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Rigid production networks☆

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ABSTRACT

This paper studies a production network model with quantity rigidities and informational frictions, where (i) firms may be restricted in how effectively they can adjust (some or all of) their intermediate input quantities in response to changes in the economic environment and (ii) they need to choose their quantities under incomplete information about the realizations of shocks. Our characterization results show that these two frictions lead to a reduction in aggregate output, as firms may find it optimal to rely more heavily on less volatile suppliers, even if it comes at the cost of forgoing more efficient ones. We also find that the interaction between informational frictions and quantity rigidities dampens the impact of productivity and aggregate demand shocks on aggregate output, while increasing the inflationary effects of positive shocks to nominal aggregate demand. The magnitudes of these effects depend on the distribution of the two frictions over the production network.

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1. Introduction

Firms in any modern economy rely on a wide range of goods and services for production, while simultaneously serving as input suppliers of other producers in the economy. For example, as documented by Bernard et al. (2022), the median firm in Belgium uses inputs from 53 suppliers and sells to 26 different customers. The extent of such firm-to-firm linkages can become significantly more skewed for larger firms, as a firm like Airbus works with roughly 12,000 different suppliers that provide products and services for flying and non-flying parts.

While clearly an integral part of the production process, supply chain linkages between different firms can function as a source of macroeconomic risk, as disruptions due to natural disasters (Carvalho et al., 2021), wars (Korovkin and Makarin, 2022), or foreign trade shocks (Dhyne et al., 2022) can escalate from localized events into broader disruptions. Not surprisingly then, an extensive (and growing) body of work in macroeconomics studies how the economy's production network can serve as a mechanism for propagation and amplification of shocks.[1]

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[1] For example, see Long and Plosser (1983) and Acemoglu et al. (2012). More recent examples include production network models with fairly general production functions (Baqaee and Farhi, 2019), endogenous technologies (Acemoglu and Azar, 2020), nominal rigidities (La'O and Tahbaz-Salehi, 2022; Rubbo, 2022), and extensive margin adjustments (Acemoglu and Tahbaz-Salehi, 2020; Baqaee and Farhi, 2021).

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However, this literature, for the most part, abstracts from two realistic frictions. First, the benchmark models of production networks assume that firms can adjust their input and output quantities frictionlessly in response to shocks. This is despite the fact that, in reality, many production processes, especially in manufacturing, require advance planning and setting up production lines that cannot be ramped up or down instantaneously. Similarly, while firms may be able to produce using different mixes of inputs, switching from one mix to another may require reorganizing the production process, a potentially costly and time-consuming endeavor. Yet another factor that may reduce firms' short-term ability to drastically adjust their production process in response to shocks is the presence of significant lead times in acquiring inputs: according to the Institute for Supply Management, in January 2023, the average lead time for obtaining production materials for manufacturing firms in the United States was 87 days. In the same month, the average lead time for acquiring capital inputs—such as machinery, plant equipment, software and the like—was 166 days, with 23% of firms facing lead times exceeding one year (Institute for Supply Management, 2023).

Of course, frictions in quantity adjustments may not be of first-order importance if firms can perfectly anticipate future shocks and can set up contingency plans accordingly. This brings us to the second friction missing from the benchmark models. Whereas benchmark models of production networks assume that firms make their production decisions under perfect information about all the shocks in the economy, this is not a realistic assumption either: at best, firms have only partial information about the wide range of supply and demand shocks that hit different parts of the economy.

The relevance of the above-mentioned frictions became more visible during the COVID-19 pandemic, as various industries experienced significant disruptions in their supply chains. For example, at the onset of the pandemic, U.S. automakers "underestimated demand for their products," and "expecting weak demand, they cancelled orders of semiconductors, an item with a long lead time and with a secular increase in demand from other industries" (Helper and Soltas, 2021). This led to significant disruptions and price increases in the motor vehicle sector in the later stages of the pandemic.

In this paper, we develop a model that incorporates quantity rigidities and informational frictions into an otherwise standard model of production networks, where (i) firms may be restricted in how effectively they can adjust their input quantities in response to changes in the economic environment, and (ii) they may have to choose those quantities with only incomplete information about the realizations of shocks. Specifically, we consider a multisector general equilibrium economy à la Long and Plosser (1983) and Acemoglu et al. (2012) in which firms are linked to one another via input-output linkages and are subject to industry-level productivity and aggregate demand shocks. Firms in each industry use Cobb-Douglas production technologies with constant returns to transform labor and intermediate inputs into output. Additionally, as in Baqaee and Farhi (2022), we allow for downward nominal wage rigidities. However, in a departure from the rest of the literature, we assume that firms make (some or all of) their intermediate input decisions in the presence of incomplete information about the realization of supply and demand shocks. This modeling approach has two key implications. First, it ensures that by the time the shocks are realized (or observed), certain input decisions made by the firms are sunk and hence cannot be adjusted. Second, while firms in our model are subject to quantity adjustment frictions, they nonetheless optimally plan their production in anticipation of future shocks (subject to their information sets).

As our main theoretical result, we provide a system of equations that (implicitly) characterizes equilibrium prices and quantities in terms of model primitives, namely, the realized supply and demand shocks, the economy's production network structure, each industry's set of rigid and flexible inputs, and the information sets of all firms in the economy. Despite being implicit, this characterization result captures the key economic forces that are active in the model. Specifically, it shows that, when deciding on their quantities under incomplete information, firms need to make forecasts about prices charged by their suppliers as well as the quantity demanded by their customers. As such, our characterization result highlights that equilibrium prices and quantities depend on firms' expectations of shocks both upstream and downstream their supply chains.

We then apply our implicit characterization result to three specific environments that lend themselves to closed-form solutions. As our first case study, we consider an economy consisting of only a single rigid industry subject to informational frictions, with the remaining industries capable of adjusting their quantities with no frictions. Focusing on such an environment allows us to identify the role played by quantity rigidities and informational frictions at each industry separately, and in particular, identify the industries that can act as production bottlenecks for the rest of the economy. We find that these two frictions result in a reduction in aggregate output. This is because when firms make their intermediate input decisions under uncertainty about the realizations of productivity shocks, they find it optimal to rely more heavily on less volatile suppliers, even if this comes at the cost of forgoing more efficient ones. Additionally, our result indicates that, all else equal, a rigid industry functions as a tighter "production bottleneck" for the entire economy if it is simultaneously (i) an overall large supplier in the economy and (ii) an important direct or indirect customer of other firms in the economy.

We then apply our results to study how incomplete information and the frictions in quantity adjustments—which we refer to as *real rigidities*—change the mapping from supply and demand shocks to aggregate output and inflation. We find that, in the presence of real rigidities and informational frictions, the first-order impact of productivity shocks is dampened compared to the fully flexible benchmark; that this dampening effect is stronger the higher the degree of real rigidities; and that the extent to which shocks to an industry propagate to aggregate outcomes depends on the size of the rigid industry and its exposure to the shock. As for shocks to aggregate demand, we find that, compared to the benchmark without informational frictions, the real effect of aggregate demand shocks is dampened, a positive demand shock is inflationary, and that the magnitudes of both effects depend on the exact position of the rigid industry in the production network.

We follow up these results by focusing on two other information structures: one in which all firms in the economy observe the same public signal, and a more general case with an arbitrary information structure (albeit for a simplified production network structure). Focusing on these environments, we show how the effect of real rigidities and informational frictions can build up over the production network.

We conclude the paper with a simple quantitative assessment of our model's implications.

Related Literature. Our paper belongs to the literature on production networks, which explores the implications of the disaggregated structure of the economy for aggregate, macroeconomic outcomes. In addition to the papers already mentioned, some of the more recent works in this literature include Bigio and La'O (2020), Liu and Tsyvinski (2023), and Baqaee and Farhi (2022). See Carvalho and Tahbaz-Salehi (2019) and Baqaee and Rubbo (2022) for recent surveys.[2] We contribute to this literature by relaxing two of the key standing assumptions in most production network models: that firms can make decisions under complete information and can frictionlessly adjust their intermediate input decisions in response to changes in the economic environment. We study how incomplete information together with frictions in quantity adjustments change the mapping from supply and demand shocks to aggregate output and inflation.

Our approach in using incomplete information in modeling frictions builds on earlier works, such as Mankiw and Reis (2002), Woodford (2003), and Maćkowiak and Wiederholt (2009), among others. For the most part, this literature relies on incomplete information as a source of *nominal* rigidities, with the assumption that firms set their nominal prices without complete information about the economy's fundamentals. In contrast to the bulk of this literature, firms in our framework are subject to *real* rigidities and choose their input quantities in the presence of incomplete information. As such, our paper is more closely related to Angeletos et al. (2016) and Angeletos and La'O (2020), who consider models in which firms' incomplete information about the shocks is a source of both real and nominal rigidities. Our point of departure from these two papers is our focus on how real rigidities arising from firms' incomplete information interact with the economy's production network structure.

More closely related to our work are two recent papers that also explore the role of incomplete information in the context of supply chains. Kopytov et al. (2022) develop a model of endogenous network formation to investigate how uncertainty about the productivity of suppliers impacts firms' choice of technology. As in our paper, one of the key tradeoffs faced by firms in their framework is that supply chain uncertainty induces firms to rely more heavily on less volatile inputs, even if this comes at the cost of forgoing more efficient one.[3] They key distinction, however, is in the two papers' modeling approach: Kopytov et al. (2022) assume that firms choose their production technology under incomplete information, but can flexibly adjust their quantity demand in response to shocks. As such, and given the assumption of constant returns, firms in their framework only need to form forecasts about their marginal costs. In contrast, firms in our framework are forced to make (some or all of) their quantity decisions prior to observing the shocks. As a result, they not only need to form forecasts about their upstream prices, but also about their downstream demand.

