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Disentangling Supply and Demand Shocks in a Networked Economy*

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Abstract

We develop a multi-sector general-equilibrium model with production networks that can be used to identify sector-level supply and demand shocks from observed price and output data. In our model, decreasing returns to scale in production create an upward-sloping supply curve at the sector level. Applying our model to the COVID-19 crisis in Japan, we find that negative demand shocks were the key driver of the economic downturn in 2020 and that negative supply shocks mitigated the decline in prices. We also find that sector-level demand stimulus can increase real GDP and that its effects depend importantly on targeted sectors.

JEL: C67, E21, E32, E62

Keywords: COVID-19; Demand vs Supply; Input-Output Table; Production Networks; Sectoral Shocks

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1 Introduction

Our economy is characterized by a complex network. Shutdowns of component suppliers affect a wide range of final goods production (Carvalho et al., 2021). Changes in foreign demand propagate to sectors not directly engaged in exports (Ferrari, 2023). Supply shocks can propagate downstream, whereas demand shocks can propagate upstream. In such a networked economy, the macroeconomic implications of a shock hinge on how the shock affects each sector of the economy. Thus, it is crucial to identify which sectors are hit by what types of shocks for a complete understanding of the macroeconomy.

In this paper, we develop a multi-sector general-equilibrium model with production networks that can be used to identify sector-level supply and demand shocks from observed price and output data. The key feature of our model is decreasing returns to scale (DRS) in production. Under DRS, the marginal cost of production increases with sector-level output, which in turn generates an upward-sloping supply curve at the sectoral level. When the supply curve is upward-sloping, both price and output change in response to demand shocks. In contrast, if the supply curve is flat—a case with constant returns to scale (CRS)—only output changes in response to demand shocks. Thus, observed changes in prices would be fully attributed to supply shocks under CRS. Hence, DRS is essential for the identification of supply and demand shocks from observed output and prices.

We use our model to identify sector-level supply and demand shocks during the COVID-19 pandemic in Japan. The pandemic provides us with a natural laboratory to examine supply and demand at a sectoral level, as different sectors were affected differently by the pandemic. Using sector-level price and output data, we recover sector-specific supply and demand shocks by matching the model to observed changes in price and output from 2019 to 2020. We also use our model to evaluate the effectiveness of sector-specific demand-stimulus policies often adopted in recessions.

We find that demand shocks were the predominant driver of the decline in output and prices in 2020. Negative demand shocks account for approximately three-quarters of the observed 3.8% decline in real GDP. Negative demand shocks pushed down prices by 1.8 percentage points, about half of which was offset by upward price pressures from negative supply shocks. The magnitude of demand and supply shocks was heterogeneous across sectors; in line with the nature of the pandemic, negative demand shocks were particularly severe in sectors sensitive to the degree of human mobility, such as the transport sector. The importance of negative demand shocks is robust to a small open-economy extension, discussed in Appendix D.

Identification of these shocks depends importantly on two structural features of our model: production networks and DRS. In the model without production networks, we would fail to capture the propagation of sectoral shocks from one sector to another. In this model, almost all declines in real GDP and GDP deflator are driven by negative demand shocks. Without DRS—and thus horizontal supply curves—we would attribute price declines entirely to positive supply shocks. In this model, negative demand shocks push down real GDP by 4.9%, which is offset by a positive contribution from supply shocks of the magnitude 1.2%.

Turning to the analysis of sector-specific demand stimulus, we find that government purchase multipliers on the aggregate real GDP are positive but below one for all sectors. A government purchase of the final goods in sector i increases output. An increase in output in sector i requires an increase in labor employed in sector i, which reduces labor allocated to other sectors and thus reduces output in those sectors (labor crowding-out effect). Labor crowding-out effects are larger with production networks and DRS than without them: production networks propagate the labor demand increase in sector i to its upstream sectors, whereas DRS forces the firm in sector i to demand more labor to increase a given amount of output.

Our paper is related to three strands of the literature. First, our paper builds upon the literature on production networks. Since the foundational work of Acemoglu et al. (2012), this literature shows that sector-specific shocks propagate to the rest of the economy via the input–output linkages and contribute importantly to aggregate fluctuations. Theoretical contributions include Baqaee and Farhi (2018), Baqaee and Rubbo (2023), Baqaee and Farhi (2019), Bigio and La'o (2020), Flynn et al. (2022), Liu and Tsyvinski (2024), Osotimehin and Popov (2023), and Rubbo (2023), among others. Empirical contributions include Acemoglu et al. (2016), Barrot and Sauvagnat (2016), Boehm et al. (2019), Carvalho et al. (2021), and Ferrari (2023), among others. These papers assume CRS in production, which would imply horizontal sectoral supply curves in the absence of other frictions. We differ from these papers because we assume DRS.

Within the literature on production networks, our paper is particularly close to several papers that aim to identify supply and demand shocks at a sectoral level (Baqaee and Farhi, 2022; Guerrieri et al., 2022; Ferrante et al., 2023; Rubbo, 2024). These authors generate upward-sloping supply curves through nominal rigidities. Our work complements these studies by generating upward-sloping supply curves via an alternative approach—DRS.

Finally, our work is related to the literature aimed at identifying supply and demand shocks during, and in the aftermath of, the COVID-19 crisis. See, for example, Balleer et al. (2024), Baqaee and Farhi (2022), Brinca et al. (2021), Das et al. (2021), del Rio-Chanona et al. (2020), and Chang et al. (2023). Some authors have examined the role played by supply and demand shocks in driving the inflation surge in the aftermath of the pandemic

(Bianchi et al., 2023; Comin et al., 2023; Firat and Hao, 2023; Giannone and Primiceri, 2024; Nakamura et al., 2024; Sunakawa, 2025). We contribute to this literature by analyzing the role of supply and demand shocks during the COVID-19 crisis in Japan.

The rest of the paper is organized as follows. Section 2 presents our model. Section 3 applies our model to quantify the role of supply and demand shocks during the COVID-19 crisis in Japan. Section 4 presents the analysis of sector-specific demand stimulus. Section 5 concludes.

2 Model

This section develops a multi-sector general-equilibrium model with production networks and decreasing returns to scale (DRS) technology.

The model is static. A representative household makes consumption and labor supply decisions to maximize utility subject to its budget constraint. There are N sectors for production, indexed by i. In each sector, there is a representative firm that produces a sector-specific good using labor and intermediate inputs from other sectors. The wage serves as the numeraire.

2.1 Household

The representative household derives utility from the consumption of final goods and disutility from supplying labor. The household's preferences are represented by:

$$\max_{\{c_i\}_{i=1}^N, L} \frac{C^{1-\sigma}-1}{1-\sigma} - \chi \frac{L^{1+\xi}}{1+\xi} \tag{2.1}$$
$$\text{with } C = \left(\sum_{i=1}^{N} \delta_i^{\frac{1}{\eta_H}} c_i^{\frac{\eta_H - 1}{\eta_H}} \right)^{\frac{\eta_H}{\eta_H - 1}}$$

where C is the aggregate consumption and is given by a constant-elasticity-of-substitution (CES) aggregate of a sector-specific consumption good c_i. L is labor supply. σ is the elasticity of the marginal utility of consumption, χ is a scaling parameter for labor disutility, and ξ is the inverse of the Frisch elasticity of labor supply.[1] In the CES aggregator for consumption, η_H is the elasticity of substitution across final goods. δ_i is the household's *preference shifter* for good i, capturing the primitive taste for sector i's good. δ_i is a key object in the empirical

[1] We refer to σ as the elasticity of the marginal utility of consumption rather than the inverse of the intertemporal elasticity of substitution, reflecting the static nature of our model.

part of our analysis. We will identify a change in δ_i from data and interpret it as a demand shock.

The household faces a budget constraint:

$$\sum_{i=1}^{N} p_i c_i = L + \Pi \tag{2.2}$$

where p_i is the price of good i, L is labor income—recall that the wage is normalized to one—and Π denotes total profits of firms in all sectors. The household receives these profits because it is the owner of the firms.

Using the household's price index $P_H \equiv \left(\sum_{i=1}^{N} \delta_i p_i^{1-\eta_H}\right)^{\frac{1}{1-\eta_H}}$ and the associated aggregate demand shifter $\Delta_H \equiv (P_H)^{\eta_H} C$, the household's optimization problem over sectoral goods yields the following demand function for each sectoral good:

$$c_i = p_i^{-\eta_H} \underbrace{\delta_i \Delta_H}_{\Delta_{H,i}} \tag{2.3}$$

where $\Delta_{H,i} \equiv \delta_i \Delta_H$ is a *direct sectoral demand shifter* for sector i. According to this equation, demand for good i consists of (i) its own price p_i and (ii) the demand shifter $\Delta_{H,i}$, which in turn consists of the household's preference shifter δ_i and the aggregate demand shifter Δ_H.

Finally, the optimal consumption-labor choice satisfies:

$$L = \left(\frac{C^{-\sigma}}{\chi P_H}\right)^{\frac{1}{\xi}}.$$

2.2 Firm

A representative firm in sector i produces output using labor and intermediate inputs from all sectors. The production function for sector i is:

$$y_i = \phi_i B_i^{\rho_i}$$

where y_i is output, B_i is an input bundle, and ρ_i is the degree of returns to scale. We assume DRS in production; that is, $\rho_i < 1$. ϕ_i is sector i's *productivity shifter.* ϕ_i is a key object in the empirical part of our analysis. We will identify a change in ϕ_i from data and interpret it as a supply shock.

