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Propagation of shocks in an input-output economy: Evidence from disaggregated prices[☆]

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ABSTRACT

Using disaggregated industry-level data, this paper empirically evaluates predictions for the cross-sectional price change distribution made by input-output models with sticky prices. The response of prices to shocks is found to be consistent with the price sensitivities predicted by the input-output model. Moreover, moments of the sectoral price change distribution vary over time in response to the evolution of the network structure. Finally, through a quantitative analysis, demand and supply shocks are disentangled during the pandemic period. Counterfactual analyses show that sectoral supply shocks, aggregate demand shocks and the production network structure contributed significantly to the inflation surge in 2021–2022.

1. Introduction

How prices respond to shocks has long been understood to be crucial to determine how monetary policy works. Sticky prices naturally play an important role in this, and there is a long literature studying how price stickiness affects the transmission of monetary shocks (e.g. Caplin and Spulber, 1987; Golosov and Lucas, 2007, among many others). It has also been known for some time that when the economy operates under a production network with input-output (I-O) linkages across firms and sectors, the real effects of monetary shocks can be amplified (see, for example, Basu, 1995; Nakamura and Steinsson, 2010). In recent years there has also been a great deal of theoretical work done to develop rich production network models with sticky prices and derive implications for monetary non-neutrality and for the conduct of monetary policy (La'O and Tahbaz-Salehi, 2022; Pasten et al., 2020; Rubbo, 2020). However, while there is broad agreement that a production

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network plays an important role in the transmission of monetary shocks, there is little direct or indirect evidence for the strength of the mechanisms responsible for this.[1]

This paper empirically evaluates the predictions of the input-output models with sticky prices. While these models have implications for monetary non-neutrality and monetary policy generally, they also make clear predictions about how individual sectoral prices should respond to aggregate and sectoral shocks through the input-output linkages. Through several empirical tests, this paper evaluates to what extent the mechanisms that are key to models of production networks are present in actual price-setting behavior.

First, the I-O models with price rigidity imply that the degree to which sectoral prices respond to shocks is determined by a set of factors related to the input-output structure of the economy and to differential price rigidity across sectors (see for example Afrouzi and Bhattarai, 2022; La'O and Tahbaz-Salehi, 2022; Pasten et al., 2020; Rubbo, 2020). Shocks propagate along the supply chain and affect the prices of different sectors through direct and indirect connection. As shown in Section 2, the following equation describes how sectoral prices respond in a two stage static model, where some firms have the opportunity to re-optimize their prices after shocks are realized,

$$\tilde{p} = \Phi(I - \Omega\Phi)^{-1}(D_\alpha \tilde{w} - \tilde{z}).$$

This equation relates price changes ($\tilde{p}$) to factors determined by the production network (Ω, the matrix of input shares) and price stickiness (Φ, a diagonal matrix of price adjustment flexibility). Thus, sectoral wage (w) and technology (z) changes pass-through to prices of connected sectors through the I-O structure (along with the diagonal matrix of labor share D_α).

To evaluate the theoretical prediction on sectoral price responses, three types of empirical tests are conducted. First, consistent with the model's prediction, we find that the correlation between sectoral price changes and the model-implied sectoral price sensitivity to aggregate shocks is highly procyclical. Furthermore, in addition to finding support for the mean price responses predicted by the equation above, higher moments of the sectoral price change distribution vary over time in response to the evolution of the network structure. Thus, these findings provide further stylized facts for how prices at the sectoral level respond to changes in production network structures.

The second type of tests directly estimates the price responsiveness of different sectoral prices using identified monetary policy shocks from the high-frequency identification literature, and determine whether the most price-sensitive sectors are those predicted by the model. Looking at the sectoral price changes in response to policy rate, forward guidance, and large-scale asset purchases (LSAP) shocks identified by Swanson (2021), a larger price response to forward guidance monetary shocks is observed for sectors predicted by the model to be more sensitive to aggregate demand shocks. However, no such relation is found for other types of monetary shocks, such as LSAP shocks.

In addition, the third type of tests studies whether sectoral shocks propagate to other sectors and affect sectoral prices in the way that the model predicts. Measuring sectoral productivity as supply shocks and changes in trade patterns as demand shocks, strong downstream propagation of supply shocks on sectoral prices and both downstream and upstream propagation of demand shocks are found. These findings strongly support the prediction of the model. In particular, a one standard deviation increase in import penetration from China in a sector's suppliers (buyers) would reduce the cumulative 2-year inflation by about 3.8 (1.3) log points in that sector. And an increase of one standard deviation in TFP among suppliers of a given sector results in a decline of 3.4 log points in cumulative 2-year inflation for the same sector.

Taken together, the empirical analyses provide support for the importance of input-output linkages and price rigidity in determining sectoral price changes. Then a quantitative analysis using the I-O model is performed to determine what possible roles the structure of the production network played in the large rise in inflation seen in the United States from 2021 to 2022. The pandemic period has brought a great deal of attention to various kinds of supply disruptions. The model is calibrated to the empirical input-output structure and to the changes in sectoral employment, consumption, and prices since the start of the COVID-19 pandemic. By solving the model under various counterfactuals regarding the presence of different kinds of shocks and the presence or absence of the input-output structure, we find that the reduction of production possibilities at the sectoral-level, the aggregate demand shock and the input-output structure have been major contributors to the surge in inflation. In particular, in the benchmark I-O economy, the sectoral TFP shock (as the major contributor) accounts for 42% of the high inflation, greater than the contribution of the aggregate demand shock. However, compared to a multi-sector model with no input-output linkages that is calibrated to match the same changes in sectoral prices, the model without input-output linkages understates the contribution of the TFP shocks by 7%, making the aggregate demand shock a larger contributor of high inflation. This comparison provides context for the quantitative analysis and highlights the importance of considering input-output linkages in the model.

Related Literature. This paper relates to a few strands of literature. First, it fits most directly into the recent line of work on multi-sector models with sticky prices and production networks (such as Afrouzi and Bhattarai, 2022; Ghassibe, 2021a; 2021b; La'O and Tahbaz-Salehi, 2022; Pasten et al., 2020; Rubbo, 2020). The model considered in this paper is similar to the ones featured in these studies. Most of the existing work in this field has focused quite intensively on understanding and measuring the extent to which the transmission of monetary policy is affected by the economy's network structure, or on how this network structure affects what is the optimal monetary policy (particularly La'O and Tahbaz-Salehi, 2022; Rubbo,

[1] One notable exception is Ghassibe (2021b), who provides an empirical test for how important input-output linkages are for the transmission of monetary shocks using high-frequency disaggregated consumption data. This paper instead makes a series of tests for these mechanisms using industry-level price data.

2020). This paper investigates the I-O structure and price stickiness from a different angle: their joint implication for the cross-sectional distribution of price responses to shocks. Because these models make strong predictions about how sectors respond to aggregate and sectoral shocks, our empirical tests provide an important validation for this class of models.

This paper is also connected to the literature on the propagation of shocks in a network economy. There have been papers theoretically or empirically studying how shocks propagate along the supply chain or financial linkages (for example Acemoglu et al., 2016a; 2015; Baqaee, 2018; Luo, 2020). However, most of these papers focus on the response of production and employment. The focus of this paper is naturally on the price effect of shocks.

The analysis on the propagation of demand shocks relates to the literature on the effects of increasing import competition from China and use changes in Chinese import penetration as demand shocks. Papers such as (Acemoglu et al., 2016b; Autor et al., 2013; 2019; Pierce and Schott, 2016) find that the rise in imports from China in the past few decades had a very large negative effect on employment in the U.S. manufacturing sector. Jaravel and Sager (2022) have also studied the effect of Chinese imports on prices in the United States. Their analysis has focused on consumer prices and on evaluating the predictions of models of international trade. We instead use producer prices (the U.S. Producer Price Index, PPI) and consider the propagation of these shocks: that is, how shocks to a group of sectors can affect prices in another sector through input-output linkages.

Finally, the quantitative analysis in this paper contributes to the growing literature on the macroeconomic consequences of the disruptions caused by the COVID-19 pandemic. In particular, we follow other papers in highlighting the role of sectoral shocks in raising inflation. For example, Guerrieri et al. (2021) develop a multi-sector model in which a demand reallocation shock raises inflation, and they study optimal monetary policy in such a setting. Ferrante et al. (2022) present a model similar to ours, with multiple sectors, heterogeneous price stickiness, and input-output linkages. They consider a shock that shifts demand away from services and towards goods and find that in their model such a shock can explain a large share of the inflation seen in the pandemic recovery. Nonetheless, our analysis focuses on testing the importance of input-output linkages in generating heterogeneous price changes at the cross-sectional level. We disentangle sectoral supply and demand shocks using the observed price changes and then study the factors that contribute to the inflation surge in 2021–2022.

The remainder of the paper is organized as follows. Section 2 presents a production network model with sticky-price and derives predictions for how sectoral prices respond to aggregate and sectoral shocks. Section 3 briefly describes the data used in the empirical tests and in the calibration of the quantitative model. Section 4 describes the results of various empirical tests of the model's predictions for sectoral prices. Section 5 presents the quantitative exercise in which we calibrate a modified version of the model to the pandemic period and run counterfactual analyses to estimate the contribution of the production network and of different shocks to inflation. Finally, Section 6 concludes.

2. An input-Output economy with price rigidity

This section presents and discusses model predictions regarding the response of prices to shocks, which will be evaluated in Sections 4 and 5. The model is based on the I-O model with price rigidity presented by La'O and Tahbaz-Salehi (2022), with the CES production function and segmented labor markets across sectors.

2.1. Model set-up

Consider a static economy with N sectors. In each sector i, a continuum of firms k (distributed from 0 to 1) produce differentiated products. They face a CES production function, given by

$$y_{ik} = z_i \left[\alpha_i^{1/\theta} l_{ik}^{\frac{\theta-1}{\theta}} + (1-\alpha_i)^{1/\theta} \sum_j \omega_{ij}^{1/\theta} x_{ij,k}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{1}$$

where l_{ik} is the labor input, $x_{ij,k}$ denotes the amount of intermediate inputs produced by sector j used by the firm. z_i is the sectoral TFP. α_i is the labor share. ω_{ij} refers to the share of input j over the total intermediate inputs, which captures the I-O structure. θ is the elasticity of substitution across production inputs.[2]

There is a final producer in each industry that aggregates these differentiated products into one sectoral product following $y_i = \left(\int_k y_{ik}^{\frac{\epsilon-1}{\epsilon}} \right)^{\epsilon/(\epsilon-1)}$. ϵ is the within-industry elasticity of substitution. Furthermore, an industry-specific revenue tax or subsidy levied by the government is set to eliminate the distortions that arise under the CES demand structure in each industry.

It is straightforward to show that sector-level marginal costs follow

$$mc_i = z_i^{-1} \left[\alpha_i w_i^{1-\theta} + (1-\alpha_i) \sum_{j=1}^{n} \omega_{ij} \left(p_j\right)^{1-\theta} \right]^{\frac{1}{1-\theta}} \tag{2}$$

[2] For simplicity, we ignore capital and consider homogeneous elasticity of substitution across production inputs in this section. These assumptions will be relaxed in Section 5.

where w_i denotes the nominal wage of sector i.

Furthermore, nominal rigidities are introduced using the noisy information structure following La'O and Tahbaz-Salehi (2022). Specifically, a fraction ϕ_i of firms in industry i receive perfect information about the realized shocks, while a fraction $1-\phi_i$ of firms in industry i receive no signals during a given time period.[3] Thus, the sectoral price p_i deviation from the steady state level follows:

$$\tilde{p}_i = \phi_i \tilde{mc}_i. \tag{3}$$

Marginal cost changes ($\tilde{mc}_i$) will only partially pass-through into prices, and ϕ_i proxies the sectoral level of price stickiness. The higher is ϕ_i the more flexible price adjustment is. Henceforth, variables with tilde refer to log deviation from steady state values.

