Forecast Shocks in Production Networks^{*}

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Abstract

This paper proposes a dynamic multi-sector production network model in which firms receive news on the future product-specific demand of a representative household. Since production takes time and firms in the production sectors are connected via input-output links, news on the future final demand of an individual product changes firms' forecasts of their future sales, creating economy-wide effects named as forecast shocks. Forecast shocks are transferred upwards through the supplier-customer connections in the network, from the buyer of an input good to the producer. The model explains the asymmetry in the transmission of individual shocks in the network and how shocks to the expectations generate real, persistent effects. The equilibrium is analytically solved and calibrated to the U.S. economy. A preliminary estimation under the assumptions for the shock processes shows the importance of the forecast shocks.

Keywords: Input-Output Network, Business Cycles, Forecast Shocks, Ripple Effects

JEL Classification Codes: D57, D83, E32, E37

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1 Introduction

A key theme of macroeconomics is the search for the causes of aggregate economic fluctuations. While many model the driving force as shocks to aggregate fundamentals, a large branch of literature, pioneered by Long and Plosser (1983) and Jovanovic (1987), attributes the observed aggregate fluctuations to a micro origin. Idiosyncratic shocks at the firm- or industry-level can't explain the observed aggregate economic fluctuation to a large extent. However, this literature typically overlooks the non-trivial role of the topology of the customer-supplier network in determining the direction of the transmission of idiosyncratic shocks. For example, Shea (2002) and Conley and Dupor (2011) show that, at the sectorial level, the demand-side linkage is more important. More recently, Kelly, Lustig, and Van Nieuwerburgh (2013) suggest that firm volatility data favor firm-level shock transmission in the customer-to-supplier direction over the opposite.

This paper introduces forecast shocks into the dynamic framework of Long and Plosser (1983) and addresses the paths of shock transmission. In particular, I assume that in each period, agents in the economy observe a common external signal (news) on the consumer's preference for different products in the future. Firms forecast their sales relative to the total value added in the following period. Since each sector has to decide its inputs one period ahead, in equilibrium, the formation of their forecasts has a recursive structure and every current forecast in fact summarizes future forecasts. Once agents in the economy at period t_0 observe the news and anticipate a change in forecast by sector i in the future at period $t_0 + T$, such anticipation will immediately show up in the formation of current-period forecasts by relevant sectors. Specifically, anticipating the change in forecast by sector i at $t_0 + T$, i 's direct upstream sectors (suppliers) will change their forecasts accordingly at $t_0 + T - 1$, which in turn leads the suppliers' suppliers to adjust their forecasts at $t_0 + T - 2$, and so forth. Hence, a path of transmission of fluctuation from the downstream sectors to the upstream sectors is constructed. Notice that in my model, once external news of the demand arrives, all agents in the economy receive such information. As a result, there is no heterogeneous information issue in my model.

The input-output network plays a dual role in this model. In the formation of forecasts, shocks to future forecasts are transferred upwards through the supplier-customer connections in the network, from the buyer of an input good to the producer. The shares of industrial sales then reflect the updated forecasts, which have real effects on levels of output, consumption, input, etc. There is also a conventional role in the transmission of real effects. Any shock that changes the current-period output of a sector will have a prolonged effect on the economy through the one-period-ahead input choices downwards to its customer sectors. This is also how productivity shocks are transferred.

Figure 1: Vehicle Buying Conditions (VBC) and Industrial Production (IP) of NAICS sectors 3361-3. The top panel shows the raw, demeaned data of the two sequences and the bottom two panels are the HP trends and residuals with monthly smoother 14400. Red line: monthly VBC from Jan 1985 to Mar 2013. Blue line: monthly IP 3361-3 from Jan 1986 to Aug 2013.

Figure 2: Cross-Correlogram: $VBC(t)$ versus IP 3361-3 ($t - 50, t + 50$). The correlation coefficients achieve their maximum around $k = 10$. This indicates that the VBC leads the production.

Figure 3: Industrial Production: NAICS Sectors 3361-3, 331, and 332.

Figure 4: Cross-Correlogram: VBC(t) versus IP 331, IP 332 ($t-50, t+50$) and IP 3361-3 (t) versus IP 331, IP 332 ($t-50, t+50$).

This paper treats the news on demand as a source of aggregate volatility. In particular, I focus on the shocks to the expectation of product-specific demand which can lead to changes in real economic activities. In general, the future demand of households depends on many factors such as their income, the price of the product, their expectations of the prices of the product in the future, and fiscal policy. Consider motor vehicle production as an example. As part of the Survey of Consumers conducted by University of Michigan, the time series of indices of Buying Conditions for Vehicles (henceforth VBC) show the consumers' willingness to buy and/or the economic conditions of buying household motor vehicles in the following year.¹ I interpret this indicator as the expected demand for motor vehicles. Figure 1 plots the co-movement between the monthly VBC and the monthly index for industrial production of NAICS sectors 3361-3, producers of motor vehicles. The time series data of indices for industrial production are part of the G.17 series, calculated and released by the Board of Governors of the Federal Reserve System. The VBC, or the expected demand, seems to lead the output of motor vehicles when the data are in their raw form, HP filtered, or even in the trend. Reporting the cross-correlogram between these two series, Figure 2 confirms the lead/lag relationship. I then turn to the major suppliers of inputs required by vehicle producers. In fact, around 38.8% of the input expenditure of this sector is spent on its own products, 9.3% on fabricated metal products, and 8.6% on primary metals, which are products of NAICS sectors 332 and 331, respectively. Not surprisingly, the suppliers' output levels comove with that of the customer, as shown by Figure 3. Additionally, the top two panels of Figure 4 depict the lead/lag relationship between VBC and the output of each supplier sector. Figure 4 shows a similar pattern to Figure 2. This evidence supports my claim that the expectation regarding the demand for a certain product, in this example, vehicles, has real impact not only on the producer but also on the producer's input suppliers. The bottom two panels of Figure 4 show that the outputs of the two supplier sectors also comove with that of the customer sector. Meanwhile, the positive relationship between the lagged output of the suppliers and the current output of the customer, albeit weak, suggests a timing difference between the input purchase and the production, as assumed by Long and Plosser (1983).

The forecast shocks feature upward transmission direction, contrary to the downward transmission of productivity shocks in the same model. In reality, one expects the shock transmission through the supplier-customer links to move in both directions, instead of uni-directionally. However, recent empirical studies provide evidence that suggests the upward direction from the cus-

¹In the survey, consumers are asked the following question: "Speaking now of the automobile market – do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van, or sport utility vehicle?" Among the consumers who feel it will be a good time to buy a vehicle, low loan interest rates and low price expectation are among the main reasons cited for buying one.

customer to the supplier is more important. Estimating structural equilibrium models, Shea (2002) finds that demand-side linkage is important in generating output comovement at the sector level, hence the upward transmission of sector-specific shock is important at the aggregate level. Conley and Dapor (2003) find the strongest evidence for complementarity when sectors are "close" to each other according to a distance measure that captures Shea's demand-side linkage. At the firm level, Kelly, Lustig and Van Nieuwerburgh (2013) suggest that upstream shock propagation provides a better description of firm volatility data than downstream. Among publicly traded firms, Cohen and Frazzini (2008) find evidence of "customer momentum", that is, predictable stock return for the supplier firm when there are shocks to its linked customer firms. Additionally, they show that present customer shocks have significant predictability over the supplier's future real activity while the predictability does not exist without the link.

I solve the model analytically and use the U.S. Bureau of Economic Analysis (BEA) Annual Industrial Accounts to calibrate the model and quantitatively illustrate the importance of forecast dynamics. Using the calibrated model, I compute the sector-specific forecast sequences from the standard use tables between 1998 and 2011. Under the assumptions that final consumption shares follow the Dirichlet distribution and that the news follows the multinomial distribution, I estimate the parameters for the processes and simulate the model. The simulation shows that without any productivity shock the model can generate non-trivial aggregate fluctuations measured as the standard deviation of the real total value added (GDP).

In the main model, I assume that the source of the forecast fluctuation is driven by news shocks based on the consumers' preference parameters in the future. The news is received by all agents in the economy, so there is no asymmetric information across agents. The forecast dynamics can also be driven by fundamental irrelevant factors, which is similar to the sentiment shock in Angeletos and La'O (2013). The two mechanisms are observationally equivalent in the current framework.

The rest of this paper is organized as follows. In section 2 I present the model and its equilibria. In section 3 I discuss the dynamics of forecast in the equilibrium. In section 4, I calibrate the model and quantitatively explore the importance of forecast shock. Section 5 concludes.

1.1 Related Literature

First, my paper is directly related to the multi-sector real business cycle models. There is a longstanding debate: Can idiosyncratic *productivity* fluctuations cause business cycles at the aggregate level. To the best of my knowledge, Long and Plosser (1983) develop the first model to study this issue. Horvath (1998, 2000) and Dapor (1999) introduce capital accumulation into Long and Plosser (1983). However, this literature ignores that the aggregation of idiosyncratic shock critically depends on the topology of the input-output network. Hence, there is an emerging

literature that studies the role of the topology of the IO network in macroeconomics. Acemoglu et al. (2012) consider a static multi-sector model and study the role of the input-output network in the aggregation of idiosyncratic productivity shock in different sectors. They show that independent idiosyncratic shocks in different sectors cannot offset each other when the network is asymmetric. In contrast to the previous literature, my paper studies news shock instead of productivity shock. In Long and Plosser (1983)'s framework, the productivity shock does not affect the share of sales. However, the share changes over time, which indicates the existence of another source of fluctuation. I introduce sector-specific forecast shock. I also study how the network structure determines the transmission mechanism of sector-specific forecast shocks. Unlike Horvath (1998, 2000) and Dupor (1999), the dynamics in my model come purely from the information and time-to-produce mechanism instead of from capital accumulation. In addition, in my model, the forecast shock is transmitted from the downstream sectors to the upstream sectors, which is consistent with the recent firm-level empirical studies by Kelly, Lustig and Van Nieuwerburgh (2013). Oberfield (2013) studies the endogenous formation and evolution of input-output networks.

Second, my paper is closely related to La'O (2013) which combines Angeletos and La'O (2013) and Long and Plosser (1983) to study the role of sentiment and ripple in macroeconomy. My paper is different from La'O in two aspects: (1) La'O studies a special topology of input-output network, the production chain, while I consider an input-output network that is calibrated to the real economy. (2) The source of fluctuation in La'O is the sentiment fluctuation and agents hold heterogeneous information, while in my model, the fluctuation derives from the *common* forecast shock, which is driven by news shock. (3) In La'O, the distribution of sales is unchanging over time as in Long and Plosser (1983).