The input bundle B_i is a Cobb-Douglas aggregate of labor l_i and intermediate inputs M_i:

$$B_i = \frac{1}{\alpha_i^{\alpha_i}(1-\alpha_i)^{1-\alpha_i}} l_i^{\alpha_i} M_i^{1-\alpha_i}$$

where $\alpha_i \in (0,1)$ is the labor share in sector i's cost. The normalization ensures that the marginal cost of the bundle equals a simple weighted geometric average of input prices.

The intermediate inputs bundle M_i is a CES aggregate of goods across sectors:

$$M_i = \left(\sum_{j=1}^{N} a_{ij}^{\frac{1}{\eta_F}} x_{ij}^{\frac{\eta_F - 1}{\eta_F}} \right)^{\frac{\eta_F}{\eta_F - 1}}$$

where x_{ij} denotes sector i's use of good j as an intermediate input, and a_{ij} represents the weight on input j in sector i's production. η_F is the elasticity of substitution across intermediate inputs. Taking prices as given, the competitive firm in sector i maximizes profits:

$$\max_{y_i, l_i, \{x_{ij}\}_{j=1}^{N}} p_i y_i - l_i - \sum_{j=1}^{N} p_j x_{ij}$$

subject to the production technology described above. The first-order condition for output choice yields:

$$p_i \rho_i \phi_i^{\frac{1}{\rho_i}} y_i^{\frac{\rho_i - 1}{\rho_i}} = q_i \tag{2.4}$$

where q_i is the unit cost of the input bundle B_i.

Cost minimization yields the following unit cost of the input bundle:

$$q_i = r_i^{1-\alpha_i}. \tag{2.5}$$

r_i is the price index for intermediate inputs used by sector i:

$$r_i = \left(\sum_{j=1}^{N} a_{ij} p_j^{1-\eta_F} \right)^{\frac{1}{1-\eta_F}}. \tag{2.6}$$

Finally, we obtain the demand for intermediate input j by sector i as:

$$x_{ij} = a_{ij}(1-\alpha_i) p_j^{-\eta_F} \Delta_i \tag{2.7}$$

where Δ_i is sector i's *indirect sectoral demand shifter* for intermediate inputs:

$$\Delta_i = r_i^{\eta_F - \alpha_i} \left(\frac{y_i}{\phi_i} \right)^{\frac{1}{\rho_i}}.$$

This demand shifter captures how sector i's demand for inputs responds to its intermediate inputs price index and its output level.

Note that profits for sector i equal:

$$\pi_i = (1 - \rho_i) p_i y_i. \tag{2.8}$$

Profits are zero under CRS but are positive under DRS. We assume that profits are distributed to the household.

2.3 Market Clearing Conditions

Sector i's output must equal the sum of its use for consumption and its use as an intermediate input in all sectors:

$$y_i = c_i + \sum_{j=1}^{N} x_{ji}. \tag{2.9}$$

The household's labor supply must equal the sum of sectoral labor demands:

$$L = \sum_{i=1}^{N} l_i.$$

Total profits distributed to the household equal the sum of sectoral profits:

$$\Pi = \sum_{i=1}^{N} \pi_i.$$

2.4 Equilibrium

Given the productivity shifter $\{\phi_i\}$ and the preference shifter $\{\delta_i\}$, an equilibrium is a vector of output $\{y_i\}$ and prices $\{p_i\}$ such that: (i) the household maximizes its utility taking prices as given, (ii) firms maximize profits taking prices as given, and (iii) all markets clear.

2.5 Equilibrium Price and Output

From the firms' production choice (2.4), (2.5), and (2.6), we obtain:

$$p_i = y_i^{\frac{1-\rho_i}{\rho_i}} \frac{1}{\rho_i \phi_i^{\frac{1}{\rho_i}}} \left(\left(\sum_{j=1}^{N} a_{ij} p_j^{1-\eta_F} \right)^{\frac{1}{1-\eta_F}} \right)^{1-\alpha_i}. \tag{2.10}$$

for each sector i. From the household consumption choice (2.3), firms' input choice (2.7), and the goods-market clearing condition (2.9), we obtain

$$y_i = p_i^{-\eta_H} \underbrace{\delta_i \Delta_H}_{=\Delta_{H,i}} + p_i^{-\eta_F} \sum_{j=1}^{N} a_{ji}(1-\alpha_j) \underbrace{r_j^{\eta_F - \alpha_j} \left(\frac{y_j}{\phi_j} \right)^{\frac{1}{\rho_j}}}_{=\Delta_j} \tag{2.11}$$

for each sector i.

By taking the log and totally differentiating both sides of these two equations, we can express changes in output and prices as follows.

$$\overbrace{\frac{dp_i}{p_i} = \underbrace{\frac{1-\rho_i}{\rho_i}\frac{dy_i}{y_i}}_{\text{Equilibrium Effect on Price}}}^{\text{Supply Curve w/o Disturbance}} \underbrace{- \frac{1}{\rho_i}\frac{d\phi_i}{\phi_i}}_{\text{Direct Supply Disturbance}} \underbrace{+ \sum_{j=1}^{N} W_{ij}\frac{dp_j}{p_j}}_{\text{Indirect Supply Disturbance}} \tag{2.12}$$

$$\overbrace{\frac{dy_i}{y_i} = \underbrace{-\eta_i \frac{dp_i}{p_i}}_{\text{Equilibrium Effect on Output}}}^{\text{Demand Curve w/o Disturbance}} \underbrace{+ \frac{c_i}{y_i}\frac{d\Delta_{H,i}}{\Delta_{H,i}}}_{\text{Direct Demand Disturbance}} \underbrace{+ \sum_{j=1}^{N} w_{ji}\frac{d\Delta_j}{\Delta_j}}_{\text{Indirect Demand Disturbance}} \tag{2.13}$$

where

$$W_{ij} = (1-\alpha_i)\frac{p_j x_{ij}}{\sum_{j'=1}^{N} p_{j'} x_{ij'}}$$

are expenditure-based network weights, and

$$w_{ji} = \frac{x_{ji}}{y_i}$$

are quantity-based network weights.

$$\eta_i = \frac{c_i}{y_i}\eta_H + \sum_{j=1}^{N} w_{ji}\eta_F$$

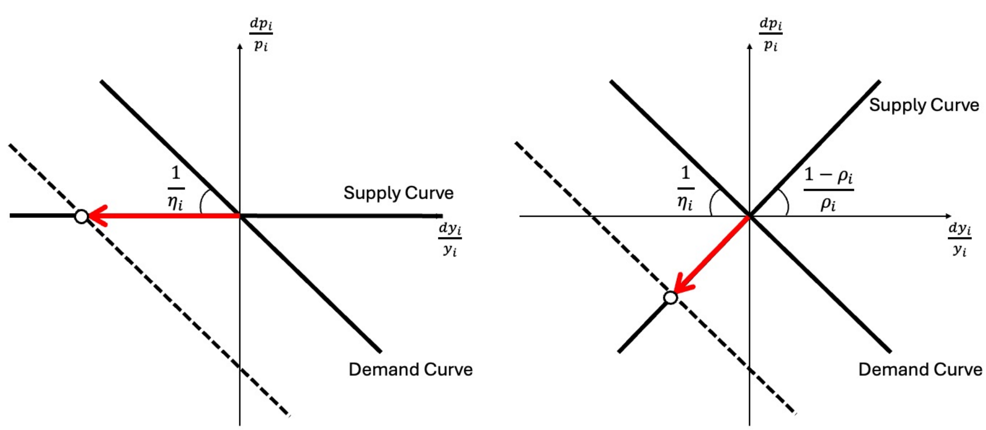
represents the weighted average of the elasticities of substitution, weighted by the shares of final and intermediate demand for sector i.

In equation (2.12), the first term on the right-hand side captures the supply curve in sector i in the absence of any disturbance. The supply curve is flat under CRS ($\rho_i = 1$)

but is upward-sloping under DRS ($\rho_i < 1$). The supply curve is upward-sloping under DRS because the marginal costs of production increase as a sector expands its output.

The supply curve can shift due to two types of disturbance captured by the second and third terms. First, the direct supply disturbance—the second term—shifts the supply curve due to productivity changes. The negative sign indicates that productivity improvements lower prices, holding quantity and network effects constant. Second, the indirect supply disturbance (the third term) captures how price changes in upstream sectors are transmitted to sector i through input costs. When upstream suppliers experience price increases, increased input costs of sector i shift its supply curve upward. The expenditure-based network weights (W_{ij}) determine how much the price of the upstream sector j matters to i. If the sector depends highly on the intermediate inputs (low α_i), or the upstream sector j is a producer of relevant intermediate inputs (high a_{ij}), the downstream spillover mechanism becomes stronger.

In equation (2.13), the first term on the right-hand side captures the demand curve in sector i in the absence of any disturbance. The demand curve is downward-sloping because both households and downstream firms reduce their demand in response to a price increase. The magnitude of this response is determined by η_i, which aggregates the elasticities of substitution for final goods (η_H) and intermediate inputs (η_F).



(a) Flat Supply Curve **(b)** Upward-Sloping Supply Curve

Figure 1: Effects of a Shift in the Demand Curve on Output and Prices

The demand curve can shift due to the two types of disturbances—captured by the second and third terms. First, the direct demand disturbance (the second term) represents horizontal shifts in the demand curve due to changes in final demand. The weighting by $\frac{c_i}{y_i}$ reflects that this disturbance affects only the final demand component of sector i's output.

Second, the indirect demand disturbance (the third term) captures how demand changes in downstream sectors affect sector i through the input-output networks. When downstream sectors increase production, they increase demand for intermediate inputs from sector i, shifting its demand curve outward. The quantity-based network weights w_{ji} determine the strength of these linkages. If downstream sectors produce a large amount of goods, they also demand a large amount of sector i's output as inputs.