Lastly, households solve a standard utility maximization problem with risk aversion γ and elasticity of labor supply η,

$$\max \frac{C^{1-\gamma}}{1-\gamma} - \sum_i \chi_i \frac{l_i^{1+1/\eta}}{1+1/\eta}, \tag{4}$$

$$s.t. \quad PC = \sum_i w_i l_i + T + \Pi. \tag{5}$$

Preferences over consumption goods is given by a CES aggregator $C = \left(\sum_i \beta_i^{1/\varepsilon} c_i^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$, where c_i is the consumption of goods produced by sector i, β_i is the preference parameter, and ε is the elasticity of substitution. Thus, the aggregate price follows $P \equiv \left(\sum_i \beta_i p_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$. Moreover, χ_i controls the steady state labor share by industry. T is the transfer from the government. Π is the transfer from firms. And it is noteworthy that labor markets are segmented, and wages are heterogeneous across sectors.

2.2. Propagation of shocks and price responses

This subsection discusses model predictions about how the propagation of shocks affects prices. These predictions will be evaluated in the empirical analysis.

First, the nominal expenditure of the economy is denoted as $E \equiv CP$. The Domar weight of sector i is denoted as $\lambda_i \equiv p_i y_i / E$, which is the sales share as a fraction of GDP. Φ denotes a diagonal matrix of price stickiness with diagonal element ϕ_i. Moreover, two I-O matrices are defined. The input matrix Ω has entries $(1-\alpha_i)\omega_{ij}$, which capture the amount of j used as an input in producing product i (i.e., $\frac{Sales_{j\to i}}{Sales_i}$). The output matrix $\hat{\Omega}$ has entries $(1-\alpha_i)\omega_{ij}\frac{\bar{p}_i\bar{y}_i}{\bar{p}_j\bar{y}_j}$, which corresponds to the proportion of sales from j to i relative to the total sales of j (i.e., $\frac{Sales_{j\to i}}{Sales_j}$). In addition, D refers to diagonal matrices, for example D_α denotes a diagonal matrix with diagonal element α_i, and $D_{\bar{\beta}/\bar{\lambda}}$ denotes a diagonal matrix with diagonal element $\bar{\beta}_i/\bar{\lambda}_i$. Variables with bars refer to steady state values. Variables without subscript i refer to vectors of the corresponding sectoral values. For instance, $\tilde{p}$ refers to a vector of $\tilde{p}_i$.

The focus is on the changes of sectoral prices subject to three types of shocks (1) sectoral TFP shocks, $\tilde{z}_i$, (2) sectoral demand shocks, $\tilde{\beta}_i$, and (3) aggregate expenditure shocks, $\tilde{E}$. First-order approximations of the endogenous equilibrium are considered in this section, but the model will be solved quantitatively at its global solution in Section 5.

Proposition 1. *Changes in the sectoral product prices and sectoral wages can be approximated to the first order by the following equations:*

$$\tilde{p} = \Phi(I - \Omega\Phi)^{-1}(D_\alpha \tilde{w} - \tilde{z}) \tag{6}$$

$$\tilde{w} = \left(\frac{\theta-1}{\theta}\right)\tilde{z} + \frac{1}{\theta}(\tilde{\lambda} + \tilde{E}\cdot \mathbf{1}_N) + \left(\Phi^{-1} - \frac{1}{\theta}I\right)\tilde{p} - \frac{1}{\theta}\tilde{l} \tag{7}$$

and the Domar weight and sectoral labor responses follow

$$\tilde{\lambda} = [I - \hat{\Omega}']^{-1}\left\{(\theta-1)\hat{\Omega}'\tilde{z} + D_{\bar{\beta}/\bar{\lambda}}\tilde{\beta} + Q\tilde{p} - (1-\varepsilon)D_{\bar{\beta}/\bar{\lambda}}\tilde{P}\cdot\mathbf{1}_N\right\} \tag{8}$$

$$\tilde{l} = -\gamma\eta\tilde{E}\cdot\mathbf{1}_N + \eta(\gamma-1)\tilde{P}\cdot\mathbf{1}_N + \eta\tilde{w}, \tag{9}$$

with aggregate price $\tilde{P} = \bar{\beta}'\tilde{p}$ *and* $Q \equiv \left[\hat{\Omega}'\left(\theta\Phi^{-1} - I\right) + D\left(1 - \theta + (\theta-\varepsilon)\frac{\bar{\beta}}{\bar{\lambda}}\right)\right]$.

[3] The nominal rigidity set-up is close to the Calvo setting (similar as Rubbo, 2020) and the solution of the sectoral price vector (Eq. 6) is the same under this alternative price setting.

Proofs are provided in Online Appendix A.1.

Three effects are responsible for the propagation of shocks in this economy: (1) the I-O structure, Ω and $\hat{\Omega}'$, (2) price stickiness, Φ, and (3) elasticity of substitution in production, θ. All types of shocks propagate in the I-O economy and impact sectoral prices through these three effects. In particular, the sectoral price change vector can be expressed as:

$$\tilde{p} = \Theta^{-1}\left\{-A_z\tilde{z} + A_\beta\tilde{\beta} + A_E\tilde{E}\cdot\mathbf{1}_N\right\}, \tag{10}$$

with $\Theta = [I - \frac{\theta^{-1}}{1+\theta^{-1}\eta}\Phi(I-\Omega\Phi)^{-1}D_\alpha F]$,[4] and

$$A_z \equiv \Phi(I-\Omega\Phi)^{-1}D_\alpha\left[D_\alpha^{-1} - \frac{1-\theta^{-1}}{1+\theta^{-1}\eta} - \frac{1-\theta^{-1}}{1+\theta^{-1}\eta}(I-\hat{\Omega}')^{-1}\hat{\Omega}'\right],$$

$$A_\beta \equiv \frac{\theta^{-1}}{1+\theta^{-1}\eta}\Phi(I-\Omega\Phi)^{-1}D_\alpha(I-\hat{\Omega}')^{-1}D_{\bar{\beta}/\bar{\lambda}},$$

$$A_E \equiv \frac{\theta^{-1}(1+\gamma\eta)}{1+\theta^{-1}\eta}\Phi(I-\Omega\Phi)^{-1}D_\alpha.$$

Θ^{-1} corresponds to the general equilibrium multiplier, which comes from nominal wage responses that further affect prices. It captures higher order transmission of shocks in the economy. By ignoring Θ^{-1}, A_z, A_β, and A_E capture the sensitivity of sectoral prices to sectoral TFP, sectoral demand, and aggregate expenditure shocks, respectively.

(1) The I-O Structure. All shocks propagate upstream and downstream through the supply chain. On the one hand, shocks transmit downstream through $(I-\Omega)^{-1}$, the Leontief inverse matrix. Mathematically, this matrix equals the geometric summation of the input matrix Ω and captures the direct as well as indirect uses of inputs in the production network. Thus, the Leontief inverse matrix captures how sectoral price changes propagate downstream through costs.[5] On the other hand, shocks transmit upstream through $(I-\hat{\Omega}')^{-1}$, the sale-based Leontief inverse matrix. It reflects the upstream propagation of shocks and reflects how changes in sales propagate upstream through demand.

(2) Price Stickiness. Price rigidity directly affects the response of prices to marginal costs. The I-O structure amplifies price stickiness due to strategic complementarity, and price rigidity restricts the downstream pass-through of prices. Eq. 6 shows that Φ plays an important role in the sectoral price responses to cost changes. Indeed, $(I-\Omega\Phi)^{-1}$ is the price-flexibility-adjusted Leontief inverse matrix. Similar to the Leontief inverse matrix, it reflects the downstream propagation of shocks through the input matrix Ω. However, price rigidity has no direct effect on the upstream pass-through of prices, but it indirectly affect the upstream propagation through the general equilibrium multiplier Θ^{-1}.

(3) Elasticity of Substitution. The elasticity of substitution affects price responses to shocks if labor markets are segmented across sectors. Specifically, it generates no direct impact on prices (according to Eq. 6), but indirectly through sectoral nominal wage adjustments.

As discussed in the literature on the micro origin of macro fluctuations (e.g. Atalay, 2017; Horvath, 2000), a lower elasticity of substitution across sectoral products (as production inputs) leads to greater sectoral comovement. Empirical estimates of this elasticity are very low, suggesting that sectoral products are complements (see Atalay, 2017). Eq. 10 indicates that a lower elasticity of substitution generates greater sectoral price response to all types of shocks. The sensitivity values given by A_z, A_β and A_E decrease with θ.

One notable result is that TFP shocks only propagate downstream in the Cobb-Douglas setting (i.e. $\theta = 1$, $\varepsilon = 1$).[6] Nonetheless, in a CES setting, sectoral TFP shocks also propagate upstream. In addition, a reduction in θ amplifies both the upstream and downstream propagation of TFP shocks. This has an intuitive explanation: suppose both sector i and sector k supply intermediate inputs to sector j. If the input elasticity of sector j, θ_j, is large, sector j can easily substitute towards product i if p_k increases, which weakens the impact on sector j's price. If, instead, θ_j is small, sector j has limited ability to substitute its inputs away from k, and the effect on p_i is larger. Simply put, the transmission of shocks across sectors is stronger when the flexibility of adjusting the input structure is weaker, which is the case when the elasticity of substitution is low.

Sectoral Price Response to Aggregate Expenditure Shocks. Eq. 10 also shows that the sensitivity of the sectoral price changes to the aggregate expenditure shock follows,

$$\Psi^* \equiv \frac{\partial p}{\partial E} = \underbrace{\Theta^{-1}}_{\text{GE Multiplier}} \underbrace{\frac{\theta^{-1}(1+\gamma\eta)}{1+\theta^{-1}\eta}}_{\Delta \text{ real wage}} \underbrace{\Phi(I-\Omega\Phi)^{-1}\alpha}_{\text{direct pass-through}}. \tag{11}$$

The GE multiplier contains higher order transmission of shocks, which is dominated by the direct pass-through term. The response of real wages is homogeneous across sectors. Thus, the cross-sectional sectoral price distribution mostly depends

[4] $F \equiv \left[(I-\hat{\Omega}')^{-1}Q + \left(\theta\Phi^{-1} - I\right) - \eta(\gamma-1)\left[I + \frac{1}{\eta(\gamma-1)}(I-\hat{\Omega}')^{-1}D\left(\frac{\bar{\beta}}{\bar{\lambda}}\right)(1-\varepsilon)\right]B\right]$. And, B is an $N \times N$ matrix with each row being $\bar{\beta}'$.

[5] For example, a TFP shock of a supplier j affects the price of customer i. The direct impact of the shock depends on the input share of production j in the production of i (captured by ω_{ij}). The indirect impact of the shock may depend on a third sector k that uses product j and supplies sector i, which is captured by $\omega_{ik}\omega_{kj}$.

[6] In a Cobb-Douglas setting, the $\hat{\Omega}'$ term in A_z disappears.

on the direct pass-through factor

$$\Psi \equiv \Phi(I - \Omega\Phi)^{-1}\alpha, \tag{12}$$

which corresponds to the price response to sectoral nominal wages. And the i-th entry of Ψ is denoted as ψ_i.[7] Furthermore, as shown by Eq. 10, the sensitivity of prices to aggregate TFP shocks (captured by A_z) is influenced by several factors, including Ψ. Notably, given the relatively greater impact of aggregate demand shocks on price setting compared to aggregate supply shocks, we focus on Ψ to investigate the connection between the I-O structure and the sectoral price changes in Section 4.

Moreover, Online Appendix B discusses the aggregate price response to shocks. The I-O structure attenuates the aggregate price impact of aggregate expenditure shocks, thereby amplifying monetary non-neutrality. This result has been discussed by various papers on price rigidity in an I-O economy (see Afrouzi and Bhattarai, 2022; La'O and Tahbaz-Salehi, 2022; Rubbo, 2020). Fundamentally, it is the strategic complementarity in firms' price-setting behavior that amplifies monetary non-neutrality. Intermediate inputs in the I-O structure generate a substantial amount of strategic complementarity (see Nakamura and Steinsson, 2010).

Finally, it is noteworthy that segmented labor markets are crucial to generating a price impact of shocks.

Lemma 1. *If labor markets are not segmented, the solution to first order shows that*

1. *the elasticity of substitution has no effect on price changes,*
2. *shocks do not impact prices through upstream propagation.*

As shown in Online Appendix A.3, in a unified labor market, the wage rate does not depend on the Domar weight. Thus, prices are independent of the elasticity of substitution. Moreover, aggregate expenditure shocks and sectoral TFP shocks affect prices through downstream propagation only, while sectoral demand shocks have no price impact. However, empirical analyses in Section 4 show that demand shocks affect sectoral prices through both upstream and downstream propagation. Thus, a segmented labor market is important for generating price change patterns that are consistent with the data.

