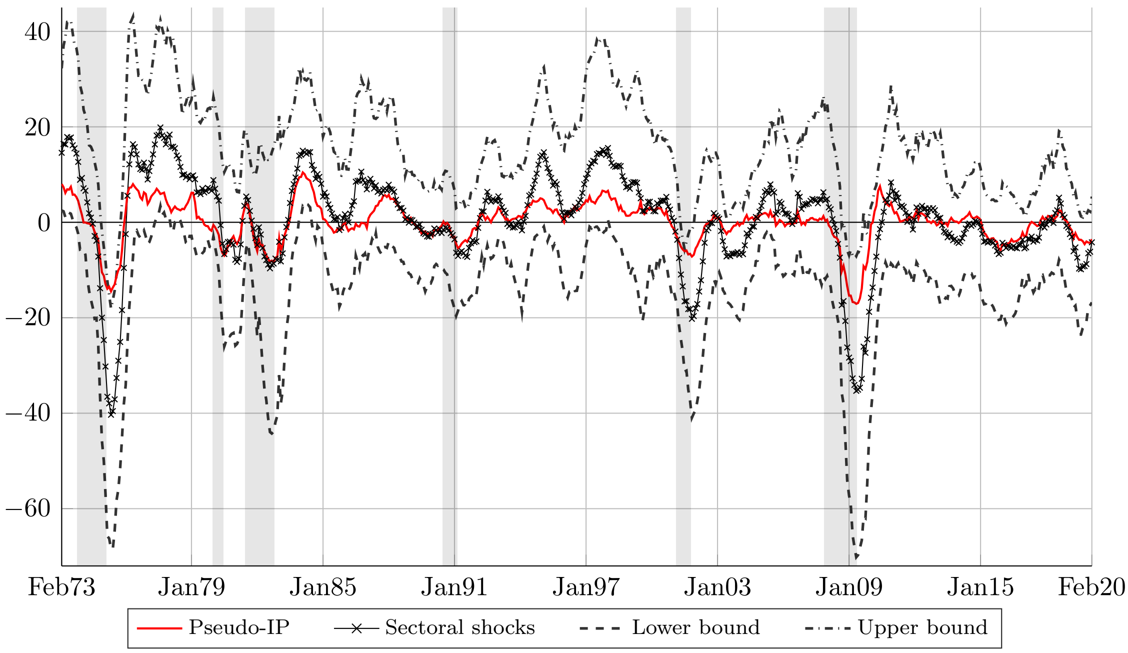
Notes: The shaded areas correspond to the three sub-samples in the robustness analysis. IP refers to year-on-year (y-o-y), aggregate industrial production growth (non-demeaned). The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on only sectoral shocks. This historical contribution is the sum of all effects that the identified sectoral up- and downstream shocks have on IP growth, reported at the median. In addition, the blue ("+"-marked) series shows IP growth conditional on only sectoral shocks that is constructed from the three separate sub-sample models. Sub-sample-dependent model parameterization is also summarized in Appendix Table A.4.

Figure A.4: IP conditional on sectoral shocks: 88 sectors (demeaned, y-o-y growth, in percent)