To highlight the importance of DRS in our identification, we graphically illustrate the effect of a shift in the demand curves with flat and upward-sloping supply curves in Figure 1, respectively. When the supply curve is flat, a negative demand shock reduces output, but not prices, as shown in Panel 1a. When the supply curve is upward-sloping, a negative demand shock reduces both output and prices, as shown in Panel 1b.

3 Supply and Demand Shocks during COVID-19

We apply our model to identify sector-level supply and demand shocks during the COVID-19 crisis in Japan and understand the relative importance of supply and demand shocks in the decline in economic activities in 2020. The pandemic likely affected different sectors of the economy differently, providing us with an interesting laboratory for identifying supply and demand shocks using our model.

3.1 Economic Activities in 2020

We use the Japan Industrial Productivity (JIP) database from the Research Institute of Economy, Trade and Industry (RIETI) to construct nominal GDP, real GDP, and GDP deflator in 2019 and 2020.

Nominal GDP—denoted by $NGDP$—equals total expenditures on final goods:

$$NGDP_t = \sum_{i=1}^{N} p_{i,t} c_{i,t}.$$

Real GDP—denoted by $RGDP$—is computed using a base-year price vector p_i^{base}:

$$RGDP_t = \sum_{i=1}^{N} p_i^{\text{base}} c_{i,t}. \tag{3.1}$$

In our empirical analysis, we use 2019 as the base year to compute real GDP. Finally, GDP deflator—denoted by Π_{GDP}—is given by the ratio of nominal to real GDP:

$$\Pi_{GDP,t} = \frac{NGDP_t}{RGDP_t}.$$

JIP provides data on the final good consumption and prices at the 2-digit sector level. We aggregate these 2-digit sectors into 11 broader sectors to balance tractability with meaningful heterogeneity.

We focus on percent changes in real GDP and GDP deflator from 2019 to 2020. They are given by

$$\Delta RGDP_{2020} = 100\left(\frac{RGDP_{2020}}{RGDP_{2019}} - 1\right),$$

and

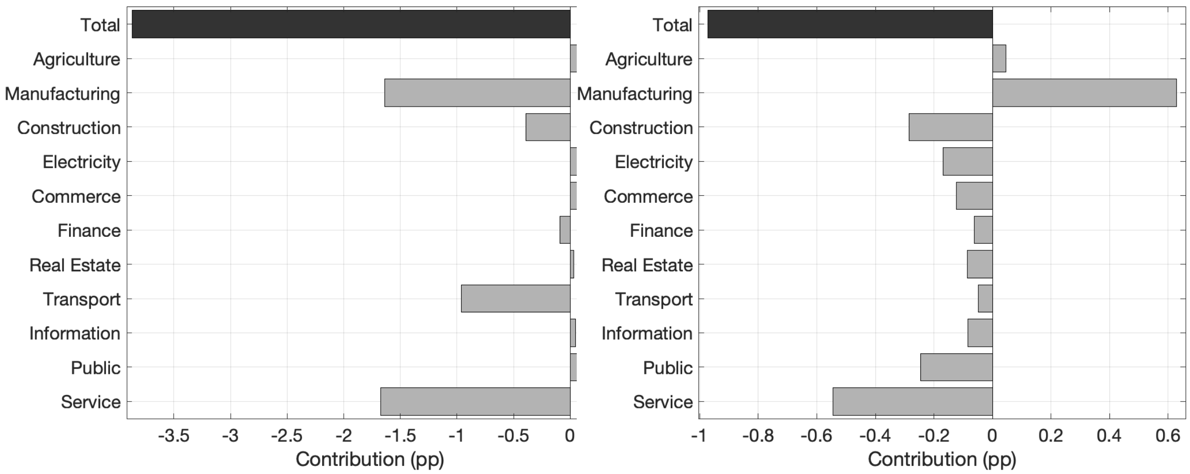
$$\Delta\Pi_{GDP,2020} = 100\left(\frac{\Pi_{GDP,2020}}{\Pi_{GDP,2019}} - 1\right).$$

According to our calculation, real GDP declined by 3.8%, and the GDP deflator fell by 1.0%, which are shown by the top bars in Figure 2. Note that, in computing these numbers, we normalize all observed prices by the growth rate of average wages from the JIP Database to maintain consistency with our model. This normalization results in a discrepancy between our computed GDP deflator and the SNA-based GDP deflator reported by the Cabinet Office. While the SNA-based GDP data indicate 0.7% inflationary pressure, the GDP deflator derived from our data, in contrast, shows a declining pattern mainly due to the observed 2.2% wage growth in the JIP data. The decline in real GDP based on SNA-based computation (-3.9%) is very close to our computed decline because real GDP is little affected by the normalization.

The rest of Figure 2 shows sectoral contributions to these aggregate changes in real GDP and prices. According to the left panel, "Manufacturing"—which includes Mining and Manufacturing—and "Service" sectors were the two largest contributors to the real GDP decline, reflecting both their large shares in the economy and the magnitude of shocks they experienced. "Transport"—which includes Transport and Postal Services—contributed significantly to the aggregate decline despite being a smaller sector, likely due to the severity of their output contraction. According to the right panel, "Agriculture"—which includes Agriculture, Forestry, and Fishery—and "Manufacturing" put upward pressures on prices, whereas all the other sectors put downward pressures.

The magnitude of these sectoral contributions depends importantly on sectoral shares, shown in Figure 3.[2] According to the figure, the service sector represents the largest share in

[2]We exclude the "uncategorized" sector in the original JIP Database, which accounts for 0.4% of GDP



(a) Real GDP **(b)** GDP Deflator

Figure 2: Changes in real GDP and GDP deflators from 2019 to 2020

Note: Our measures of real GDP and GDP deflator are adjusted for wage inflation. Thus, these numbers differ from SNA-defined counterparts. See discussion in the main text.

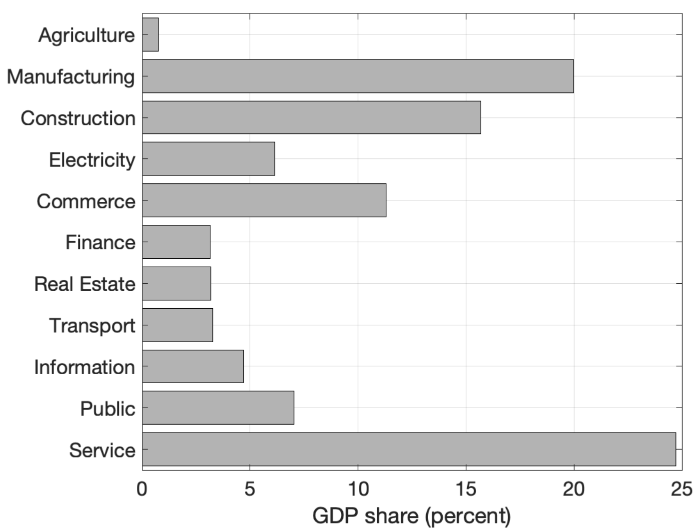


Figure 3: Sectoral Share of Real GDP in 2019

the real GDP—accounting for a quarter of the entire GDP—followed by "Manufacturing," "Construction," and "Commerce."

3.2 Shock Identification

Our goal is to identify changes in productivity and preference shifters—supply and demand shocks, respectively—from 2019 to 2020. We do so by matching the observed changes in sectoral outputs and prices during the same period. Towards that goal, we begin by calibrating the model's structural parameters to match the Japanese economy in 2019.

Table 1 summarizes the baseline parameter values chosen to fit the Japanese economy in 2019. The elasticity of substitution across final goods η_H is set to 1.5, in line with estimates in the literature (Hobijn and Nechio, 2019; Hottman and Monarch, 2020; Redding and Weinstein, 2024). The elasticity of substitution across intermediate inputs η_F is set to 0.6, following Baqaee and Farhi (2022). The disutility of labor parameter (χ) is normalized to 1. The inverse Frisch elasticity of labor supply (ξ) is set to 2.5, following Kuroda and Yamamoto (2008) estimates for Japan. We set the elasticity of marginal utility of consumption (σ) to 0.5. Although this value is smaller than standard CRRA (Constant Relative Risk Aversion) parameters in dynamic models (typically ≥ 1), it is appropriate for our static framework because $\sigma < 1$ ensures a positive comovement between productivity shocks and labor supply. We demonstrate that our findings are robust to alternative values of η_H, η_F, ξ, and σ in Appendix B.

Table 1: Parameter values and their sources

Parameter	Description	Value	Target/Source
η_H	EoS across final goods	1.5	Literature
η_F	EoS across intermediate inputs	0.6	Literature
ξ	Inverse of Frisch elasticity	2.5	Kuroda and Yamamoto (2008)
σ	Elas. of MU of consumption	0.5	Assumed
ρ_i	Degree of DRS	Table 2	Profit rate, JIP
α_i	Labor share	Table 2	Labor share, JIP
ϕ_i	Productivity shifter	1	Normalization
δ_i	Preference shifter	Table 2	Final goods expend., JIP
a_{ij}	Weight on intermediate inputs	Figure A.2	Intermediate inputs expend., JIP

For each sector i, we use observed profit shares in JIP Database statistics to calibrate the degree of DRS (ρ_i), based on equation (2.8) relating a firm's profit to ρ_i. The labor share (α_i) is also from the JIP Database. We normalize the productivity shifter (ϕ_i) in 2019 to 1 for all sectors. The preference shifter (δ_i) is calibrated so that the model replicates observed

in Japan in 2019.

final goods expenditure shares in 2019. Finally, we calibrate the matrix of intermediate input weights (a_{ij}) using the 2019 Input-Output Tables. These weights determine how much each sector i relies on inputs from sector j.

