Online Appendix for Noisy Global Value Chains*

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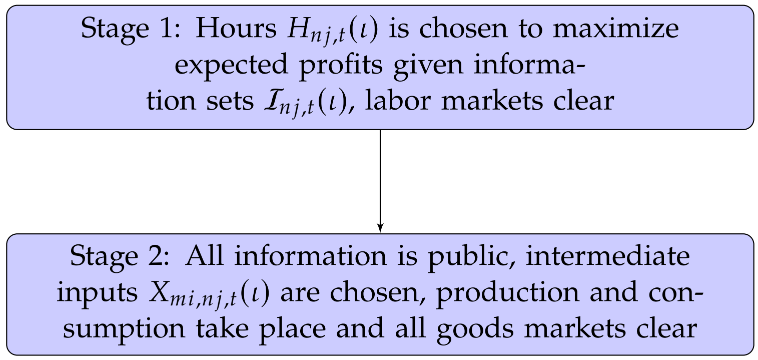
A. Proofs

A.1 Timing

Figure A1: Model Timing



A.2 Proof of Lemma 1

The market clearing condition for the sales in country n sector j in levels is

$$P_{nj,t}Y_{nj,t} \quad = \quad \sum_{m,i}\eta_i P_{mi,t}Y_{mi,t}\pi_{nj,m} + \sum_{m,i}(1-\eta_i)P_{mi,t}Y_{mi,t}\omega_{nj,mi}.$$

Note that with financial autarky, the total sales of final goods is the same as the value added across sectors

$$P_{m,t}\mathcal{F}_{m,t} = \sum_i \eta_i P_{mi,t}Y_{mi,t}.$$

The market clearing condition is then

$$P_{nj,t}Y_{nj,t} = \sum_m\sum_i \eta_i P_{mi,t}Y_{mi,t}\pi_{nj,m} + \sum_m\sum_i(1-\eta_i)P_{mit}Y_{mit}\omega_{nj,mi}.$$

Note that $P_{nj,t}Y_{nj,t}$ remains constant for all (n,j) satisfies the equilibrium condition. This implies

$$\ln P_{nj,t} = -\ln Y_{nj,t}$$

In the second-stage of a period, the first-order condition on the intermediate goods is that

$$(1-\eta_{nj})P_{nj,t}Y_{nj,t} = P^x_{nj,t}X_{nj,t},$$

where $X_{nj,t} = \prod_{m,i} X_{mi,nj,t}^{\omega_{mi,nj}}$ and $P^x_{nj,t} = \prod_{m,i} P_{mi,t}^{\omega_{mi,nj}}$ is the corresponding price index. It follows that

$$\begin{aligned}
\ln X_{nj,t} &= \ln Y_{nj,t} + \ln P_{nj,t} + \ln\left(1-\eta_{nj}\right) - \ln P^x_{nj,t} \\
\ln P^x_{nj,t} &= \sum_{m,i}\omega_{mi,nj}\ln P_{mi,t},
\end{aligned}$$

which implies that

$$\ln X_{nj,t} = \ln Y_{nj,t} + \ln P_{nj,t} + \ln\bigl(1-\eta_{nj}\bigr) - \sum_{m,i} \omega_{mi,nj} \ln P_{mi,t}.$$

The production technology implies that

$$\ln Y_{nj,t} = z_{nj,t} + \eta_j \alpha_j \ln H_{nj,t} + (1-\eta_j) \ln X_{nj,t}.$$

In matrix form, using the relationship between $P_{mi,t}$ and $Y_{mi,t}$, we have

$$\begin{aligned}
\ln \mathbf{Y}_t =& \boldsymbol{z}_t + \boldsymbol{\eta}\boldsymbol{\alpha} \ln \mathbf{H}_t + (\mathbf{I}-\boldsymbol{\eta}) \ln \mathbf{X}_t, \\
=& \boldsymbol{z}_t + \boldsymbol{\eta}\boldsymbol{\alpha} \ln \mathbf{H}_t + (\mathbf{I}-\boldsymbol{\eta})(\ln \mathbf{Y}_t + (\mathbf{I}-\boldsymbol{\omega}) \ln \mathbf{P}_t) + \text{const}, \\
=& \boldsymbol{z}_t + \boldsymbol{\eta}\boldsymbol{\alpha} \ln \mathbf{H}_t + (\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega} \ln \mathbf{Y}_t + \text{const}.
\end{aligned}$$

Solving for $\ln \mathbf{P}_t$ leads to

$$\ln \mathbf{P}_t = -\ln \mathbf{Y}_t = -(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1} \left(\boldsymbol{z}_t + \boldsymbol{\eta}\boldsymbol{\alpha} \ln \mathbf{H}_t\right) + \text{const}.$$

We make the conjecture that the hours $\mathbf{H}_t$ are log-normally distributed, which will be verified in proofs of Lemma 2 and Proposition 2.2. Under this conjecture, it is straightforward to see that both output $\mathbf{Y}_t$ and prices $\mathbf{P}_t$ are both log-normally distributed. Let $\overline{\mathbf{P}}$ and $\overline{\mathbf{H}}$ denote the levels when aggregate shocks stay at their unconditional means, and let $\boldsymbol{p}_t$ and $\boldsymbol{h}_t$ denote the corresponding log-deviations

$$\begin{aligned}
\ln \mathbf{P}_t &= \boldsymbol{p}_t + \ln \overline{\mathbf{P}}, \\
\ln \mathbf{H}_t &= \boldsymbol{h}_t + \ln \overline{\mathbf{H}}.
\end{aligned}$$

It follows that

$$\boldsymbol{p}_t = -(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}(\boldsymbol{z}_t + \boldsymbol{\eta}\boldsymbol{\alpha}\boldsymbol{h}_t).$$

A.3 Proof of Lemma 2

In the first stage, the local labor supply condition at island (n, j, ι) is

$$W_{nj,t}(\iota) = H_{nj,t}^{\frac{1}{\psi}}(\iota)\mathbb{E}[P_{n,t}|\mathcal{I}_{nj,t}(\iota)].$$

The labor demand solves firms' problem

$$\max_{H_{nj,t}(\iota)} \mathbb{E}[\Omega_{nj,t}(H_{nj,t}(\iota))|\mathcal{I}_{nj,t}(\iota)] - W_{nj,t}(\iota)H_{nj,t}(\iota),$$

which leads to the following first-order condition

$$H_{nj,t}(\iota)W_{nj,t}(\iota) = \alpha_j\eta_j(1-\eta_j)^{\frac{1}{\eta_j}-1}\mathbb{E}\left[\left(P^x_{nj,t}\right)^{1-\frac{1}{\eta_j}} P_{nj,t}^{\frac{1}{\eta_j}} \exp\bigl(z_{nj,t}\bigr)^{\frac{1}{\eta_j}}\middle|\mathcal{I}_{nj,t}(\iota)\right] K_{nj}^{1-\alpha_j} H_{nj,t}(\iota)^{\alpha_j}.$$

Combining demand and supply leads to

$$H_{nj,t}(\iota)^{1+\frac{1}{\psi}-\alpha_j}\mathbb{E}\left[P_{n,t}\middle|\mathcal{I}_{nj,t}(\iota)\right] = \alpha_j\eta_j(1-\eta_j)^{\frac{1}{\eta_j}-1}\mathbb{E}\left[\left(P^x_{nj,t}\right)^{1-\frac{1}{\eta_j}} P_{nj,t}^{\frac{1}{\eta_j}} \exp\bigl(z_{nj,t}\bigr)^{\frac{1}{\eta_j}}\middle|\mathcal{I}_{nj,t}(\iota)\right] K_{nj}^{1-\alpha_j}, \quad \text{(A.1)}$$

where $P_{n,t} = \prod_{m,i} P_{mi,t}^{\pi_{mi,n}}$ and $P^x_{nj,t} = \prod_{m,i} P_{mi,t}^{\omega_{mi,nj}}$.