3. Data

This section provides a detailed explanation of the industry-level data used to test the model's implications on sectoral price setting and response to various shocks, including the process of matching industries across different data sources. Further details are provided in Online Appendix C.

3.1. I-O Structure, price stickiness and prices

I-O Structure. The make-use tables of the I-O Accounts created by the Bureau of Economic Analysis (BEA) are used to estimate the economy's I-O structure, as well as labor share α_i and consumption preference β_i.[8]

Most of the empirical analysis is based on the detailed I-O tables, and these are referred as detailed industries or I-O detailed industries. Roughly speaking, detailed industries correspond to 6-digit NAICS industries. However, the I-O tables at the detailed industry level is reported every 5-years with long lag, with the most recent ones from 2012. Overall, 337 detailed industries are matched with price and price stickiness data for our analysis.

The quantitative exercises in Section 5 are based on a model calibrated to a broader set of industries, which is referred to as industry groups, which correspond to 3-digit NAICS industries. At the industry group level, the BEA reports the make-use tables from 1997 to 2020 at an annual frequency. These tables feature 71 industry groups, and we identify 66 that can be merged with the price and stickiness data used in the rest of the empirical analysis.

Price Stickiness. Estimates of the frequency of price change by industry are from Pasten et al. (2020), which the authors kindly provided to us. In taking the model to the data, each sector's ϕ_i is set to be equal to these estimated frequency of price changes. These estimates are based on the micro data underlying the U.S. Producer Price Index (PPI), and are reported by detailed industry in the 2002 I-O tables. For this reason, our empirical analysis is based on the detailed industries in the 2002 tables. There are frequency of price change estimates for 341 detailed industries, and 337 of those are matched to an adequate price index. These 337 detailed industries form the sample for our empirical analysis. The production network is estimated using the flows reported in the 2002 I-O tables using only those 337 detailed industries. Based on the 2002 I-O tables, these 337 industries account for 60% of total value added in the economy, and 73% of value added excluding the federal government. In addition, estimates of the frequency of price change for broader industry groups are obtained by collapsing the detailed industry frequency estimates using industry sales as weights. Because some of the industry groups

[7] Our empirical analysis will be based on the direct pass-through factor Ψ, which is constructed using the data described in Section 3. Using the same data and calibrated values of the parameters, estimates of Ψ^* can also be constructed (using the same elasticity of substitution parameter for all sectors). The values of Ψ and Ψ^* are similar, and almost perfectly correlated across sectors. Since all of our analysis is based on differences in ψ_i across sectors, this suggests that incorporating the GE multiplier and real wage factor would make little difference.

[8] The BEA report a "make" table and a "use" table that consists of industry-commodity production and usages. The "make" and "use" tables are converted to the industry-by-industry I-O matrix following the approach of Pasten et al. (2020). The tables also report the total sales, value added, and labor compensation of each sector, along with other variables relevant to the national income accounts.

do not have a relevant frequency estimate available, our list of estimated frequencies is augmented with estimates from the Consumer Price Index (CPI) used in Nakamura et al. (2018) and Luo and Villar (2021b).

Sectoral Prices. Sectoral prices are taken from the Bureau of Labor Statistics (BLS)'s Producer Price Index (PPI) program. As mentioned above, 337 detailed industries are matched with relevant PPI industry prices. To analyze industry groups, the method used by Baqaee and Farhi (2022) is followed, where PPI series are matched to slightly more detailed industries, and price changes are computed by industry group as a weighted average of the corresponding PPI price changes with industry sales used as weights. Further details on the price construction are provided in Online Appendix C.1.

Employment and Wages. Measures of wages and employment are taken mostly from the BLS' Current Employment Statistics (CES, also known as the establishment survey), which publishes estimates of payroll employment, hours, and average hourly earnings. Employment is measured as total payroll employment by industry, and wages are measured using average hourly earnings for production and nonsupervisory workers.

To perform the quantitative analysis for the broader industry groups, it is necessary to use measures of wages and employment beyond the CES, as some industry groups are not covered by the CES. For those industry groups, the Quarterly Census of Employment and Wages (QCEW) is used. The QCEW collects counts of employment and total earnings for all workers covered by the unemployment insurance system, and these are available for all NAICS industries as narrow as 6-digit. More details are provided in Online Appendix C.2.

3.2. Measures of shocks

In order to test the price responsiveness of different sectors to aggregate demand shocks, monetary policy shocks estimated with the high-frequency approach of Swanson (2021) are used. These shocks are constructed based on changes in interest rates and asset prices in a short period surrounding scheduled Federal Open Market Committee (FOMC) announcements. The shocks are decomposed into separate components corresponding to policy rates, forward guidance, and large-scale asset purchases (LSAP), and these shocks are considered separately. The shocks are available for the period 1991–2019, with about eight observations per year, each corresponding to an FOMC meeting. Observations in each quarter are summed to create a quarterly series in our analysis. An important advantage that these shocks have over the monetary shocks constructed by Romer and Romer (2004) is that they cover the zero lower bound period between 2009 and 2015. Because many of the industries in our sample only have PPI data starting in 2003, extending the sample past 2009 is very helpful.

Additionally, the upstream and downstream propagation of shocks are tested, or the degree to which shocks in one industry affect prices in another industry through production network linkages, as predicted by the model in Proposition 1. To perform this analysis, demand and supply shocks must be measured by industry. Thus, the trade and TFP shocks utilized by Acemoglu et al. (2016a) are used as our source of sectoral shocks.

Trade shocks are constructed as the change in Chinese import penetration by industry, which is calculated by taking the negative of the change in import value from China as a share of the size of the U.S. market.[9] Since changes in Chinese imports are potentially correlated with various U.S. industry factors, an instrumental variable approach is employed. Specifically, the trade shock is instrumented by Chinese exports to other developed countries. This approach is frequently used in the extensive literature on the "China trade shock," which has found numerous effects of growing imports from China on various aspects of the U.S. economy and society.[10] Trade shocks are constructed using the trade and market size data featured in Acemoglu et al. (2016b) and Autor et al. (2019). In addition, TFP shocks are constructed using the change of TFP measured in the NBER-CES manufacturing database (Becker et al., 2021), following Acemoglu et al. (2016a). Finally, note that these shocks can only be constructed for manufacturing industries. As a result, this analysis is restricted to manufacturing industries. Online Appendix C.3. presents further details.

With the data available, annual measures for these different shocks are obtained for 266 detailed I-O industries for the period 1991–2014. Although our main analysis is based on annual data, we also consider shocks based on changes in prices and trade patterns over longer periods of time, as "long-difference" versions of these shocks. For example, the "long-difference" version of trade shocks are changes in Chinese import penetration over five years, for a time sample covering 1991–2011. This follows some of the literature on Chinese import competition (such as Acemoglu et al., 2016a; 2016b; Jaravel and Sager, 2022). The longer differences can potentially smooth through some of the factors that drive year-to-year changes in trade patterns and prices that might represent noise from the perspective of our analysis.

4. Empirical analysis

This section presents the results of our empirical analysis. Balke and Wynne (2000) were the first to evaluate how the network structure affects the cross-sectional distribution of prices, although in a flexible price setting. Following this line of work, further investigation is conducted on the interaction between the network structure, price rigidity, and price setting.

[9] Chinese import penetration is defined as the value of imports from China as a share of the size of the U.S. market (industry shipments plus net industry imports, measured in an initial period which in our case is 1991) for a particular industry: $\text{Trade}_{j,t} = -\Delta \frac{\textit{U.S. Imports from } \text{China}_{j,t}}{\textit{U.S. market } \text{size}_j}$.

[10] To cite just a few examples in this literature: Acemoglu et al. (2016b); Autor et al. (2013, 2019); Jaravel and Sager (2022). Jaravel and Sager (2022) study the effect of increased trade with China on consumer prices in the United States. We instead focus on how these changes to trade patterns, by affecting demand in different industries, propagate to affect production prices according to the production network of the economy.

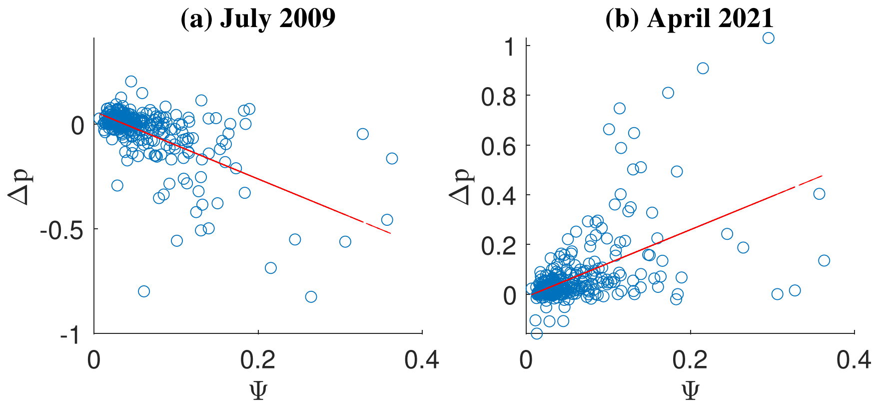

Fig. 1. Sectoral Price Change and Price Sensitivity-Ψ: Snapshot. Note: Each dot represents one subsector at the detail industry level. Panel (a) corresponds to the depths of the Great Recession. Panel (b) corresponds to the early stages of the pandemic recovery.

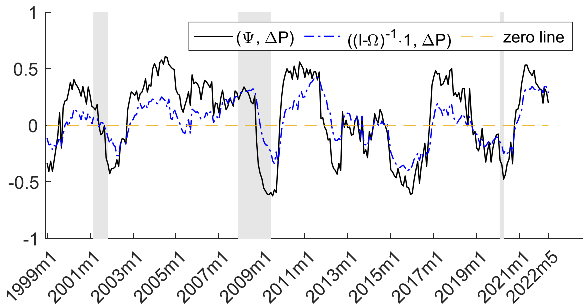

Fig. 2. The Correlation Between Sectoral Price Changes and Price Sensitivity-Ψ Over Time. Note: The correlation between sectoral price changes and the price sensitivity measure ψ_i at monthly frequency and the detailed industry level is plotted using the solid line, while the correlation between sectoral price changes and $(I-\Omega)^{-1}\cdot\mathbf{1}$ is plotted using the dash line. Grey areas highlight recessions.

A series of tests are conducted to examine whether sectoral prices respond to aggregate and sectoral shocks in a way that is consistent with the model predictions, and to assess the presence of upstream and downstream propagation of shocks on sectoral prices.

4.1. The distribution of price changes and the network structure

The evidence that the network structure affects the cross-sectional distribution of price changes is first examined. As discussed in Section 2, Eqs. 10 and 11 demonstrate that Ψ captures the sensitivity of sectoral price changes to aggregate shocks, reflecting both the network structure and price rigidity. As a result, co-movement of sectoral prices with the ψ_i's is expected, although this relationship may be obscured by the presence of sectoral shocks. This suggests that the cross-sectional distribution of sectoral price changes should correlate with the distribution of ψ_i. For instance, following an aggregate expenditure shock, a highly dispersed distribution of ψ_i would likely lead to a similarly high-dispersed distribution of price changes. This prediction is empirically investigated through two exercises.

The first exercise analyzes the cyclicality of the correlation between sectoral price changes and Ψ. According to our model, the correlation should be positive during periods of demand growth and negative during contractions, indicating a procyclical relationship. To conduct this analysis, estimates of Ψ and price changes at the detailed industry level are used. The Ψ estimates are based on the 2002 BEA I-O tables and are held constant at their 2002 values. Sectoral price changes are 12-month log price changes from January 1999 to May 2022. As a snapshot, Fig. 1 presents a scatterplot of Δp against Ψ at two specific time periods. In Panel (a), which corresponds to the depths of the Great Recession in July 2009, a strong negative correlation is evident between sectoral price changes and Ψ. Conversely, in Panel (b), corresponding to the early stages of the pandemic recovery in April 2021, a strong positive correlation is apparent between Δp and Ψ. Moreover, Fig. 2 displays the correlation between sectoral price changes and Ψ over time using a black solid line. The correlation is highly procyclical and tracks the cyclical movements of aggregate price levels in general. The dashed blue curve represents the correlation between Δp and $(I-\Omega)^{-1}\cdot\mathbf{1}$ and illustrates the impact of the I-O structure alone. A comparison between the solid and dashed curves suggests that both sectoral price rigidity heterogeneity and the I-O structure play significant roles in shaping the distribution of sectoral price changes.