Table 2 displays the calibrated values of ρ_i, α_i, and δ_i for each of the eleven sectors. According to the table, there is heterogeneity in both the DRS parameter and the labor share parameter across sectors. The value of the DRS parameter ranges from 0.49 (Real Estate) to 0.87 (Manufacturing). For all sectors, the degree of DRS is less than one. Thus, supply curves are upward-sloping for all sectors. The value of the labor share ranges from 0.21 (Manufacturing) to 0.54 (Service).

Table 2: Sector-specific parameter values

Sector	ρ	α	ϕ_{2019}	δ_{2019}
Agriculture	0.76	0.30	1	0.01
Manufacturing	0.87	0.21	1	0.24
Construction	0.54	0.33	1	0.14
Electricity	0.78	0.30	1	0.06
Commerce	0.80	0.47	1	0.11
Finance	0.68	0.44	1	0.02
Real Estate	0.49	0.32	1	0.02
Transport	0.85	0.52	1	0.03
Information	0.79	0.31	1	0.04
Public	0.67	0.52	1	0.06
Service	0.82	0.54	1	0.27

Given these parameter values, we compute changes in the productivity and preference shifters to match the observed changes in sectoral outputs and prices from 2019 to 2020. Specifically, we choose these shifters to minimize the distance between model-predicted and data-observed values of real GDP and their prices for each sector. Thus, we are computing 22 shocks (two shocks for each of the eleven sectors) to match 22 targeted moments.

Figure 4 shows the identified changes in preference and productivity shifters for all sectors. According to the figure, almost all sectors were hit by a large negative demand shock, except for Agriculture. The transport sector was hit particularly hard by a large demand shock (almost 40 percent). In contrast, the signs of identified supply shocks are heterogeneous across sectors. For example, “Electricity” and “Public” sectors were hit by positive supply shocks, whereas “Agriculture” and “Manufacturing” sectors were hit by negative ones. Figure A.1 in the Appendix demonstrates that the identified shocks successfully replicate the observed changes in output and price across all eleven sectors.

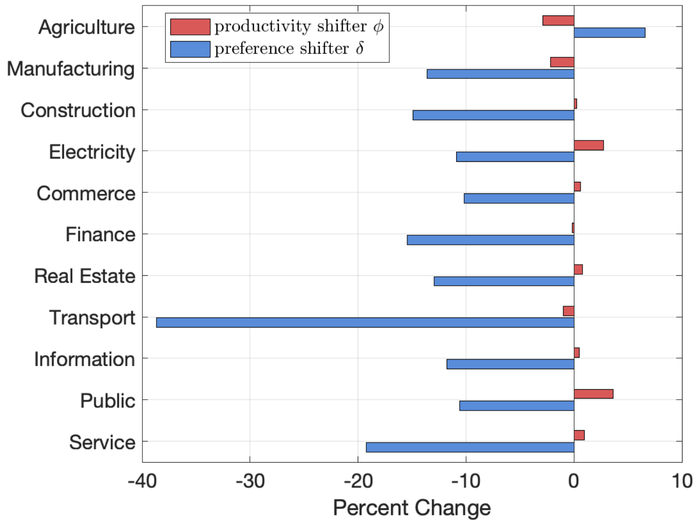


Figure 4: Identified Supply and Demand Shocks (in 2020)

3.3 Results

Using the identified shocks, we conduct two counterfactual exercises to quantify the contributions of supply and demand shocks to the observed macroeconomic outcomes in 2020. In the first counterfactual, we compute real GDP and the GDP deflator in the economy with only supply shocks. Here, we allow only the productivity shifter ϕ_i to change from 2019 to 2020 consistently with the estimation results, holding the preference shifter δ_i constant at 2019 values. In the second counterfactual exercise, we compute real GDP and the GDP deflator in the economy with only demand shocks. Here, we allow the preference shifter δ_i to change from 2019 to 2020 consistently with the estimation results, holding the productivity shifter ϕ_i constant at 2019 values.

Panel (a) of Table 3 presents changes in the aggregate output and price in the supply-shock-only economy and the demand-shock-only economy. According to the panel, demand shocks played a key role in pushing down real GDP and the GDP deflator during COVID-19. The demand shocks alone generate a 3.0% decline in real GDP, accounting for roughly three-quarters of the total GDP decline. The supply shocks generate only a 0.9% GDP decline, explaining approximately one-quarter of the aggregate output contraction. For prices, the negative demand shocks pushed down the GDP deflator by 1.8%, creating strong deflationary pressure. In contrast, the negative supply shocks exerted upward pressure on prices, raising the GDP deflator by 0.8%. The observed 1.0% decline in the deflator thus reflects the net effect of these opposing forces.

To assess the importance of production networks and decreasing returns to scale (DRS)

Table 3: Percent Change in Real GDP and GDP Deflator from 2019 to 2020

	Real GDP (% Change)	GDP Deflator (% Change)
Data	-3.8	-1.0
(a) Baseline Model		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(b) Model w/o Network		
Supply Shock	-0.1	0.1
Demand Shock	-3.9	-1.1
(c) Model w/o DRS		
Supply Shock	1.2	-1.0
Demand Shock	-4.9	0.0

Note: Our measures of real GDP and GDP deflator are adjusted for wage inflation. Thus, these numbers differ from SNA-defined counterparts. See discussion in the main text.

for the results above, we conduct the same counterfactual exercises under two alternative model specifications. In the first specification, we eliminate production linkages by setting $\alpha_i = 1$ (i.e., production only requires labor), while maintaining DRS. In the second specification, we assume constant returns to scale in the production functions by setting all $\rho_i = 1$, while maintaining production networks. In these two specifications, we recalibrate sectoral share parameters to the base year, recover sectoral supply and demand shocks, and recompute real GDP and GDP deflator in supply–shock-only or demand-shock-only economies.

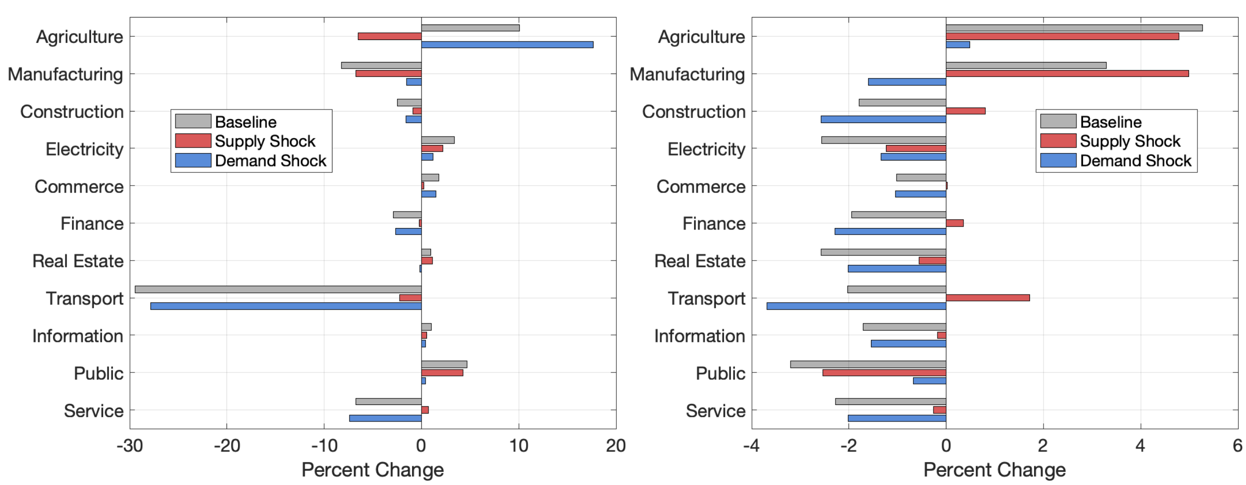
In the model without production networks—shown in Panel (b) of Table 3—supply shocks explain almost none of the GDP decline (-0.1%) and deflator change (+0.1%), while demand shocks explain essentially all of both (-3.9% and -1.1% respectively). When sector i experiences a negative demand shock, its output and price decline. In the baseline model with production networks, sectors connected by supply chains also experience a price decline: the price decline propagates to the downstream sectors, and the output decline propagates to the upstream sectors, leading to price declines in the upstream sectors via each sector-level equilibrium mechanism. In the model without networks, this channel is absent. Thus, to match the observed price decline in the data, the model without networks requires stronger negative demand shocks, leaving less room for the supply shocks to explain the observed decline in real GDP.

In the specification without DRS—shown in Panel (c) of Table 3—supply shocks are estimated to increase real GDP by 1.2% and reduce the GDP deflator by 1.0%, while demand shocks are estimated to reduce real GDP by 4.9%—larger than in the model with DRS—with no effect on the price level. With CRS ($\rho_i = 1$), supply curves become flat. When the supply curve is flat, demand shocks move output but not prices. Thus, all fluctuations in prices must be explained by supply shocks. To explain price declines in data with the model with CRS, we would then need positive supply shocks (falling production costs). Because positive supply shocks raise output, the model with CRS would require larger negative demand shocks to match the observed GDP decline than the model with DRS.

Taken together, the identification of shocks depends importantly on both production networks and DRS.

3.4 Sectoral Implications

Next, we examine the roles of supply and demand shocks during the pandemic at the sector level. Figure 5 shows changes in sectoral output and prices in the baseline economy (gray bars), the supply-shock-only economy (red bars), and the demand-shock-only economy (blue bars). According to the sectoral output changes presented in Panel 5a of the figure, the transport sector and the Service sector exhibit particularly large contractions due to negative demand shocks, consistent with pandemic-related restrictions on in-person services. While supply shocks generally contribute less to output changes, negative supply shocks lead to a strong contraction in the manufacturing sector and the agriculture sector.