Last, in my paper, one possible source of forecast shock is the news shock about the consumer's preference. Hence, my paper is also related to the news shock literature. See Lorenzoni (2011) for a detailed survey. In this literature, one assumes that the consumers and firms receive expectation shock on the technology in the future, and studies how the news shock affects the demand and output.

2 Model

2.1 Setup

I consider a multi-sector model following Long and Plosser (1983). Time is discrete with infinite horizon, $t = 0, 1, 2, \dots$. The economy consists of n competitive sectors denoted by $\{1, 2, \dots, n\}$, each of which produces a distinct type of good. Each good can be consumed by consumers or used as

an input for the production of other goods in the following period.

Firms. At time t , the production of good i requires labor hired at t and a basket of goods as inputs, the amount of which is determined in the previous period. Firms in the same sector employ a common time-invariant Cobb-Douglas production technology with constant returns to scale. In addition, the production at each sector is subject to some idiosyncratic productivity shock. Specifically, the technology of sector i transforms h_{it} units of labor and x_{ijt-1} units of pre-determined amount of good j , $\forall j = 1, \dots, n$, into y_{it} units of output, determined by

$$y_{it} = z_{it} h_{it}^{1-\alpha_i} \prod_j x_{ijt-1}^{\alpha_i \omega_{ij}}$$

where z_{it} is the realized productivity term. Define the productivity vector at time t as $\mathbf{z}_t = (z_{1t}, \dots, z_{nt})'$, which is drawn from a stationary process,

$$\mathbf{z}_t \sim \Xi^z(\cdot | \mathbf{z}_{t-1})$$

with unconditional mean $\mathbf{z} = (z_1, \dots, z_n)$

$$E(\mathbf{z}_t) = \mathbf{z}.$$

$\alpha_i \in (0, 1)$ is i 's total share of input use and $1 - \alpha_i$ is the labor share. Out of i 's total input use, the share of j 's product as input is $\omega_{ij} \geq 0$, which captures the importance of good j in producing i . When $\omega_{ij} > 0$, industry i is a customer of good j and sector j is a supplier. The constant returns to scale technologies require that $\sum_j \omega_{ij} = 1$ for each sector i . Define

$$\mathbf{A} = \begin{bmatrix} \alpha_1 & & & \\ & \alpha_2 & & \\ & & \ddots & \\ & & & \alpha_n \end{bmatrix}, \Omega = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1n} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2n} \\ \vdots & \vdots & & \vdots \\ \omega_{n1} & \omega_{n2} & \cdots & \omega_{nn} \end{bmatrix}$$

Ω determines the production architecture, which is in fact a directed network amongst all industries with weighted links, in which the direction is simply that of the flow of input goods. The importance of a link from industry j to i is captured by the value of ω_{ij} . Generically, Ω is an asymmetric matrix.

Sector i is represented by one firm i with flow profit π_{it} , which is the sales of good i minus the labor compensation and the input purchase for production in the following period:

$$\pi_{it} = p_{it} y_{it} - w_{it} h_{it} - \sum_j p_{jt} x_{ijt}.$$

Consumers. In addition to the firms, there is a representative long-lived household that gains utility from consuming a variety of goods and supplies labor to each sector. The preference (flow payoff) is modeled as

$$\eta_t \sum_i \theta_{it} u(c_{it}) - \sum_i v(h_{it}),$$

where η_t is the aggregate preference parameter, θ_{it} governs the good- i -specific preference, c_{it} is the amount of good i consumed at time t , and h_{it} is the labor supplied to sector i at t . Assume the preference parameter $\eta_t > 0$ follows a Markovian process such that

$$\begin{aligned} \eta_{t+1} &\sim \Xi^\eta(\cdot|\eta_t), \text{ and} \\ E\left(\frac{\eta_{t+1}}{\eta_t}\right) &= E\left(\frac{\eta_{t+1}}{\eta_t}|\eta_t\right) = 1. \end{aligned}$$

The utility takes the logarithm form $u(c) = \ln c$, and the disutility of working, $v(h) = h^{1+\varepsilon}/(1+\varepsilon)$, $\varepsilon \geq 0$. Let vector $\boldsymbol{\theta}_t$ summarize product-specific preference parameters at time t such that $\boldsymbol{\theta}_t = (\theta_{1t}, \theta_{2t}, \dots, \theta_{nt})'$ and $\sum_{i=1}^n \theta_{it} = 1$, $\theta_{it} \geq 0$. Assume that nature draws all $\{\boldsymbol{\theta}_t\}_{t=0}^{+\infty}$ at the beginning of time while all agents in the economy share a common prior belief that $\boldsymbol{\theta}_t$ is independent and identically distributed over time,

$$\boldsymbol{\theta}_t \sim \Xi^\theta(\cdot)$$

with the expectation $\boldsymbol{\theta} = (\theta_1, \dots, \theta_n)'$, and $\sum_{i=1}^n \theta_i = 1$, $\theta_i \geq 0$, $\forall i$

$$E(\boldsymbol{\theta}_t) = \boldsymbol{\theta}$$

As will be shown later, θ_{it} is the equilibrium share of consumption expenditure on good i at time t . The household receives labor income and all profits and discounts the future at rate $\beta \in (0, 1)$.

Input-Output Structure. Following Acemoglu et al. (2012), one can define the *influence vector* of this economy, given the set of parameters, $(\boldsymbol{\theta}, \mathbf{A}, \Omega)$. The influence vector measures the contribution of sector-specific shocks to aggregate volatility. This model differs from the static version studied by Acemoglu et al. (2012) in the intertemporal concern of the firms when deciding the input purchase for the use in production in the following period, so the contribution of sector-specific shocks to the aggregate economy may vary over time. However, in a situation without forecast shocks, the contribution of sector-specific shocks to the aggregate fluctuations is time-invariant regardless of sector-specific productivity shocks, so one can define the stationary version of the influence vector as follows.

Definition 1. *The stationary influence vector of the economy, given input-output matrix Ω , the input shares $\mathbf{A}$, the consumption shares $\boldsymbol{\theta}$, and the discount rate β , is a vector $\mathbf{v} = (v_1, v_2, \dots, v_n)'$*

such that

$$\mathbf{v} = (I - \beta (\Omega' - \Theta) \mathbf{A})^{-1} \boldsymbol{\theta}$$

where Θ is an $n \times n$ matrix such that each column is $\mathbf{v}$. An alternative way to write $\mathbf{v}$ is in a recursive fashion such that for each i ,

$$v_i = \theta_i + \beta \sum_{j=1}^n \alpha_j (\omega_{ji} - \theta_i) v_j. \quad (1)$$

As will be shown later, each element of the stationary influence vector is in fact the ratio between the revenue of a sector divided by the aggregate value added. When external information arrives in each period, the influence of each sector on the aggregate economy varies over time.

Information Structure. Assume that at any time t , all agents share a common information set $\mathcal{I}_t$. The economy evolves according to the following timeline. At the beginning of period t , firms in each sector inherit from the previous period the input goods, $\{x_{ijt-1}\}_{j=1}^n$ for all sector i . All shocks to fundamentals of the current period are realized and become observable, including $(\{z_{it}, \theta_{it}\}_{i=1}^n, \eta_t)$. At the same time, agents in this economy receive a set of signals M_t from an exogenous source and the information set updates such that $\mathcal{I}_t = \mathcal{I}_{t-1} \cup \{\{z_{it}, \theta_{it}\}_{i=1}^n, \eta_t; M_t\}$. I assume the signals contain information about future product-specific demand. The specific form of the signals M_t will be discussed with greater detail in due course. However, it is worth noting that M_t is commonly known by all parties in the economy, so there is no heterogenous information in my model. Seeing the wages and prices, firms of all sectors make employment choices and the household provides labor to each sector. Production takes place. Firms decide on input purchase for production in the next period while the household buys the basket of goods for consumption.

2.2 Decisions and Equilibrium

Household's Choice. At each time t , after the realization of η_t and $\boldsymbol{\theta}_t$, the household takes wages $\{w_{it}\}_i$, prices $\{p_{it}\}_i$, and profits $\{\pi_{it}\}_i$ as given and chooses labor supply $\{h_{it}\}$ and consumption bundle $\{c_{it}\}$ subject to the budget constraint:

$$\sum p_{it} c_{it} \leq \sum w_{it} h_{it} + \sum \pi_{it}.$$

Let λ_t be the Lagrangian multiplier of this constraint, then household maximization yields the following first order conditions:

$$\begin{aligned} \beta^t h_{it}^\varepsilon &= \lambda_t w_{it} \\ \beta^t \eta_t \theta_{it} &= \lambda_t p_{it} c_{it}. \end{aligned}$$

Define consumption index C_t and consumption price index P_t^C

$$C_t = \prod_i c_{it}^{\theta_{it}}, P_t^C = \prod_i \left(\frac{p_{it}}{\theta_{it}} \right)^{\theta_{it}}.$$

Given price $\{p_{it}\}$ and wage $\{w_{it}\}$, the household's demand $\{c_{it}\}$ and labor supply $\{h_{it}\}$ can be rewritten as follows.

$$p_{it}c_{it} = \theta_{it}P_t^C C_t \quad (2)$$

$$h_{it}^{1+\varepsilon} = \eta_t \frac{w_{it}h_{it}}{P_t^C C_t} \quad (3)$$

$$\lambda_t = \beta^t \frac{\eta_t}{P_t^C C_t} \quad (4)$$

Firms' Choice. At each time t , after the realization of z_{it} , firm i chooses labor demand l_{it} for current production and buys inputs $\{x_{ijt}\}_j$ for future production to maximize profit, facing wage w_{it} and prices $\{p_{jt}\}_j$ and expecting a discount factor $\Lambda_{t,t+1}$. Define firm i 's sales at time t as

$$s_{it} = p_{it}y_{it}. \quad (5)$$

Firm i 's labor demand is given as follows:

$$w_{it}h_{it} = (1 - \alpha_i) s_{it}.$$

Define input index of firm i , X_{it} , and input price index P_{it}^X ,

$$X_{it} = \prod_j x_{ijt}^{\omega_{ij}}$$

$$P_{it}^X = \prod_j \left(\frac{p_{jt}}{\omega_{ij}} \right)^{\omega_{ij}}$$

Firms form expectations based on the common information set at time t , $\mathcal{I}_t$, which summarizes all previous signals $\{M_\tau\}_{\tau \leq t}$. Denote $E_t(\cdot) = E(\cdot | \mathcal{I}_t)$. Given the price $\{p_{jt}\}$ and the current information set $\mathcal{I}_t$, one can rewrite firm i 's input demand $\{x_{ijt}\}$ as follows:

$$p_{jt}x_{ijt} = \omega_{ij}P_{it}^X X_{it} \quad (6)$$

$$P_{it}^X X_{it} = \alpha_i E_t(\Lambda_{t,t+1} s_{i,t+1}). \quad (7)$$

At equilibrium, a firm's discount factor is consistent with the household's intertemporal concern,

$$\Lambda_{t,t+1} = \frac{\lambda_{t+1}}{\lambda_t} = \beta \frac{\eta_{t+1}}{\eta_t} \frac{P_t^C C_t}{P_{t+1}^C C_{t+1}}. \quad (8)$$