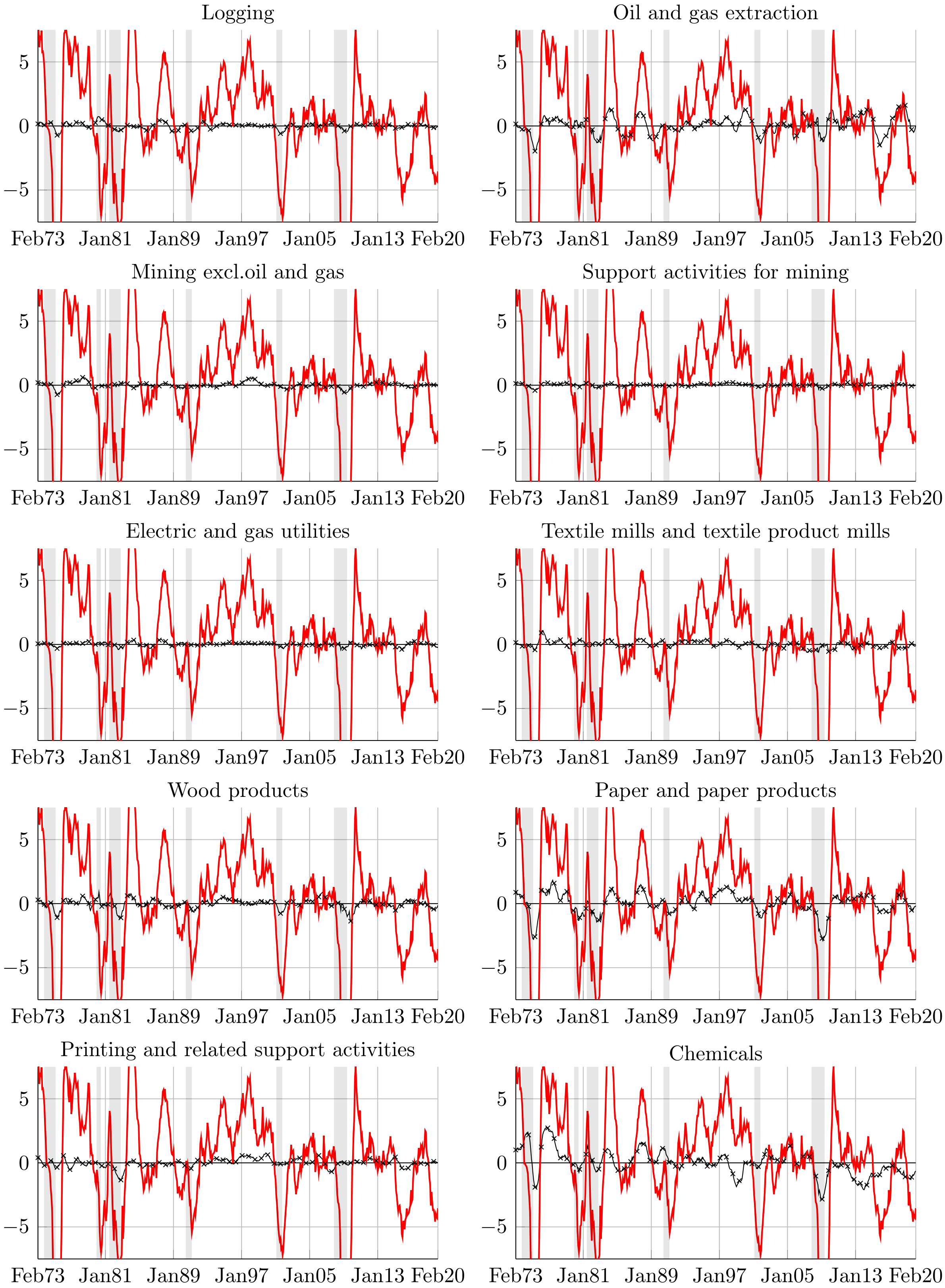
Notes: IP refers to demeaned, year-on-year (y-o-y), aggregate industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on only sectoral shocks. This historical contribution is the sum of all effects that the identified sectoral up- and downstream shocks have on IP growth, reported at the median and a 95%-percentile band. This figure, in contrast to Figure 3 of the main text, is alternatively based on a finer disaggregation of IP into 88 sectors. Here the number of unobserved factors targets to explain at least 50, rather than 80, percent of sectoral growth rates in X, on average, for reasons of parsimony.

Figure A.5: IP conditional on sectoral shocks: identified set (demeaned, y-o-y growth, in percent)



Notes: In contrast to Figure 3 of the main text, this figure shows the identified set of identified shocks without estimation uncertainty. IP refers to demeaned, year-on-year (y-o-y), aggregate industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on only sectoral shocks. This historical contribution is the sum of all effects that the identified sectoral up- and downstream shocks have on IP growth, reported at the median and the lower and upper bound.