To more rigorously evaluate the cyclicality of the correlation between price changes and Ψ, the relationship with employment changes is investigated. Specifically, the correlation between ψ_i and the log of detailed industry prices over a

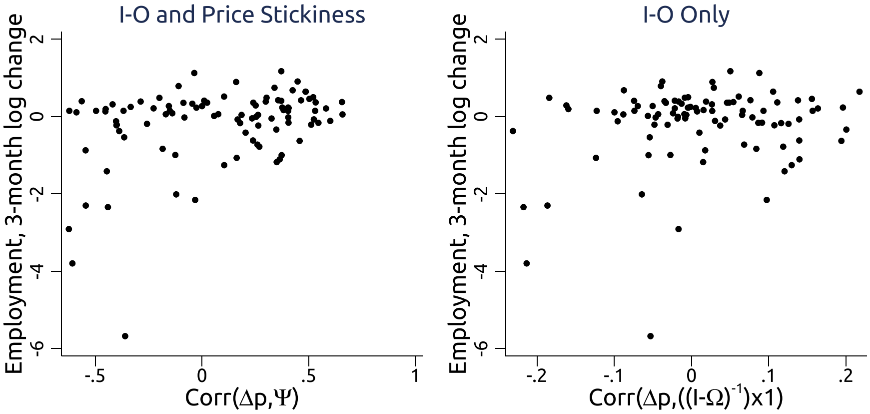

Fig. 3. The Correlation Between Sectoral Price Changes and Price Sensitivity-Ψ V.S. Employment Growth. Note: This figure illustrates the relationship between the correlation (Δp, Ψ) at the detailed industry level and the employment change measure for the entire industry sample across quarters. Each data point represents the results for a particular quarter.

3-month period, resulting in a quarterly series, is calculated, and an employment measure for the 337 detailed industries in the sample is constructed.[11] Fig. 3 presents a scatter plot of the correlation between Ψ and Δp against log changes in our measure of industry employment. Despite the fact that the changes in employment are usually modest over the periods analyzed, there is a noticeable positive correlation between the variables.[12] In particular, the recessionary periods in which employment declined the most clearly featured a negative correlation between price changes and Ψ. Furthermore, a comparison of the left and right panels of the figure suggests that the input-output structure and the degree of price rigidity both contribute to shaping this relationship.

The second exercise studies whether moments of the distribution of sectoral price change correlate with those of Ψ over time. The data for this exercise consists of measures of ψ_i of the broader industry groups from 1997 to 2020 at annual frequency.[13] For price changes, the moments of the price change distribution are first calculated by industry groups each month. These monthly moments are then averaged within each year to construct annual moments of the price change distribution, which are compared to the annual moments of the ψ_i distribution for each year. The moments being compared include the standard deviation, the absolute value of skewness, and the kurtosis.[14] It is important to note that price flexibility is constant over time, while the I-O structure is time-varying. Thus, this exercise highlights the role of the I-O structure in shaping the price change distribution.

Fig. 4 presents a scatterplot of moments of Δp distribution against those of ψ_i and demonstrates how the evolution of the network structure affects price change patterns over time. The results suggest a positive relationship for the standard deviation, skewness, and kurtosis measures. However, various sectoral shocks are likely to be important in shaping the distribution of price changes in practice, which could obscure the relation with the network distribution. Additionally, estimates of the kurtosis of price changes, or of any distribution, are challenging to obtain accurately in small samples, which may affect the empirical relation for kurtosis shown in Fig. 4. Nevertheless, the overall evidence suggests that the network structure has an influence over the distribution of price changes over time.

Overall, the two exercises confirm that the I-O structure has a significant impact on the shape of the price change distribution. Our finding is in line with research on the interaction between the sectoral structure and the price change distribution. First, Balke and Wynne (2000) find that an input-output economy with flexible prices can generate the observed positive correlation between inflation and skewness of sectoral price changes. Therefore, the observed moments of the price change distribution do not purely reflect sluggishness in the adjustment of individual prices in response to shocks. Moreover, recent work by Cotton and Garga (2022) shows that the shift in industrial composition contributes to the reduction in monthly frequency of price change, since the economy shifts from primary and secondary industries toward service industries.

Besides providing some evidence to support the model's predictions, these patterns are also relevant to the literature on higher order moments of the price change distribution. For example, studies such as Baley and Blanco (2021) and

[11] The employment measures is based on changes in employment among industries that remain in the sample. This helps deal with the fact that some industries enter the sample after others.

[12] Because our sample of industries over-represents manufacturing industries relative to the overall economy the cycle implied by this employment measure is somewhat different from the overall U.S. economic cycle. Notably, much of the early part of our time sample sees a steady decline in employment as manufacturing employment was declining during this period.

[13] The more aggregated industry groups instead of the detailed industries are used for this analysis because estimates of the I-O tables are available at the annual frequency for industry groups, but only every five years for detailed industries.

[14] The absolute value of skewness is chosen as the relevant third moment, because the skewness of the price change distribution changes signs over time depending on the direction of shocks. However, the skewness of ψ_i is always positive.

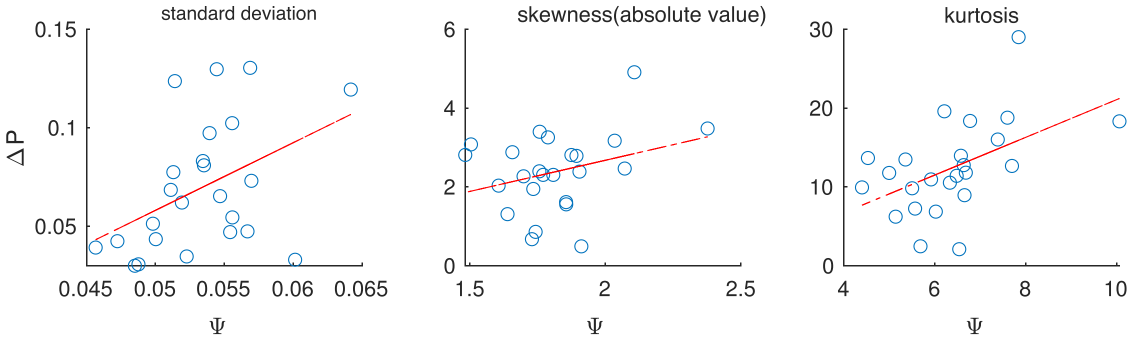

Fig. 4. Moments of the Price Change Distribution and the Price Sensitivity (ψ_i) Distribution. Note: This figure illustrates the relationship between the moments of the price change distribution and the price sensitivity distribution at the annual frequency for the period 1997–2020. Each dot on the graph represents the moments of the two distributions for a specific year at the broader industry group level.

Alvarez et al. (2016) find that moments such as the dispersion and kurtosis of the adjustment distributions of individual economic agents provide important information about how the overall economy adjusts to aggregate shocks. And, most of the studies that use moments of price changes to evaluate monetary non-neutrality or sticky price models are abstracted from the production network structure (see for example Costain and Nakov, 2011; Luo and Villar, 2021a; Midrigan, 2011; Nakamura and Steinsson, 2008, and many others). According to our model, the I-O linkages across sectors can shape the distribution of sectoral price changes, and the empirical correlations presented suggest evidence to support this hypothesis. This implies that the structure of the economy's production network could matter for interpreting information from the shape of the distribution of price changes. In this way, the observed price change distribution reflects more than the sluggish price-setting behavior of firms.[15]

4.2. Responses of sectoral prices to monetary policy shocks

This section aims to assess the consistency between the model-implied sensitivities Ψ and the sensitivity of sectoral prices to monetary policy shocks. This prediction is taken to the data by estimating the price response of the 337 I-O detailed categories to the monetary shocks constructed by Swanson (2021). The price response is estimated using local projections following Jordà (2005), based on the following sets of regressions:

$$\pi^k_{t-1,t+h} = \alpha + \beta^k_h \eta_t + \sum_{j=1}^{3} \delta^j \pi^k_{t-j} + \sum_{j=1}^{3} \gamma^j \eta_{t-j} + \beta^{Controls} X_t + \varepsilon_t, \tag{13}$$

for $h = 0, \ldots, 12$. $\pi^k_{t-1,t+h}$ is the change in the log price level for detailed industry k between period $t-1$ and $t+h$, π^k_t is the log change in price k between t and $t-1$, and η_t is the exogenous monetary policy shock. X_t is a vector of controls, which include credit spreads and changes in commodities prices.[16] The regression is run separately for each detailed industry on quarterly data for all periods available in each industry. We are interested in the sets of parameters β^k_h, which give the cumulative price response of industry k after h quarters. To allow for the possibility that the price response reverts at least partially to zero before 12 quarters, for each industry the β^k_h with largest magnitude beyond $h = 4$ is kept.

Fig. 5 shows scatter plots between the industry's ψ and the peak β_h, for the three different monetary shocks estimated by Swanson (2021). Clearly, the forward guidance shock produces the most significant negative relation between industry's ψ and the peak impulse response. This is consistent with the model's predictions: the industries with the most price sensitivity to aggregate shocks see their prices decline the most in response to this identified monetary shock. However, when estimated using the policy rate and LSAP shocks, the relationship is much weaker. Additionally, in Online Appendix F, Figure F.2 plots the impulse responses of aggregate price levels, including core PCE prices and core goods PPI, to the different shocks to determine which shocks are informative for aggregate demand relevant to prices. Similar to the sectoral level price analysis, both price indexes show a modest decline in response to the forward guidance shock. This finding reassures that

[15] Papers that use empirical estimates of higher moments to draw inference about aggregate responses to shocks, such as Alvarez et al. (2016) and Baley and Blanco (2021), focus on the distribution of individual and not sectoral responses. Furthermore, Alvarez et al. (2016) estimate the kurtosis of price changes controlling for sectoral heterogeneity. Despite the fact that sectoral factors may not directly influence the distribution of price changes or adjustments among individual firms, our findings still have some relevance. Our results demonstrate how inter-sector input-output linkages can impact the distribution of price changes across sectors. Given that similar linkages exist among individual firms, our analysis implies that these linkages may also have an impact on the distribution of adjustments among individual firms.

[16] Studies such as Gertler and Karadi (2015) have shown that a key source of transmission of monetary shocks is through credit costs. In addition, commodity prices are important costs for the manufacturing industries that compose a large share of our sample, and commodity prices are likely also affected by financial conditions. This leads us to control for credit spreads and commodity prices in the local projections, but results are broadly similar if no controls are used.

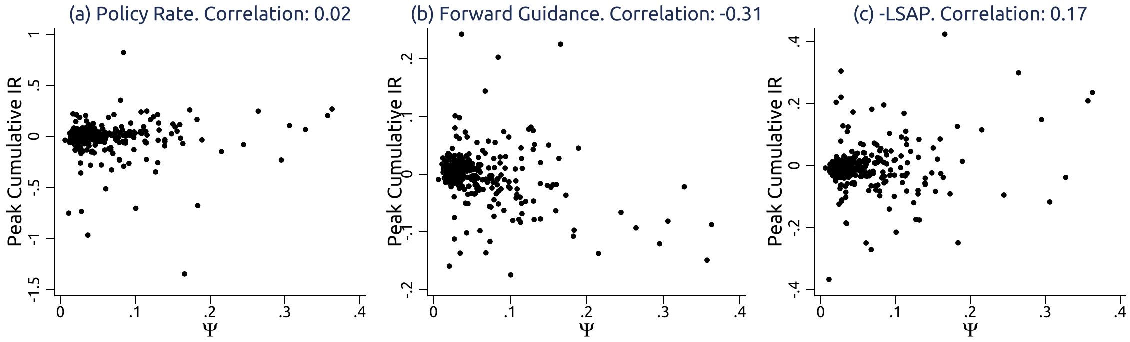

Fig. 5. Cumulative Price Response to Monetary Shocks and Price Sensitivity-Ψ. Note: This figure presents the relationship of the price sensitivity measure ψ_i and the peak of the cumulative price response β_h^i for the three monetary shocks estimated by Swanson (2021). Each dot represents one subsector at the detail industry level. In panel (c), the sign of the LSAP factor is flipped, so that an increase of the factor corresponds to a tightening of monetary policy, similar to the other two factors. One outlier is excluded from panels (a) and (c) for better illustration. The full sample scatter plot is presented in Online Appendix Figure F.1. For the full sample, the correlation using the policy rate factor is 0.05, while the correlation using the LSAP factor is 0.03.

the forward guidance shock produces more negative industry-level impulse responses for industries with a large Ψ as seen in Fig. 5, providing support for the model's predictions.