Hence, combining equations (7) and (8) yields the following Euler equation:

$$\begin{aligned} P_{it}^X X_{it} &= \alpha_i E_t (\Lambda_{t,t+1} s_{i,t+1}) \\ &= \beta \alpha_i E_t \left(\frac{\eta_{t+1}}{\eta_t} \frac{s_{i,t+1}}{P_{t+1}^C C_{t+1}} \right) P_t^C C_t. \end{aligned}$$

Define firm i 's one-period-ahead forecast at t as

$$\tilde{f}_{it} = E_t \left(\frac{\eta_{t+1}}{\eta_t} \frac{s_{i,t+1}}{P_{t+1}^C C_{t+1}} \right). \quad (9)$$

Notice that firms form their expectations based on a common information set that includes previous and current news $\{M_\tau\}_{\tau \leq t}$, so the arrival of news in each period affects firms' decisions by changing their expectations.

Formally, the equilibrium concept is defined as follows.

Definition 2. A Competitive Equilibrium consists of a list of prices $\{\{w_{it}, p_{it}\}_{i=1}^n\}_{t=0}^\infty$, allocations $\left\{ \left\{ h_{it}, c_{it}, (x_{ijt})_{j=1}^n, y_{it} \right\}_{i=1}^n \right\}_{t=0}^\infty$ associated with forecasts $\left\{ \left\{ \tilde{f}_{it} \right\}_{i=1}^n \right\}_{t=0}^\infty$ and information sets $\{\mathcal{I}_t\}_{t=0}^\infty$, such that for each period t , (1) agents form their forecasts $\left\{ \tilde{f}_{it} \right\}_{i=1}^n$ based on $\mathcal{I}_t$, (2) household optimize given prices and firms optimize given prices and $(x_{ijt-1})_{i,j=1}^n$, (3) wages clear all labor markets, (4) product prices clear goods markets, $c_{it} + \sum_j x_{jit} = y_{it}$, $\forall i$, and (5) information set evolves based on the realizations of exogenous processes and the law of motions of forecasts are consistent with agents' optimal choices and markets-clearing conditions.

2.3 Equilibrium Analysis

The model equilibrium has analytical solutions. I show in this subsection that the analysis of equilibrium forecasts can be separated from the rest of the equilibrium components.

Lemma 1. On the equilibrium path, at any time t , given $\left\{ \tilde{f}_{jt} \right\}_j$, the ratio of sector i 's total sales to the aggregate value added is determined by

$$\frac{s_{it}}{P_t^C C_t} = \theta_{it} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt}, \forall i.$$

According to this lemma, the revenue of sector i from the sales of its product i depends on two parts: final consumption of product i by the household and i 's customer sectors' forecasts of their future sales. Since production takes time, the forecast of a customer j 's sales in the next period determines j 's use of product i as input purchased in the current period. Therefore, for the supplier of a product, the customers' forecasts matter.

Given the forecasts, the real equilibrium allocations are uniquely pinned down. The labor hired by sector i is determined by

$$h_{it} = \left[(1 - \alpha_i) \eta_t \left(\theta_{it} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt} \right) \right]^{\frac{1}{1+\varepsilon}},$$

where the forecasts of the customer sectors future sales have a real effect in the supplier sector's employment decision. Consequently, the current level of labor then determines real output of sector i given the inputs purchased in the previous period

$$y_{it} = z_{it} h_{it}^{1-\alpha_i} X_{it-1}^{\alpha_i}.$$

The final consumption of product i by the household is a fraction of sector i 's output,

$$c_{it} = y_{it} \frac{\theta_{it}}{\theta_{it} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt}},$$

and i 's customer sector j gets x_{jit} as input,

$$x_{jit} = y_{it} \frac{\beta \alpha_j \omega_{ji} \tilde{f}_{jt}}{\theta_{it} + \beta \sum_k \alpha_k \omega_{ki} \tilde{f}_{kt}}.$$

To set the prices, I make the normalization such that $\sum_j s_{jt} = 1$, and so s_{it} is also sector i 's share of total industrial sales at time t . Under this normalization, the shares of sales are solved for, as well as the consumption expenditure and the input purchases.

Proposition 1. *On the equilibrium path, at any time t , given $\{\tilde{f}_{jt}\}_j$, the normalized equilibrium outcome is described as follows:*

1. *sector i 's share of the total industrial sales:*

$$s_{it} = \frac{\theta_{it} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt}}{1 + \beta \sum_j \alpha_j \tilde{f}_{jt}},$$

2. *the total consumption expenditure and the consumption expenditure on the output of sector i :*

$$P_t^C C_t = \frac{1}{1 + \beta \sum_j \alpha_j \tilde{f}_{jt}} \text{ and } p_{it} c_{it} = \frac{\theta_{it}}{1 + \beta \sum_j \alpha_j \tilde{f}_{jt}}, \quad (10)$$

and

3. sector i 's total input expenditure and its input expenditure on product j :

$$P_{it}^X X_{it} = \frac{\beta \alpha_i \tilde{f}_{it}}{1 + \beta \sum_j \alpha_j \tilde{f}_{jt}} \text{ and } p_{jt} x_{ijt} = \frac{\beta \alpha_i \omega_{ij} \tilde{f}_{it}}{1 + \beta \sum_j \alpha_j \tilde{f}_{jt}}. \quad (11)$$

Additionally, the equilibrium price of product i is simply $p_{it} = s_{it}/y_{it}$, and sector i pays the wage $w_{it} = (1 - \alpha_i) s_{it}/h_{it}$.

Now we turn to the forecasts. Define the combined vector of forecasts at time t as $\tilde{\mathbf{f}}_t$ such that $\tilde{\mathbf{f}}_t = (\tilde{f}_{1t}, \dots, \tilde{f}_{nt})$. The following theorem establishes the recursive formation of the one-period-ahead forecasts.

Theorem 1. *The equilibrium forecast of each sector summarizes the expectation of its future share in consumption and the future forecasts of its customer sectors:*

$$\tilde{\mathbf{f}}_t = E_t(\boldsymbol{\theta}_{t+1}) + \beta \Omega' \mathbf{A} E_t(\tilde{\mathbf{f}}_{t+1}). \quad (12)$$

For any sector i , at any time t , the equilibrium one-period-ahead forecast $\tilde{f}_{it}$ has a recursive feature in that it summarizes sector i 's beliefs about future forecasts by other sectors:

$$\begin{aligned} \tilde{f}_{it} &= E_t \left(\frac{\eta_{t+1}}{\eta_t} \left(\theta_{it+1} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt+1} \right) \right) \\ &= E_t \theta_{it+1} + \beta \sum_j \alpha_j \omega_{ji} E_t(\tilde{f}_{jt+1}). \end{aligned} \quad (13)$$

The second equality holds because of the assumption that, conditional on $\mathcal{I}_t$, the change in the aggregate preference parameter η_{t+1}/η_t is independent of both $\{\theta_{i\tau}\}_{\tau>t}$ and future $\{\eta_{\tau+1}/\eta_\tau\}_{\tau>t}$, and therefore, η_{t+1}/η_t is also independent of future forecasts $\{\tilde{f}_{i\tau}\}_{\tau>t}$. The impact of j 's future forecast on i is weighted by the importance of j 's input use of good i , that is, the production function parameter $\alpha_j \omega_{ji}$. In other words, the more industry j 's production relies on good i as an input, the more industry i values its belief about j 's forecasts.

Note that the productivity plays no role in the formation of forecasts. Under the functional-form assumptions of the household's preference and the production technologies, both of which are in the Cobb-Douglas forms, the effects of productivity shocks on allocations and on prices cancel each other out completely. Therefore, the forecast of a sector's future sales summarize only the expectation of future demands of its product, by the household and by the customer sectors. This also eliminates the potential room for signals about future productivities.

Comparative Statics. Here I analyze some simple comparative statics with respect to sector-specific productivity and aggregate demand shock. First of all, the productivity term of sector

i at time t , z_{it} , has a direct impact on its output, y_{it} , on the consumption of good i , c_{it} , on the price of good i , p_{it} , and on other industries' intermediary use of good i , x_{jit} , $\forall j$. Other conditions held equal, an increase in z_{it} leads to increases in y_{it} , c_{it} , and x_{jit} , $\forall j$ such that $\omega_{ji} > 0$. It also leads to a decrease in p_{it} . Because of the assumptions on the functional forms of the household preference and the production technology of the firms, the impacts of any change in productivity in prices $\{p_{it}\}$ and in levels $\{y_{it}, c_{it}, \{x_{jit}\}_j\}$ completely cancel each other out. Hence, changes in productivity do not show in the price-adjusted terms, that is, sales $\{s_{it}\}$, consumption expenditures $\{p_{it}c_{it}\}$, and input purchases $\{p_{it}x_{jit}\}$. Moreover, a change in the productivity of a specific sector propagates to other sectors through the input choices in a downstream direction, traveling only from the producer of a certain product to its immediate customers and then to these customers' customers. Second, while similar in direction to the productivity term, a change in η_t affects all industries as well as the household. Furthermore, the scale of the impact differs from industry to industry or good to good.

3 Discussion of Dynamics

3.1 Stationary Forecasts

As a benchmark, it is worthwhile to characterize the equilibrium path on which there is no external signal, $M_t = \emptyset$, $\forall t$. Under the current assumptions on the stochastic processes, the lack of further information ensures a time-invariant sequence of forecasts, $\tilde{\mathbf{f}}_t = \tilde{\mathbf{f}}$.