The second related paper is the contemporaneous work of Bui et al. (2023), who introduce informational frictions into a multi-country, multi-sector model with global value chains. As in our paper, firms do not observe the shocks and only have access to imperfect signals about productivities of various industries and countries. However, whereas Bui et al. (2023) assume that firms choose their primary inputs (e.g., labor) under incomplete information, firms in our model need to choose their intermediate inputs before learning the realizations of the shocks. This distinction is consequential: since in Bui et al. (2023) firms face no frictions in choosing their intermediate inputs, the equilibrium only depends on firms' expectations of their suppliers' decisions. In contrast, in our model, the equilibrium depends not only on firms' forecasts of their suppliers' forecasts, but also on their forecasts of their customers' forecasts.

Finally, our paper is related to the growing body of works that studies network interactions in the presence of incomplete information. Examples include Calvó-Armengol et al. (2015), de Martí and Zenou (2015), Bergemann et al. (2017), and Golub and Morris (2018). We complement this literature, which is mostly focused on reduced-form games over networks, by studying a micro-founded, general equilibrium macro model where firms' decisions and outcomes are interlinked with one another as a result of the economy's disaggregated production network structure.

Outline The rest of the paper is organized as follows. Section 2 sets up the environment and defines the equilibrium concept. Section 3 contains the main characterization result of the paper, where we show how informational frictions and real rigidities shape equilibrium prices and quantities. In Section 4, we consider a few special cases of the general model that lend themselves to explicit characterizations. We present a quantitative analysis of the model in Section 5. All proofs and some additional technical details are presented in the Online Appendix.

2. Model

In this section, we present a multisector model that forms the basis of our analysis. The model, which is in the spirit of general equilibrium models of Long and Plosser (1983) and Acemoglu et al. (2012), closely follows the framework in La'O

[2] Also see Barrot and Sauvagnat (2016), Boehm et al. (2019), and Carvalho et al. (2021) for empirical studies of the role of production networks in propagation and amplification of shocks.

[3] Also see Grossman et al. (2023) for a related mechanism in the context of global supply chains and in the presence of relationship-specific risk and country-wide supply disturbances.

and Tahbaz-Salehi (2022). As our main point of departure from the prior literature, we assume that firms may have to make some of their intermediate input quantity decisions under incomplete information about the realizations of shocks.

2.1. Firms and production

Consider an economy consisting of n industries indexed by $i \in \mathcal{N} = \{1, 2, \dots, n\}$. Each industry consists of two types of firms: (i) a unit mass of monopolistically-competitive firms, indexed by $k \in [0, 1]$, producing differentiated goods and (ii) a competitive producer whose sole purpose is to aggregate the industry's differentiated goods into a single sectoral output. The output of each industry can be either consumed by the households or used as an intermediate input for production by firms in other industries.

The monopolistically-competitive firms within each industry use a common constant-returns-to-scale technology to transform labor and intermediate inputs into their differentiated products. More specifically, the production function of firm $k \in [0, 1]$ in industry i is given by

$$y_{ik} = z_i \zeta_i l_{ik}^{\alpha_i} \prod_{j=1}^{n} x_{ij,k}^{a_{ij}}, \tag{1}$$

where y_{ik} is the firm's output, l_{ik} is the firm's labor input, $x_{ij,k}$ is the quantity of sectoral commodity j purchased by the firm, and z_i is an industry-specific productivity shock. The constant $\alpha_i > 0$ denotes the share of labor in industry i's production technology, $a_{ij} \geq 0$ parameterizes the importance of good j in the production technology of firms in industry i, and $\zeta_i = \alpha_i^{-\alpha_i} \prod_{j=1}^{n} a_{ij}^{-a_{ij}}$ is a normalization constant. As is standard in this literature, we summarize input-output linkages in this economy by matrix $\mathbf{A} = [a_{ij}]$, which with some abuse of terminology, we refer to as the economy's *input-output matrix*. We also define the economy's *Leontief inverse* as $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$, whose (i, j) element captures the role of industry j as a direct or indirect intermediate input supplier to industry i. Throughout the paper, we normalize the steady-state value of all (log) productivity shocks to 0, i.e., $\log z_i^{\mathrm{ss}} = 0$ for all i.

Given the production technology (1), the nominal profits of firm k in industry i are given by

$$\pi_{ik} = (1 - \tau_i) p_{ik} y_{ik} - w l_{ik} - \sum_{j=1}^{n} p_j x_{ij,k}, \tag{2}$$

where p_{ik} is the nominal price charged by the firm, p_j is the nominal price of industry j's sectoral output, w denotes the nominal wage, and τ_i is an industry-specific revenue tax or subsidy levied by the government.

As already mentioned, each industry also contains a competitive producer, which transforms the differentiated products produced by the unit mass of firms in that industry into a sectoral good using a constant-elasticity-of-substitution (CES) production technology, with elasticity of substitution $\theta_i > 1$:

$$y_i = \left(\int_0^1 y_{ik}^{(\theta_i - 1)/\theta_i} \mathrm{d}k \right)^{\theta_i/(\theta_i - 1)}.$$

The sole purpose of this producer is to ensure that each industry produces a single sectoral good, while at the same time allowing for monopolistic competition among firms within the same industry. Throughout the paper, we assume that the industry-specific tax in (2) is set to $\tau_i = 1/(1 - \theta_i)$. As is well-known, this choice undoes the effect of monopolistic markups and ensures that the distortions in the economy are not due to firms' market power.

2.2. Households

In addition to the firms, the economy consists of a representative household, with preferences

$$U(C, L) = \log C - \chi \frac{L^{1+1/\eta}}{1 + 1/\eta},$$

where C and L denote the household's consumption and total labor supply, respectively, η is the Frisch elasticity of labor supply, and $\chi > 0$ is a constant that parameterizes the representative household's disutility of labor supply. The representative household's final consumption basket is a Cobb-Douglas aggregator of the sectoral goods produced in theMONEC3487 economy,

$$C = \prod_{i=1}^{n} (c_i / \beta_i)^{\beta_i},$$

where c_i is the amount of good i consumed and $(\beta_1, \dots, \beta_n)$ are nonnegative constants that measure various goods' shares in the household's consumption basket, normalized such that $\sum_{i=1}^{n} \beta_i = 1$. The representative household's budget constraint is therefore given by

$$PC = \sum_{i=1}^{n} p_i c_i = w \sum_{i=1}^{n} \int_0^1 l_{ik} \mathrm{d}k + \sum_{i=1}^{n} \int_0^1 \pi_{ik} \mathrm{d}k + T,$$

where $P = \prod_{i=1}^{n} p_i^{\beta_i}$ is the nominal price of the household's consumption bundle, w denotes the nominal wage, π_{ik} is given by (2), and T denotes lump-sum transfers from the government. To ensure that the government's budget constraint is satisfied, we assume that $T = \sum_{i=1}^{n} \tau_i \int_0^1 p_{ik} y_{ik} \mathrm{d}k$.

Finally, we assume that the representative household is subject to the following cash-in-advance constraint:

$$PC = m,$$

where m denotes the nominal aggregate demand in the economy. In what follows, we interpret a decrease in m as a negative aggregate demand shock. While the most natural source of such a shock is a monetary policy shock (say, due to a reduction in money supply), as shown by Baqaee and Farhi (2022) in a simple dynamic extension of the model, a decrease in expected future output, an increase in nominal interest rate, an increase in the household's discount factor, or a decrease in future prices—which can be thought of as a proxy for forward guidance—can all generate effects that are isomorphic to a decrease in m.

2.3. Real rigidities and informational frictions

While the benchmark models of production networks assume that firms can adjust their input and output quantities in response to supply and demand shocks, in reality, many firms may have limited ability to do so, at least in the short run. For example, many production processes, especially in manufacturing, require advance planning, setting up production lines that cannot be ramped up or down instantaneously, or acquiring inputs with significant lead times.[4] Similarly, while firms may be able to produce using different mixes of inputs, switching from one mix to another may require reorganizing the production process, a potentially costly and time-consuming endeavor. Additionally, firms may not even have access to all the relevant information that would be necessary for adopting their production plans in response to economic disturbances.

We model the presence of such frictions by following Angeletos et al. (2016) and Angeletos and La'O (2020) and assuming that firms make (some or all of) their intermediate input decisions under incomplete information about supply and demand shocks. Specifically, we assume that the economy lasts for two periods, $t \in \{0, 1\}$. At $t = 0$, firms in industry i receive a common signal $\omega_i \in \Omega_i$ about the realizations of the supply and demand shocks (z, m), where $z = (z_1, \ldots, z_n)$. Given ω_i, each firm k in industry i chooses the intermediate input quantities $x_{ij,k}$ for any input $j \in \mathcal{R}_i$ at $t = 0$, where $\mathcal{R}_i \subseteq \mathcal{N}$ denotes the set of *rigid* inputs of industry i. The productivity and demand shocks are then observed by all firms at $t = 1$, which is when firms set prices, choose their labor input l_{ik}, and choose the remainder of their intermediate inputs, $\{x_{ij,k}\}_{j \in \mathcal{F}_i}$, where $\mathcal{F}_i = \mathcal{N} \setminus \mathcal{R}_i$ denotes the set of *flexible* inputs of industry i. Production and consumption also take place at $t = 1$.