While results suggest that the expected relation between theoretical and empirical price sensitivity does not hold for all types of monetary shocks, it notable that the forward guidance shock produces the predicted relation. And we have the following reasons to focus on this shock. First, as mentioned in Section 3, many of the industries in our sample have price data available only after 2003, making the zero lower bound period between 2009–2015 especially important to estimate the impulse responses. Thus, the decomposition of shocks carried out by Swanson (2021) into policy rate, forward guidance, and LSAP components seems particularly important. Policy rates obviously did not change while at the ZLB, and unsuprirsingly the policy rate shocks are smaller during this period. Moreover, LSAP programs are difficult to interpret by the general public. In contrast, forward guidance shocks not only displayed significant variation in the zero lower bound period, but also likely represent changes to demand that are perceived to be persistent by markets, and are therefore more likely to be important for price setting. It is therefore not surprising to observe results with forward guidance shocks, while not seeing them with the other monetary shocks.[17]

It is also worth highlighting from Fig. 5 that many sectoral prices respond positively even to the forward guidance shock, which is contrary to what is expected. This positive response of certain prices to contractionary monetary shocks is often referred to as the "price puzzle," and has been extensively studied in the literature. Our analysis covers the response up to four years after a shock, which is longer than the horizon over which the price puzzle is usually observed. Furthermore, some of the positive responses estimated may be due to noise, as the estimates are not always very precise. However, it is also possible that certain industries face demand or financing conditions that make them more likely to respond positively to monetary shocks. Previous research has already shown that there is considerable dispersion in the response of sectoral prices to monetary shocks (see Balke and Wynne, 2007). In a production network model with capital requirement constraints, some firms will raise prices in response to a monetary tightening or lower prices after a monetary loosening, as shown by Mandel et al. (2019).

Overall, we find some evidence in support of the model's prediction about which sectors should be most responsive to aggregate demand shocks. However, the ambiguity of how prices in general respond to these monetary shocks makes the evidence less than fully compelling.

4.3. Propagation of shocks through the network structure

Now turning to the testing of the model's predictions on the propagation of shocks through the production network. Up to this point in the section, examination has been carried out to determine whether the key network structure vector explains how sectoral prices respond to aggregate shocks, and the results are in line with this hypothesis. This subsection investigates how shocks specific to certain sectors affect the prices of other sectors that are connected to them through the production network. To this end, "upstream" and "downstream" shocks are constructed as linear combinations of the shocks faced by all sectors, with coefficients determined by the production network.

In particular, the propagation of trade and productivity shocks are examined, which represent important industry-specific demand and supply shocks that are likely to affect price-setting. The shocks identified by Acemoglu et al. (2016a) and

[17] We also carry out this analysis with the monetary shocks estimated by Nakamura and Steinsson (2018) and Jarociński and Karadi (2020), who also use high-frequency identification. Jarociński and Karadi (2020) estimate separate policy rate and "information" components, where the information component represents news revealed about the FOMC's expectations about the economy. Scatter plots similar to those are presented in Figure F.3 in the Online Appendix, but do not find the expected relation between impulse response and Ψ across industries. These shocks mostly also produce counter-intuitive effects on aggregate prices as shown in the Online Appendix Figure F.4.

Acemoglu et al. (2016b) are relied upon, and the analysis is limited to 266 manufacturing detailed industries where the necessary data is available (as mentioned in Section 3).

The measures of upstream and downstream shocks are constructed based on the model solutions using the measures of shocks at the detailed industry-level. According to Eq. 10, sectoral demand shocks affect prices through $\Theta^{-1}A_\beta$, while sectoral supply shocks affect prices through $\Theta^{-1}A_z$. Sectoral price sensitivity to sectoral demand and supply shocks ($\partial\tilde{p}/\partial\tilde{\beta}$ and $\partial\tilde{p}/\partial\tilde{z}$) can be expressed as

$$\frac{\partial\tilde{p}}{\partial\tilde{\beta}} = \frac{\theta^{-1}}{1+\theta^{-1}\eta}\left[\underbrace{\Phi D_\alpha D_{\bar{\beta}/\bar{\lambda}}}_{own} + \underbrace{\Phi\Omega\Phi D_\alpha D_{\bar{\beta}/\bar{\lambda}}}_{Downstream\_Prop} + \underbrace{\Phi D_\alpha \hat{\Omega}' D_{\bar{\beta}/\bar{\lambda}}}_{Upstream\_Prop}\right] + \text{higher order propagation}, \tag{14}$$

$$\frac{\partial\tilde{p}}{\partial\tilde{z}} = \underbrace{\Phi}_{own}\left(I - \frac{\theta-1}{\theta+\eta}D_\alpha\right) - \frac{\theta-1}{\theta+\eta}\underbrace{\Phi D_\alpha\hat{\Omega}'}_{Upstream\_Prop} + \underbrace{\Phi\Omega\Phi}_{Downstream\_Prop}\left(I - \frac{\theta-1}{\theta+\eta}D_\alpha\right)$$
$$+\text{higher order propagation}, \tag{15}$$

where the "own" term captures the direct effect from shocks of the sector itself, the "Downstream_Prop" term captures the impacts from shocks to its suppliers; the "Upstream_Prop" terms captures the impacts from shocks to its customers. Higher order propagation terms, such as Ω^n with $n > 1$, are ignored. Correspondingly, the following three import shock variables are constructed

$$Own^{Trade} = \Phi D_\alpha D_{\bar{\beta}/\bar{\lambda}} * (\text{import shock}), \tag{16}$$

$$Down^{Trade} = \Phi\Omega\Phi D_\alpha D_{\bar{\beta}/\bar{\lambda}} * (\text{import shock}), \tag{17}$$

$$Up^{Trade} = \Phi D_\alpha \hat{\Omega}' D_{\bar{\beta}/\bar{\lambda}} * (\text{import shock}), \tag{18}$$

and the following three TFP shock variables

$$Own^{TFP} = \Phi * (\text{TFP shock}), \tag{19}$$

$$Down^{TFP} = \Phi\Omega\Phi * (\text{TFP shock}). \tag{20}$$

$$UP^{TFP} = \Phi D_\alpha \hat{\Omega}' * (\text{TFP shock}). \tag{21}$$

These calculations consider only the direct I-O linkages between sectors and not the indirect effects arising from input industries' input structure, for example. This can be thought of as a first-order approximation to the model-implied propagation of shocks. Additionally, the matrix Φ is adjusted for annual frequency of price change to match the annual data used for these regressions.

The constructed shocks are similar to the ones in Acemoglu et al. (2016a). To compare, measures of shocks from Acemoglu et al. (2016a) (labeled "AAK") are also considered, which include higher-order transmissions but ignore price rigidity:

$$Own^{Trade,AAK} = \text{import shock}, \tag{22}$$

$$Down^{Trade,AAK} = (I-\Omega)^{-1}\Omega * (\text{import shock}), \tag{23}$$

$$UP^{Trade,AAK} = (I-\hat{\Omega}')^{-1}\hat{\Omega}' * (\text{import shock}). \tag{24}$$

Upstream and downstream TFP-AAK shocks are defined in the same way, applying the log change in TFP to the equations above.

Moreover, the trade and TFP shocks are standardized by dividing them by their respective standard deviation, following Acemoglu et al. (2016a). Importantly, this standardization is implemented before computing the own, upstream and downstream shocks. As Acemoglu et al. (2016a) note, this ensures the estimated regression coefficients are comparable in the case of the AAK shocks, as they represent the effect of a one-standard deviation increase in an industry's own shock (for the own shock) or of a one-standard deviation increase in the shock of all customers or suppliers of an industry. Note that this comparability does not necessarily apply for the shocks derived from our model, as heterogeneous price rigidity lowers

Table 1
Propagation of Sectoral Trade Shocks, Annual.

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Own, Lag1	-0.017	-0.017	-0.001	0.008	0.008	0.005
	(0.016)	(0.011)	(0.008)	(0.021)	(0.016)	(0.011)
Own, Lag2	0.003	0.003	-0.006	-0.016	-0.016	-0.006
	(0.022)	(0.020)	(0.008)	(0.018)	(0.013)	(0.010)
Upstream, Lag1	0.159***	0.159	0.039***	-0.011	-0.011	0.059**
	(0.053)	(0.119)	(0.014)	(0.286)	(0.091)	(0.029)
Upstream, Lag2	0.074	0.074	0.038**	0.151	0.151***	0.036
	(0.055)	(0.050)	(0.016)	(0.256)	(0.056)	(0.024)
Downstream, Lag1	0.786***	0.786***	0.330*	0.582**	0.582***	0.547*
	(0.298)	(0.173)	(0.172)	(0.239)	(0.140)	(0.325)
Downstream, Lag2	0.554*	0.554***	0.502***	0.265	0.265*	0.531*
	(0.320)	(0.168)	(0.163)	(0.218)	(0.143)	(0.303)
p(Sum Own Lags=0)	0.646	0.650	0.442	0.778	0.773	0.913
p(Sum Upstream Lags=0)	0.002	0.165	0.000	0.079	0.163	0.000
p(Sum Downstream Lags=0)	0.000	0.000	0.000	0.001	0.001	0.000
Observations	4053	4053	4053	3912	3912	3912
R2	0.301	0.301	0.084	0.354	0.354	0.082
Value Added Weights	Yes	Yes	No	Yes	Yes	No
Clustered SEs	No	NAICS4	No	No	NAICS4	No

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is one-year changes in sectoral prices. Own, Upstream, and Downstream trade shocks are constructed according to the model. In the IV regressions, the trade shocks are instrumented using Chinese trade penetration in countries other than the U.S., as previously described. Different columns correspond to different regression specifications: whether observations are weighted according to sectoral value added, and whether standard errors are clustered at the 4-digit NAICS level. All regressions include time (year) fixed effects. P-values are reported for the separate tests of whether the sum of coefficients on lags of particular types of shocks (own, upstream, downstream) are significant.

the importance of different industries' shocks to different degrees. The significance of the effect of the model-implied upstream and downstream shocks are still tested. Finally, the original changes in trade and TFP are winsorized by setting the values in the lowest 1 percent to equal the first percentile, and setting the values in the highest 1 percent to equal the 99th percentile. Again, this is applied before computing the upstream and downstream shocks.

The Propagation of Import Shocks. Instruments for the own, upstream, and downstream trade shocks are constructed using exports from China to developed countries following the literature on the China trade shock. The regressions for our analysis take the following form:

$$\Delta p_{i,t} = \delta_t + \sum_{k=1,2} \psi_k \Delta p_{i,t-k} + \beta_k^{Own} \mathrm{Own}_{i,t-k}^{Trade} + \beta_k^{Up} \mathrm{Up}_{i,t-k}^{Trade} + \beta_k^{Down} \mathrm{Down}_{i,t-k}^{Trade} + \epsilon_{i,t}. \quad (25)$$

In the annual regressions, time periods are years, and price changes are calculated as the log change in prices from December to December of the previous year. Year fixed effects (δ_t) are included to control for aggregate factors, and two lags of each explanatory variable to allow for autocorrelation in inflation and for shocks to have delayed price effects. In the 5-year regressions (which are denoted as "long-difference"), periods are the changes between the following years: 1991, 1996, 2001, 2006, 2011. The log price change between the December value of each of those years are used, and shocks are based on changes in import penetration between those years. The long-difference regressions do not include lags of price changes or trade shocks, and the model implied shocks are constructed under flexible price setting with $\Phi = I$.[18] Also, similar sets of regressions using the AAK shocks are performed, both annual and long-difference. Simple ordinary least squares regressions and two-stage least squares regressions using the instrumental variable approach are used for all the regression sets featuring the trade shocks.