We proceed with a guess-and-verify approach. We conjecture that hours are log-normally distributed. As shown in Lemma 1, prices follow a log-normal distribution as well. With Cobb-Douglas aggregators, both final-goods prices and intermediate-goods price indices are also log-normally distributed

$$\ln P_{n,t} = \sum_{m,i} \pi_{mi,n} p_{mi,t} + \text{const},$$
$$\ln P^x_{nj,t} = \sum_{m,i} \omega_{mi,nj} p_{mi,t} + \text{const}.$$

Note that for a random variable, $\exp(G_t)$, that follows a log-normal distribution, its expected value based on Gaussian signals F_t follows

$$\mathbb{E}[\exp(G_t)|F_t] = \exp\left(\mu_{G|F} + \frac{1}{2}\sigma_{G|F}\right).$$

Based on this observation, condition (A.1) then can be expressed as

$$\left(1 + \frac{1}{\psi} - \alpha_j\right) \ln\big(H_{nj,t}(\iota)\big) = \mathbb{E}\left[\frac{1}{\eta_j} z_{nj,t} + \frac{1}{\eta_j} p_{nj,t} + \left(1 - \frac{1}{\eta_j}\right) p^x_{nj,t} - p_{n,t} \middle| \mathcal{I}_{nj,t}(\iota)\right] + \text{const}.$$

The constant term contains the conditional variance which does not vary in a stationary environment. Therefore, due to the compatibility of the power functional form and that the signals follow normal distributions, the hours $H_{nj,t}(\iota)$ will indeed follow a log-normal distribution. The exact solution to hours is given explicitly in Proposition 2.2.

Denote $h_{nj,t}(\iota)$ as the deviation from its steady-state level,

$$\ln H_{nj,t}(\iota) = h_{nj,t}(\iota) + \text{const},$$

and it satisfies

$$h_{nj,t}(\iota) = \left(1 + \frac{1}{\psi} - \alpha_j\right)^{-1} \left(\mathbb{E}\left[\frac{1}{\eta_j} z_{nj,t} + \frac{1}{\eta_j} p_{nj,t} + \left(1 - \frac{1}{\eta_j}\right) p^x_{nj,t} - p_{n,t} \middle| \mathcal{I}_{nj,t}(\iota)\right]\right).$$

At the country-sector level, we have

$$\begin{aligned} h_{nj,t} &= \left(1 + \frac{1}{\psi} - \alpha_j\right)^{-1} \left(\overline{\mathbb{E}}_{nj,t}\left[\frac{1}{\eta_j} z_{nj,t} + \frac{1}{\eta_j} p_{nj,t} + \left(1 - \frac{1}{\eta_j}\right) p^x_{nj,t} - p_{n,t}\right]\right) \\ &= \left(1 + \frac{1}{\psi} - \alpha_j\right)^{-1} \left(\overline{\mathbb{E}}_{nj,t}\left[\frac{1}{\eta_j} z_{nj,t} + \frac{1}{\eta_j} p_{nj,t} + \left(1 - \frac{1}{\eta_j}\right) \sum_{m,i} \omega_{mi,nj} p_{mi,t} - \sum_{m,i} \pi_{mi,n} p_{mi,t}\right]\right). \end{aligned}$$

In matrix form, the variations in hours satisfy

$$
\begin{aligned}
\left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\right)\boldsymbol{h}_t &= \boldsymbol{\eta}^{-1}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] + \left(\boldsymbol{\eta}^{-1} + (\mathbf{I}-\boldsymbol{\eta}^{-1})\boldsymbol{\omega} - \boldsymbol{\pi}\right)\overline{\mathbb{E}}_t\left[\boldsymbol{p}_t\right], \\
\left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\right)\boldsymbol{h}_t &= \boldsymbol{\eta}^{-1}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] - \left(\boldsymbol{\eta}^{-1} + (\mathbf{I}-\boldsymbol{\eta}^{-1})\boldsymbol{\omega} - \boldsymbol{\pi}\right)\overline{\mathbb{E}}_t\left[(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}(\boldsymbol{z}_t + \boldsymbol{\eta}\boldsymbol{\alpha}\boldsymbol{h}_t)\right], \\
\left(\frac{1+\psi}{\psi}\boldsymbol{\eta}-\boldsymbol{\alpha}\boldsymbol{\eta}\right)\boldsymbol{h}_t &= \boldsymbol{\eta}\boldsymbol{\pi}(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] - \left(\mathbf{I}-\boldsymbol{\eta}\boldsymbol{\pi}(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}\right)\boldsymbol{\eta}\boldsymbol{\alpha}\overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right].
\end{aligned}
$$

Denote $\mathbf{M} \equiv \boldsymbol{\pi}(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}$. It follows that

$$
\begin{aligned}
\boldsymbol{h}_t &= \left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\right)^{-1}\boldsymbol{\pi}(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] + \left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\right)^{-1}\left(\boldsymbol{\pi}(\mathbf{I}-(\mathbf{I}-\boldsymbol{\eta})\boldsymbol{\omega})^{-1}\boldsymbol{\eta}\boldsymbol{\alpha}-\boldsymbol{\alpha}\right)\overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right], \\
&= \left(\frac{1+\psi}{\psi}-\boldsymbol{\alpha}\right)^{-1}\mathbf{M}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] + \left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\right)^{-1}\left(\mathbf{M}\boldsymbol{\eta}\boldsymbol{\alpha}-\boldsymbol{\alpha}\right)\overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right].
\end{aligned}
$$

Under the assumption that firms can observe their own country-sector's hours, we have

$$
\boldsymbol{h}_t = \left(\frac{1+\psi}{\psi}-\boldsymbol{\alpha}\right)^{-1}\mathbf{M}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] + \left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\right)^{-1}\left(\mathrm{diag}(\mathbf{M})\boldsymbol{\eta}\boldsymbol{\alpha}-\boldsymbol{\alpha}+(\mathbf{M}-\mathrm{diag}(\mathbf{M}))\boldsymbol{\eta}\boldsymbol{\alpha}\right)\overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right],
$$

which leads to

$$
\boldsymbol{h}_t = \left(\frac{1+\psi}{\psi}\mathbf{I}-\boldsymbol{\alpha}\boldsymbol{\eta}\mathrm{diag}(\mathbf{M})\right)^{-1}\left(\mathbf{M}\overline{\mathbb{E}}_t\left[\boldsymbol{z}_t\right] + (\mathbf{M}-\mathrm{diag}(\mathbf{M}))\boldsymbol{\alpha}\boldsymbol{\eta}\overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right]\right). \tag{A.2}
$$

A.4 Proof of Proposition 2.1

It follows from the main text directly.