Corollary 1. Define $\tilde{\mathbf{f}} = (\tilde{f}_1, \dots, \tilde{f}_n)'$, such that

$$\tilde{\mathbf{f}} = (I - \beta\Omega'\mathbf{A})^{-1}\boldsymbol{\theta}$$

then $\tilde{\mathbf{f}}$ is the unique set of time-invariant forecasts on the stationary equilibrium path on which $M_t = \emptyset$, $\forall t$. Equivalently written,

$$\tilde{f}_i = \theta_i + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_j.$$

Given the time-invariant $\tilde{\mathbf{f}}$, the share of sales of sector i varies over time only if the consumption share of product i , θ_{it} , changes over time.

$$s_{it} = \frac{\theta_{it} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_j}{1 + \beta \sum_j \alpha_j \tilde{f}_j} = \frac{(\theta_{it} - \theta_i) + \tilde{f}_i}{1 + \beta \sum_j \alpha_j \tilde{f}_j}.$$

Figure 5: Stationary distribution of shares on industrial sales and actual shares. Solid line: data shares averaged over time, 1998-2011; shaded area: the lower and upper bounds of the actual shares; dashed line: predicted stationary shares by the Long and Plosser (1983) model family. Data source: BEA Annual Industrial Accounts.

When the consumption expenditure shares are constant ($\theta_t = \theta$), the vector of sales shares is also time-invariant and equal to the dynamic influence vector,

$$s_i = v_i.$$

Note that, because of the assumptions on Cobb-Douglas production technologies and utility function, any productivity shock that can change z_{it} (which in turn changes y_{it}) is fully absorbed in prices. The case in which $\{z_{it}\}$ is the only source of variation is the one studied by Long and Plosser (1983). In the absence of forecast shocks, the distribution of sales across sectors $\{s_{it}\}$ is constant over time regardless of sector-specific productivity shocks or shocks to the news on future productivity. However, Figure 5 shows that when the input-output structure is calibrated, not only does the actual stationary distribution of industrial sales vary over time but the predicted stationary sales distribution also seems to differ quite a bit from the true distribution. As I will show, forecast shocks help amend this issue.

A more special case is the steady state of the economy when all processes are set at the determinant mean levels. The steady state will serve as the starting point in the quantitative exploration.

Proposition 2. *The equilibrium outcome at the steady state of the economy consists of $\{p_i, w_i,$*

$h_i, y_i, c_i, \{x_{ji}\}_j$ such that

1. The labor supply at any sector i is $h_i = \left[(1 - \alpha_i) \eta \tilde{f}_i \right]^{\frac{1}{1+\varepsilon}}$ and the corresponding wage is $w_i = \frac{1}{h_i} \frac{(1-\alpha_i)\tilde{f}_i}{1+\beta \sum_j \alpha_j \tilde{f}_j}$;
2. For any sector i , given the steady state output y_i , the price of product i , p_i ; the consumption of product i , c_i ; and sector j 's use of product i as input, x_{ji} ; are given by

$$\begin{aligned} p_i &= \frac{1}{y_i} \frac{\tilde{f}_i}{1 + \beta \sum_j \alpha_j \tilde{f}_j}, \\ c_i &= \frac{\theta_i}{\tilde{f}_i} y_i, \\ x_{ji} &= \beta \alpha_j \omega_{ji} \frac{\tilde{f}_j}{\tilde{f}_i} y_i; \end{aligned}$$

3. The set of steady state outputs $\{y_i\}$ is the unique solution to the following system

$$y_i = z_i h_i^{1-\alpha_i} \prod_j \left(\beta \alpha_j \omega_{ji} \frac{\tilde{f}_j}{\tilde{f}_i} y_j \right)^{\alpha_i \omega_{ij}}, \forall i.$$

3.2 News about Product-Specific Demand As Driving Force

In the introductory example of motor vehicle production, the series of indices for Vehicle Buying Conditions can be viewed as a measure of the consumers' expected buying capacity of household motor vehicles. Under the lens of this model, this buying capacity of a particular good corresponds to product-specific demand, which is captured by the expectation of the equilibrium consumption share of this good. Therefore, in this subsection, I model the external signals as shocks that can change the expectation of future consumption shares.

Recall the recursive formation of the forecasts

$$\begin{aligned} \tilde{\mathbf{f}}_t &= E_t(\boldsymbol{\theta}_{t+1}) + \beta \Omega' \mathbf{A} E_t(\tilde{\mathbf{f}}_{t+1}) \\ &= E_t(\boldsymbol{\theta}_{t+1}) + \beta \Omega' \mathbf{A} E_t(\boldsymbol{\theta}_{t+2}) + \beta^2 (\Omega' \mathbf{A})^2 E_t(\boldsymbol{\theta}_{t+3}) + \dots \end{aligned} \tag{14}$$

hence for any sector i , the expected sales-value added ratio $\tilde{f}_{it}$ summarizes the expectations of all future consumption distribution, $\{\boldsymbol{\theta}_{t+\tau}\}_{\tau=1}^{\infty}$. The weights depend on the input-output structure and the discount factor. To understand the recursive structure of expectations, consider the decision of a specific sector i whose $\tilde{f}_{it}$ is given by

$$\tilde{f}_{it} = E_t(\theta_{i,t+1}) + \beta \sum_j \alpha_j \omega_{ji} E_t(\theta_{j,t+2}) + \beta^2 \sum_j \sum_{j'} \alpha_j \omega_{ji} \alpha_{j'} \omega_{j'j} E_t(\theta_{j',t+3}) + \dots$$

where the first term $E_t(\theta_{i,t+1})$ is the one-period-ahead forecast of sector i 's own consumption share; the second term $\beta \sum_j \alpha_j \omega_{ji} E_t(\theta_{j,t+2})$ is the time-discounted weighted sum of i 's customers' two-period-ahead forecasts, weighted by the importance of product i in the production of customer j 's output; the third term $\beta^2 \sum_j \sum_{j'} \alpha_j \omega_{ji} \alpha_{j'} \omega_{j'j} E_t(\theta_{j',t+3})$ is the discounted weighted sum of three-period-ahead forecasts of i 's customers' customers, twice weighted; and so on for further terms.

To formalize the process of updating beliefs while preserving the tractability of the model, consider a specific form of the set of external signals M_t received at time t such that M_t contains information about future product-specific consumption demand that arrives T periods ahead, $T \geq 1$. Specifically,

$$M_t = \{\mathbf{m}_{t+1}^t, \mathbf{m}_{t+2}^t, \dots, \mathbf{m}_{t+T}^t\}$$

such that for each $\tau = 1, \dots, T$, $\mathbf{m}_{t+\tau}^t$ is drawn independently from a distribution determined by $\boldsymbol{\theta}_{t+\tau}$,

$$\mathbf{m}_{t+\tau}^t \sim \Xi^m(\cdot | \boldsymbol{\theta}_{t+\tau})$$

All sectors receive the same signals in each period and update their expectations of $\boldsymbol{\theta}_{t+\tau}$.

The structure of the signal set is designed to capture the idea that agents receive information and form expectations of future demand. The information is allowed to accumulate over time and the forecasts get more precise as available information grows. For example, comparing the current forecasts of demand for cars in one year and demand for cars in five years, one should expect the former to be more reliable because there are more signals observed. The assumption of multinomial signals is for technical simplicity. It accompanies the common prior Dirichlet distribution of product-specific preference vector $\boldsymbol{\theta}_{t+\tau}$ so that the updated posterior of the preference vector remains a Dirichlet distribution, which allows for simple explicit expression of the updated expectations. I do not wish to over-emphasize this functional form assumption on the signals for it merely complements the Dirichlet distribution in a Bayesian updating process.

At each time t , $\mathcal{I}_t$ contains $T - \tau + 1$ signals of $\boldsymbol{\theta}_{t+\tau}$, $1 \leq \tau \leq T$, which are $\mathbf{m}_{t+\tau}^{t-(T-\tau)}$, $\mathbf{m}_{t+\tau}^{t-(T-\tau)+1}$, ..., and $\mathbf{m}_{t+\tau}^t$. For example, $\mathbf{m}_{t+T}^t$ is the only signal vector of $\boldsymbol{\theta}_{t+T}$ at time t , and there are T signal vectors of $\boldsymbol{\theta}_{t+1}$, of which the first one was received $T - 1$ periods earlier. In fact, the explicit forms of the posterior expectations are given by:

$$\begin{aligned} E_t(\boldsymbol{\theta}_{t+1}) &= E\left(\boldsymbol{\theta}_{t+1} | \mathbf{m}_{t+1}^{t-(T-1)}, \mathbf{m}_{t+1}^{t-(T-2)}, \dots, \mathbf{m}_{t+1}^t\right) \\ E_t(\boldsymbol{\theta}_{t+2}) &= E\left(\boldsymbol{\theta}_{t+2} | \mathbf{m}_{t+2}^{t-(T-2)}, \mathbf{m}_{t+2}^{t-(T-3)}, \dots, \mathbf{m}_{t+2}^t\right) \\ &\vdots \\ E_t(\boldsymbol{\theta}_{t+T}) &= E\left(\boldsymbol{\theta}_{t+T} | \mathbf{m}_{t+T}^t\right). \end{aligned}$$

The longer the time horizon, the less precise the available information is. $\mathcal{I}_t$ does not contain any additional information on future periods beyond $t+T$ besides the prior distribution of consumption shares. Therefore,

$$\tilde{\mathbf{f}}_t = \sum_{\tau=1}^T \beta^{\tau-1} (\Omega' \mathbf{A})^{\tau-1} E_t(\boldsymbol{\theta}_{t+\tau}) + \beta^T (\Omega' \mathbf{A})^T \tilde{\mathbf{f}}.$$

I call the changes in the expectations $E_t(\boldsymbol{\theta}_{t+\tau})$ the result of forecast shocks, which in turn affect the forecasts and decisions of firms. Under the assumption of a common information set, I am able to maintain tractability of the model and step aside from the complexity of extracting information from prices and higher order beliefs when agents have heterogeneous information. The forecast shocks have the following features. First, the shocks to expectations have real impact because agents are forward-looking in making decisions. In particular, the forecasts enter the input purchase decisions of firms due to the timing restriction that requires the firms to decide on the amount of inputs without knowing future prices. In principle, the news on future productivity should affect the current decisions via the same intertemporal-concern channel. However, under the functional assumptions of this model, the expected change in productivity and the expected change in price cancel each other out. Therefore, I can isolate the effect of the novel news-on-demand shocks. Second, the shocks are transmitted upwards from customers to suppliers through the input-output links and these are the only upward-transmitting shocks under the model specifications. In reality, shock transmission in the economy is more plausibly bi-directional than either downwards only or upwards only and this should be the case for transmission of productivity shocks, news shocks, or other shocks. In the static variant of this model studied by Acemoglu et al. (2012), the productivity shocks have immediate impact on real output of both upstream and downstream sectors because of market clearing prices. Third, the shocks affect the size distribution of the sectors and have decaying and lasting real effects over time. Compared to productivity shocks and news shocks to productivity, which cannot generate changes in the distribution of sectors' sales shares, the effects of forecast shocks on prices and on quantities do not cancel each other out. Hence they show in sales, consumption expenditure, input expenditure, etc. Moreover, the effects on quantities last and decay over time through the firms' input purchase decisions. Lastly, in addition to its more conventional role in prolonging and propagating real effects on outputs, the input-output structure plays an essential role in determining the scale and direction of a forecast shock. Suppose a signal in favor of sector j' arrives at time t such that all agents expect that the consumer will spend relatively more on good j' at time $t + \tau$, hence $E_t(\theta_{j',t+\tau})$ goes up by $\Delta_{j'}$ (and surely the expectations of consumption shares on other goods will decrease accordingly). The scale and direction of the impact of this change depends both on the position of sector j' in the production network and on how large τ is. Notice that the influence of the change $\Delta_{j'}$ varies

as a result of two simultaneous effects as τ becomes larger: (1) the change will affect more sectors through the input-output connection in the upstream direction, while (2) the weight on $\Delta_{j'}$ gets smaller and more heavily discounted. Furthermore, the shocks to expectations of the future, even the distant future, have prolonged real effects through the input purchase decisions. The net effect of such a change is further discussed and demonstrated quantitatively in the simulation section.