A few remarks are in order. First, note that since firms choose their rigid intermediate inputs before the realization of shocks, these input choices are subject to a measurability constraint: $\{x_{ij,k}\}_{j \in \mathcal{R}_i}$ can be contingent on ω_i, but not on (z, m). While related, this measurability constraint on quantities is distinct from measurability constraints on nominal prices, which are a source of *nominal* rigidities as opposed to real ones.[5] Second, it is immediate to see that if either (i) all firms observe perfectly informative signals about the realizations of the shocks, i.e., $\omega_i = (z, m)$ for all i; or (ii) all inputs of all firms are flexible, i.e., $\mathcal{F}_i = \mathcal{N}$ for all i, then the above framework reduces to a standard production network model, such as Acemoglu et al. (2012). Third, note that firms face no frictions in adjusting their labor input, as we assume they choose l_{ik} at $t = 1$. This is to ensure that at least one input is free to adjust in response to realized demand, as otherwise markets may fail to clear.[6]

We conclude this discussion by introducing a measure for firms' uncertainty about the shocks' realizations. For any given pair of industries i and j, define

$$\kappa_{ij} = \frac{\mathbb{E}[\mathrm{var}_i(\log z_j)]}{\mathrm{var}(\log z_j)}, \tag{3}$$

where $\log z_j$ is the log productivity shock to industry j, $\mathrm{var}_i(\cdot)$ denotes the variance conditional on the information set of firms in industry i, and $\mathbb{E}[\cdot]$ and $\mathrm{var}(\cdot)$ denote the unconditional expectation and variance operators, respectively. The interpretation of κ_{ij} as a measure of uncertainty is fairly natural: it captures the (ex ante) volatility of $\log z_j$ conditional on i's information set as a fraction of its unconditional volatility. By the law of total variance, κ_{ij} is always in the unit interval, [0,1], and obtains its maximum value of 1 if firms in industry i receive no informative signals about the realization of $\log z_j$ (in which case, $\mathrm{var}(\mathbb{E}_i[\log z_j]) = 0$). At the other end of the spectrum, $\kappa_{ij} = 0$ if firms in industry i face no uncertainty about the shock to industry j (i.e., $\mathrm{var}_i(\log z_j) = 0$).[7]

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[4] As pointed out in the Introduction, such lead times can be particularly significant for capital inputs, such as machinery, plant equipment, and software. According to the Institute of Supply Management (ISM), in January 2023, only 15% of firms in the U.S. manufacturing sector faced lead times that were less than 30 days, whereas 59% of firms faced lead times that exceeded 6 months (Institute for Supply Management, 2023). The ISM defines lead time as "the time that elapses from placement of an order until receipt of an order, including time for order transmittal, processing, preparation and shipping."

[5] See Mankiw and Reis (2002), Maćkowiak and Wiederholt (2009), and La'O and Tahbaz-Salehi (2022) for examples of models with informational frictions as a source of nominal rigidities.

[6] This is also the key modeling distinction between our framework and that of Bui et al. (2023), who assume that labor input decisions are made under incomplete information, while all intermediate input quantities can adjust freely in response to shocks.

[7] In the special case that all (log) shocks and signals are normally distributed, κ_{ij} takes a familiar form in terms of the signal-to-noise ratio. In particular, suppose firm i observes a single signal given by $\omega_i = \log z_j + \epsilon_i$, where $\log z_j$ and ϵ_i are independent and normally distributed with variances σ_z^2 and σ_ϵ^2, respectively. In that case, $\kappa_{ij} = \sigma_\epsilon^2/(\sigma_z^2 + \sigma_\epsilon^2)$. The expression in (3) generalizes this concept to any arbitrary joint distribution of shocks and signals.

We can define a similar object to measure firms' uncertainty about the realization of the demand shock:

$$\mu_i = \frac{\mathbb{E}[\mathrm{var}_i(\log m)]}{\mathrm{var}(\log m)}, \tag{4}$$

where m is the nominal aggregate demand. Once again, $\mu_i = 0$ if firms in industry i face no uncertainty about aggregate demand shocks, whereas $\mu_i = 1$ if they receive no informative signals about the realization of m.

2.4. Downward nominal wage rigidities

While firms can set their prices p_{ik} flexibly at $t = 1$ after observing productivity and demand shocks, we allow for downward nominal wage rigidities by assuming that the nominal wage w cannot fall below an exogenously-specified value $\bar{w}$. This restriction on nominal prices means that there are two possibilities. One possibility is that $w > \bar{w}$ and the labor market clears. The other possibility is that the constraint on the nominal wage binds (so that $w = \bar{w}$), in which case the labor market is slack and does not clear, in the sense that the total demand for labor falls short of what the representative household is willing to supply at that wage. Taken together, we say the labor market is in equilibrium if

$$(w - \bar{w})\left(L - \sum_{i=1}^{n} \int_0^1 l_{ik}\mathrm{d}k\right) = 0, \qquad w \geq \bar{w}, \qquad L \geq \sum_{i=1}^{n} \int_0^1 l_{ik}\mathrm{d}k, \tag{5}$$

where L denotes the household's labor supply and l_{ik} is the labor demand of firm k in industry i. Clearly, the special case that $\bar{w} = 0$ corresponds to an economy with no nominal rigidities.

2.5. Equilibrium

With the various model ingredients in hand, we are now ready to define our solution concept.

Definition 1. An *equilibrium* is a collection of nominal prices, nominal wage, and quantities such that

(i) at $t = 0$, monopolistically-competitive firms in each industry choose their rigid intermediate input quantities to maximize expected real value of their profits given their information;
(ii) at $t = 1$, firms set their nominal prices and choose their labor and flexible intermediate inputs to maximize profits, taking the realized demand and their rigid input quantities as given;
(iii) the competitive producer in each industry chooses inputs to maximize its profits given prices;
(iv) the representative household chooses consumption and labor supply to maximize utility subject to its budget constraint;
(v) the labor market is in equilibrium, i.e., condition (5) is satisfied;
(vi) all sectoral good markets clear, i.e.,

$$y_i = c_i + \sum_{j=1}^{n} \int_0^1 x_{ji,k}\mathrm{d}k \qquad \text{for all } i \in \mathcal{N}. \tag{6}$$

Equilibrium conditions (ii)–(vi) are all standard—capturing firm and household optimizing behavior and consistency restrictions on quantities—with the measurability constraints on the rigid quantities captured by condition (i). Note that while firms in our model are subject to quantity adjustment frictions, they nonetheless optimally plan their production process in anticipation of future shocks subject to their information sets.

3. Equilibrium characterization

In this section, we characterize the equilibrium in terms of model primitives, namely, the economy's production network structure, the set of rigid and flexible intermediate inputs, and the information sets of firms in each industry. We do so via backward induction.

Starting with decisions at $t = 1$, recall that firms optimally choose their labor and flexible intermediate input quantities to meet the realized demand. This means that firm k in industry i faces the following cost-minimization problem:

$$\begin{aligned} (l_{ik}, \{x_{ij,k}\}_{j\in\mathcal{F}_i}) \in \arg\min \quad & w l_{ik} + \sum_{j\in\mathcal{F}_i} p_j x_{ij,k} \\ \text{s.t.} \quad & y_{ik} = z_i \zeta_i l_{ik}^{\alpha_i} \prod_{j=1}^{n} x_{ij,k}^{a_{ij}}, \end{aligned} \tag{7}$$

while taking prices, realized demand, and rigid intermediate input quantities as given. Next, turning to the firm's price-setting decision, the firm sets its nominal price optimally to maximize profits while taking its rigid intermediate inputs and all other nominal prices as given, that is,

$$p_{ik} \in \arg\max \quad (1-\tau_i)p_{ik}y_{ik} - wl_{ik} - \sum_{j\in\mathcal{F}_i} p_j x_{ij,k} \tag{8}$$

subject to the demand curve $y_{ik} = (p_{ik}/p_i)^{-\theta_i} y_i$ and the labor and flexible intermediate input optimality condition (7). Finally, at $t=0$, firm k in industry i chooses its rigid intermediate input quantities to maximize expected real value of its profits given its information, that is,

$$(\{x_{ij,k}\}_{j\in\mathcal{R}_i}) \in \arg\max \quad \mathbb{E}_i\left[\frac{U'(C)}{P}\left((1-\tau_i)p_{ik}y_{ik} - wl_{ik} - \sum_{j=1}^{n} p_j x_{ij,k}\right)\right], \tag{9}$$

where $\mathbb{E}_i[\cdot]$ denotes the expectation operator with respect to the information set of firms in industry i, $U'(C) = 1/C$ is the household's marginal utility, and P is the nominal price of the consumption good bundle.