Figure A.6: Contributions of sectoral shocks to IP (demeaned, y-o-y growth, in percent)



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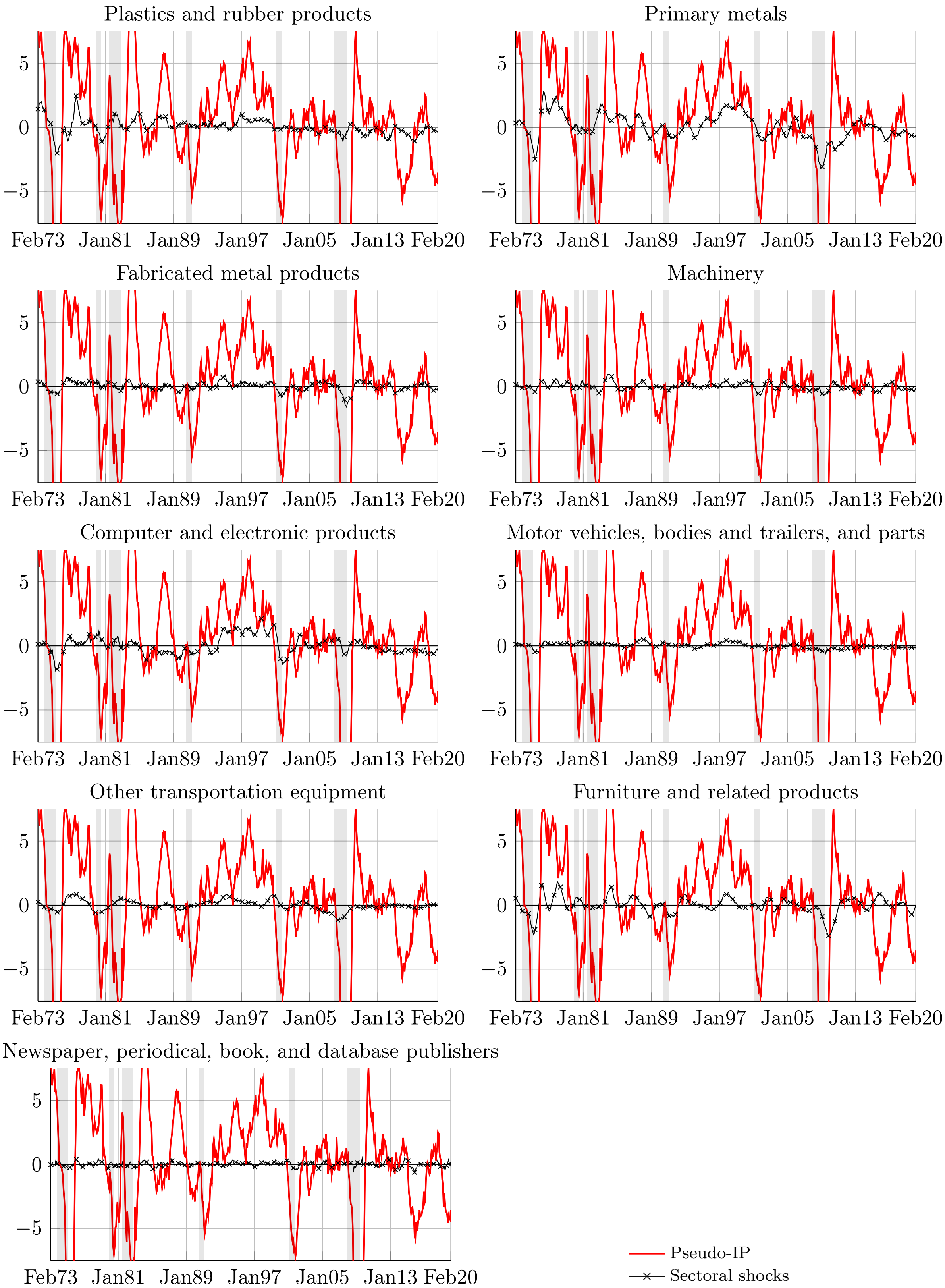
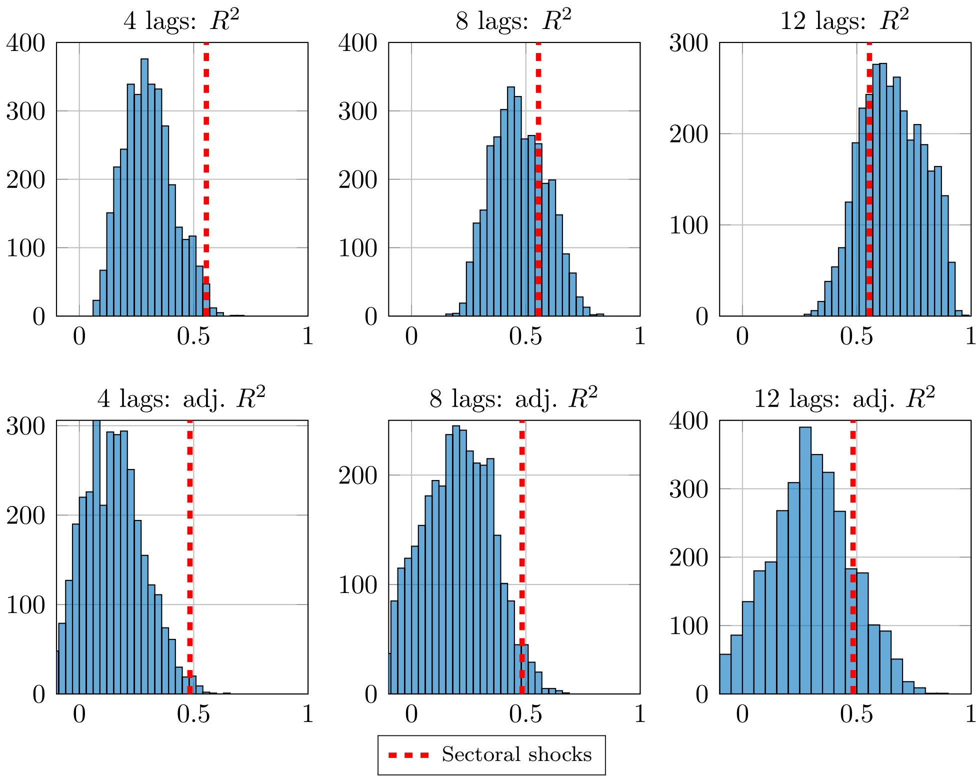