Unlike the demand parameter η_t and the productivity indices $\{z_{it}\}_i$, both of which are conventional in the business cycle literature and directly affect the fundamentals, the forecast shocks and the interplay between forecast shocks and input-output connections are newly introduced in this paper. Moreover, they are not explicitly related to any of the *current* fundamental variables in the economy, but rather reflect the future economic conditions. The formation of forecasts also captures the second role the supplier-customer network plays in reality: it allows communication of information between a supplier and a customer when trading. In a very stylized fashion, the forecast formation process shows how a firm or an industry gathers and exploits information from its business activity, and how it makes production and input purchase decisions based on this information.

Notice that external signals affect the economic activities only by changing agents' forecasts, and the change of forecasts is driven by the arrival of external signals only. Consequently, one can understand how the arrival of external signals affects the economy by studying how the changes in forecasts affect the economy. In the following analysis, I show that the sector specific forecast $\tilde{f}_{it}$ has a non-trivial effect both on the distribution of sales and on total output. Not only does $\tilde{f}_{it}$ affect industry i , but it also has a direct impact on other industries that are connected to i through the input-output link. Sector i 's output is increasing in its own forecast $\tilde{f}_{it}$. Also, sector j 's output is increasing in i 's forecast if sector i uses product j as an input. In other words, the impact of one sector's forecast on the output level of another sector goes upstream from a customer (i) of a certain product (j) to its producer (j).

$$\begin{aligned} \frac{dy_{it}}{d\tilde{f}_{it}} &> 0 \\ \text{and } \frac{dy_{jt}}{d\tilde{f}_{it}} &> 0 \text{ if } \alpha_i \omega_{ij} > 0 \end{aligned}$$

Sector i increases its input expenditure when its own forecast increases. Sector j decreases its output expenditure when i 's forecast increases.

$$\begin{aligned} \frac{d(P_{it}^X X_{it})}{d\tilde{f}_{it}} &= \beta \alpha_i P_t^C C_t (1 - \beta \alpha_i P_t^C C_t) > 0 \\ \text{and } \frac{d(P_{jt}^X X_{jt})}{d\tilde{f}_{it}} &< 0 \text{ if } \alpha_j > 0 \end{aligned}$$

When sector i 's forecast increases, whether its share of total industrial sales increases or not depends on how heavily sector i uses its own product as an input. In fact, most of the sectors retain a large fraction of their outputs for each period.

$$\frac{ds_{it}}{d\tilde{f}_{it}} = \beta\alpha_i P_t^C C_t(\omega_{ii} - s_{it}) \begin{cases} \geq 0 & \text{if } \omega_{ii} \geq s_{it} \\ < 0 & \text{if } \omega_{ii} < s_{it} \end{cases}$$

Similarly, in response to the same increase in i 's forecast, sector j 's share of sales increases only if i is an important customer of product j , that is, out of i 's input purchases, the fraction spent on product j is larger than sector j 's share of total industrial sales.

$$\frac{ds_{jt}}{d\tilde{f}_{it}} = \beta\alpha_i P_t^C C_t(\omega_{ij} - s_{jt}) \begin{cases} \geq 0 & \text{if } \omega_{ij} \geq s_{jt} \\ < 0 & \text{if } \omega_{ij} < s_{jt}. \end{cases}$$

Hence, the change in distribution of shares of industrial sales reflects the impact of changing forecasts. Such change travels upstream through supplier-customer connections similar to the way the impact of forecasts on output levels does. However, unlike the case of output levels, whether and how much the sales share will increase depends on the importance of the seller's product as an input to the customer.

3.3 Impact Paths of News

As in previous discussion, due to the forward-looking and recursive fashion of the forecast formation, a change in expected future forecasts shows up immediately in current forecasts via the supplier-customer connections, which in turn affect the distribution of sales shares in the present period. The real effect of such change will last into the following periods because of the dynamic input choices. In this section, I illustrate the model mechanism by a counterfactual exercise. The parameterization of the model is discussed in the calibration and estimation section.

To highlight the effects of changes in forecasts, let the realization of the product-specific preference vector, i.e., the consumption shares, be fixed at the mean, $\theta_t = \theta$, while preserving the common prior distribution of θ_t . Moreover, fix the level of productivity $\mathbf{z}_t = \mathbf{z}$ and fix the aggregate preference $\eta_t = \eta$. Consider a simplified version of the posterior updating process, in which only one external signal arrives so the forecasts are updated once upon its arrival. Let t_0 be the time of impact when an external signal arrives. Before this period, the agents form stationary forecasts $\tilde{\mathbf{f}}$ and expect no change in future consumption shares. Let the signal be such that the updated expected consumption share of good i in T periods changes relatively by fraction δ , and

Figure 6: Response of forecasts on the selected chain. X axis is time and Y axis is the ratio between forecasts $\tilde{f}_{jt}$ and stationary forecasts $\tilde{f}_j$. Solid line: underlining sector 324; dashed line with Δ : direct upstream sector 3; broken line with $\bigcirc$: 2nd-order upstream sector 532; dotted line with ∇ : immediate downstream sector 481. Impact time $t_0 = 1$, $i = \text{NAICS 324}$, change in θ_i $\delta = 0.1$, $T = 3$. All prior uncertainty resolves at $t_0 + T = 4$.

the other shares change accordingly:

$$E_{t_0}(\theta_{i,t_0+T}) = \frac{\theta_i(1+\delta)}{1+\delta\theta_i},$$

$$E_{t_0}(\theta_{j,t_0+T}) = \frac{\theta_j}{1+\delta\theta_i}, \forall j \neq i.$$

Here T is called the target time and i the target sector. In addition, since there is no further signal in the following periods, $E_t(\theta_T) = E_{t_0}(\theta_T)$ for $t_0 \leq t \leq T - 1$.

For the purpose of illustration, consider a specific experiment in which $\delta = 0.1$, $T = 3$, and sector i that undertakes the δ change is $i = \text{'Petroleum and coal products'}$ with NAICS code 324. In general, at the industry level, an industry is connected to several others by the input-output relation. Hence, instead of production chains, one observes a production network measured by the matrices $\mathbf{A}$ and Ω . I pick a "chain-like" subset of this network for better demonstration and the logic holds for more general cases. One of Petroleum and coal products's major downstream sectors, namely its customers, is NAICS 481 'Air transportation'. Its most important immediate supplier is NAICS 3 'Oil and gas extraction' whose major suppliers include NAICS 532RL 'Rental and leasing services and lessors of intangible assets'.

Figure 7: Response shares of sales on the selected chain. X axis is time and Y axis is the shares s_{jt} relative to stationary shares s_j . Solid line: underlining sector 324; dashed line with Δ : direct upstream sector 3; broken line with $\bigcirc$: 2nd-order upstream sector 532; dotted line with ∇ : immediate downstream sector 481. Impact time $t_0 = 1$, $i = \text{NAICS } 324$, change in θ_i $\delta = 0.1$, $T = 3$. All prior uncertainty resolves at $t_0 + T = 4$.

Figure 8: Response of outputs on the selected chain. X axis is time and Y axis is the output levels y_{jt} relative to the steady state outputs y_j . Solid line: underlining sector 324; dashed line with Δ : direct upstream sector 3; broken line with $\bigcirc$: 2nd-order upstream sector 532; dotted line with ∇ : immediate downstream sector 481. Impact time $t_0 = 1$, $i = \text{NAICS } 324$, change in θ_i $\delta = 0.1$, $T = 3$. All prior uncertainty resolves at $t_0 + T = 4$.

Figure 9: Responses of consumption on the selected chain. X axis is time and Y axis is the ratio between consumption at t , c_{it} and steady state consumption, c_i . Solid line: underlining sector 324; dashed line with Δ : direct upstream sector 3; broken line with $\bigcirc$: 2nd-order upstream sector 532; dotted line with ∇ : immediate downstream sector 481. Impact time $t_0 = 1$, $i = \text{NAICS 324}$, change in θ_i $\delta = 0.1$, $T = 3$. All prior uncertainty resolves at $t_0 + T = 4$.

Now, at time $t_0 = 1$, the economy receives the external signal and all agents update their expected future consumption shares: The expected consumption share of i at time $t_0 + T = 4$ increases about 10% and the expected shares of other sectors adjust accordingly. The updated expectations show up directly in the forecasts upon impact. This impact then affects the distribution of shares of industrial sales, and the real terms: output levels, consumption, input purchase, etc. Figure 6 shows the changes of forecasts formed by sectors on the "chain" over time. All four sequences of forecasts change immediately upon the arrival of the signal at time 1. However, each spikes at a separate time. For the underlining sector, the forecast sequence spikes at time 3, one period before the uncertainty is resolved. For its supplier and the supplier's supplier, the maximum forecasts occur at time 2 and time 1, respectively. The customer's forecast does not change significantly. It is important to notice how the impact of shocks to expectation is transferred in the upstream direction. Upon impact, the underlining sector anticipates a higher consumption share of its own product in three periods and its forecasts of future sales relative to total consumption are adjusted accordingly. Its direct supplier anticipates the same and the increased expectation of customer sales will drive the purchase of the supplier's product as input, which will happen in two periods. The same logic explains the spike in the forecast of the supplier's supplier. Therefore, a shock to the forecasts acts as a demand-side shock and travels upstream through the supplier-customer

Figure 10: Responses of inputs on the selected chain. X axis is time and Y axis is the ratio between j 's use of product k as input at t , x_{jkt} and steady state x_{jk} . Solid line: underlining sector 324's use of its supplier sector 3's product; dashed line with Δ : supplier sector 3's use of the supplier's supplier 532's product; dotted line with ∇ : customer sector 481's use of 324's product. Impact time $t_0 = 1$, $i = \text{NAICS } 324$, change in θ_i $\delta = 0.1$, $T = 3$. All prior uncertainty resolves at $t_0 + T = 4$.