Given the above, we can characterize the equilibrium by solving for optimization problems (7)–(9) recursively and imposing market-clearing condition (6) for all industries i. To present the equilibrium characterization result, let $\lambda_i = p_i y_i/PC$ denote industry i's *Domar weight*, defined as its sales as a fraction of GDP. Given that all firms in the same industry have identical technologies and information sets, we can drop the firm index k in our characterization. We have the following result:

Proposition 1. *Equilibrium nominal prices and Domar weights solve the system of equations:*

$$p_i = \frac{1}{z_i} w^{\alpha_i} \prod_{j\in\mathcal{F}_i} p_j^{a_{ij}} \prod_{j\in\mathcal{R}_i}\left(m\frac{\mathbb{E}_i[p_j/m]}{\mathbb{E}_i[\lambda_i]/\lambda_i}\right)^{a_{ij}} \tag{10}$$

and

$$\lambda_i = \beta_i + \sum_{j:i\in\mathcal{F}_j} a_{ji}\lambda_j + \sum_{j:i\in\mathcal{R}_j} a_{ji}\mathbb{E}_j[\lambda_j]\frac{p_i/m}{\mathbb{E}_j[p_i/m]} \tag{11}$$

for all $i \in \mathcal{N}$, where m is the nominal aggregate demand and w is the nominal wage.

Proposition 1 provides a system of $2n$ equations and $2n$ unknowns that expresses sectoral Domar weights $(\lambda_1, \dots, \lambda_n)$ and nominal prices $(p_1, \dots, p_n)$ in terms of the firms' information sets, the realized productivity shocks, the nominal wage, and nominal aggregate demand, m.

Focusing on Eq. (10), it is easy to verify that if firms in industry i are not subject to real rigidities—either because all their inputs are flexible or because they receive completely informative signals—then (10) reduces to $p_i = \frac{1}{z_i} w^{\alpha_i}\prod_{j=1}^{n} p_j^{a_{ij}}$. In other words, the nominal price of industry i is simply equal to its nominal marginal cost, as anticipated. More generally, however, as Eq. (10) indicates, the nominal price of industry i depends on industry i's expectation of the prices of its rigid intermediate inputs relative to nominal aggregate demand, $\mathbb{E}_i[p_j/m]$, as well as its expectation of its own equilibrium Domar weight, $\mathbb{E}_i[\lambda_i]$. To see the intuition for these dependencies, note that either an increase in $\mathbb{E}_i[p_j/m]$ or a decrease in $\mathbb{E}_i[\lambda_i]$ result in a reduction in the quantity x_{ij} of good j that firms in industry i demand at $t=0$. Given that this quantity is sunk by the time firms set their prices at $t=1$, a lower x_{ij} is akin to a lower productivity from the point of view of firms at $t=1$, thus inducing firms in industry i to set a higher nominal price.

The intuition underlying Eq. (11) is similar. Recall that the Domar weight of industry i—which represents that industry's size in equilibrium—would be larger when it faces higher demand from its downstream customers (larger x_{ji}'s). Also recall that the demand from a customer j that is subject to real rigidities is increasing in $\mathbb{E}_j[\lambda_j]$ and is decreasing in $\mathbb{E}_j[p_i/m]$. Therefore, as is evident from (11), λ_i increases in its customers' expectations of their size and decreases in their expectations of i's price. Finally, note that, if none of i's customers are subject to quantity adjustment or informational frictions, then Eq. (11) implies that $\lambda_i = \beta_i + \sum_{j=1}^{n} a_{ji}\lambda_j$, as would be the case in the benchmark models of production networks (Baqaee and Rubbo, 2022; Carvalho and Tahbaz-Salehi, 2019).

As already mentioned, Proposition 1 characterizes equilibrium nominal prices and Domar weights in terms of the nominal wage and nominal aggregate demand. Given prices and Domar weights, one can then characterize the entire allocation in terms of m and w. In particular, from the definition of λ_i, it follows immediately that the output of industry i is given by $y_i = \lambda_i m/p_i$. Also, as we show in the proof of Proposition 1, industry i's demand for its flexible and rigid intermediate inputs are given by

$$x_{ij} = \begin{cases} a_{ij} m\lambda_i/p_j & \text{if } j\in\mathcal{F}_i \\ a_{ij}\mathbb{E}_i[\lambda_i]/\mathbb{E}_i[p_j/m] & \text{if } j\in\mathcal{R}_i, \end{cases} \tag{12}$$

respectively. Finally, the household's first-order conditions imply that $c_i = \beta_i m/p_i$.

To see how quantity adjustment and informational frictions shape firms' sourcing decisions, it is instructive to consider the log-quadratic approximation to Eq. (12) for inputs $j \in \mathcal{R}_i$:

$$\log x_{ij} = \log a_{ij} + \mathbb{E}_i[\log s_i] + \frac{1}{2}\mathrm{var}_i(\log s_i) + \mathrm{cov}_i(\log s_i, \mathrm{sdf}) - \mathbb{E}_i[\log \hat{p}_j] - \frac{1}{2}\mathrm{var}_i(\log \hat{p}_j) - \mathrm{cov}_i(\log \hat{p}_j, \mathrm{sdf}),$$

where $s_i = p_i y_i / P$ is the real sales of industry i, $\hat{p}_j = p_j / P$ is the real price of good j, $\text{sdf} = \log U'(C)$ is the log stochastic discount factor (SDF), and $\text{var}_i(\cdot)$ and $\text{cov}_i(\cdot, \cdot)$ denote, respectively, the variance and covariance operators conditional on the information sets of firms in industry i. A few observations follow. First, note that $\log x_{ij}$ is not only decreasing in the expected value of the (log) real price of industry j, but also in its variance. This reflects the fact that the two frictions induce firms in industry i to rely more heavily on suppliers with less volatile prices, even if this comes at the cost of forgoing inputs that are cheaper in expectation. Second, observe that $\log x_{ij}$ is decreasing in the covariance of the log price of good j with the log SDF. This term reflects the fact that firms in industry i reduce their demand for input j if it tends to be more expensive in the states of the world with a high marginal utility of consumption. Finally, the term $\text{cov}_i(\log s_i, \text{sdf})$ indicates that firms in industry i increase their demand for all inputs if they have higher sales in the states of the world with high marginal utility.

As a final remark on Proposition 1, we note that while nominal aggregate demand m is a model primitive (and a proxy for demand shocks), the nominal wage w is an endogenous object that is determined in equilibrium. The following simple lemma completes the characterization of equilibrium by providing an additional equation that expresses the nominal wage in terms of nominal aggregate demand, the minimum nominal wage, and sectoral Domar weights:

Lemma 1. *The nominal wage is given by*

$$w = \max\left\{ m\chi^{\frac{\eta}{1+\eta}} \left(\sum_{i=1}^{n} \alpha_i \lambda_i \right)^{\frac{1}{1+\eta}}, \bar{w} \right\}. \tag{13}$$

Furthermore, in the special case that labor supply is fully elastic, $w = \max\{\chi m, \bar{w}\}$.

Taken together, Proposition 1 and Lemma 1 provide a complete (albeit implicit) characterization of equilibrium in the presence of informational frictions and real rigidities. Unfortunately, in general—and unless one imposes some discipline on the economy's information structure—system of Eqs. (10)–(13) does not lend itself to a closed-form solution. This is due to two sources of complexity in the model. First, as in Golub and Morris (2018), La'O and Tahbaz-Salehi (2022), and Bui et al. (2023), the presence of network interactions in the economy means that the equilibrium depends not only on the firms' first-order expectations, but also on their expectations of higher order. This is because firms need to forecast their Domar weights and input prices, which depend not only on the firms' own forecasts of the realized shocks, but also on their forecasts of other firms' forecasts, and so on. Second, and in contrast to the prior literature, the relevant higher-order expectations do not have a simple iterative representation in terms of cross-sectional (weighted) averages of firms' lower-order expectations. To see this, note that, according to (10), the nominal price set by firms in industry i depends on i's expectation of its input prices—an object that depends on the actions of its *upstream* suppliers—as well as on i's expectation of its own Domar weight—an object that is determined by the demand from its *downstream* customers. This means that the equilibrium depends on iterations of expectations both upstream and downstream over the network, significantly complicating how informational frictions interact with the production network structure.[8]

To explore the implications of Proposition 1 in a transparent manner, in the next section we study various special cases of the general setting in Section 2 by focusing on particular information structures. However, before doing so, we conclude this section by studying the equilibrium's efficiency properties.

Recall that if either (i) all firms observe perfectly informative signals about the realizations of the shocks or (ii) all inputs of all firms are flexible, then the model in Section 2 reduces to a standard production network model, where all firms price at marginal cost.[9] This means that in the absence of informational frictions and real rigidities—and as long as the downward nominal wage rigidity constraint does not bind—the equilibrium is (first-best) efficient. However, such a strong efficiency result no longer holds if frictions limit firms' ability to adjust their input quantities in response to shocks, as a planner could improve welfare by changing firms' input and output quantities contingent on the shocks' realizations. Nonetheless, our next result establishes that, despite the frictions, the equilibrium remains *constrained* efficient in the sense of Angeletos and Pavan (2007): a planner who is subject to the same informational and quantity rigidity frictions cannot improve upon the equilibrium welfare.

Proposition 2. *If the downward nominal wage rigidity constraint does not bind, then the equilibrium is constrained efficient.*

This proposition extends the constrained efficiency result of Angeletos et al. (2016) to an economy with non-trivial input-output linkages and an arbitrary specification of rigid and flexible inputs. It establishes that, in the absence of nominal rigidities, the equilibrium remains constrained efficient irrespective of the economy's production network structure, the set of rigid and flexible inputs of each industry, and the particular information structure. Proposition 2 also establishes that, despite the complex nature of interactions between firms' expectations over the production network captured by Eqs. (10) and (11), more precise information unambiguously improves equilibrium welfare: since more precise information improves welfare in the planner's solution, it would also do so in equilibrium.

[8] See the economy in Subsection 4.3 for a more detailed discussion.