A.5 Proof of Proposition 2.2

Consider the response to shocks take place in country-sector (m,i). The aggregate response of firms in country-sector (n,j) takes the following form

$$
h_{nj,t} = G^z_{nj,mi}z_{mi,t} + G^\varepsilon_{nj,mi}\varepsilon_{mi,t} = \mathbf{G}_{nj,mi}\begin{bmatrix} z_{mi,t} & \varepsilon_{mi,t}\end{bmatrix}'.
$$

The best response requires that

$$
\begin{aligned}
h_{nj,t} =& \varphi_{nj,mi}\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] + \sum_{k,q}\overline{\mathbb{E}}_{nj,t}[\gamma_{nj,kq}h_{kq,t}] \\
=& \varphi_{nj,mi}\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] + \sum_{k,q}\overline{\mathbb{E}}_{nj,t}[\gamma_{nj,kq}h_{kq,t}] \\
=& \begin{bmatrix}\varphi_{nj,mi} & 0\end{bmatrix}\overline{\mathbb{E}}_{nj,t}\begin{bmatrix} z_{mi,t} & \varepsilon_{mi,t}\end{bmatrix}' + \sum_{k,q}\gamma_{nj,kq}\mathbf{G}_{kq,mi}\overline{\mathbb{E}}_{nj,t}\begin{bmatrix} z_{mi,t} & \varepsilon_{mi,t}\end{bmatrix}' \\
=& \begin{bmatrix}\varphi_{nj,mi} & 0\end{bmatrix}\boldsymbol{\Lambda}_{nj,mi}\begin{bmatrix} z_{mi,t} & \varepsilon_{mi,t}\end{bmatrix}' + \sum_{k,q}\gamma_{nj,kq}\mathbf{G}_{kq,mi}\boldsymbol{\Lambda}_{nj,mi}\begin{bmatrix} z_{mi,t} & \varepsilon_{mi,t}\end{bmatrix}'
\end{aligned}
$$

In equilibrium, it requires that

$$\mathbf{G}_{nj,mi} = \begin{bmatrix}\varphi_{nj,mi} & 0\end{bmatrix} \mathbf{\Lambda}_{nj,mi} + \sum_{k,q} \gamma_{nj,kq} \mathbf{G}_{kq,mi} \mathbf{\Lambda}_{nj,mi}.$$

Solving for the fixed point, the policy function $\mathbf{G}_{mi} \equiv \begin{bmatrix}\mathbf{G}_{11,mi} & \mathbf{G}_{12,mi} & \dots & \mathbf{G}_{NJ,mi}\end{bmatrix}'$ is given by

$$\mathbf{vec}(\mathbf{G}') = \left(\mathbf{I} - \begin{bmatrix}\gamma_{11} \otimes \mathbf{\Lambda}'_{11,mi} & \dots & \gamma_{NJ} \otimes \mathbf{\Lambda}'_{NJ,mi}\end{bmatrix}'\right)^{-1} \begin{bmatrix}\begin{bmatrix}\varphi_{11,mi} & 0\end{bmatrix} \mathbf{\Lambda}_{11,mi} & \dots & \begin{bmatrix}\varphi_{NJ,mi} & 0\end{bmatrix} \mathbf{\Lambda}_{NJ,mi}\end{bmatrix}'.$$

A.6 Proof of Corollary 2.1

Suppose that the policy function takes the following form:

$$h_t = \mathbf{G}_z \boldsymbol{z}_t + \mathbf{G}_\varepsilon \boldsymbol{s}_t.$$

With common information structure, we use the notation $\overline{\mathbb{E}}_t[\cdot]$ to indicate average expectation, which is common across country sectors. Notice that

$$\overline{\mathbb{E}}_t[\boldsymbol{z}_t] = \lambda_z \boldsymbol{z}_t + \lambda_\varepsilon \boldsymbol{s}_t, \qquad \overline{\mathbb{E}}_t[\boldsymbol{s}_t] = \boldsymbol{s}_t.$$

The best response requires that

$$\begin{aligned}\boldsymbol{h}_t &= \boldsymbol{\varphi}\overline{\mathbb{E}}_t[\boldsymbol{z}_t] + \boldsymbol{\gamma}\overline{\mathbb{E}}_t[\boldsymbol{h}_t] \\ \mathbf{G}_z \boldsymbol{z}_t + \mathbf{G}_\varepsilon \boldsymbol{s}_t &= \boldsymbol{\varphi}(\lambda_z \boldsymbol{z}_t + \lambda_\varepsilon \boldsymbol{s}_t) + \boldsymbol{\gamma}(\mathbf{G}_z(\lambda_z \boldsymbol{z}_t + \lambda_\varepsilon \boldsymbol{s}_t) + \mathbf{G}_\varepsilon \boldsymbol{s}_t).\end{aligned}$$

Matching the coefficients leads to

$$\begin{aligned}\mathbf{G}_z &= \boldsymbol{\varphi}\lambda_z + \boldsymbol{\gamma}\lambda_z \mathbf{G}_z, \\ \mathbf{G}_\varepsilon &= \boldsymbol{\varphi}\lambda_\varepsilon + \boldsymbol{\gamma}(\lambda_\varepsilon \mathbf{G}_z + \mathbf{G}_\varepsilon).\end{aligned}$$

The policy functions are thus given by

$$\begin{aligned}\mathbf{G}_z =& (\mathbf{I} - \lambda_z \boldsymbol{\gamma})^{-1} \boldsymbol{\varphi}\lambda_z, \\ \mathbf{G}_\varepsilon =& (\mathbf{I} - \boldsymbol{\gamma})^{-1}(\mathbf{I} + \boldsymbol{\gamma}\lambda_z(\mathbf{I} - \lambda_z\boldsymbol{\gamma})^{-1})\boldsymbol{\varphi}\lambda_\varepsilon = (\mathbf{I} - \boldsymbol{\gamma})^{-1}(\mathbf{I} - \lambda_z\boldsymbol{\gamma})^{-1}\boldsymbol{\varphi}\lambda_\varepsilon = (\mathbf{I} - \lambda_z\boldsymbol{\gamma})^{-1}(\mathbf{I} - \boldsymbol{\gamma})^{-1}\boldsymbol{\varphi}\lambda_\varepsilon.\end{aligned}$$

A.7 Proof of Proposition 2.3

Part 1 follows as only the total sum of $\mathcal{T}^{(k)}_{nj,mi}$ matters, and this holds by construction.

For part 2, let $\{m(1), m(2), \dots, m(k)\}$ denote the names of a selection of k country sectors. Denote the response of first-order and higher-order expectations as

$$\begin{aligned}\overline{\mathbb{E}}_{m(1),t}[z_{mi,t}] &= g^z_1 z_{mi,t} + g^\varepsilon_1 s_{mi,t}, \\ \overline{\mathbb{E}}_{m(1),t}[\overline{\mathbb{E}}_{m(2),t}[z_{mi,t}]] &= g^z_2 z_{mi,t} + g^\varepsilon_2 s_{mi,t}, \\ &\vdots \\ \overline{\mathbb{E}}_{m(1),t}[\dots[\overline{\mathbb{E}}_{m(k),t}[z_{mi,t}]\dots] &= g^z_k z_{mi,t} + g^\varepsilon_k s_{mi,t}.\end{aligned}$$

For j-th order expectation, the total response to the technology shock is $g^z_j + g^\varepsilon_j$ and the response to the noise shock is g^ε_j. We will prove that: (1) $g^z_j + g^\varepsilon_j < g^z_{j-1} + g^\varepsilon_{j-1}$; (2) $g^\varepsilon_j > g^\varepsilon_{j-1}$.

Note that Bayesian forecast implies that for country sector $m(j)$,

$$\overline{\mathbb{E}}_{m(j),t}[z_{mi,t}] \equiv \lambda_j z_{mi,t} + \mu_j s_{mi,t} = \frac{\tau_{m(j),mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} z_{mi,t} + \frac{\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} s_{mi,t}.$$

This implies that the higher-order expectations satisfy the following recursive structure

$$g_j^z = \lambda_j g_{j-1}^z \quad \text{and} \quad g_j^\varepsilon = \mu_j + \lambda_j g_{j-1}^\varepsilon.$$

and the recursion starts from $g_1^z = \lambda_1$ and $g_1^\varepsilon = \mu_1$.