(a) Output **(b)** Price

Figure 5: Sectoral change in output and price

Panel 5b shows sectoral price changes. We observe the deflationary pressure due to negative demand shocks across many sectors, most saliently in the transport sector. In the agriculture and manufacturing sectors, where negative supply shocks put downward pressure on sectoral output, we observe price increases due to the inflationary nature of the negative supply shocks. We can derive qualitatively similar implications from Figure A.5 in the Appendix that decomposes sectoral contributions to the aggregate real GDP and GDP deflator into supply and demand shocks.

4 Sector-Specific Demand Stimulus

In this section, we analyze the effects of sector-specific demand stimulus in our model. Sectoral demand stimulus is a common policy tool to stimulate the economy. For example, the Japanese government adopted large-scale public works spending in construction during the "Lost Decade" of the 1990s and renewable-energy equipment procurement following the 2011 Great East Japan Earthquake. More recently, it also adopted travel subsidies to households during the COVID-19 pandemic ("Go-To-Travel" policy) and ordered semiconductor manufacturing equipment in recent industrial policy packages. It is useful to understand how targeted sectoral demand stimulus propagates through production networks and affects the macroeconomy.

4.1 Equilibrium with Sector-specific Demand Stimulus

For each sector $i \in \{1, \ldots, N\}$, we solve for an equilibrium where the government purchases goods g_i from sector i. Specifically, we modify the goods market clearing condition, equation (2.9), to include the government purchase:

$$y_i = c_i + g_i + \sum_{j=1}^{N} x_{ji}.$$

The government expenditure is assumed to be funded by a lump-sum tax T:

$$T = p_i g_i$$

The household's budget constraint, equation (2.2), is modified as follows:

$$\sum_{j=1}^{N} p_j c_j = L + \Pi - T.$$

NGDP and RGDP are redefined from (3.1) to include the government purchase:

$$NGDP_t = \sum_{j=1}^{N} p_{j,t}(c_{j,t} + g_{j,t})$$
$$RGDP_t = \sum_{j=1}^{N} p_j^{\text{base}}(c_{j,t} + g_{j,t}).$$

We solve for the equilibrium with government spending on sector i, holding all parameters at their 2020 values. For any variable x, let $x^{(0)}$ be its equilibrium value without any government spending. Let $x^{(i)}$ be the value of x in the equilibrium where sector i gets demand stimulus. We assume that the level of government purchase $g_i^{(i)}$ is 20% of the level of the consumption in the sector in 2019. We define the *GDP multiplier* for sector i as follows:

$$\lambda^{(i)} := \frac{RGDP_{2020}^{(i)} - RGDP_{2020}^{(0)}}{p_i^{base} g_i^{(i)}}$$

4.2 GDP Multiplier

Figure 6 presents the GDP multipliers for each sector i. According to the figure, all multipliers are positive. A government purchase means an increase in lump-sum tax for households, which increases their labor supply via negative income effects. In our model without capital, labor is the only primary factor in production. Thus, real GDP increases when the government purchases a good in sector i.

All multipliers are less than one. When the government increases its purchases of a good in sector i, all else equal, sector-i production expands one-for-one. However, in order to increase the production of i, the sector-i firm needs to hire more labor, which needs to be reallocated from other sectors and exerts downward pressure on labor in other sectors. That is, an increase in labor demand in sector i crowds out labor in other sectors.

GDP multipliers vary across sectors. The "Transport" sector exhibits the largest GDP multiplier (0.13), followed by "Service" (0.12) and "Commerce" (0.10). In contrast, the GDP multiplier is only 0.03 in "Agriculture." The multiplier depends on the structure of networks as well as the degree of DRS in each sector in a complex way. The heterogeneous effects of sectoral demand stimulus suggest the importance of understanding these details in designing policies if the government aims to use this type of policy to increase the aggregate real GDP.

Figure 7 shows the GDP multipliers from our baseline model and two alternative models:

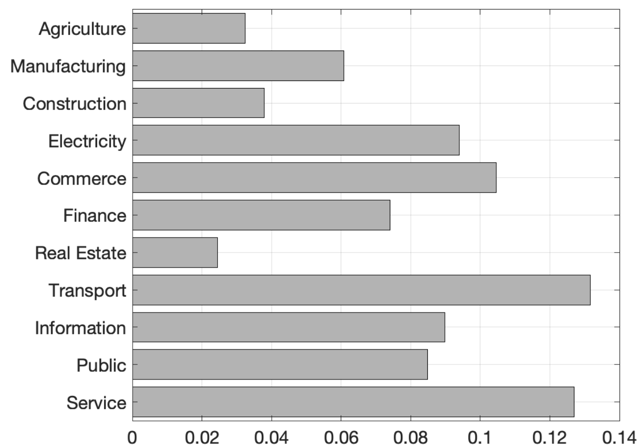


Figure 6: GDP multipliers

Model without production networks ($\alpha_i = 1$ for all i) and model without DRS ($\rho_i = 1$ for all i). According to the figure, GDP multipliers are larger in these two alternative models than in the baseline model for all sectors.

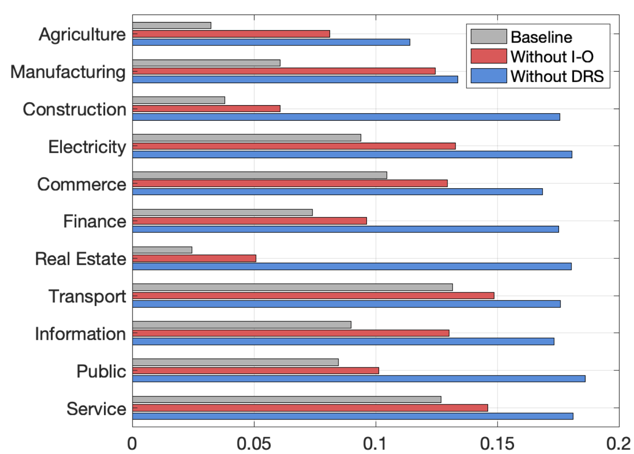


Figure 7: GDP multipliers: Alternative Specifications

The presence of production networks dampens GDP multipliers in the following mechanism. A government purchase stimulates demand in sector i and increases output in that sector. However, that requires drawing labor away from other sectors (labor crowding-out effects). In the baseline model with production linkages, upstream sectors that supply intermediate inputs to sector i must also expand their production to meet the increased demand for their goods. This upstream propagation means that not only sector i itself, but also its suppliers (and their suppliers, and so on) compete for labor, intensifying the aggregate crowding-out effect. In contrast, in a model without production networks, only sector i directly competes for labor, leaving more labor available for other sectors and thus generating smaller labor crowding-out effects. Consistent with this mechanism, the dampening effects tend to be larger in downstream sectors, as shown in Figure A.3 in the Appendix.

DRS dampens GDP multipliers in the following mechanism. When the government purchase increases output in sector i, the marginal productivity of labor declines under DRS. Therefore, the firm needs to increase labor by a larger amount to achieve a given increase in output, leading to a more severe labor crowding-out effect. Consistent with this mechanism, the dampening effects tend to be larger in sectors with larger degrees of DRS, as shown in Figure A.4 in the Appendix.

5 Conclusion

We developed a model with production networks and DRS that can be used to identify sector-level supply and demand shocks from observed price and output data. Applying this model to the COVID-19 crisis in Japan, we found that negative demand shocks were the predominant driver of the recession: they accounted for approximately three-quarters of the observed 3.8% decline in real GDP and put 1.8% downward pressure on the GDP deflator. The decline in the GDP deflator was partly offset by a 0.8% upward push from negative supply shocks. We also computed GDP multipliers associated with sector-specific demand stimulus and found that they were positive, but below one in all sectors.

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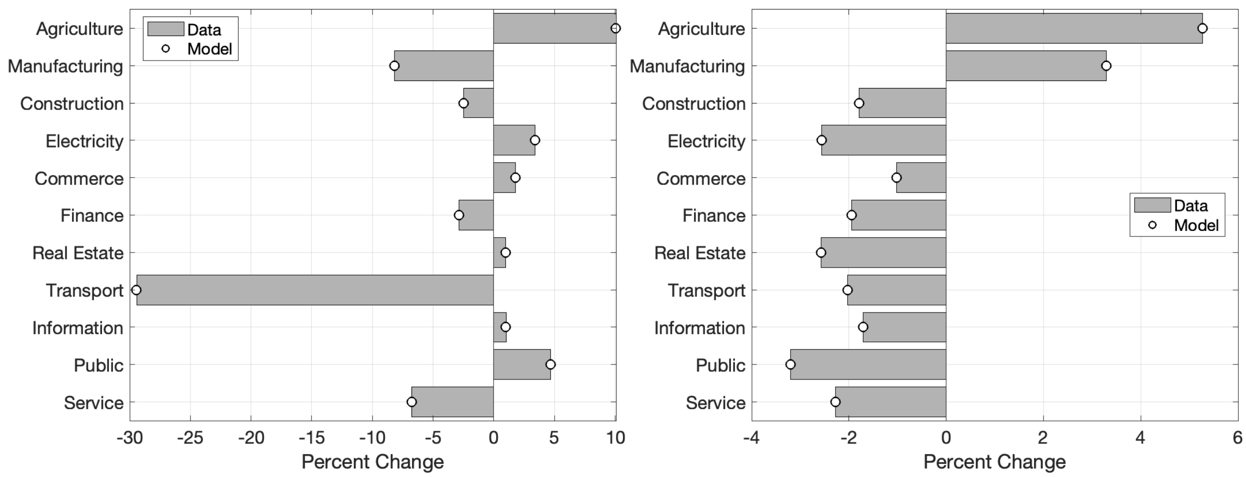
Appendices