Figure 11: Response of $\log(\text{GDP})$. X axis is time and Y axis is the difference between $\log(\text{GDP}_t)$ and $\log(\text{GDP})$ at the steady state. Impact time $t_0 = 1$, $i = \text{NAICS } 324$, change in θ_i $\delta = 0.1$, $T = 3$. All prior uncertainty resolves at $t_0 + T = 4$.

Figure 12: Responses of $\log(GDP_t)$ to the changes in $E_{t_0}(\theta_{t_0+T})$, $T = 1, 2, 3, 4$. Each panel represents a different underlining sector i and reports the changes in $\log(GDP_t)$. The solid line, dashed line, broken line, and dotted line represent the change in expectation one, two, three, and four periods ahead, respectively. $\delta = 0.1$.

connections. In the downstream direction, however, the main blow of the forecast shock does not directly affect the customer. Once the uncertainty resolves, in this case when the signal is proven to be "wrong", the forecasts instantly adjust back to the stationary levels. Figure 7 illustrates the corresponding series of sales shares of the four sectors. Under the current model specification, neither productivity shocks nor shocks to the expectations of productivity can change the shares of industrial sales. As in the discussion on comparative statics, in response to an increase in sector j 's forecast, j 's own share of sales increases if j heavily relies on its own product as input and j 's supplier's share of sales increases if j is a major customer of the supplier. It is not surprising that the shares of sales of the four sectors move in the way shown due to how the "chain" is selected. Since the shares of sales depend only on the forecasts formed in the same period, the shares return to the stationary case when the forecasts do.

The responses of the real output, consumption, and input uses are shown in Figure 8, Figure 9, and Figure 10, respectively. Obviously, not only does the transitory shock to forecasts have real effects but these real effects also last because of the one-period-ahead input decisions. At each time, the real effects come from two sources: one is the change in the forecasts formed in that period and the other is the lasting impact of changes in previous periods through the input decisions. Since the forecasts return to the stationary levels at time 4, deviation of output, consumption, and input uses from their steady state levels from time 4 onwards is the cumulated result of the

effect from the latter source. This is the same as the lasting impact of a transitory productivity shock.

At the aggregate level, Figure 11 shows how the logarithm of real GDP, $\log(GDP_t)$, responds to the same shock to forecasts, where $\log(GDP_t) = \log(P_0^C C_t)$. With the prices normalized at a fixed level, changes in real GDP are in fact changes in the consumption index and the logarithm of real GDP is equivalent to the utility gained from consuming the basket of goods. The impact of the shock to forecasts on $\log(GDP_t)$ is, in general, not monotonic over time. Similar to the case of consumption of an individual product, before the uncertainty resolves, $\log(GDP_t)$ is under the direct impact of current-period forecasts and the indirect impact from previous forecasts carried through the input-output links; while after the uncertainty resolves, the lasting effect is solely due to the inputs.

Due to the timing constraint on the input decision, any shock to the forecasts at impact time t_0 has a persistent effect. I report the impact results when $T = 3$ so that the upward shock transmission from the customers to their suppliers is clearly shown in Figures 6 to 10. However, it is expected that when the target time T changes, the resulting paths of impact on each variable will not be the simple horizontal shifts along the time line. In addition, a sector's position in the production network also helps shape the impact paths. Figure 12 plots the responses of $\log(GDP_t)$ for different target times, $T = 1, 2, 3, 4$, and for three other target sectors, with $\delta = 0.1$ unchanged. After the impact, the resulting changes in $\log(GDP_t)$ differ both in the scale and in the direction across sectors and across various target times.

4 Quantitative Explorations

An important feature of the model is that in equilibrium, the evolvement of the forecasts sequence $\{\tilde{\mathbf{f}}_t\}$ relies only on the distributions of future product-specific preference shocks $\{\boldsymbol{\theta}_\tau\}_{\tau>t}$ and the news about future demand. Once the values of forecasts are given, the rest of the equilibrium components are also determined. The parameterization of the model goes backwards: I calibrate part of the model to match the observed variables in the data and then calculate the forecasts sequence from the data; then I estimate the distribution of the news. Using the estimation results, I show the importance of the news about future demand as a driving force of the aggregate economic volatility.

4.1 Calibration

The main data set used to calibrate and estimate the model is taken from the Annual Industry Accounts at the Bureau of Economic Analysis. In particular, the annual use table (after redefinitions) sets the targets of calibrating the most important set of parameters, which contains the shares of input goods in each industry, $\mathbf{A} = \text{diag}(\alpha_1, \dots, \alpha_n)$; the specific share of each certain good used as input, Ω with $\Omega(i, j) = \omega_{ij}$; and the mean of the prior distribution of product-specific demand parameters, $\boldsymbol{\theta} = (\theta_1, \dots, \theta_n)$. The use table is essentially a matrix that shows the uses of commodities by industries as intermediate inputs and by final users in a given year from 1998 to 2011. The uses are measured in terms of dollar expenditures. Excluding the governments, the annual use tables report the information on 61 industries/commodities.

Table 1. Parameter Values

Standard Parameters	
$\beta = 0.96$	Discount factor
$\varepsilon = 1$	Disutility in labor
$z = 10$	Mean productivity
Calibrated Parameters	
$\eta = 9.49$	Mean aggregate demand s.t. $\bar{h}_i = 1/3$
$\mathbf{A}$	Complements of labor share
Ω	Input requirements
$\boldsymbol{\theta}$	Mean product-specific demand

From the analysis of the model, the shares of input goods $\mathbf{A}$ are in fact the complements of labor shares, each of which is the fraction of total industrial sales used for labor compensation:

$$\alpha_i = 1 - \frac{\sum_t (\text{labor compensation in } i \text{ at } t)}{\sum_t (\text{total sales of } i \text{ at } t)}.$$

In equilibrium, the realized product-specific preference parameters $\boldsymbol{\theta}_t$ are the current-period total consumption expenditure shares of each product. Hence $\boldsymbol{\theta}_t$ can be chosen such that the equilibrium composition of consumption expenditure lines up perfectly to the data. The consumption expenditure on each commodity is measured as the final use of that commodity, including the amount imported.

$$\theta_{it} = \frac{\text{Final use on } i \text{ at } t}{\text{Total final uses at } t},$$

and the unconditional mean of the consumption shares $\boldsymbol{\theta}$ is set at the simple average over the 1998 to 2011 period,

$$\boldsymbol{\theta} = \frac{\sum_t (\text{Final use of each commodity at } t)}{\sum_t (\text{Total final uses at } t)}.$$

The production technology matrix Ω determines the input requirements of each sector, and this is obtained by normalizing the total input expenditure by each sector to one:

$$\omega_{ij} = \frac{\sum_t (i\text{'s purchase of } j \text{ at } t)}{\sum_t (i\text{'s total input purchase at } t)}.$$

The discount factor β is set to be 0.96 to match the annual frequency of the data set. In addition, I set $\varepsilon = 1$ so that the disutility in labor has a quadratic form. The unconditional mean of the aggregate preference shock, η , is set at 9.49 which ensures the average labor supply at the steady state is 1/3. Moreover, since the process of aggregate preference η_t and that of the sector-specific productivity $\{z_{it}\}_{i=1}^n$ do not affect the sequence of $\{\tilde{f}_{it}\}$ under the assumption of the model, the uncertainty is shut down such that the aggregate preference is fixed over time, $\eta_t = \eta$, $\forall t$ and all sectors share the same time-invariant productivity $z_{it} = z_i = z$, $\forall i, t$. The unconditional mean of the productivity z is 10.

4.2 Recovering the Forecast Process

The featured driving force of the model is the news about future product-specific demand, $\{M_t\}$, which leads to the changes in the forecast sequence $\{\tilde{\mathbf{f}}_t\}$ and in turn causes the fluctuations in the other equilibrium components. Apparently, both the news and the forecasts are unobservable in the data. However, under the stark model assumptions, the equilibrium forecasts can be recovered as a function of the observable variables. In fact, the Euler equations of the firms can be rewritten to get the following result.

Lemma 2. *For each sample period t , for each industry i , the forecast term $\tilde{f}_{it}$ is uniquely pinned down by the following equation:*

$$\tilde{f}_{it} = \frac{P_{it}^X X_{it}}{\beta \alpha_i P_t^C C_t}.$$

According to this lemma, the standard use table is used to recover the forecasts from 1998 to 2011, where $P_{it}^X X_{it}$ is industry i 's total input expenditure at t , and $P_t^C C_t$ is the total value added (GDP) at t . Descriptive statistics of the calculated sequence of forecasts can be found in the appendix.

In the model, the shares of sectorial sales change only when the forecasts do, so I check how much more the estimated sequence of forecasts $\{\tilde{f}_{it}\}$ captures the distribution of industries' sales shares than the stationary $\tilde{\mathbf{f}}$. Define the sales shares calculated from the data as $\{s_{it}^{Data}\}$. Using the estimated $\{\tilde{f}_{it}\}$, I can get the model-predicted sales shares from

$$s_{it}^{Model} = \frac{\theta_{it} + \beta \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt}}{1 + \beta \sum_j \alpha_j \tilde{f}_{jt}}.$$

To highlight the importance of forecasts, the unconditional mean of consumption shares $\boldsymbol{\theta}$ enters this equation, instead of the actual shares $\boldsymbol{\theta}_t$. The labor shares $\{\alpha_j\}$ are also the time-invarying calibrated values. The model-predicted sales shares will also differ from the actual sales shares due to the stark assumptions made in the model. Define the unexplained cross-sectional variation in sales shares (UEVS) at time t as

$$UEVS_t = \frac{\sum_i (s_{it}^{Data} - s_{it})^2}{\sum_i (s_{it}^{Data})^2},$$

where shares $\{s_{it}\}$ are either the stationary shares $\{s_i\}$ of the model or the model-predicted shares $\{s_{it}^{Model}\}$ using the estimated $\{f_{it}\}$. A lower level of UEVS means a better fit of the sales shares and an ideal fit yields zero UEVS. In fact, taking the average over time, we have

$$\begin{aligned}\overline{UEVS^{Stat}} &= 0.2304 \\ \overline{UEVS^{Model}} &= 0.0815.\end{aligned}$$

Figure ?? illustrates the model-predicted distribution of industrial sales using the forecasts backed up from the data.