First, we establish that $g_j^\varepsilon < \frac{\kappa_{mi}}{1+\kappa_{mi}}$ for all j. It is easy to see that $g_1^\varepsilon = \frac{\kappa_{mi}}{1+\tau_{m(1),mi}+\kappa_{mi}} < \frac{\kappa_{mi}}{1+\kappa_{mi}}$. For $j>1$, supposing that $g_{j-1}^\varepsilon < \frac{\kappa_{mi}}{1+\kappa_{mi}}$, it follows that

$$g_j^\varepsilon = \mu_j + \lambda_j g_{j-1}^\varepsilon < \frac{\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} + \frac{\tau_{m(j),mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} \frac{\kappa_{mi}}{1+\kappa_{mi}} = \frac{\kappa_{mi}}{1+\kappa_{mi}}.$$

Next, we establish that $g_j^z + g_j^\varepsilon > \frac{\kappa_{mi}}{1+\kappa_{mi}}$ for all j. When $j=1$, it is straightforward to show $g_1^z + g_1^\varepsilon = \frac{\tau_{m(1),mi}}{1+\tau_{m(1),mi}+\kappa_{mi}} > \frac{\kappa_{mi}}{1+\kappa_{mi}}$. For $j>1$, supposing that $g_{j-1}^z + g_{j-1}^\varepsilon > \frac{\kappa_{mi}}{1+\kappa_{mi}}$, it follows that

$$g_j^z + g_j^\varepsilon = \mu_j + \lambda_j (g_{j-1}^z + g_{j-1}^\varepsilon) > \frac{\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} + \frac{\tau_{m(j),mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} \frac{\kappa_{mi}}{1+\kappa_{mi}} = \frac{\kappa_{mi}}{1+\kappa_{mi}}.$$

To prove the property of the response to the noise shock, note that:

$$g_j^\varepsilon - g_{j-1}^\varepsilon = \mu_j - (1-\lambda_j) g_{j-1}^\varepsilon > \frac{\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} - \frac{1+\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} \frac{\kappa_{mi}}{1+\kappa_{mi}} = 0,$$

where the inequality is due to $g_{j-1}^\varepsilon < \frac{\kappa_{mi}}{1+\kappa_{mi}}$.

Similarly, to prove the property of the response to the TFP shock, note that

$$(g_{j-1}^z + g_{j-1}^\varepsilon) - (g_j^z + g_j^\varepsilon) = (1-\lambda_j)(g_{j-1}^z + g_{j-1}^\varepsilon) - \mu_j > \frac{1+\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} \frac{\kappa_{mi}}{1+\kappa_{mi}} - \frac{\kappa_{mi}}{1+\tau_{m(j),mi}+\kappa_{mi}} = 0,$$

where the inequality is due to $g_{j-1}^z + g_{j-1}^\varepsilon > \frac{\kappa_{mi}}{1+\kappa_{mi}}$.

Now we have proved that: (1) $g_j^z + g_j^\varepsilon < g_{j-1}^z + g_{j-1}^\varepsilon$; (2) $g_j^\varepsilon > g_{j-1}^\varepsilon$. It follows that the response of higher-order expectations to the noise shock is always larger than that of the first-order expectation, and the the response of higher-order expectations to the TFP shock is always smaller than that of the first-order expectation.

When firms observe the labor market outcomes in their own sector, the beauty contest is characterized by condition (A.2). Note that $\frac{1+\psi}{\psi} > 1$ and all elements of $\mathbf{M}$ are non-negative and less than 1, which implies that the corresponding φ and γ contain only non-negative elements. It follows that the elasticities, $\mathcal{T}_{nj,mi}^{(k)}$, are all non-negative. Given that the selection $\{m(1), m(2), \ldots, m(k)\}$ is arbitrary and that k can be any positive integer, the perturbation that increases the weight on higher-order expectations necessarily leads to the properties in part 2 of the proposition.

A.8 Proof of Proposition 2.4

Since $h_{k,t} = \overline{\mathbb{E}}^k_{k,t}[z_{1,t}]$, it is sufficient derive the expressions for higher-order expectations about $z_{1,t}$. These higher-order expectations can be derived recursively as

$$\begin{aligned}
\overline{\mathbb{E}}_t[z_{1,t}] &= \lambda_z z_{1,t} + \lambda_\varepsilon s_{1,t} \\
\overline{\mathbb{E}}^2_t[z_{1,t}] &= \lambda_z(\lambda_z z_{1,t} + \lambda_\varepsilon s_{1,t}) + \lambda_\varepsilon s_{1,t} = \lambda_z^2 z_{1,t} + \lambda_\varepsilon(1+\lambda_z)s_{1,t} \\
&\vdots \\
\overline{\mathbb{E}}^k_t[z_{1,t}] &= \lambda_z^k z_{1,t} + \lambda_\varepsilon(1+\lambda_z+\ldots+\lambda_z^{k-1})s_{1,t},
\end{aligned}$$

where λ_z and λ_ε are as defined in Corollary 2.1, and pertain to the signals about the shock in sector 1. The last equation can also be expressed as

$$\overline{\mathbb{E}}^k_t[z_{1,t}] = \left(\frac{\lambda_\varepsilon}{1-\lambda_z} + \frac{1-\lambda_z-\lambda_\varepsilon}{1-\lambda_z}\lambda_z^k\right) z_{1,t} + \left(\frac{\lambda_\varepsilon}{1-\lambda_z} - \frac{\lambda_\varepsilon}{1-\lambda_z}\lambda_z^k\right)\varepsilon_{1,t}.$$

Rearranging, we get:

$$\overline{\mathbb{E}}^k_{k,t}[z_{1,t}] = \lambda_\varepsilon \frac{1-\lambda_z^k}{1-\lambda_z}\varepsilon_{1,t} + \left(\frac{\lambda_\varepsilon}{1-\lambda_z} + \frac{1-\lambda_z-\lambda_\varepsilon}{1-\lambda_z}\lambda_z^k\right) z_{1,t}.$$

Substituting the definition for λ_z and λ_ε leads to the desired result.

A.9 Alternative Vertical Network

While the main text defines a vertical network directly in terms of impact matrices φ and γ, this section presents the results of a more familiar vertical network that is defined by a "snake" input-output matrix instead. Consider an Armington-type model where each country has one sector ($J = 1$). We order each country by its upstreamness, where the most upstream is country 1 and the most downstream is country N. For simplicity, let the final goods consumption in each country only source from their domestic sector – i.e., $\boldsymbol{\pi} = \mathbf{I}$, $\alpha_i = \alpha$, and $\eta_i = \eta$ for all countries i, and let the input-output matrix be:

$$\boldsymbol{\omega} = \begin{bmatrix} 0 & 0 & \ldots & 0 & 0 \\ 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \ldots & 1 & 0 \end{bmatrix}.$$

In this economy, each country will respond to their own productivity shock and the productivity shocks in their upstream countries. Under perfect information, the hours response to a country 1 TFP shock as a function of network distance is depicted by the solid line in the left panel of Figure A2. Without information frictions, the response of hours in country i is:

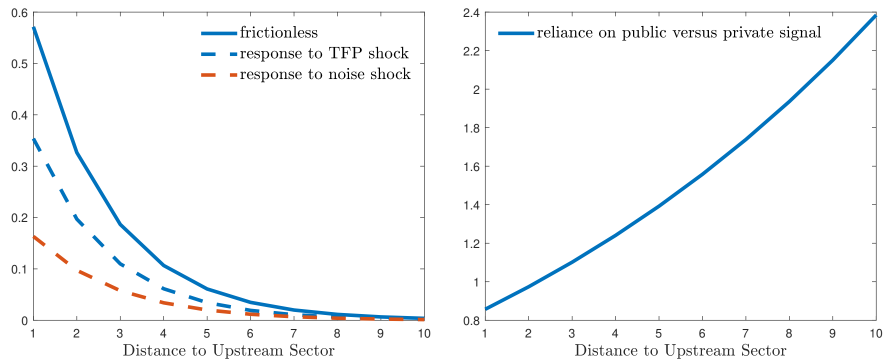
$$h_{i,t} = \frac{\psi}{1+(1-\alpha\eta)\psi}\left(\frac{(1-\eta)(1+\psi)}{1+(1-\alpha\eta)\psi}\right)^{i-1} z_{1,t}.$$

All countries will respond to a shock to country 1, though the responses decay further downstream.