Table 1 shows the results of the regressions involving the annual model-derived trade shocks. The table also reports the p-value for the test on the sum of the two lag coefficients for each type of shock being zero. This is trying to capture the significance of the total effect over two years. Based on this, upstream and downstream trade shocks both have significant effects on sectoral price inflation, as predicted by the model. Note that because the trade shock is constructed as the negative of the change in trade exposure, the positive coefficient means that an increase in trade exposure lowers prices, which is as expected. Our baseline results weigh observations based on industry-level value added in 2000. Results show that the own shock generally does not have a significant effect, while the upstream and downstream shocks have significant effects. Moreover, the sum is significant under all specifications for the downstream shocks. However, the upstream shocks become marginally insignificant when standard errors are clustered, although in the IV regression the coefficient on the second lag

[18] To construct the shocks based on 5-year changes in TFP and trade, price rigidity is ignored as it is unlikely to matter significantly over such a long horizon.

Table 2
Propagation of Sectoral Trade Shocks, Annual with AAK Construction.

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Own, Lag1	0.003	0.003	0.001	0.002	0.002	-0.000
	(0.003)	(0.002)	(0.001)	(0.012)	(0.002)	(0.002)
Own, Lag2	-0.000	-0.000	0.001	-0.004	-0.004	0.002
	(0.003)	(0.003)	(0.001)	(0.011)	(0.006)	(0.002)
Upstream, Lag1	0.015**	0.015***	0.003*	0.005	0.005	0.004*
	(0.007)	(0.004)	(0.002)	(0.008)	(0.004)	(0.002)
Upstream, Lag2	0.008*	0.008*	-0.000	0.008	0.008**	-0.001
	(0.005)	(0.005)	(0.002)	(0.007)	(0.003)	(0.002)
Downstream, Lag1	0.032***	0.032***	0.020***	0.024***	0.024***	0.014**
	(0.007)	(0.006)	(0.005)	(0.008)	(0.007)	(0.006)
Downstream, Lag2	0.016**	0.016***	0.016***	0.014*	0.014***	0.021***
	(0.007)	(0.005)	(0.005)	(0.008)	(0.004)	(0.006)
p(Sum Own Lags=0)	0.481	0.482	0.165	0.676	0.719	0.300
p(Sum Upstream Lags=0)	0.006	0.008	0.186	0.131	0.047	0.271
p(Sum Downstream Lags=0)	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4053	4053	4053	3912	3912	3912
R2	0.323	0.323	0.086	0.377	0.377	0.086
Value Added Weights	Yes	Yes	No	Yes	Yes	No
Clustered SEs	No	NAICS4	No	No	NAICS4	No

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is one-year changes in sectoral prices. Own, Upstream, and Downstream trade shocks are constructed according to the AAK procedure, which essentially weighs the shocks faced by other sectors according to input-output requirements without considering differential price stickiness across sectors. In the IV regressions, the trade shocks are instrumented using Chinese trade penetration in countries other than the U.S., as previously described. Different columns correspond to different regression specifications: whether observations are weighted according to sectoral value added, and whether standard errors are clustered at the 4-digit NAICS level. All regressions include time (year) fixed effects. P-values are reported for the separate tests of whether the sum of coefficients on lags of particular types of shocks (own, upstream, downstream) are significant.

of the upstream shock is large and significant, while the coefficient on the first lag is close to zero. Finally, the IV estimates of the downstream and upstream shock coefficients are generally slightly smaller than the OLS estimates.[19]

Table 2 presents our regression results with annual AAK shocks. Again relying on the tests for the sum of coefficients on the lagged shocks, significant positive effects on inflation from downstream shocks are found in almost every specification. The upstream shocks have a smaller effect, which is significant in the OLS regressions but not in most of the IV regressions. Own shocks have an estimated effect that is close to zero and statistically insignificant, as in the regressions with the model-based shocks.

To quantify the effects of these shocks, the focus is on the regressions with AAK shocks, as the interpretation of those coefficients is more straightforward. The model-implied shocks are calculated using the estimates of price rigidity so that sectors' shocks are effectively discounted based on their degree of price rigidity. This makes it more difficult to interpret the meaning of a model-implied shock of a specific magnitude. Looking at Table 2, the estimates based on a weighted IV regression imply that a one standard deviation increase in import penetration in a sector's suppliers would reduce inflation over two years by about 3.8 log points cumulatively (the sum of the downstream lag coefficients).[20] Similarly, a one standard deviation shock to a sector's buyers would lower inflation over two years by about 1.3 log points. To give a sense of how important these effects are, the unweighted standard deviation of the sectoral inflation rate over two years is about 12 log points. This suggests that the propagation of sectoral shocks through the production network is a meaningful source of variation for inflation across sectors.

Furthermore, Table 3 shows the results of the long-difference regressions. Because these regressions use 5-year changes, they include fewer time observations and thus a smaller sample. Both upstream and downstream shocks have a consistently significant effect on inflation in the IV regressions and the weighted OLS regressions, while the own trade shock has a very small and insignificant effect. The results of the long-difference regressions with the AAK shocks are shown in Table 4 and are mostly similar. Significant effects of the upstream and downstream shocks are found again, although the downstream shocks are insignificant in the IV regression with clustered standard errors. Another difference is that here the own shocks have a positive effect on inflation that is significant in the IV and weighted OLS regressions. The own trade shock is significant only in these regressions.

Overall, it is noteworthy that we consistently find strong and significant downstream propagation of demand shocks on sectoral inflation with both the model-implied and the more simple to construct AAK shocks. Additionally, weaker yet

[19] When standard errors are clustered, they are clustered by an input-output table category that roughly corresponds to 4-digit NAICS industries. The 266 manufacturing detailed industries are split into 53 such clusters.

[20] The way to think about a one standard deviation shock to suppliers is to consider all other sectors facing, on average, a one standard deviation increase in import penetration, with the average calculated using weights based on the downstream sector's input shares. A one standard deviation shock to buyers can be thought of in an analogous way.

Table 3
Propagation of Sectoral Trade Shocks, 5-year changes.

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Own	0.073	0.073	-0.004	0.029	0.029	0.038
	(0.257)	(0.155)	(0.042)	(0.260)	(0.178)	(0.042)
Upstream	1.024***	1.024*	0.178*	0.926**	0.926*	0.261***
	(0.333)	(0.529)	(0.091)	(0.387)	(0.558)	(0.086)
Downstream	3.907**	3.907***	0.930	4.319***	4.319***	1.289*
	(1.955)	(0.677)	(0.636)	(1.538)	(0.740)	(0.706)
Observations	662	662	662	662	662	662
R2	0.229	0.229	0.100	0.227	0.227	0.086
Value Added Weights	Yes	Yes	No	Yes	Yes	No
Clustered SEs	No	NAICS4	No	No	NAICS4	No

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is five-year changes in sectoral prices. Own, Upstream, and Downstream trade shocks are constructed according to the model. In the IV regressions, the trade shocks are instrumented using Chinese trade penetration in countries other than the U.S., as previously described. Different columns correspond to different regression specifications: whether observations are weighted according to sectoral value added, and whether standard errors are clustered at the 4-digit NAICS level. All regressions include time (five-year period) fixed effects.

Table 4
Propagation of Sectoral Trade Shocks, 5-year changes with AAK Construction.

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Own	0.060**	0.060**	0.014	0.158***	0.158*	0.043***
	(0.029)	(0.026)	(0.012)	(0.014)	(0.082)	(0.012)
Upstream	0.164***	0.164***	0.009	0.190***	0.190***	0.021
	(0.019)	(0.023)	(0.019)	(0.013)	(0.028)	(0.013)
Downstream	0.315***	0.315***	0.154***	0.163***	0.163	0.138***
	(0.088)	(0.048)	(0.058)	(0.033)	(0.142)	(0.040)
Observations	662	662	662	662	662	662
R2	0.501	0.501	0.120	0.399	0.399	0.102
Value Added Weights	Yes	Yes	No	Yes	Yes	No
Clustered SEs	No	NAICS4	No	No	NAICS4	No

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is five-year changes in sectoral prices. Own, Upstream, and Downstream trade shocks are constructed according to the AAK procedure, which essentially weighs the shocks faced by other sectors according to input-output requirements without considering differential price stickiness across sectors. In the IV regressions, the trade shocks are instrumented using Chinese trade penetration in countries other than the U.S., as previously described. Different columns correspond to different regression specifications: whether observations are weighted according to sectoral value added, and whether standard errors are clustered at the 4-digit NAICS level. All regressions include time (five-year period) fixed effects.

noticeable propagation of upstream shocks is found, although the statistical significance is more sensitive to the regression specification. Note also that because all of the regressions use year fixed effects, the results do not reflect the effect of movements in aggregate demand. Taken together with our results on the shocks derived from our model, this analysis suggests that the network structure plays a key role in how shocks to certain industries propagate to other industries in affecting their prices. To the extent that the identification strategy behind the IV regressions is valid, these results are telling us how exogenous demand throughout the production network causally affects price changes in specific sectors.

The Propagation of TFP Shocks. Turning to the analysis of TFP shocks, we do not know of an instrumental variables strategy to identify exogenous movement in productivity, so these effects should not be thought of as causal. The regressions take the same form as the trade shock regressions (Eq. 25), except that the shocks are constructed based on changes in TFP. Table 5 presents the regression results, using both the model-based and AAK shocks. In the weighted regressions, it is found that own TFP shocks have a significant negative effect on price inflation after two periods. Downstream effects are always significant in the weighted regressions, but not in the unweighted ones. Finally, insignificant effects of upstream TFP shocks are also found. This is consistent with the model, which predicts a weaker upstream propagation than downstream propagation, according to Eq. 15. Notice that the upstream propagation of TFP shocks disappears when $\theta = 1$ (in a Cobb-Douglas setting).

The coefficients in Table 5 imply that a one-standard deviation increase of own-industry shock on TFP decreases the cumulative inflation in two years by 0.8 log points (again focusing on the results of the weighted regressions in column 5). However, a one-standard deviation increase in TFP among a sector's suppliers leads to a decline of 3.4 log points in cumulative inflation in that sector over two years. This is again a substantial effect, similar in magnitude to the effect of the Chinese import penetration. However, an increase in TFP among a sector's buyers has a negligible and insignificant effect on inflation in that sector.

The results of the long-difference regressions with TFP shocks are presented in Table 6. Here, only the AAK construction of upstream and downstream shocks are used, because the model implied and the AAK constructions are very close when $\Phi = I$ (that is, when price stickiness is disregarded). Again, the downstream shocks have a large and significant negative

Table 5
Propagation of Sectoral TFP Shocks, Annual.

	(1) Model	(2) Model	(3) Model	(4) AAK	(5) AAK	(6) AAK
Own, Lag1	-0.000	-0.000	0.000	-0.002	-0.002	-0.001
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.001)
Own, Lag2	-0.005**	-0.005***	-0.005**	-0.006***	-0.006***	-0.003**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Upstream, Lag1	-0.042	-0.042	0.002	-0.004	-0.004	0.002
	(0.030)	(0.033)	(0.009)	(0.005)	(0.005)	(0.002)
Upstream, Lag2	-0.012	-0.012	-0.006	0.001	0.001	0.000
	(0.023)	(0.010)	(0.008)	(0.004)	(0.002)	(0.001)
Downstream, Lag1	-0.044***	-0.044***	0.002	-0.018***	-0.018***	-0.000
	(0.012)	(0.014)	(0.010)	(0.005)	(0.006)	(0.003)
Downstream, Lag2	-0.046***	-0.046***	-0.008	-0.016***	-0.016***	-0.004
	(0.012)	(0.008)	(0.010)	(0.005)	(0.004)	(0.003)
p(Sum Own Lags=0)	0.098	0.231	0.101	0.002	0.046	0.048
p(Sum Upstream Lags=0)	0.163	0.138	0.711	0.685	0.656	0.230
p(Sum Downstream Lags=0)	0.000	0.000	0.695	0.000	0.000	0.238
Observations	4184	4184	4184	4184	4184	4184
R2	0.371	0.371	0.074	0.361	0.361	0.075
Value Added Weights	Yes	Yes	No	Yes	Yes	No
Clustered SEs	No	NAICS4	No	No	NAICS4	No

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is one-year changes in sectoral prices. Own, Upstream, and Downstream trade shocks are constructed according to the model or the AAK procedure, as denoted in the heading. Different columns correspond to different regression specifications: whether observations are weighted according to sectoral value added, and whether standard errors are clustered at the 4-digit NAICS level. All regressions include time (year) fixed effects. P-values are reported for the separate tests of whether the sum of coefficients on lags of particular types of shocks (own, upstream, downstream) are significant.