4.3 Estimation and Simulation

The analysis of the forecast formation does not require any specific distributions of the product-specific preference shocks or of the news process. For the purpose of estimation and simulation, I impose further assumptions on these distributions, $\Xi^\theta(\cdot)$ and $\Xi^m(\cdot|\boldsymbol{\theta}_t)$.

Assume that the independent and identical prior $\Xi^\theta(\cdot)$ of the product-specific preference shocks $\boldsymbol{\theta}_t$ is a Dirichlet distribution of order n with concentration parameters $\boldsymbol{\theta}$ and a scale parameter $\kappa > 0$,

$$\boldsymbol{\theta}_t \sim \text{Dirichlet}_n(\kappa\boldsymbol{\theta})$$

hence $E(\boldsymbol{\theta}_t) = \boldsymbol{\theta}$ and κ determines the scale of the variance-covariance matrix of $\boldsymbol{\theta}_t$. The unconditional expectation $\boldsymbol{\theta}$ is pinned down in the calibration. To accommodate the Dirichlet prior, let the news that contains the information on $\boldsymbol{\theta}_t$ be drawn from a multinomial distribution. Specifically, for each t , the distribution of news $\mathbf{m}_t^{t-\tau}$ about $\boldsymbol{\theta}_t$ that arrives in period $t - \tau$ is

$$\mathbf{m}_t^{t-\tau} \sim \text{Multinomial}(N, \boldsymbol{\theta}_t), \forall \tau = 1, \dots, T,$$

where the integer $N \geq 1$ is the number of trials and $\boldsymbol{\theta}_t$ represents the probability associated with each possible outcome in one trial. Conditional on the news, the posterior distribution of $\boldsymbol{\theta}_t$

remains Dirichlet. In each period t , the posterior distributions of future $\boldsymbol{\theta}_{t+\tau}$ have the following expectations,

$$\begin{aligned} E_t(\boldsymbol{\theta}_{t+1}) &= \frac{\kappa \boldsymbol{\theta} + \sum_{\tau'=0}^{T-1} \mathbf{m}_{t+1}^{t-\tau'}}{\kappa + TN} \\ E_t(\boldsymbol{\theta}_{t+2}) &= \frac{\kappa \boldsymbol{\theta} + \sum_{\tau'=0}^{T-2} \mathbf{m}_{t+2}^{t-\tau'}}{\kappa + (T-1)N} \\ &\vdots \\ E_t(\boldsymbol{\theta}_{t+T}) &= \frac{\kappa \boldsymbol{\theta} + \mathbf{m}_{t+T}^t}{\kappa + N}, \end{aligned}$$

hence

$$\tilde{\mathbf{f}}_t = \sum_{\tau=1}^T \beta^{\tau-1} (\Omega' \mathbf{A})^{\tau-1} \frac{\kappa \boldsymbol{\theta} + \sum_{\tau'=0}^{T-\tau} \mathbf{m}_{t+\tau}^{t-\tau'}}{\kappa + (T+1-\tau)N} + \beta^T (\Omega' \mathbf{A})^T \tilde{\mathbf{f}}.$$

The specific information structure discussed in the theoretical model is very stylized, according to which the changes in forecasts solely come from the news about future product-specific demands. Therefore, the variation in forecasts provides the target in the estimation of the news process. Specifically, the remaining parameters to be estimated are κ , N , and T , where κ controls the scale of the variance matrix of the prior distribution of $\boldsymbol{\theta}_t$, N determines the precision of news, and T sets how far into the future the news can reach.

Table 2. Forecast Process Parameters

Parameters to be estimated

κ Scale of prior variance of $\boldsymbol{\theta}_t$

N Precision of news

T Maximum number of news

Denote the unconditional variance-covariance matrix of $\boldsymbol{\theta}_t$ as $\Sigma^\theta(\kappa)$, such that:

$$\begin{aligned} \Sigma^\theta(\kappa) &= \text{Var}(\boldsymbol{\theta}_t; \kappa), \\ \Sigma_{ii}^\theta(\kappa) &= \text{Var}(\theta_{it}; \kappa) = \frac{\theta_i(1-\theta_i)}{\kappa+1}, \forall i \\ \Sigma_{ij}^\theta(\kappa) &= \text{Cov}(\theta_{it}, \theta_{jt}; \kappa) = -\frac{\theta_i \theta_j}{\kappa+1}, \forall i \neq j. \end{aligned}$$

The news about $\boldsymbol{\theta}_t$ received in period s , $\forall s < t$, is independently drawn from the multinomial distribution with N trials, $\mathbf{m}_t^s := (m_{1t}^s, \dots, m_{nt}^s)' \sim \text{Multinomial}(N, \boldsymbol{\theta}_t)$. Conditional on $\boldsymbol{\theta}_t$, the moments of the news satisfies

$$\begin{aligned} E(\mathbf{m}_t^s | \boldsymbol{\theta}_t) &= N \boldsymbol{\theta}_t \\ \text{Var}(m_{it}^s | \boldsymbol{\theta}_t) &= N \theta_{it} (1 - \theta_{it}), \forall i, \forall s \\ \text{Cov}(m_{it}^s, m_{jt}^s | \boldsymbol{\theta}_t) &= -N \theta_{it} \theta_{jt}, \forall i \neq j, \forall s. \end{aligned}$$

Therefore, the unconditional variance-covariance matrix of the news, denoted as Σ^m , is such that

$$\begin{aligned}\Sigma^m(\kappa, N) &= E(E(\mathbf{m}_t^s \mathbf{m}_t^{s'} | \boldsymbol{\theta}_t)) - E(E(\mathbf{m}_t^s | \boldsymbol{\theta}_t)) E(E(\mathbf{m}_t^{s'} | \boldsymbol{\theta}_t)) \\ &= N(N + \kappa) \Sigma^\theta(\kappa), \forall t, \forall s < t.\end{aligned}$$

Note that, for each piece of news, the unconditional variance-covariance matrix $\Sigma^m(\kappa, N)$ is the same, namely, $\Sigma^m(\kappa, N)$ depends neither on the target time t nor on the news arrival time $s < t$. In fact, $\Sigma^m(\kappa, N)$ remains the same for any T .

For a given T , the forecast vector at each time t can be written as

$$\tilde{\mathbf{f}}_t = Const + \sum_{\tau=1}^T \beta^{\tau-1} (\Omega' \mathbf{A})^{\tau-1} \frac{\sum_{\tau'=0}^{T-\tau} \mathbf{m}_{t+\tau}^{t-\tau'}}{\kappa + (T+1-\tau)N},$$

where $Const$ is a time-invariant constant vector. Consequently, due to the independence assumption on the news, the unconditional variance-covariance matrix of $\tilde{\mathbf{f}}_t$, $\Sigma^f(\kappa, N, T)$, has the following form

$$\begin{aligned}\Sigma^f(\kappa, N, T) &= Var(\tilde{\mathbf{f}}_t; \kappa, N, T) \\ &= N(N + \kappa) \sum_{\tau=1}^T \frac{\beta^{2(\tau-1)} (T - \tau + 1)}{(\kappa + (T+1-\tau)N)^2} (\Omega' \mathbf{A})^{\tau-1} \Sigma^\theta(\kappa) (\mathbf{A} \Omega)^{\tau-1}.\end{aligned}$$

The data counterpart of the unconditional variance-covariance matrix of forecasts $\widehat{\Sigma}^f$ can be directly calculated from the recovered forecast sequence. Similarly, the unconditional variance-covariance matrix of product-specific preference $\widehat{\Sigma}^\theta$ can also be calculated using the realized $\boldsymbol{\theta}_t$. The estimation strategy consists of two steps and picks κ and (N, T) sequentially. Step one picks $\hat{\kappa}$ to match $\widehat{\Sigma}^\theta$ and step two chooses $(\hat{N}, \hat{T})$ to match $\widehat{\Sigma}^f$ given $\hat{\kappa}$.

Table 3. Estimation Result of (κ, N, T)

	Step 1	Step 2
Result	$\hat{\kappa} = 6651$	$\hat{N} = 25000, \hat{T} = 1$
Objective	$\min_{\kappa} \sum_i \overline{s_i^{Data}} \left \widehat{\Sigma}_{ii}^\theta - \Sigma_{ii}^\theta(\kappa) \right $	$\min_{(N, T)} \sum_i \overline{s_i^{Data}} \left \widehat{\Sigma}_{ii}^f - \Sigma_{ii}^f(\hat{\kappa}, N, T) \right $

According to the estimation result, at the annual frequency, the news that arrives in each period contains only information on the product-specific preference in the following period, $\hat{T} = 1$. Consequently, in the model language,

$$\tilde{\mathbf{f}}_t = \frac{\hat{\kappa} \boldsymbol{\theta} + \mathbf{m}_{t+1}^t}{\hat{\kappa} + \hat{N}} + \beta \Omega' \mathbf{A} \tilde{\mathbf{f}}.$$

To see how much aggregate fluctuation can result from the changing forecasts driven by continual arrivals of news, I do the following three experiments, each of which starts from the steady state of the model and evolves under a particular driving force. In the first experiment (E1), the product-specific preference in each period, θ_t , is independently drawn from the Dirichlet distribution with concentration parameters $\hat{\kappa}\theta$, the news is informative, $\mathbf{m}_{t+1}^t \sim MN(\hat{N}, \theta_{t+1})$, and the prior distribution of θ_t is "correct". The θ_t sequence in the second experiment (E2) is fixed at its mean, $\theta_t = \theta$, the news is then iid, $\mathbf{m}_{t+1}^t \sim MN(\hat{N}, \theta)$, while the agents holds the Dirichlet prior. In the third experiment (E3), the only driving force is the changing θ_t . The aggregate volatility is measured as the standard deviation in the growth rate of real GDP. During the sample period, between 1998 and 2011, this standard deviation is 0.0202. The model counterpart is $\text{Std}(\Delta gdp_t^{Model})$, where Δgdp_t^{Model} is defined as the following

$$\Delta gdp_t^{Model} = \log \left(\sum_i \frac{p_{it}}{P_t^C} c_{it} \right) - \log \left(\sum_i \frac{p_{it-1}}{P_{t-1}^C} c_{it-1} \right) = \log \frac{C_t}{C_{t-1}}.$$

Table 4 reports the simulation results. The driving force of the economy in E1 is a mixture of product-specific preference shocks and news that reflects the changing θ_t , which is capable of generating the aggregate volatility 0.0156. This level is around 77% percent of the actual volatility in the growth rate of real GDP. In E2, the news process is the only source of shocks. Note that because θ_t is fixed at θ , the distribution of news is fixed as well. With all relevant fundamentals fixed at their steady state levels, the iid news alone generates significant fluctuation at the aggregate level, more than 6%. E3 illustrate the importance of the product-specific preference shocks, without news arrivals.