The dashed lines in the left panel of Figure A2 display the responses under information frictions.

As we found elsewhere, information frictions attenuate the impact of TFP shocks, but introduce transmission of noise shocks. The responses to both shocks decay in network distance. However, the noise shock becomes relatively more important as we move downstream. The right panel plots the ratio of the responses to the public signal compared to the private signal. As in the main text, the relative response to the public signal increases with downstreamness.

Figure A2: Hours Response in a Vertical Network



Notes: The left panel displays the response of hours in a vertical network shocks in the most upstream sector as a function of sector downstreamness. The solid line displays the response to a TFP shock in the environment without information frictions. The dashed lines display the hours responses to a TFP shock (blue) and noise shock (red). The right panel plots the ratio of the responses to the public signal relative to the private signal. The parameters are set to $\lambda_z = \lambda_\varepsilon = 0.3$, $\alpha = \eta = 0.5$.

B. Data Appendix

B.1 International News Data

We collect the frequency of sectors mentioned in newspapers using Down Jones Factiva in the period of 1995-2020. It is a digital global news database, covering nearly 33,000 sources including publications, web news, blogs, pictures, and videos from 159 countries. We focus on 11 top newspapers by circulation in G7+Spain. In particular, we cover the leading newspaper(s) in Canada (The Globe and Mail), France (Le Figaro), Germany (Süddeutsche Zeitung), Italy (Corriere della Sera), Japan (Mainichi Shimbun, Sankei Shimbun), Spain (El País), the UK (Financial Times), and the US (Wall Street Journal, USA Today, New York Times). The criteria that we use to select the newspapers are (i) it is the top newspaper(s) by circulation in each country, (ii) it covers important economic and business news, and (iii) Factiva has a consistent coverage of the newspaper for the whole period of 1995-2020. The frequency data are from both paper and online editions of each newspaper. Factiva allows user to exclude identical articles from search results, so we can avoid duplicate articles across different editions of the same newspapers or duplicates due to minor changes in the articles like typos.

One advantage of Factiva is that Factiva develops and maintains a list of Dow Jones Intelligent Identifiers (DJID) Codes for sectors and regions. They are descriptive terms attached to each article as metadata. Users can search on these codes instead of using keywords. It allows us to search and obtain frequency data consistently across different newspapers and countries regardless of the languages used in the newspaper and its editions.

Factiva has more than 1,150 DJID codes covering a huge range of sectors. There are five levels in the industry coding hierarchy, which allows users to search at broad or detailed levels. For example, agriculture is the broadest level. It includes farming which can be disaggregated into more refined sectors like coffee growing or horticulture. Horticulture includes subsectors like vegetable growing or fruit growing which can be refined to even more detailed categories such as citrus groves and non-citrus fruit/tree nut farming. We use the second broadest aggregation level of sectors as defined by Factiva (for example, farming) and create a concordance with ISIC Rev. 4 to merge with other datasets.

When using data from Factiva we need to be careful with data prior and after 2000. In early 2000, Factiva expanded and modified the Reuters Business Briefing indexing hierarchy to build the new Factiva Intelligent Indexing hierarchy, which later developed into Dow Jones Intelligent Identifiers Codes. Therefore, we observe a step increase in frequency of sectors across newspapers and countries after 2000.

B.2 Forecast Data

Consensus Forecasts assembles forecaster-level data for GDP now-casts and 1-year ahead forecasts by major organizations in financial services and research. (For instance, in the United States forecasters include both major investment banks such as Goldman Sachs and JP Morgan, and academic-based economic analysis units such as the University of Michigan's Research Seminar on Quantitative Economics). On average in our sample, there are 21 forecasters per country per month. The set of forecasters polled by Consensus changes somewhat over time. We use data over the period 1995-2019, to match the time span of our news data. To match the frequency of the news data, we take means across the months within each quarter for each forecaster×country.

We combine the Consensus data with the actual GDP growth realizations to compute the forecast errors. The GDP growth data come the IMF's World Economic Outlook database. To more closely align the forecasters' information sets with the potentially available information, we use the first vintage GDP release for each year. That is, the "actual" GDP we compare the forecasts to does not include any revisions to the GDP subsequent to the first release. The IMF WEO database comes out twice per year, in April and October. The first release GDP number for year t comes out in the April $t+1$ WEO. Note that actual GDP data and forecast errors pertain to annual GDP outcomes. However, we have up to 4 now-casts and up to 4 one-year ahead forecasts for each annual GDP number, since the forecast data are quarterly, and each forecaster is asked repeatedly about current/future annual GDP. Our measure of forecast error is the absolute deviation of the forecast from the actual. Unfortunately, to our knowledge comprehensive data on sectoral forecasts does not exist. Thus, we are forced to collapse the sectoral dimension of our news coverage data for this exercise, and relate GDP forecast errors to the intensity of news coverage at the country level.

Table A1: Factiva - ISIC Rev-4 Sector Concordance

No	ISIC Rev-4 sector	ISIC Rev-4 sector description	Factiva sector
1	A	Agriculture, Forestry and Fishing	Farming
2	A	Agriculture, Forestry and Fishing	Fishing
3	A	Agriculture, Forestry and Fishing	Forestry/Logging
4	A	Agriculture, Forestry and Fishing	Hunting/Trapping
5	A	Agriculture, Forestry and Fishing	Seeds
6	A	Agriculture, Forestry and Fishing	Support Activities for Agriculture
7	A	Agriculture, Forestry and Fishing	Agriculture Technology
8	B	Mining and Quarrying	Mining/Quarrying
9	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Clothing/Textiles
10	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Baby Products
11	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Food/Beverages
12	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Leather/Fur Goods
13	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Leisure/Travel Goods
14	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Marijuana Products
15	10-15	Food Products, Beverages and Tobacco; Textiles, Wearing Apparel, Leather and Related Products	Tobacco Products
16	16-18	Wood and Paper Products; Printing and Reproduction of Recorded Media	Paper/Pulp
17	16-18	Wood and Paper Products; Printing and Reproduction of Recorded Media	Wood Products
18	16-18	Wood and Paper Products; Printing and Reproduction of Recorded Media	Converted Paper Products
19	16-18	Wood and Paper Products; Printing and Reproduction of Recorded Media	Media Content Distribution
20	16-18	Wood and Paper Products; Printing and Reproduction of Recorded Media	3D/4D Printing
21	19	Coke and Refined Petroleum Products	Alternative Fuels
22	19	Coke and Refined Petroleum Products	Fossil Fuels
23	19	Coke and Refined Petroleum Products	Downstream Operations
24	20-21	Chemicals and Chemical Products	Chemicals
25	20-21	Chemicals and Chemical Products	Nondurable Household Products
26	20-21	Chemicals and Chemical Products	Personal Care Products/Appliances
27	20-21	Chemicals and Chemical Products	Pharmaceuticals
28	22-23	Rubber and Plastics Products, and Other Non-Metallic Mineral Products	Abrasive Products
29	22-23	Rubber and Plastics Products, and Other Non-Metallic Mineral Products	Glass/Glass Products