A Additional Figures



(a) Real GDP **(b)** GDP Deflator

Figure A.1: Change in real GDP and GDP Deflator in 2020: Data vs model

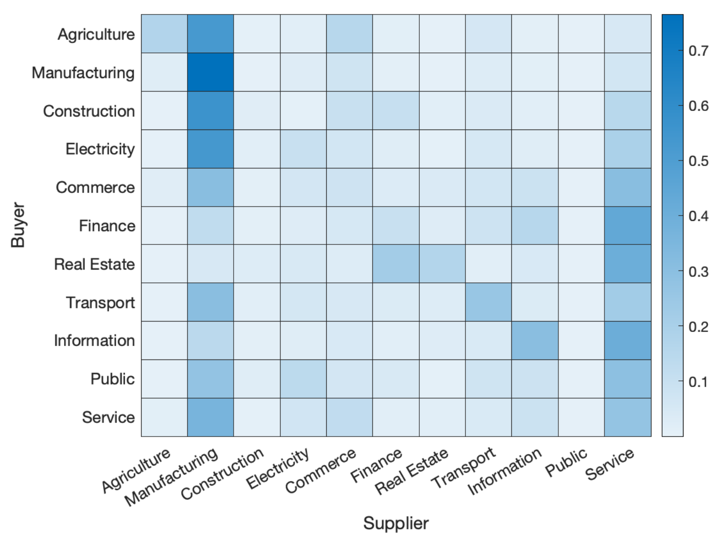


Figure A.2: Weight on intermediate inputs

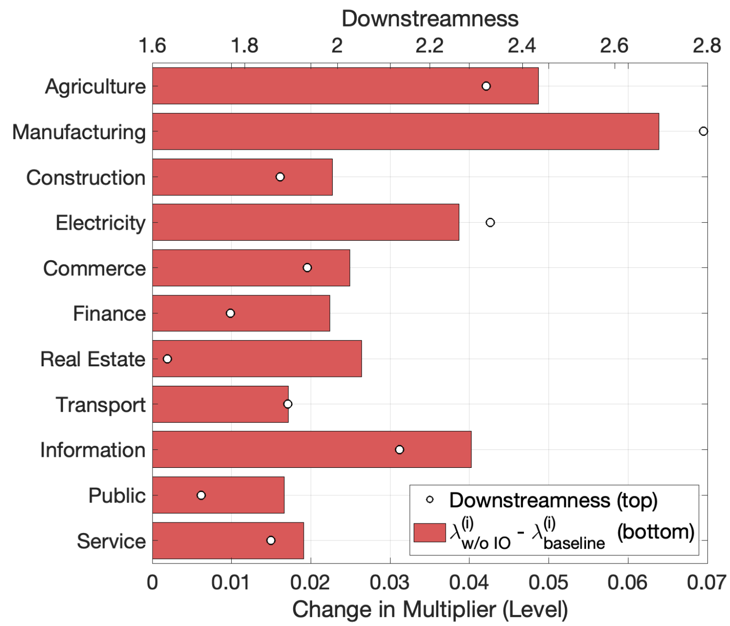


Figure A.3: GDP Multipliers: Dampening Effects of Production Networks

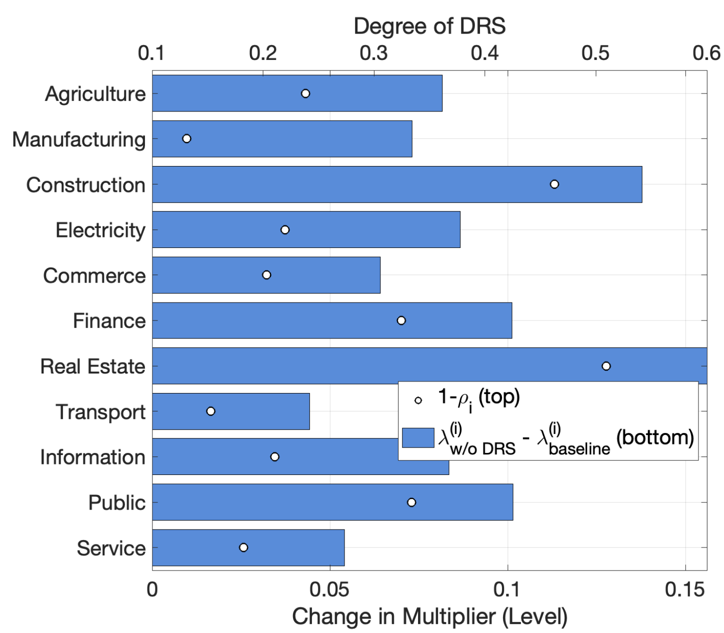
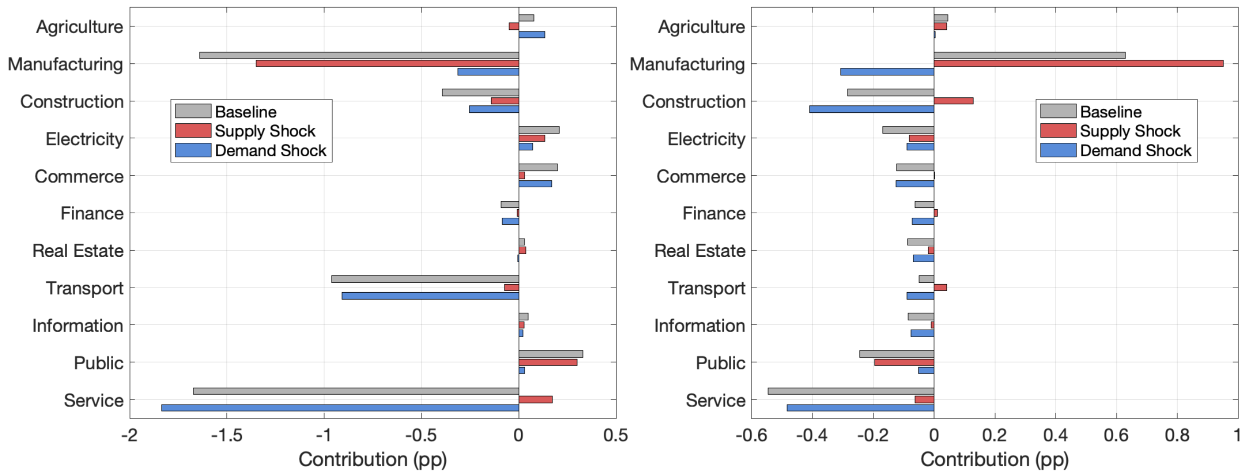


Figure A.4: GDP Multipliers: Dampening Effects of DRS



(a) Real GDP **(b)** GDP Deflator

Figure A.5: Sectoral contribution to changes in real GDP and GDP deflator

B Sensitivity Analysis

Table B.1: Percent change in real GDP and GDP deflator: Alternative values of σ

	Real GDP (% Change)	GDP Deflator (% Change)
Data	-3.8	-1.0
(a) $\sigma = 0.5$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(b) $\sigma = 0.1$		
Supply Shock	-1.0	0.8
Demand Shock	-2.9	-1.7
(c) $\sigma = 0.9$		
Supply Shock	-0.8	0.8
Demand Shock	-3.0	-1.8

Table B.2: Percent change in real GDP and GDP deflator: Alternative values of ξ

	Real GDP (% Change)	GDP Deflator (% Change)
Data	-3.8	-1.0
(a) $\xi = 2.5$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(b) $\xi = 1.5$		
Supply Shock	-1.0	0.8
Demand Shock	-2.9	-1.7
(c) $\xi = 5.0$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8

Table B.3: Percent change in real GDP and GDP deflator: Alternative Values of η_H

	Real GDP (% Change)	GDP Deflator (% Change)
Data	-3.8	-1.0
(a) $\eta_H = 1.1$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(b) $\eta_H = 1.2$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(c) $\eta_H = 1.8$		
Supply Shock	-0.8	0.7
Demand Shock	-3.0	-1.7

Table B.4: Percent change in real GDP and GDP deflator: Alternative values of η_F

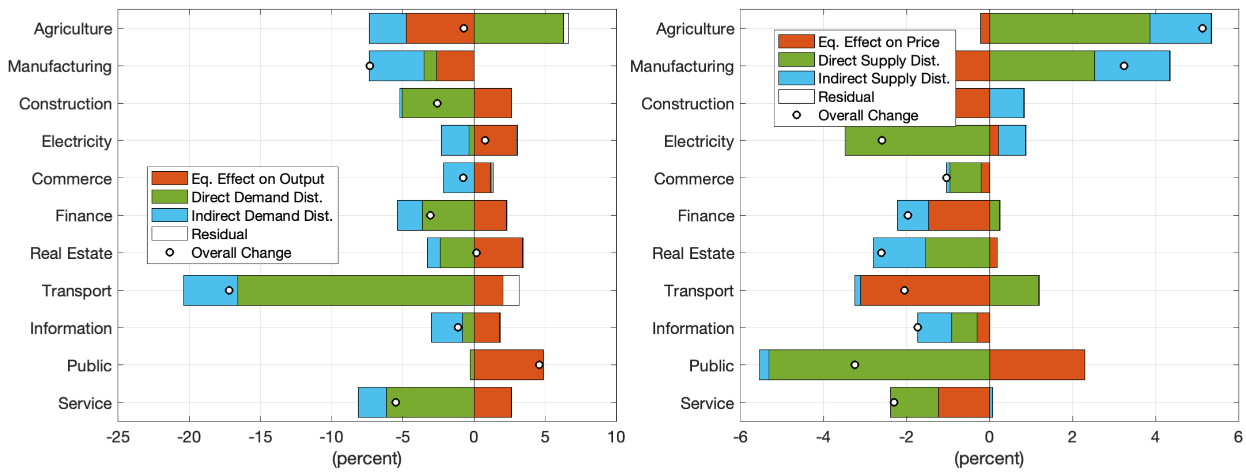
	Real GDP (% Change)	GDP Deflator (% Change)
Data	-3.8	-1.0
(a) $\eta_F = 0.6$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(b) $\eta_F = 0.1$		
Supply Shock	-0.9	0.8
Demand Shock	-3.0	-1.8
(c) $\eta_F = 3$		
Supply Shock	-1.2	0.7
Demand Shock	-2.7	-1.6