[9] Even though firms in each industry are monopolistically competitive, setting the industry-specific taxes in (2) to $\tau_i = 1/(1-\theta_i)$ undoes the effect of monopolistic markups and ensures that there are no distortions due to market power.

4. Closed-Form results

As discussed in the previous section, unless one imposes some discipline on either the economy's information structure or its production network architecture, equilibrium conditions (10)–(13) do not lend themselves to closed-form solutions. Therefore, to explore the implications of Proposition 1 and Lemma 1 in a transparent manner, we next focus on various special cases of the general setting in Section 2 that allow us to explicitly characterize the equilibrium in terms of model primitives.

4.1. Frictions in a single industry

As a first special case of the general setting in Section 2, we assume that only one single industry is subject to the quantity adjustment and informational frictions. Specifically, we assume that firms in industry r are the only firms in the economy with incomplete information about the realizations of productivity shocks $(z_1, \dots, z_n)$ and the aggregate demand shock, m. Firms in all other industries are not subject to real rigidities and make all their decisions at $t = 1$, that is, $\mathcal{R}_i = \varnothing$ for all $i \neq r$. Focusing on this special case allows us to identify the role played by real rigidities and informational frictions at each industry separately.

We also impose the following assumption on the economy's production network structure:

Assumption 1. $\ell_{ir}\ell_{ri} = 0$ for all industries $i \neq r$.

To interpret the above assumption, recall that the (i, j) element of the economy's Leontief inverse, ℓ_{ij}, captures the extent to which industry i relies on industry j as a (direct or indirect) input supplier. Therefore, under Assumption 1, there is no industry i in the economy that is simultaneously upstream and downstream to r. We impose this assumption to tease out the role of upstream and downstream relationships vis-à-vis industry r in the most transparent manner. Finally, to investigate the impact of supply shocks separately from that of demand shocks, we first assume that the downward nominal wage rigidity constraint does not bind, making shocks to nominal aggregate demand neutral for real outcomes. We have the following result.

Proposition 3. *Suppose r is the only rigid industry, Assumption 1 is satisfied, and the downward nominal wage rigidity constraint does not bind.*

(a) *Then, to a first-order approximation,*

$$\log C = \log C^* - \frac{\lambda_r^{ss}}{1 + 1/\eta\left(1 - \lambda_r^{ss}\sum_{i\in\mathcal{R}_r} a_{ri}\right)} \sum_{j\in\mathcal{R}_r}\sum_{i=1}^{n} a_{rj}\ell_{ji}(\log z_i - \mathbb{E}_r[\log z_i]), \tag{14}$$

where $\log C^* = \sum_{i=1}^{n}\lambda_i^{ss}\log z_i - \frac{1}{1+1/\eta}\log\chi$ *is the log output in the absence of frictions.*

(b) *Additionally, if labor supply is fully elastic ($\eta \to \infty$), then*

$$\log C = \log C^* - \lambda_r^{ss}\sum_{j\in\mathcal{R}_r} a_{rj}\mathbb{K}_r\left(-\sum_{i=1}^{n}\ell_{ji}\log z_i\right), \tag{15}$$

where $\mathbb{K}_r[x] = \log\mathbb{E}_r[e^x] - x$.

Proposition 3 characterizes the impact of productivity shocks on aggregate output when firms in industry r face informational frictions in setting up their production processes. Statement (a) characterizes aggregate output in terms of model primitives to a first-order approximation, whereas statement (b) provides an exact characterization for the special case that labor supply is fully elastic. It is immediate to see that the last terms on the right-hand sides of (14) and (15) vanish when firms in industry r have complete information about the realizations of productivity shocks—and hence make all their price and quantity decisions with full anticipation of all shocks. In such a case, the expressions in (14) and (15) reduce to the standard result in the literature, according to which the impact of a productivity shock to industry i on aggregate output is equal to its pre-shock Domar weight, λ_i^{ss}. However, (14) and (15) also show that such a simple relationship no longer holds if firms in industry r face uncertainty about the productivity of their upstream supply chains. Specifically, the result in Proposition 3 leads to the following observations.

First, the expression in (15) illustrates that an increase in the uncertainty faced by firms in the industry with rigid inputs translates into unambiguously lower (expected) aggregate output. In particular, taking unconditional expectations from both sides of (15) and using the observation that $\mathbb{E}[\log\mathbb{E}_r[e^x] - x] > 0$ for any non-degenerate random variable x implies that $\mathbb{E}[\log C] < \mathbb{E}[\log C^*]$. This is, of course, intuitive: the fact that firms in industry r make (some or all of) their intermediate input decisions under incomplete information about productivity shocks induces them to rely more heavily on less volatile suppliers, even if this comes at the cost of forgoing more efficient ones. This role of uncertainty can be seen more clearly if one considers a second-order approximation to (15):

$$\mathbb{E}[\log C] = \mathbb{E}[\log C^*] - \frac{1}{2}\lambda_r^{ss}\sum_{j\in\mathcal{R}_r} a_{rj}\mathbb{E}\left[\operatorname{var}_r\left(\sum_{i=1}^{n}\ell_{ji}\log z_i\right)\right], \tag{16}$$

which captures how higher uncertainty—as measured by the conditional variance of productivities—reduces expected aggregate output.

Second, the last term on the right-hand side of (15) (or its second-order approximation in (16)) indicates that the negative impact of informational frictions on aggregate output is increasing in industry r's Domar weight, as well as in r's uncertainty about the supply chains of each of its rigid intermediate inputs separately, $\mathrm{var}_r\left(\sum_{i=1}^n \ell_{ji}\log z_i\right)$. Not surprisingly, this uncertainty is weighted by the importance of industry j in r's production technology (as captured by the expenditure share a_{rj}). This means that, all else equal, a rigid industry r functions as a tighter "production bottleneck" for the entire economy if it is simultaneously (i) a larger supplier in the economy (as captured by the larger Domar weight, λ_r^{ss}) and (ii) a more important direct or indirect customer of other firms in the economy (proxied by greater a_{rj} and ℓ_{ji}).

Third, one can use Proposition 3 to obtain an expression for how microeconomic shocks translate into macroeconomic outcomes. Under the assumption that industry-level productivity shocks are independent, equation (14) implies that the slope coefficient of regression

$$\log C = \gamma_0 + \gamma_i \log z_i + \varepsilon_i \tag{17}$$

—which captures the (average) first-order impact of shocks to industry i on aggregate output—is given by

$$\gamma_i = \lambda_i^{ss} - \left(\frac{\lambda_r^{ss}}{1+1/\eta\left(1-\lambda_r^{ss}\sum_{i\in\mathcal{R}_r} a_{ri}\right)}\sum_{j\in\mathcal{R}_r} a_{rj}\ell_{ji}\right)\kappa_{ri}, \tag{18}$$

where $\kappa_{ri} = \mathbb{E}[\mathrm{var}_r(\log z_i)]/\mathrm{var}(\log z_i)$ parameterizes the uncertainty of firms in industry r about shocks to industry i (as defined in (3)).[10] Eq. (18) establishes that, in the presence of real rigidities and informational frictions, (i) the first-order impact of productivity shocks is dampened compared to the predictions of Hulten's theorem for the fully flexible benchmark, for which the first-order impact of a shock to industry i is equal to λ_i^{ss} irrespective of the value of η; (ii) this dampening effect is stronger the more uncertain firms in industry r are about the shock's realization and the more elastic the labor supply is; and (iii) the extent to which shocks to industry i shape aggregate outcomes depends on the size of the rigid industry r and the extent to which r is exposed (directly or directly) to those shocks (as captured by $\sum_{j\in\mathcal{R}_r} a_{rj}\ell_{ji}$).

Finally, it is worth pointing out that whereas aggregate labor supply in the frictionless economy is independent of the shocks (because of the household's logarithmic utility), that is no longer the case in the presence of informational frictions. This is because of the fact that rigid input choices of firms in industry r are not indexed to the realization of shocks, and yet, all good markets have to clear irrespective of the shocks' realizations. The only way this can happen is for aggregate labor supply to adjust in response to the shocks. For example, aggregate labor supply has to rise if realized shocks turn out to be smaller than the firm's expectations.

We next turn to the implications of demand shocks for output and inflation. To ensure that such shocks have a nontrivial impact on real variables, we focus on the case in which the downward nominal wage rigidity constraint bind. We have the following counterpart to Proposition 3.

Proposition 4. *Suppose r is the only rigid industry and Assumption 1 is satisfied. If the downward nominal wage rigidity constraint binds, and in the absence of productivity shocks,*

$$\log C = \log m - \log\bar{w} - \left(\lambda_r^{ss}\sum_{j\in\mathcal{R}_r} a_{rj}\right)\mathbb{K}_r(-\log m) \tag{19}$$

$$\log P = \log\bar{w} + \left(\lambda_r^{ss}\sum_{j\in\mathcal{R}_r} a_{rj}\right)\mathbb{K}_r(-\log m), \tag{20}$$

where $\mathbb{K}_r[x] = \log\mathbb{E}_r[e^x] - x$.

This result shows that real rigidities and firms' uncertainty about the realization of demand shocks reduce aggregate output, while increasing the price level (which serves as a proxy for inflation in our model). For example, it is immediate to see that the expression for $\log C$ in (19) can be approximated by $\log C = \log m - \log\bar{w} - (\log m - \mathbb{E}_r[\log m] + \frac{1}{2}\mathrm{var}_r(\log m))\lambda_r^{ss}\sum_{j\in\mathcal{R}_r} a_{rj}$ to a second order, thus indicating that an increase in $\mathrm{var}_r(\log m)$ would reduce aggregate output.