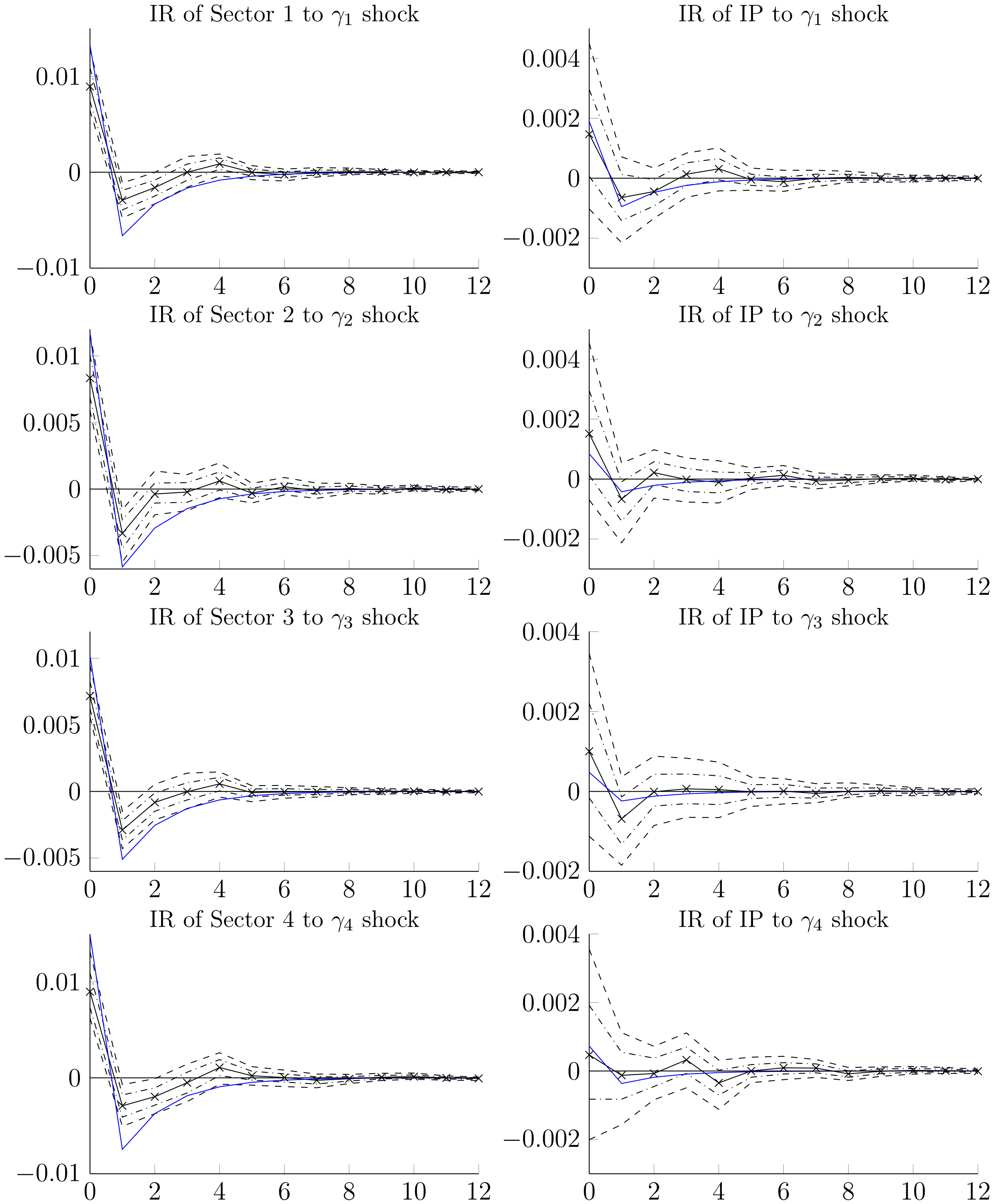
Notes: IP refers to demeaned, year-on-year (y-o-y), aggregate industrial production growth. The series is created from individual sector output growth and sectors' relative importance weights, hence called Pseudo-IP. The black (x-marked) series shows IP growth conditional on the respective sectoral shocks. The series in the respective panels includes either a sectoral downstream, upstream, or both types of shocks (if available) originating in the indicated sector, reported at the median.