Table 6
Propagation of Sectoral TFP Shocks, 5-year changes with AAK Shocks.

	(1) Unclustered SE	(2) Clustered SE	(3) Unweighted
Own	-0.052**	-0.052***	-0.026**
	(0.026)	(0.013)	(0.012)
Upstream	-0.061**	-0.061***	-0.009
	(0.030)	(0.018)	(0.015)
Downstream	-0.174***	-0.174***	-0.059***
	(0.046)	(0.049)	(0.023)
Observations	662	662	662
R2	0.454	0.454	0.159
Value Added Weights	Yes	Yes	No
Clustered SEs	No	NAICS4	No

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is five-year changes in sectoral prices. Own, Upstream, and Downstream trade shocks are constructed according to the AAK procedure. Different columns correspond to different regression specifications: whether observations are weighted according to sectoral value added, and whether standard errors are clustered at the 4-digit NAICS level. All regressions include time (five-year period) fixed effects.

effect. The own shocks have a small negative effect. These regressions also find a negative effect for the upstream TFP shock, and it is significant in the weighted regressions. However, the effect of the upstream shock is much smaller than that of the downstream shock.

Overall, the findings provide evidence in support of the model's prediction that productivity shocks propagate downstream along the supply chain, whereas the shocks propagate upstream with less intensity.

5. A Quantitative Analysis of the post-Pandemic inflation

The COVID-19 pandemic has led to a surge in inflation in 2021 and 2022, with inflation reaching levels not seen in about 40 years in the United States. Multiple factors have contributed to this surge, including various types of shocks and the propagation of shocks through the supply chain. It is observed in the data that sectors with the larger price increases tend to have higher levels of price flexibility, higher levels of ψ_i and are relatively upstream, as illustrated in Online Appendix Figure F.5.

In this section, a modified version of the model in Section 2 is solved to investigate the high inflation episode of 2021–2022. The model is generalized by including capital inputs, while the supply of both labor and capital at the sectoral-level are exogenous. Unlike the first-order approach presented in Section 2, the model is solved at true levels; and the equilibrium conditions of the model are presented in Online Appendix D. The objective of this exercise is to disentangle sectoral supply and demand shocks and conduct counterfactual analyses to investigate the roles of the I-O structure, price rigidity and elasticity of substitution.

In terms of details, responses of the economy from 2020 to 2022 are modeled with a combination of supply and demand shocks, in a similar fashion to Baqaee and Farhi (2022). First, supply shocks are considered to be changes in the economy's production possibilities and labor. On the one hand, the pandemic imposed production restrictions due to voluntary or mandated policies, such as lock-downs, business closures, and social distancing. Relatedly, certain sectors are naturally less capable of accommodating remote work productively. These changes are captured through estimation of sectoral TFP (z_i) changes. On the other hand, the same type of restrictions reduced the supply of labor. Labor supply (l_i) is set as exogenous and calibrate it using employment data. Second, the aggregate demand shock is considered as the aggregate expenditure (E) change, which is calibrated using nominal GDP data.[21] Finally, households' preferences over different consumption goods changed before and during the pandemic. This can be captured by the change of expenditure share (β_i). The sectoral demand shock is calibrated using sectoral consumption data.

5.1. Calibration

Parameters. The quantitative model is calibrated at the industry group level containing 66 industries. 2019 BEA I-O tables are used to construct the I-O matrix. The BEA tables are also used to calculate labor and capital shares (α_{Li} and α_{Ki}) as well as the consumption share at steady state ($\bar{\beta}_i$). The degree of an industry's price adjustment flexibility is still captured by ϕ_i. Since the deviation of the economy at 2022Q1 from two-years ago is examined, $\phi_i = 1 - (1 - FPA_i)^{24}$ is calculated as a two-year price adjustment frequency, where FPA_i is sector i's monthly frequency of price adjustment as measured by Pasten et al. (2020).

All the elasticities of substitution are homogeneous across sectors. Following the literature (e.g. Atalay, 2017; Baqaee and Farhi, 2022, etc.), the elasticity of substitution across intermediates is set to be 0.2; and the elasticity of substitution between labor, capital and the intermediate input bundle is 0.6. The within-industry elasticity of substitution is set to 6 in order to match steady-state markups, following La'O and Tahbaz-Salehi (2022) and others. Lastly, household preferences are Cobb-Douglas.

Demand Shocks. The aggregate demand shock is calibrated to match the change of nominal GDP from its linear trend from 2016 to 2019. Sectoral demand shocks are calibrated to match the change in consumption shares from their 2019 annual average to shares of 2022 Q1 using the PCE data. The calibrated sectoral demand shocks are presented in Online Appendix Figure F.6.

Supply Shocks. Sectoral labor supply is calibrated based on the log difference between the level of sectoral employment of 2022 Q1 and the level of sectoral employment in 2019 Q4, using data from CES and QCEW (as discussed in Section 3). The calibrated employment change is illustrated in Online Appendix Figure F.6. Sectoral TFP shocks are calculated by solving the equilibrium system imposing the observed sectoral price changes.[22] Sectoral price changes are calculated as the observed sectoral price deviation at 2022 Q1 from their pre-pandemic log-linear trends of 2016–2019 (presented in Figure F.7 in Online Appendix F).

Finally, as a test of out-of-sample fit, the model implied sectoral wage changes are compared with the actual wage changes. The equilibrium wages are crucial in the model and have a strong connection to the equilibrium prices. It is therefore important to evaluate whether wages actually responded to the various shocks in a way that is consistent with the model. The actual wage change is constructed using wage data from CES and QCEW, as described in Section 3. The wage change is defined as the deviation from the pre-pandemic linear trend of 2016–2019, evaluated by sector.

5.2. Results and counterfactuals

This subsection discusses the model solution. First, the model's out-of-sample fit is checked to evaluate its performance. Figure F.8 in Online Appendix F shows a scatterplot of wage changes implied by the model against the actual wage changes. Overall, the model performs reasonably well in predicting the wage changes quantitatively.[23]

The estimated sectoral TFP shocks are listed in Online Appendix Figure F.6. In addition, Fig. 6 presents the scatter plot of the sectoral TFP and labor supply shocks against price adjustment frequency of each sector and their downstreamness.[24]

[21] A two-period model following Baqaee and Farhi (2022) can be set up as an alternative approach, considering the aggregate demand shock as a combination of monetary policy shocks and inter-temporal preference shocks. Targeting the nominal expenditure can result in the same solutions in the two-period model as the static model presented here.

[22] The endogenous variables of the equilibrium system of equations presented in Online Appendix D, including sectoral price changes, can be solved, given levels of exogenous shocks. Conversely, sectoral TFP shocks that satisfy the equilibrium system are solved, given the observed sectoral price along with the calibrated demand shocks and sectoral labor supply shocks. The system of non-linear equations is solved using the PETSc library developed by Argonne National Laboratory.

[23] The three outlier sectors are relatively small size sectors in terms of employment. The two at the bottom right corner are both energy related sectors. Employment declined significantly in these two industries (see Figure F.6 in Online Appendix) and remained depressed in early 2022, which drives the high wage increase in simulated data. However, the observed wage has declined. Many factors may contribute to the bad fit of these industries, such as idiosyncratic labor demand shocks, trade impacts or commodity price shocks.

[24] Downstreamness is measured using the vector of $[(I - \Omega)^{-2}\beta \circ \bar{\lambda}^{-1}]^{-1}$. This measure follows Antràs and Chor (2013) and captures how intensive is the product use as a direct input for final-use production. The measure increases with downstreamness.

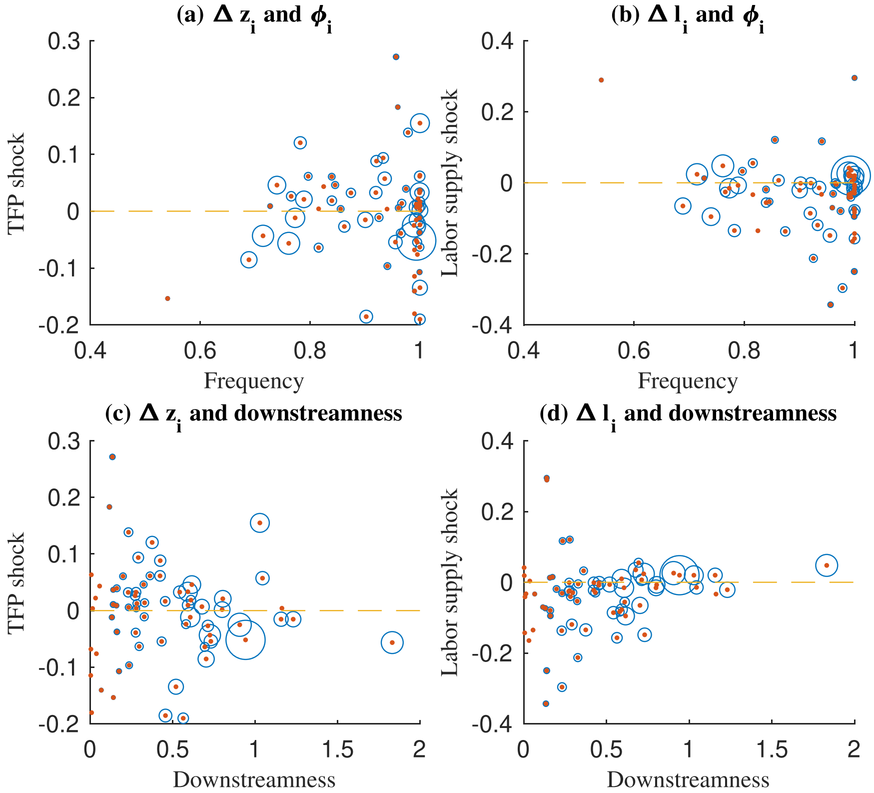

Fig. 6. Estimated Supply Shocks. Note: Panels (a) and (b) present the relationship between sectoral supply shocks and sectoral price adjustment frequency (ϕ_i). Panels (c) and (d) illustrate the relationship between sectoral supply shocks and measures of sectoral downstreamness. Sectoral price adjustment frequency is calculated at the 2-year flexibility level. Each dot represents one subsector at the broader industry group level. Size of blue circle reflects the relative size of $\beta' * \Psi$, which approximates the influence of sectoral shocks on aggregate inflation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
Inflation: I-O Economy V.S. Horizontal Economy.

	(1) All shocks	(2) TFP shock	(3) Labor supply shock	(4) Aggregate demand shock	(5) Sectoral demand shock
Bechmark-IO (IO-implied-shocks)	6.82%	2.84%	1.35%	2.62%	0.30%
Horizontal (Horizontal-implied-shocks)	6.82%	2.38%	2.06%	2.59%	0.47%
Horizontal (IO-implied-shocks)	5.36%	0.70%	2.06%	2.59%	0.47%

Note: The table presents the estimated inflation levels for an economy with the benchmark IO structure and a horizontal structure with no sectoral linkages. In the case of the horizontal economy, two sets of shocks are considered: one re-estimated using the horizontal structure (labeled as Horizontal-implied-shocks), and the other estimated by the benchmark IO model (labeled as IO-implied-shocks). Inflation under various shocks is separately reported in each column.

Panels (a) and (b) of Fig. 6 show that shocks are dispersed with little relation to frequency. Panel (c) of Fig. 6 shows that sectoral TFP shocks of upstream sectors are dispersed across a relatively wide range, while the shocks of the downstream sectors are concentrated in a smaller negative range. Panel (d) of Fig. 6 shows that upstream sectors experienced stronger negative labor supply shocks than downstream sectors.