As with supply shocks, one can use Proposition 4 to characterize the (average) first-order impact of demand shocks on output and inflation by calculating the slope coefficients of the following regressions:

$$\log C = \gamma_0 + \gamma_m \log m + \varepsilon_m \tag{21}$$

$$\log P = \delta_0 + \phi_m \log m + \varepsilon_m. \tag{22}$$

[10] Regression coefficient γ_i serves as the counterpart to $\mathrm{d}\log C/\mathrm{d}\log z_i$ in our incomplete-information economy.

Using Eqs. (19) and (20), it is easy to verify that

$$\gamma_m = 1 - \phi_m \qquad \text{and} \qquad \phi_m = \left(\lambda_r^{ss} \sum_{j \in \mathcal{R}_r} a_{rj} \right) \mu_r, \tag{23}$$

where $\mu_r = \mathbb{E}[\mathrm{var}_r(\log m)]/\mathrm{var}(\log m)$ parameterizes the uncertainty of firms in industry r about the realization of $\log m$, as defined in (4). Given that $\phi_m > 0$ whenever $\mu_r(\log m) > 0$, it follows immediately that real rigidities and informational frictions dampen the real effect of positive aggregate demand shocks, while increasing their inflationary effects. Not surprisingly then, both of these effects are determined by the size of the rigid industry, λ_r^{ss}, and the extent to which it relies on rigid intermediate inputs, $\sum_{j \in \mathcal{R}_r} a_{rj}$.

It is also instructive to compare the coefficients γ_m and ϕ_m in (23) with the results of Baqaee and Farhi (2022), who find that, in a Cobb-Douglas economy with a single factor of production subject to nominal wage rigidity, aggregate demand shocks translate one-for-one to aggregate output, with no impact on inflation. They also show that, holding sectoral Domar weights constant, the details of the economy's production network structure are irrelevant for how aggregate demand shocks impact aggregate output. As is evident from (23), neither statement is no longer true in the presence of informational frictions: the real effect of aggregate demand shocks is dampened, a positive demand shock leads to an increase in the price level, and both effects depend on the production network structure.

4.2. Public information

By focusing on an economy with a single rigid industry, the results in Subsection 4.1 abstract from the possibility that firms may be subject to multiple rigid suppliers and customers. In this subsection, we apply the general result in Proposition 1 to an economy in which firms in all industries have access to the same public information about the shocks (that is, $\omega_i = \omega$ for all industries i). Focusing on such an economy allows us to explore how the impact of real rigidities can build up over production chains.

To express our results in this more general case, it is convenient to define the following objects. Let $\mathbf{A}_f$ denote the matrix whose (i, j) element is equal to the corresponding element of matrix $\mathbf{A}$ if $j \in \mathcal{F}_i$ and is equal to zero otherwise. Therefore, $\mathbf{A}_f$ captures input-output relationships that are flexible and are not subject to quantity adjustment frictions. Similarly, we define matrix $\mathbf{A}_r = \mathbf{A} - \mathbf{A}_f$ to capture input-output relationships that are subject to frictions. Finally, let $\mathbf{L}_f = (\mathbf{I} - \mathbf{A}_f)^{-1}$ denote the Leontief inverse corresponding to the flexible inputs in the economy. We have the following result.

Proposition 5. *Suppose all firms share a common information set and the downward nominal wage rigidity constraint does not bind. If labor supply is fully elastic, then*

$$\mathbb{E}[\log C] = \mathbb{E}[\log C^*] - \frac{1}{2}\lambda^{ss\prime}\mathbf{A}_r \,\mathrm{diag}(\mathbf{Q}) + \frac{1}{2}\lambda^{ss\prime}\,\mathrm{diag}(\mathbf{A}_r\mathbf{1})\,\mathrm{diag}(\mathbf{H}'\mathbf{QH}) \tag{24}$$

to a second-order approximation, where $\mathbf{H} = \mathrm{diag}(\mathbf{A}_r'\lambda^{ss})\mathbf{L}_f\mathrm{diag}^{-1}(\lambda^{ss})$,

$$\mathbf{Q} = \sum_{k=0}^{\infty}\left(\mathbf{L}_f\,\mathrm{diag}(\mathbf{A}_r\mathbf{1})\mathbf{H}'\right)^k \mathbb{E}[\mathrm{var}_\omega(\mathbf{L}_f \log z)]\left(\mathbf{H}\,\mathrm{diag}(\mathbf{A}_r\mathbf{1})\mathbf{L}_f'\right)^k,$$

and $\mathrm{var}_\omega(\cdot)$ *denotes the conditional variance-covariance matrix with respect to the firms' common information set.*

This result generalizes Proposition 3 by allowing for multiple rigid industries and an arbitrary pattern of rigid and flexible inputs, while also relaxing Assumption 1. In fact, it is easy to verify that if there is a single industry with rigid inputs r and if Assumption 1 is satisfied, then $\mathbf{H}\,\mathrm{diag}(\mathbf{A}_r\mathbf{1}) = 0$, in which case $\mathbf{Q} = \mathbb{E}[\mathrm{var}_\omega(\mathbf{L}_f \log z)]$ and as a result, (24) reduces to the expression in (16). Given its generality, we will use the characterization in Proposition 5 as the basis of our quantification exercise in Section 5.

While significantly more involved than Proposition 3, the above result captures the same economic force, according to which an increase in firms' uncertainty about the shocks reduces aggregate output. The intuition is also similar: the fact that intermediate input decisions are sunk by the time firms observe the realized productivities means that they shift their demand from more uncertain suppliers to more reliable ones, even if it comes at the cost of lower (expected) productivity.

Next, turning to demand shocks in this setting, we can establish the following result:

Proposition 6. *Suppose all firms share a common information set, the downward nominal wage rigidity constraint binds, and labor supply is fully elastic. Then, in the absence of productivity shocks,*

$$\mathbb{E}[\log C] = \mathbb{E}[\log m] - \log\bar{w} - \frac{1}{2}\lambda^{ss\prime}\left(\mathbf{A}_r\,\mathrm{diag}(\mathbf{G}) - \mathrm{diag}(\mathbf{A}_r\mathbf{1})\,\mathrm{diag}(\mathbf{H}'\mathbf{GH})\right)\mathbb{E}[\mathrm{var}_\omega(\log m)] \tag{25}$$

$$\mathbb{E}[\log P] = \log\bar{w} + \frac{1}{2}\lambda^{ss\prime}\left(\mathbf{A}_r\,\mathrm{diag}(\mathbf{G}) - \mathrm{diag}(\mathbf{A}_r\mathbf{1})\,\mathrm{diag}(\mathbf{H}'\mathbf{GH})\right)\mathbb{E}[\mathrm{var}_\omega(\log m)] \tag{26}$$

Fig. 1. Vertical Production Network. *Notes:* Each vertex corresponds to an industry, with a directed edge present from one vertex to another if the former is an input-supplier to the latter. In addition to intermediate inputs, all firms use labor as an input for production (not depicted in the figure).

to a second-order approximation, where

$$\mathbf{G} = \sum_{k=0}^{\infty} (\mathbf{L}_f \operatorname{diag}(\mathbf{A}_r \mathbf{1})\mathbf{H}')^k \mathbf{L}_f \alpha\alpha' \mathbf{L}_f' (\mathbf{H} \operatorname{diag}(\mathbf{A}_r \mathbf{1}) \mathbf{L}_f')^k.$$

4.3. Dispersed information and higher-Order expectations

While the information structure in Subsection 4.2 exhibits incomplete information throughout the economy, it abstracts from the possibility that information may be dispersed among different firms, as all signals are assumed to be publicly observable. This allows for a significant degree of coordination between different firms in the economy: firms can use these public signals to coordinate not only with their direct suppliers and customers, but also with potentially distant firms on their supply chains. We therefore conclude this section by studying the implications of heterogeneity in the firms' information sets. In order to keep the analysis tractable, we focus on a simple production network structure.

Consider the economy depicted in Fig. 1 consisting of three industries organized on a vertical production chain, where industry 3 is the sole input supplier to industry 2 (with expenditure share $a_{23} = a_2$) and industry 2 is the sole input supplier to industry 1 (with expenditure share $a_{12} = a_1$). Furthermore, assume that industry 3 only uses labor for production ($\alpha_3 = 1$) and that industry 1 is the only industry that sells to the households ($\beta_1 = 1$). We have the following result:

Proposition 7. *Suppose labor supply is fully elastic and that $m < \bar{w}/\chi$. In the absence of productivity shocks,*

$$\log C = \log m - \log \bar{w} - a_1(1-a_2) \sum_{s=0}^{\infty} a_2^s \Big(\log m - (\mathbb{E}_1\mathbb{E}_2)^s \mathbb{E}_1[\log m] \Big) \tag{27}$$

$$\log P = \log \bar{w} + a_1(1-a_2) \sum_{s=0}^{\infty} a_2^s \Big(\log m - (\mathbb{E}_1\mathbb{E}_2)^s \mathbb{E}_1[\log m] \Big) \tag{28}$$

to a first-order approximation, where $(\mathbb{E}_1\mathbb{E}_2)^{s+1}[\cdot] = \mathbb{E}_1\mathbb{E}_2[(\mathbb{E}_1\mathbb{E}_2)^s[\cdot]]$.