Figure A.7: Explanatory power of sectoral and aggregate shocks



Notes: Histograms contain the (adjusted) R^2 of regressing IP growth (at quarterly frequency) on a monetary, fiscal, and technology shock from Ramey (2016), iterating through all possible combinations of available shock proxies. Each regression contains the contemporaneous shock and respectively one, two, or three years of its lags, without additional controls. The vertical line shows the (adjusted) R^2 of regressing IP growth on all the contemporaneous sectoral shocks jointly at quarterly frequency, without lags or additional controls.

Figure A.8: Model-generated data: theoretical and structural empirical IRFs



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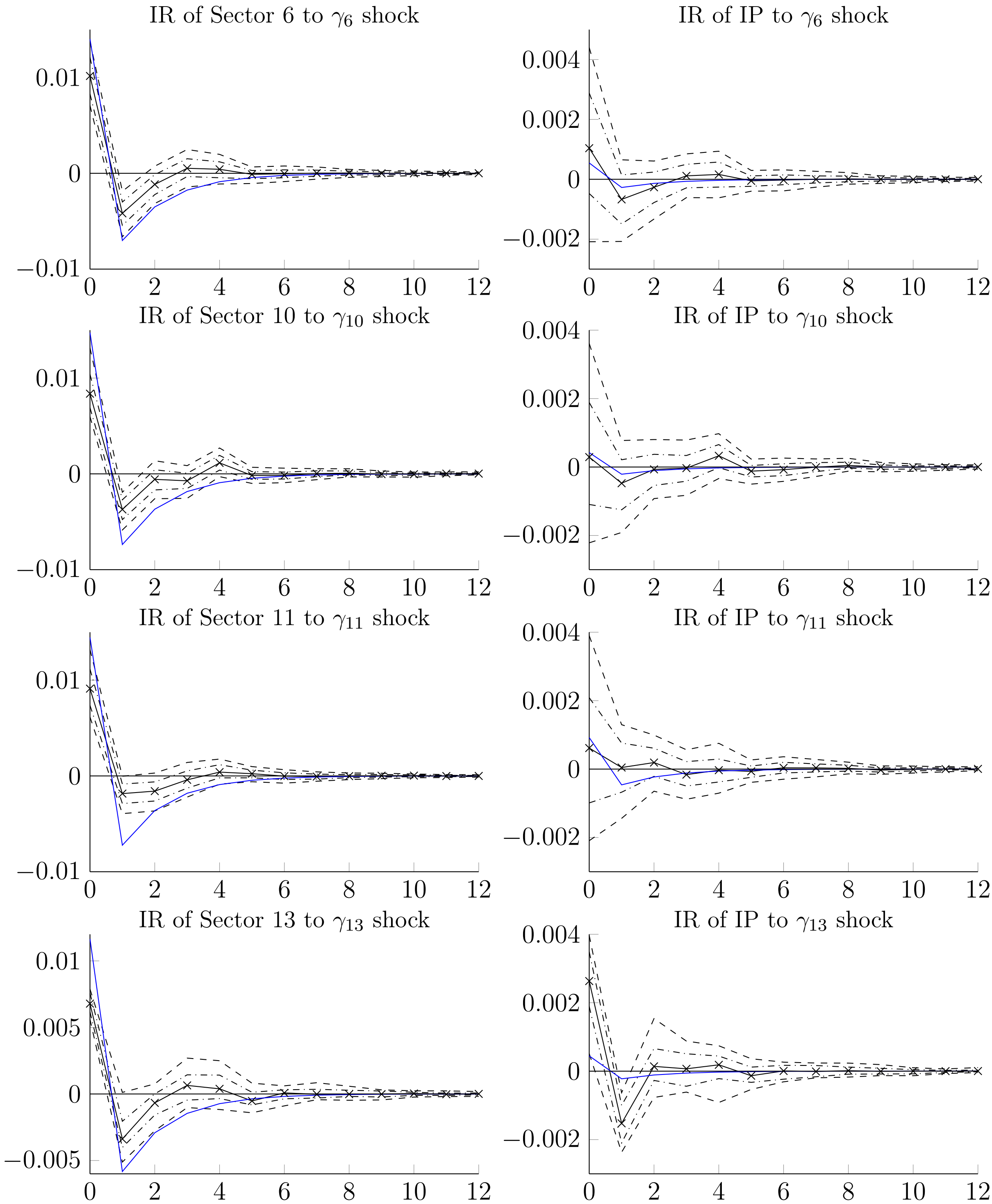