To decompose the origin of the high inflation episode, several counterfactual analyses are conducted. First, the model is solved under various shocks separately, and results are compared with those under a horizontal structure, that is, without an I-O structure. The horizontal economy has $\Omega^H = 0$, $\alpha^H_{Li} = \alpha_{Li}/(\alpha_{Li} + \alpha_{Ki})$, $\alpha^H_{Li} + \alpha^H_{Ki} = 1$, and the same Φ and β as the I-O economy. Inflation of the horizontal economy is calculated through two separate approaches. First, TFP shocks in the horizontal economy are re-estimated following the same approach as the benchmark model. Notice that labor supply, aggregate demand and sectoral demand shocks are calibrated, thus are the same in the horizontal economy as in the I-O economy. Second, inflation of the horizontal economy is directly calculated using the I-O economy implied shocks. Accordingly, Table 7 presents the estimated inflation rate under various types of shocks in the Benchmark I-O economy, the horizontal economy with re-estimated shocks (horizontal-implied-shocks), and the horizontal economy with shocks estimated by the Benchmark I-O model (IO-implied-shocks). Online Appendix Figure F.9 presents the scatterplot of the I-O implied TFP shock against the horizontal-implied TFP shock.

As shown in the first row of Table 7, the aggregate price level is above its trend by 6.82% in the first quarter of 2022. About 42% of the high inflation comes from the reduction of production possibilities (captured by the TFP shock in the model). About 20% of the high inflation comes from labor supply reductions. Finally, 38% of the inflation rate is accounted for by the aggregate demand shocks. Sectoral demand shocks barely generate any aggregate price responses. Thus, the TFP shocks have a larger inflation impact than the other shocks. However, if instead the TFP shocks are estimated using a horizontal production structure, the contribution of the aggregate demand shock outweights that of the sectoral TFP shocks, as shown in the second row of Table 7. This finding implies that a mis-specified production network structure could lead to qualitatively different equilibrium results.

The noticeable discrepancies in estimation stem from the fundamentally different network structures of the I-O and horizontal economies, leading to differing effects of sectoral shocks on aggregate inflation in these two systems. The horizontal economy assigns a different level of influence to each sector's shock on aggregate inflation compared to the I-O economy.[25,26] Recall that both economies face the same level of calibrated demand shocks and sectoral labor supply shocks, with the TFP shocks estimated to match the observed price level. Given the different level of influence of each sector's shocks, the inflation contribution of the calibrated shocks is different in the two economies, and so are the TFP shock estimates. Results in Column 3 of Table 7 show that the contribution of labor supply shocks in the horizontal economy is larger than that of the I-O economy, although the inflation impact of demand shocks are similar in the two economies (Columns 4 and 5).[27] As a consequence, the inflation impact of the sectoral TFP shock of the horizontal economy must be smaller to match the same observed sectoral prices as the I-O economy, which is indeed observed in Column 2. Another interesting point is that the magnitude of the TFP shock estimated from the horizontal economy is larger than that of the I-O economy, by a magnitude of five basis points on average, as illustrated by Online Appendix Figure F.9. It is clear that the additional indirect network effect of TFP shocks appears in the I-O economy, but is absent in the horizontal economy. The indirect network effect further amplifies the aggregate impact of TFP shocks. As a result, the I-O economy needs a weaker TFP shock than the horizontal economy to achieve the same price levels.

The third row of Table 7 presents results of the horizontal economy using shocks implied by the benchmark I-O model. The comparison of the first and third rows shows that the I-O structure plays an important role in amplifying the price impact of shocks, in particular the TFP shocks. Indeed, without the I-O structure, inflation would be 21% lower than its observed level. From the perspective of the propagation of shocks, the I-O structure amplifies the aggregate price effect of TFP shocks and attenuates the effect of labor supply shocks.[28] Moreover, as will be discussed shortly, the I-O structure amplifies the distortion effect, which lowers production and increases inflation.

In addition, to study the role of the elasticity of substitution, a Cobb-Douglas economy of the model is solved (using shocks implied by the benchmark I-O model). The Cobb-Douglas economy has all elasticities of substitution equal to one, larger than those in the benchmark economy. The aggregate inflation of the Cobb-Douglas economy is 6.32%, smaller than 6.82% in the benchmark I-O economy. Thus, complementarity amplifies price responses, which is consistent with the discussion in Section 2.2.

Furthermore, to investigate the role of price rigidity, the model is solved with flexible prices (using shocks implied by the benchmark I-O model). The estimated aggregate inflation is 6.15%, again smaller than 6.82% in the benchmark I-O economy. On the one hand, price rigidity weakens the passthrough of both positive and negative shocks. However, the overall effect of

[25] For ease of exposition, consider results of Cobb-Douglas economies at the first order approximation and neglect the general equilibrium multiplier. On the one hand, the aggregate inflation influence vector of sectoral labor supply shocks can be captured by, $\pi_{\tilde{l}}^{IO} \equiv [\beta'\Phi(I-\Omega\Phi)^{-1}D_{\alpha_L}]'$ in the I-O economy and $\pi_{\tilde{l}}^{H} \equiv [\beta'\Phi D_{\alpha_L^H}]'$ in the horizontal economy, with the shock-implied inflation being $\pi_{\tilde{l}}^{IO'}\tilde{l}$ and $\pi_{\tilde{l}}^{H'}\tilde{l}$ correspondingly. It is clear that $\pi_{\tilde{l}}^{IO} \neq \pi_{\tilde{l}}^{H}$. Thus, the impact of labor supply shocks on inflation of the horizontal economy is different from that of the I-O economy. On the other hand, the aggregate inflation impact of sectoral TFP shocks can be captured by vectors, $\pi_{\tilde{z}}^{IO} \equiv [\beta'\Phi(I-\Omega\Phi)^{-1}]'$ and $\pi_{\tilde{z}}^{H} \equiv [\beta'\Phi]'$. It is straightforward to show that $\pi_{\tilde{z}}^{IO} > \pi_{\tilde{z}}^{H}$, due to the indirect network effect. Thus, when faced with the same TFP shock, the I-O economy experiences higher inflation compared to the horizontal economy. As a result, to achieve the same level of inflation, the I-O economy needs a smaller TFP shock than the horizontal economy.

[26] There are other ways to construct a counterfactual horizontal economy. However, there is no construction of horizontal economies that can simultaneously equalize all the influence vectors of shocks as those of the IO economy.

[27] As a complementary exercise, a roundabout economy is considered. The roundabout economy has the same parameter setting as the benchmark I-O economy, except that the input-output matrix is diagonal. Thus, each sector uses only intermediate inputs produced by its own sector. The linkages across sectors are shut-down. However, this exercise makes sure the input-share (α_L, α_K and $1-\alpha_L-\alpha_K$) stays the same as the benchmark economy. It turns out that the aggregate price responses to different shocks in this roundabout economy is very close to the horizontal economy presented here. Clearly, both the roundabout economy and the horizontal economy shut down the interconnection across sectors. However, even with the same input-share as the I-O economy, the roundabout economy generates different equilibrium results from the I-O economy. Therefore, it is the input-output linkages that plays an important role in the difference between the I-O and horizontal systems, rather than the adjusted input share.

[28] Consider the model of Section 2.1 with exogenous labor supply (i.e. $\eta = 0$) and a homogeneous labor market. Online Appendix B shows that the first order response of aggregate price to TFP shocks is $\beta'\Phi(I-\Omega\Phi)^{-1}$. The I-O structure amplifies the price effect of TFP shocks because $\beta'\Phi(I-\Omega\Phi)^{-1} > \beta'\Phi$. On the contrary, the first order response of the aggregate price to aggregate labor supply shocks is weaker in the I-O economy. However, the response to sectoral labor supply shocks depends on specific shock distribution, see proof in Online Appendix B.

passthrough depends on interplay between sectoral shocks and price rigidity.[29] On the other hand, price rigidity generates distortions in production and creates inflationary pressure at the aggregate level, as will be discussed next. Overall, price rigidity amplifies inflation.

Sectoral Distortion. Price adjustment frictions generate distortions across firms and sectors, which results in an inefficient reallocation of resources and lowers production (see Baqaee and Farhi, 2019; Bigio and La'O, 2020; Jones, 2013; Liu, 2019, etc.). There are two types of distortions in this economy: within-sector distortions and cross-sector distortions. First, price stickiness generates price dispersion within each sector, which reduces sectoral productivity (see Nakamura et al., 2018). Second, sectoral wedges between prices and marginal costs further result in an inefficient reallocation of resources across sectors, and these wedges compound through the I-O structure (see Bigio and La'O, 2020). Technical details are provided in Online Appendix E.

To a certain extent, distortions work like a negative TFP shock, which creates additional inflationary pressure. This effect can be seen directly from column 4 of Table 7. In an economy without price rigidity, inflation response to aggregate demand shock should be one-to-one, which is roughly 2.55%. The same is true in the current setting with price rigidity and exogenous factor supplies at first order (see Online Appendix B). As shown here, inflation response in the current sticky price setting is slightly larger than 2.55%, reflecting the distortion effect. Moreover, inflation in the I-O economy is larger than that in the horizontal economy, reflecting stronger distortion effect generated by the I-O structure.[30] Furthermore, it is also important to note that the Calvo price stickiness feature in the model generates larger distortion than would result from price setting under menu costs. Thus, the distortion effect shown here might be overestimated.

6. Conclusion

The I-O structure, price adjustment rigidity and the elasticity of substitution across products facilitate the propagation of shocks along the supply chain. In this paper, a standard price-setting model with a production network and price stickiness is used to derive a series of predictions about how sectoral prices respond to aggregate and sectoral shocks. Overall, the model's predictions find empirical support. Moreover, the high inflation episode of the Covid-19 pandemic recovery is investigated through a quantitative analysis. Various types of shocks during the pandemic are disentangled. We find that the I-O structure amplifies the pandemic related shocks, especially the sectoral TFP shocks, and contributes 21% of the observed inflation. Moreover, a mis-specified production network structure leads to qualitatively different equilibrium results.

Although we find that production network models can explain important patterns in sectoral price-setting, our analysis also points to some important topics for future research regarding this class of models. Two topics that seem particularly interesting are highlighted here. First, one limitation of our analysis is that the model is static while the data is based on changes in sectoral prices over time. Working with a static model (as in La'O and Tahbaz-Salehi, 2022, among others) enables us to derive predictions from the model solutions. However, this naturally abstracts from how the dynamic properties of shocks might interact with the production network to determine how shocks propagate to price changes. As this paper and others have shown, price setting in an I-O economy is much richer and more complicated than in a single sector or horizontal economy. Incorporating dynamics into these models (as presented by Afrouzi and Bhattarai, 2022) would help illustrate how the persistence and correlation of shocks interacts with the production network structure, and yield a rich set of testable predictions that could be taken to the data on price changes.

Second, the sticky price literature has long emphasized the importance of selection effect in price adjustment for the transmission of monetary shocks. However, all the existing papers that introduce I-O linkages in a sticky price setting do so by adopting Calvo-type price setting. In the Calvo setting, the frequency of sectoral price change is purely exogenous and does not move in response to aggregate or sectoral shocks. In a menu-cost setting, the frequency can endogenously respond to shocks and can depend on the I-O structure itself. This flexibility has been shown to be crucial to mediating the transmission of shocks to prices. Modeling price stickiness in this way in a production network model could both lead to different implications for monetary non-neutrality, and to additional predictions about how sectoral frequencies of price change vary over time and respond to shocks. Using price micro data, these kinds of predictions could further discipline the theory with respect to both the production network and price stickiness, which we believe represents a promising avenue for future research.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.05.004.

[29] Consider an extreme case, all sectors have perfect price adjustment flexibility except two, who are completely rigid in price setting. Suppose the two-sectors are equally important with the same aggregate price sensitivity factor. However, one sector faces a positive supply shock while the other sector has a negative supply shock. If the price rigidity assumption of the two-sectors is relaxed, the direction of the aggregate inflation change depends on the relative size of the positive and negative supply shocks of the two-sectors.

[30] Price rigidity generates two types of distortion effects in an I-O economy: an effect on aggregate TFP and an effect on the labor wedge. According to Bigio and La'O (2020), sectoral distortions have zero first order effects on aggregate TFP and non-zero first order effects on the labor wedge. Although sectoral distortions have zero first-order effects on TFP near efficiency (steady state), this effect is captured in our results by solving the model in levels and at large deviations from steady state.

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