Proposition 7 illustrates that, when information is dispersed, the impact of aggregate demand shocks on aggregate output and the price level depends on not just firms' first-order expectations but also on all expectations of higher order. As is well-known, higher-order beliefs adjust more sluggishly than first-order beliefs (Angeletos and Huo, 2021). Therefore, Eqs. (27) and (28) underscore how rigidities build up over the production chain, dampening the real effects of positive monetary shocks, while amplifying their inflationary effects.

That firms' higher-order expectations can matter for aggregate economic outcomes is not, in and of itself, novel, and it is line with prior work such as Golub and Morris (2018), Angeletos and Lian (2016, 2018), and La'O and Tahbaz-Salehi (2022), among others. What distinguishes the expressions in Proposition 7 from the results in prior work is how these higher-order expectations matter for aggregate output and price level. In particular, even though goods flow only in one direction in this economy—from upstream suppliers to their downstream customers—the macroeconomic variables in (27) and (28) depend on the iterated expectations in both directions: the supplier's expectations of the customer's expectation and vice versa. This is a consequence of the fact that, when choosing their input quantities, firms need to form forecasts not only about their suppliers' input prices, but also about demand from their customers.[11] But of course the same logic applies to those customers and suppliers as well, resulting in an infinite regress of expectations between firms in industries 1 and 2.

To further explore the implications of dispersed information in the vertical economy in Fig. 1 and the expressions in Propositions 7, it is instructive to focus on a parametric information structure with normally distributed shocks and signals.

[11] Importantly, as one can see from Eqs. (10) and (11), the suppliers' and customers' expectations do not appear symmetrically.

Specifically, suppose all firms in the economy have a common prior about the aggregate demand shock: $\log m \sim N(0,1)$. Additionally, suppose that firms in industry $i \in \{1,2\}$ receive a public and a private signal $\omega_i = (\tilde{s}, s_i)$, where

$$\begin{aligned} \tilde{s} &= \log m + \tilde{\epsilon} & \tilde{\epsilon} &\sim N(0, \sigma^2/(1-\delta)) \\ s_i &= \log m + \epsilon_i & \epsilon_i &\sim N(0, \sigma^2/\delta), \end{aligned} \tag{29}$$

noise terms $(\epsilon_1, \epsilon_2, \tilde{\epsilon})$ are independent, and $\delta \in (0,1)$ and $\sigma^2 > 0$ are parameters. Note that the parametrization in (29) implies that firms' uncertainty about $\log m$ is the same irrespective of the value of δ. In particular, $\mathrm{var}_i(\log m) = \sigma^2/(1+\sigma^2)$ for all $\delta \in (0,1)$. This means that δ parameterizes the strength of the private signal vis-à-vis the public signal: as $\delta \to 1$ all information is private, whereas at the other end of the spectrum as $\delta \to 0$ all information is public.

Corollary 1. *Under the information structure in (29), the first-order effects of an aggregate demand shock on aggregate output and the price level are given by*

$$\gamma_m = 1 - \phi_m \qquad \text{and} \qquad \phi_m = a_1\sigma^2 \frac{(1+\sigma^2) + a_2\delta\sigma^2}{(1+\sigma^2)^2 - a_2\delta^2\sigma^4},$$

where γ_m and ϕ_m are the coefficients of regressions (21) and (22), respectively.

Corollary 1 illustrates how δ, which parameterizes the extent of information dispersion, shapes the shock's aggregate impact. Specifically, it is easy to verify that a more dispersed information (i.e., a larger δ) results in greater inflation in response to positive aggregate demand shocks. This reflects the fact that with dispersed information, it is harder for firms in the supply chain to coordinate their production decisions with another. This diminishes the real effect of positive aggregate demand shocks and implies that such shocks manifest themselves as higher inflation.

5. Quantitative analysis

In this section, we use our theoretical results to quantify the effect of informational frictions and real rigidities on aggregate output in a calibrated version of the model. We calibrate our model at a quarterly frequency. This amounts to assuming that firms are unable to adjust their rigid inputs within a quarter after the realization of the shocks. For this quantitative analysis, we ignore the role of downward nominal wage rigidities by setting the lower bound on the nominal wage to $\bar{w} = 0$.

As is typical in the literature on production networks, we calibrate the model to the U.S. data using input-output tables constructed by the Bureau of Economic Analysis (BEA). These tables provide intermediate input expenditures by various industries, as well as each industry's contribution to final uses. However, to calibrate the model, we also need to specify (i) the sets of rigid and flexible inputs for each of the industries in the sample, as well as (ii) each industry's corresponding information set. We therefore start by discussing how we specify each of these.

Rigid and Flexible Inputs. To designate the sets of flexible and rigid inputs, we distinguish between intermediate inputs and investment goods each industry purchases from other industries. As mentioned in the Introduction, whereas the average lead time for obtaining production materials for manufacturing firms in the United States in January 2023 was 87 days, the average lead time for acquiring capital inputs—such as machinery, plant equipment, software and the like—was roughly twice as large (166 days). Similarly, while only 6% of firms faced lead times of over one year for their intermediate inputs, the same number was 23% for capital inputs (Institute for Supply Management, 2023). Given this disparity in lead times, for the purpose of the calibration, we designate investment goods used by each industry as that industry's rigid inputs, while treating intermediates as flexible.

To calibrate the model according to the above criterion, we rely on the "investment network" constructed by vom Lehn and Winberry (2022). Focusing on a 37-sector disaggregation of the entire private nonfarm economy, vom Lehn and Winberry (2022) construct an annual network of flows that measures the share of the total investment expenditure of a given sector i that is purchased from another sector j for each pair of sectors (i,j) in the economy. We treat these shares as the corresponding expenditure shares on rigid inputs in our model, while setting expenditure shares on intermediates equal to the expenditure shares on flexible inputs. To be more specific, we consider the following static variant of Horvath's (2000) model, where each industry i produces inputs according to the following constant returns production technology:

$$y_i = z_i\zeta_i l_i^{\alpha_i} k_i^{\rho_i} \prod_{j=1}^{n} x_{ij}^{\psi_{ij}}, \qquad \alpha_i + \rho_i + \sum_{j=1}^{n} \psi_{ij} = 1, \tag{30}$$

where ζ_i is a normalization constant, x_{ij} is the intermediate input purchased from industry j, ψ_{ij} captures the expenditure share on intermediate input j, ρ_i is the share of capital, and k_i is the capital input, which itself is produced from other industries' output:

$$k_i = \prod_{j=1}^{n} g_{ij}^{\gamma_{ij}}, \qquad \sum_{j=1}^{n} \gamma_{ij} = 1, \tag{31}$$

where g_{ij} is the amount of industry j's output used by industry i as an input into i's capital bundle. The market-clearing condition for the good produced by industry i is given by

$$y_i = c_i + \sum_{j=1}^{n} x_{ji} + \sum_{j=1}^{n} g_{ji}, \tag{32}$$

thus accounting for the fact that the output of industry i can either be consumed by the households, used as an intermediate input by other industries, or serve as an input in other industries' capital bundle.[12] Therefore, in this model—and unlike the model in Section 2—the output of industry j takes a dual role in the production technology of industry i: once as an intermediate input and once as an input in i's investment bundle. Nonetheless, the model in Eqs. (30)–(32) can be mapped to the model in Section 2 in a straightforward manner. By designating the capital bundle k_i as a separate industry whose inputs are all rigid and using the output of this industry as a (flexible) input in the production technology of industry i (with share ρ_i), equations (30)–(32) reduce to the model in Section 2, with the following (expanded) input-output matrix:

$$\mathbf{A} = \begin{bmatrix} \boldsymbol{\Psi} & \operatorname{diag}(\rho) \\ \boldsymbol{\Gamma} & \mathbf{0} \end{bmatrix},$$

where $\boldsymbol{\Psi} = [\psi_{ij}]$ and $\boldsymbol{\Gamma} = [\gamma_{ij}]$ denote the matrices corresponding to the intermediate input and investment networks in Eqs. (30) and (31), respectively, and $\operatorname{diag}(\rho)$ is a diagonal matrix with entries equal to the capital shares in each industry. We can thus calibrate matrix $\mathbf{A}$ using the network data of vom Lehn and Winberry (2022).

Information Sets. Next, we turn to specifying the information sets. To this end, we construct the variance-covariance matrix of $(\log z_1, \ldots, \log z_n)$ by first detrending the TFP process for each industry and then setting the variance-covariance matrix of the log-productivity shocks equal to the empirical variance-covariance matrix of the detrended processes. This amounts to assuming that while firms observe all past productivity shocks and are aware of their corresponding trends, they do not observe productivity innovations at the beginning of each quarter. Finally, note that this specification of information structure means that all firms share a common information set (or equivalently all signals are public).

Quantitative Analysis. With the economy's information structure and the sets of flexible and rigid inputs specified, we now turn to the quantitative assessment of our model's implications.

As a first exercise, we quantify the role of informational and quantity adjustment frictions for aggregate output. Recall that we assume that (i) all firms share the same common information structure, (ii) all intermediate inputs purchased from other industries are fully flexible, and (iii) all inputs purchased to construct the capital bundle are rigid. We can therefore use Eq. (24) in Proposition 5 to measure the drop in expected output due to the presence of frictions, where the matrices corresponding to the flexible and rigid inputs are given by

$$\mathbf{A}_f = \begin{bmatrix} \boldsymbol{\Psi} & \operatorname{diag}(\rho) \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \quad \text{and} \quad \mathbf{A}_r = \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \boldsymbol{\Gamma} & \mathbf{0} \end{bmatrix},$$

respectively.