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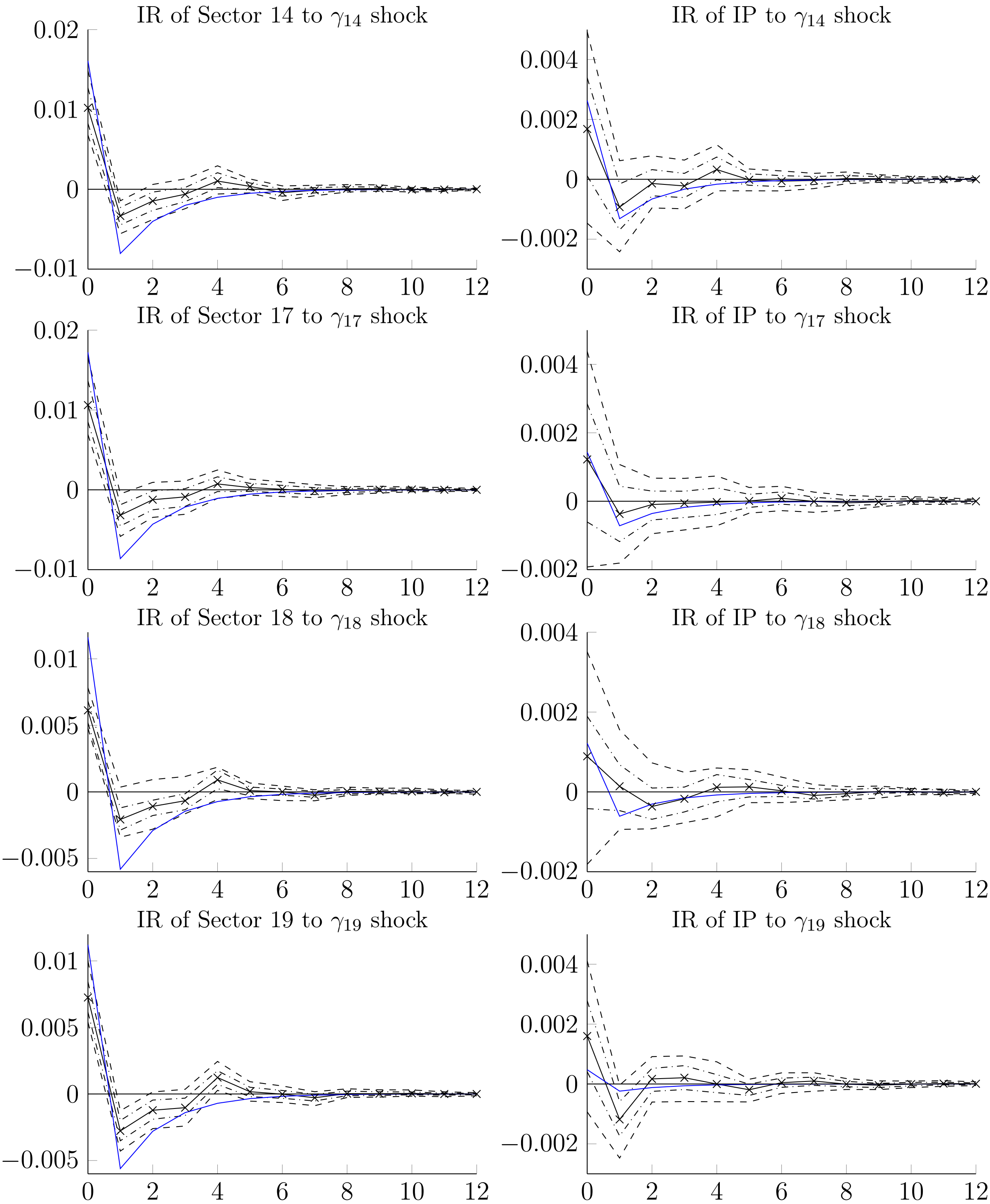