Table 4. Simulated Aggregate Volatility

	Data 1998-2011	E1: θ_t and $\mathbf{m}_{t+1}^t$	E2: $\mathbf{m}_{t+1}^t$ only	E3: θ_t only
$\text{Std}(\Delta gdp_t)$	0.0202	0.0156	0.0013	0.0138
Model/Data, %	100	77.02	6.44	68.57

5 Concluding Remarks

The paper develops a dynamic multi-sector production network model in which firms receive external information on the future demand structure. Since firms are connected via an input-output network, news on the future demand of an individual industry has a global effect. Shocks to future forecasts are transferred upwards through the supplier-customer connections in the network, from the buyer of an input good to the producer. The shares of industrial sales then reflect the updated forecasts, which have real effects and fluctuate over time. The model is able to explain (1)

the asymmetry in the transmission of individual shocks in the network, and (2) the time-varying distribution of sales across industries, which cannot be explained by multi-sector models using purely individual productivity shocks. The numerical exercise demonstrate the importance of the newly introduced forecast shocks to generate aggregate-level economic volatility.

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6 Appendix

6.1 Price Indices

Claim 2. *In equilibrium,*

$$\begin{aligned} P_t^C C_t &= \prod_i \left(\frac{p_{it} c_{it}}{\theta_{it}} \right)^{\theta_{it}} = \sum_{i=1}^n p_{it} c_{it}, \\ P_{it}^X X_{it} &= \prod_j \left(\frac{p_{jt} x_{ijt}}{\omega_{ij}} \right)^{\omega_{ij}} = \sum_{j=1}^n p_{jt} x_{ijt}. \end{aligned}$$

Proof. HH FOC

$$\beta^t \eta_t \theta_{it} = \lambda_t p_{it} c_{it}.$$

So

$$\frac{p_{it} c_{it}}{\theta_{it}} = \sum p_{it} c_{it}$$

since $\sum \theta_{it} = 1$,

$$\sum p_{it} c_{it} = \prod \left(\sum p_{it} c_{it} \right)^{\theta_{it}} = \prod \left(\frac{p_{it} c_{it}}{\theta_{it}} \right)^{\theta_{it}} = P_t^C C_t.$$

Similarly, firm i 's FOC:

$$p_{jt} x_{ijt} = \alpha_i \omega_{ij} E_t (\Lambda_{t,t+1} s_{i,t+1})$$

so

$$\frac{p_{jt} x_{ijt}}{\omega_{ij}} = \sum_j p_{jt} x_{ijt}$$

and since $\sum \omega_{ij} = 1$

$$\sum_j p_{jt} x_{ijt} = \prod \left(\sum_j p_{jt} x_{ijt} \right)^{\omega_{ij}} = \prod \left(\frac{p_{jt} x_{ijt}}{\omega_{ij}} \right)^{\omega_{ij}} = P_{it}^X X_{it}.$$

□

6.2 Proof of Lemma 1

Proof. Firm i 's FOC

$$w_{it} h_{it} = (1 - \alpha_i) s_{it}.$$

HH's budget constraint

$$\sum p_{it} c_{it} = \sum (1 - \alpha_i) s_{it} + \sum \pi_{it}.$$

Market clearing

$$p_{it}c_{it} + \sum_j p_{it}x_{jit} = \theta_{it}P_t^C C_t + \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt} P_t^C C_t = s_{it}$$

So

$$\begin{aligned} \frac{s_{it}}{P_t^C C_t} &= \theta_{it} + \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt} \\ \frac{\sum s_{it}}{P_t^C C_t} &= 1 + \sum_j \alpha_j \tilde{f}_{jt}. \end{aligned}$$

□

Note that the proof also implies

$$\begin{aligned} \frac{c_{it}}{y_{it}} &= \frac{\theta_{it}}{\theta_{it} + \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt}} \\ \frac{x_{jit}}{y_{it}} &= \frac{\alpha_j \omega_{ji} \tilde{f}_{jt}}{\theta_{it} + \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt}}. \end{aligned}$$

and HH labor supply condition

$$\begin{aligned} h_{it}^\varepsilon &= \eta_t \frac{w_{it}}{P_t^C C_t} \\ h_{it}^{1+\varepsilon} &= \eta_t \frac{(1 - \alpha_i) s_{it}}{P_t^C C_t} = \eta_t (1 - \alpha_i) \left(\theta_{it} + \sum_j \alpha_j \omega_{ji} \tilde{f}_{jt} \right). \end{aligned}$$

6.3 Discription Statistics

The means and standard deviations of the recovered forecasts and consumption shares are reported in the following table.

Code	$\text{Avg}(\tilde{f}_{it})$	$\text{Std}(\tilde{f}_{it})$	$\theta_i, \%$	$\text{Std}(\theta_{it}), \%$
111CA	0.0172	0.0014	0.64	0.06
113FF	0.0025	0.0007	0.09	0.01
211	0.0070	0.0018	0.04	0.03
212	0.0039	0.0006	0.06	0.03
213	0.0053	0.0028	0.62	0.30
22	0.0171	0.0064	1.78	0.08
23	0.0850	0.0106	8.30	1.19
321	0.0083	0.0021	0.12	0.05
327	0.0078	0.0010	0.13	0.02
331	0.0157	0.0027	0.18	0.06
332	0.0220	0.0020	0.38	0.03
333	0.0232	0.0027	2.26	0.21
334	0.0316	0.0141	3.23	0.55
335	0.0089	0.0019	0.69	0.03
3361MV	0.0412	0.0081	3.72	0.73
3364OT	0.0167	0.0020	1.33	0.11
337	0.0058	0.0013	0.61	0.11
339	0.0094	0.0008	1.26	0.04
311FT	0.0533	0.0028	3.84	0.22
313TT	0.0062	0.0024	0.31	0.05
315AL	0.0037	0.0026	1.11	0.23
322	0.0126	0.0017	0.31	0.02
323	0.0092	0.0019	0.04	0.01
324	0.0289	0.0122	1.48	0.63
325	0.0388	0.0028	2.50	0.28
326	0.0146	0.0019	0.37	0.03

Code	$\text{Avg}(\tilde{f}_{it})$	$\text{Std}(\tilde{f}_{it})$	$\theta_i, \%$	$\text{Std}(\theta_{it}), \%$
42	0.0420	0.0040	4.61	0.17
44RT	0.0468	0.0026	8.01	0.27
481	0.0083	0.0010	0.96	0.07
482	0.0039	0.0004	0.12	0.02
483	0.0020	0.0002	0.14	0.01
484	0.0156	0.0011	0.87	0.03
485	0.0013	0.0004	0.20	0.01
486	0.0015	0.0005	0.02	0.00
487OS	0.0069	0.0005	0.20	0.02
493	0.0027	0.0003	0.02	0.00
511	0.0193	0.0023	1.31	0.05
512	0.0049	0.0005	0.37	0.04
513	0.0301	0.0029	1.87	0.07
514	0.0058	0.0023	0.29	0.10
521CI	0.0409	0.0067	1.79	0.11
523	0.0349	0.0076	1.26	0.11
524	0.0316	0.0031	2.16	0.07
525	0.0086	0.0009	0.88	0.06
531	0.0549	0.0061	11.65	0.39
532RL	0.0093	0.0012	1.09	0.05
5411	0.0089	0.0010	0.76	0.03
5415	0.0216	0.0027	1.63	0.11
5412OP	0.0443	0.0017	0.98	0.10
55	0.0232	0.0013	0.42	0.11
561	0.0343	0.0017	0.32	0.01
562	0.0041	0.0004	0.12	0.00
61	0.0131	0.0005	1.87	0.20
621	0.0403	0.0025	5.23	0.37
622HO	0.0498	0.0047	6.02	0.53
711AS	0.0055	0.0008	0.39	0.04
713	0.0055	0.0005	0.99	0.03
721	0.0086	0.0011	0.67	0.05
722	0.0357	0.0011	3.66	0.09
81	0.0386	0.0023	3.69	0.16

6.4 NAICS Code and Industry Discription

111CA	Farms
113FF	Forestry, fishing, and related activities
211	Oil and gas extraction
212	Mining, except oil and gas
213	Support activities for mining
22	Utilities
23	Construction
321	Wood products
327	Nonmetallic mineral products
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
3361MV	Motor vehicles, bodies and trailers, and parts
3364OT	Other transportation equipment
337	Furniture and related products
339	Miscellaneous manufacturing
311FT	Food and beverage and tobacco products
313TT	Textile mills and textile product mills
315AL	Apparel and leather and allied products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
42	Wholesale trade
44RT	Retail trade
481	Air transportation
482	Rail transportation
483	Water transportation
484	Truck transportation
485	Transit and ground passenger transportation
486	Pipeline transportation

487OS Other transportation and support activities
 493 Warehousing and storage
 511 Publishing industries (includes software)
 512 Motion picture and sound recording industries
 513 Broadcasting and telecommunications
 514 Information and data processing services
 521CI Federal Reserve banks, credit intermediation, and related activities
 523 Securities, commodity contracts, and investments
 524 Insurance carriers and related activities
 525 Funds, trusts, and other financial vehicles
 531 Real estate
 532RL Rental and leasing services and lessors of intangible assets
 5411 Legal services
 5415 Computer systems design and related services
 5412OP Miscellaneous professional, scientific, and technical services
 55 Management of companies and enterprises
 561 Administrative and support services
 562 Waste management and remediation services
 61 Educational services
 621 Ambulatory health care services
 622HO Hospitals and nursing and residential care facilities
 624* Social assistance
 711AS Performing arts, spectator sports, museums, and related activities
 713 Amusements, gambling, and recreation industries
 721 Accommodation
 722 Food services and drinking places
 81 Other services, except government

* This industry is excluded from the main analysis to ensure all relevant matrices are invertible.