C Demand and Supply Disturbances

To understand how the sectoral output and price changes are realized in the equilibrium, we apply our sectoral supply and demand framework expressed in the supply curve (2.12) and the demand curve (2.13). For output, we focus on the total output (y_i), which includes both final and intermediate goods. For the total output changes, we identify the equilibrium effect on output (demand substitution of the household and the downstream sectors given the price change), the direct demand disturbance (changes in the direct sectoral demand shifter $\Delta_{H,i}$), and indirect demand disturbance (changes in demand from downstream sectors that use good i as an input), based on the demand curve (2.13). For price changes, we similarly identify the equilibrium effect on price (changes in the marginal cost given the total output changes), the direct supply disturbance (changes in the productivity shifter ϕ_i), and the indirect supply disturbance (cost changes transmitted from upstream suppliers), based on the supply curve (2.12). We also show a residual reflecting the non-linearities in the model that are not captured by the log-linearization in (2.12) and (2.13). The overall change (black circle) is the sum of the four components.

Panel C.1a, which decomposes the total output changes, reveals several key patterns. First, direct demand disturbances (green bars) predominantly exert downward pressure on the total output level across most sectors, consistent with the aggregate finding. Second, these effects are partially mitigated by equilibrium effects on output (red bars) in most sectors. Third, indirect demand disturbances (blue bars) make non-negligible contributions in several sectors, particularly in the Agriculture and Manufacturing sectors.

While Panel C.1b that decomposes the price change shows a more mixed pattern of each



(a) Output (incl. intermediate goods) **(b)** Price

Figure C.1: Demand and Supply Disturbances

component, we observe that equilibrium effects on price, direct supply disturbance, and indirect supply disturbance are all quantitatively important and of comparable magnitude, with sizable heterogeneity in their sign and size among sectors. These decomposition results validate our modeling choices: without DRS, supply curves would be horizontal, so the equilibrium effect on price would be missed; without input-output networks, shocks do not propagate via the sectoral linkage, so that the indirect supply disturbance would be missed.

D Extension: Open Economy Setting

The discussion in the paper has been based on the model with a closed economy setting, abstracting from international trade. However, trade can represent another important channel through which the pandemic may have affected the domestic economy. In fact, global trade volume collapsed by 8.2% in 2020 (IMF, 2021), suggesting its sizable impact on the aggregate economy. To assess whether our main findings are robust to incorporating trade dynamics, we extend the baseline model to include both imports and exports.

D.1 Model

We assume a small open economy where the foreign currency-denominated price of foreign goods i is exogenously given by p_i^f. Then, using the (endogenous) exchange rate e^f, we define the domestic currency-denominated price of foreign goods $\tilde{p}_i^f = e^f p_i^f$. Similarly, we define the foreign currency-denominated price of domestic goods i as $\tilde{p}_i = \frac{p_i}{e^f}$.

D.1.1 Household

The household's preferences are represented by:

$$\max \frac{C^{1-\sigma}-1}{1-\sigma} - \chi \frac{L^{1+\xi}}{1+\xi}.$$

Aggregate consumption C is a nested CES aggregate of sector-specific consumption goods:

$$C = \left(\sum_{i=1}^{N} c_i^{\frac{\eta_H - 1}{\eta_H}} \right)^{\frac{\eta_H}{\eta_H - 1}}.$$

and each of the consumption goods consists of the CES aggregation between domestic goods c_i^d and foreign goods c_i^f given by:

$$c_i = \left((\delta_i^d)^{\frac{1}{\nu}} (c_i^d)^{\frac{\nu-1}{\nu}} + (\delta_i^f)^{\frac{1}{\nu}} (c_i^f)^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}.$$

where δ_i^d represents the household's preference shifter for domestic good i and δ_i^f represents the household's preference shifter for foreign good i. ν is the Armington elasticity between the domestic goods and foreign goods.

The household faces a budget constraint:

$$\sum_{i=1}^{N} (p_i c_i^d + \tilde{p}_i^f c_i^f) = L + \Pi + D_T \tag{D.1}$$

where D_T is the trade deficit.

D.1.2 Competitive Firm

The production function for sector i is:

$$y_i = \phi_i B_i^{\rho_i}.$$

The input bundle is given by:

$$B_i = \frac{1}{\alpha_i^{\alpha_i}(1-\alpha_i)^{1-\alpha_i}} l_i^{\alpha_i} M_i^{1-\alpha_i}.$$

The intermediate inputs bundle M_i is a CES aggregator of each sectoral intermediate inputs input x_{ij}

$$M_i = \left(\sum_{j=1}^{N} a_{ij}^{\frac{1}{\eta_F}} x_{ij}^{\frac{\eta_F - 1}{\eta_F}} \right)^{\frac{\eta_F}{\eta_F - 1}}.$$

Lastly, profits for sector i equal

$$\pi = (1 - \rho_i) p_i y_i$$

D.1.3 Foreign Demands

We assume the demand for each good from foreign countries is as follows.

$$c_i^{ex} = \Delta_i^f \tilde{p}_i^{-\eta_H}$$

where Δ_i^f is the foreign sectoral demand shifter on goods i.

D.1.4 Market Clearing

Goods market clearing is given by:

$$y_i = c_i^d + \sum_{j=1}^{N} x_{ji} + c_i^{ex}.$$

Labor market clearing is given by:

$$L = \sum_{i=1}^{N} l_i.$$

The aggregate profit is given by:

$$\Pi = \sum_{i=1}^{N} \pi_i.$$

The trade balance is given by

$$D_T = \sum_{i=1}^{N} \tilde{p}_i^f c_i^f - \sum_{i=1}^{N} p_i c_i^{ex}.$$

National accounts: Nominal GDP equals total expenditure on final goods with nominal net export:

$$NGDP_t = \sum_{i=1}^{N} p_{i,t} c_{i,t}^{d} + \sum_{i=1}^{N} p_{i,t} c_{i,t}^{ex} - \sum_{i=1}^{N} \tilde{p}_{i,t} c_{i,t}^{f}.$$

Real GDP is computed using a base-year price vector p_i^{base} and $\tilde{p}_i^{f,\text{base}}$:

$$RGDP_t = \sum_{i=1}^{N} p_i^{\text{base}} c_{i,t}^{d} + \sum_{i=1}^{N} p_i^{\text{base}} c_{i,t}^{ex} - \sum_{i=1}^{N} \tilde{p}_i^{f,\text{base}} c_{i,t}^{f}.$$

The GDP deflator is the ratio of nominal to real GDP:

$$\Pi_{GDP,t} = \frac{NGDP_t}{RGDP_t}$$

D.1.5 Two Equilibrium Concepts

We now define two equilibrium concepts for the small open economy model, each serving a distinct purpose in our analysis.

Definition 1 (Fixed-currency Equilibrium)**.** Given the productivity shifter $\{\phi_i\}$, the domestic preference shifter $\{\delta_i^d\}$, the foreign preference shifter $\{\delta_i^f\}$, foreign currency-denominated price of $\{p_i^f\}$, and the exchange rate e^f, a static equilibrium is a vector of outputs $\{y_i\}$, prices $\{p_i\}$ and the trade deficit D_T such that: (i) the household maximizes its utility, taking prices as given, (ii) competitive firms in each sector maximize profits, taking prices as given, (iii) all markets clear (goods and labor), and (iv) the trade balance holds.

Definition 2 (Fixed-deficit Equilibrium)**.** Given the productivity shifter $\{\phi_i\}$, the domestic preference shifter $\{\delta_i^d\}$, the foreign preference shifter $\{\delta_i^f\}$, foreign currency-denominated price of $\{p_i^f\}$ and the trade deficit D_T, a static equilibrium is a vector of outputs $\{y_i\}$, prices $\{p_i\}$, and the exchange rate e^f such that: (i) the household maximizes its utility, taking prices as given, (ii) competitive firms in each sector maximize profits, taking prices as given, (iii) all markets clear (goods and labor), and (iv) the trade balance holds.

Our empirical strategy employs different equilibrium concepts at the calibration and counterfactual stages, following the discussion on different equilibrium-closure implementations in the literature on quantitative trade models (Shoven and Whalley, 1984; Hertel et al., 1997). When calibrating the model to data, we fix the observed trade deficit D_T and solve for the endogenous exchange rate e^f, which is rigorously defined as a *fixed-deficit equilibrium*. This choice is motivated by the well-documented fact that the exchange rate greatly fluctuates beyond the change in the contemporaneous real fundamentals (Meese and Rogoff, 1983;

Engel and West, 2005). The excess volatility of exchange rates relative to macroeconomic variables implies that using observed exchange rates directly as an exogenous parameter would contaminate our identification of supply and demand shocks with these unmodeled financial factors.