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Table A1 – *Factiva - ISIC Rev-4 Sector Concordance (Cont.)*

No	**ISIC Rev-4 sector**	**ISIC Rev-4 sector description**	**Factiva sector**
30	22-23	Rubber and Plastics Products, and Other Non-Metallic Mineral Products	Industrial Ceramics
31	22-23	Rubber and Plastics Products, and Other Non-Metallic Mineral Products	Plastics Products
32	22-23	Rubber and Plastics Products, and Other Non-Metallic Mineral Products	Rubber Products
33	22-23	Rubber and Plastics Products, and Other Non-Metallic Mineral Products	Building Materials/Products
34	24-25	Basic Metals and Fabricated Metal Products, Except Machinery and Equipment	Primary Metals
35	24-25	Basic Metals and Fabricated Metal Products, Except Machinery and Equipment	Metal Products
36	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Telecommunications Equipment
37	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Durable Household Products
38	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Home Improvement Products
39	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Office Equipment/Supplies
40	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Optical Instruments
41	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Watches/Clocks/Parts
42	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Electric Power Generation
43	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Industrial Electronics
44	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Machinery
45	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Wires/Cables
46	26-28	Electrical and Optical Equipment; Machinery and Equipment n.e.c.	Computers/Consumer Electronics
47	29-30	Transport Equipment	Motor Vehicle Parts
48	29-30	Transport Equipment	Motor Vehicles
49	29-30	Transport Equipment	Aerospace/Defense
50	29-30	Transport Equipment	Drones
51	29-30	Transport Equipment	Railroad Rolling Stock
52	29-30	Transport Equipment	Shipbuilding
53	31-33	Other Manufacturing; Repair and Installation of Machinery and Equipment	Product Repair Services
54	31-33	Other Manufacturing; Repair and Installation of Machinery and Equipment	Furniture
55	31-33	Other Manufacturing; Repair and Installation of Machinery and Equipment	Luxury Goods
56	31-33	Other Manufacturing; Repair and Installation of Machinery and Equipment	Medical Equipment/Supplies
57	D-E	Electricity, Gas and Water Supply	Environment/Waste Management
58	D-E	Electricity, Gas and Water Supply	Natural Gas Processing
59	D-E	Electricity, Gas and Water Supply	Nuclear Fuel
60	D-E	Electricity, Gas and Water Supply	Electricity/Gas Utilities
61	D-E	Electricity, Gas and Water Supply	Multiutilities
62	D-E	Electricity, Gas and Water Supply	Water Utilities
63	F	Construction	Construction
64	45-47	Wholesale and Retail Trade, Except of Motor Vehicles and Motorcycles	Retail
65	45-47	Wholesale and Retail Trade, Except of Motor Vehicles and Motorcycles	Wholesalers
66	49-52	Transport and Storage	Highway Operation

Continued on next page

Table A1 – *Factiva - ISIC Rev-4 Sector Concordance (Cont.)*

No	ISIC Rev-4 sector	ISIC Rev-4 sector description	Factiva sector
67	49-52	Transport and Storage	Moving/Relocation Services
68	49-52	Transport and Storage	Air Transport
69	49-52	Transport and Storage	Road/Rail Transport
70	49-52	Transport and Storage	Water Transport/Shipping
71	53	Postal and Courier Activities	Freight Transport/Logistics
72	I	Accommodation and Food Service Activities	Lodgings/Restaurants/Bars
73	J	Information and Communication	Computer Services
74	J	Information and Communication	Internet/Cyber Cafes
75	J	Information and Communication	Audiovisual Production
76	J	Information and Communication	Broadcasting
77	J	Information and Communication	Freelance Journalism
78	J	Information and Communication	Printing/Publishing
79	J	Information and Communication	Social Media Platforms/Tools
80	J	Information and Communication	Sound/Music Recording/Publishing
81	J	Information and Communication	Online Service Providers
82	J	Information and Communication	Virtual Reality Technologies
83	J	Information and Communication	Integrated Communications Providers
84	J	Information and Communication	Satellite Telecommunications Services
85	J	Information and Communication	Wired Telecommunications Services
86	J	Information and Communication	Wireless Telecommunications Services
87	K	Financial and Insurance Activities	Debt Recovery/Collection Services
88	K	Financial and Insurance Activities	Diversified Holding Companies
89	K	Financial and Insurance Activities	Shell Company
90	K	Financial and Insurance Activities	Banking/Credit
91	K	Financial and Insurance Activities	Insurance
92	K	Financial and Insurance Activities	Investing/Securities
93	K	Financial and Insurance Activities	Rating Agencies
94	K	Financial and Insurance Activities	Risk Management Services
95	K	Financial and Insurance Activities	Blockchain Technology
96	K	Financial and Insurance Activities	Financial Technology
97	L	Real Estate Activities	Real Estate
98	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Accounting/Consulting
99	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Administrative/Support Services
100	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Advertising/Marketing/Public Relations
101	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Investigation Services
102	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Legal Services
103	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Parking Lots/Garages

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Table A1 – *Factiva - ISIC Rev-4 Sector Concordance (Cont.)*

No	ISIC Rev-4 sector	ISIC Rev-4 sector description	Factiva sector
104	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Photographic Processing
105	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Recruitment Services
106	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Rental/Leasing Services
107	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Scientific Research Services
108	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Security Systems Services
109	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Security/Prison Services
110	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Services to Facilities/Buildings
111	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Technical Services
112	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Packaging
113	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Tourism
114	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Architects
115	M-N	Professional, Scientific, Technical, Administrative and Support Service Activities	Sports Technologies
116	O-Q	Public Administration and Defence, Compulsory Social Security; Education; Health and Social Work	Educational Services
117	O-Q	Public Administration and Defence, Compulsory Social Security; Education; Health and Social Work	Healthcare Provision
118	O-Q	Public Administration and Defence, Compulsory Social Security; Education; Health and Social Work	Healthcare Support Services
119	O-Q	Public Administration and Defence, Compulsory Social Security; Education; Health and Social Work	E-learning/Educational Technology
120	R-S	Arts, Entertainment and Recreation; Other Service Activities	Agents/Managers for Public Figures
121	R-S	Arts, Entertainment and Recreation; Other Service Activities	Dry Cleaning/Laundry Services
122	R-S	Arts, Entertainment and Recreation; Other Service Activities	Professional Bodies
123	R-S	Arts, Entertainment and Recreation; Other Service Activities	Specialized Consumer Services
124	R-S	Arts, Entertainment and Recreation; Other Service Activities	Artists/Writers/Performers
125	R-S	Arts, Entertainment and Recreation; Other Service Activities	Film/Video Exhibition
126	R-S	Arts, Entertainment and Recreation; Other Service Activities	Gambling Industries
127	R-S	Arts, Entertainment and Recreation; Other Service Activities	Libraries/Archives
128	R-S	Arts, Entertainment and Recreation; Other Service Activities	Performing Arts/Sports Promotion
129	R-S	Arts, Entertainment and Recreation; Other Service Activities	Sporting Facilities/Venues
130	R-S	Arts, Entertainment and Recreation; Other Service Activities	Sports/Physical Recreation Instruction
131	R-S	Arts, Entertainment and Recreation; Other Service Activities	Theaters/Entertainment Venues