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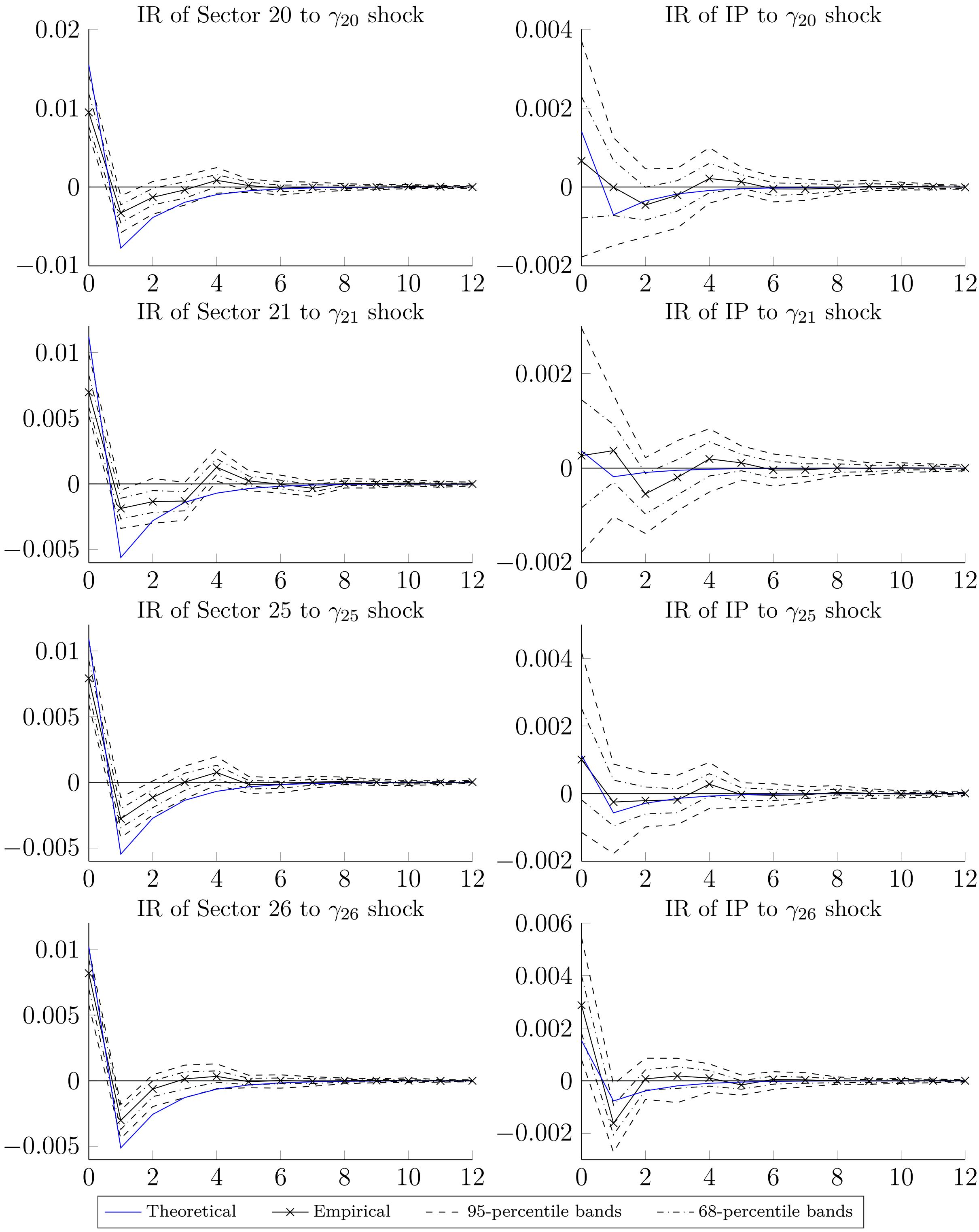

Notes: This figure compares theoretical and empirical impulse responses (IRFs) for identified sector shocks. The feasibility criterion is the same as for the main specification. The left column of each figure shows the responses in the origin sector, whereas the right column the response of aggregate output growth (IP). For the empirical impulse responses 95- and 68-percentile bands are reported.

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