Using the calibrated model to calculate the expression on the right-hand side of (24), we find that informational frictions and real rigidities result in roughly a 1% drop in aggregate output (measured as a percentage of steady-state consumption). This means that, according to our calibration, the interaction of the two frictions with the economy's production network can generate significant macroeconomic effects.

To get a more granular picture of the sources of this output loss, in a second exercise, we calculate the expected drop in aggregate output while assuming that only capital inputs purchased from a single industry r are subject to informational and quantity adjustment frictions. Specifically, we assume that whereas firms in any industry i need to commit up front to the quantity g_{ir} used for the production of their capital input, they can flexibly adjust all other capital and intermediate inputs—including the quantity of intermediate inputs x_{ir} purchased from industry r—in response to the realized productivity shocks. To calculate the corresponding drop in aggregate output, we once again use Eq. (24), but this time specifying matrices $\mathbf{A}_f$ and $\mathbf{A}_r$ to reflect the fact that only capital inputs from a single industry are rigid. Repeating this exercise for each of the 37 industries in our sample allows us to rank industries based on their role as "rigid suppliers" in the economy's production network.

Fig. 2 reports the results for the 15 industries that result in the largest drop in expected output. At the top of the list is 'Computer and electronic manufacturing,' which generates a drop in GDP equal to 0.05% of steady-state output, followed by 'Construction' and 'Motor vehicles manufacturing'. Notably the resulting output loss diminishes rapidly, indicating that rigidities in a large majority of the 37 industries do not play a significant role as bottlenecks for production. It is also worth pointing out that four out of top six industries on this list—construction, machinery manufacturing, motor vehicles manufacturing, and professional/technical services—coincide with the industries vom Lehn and Winberry (2022) identify as

[12] This model coincides with the model in vom Lehn and Winberry (2022) when the depreciation rate of capital in their model is set equal to 100%, in which case the stock of capital in each industry becomes equal to the investment good.

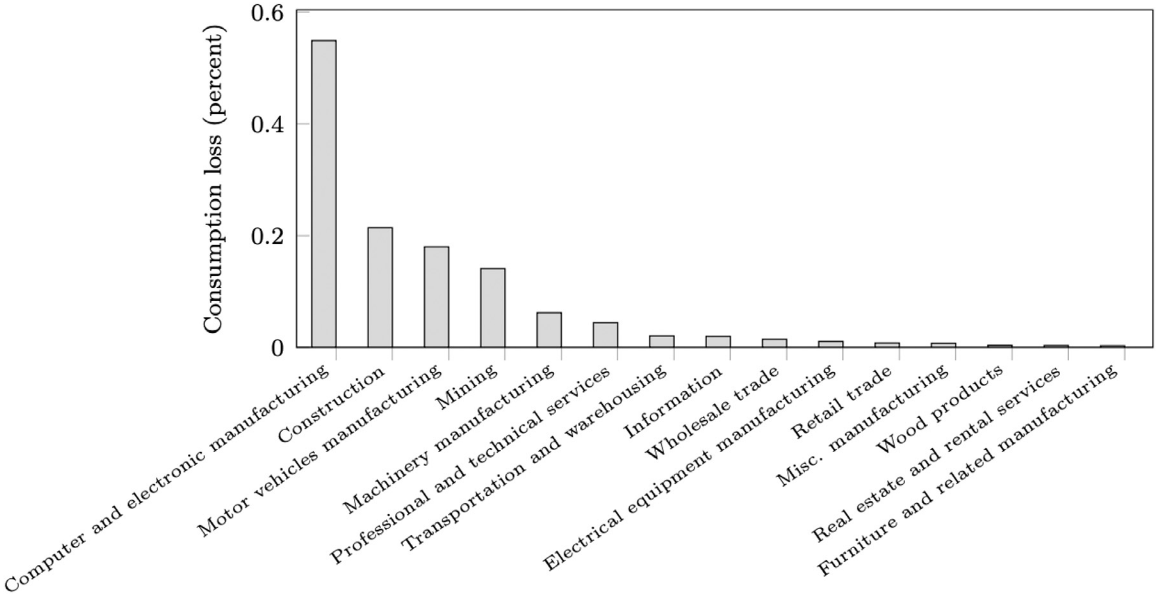

Fig. 2. The figure plots output loss as a percentage of steady-state consumption when capital inputs purchased from a single industry are subject to frictions, while all other intermediate and capital inputs can be adjusted flexibly. The figure only reports for the 15 industries with the largest corresponding output loss.

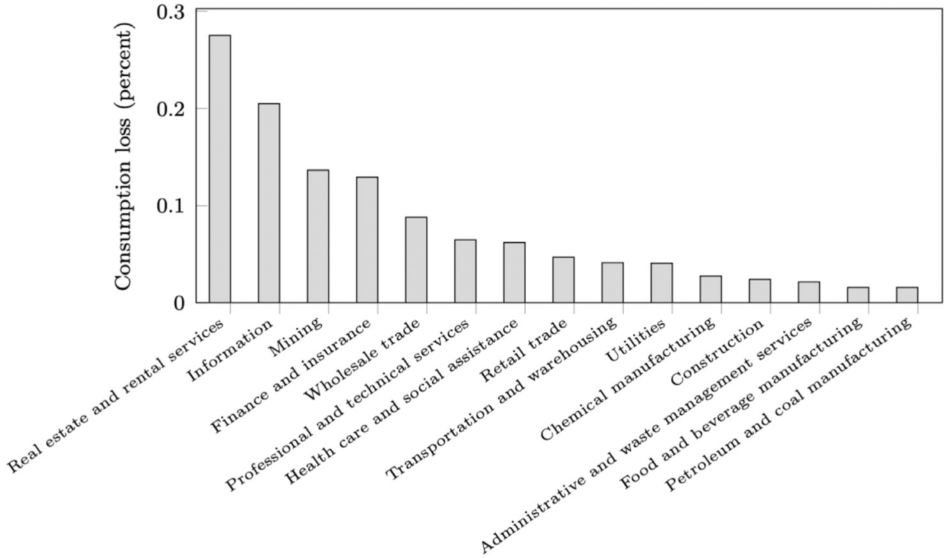

Fig. 3. The figure plots output loss as a percentage of steady-state consumption when capital inputs purchased by a single industry are subject to frictions, while all other intermediate and capital inputs can be adjusted flexibly. The figure only reports for the 15 industries with the largest corresponding output loss.

"investment hubs" that are responsible for producing nearly 70% of total investment. This is to be anticipated: since these capital inputs are used widely by many customer industries, any friction in adjusting those input quantities in response to shocks would result in more significant aggregate effects.

As our final exercise, we repeat the previous analysis but this time assuming that only a single industry r faces frictions when acquiring all its capital inputs, while all other industries $i \neq r$ face no frictions in acquiring either their intermediate or capital inputs. This exercise, which is in the spirit of the results in Subsection 4.1, allows us to rank different industries based on their roles as "rigid customers:" what fraction of output is lost because any given industry cannot adjust its investment bundle in response to shocks. Fig. 3 reports the results for the 15 industries that result in the largest drop in expected output. The picture that emerges is considerably different from the one in Fig. 2. This time industries with larger Domar weights—and not necessarily larger shares in the investment network—tend to appear towards the top of the list.

6. Conclusions

In this paper, we develop a production network model, in which firms are subject to informational frictions and real rigidities. The presence of such frictions means that (i) firms may be restricted in how effectively they can adjust their intermediate input quantities in response to changes in the economic environment and (ii) firms may have to choose their quantities only with incomplete information about the realizations of shocks. Our main theoretical result provides an implicit characterization of equilibrium nominal prices and Domar weights in terms of model primitives, namely, the economy's production network structure, the firms' information sets, and the set of rigid intermediate inputs. While only implicit, this result illustrates that equilibrium prices and quantities are determined by the firms' expectations of their upstream input prices as well as their expectations' of their downstream demand. We then consider various special cases of this economy to obtain closed-form solutions for how supply and demand shocks impact aggregate output and inflation.

A few insights emerge from the model. First, the presence of the real rigidities and informational frictions results in an unambiguous drop in aggregate output, as firms decide to shift demand from more efficient suppliers towards those that are less volatile. Second, these frictions in turn reduce the passthrough of productivity shocks to aggregate output and dampen the real aggregate effect of positive demand shock, while at the same time, increasing their inflationary effect compared to the frictionless benchmark.

While aimed at incorporating two realistic frictions into an otherwise standard model of production networks, the model developed in this paper is nonetheless still very stylized. First, one implicit assumption in the model is that firms face the same degree of rigidity irrespective of whether they decide to increase various quantities or decrease them. In reality, such frictions are most likely asymmetric, as firms can more easily reduce input and output quantities than increase them. Second, we abstracted from adjustment costs by assuming that once the intermediate input quantity decisions are made, they are completely sunk and cannot be changed. But it is easy to imagine various scenarios in which firms can adjust their production processes (even if only partially) by incurring some adjustment costs. Third, our static model ignores the role of inventory management as one of the key tools available to firms for responding to unanticipated supply and demand shocks.[13] We leave exploring the implications of these realistic features for future research.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.05.008

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[13] See Ferrari (2023) for a tractable model of production networks with inventories.

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