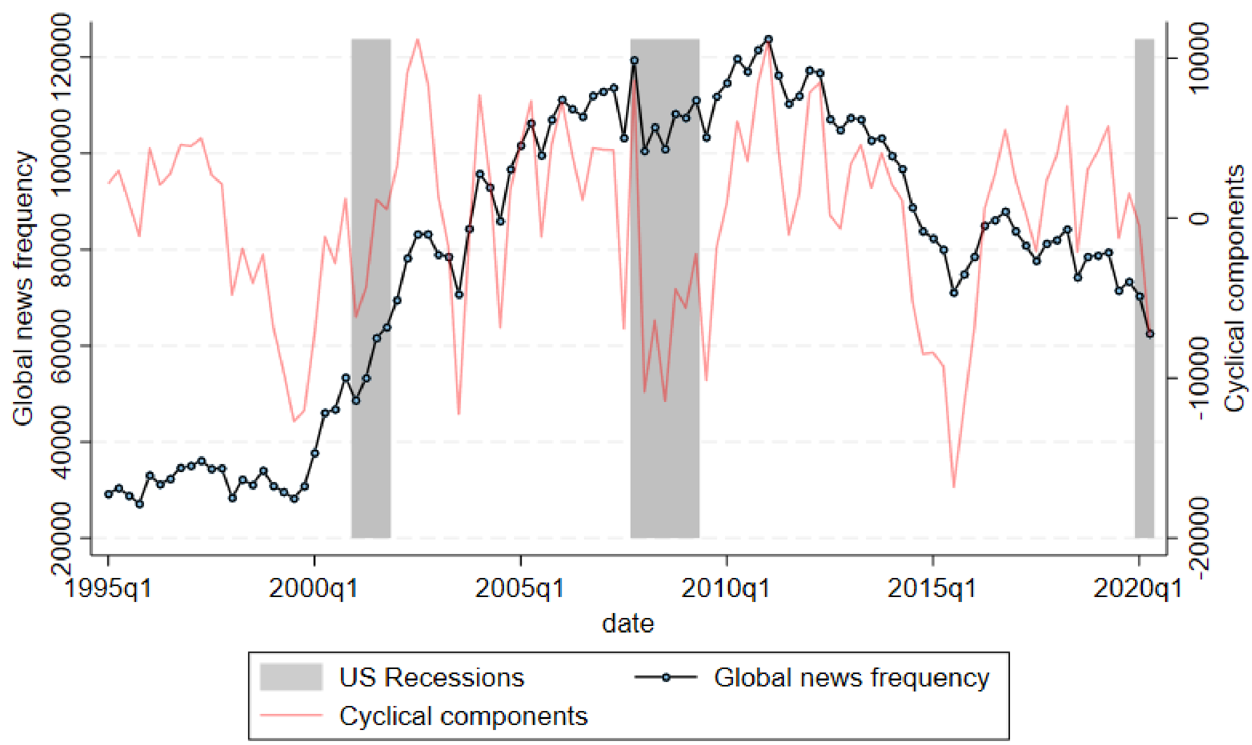
C. Empirical Appendix

C.1 Additional Stylized Facts on News Coverage, Size, and GVC Participation

Section 3 presented some broad patterns about the relationships between sector size and GVC participation and news coverage intensity. This appendix provides further details on the data and the basic correlations of news coverage with other observables such as size and GVC participation.

Heterogeneity and variation. The frequency of *total* economic news varies over time, but appears to be at best modestly correlated with recessions. Figure A3 plots global economic news coverage (the sum of the raw frequencies of news about all country-sectors in all of our newspaper sources in each quarter), along with the NBER recession dates for our sample. To minimize the effect of the level changes in tags caused by Factiva's algorithm change detailed discussed in Appendix B, we also plot the HP-filtered global economic news coverage series. Economic news coverage varies over time, and increased relative to trend at the start of the Great Recession. A clear pattern is not discernible for the 2002 recession, perhaps as it corresponds to a period with other aggregate shocks (e.g. China's WTO accession in December 2001).

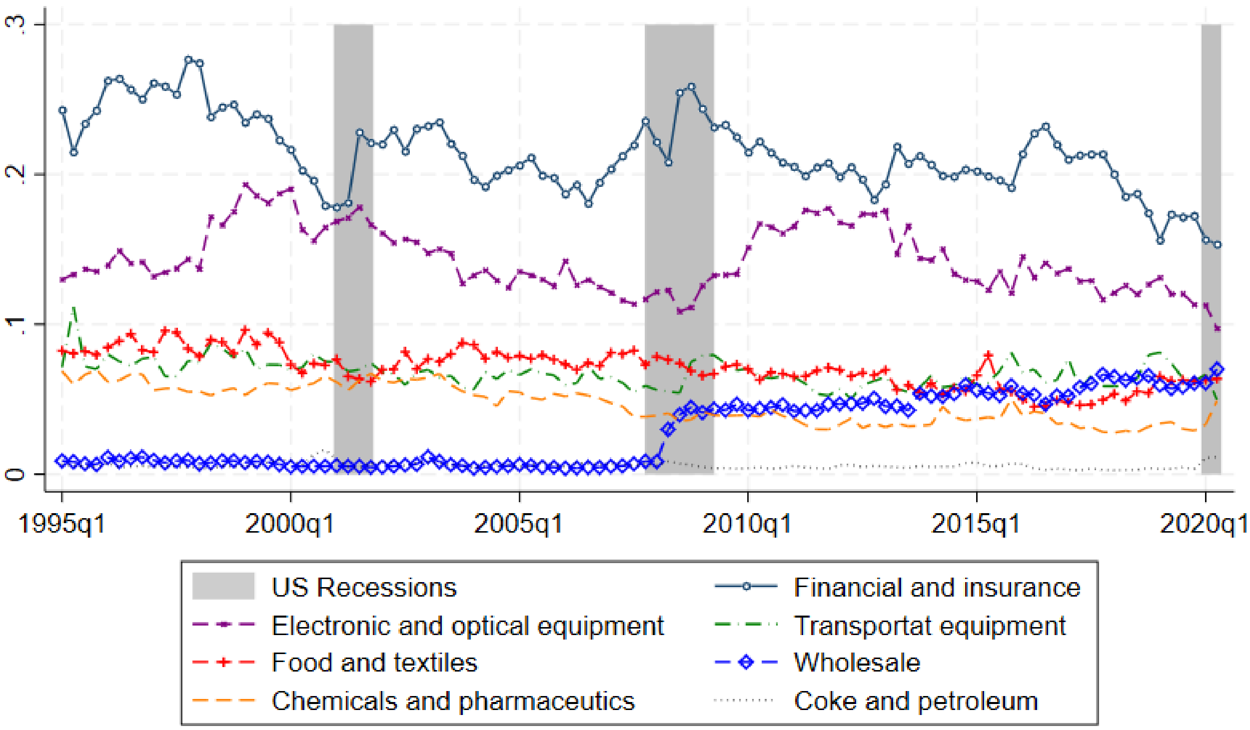
Figure A3: Economic News Frequency, 1995-2020



Notes: This figure displays the total frequency of economic news over time (solid black line), as well as its cyclical component (thin red line). The gray bars denote the NBER recessions in the US.