By contrast, in our counterfactual exercises, we fix the exchange rate at its 2019 level and allow the trade deficit to adjust endogenously, which is rigorously defined as a *fixed-currency equilibrium*. The rationale is that fixing the trade deficit at its 2020 observed level in counterfactuals mechanically forces exports and imports to adjust to the exogenous trade deficit level, which would contaminate our interpretation of the result. By endogenizing the trade deficit while fixing the exchange rate, we allow exports and imports to respond directly to the specific shocks we are analyzing.

D.2 Identification

The open economy extension requires calibrating additional parameters beyond those in the baseline model. We set the Armington elasticity ν to 3.8, consistent with standard values in the international trade literature (Bajzik et al., 2020). The weights on domestic versus foreign goods (δ_i^d, δ_i^f) are calibrated to match observed expenditure shares in 2019 from the JIP database. The trade deficit D_T is calibrated to the deficit-GDP ratio in the JIP database. Foreign currency-denominated prices of imports (p_i^f) in 2019 are normalized to 1.

For the 2020 calibration under the fixed-deficit equilibrium, we estimate changes in the productivity shifter (ϕ_i), domestic preference shifter (δ_i^d), foreign preference shifter (δ_i^f), foreign-currency-denominated prices of imported goods (p_i^f), and foreign demand shifter (Δ_i^f) to match observed changes in: (i) domestic final goods demand, (ii) price of domestic final goods, (iii) domestic currency-denominated nominal values of import goods, (iv) domestic currency-denominated nominal values of exports goods, and (v) domestic currency-denominated price of foreign goods. In total, we target $5 \times 11 = 55$ moments and estimate 55 parameters, which can be estimated in the same way as in the baseline estimates.

D.3 Supply and Demand Shocks during COVID-19

Using the fixed-currency equilibrium with the exchange rate fixed at its 2019 level, we conduct four counterfactual experiments by imposing only one type of shock in 2020. In the supply shock economy, only the domestic productivity shifter (ϕ_i) changes. In the demand shock economy, only the preference shifters (δ_i^d and δ_i^f) change. In the foreign supply shock economy, only foreign prices (p_i^f) change. Finally, in the foreign demand shock economy, only the foreign sectoral demand shifter (Δ_i^f) changes.

The counterfactual exercises reveal that domestic demand shocks remain the dominant driver of the economic downturn, reinforcing our baseline closed-economy result. As shown in Table D.1, the demand shock economy alone generates a 3.7% decline in real GDP and a 2.4% decline in the GDP deflator, confirming the primacy of domestic demand shocks in the open economy setting. Interestingly, foreign demand shocks play a non-negligible and similar role, contributing to a 1.0% decline in real GDP and a 0.2% decline in the GDP deflator. These counterfactual results highlight that deflationary pressures from the demand side were prevalent both domestically and internationally. On the supply side, the estimated impact of domestic supply shocks is almost negligible, slightly increasing real GDP by 0.1%. A plausible explanation is that estimated negative supply shocks in the baseline analysis mainly reflect the foreign supply shock component. Indeed, the negative foreign supply shock reduces real GDP by 0.3% while pushing up the GDP deflator by 0.2%.[3]

Table D.1: Changes in real GDP and GDP deflators: Open-Economy Model

	Real GDP (% Change)	GDP Deflator (% Change)
Data	-3.8	-1.0
Open-Economy Model		
Supply Shock	0.1	-0.1
Demand Shock	-3.7	-2.4
Foreign Supply Shock	-0.3	0.2
Foreign Demand Shock	-1.0	-0.2

E Derivation of the Supply and Demand Curves

Taking the log of (2.10) on both sides, we obtain

$$\log p_i = -\log \rho_i - \frac{1}{\rho_i}\log \phi_i + \frac{1-\rho_i}{\rho_i}\log y_i + \frac{1-\alpha_i}{1-\eta_F}\log\left(\sum_{j=1}^{N} a_{ij} p_j^{1-\eta_F}\right). \tag{E.1}$$

[3]The sum of the changes from the individual shock scenarios differs from the change in data. The difference arises because the counterfactuals are conducted with the exchange rate fixed at its 2019 level, while these shocks are estimated with an endogenous exchange rate.

Total differentiation on both sides yields

$$\frac{dp_i}{p_i} = -\frac{1}{\rho_i}\frac{d\phi_i}{\phi_i} + \frac{1-\rho_i}{\rho_i}\frac{dy_i}{y_i} + (1-\alpha_i)\frac{\sum_{j=1}^N a_{ij} p_j^{1-\eta_F}\frac{dp_j}{p_j}}{\sum_{j=1}^N a_{ij} p_j^{1-\eta_F}} \tag{E.2}$$

$$= -\frac{1}{\rho_i}\frac{d\phi_i}{\phi_i} + \frac{1-\rho_i}{\rho_i}\frac{dy_i}{y_i} + \sum_{j=1}^N W_{ij}\frac{dp_j}{p_j} \tag{E.3}$$

where $W_{ij} = (1-\alpha_i)\frac{p_j x_{ij}}{\sum_{j=1}^N p_j x_{ij}}$.

Taking the log of (2.9) on both sides, total differentiation on both sides yields

$$\frac{dy_i}{y_i} = \frac{c_i}{y_i}\frac{dc_i}{c_i} + \sum_{j=1}^N \frac{x_{ji}}{y_i}\frac{dx_{ji}}{x_{ji}} \tag{E.4}$$

Similarly, we have

$$\frac{dc_i}{c_i} = -\eta_H\frac{dp_i}{p_i} + \frac{d\Delta_{H,i}}{\Delta_{H,i}}. \tag{E.5}$$

from (2.3), and

$$\frac{dx_{ji}}{x_{ji}} = -\eta_F\frac{dp_i}{p_i} + \frac{d\Delta_j}{\Delta_j}. \tag{E.6}$$

from (2.7).

Substitute (E.5) and (E.6) into (E.4):

$$\frac{dy_i}{y_i} = \frac{c_i}{y_i}\left(-\eta_H\frac{dp_i}{p_i} + \frac{d\Delta_{H,i}}{\Delta_{H,i}}\right) + \sum_{j=1}^N \frac{x_{ji}}{y_i}\left(-\eta_F\frac{dp_i}{p_i} + \frac{d\Delta_j}{\Delta_j}\right) \tag{E.7}$$

Grouping terms by $\frac{dp_i}{p_i}$:

$$\frac{dy_i}{y_i} = -\left(\frac{c_i}{y_i}\eta_H + \sum_{j=1}^N w_{ji}\eta_F\right)\frac{dp_i}{p_i} + \frac{c_i}{y_i}\frac{d\Delta_{H,i}}{\Delta_{H,i}} + \sum_{j=1}^N w_{ji}\frac{d\Delta_j}{\Delta_j} \tag{E.8}$$

where $w_{ji} = x_{ji}/y_i$ $\square$

F Algorithm

The static equilibrium of our model is characterized by a system of simultaneous equations for prices $\{p_i\}$ and outputs $\{y_i\}$. Specifically, it is defined by the system of price equations (2.10) and output equations (2.11), which must hold for all sectors, along with the labor market clearing condition. Solving this system presents a computational challenge due to the high dimensionality.

In the literature on production network models, the equilibrium is often computed by solving two separate fixed-point problems. In our case, the price system, represented by equation (2.10), constitutes a *backward fixed-point* (BFP) problem, where the price of a good depends on the prices of its inputs from upstream sectors. Conversely, the output system, represented by equation (2.11), forms a *forward fixed-point* (FFP) problem, where the output of a sector is determined by demand from downstream sectors and final consumers. In standard models with constant returns to scale (CRS), the price equations are independent of output levels. This separability allows for a sequential algorithm where each fixed-point problem can be iterated to convergence independently (see, for example, Lim (2018), Huneeus (2020), and Bernard et al. (2022) for a discussion).

However, the introduction of a decreasing returns to scale (DRS) technology in our model creates a direct feedback loop from quantities to prices via the marginal cost term $y_i^{\frac{1-\rho_i}{\rho_i}}$ in equation (2.10). This interdependence breaks the separability of the two systems. Consequently, a standard sequential algorithm can fail to converge. For instance, an increase in intermediate demand for sector i raises its required output, which, under DRS, decreases the marginal productivity of input bundles of i. To compensate for the decline in productivity, i must require more inputs from i's upstream sector. This upstream propagation generates positive feedback over the networks and makes the algorithm diverge.

We address this challenge with a modified algorithm that jointly updates prices and quantities and achieves stable convergence in our numerical experiments.

0. Guess $\{y_i\}$ and Δ_H.

1. Solve the forward and backward fixed-point problems until $\{p_i\}$ and $\{y_i\}$ converge.

    (a) Given $\{y_i\}$, update $\{p_i\}$ once using the mapping defined by the RHS of the BFP, and obtain the associated $\{p_i\}, \{q_i\}, \{r_i\}$.

    (b) Given $\{q_i\}$ and $\{r_i\}$, update $\{y_i\}$ once using the mapping defined by the RHS of the FFP, and obtain $\{y_i\}$.

2. Calculate the associated $P_H, \{c_i\}, C$, and $\{l_i\}$.

3. From the consumption-labor relationship, calculate L.

4. Check the labor market clearing condition. If the labor supply is larger (smaller), decrease (increase) Δ_H.

The key part is the interdependency of (a) and (b) in 1. Instead of solving the BFP given $\{y_i\}$ and solving the FFP given $\{p_i\}$ separately, we calculate the mapping in the RHS of the BFP and FFP just once for each iteration, and update the $\{p_i\}$ and $\{y_i\}$ step by step. Intuitively, this algorithm captures partial equilibrium adjustments within the inner loop, thereby dampening the explosive feedback loops that can arise from network spillovers under DRS.