Figure A4 plots the shares of several large sectors in total global news coverage over time. While there is some time variation, the ordering of sectors in terms of news coverage shares in the cross-section remains quite stable. This suggests that within-sector variation over time is less important than cross-sectional variation. To make this more precise, we estimate a simple within-across

Figure A4: Sectoral News Coverage over Time



Notes: This figure displays the time series of the frequency shares of selected sectors in the overall economic news coverage in the newspapers in our data.

decomposition to illustrate that average cross-sectional variation is much more important than time-series variation within a sector over time:

$$F_{mi,t} = \delta_{mi} + u_{mi,t}, \tag{C.1}$$

where $F_{mi,t}$ is either the total frequency (number of mentions), or the frequency share of sector i in country m reported in total economic news coverage in quarter t, and δ_{mi} are sector-country fixed effects. The R^2 of this regression is informative of the role of cross-sectional variation, accounted for by the fixed effects.

The share of the variation explained by δ_{mi} is 0.75 for the absolute frequencies, and 0.88 for frequency shares. Thus, it appears that the large majority of the overall variation in the data is cross-sectional rather than time series.

Upstreamness and downstreamness indicators. For Figure 4, we define sector i's importance as an input as the average expenditure share on sector i's inputs in other sectors:

$$UP_i = \frac{1}{NNJ} \sum_m \sum_s \sum_j \frac{x_{mi,sj}}{\sum_{l,k} x_{lk,sj}}. \tag{C.2}$$

where $x_{mi,sj}$ is input expenditure by country-sector (s,j) on (m,i), and there are a total of N countries and J sectors. We define sector i's importance as a downstream sales destination as the average sales

Table A2: Correlates of Global News Coverage, Country-Sector Level

Dep. Var.: F_{mi}	(1)	(2)	(3)	(4)
S_{mi}	0.837*	0.385	0.967**	0.522
	(0.465)	(0.472)	(0.378)	(0.401)
UP_{mi}	0.675**	0.658**	1.160**	0.897*
	(0.294)	(0.264)	(0.575)	(0.474)
DN_{mi}	-0.582	-0.281	-0.966	-0.653
	(0.437)	(0.432)	(0.708)	(0.653)
Observations	184	184	184	184
R^2	0.192	0.250	0.603	0.647
Country FE	NO	YES	NO	YES
Sector FE	NO	NO	YES	YES

Notes: This table reports the results of estimating (C.4). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variable definitions and sources are described in detail in the text.

of upstream sectors to i:

$$DN_i = \frac{1}{NNJ} \sum_n \sum_s \sum_j \frac{x_{sj,ni}}{\sum_{l,k} x_{sj,lk}}. \tag{C.3}$$

Size and GVC participation at finer levels of disaggregation. We now document the partial correlations between news coverage and sectoral characteristics. To begin, we add the country dimension and regress the share of global coverage on these characteristics simultaneously:

$$F_{mi} = \beta_1 S_{mi} + \beta_2 UP_{mi} + \beta_3 DN_{mi} + \boldsymbol{\delta} + \varepsilon_{mi}, \tag{C.4}$$

where F_{mi} is the share of news about sector i in country m in global news coverage, S_{mi} is sector size measured by its share in global sales, $\boldsymbol{\delta}$ are fixed effects, if any, and the upstream and downstream indicators are defined at the country-sector level similarly to the main text:

$$UP_{mi} = \frac{1}{NJ} \sum_s \sum_j \frac{x_{mi,sj}}{\sum_{l,k} x_{lk,sj}} \quad DN_{mi} = \frac{1}{NJ} \sum_s \sum_j \frac{x_{sj,mi}}{\sum_{l,k} x_{sj,lk}}. \tag{C.5}$$

Table A2 reports the results. Sector size and upstream intensity are significant and some with the expected sign. Overall, even these three variables together explain less than 20% of the variation in the global news coverage across countries and sectors (column 1).

Finally, we exploit the bilateral dimension of news coverage, and assess how frequently countries report on each other's sectors:

$$F_{s,mi} = \beta_1 S_{mi} + \beta_2 UP_{s,mi} + \beta_3 DN_{s,mi} + \beta_4 1\{s = m\} + \boldsymbol{\delta} + \varepsilon_{smi}, \tag{C.6}$$

where s indexes country of the source of the news, m and i index country and sector about which news is reported, and $F_{s,mi}$ is the news coverage frequency share about (m, i) in the newspapers printed in source country s ("local news"). For this equation, we use the bilateral versions of upstream and

Table A3: Correlates of Local News Coverage, Country-Pair-Sector level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.: $F_{s,mi}$								
S_{mi}	0.226**	0.226**	0.111	0.273***	0.111	0.116	0.139	0.142
	(0.098)	(0.099)	(0.090)	(0.099)	(0.091)	(0.091)	(0.107)	(0.103)
$UP_{s,mi}$	0.365***	0.365***	0.364***	0.341***	0.364***	0.366***	0.339***	0.342***
	(0.120)	(0.120)	(0.120)	(0.103)	(0.120)	(0.119)	(0.103)	(0.102)
$DN_{s,mi}$	0.066	0.066	0.074	0.086	0.074	0.065	0.088	0.077
	(0.115)	(0.115)	(0.114)	(0.106)	(0.115)	(0.115)	(0.106)	(0.105)
$1\{s = m\}$	0.015***	0.015***	0.015***	0.015***	0.015***		0.015***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	
Observations	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472
R^2	0.390	0.390	0.392	0.504	0.393	0.406	0.506	0.520
Country s FE	NO	YES	NO	NO	YES	NO	YES	NO
Country m FE	NO	NO	YES	NO	YES	NO	YES	NO
Country pair FE	NO	NO	NO	NO	NO	YES	NO	YES
Sector FE	NO	NO	NO	YES	NO	NO	YES	YES

Notes: This table reports the results of estimating equation (C.6). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variable definitions and sources are described in detail in the text.

downstream indicators, that reflect how important is sector (m, i) for producers in country s. These are defined analogously, but at the country level.[1] We also added to the specification the indicator for whether the country of the newspaper is the same as the country of the sector, $1\{s = m\}$, to pick up the strength of the home bias in news coverage.

Table A3 reports the results. Overall, the coefficients have the expected sign, and the explanatory power of these regressors at the bilateral level is higher than at the global level, explaining 40% of the variation (column 1). There is clear home bias in news coverage, with shares on average 1.5% higher for home sectors conditional on the other observables. Larger country-sectors receive more coverage, as expected, though the coefficient becomes insignificant with country-being-covered (m) fixed effects, suggesting that it is primarily larger countries that get coverage. All in all, the highest combined R^2 of all the explanatory variables is only about 0.4, implying there is substantial cross-sectional variation in news coverage that is not systematically related to these simple observables.

[1]These indicators are:

$$UP_{s,mi} = \frac{1}{J}\sum_j \pi^x_{mi,sj} = \frac{1}{J}\sum_j \frac{x_{mi,sj}}{\sum_{l,k} x_{lk,sj}} \quad DN_{s,mi} = \frac{1}{J}\sum_j \theta_{sj,mi} = \frac{1}{J}\sum_j \frac{x_{sj,mi}}{\sum_{l,k} x_{sj,lk}}.$$

C.2 Forecast Error Regressions: Robustness

Productivity shocks. Suppose that an upward deviation in productivity growth made GDP easier to forecast, while at the same time was associated with more intense news coverage. Then, omitting productivity growth from the regression would lead to a spurious coefficient on the news coverage intensity. Of course, there are many possibilities. It could actually be that *downward* deviations in productivity growth improve forecast precision/increase coverage, or *absolute* deviations. Thus, we add controls for a variety of transformations of productivity growth to equations (4.1) and (4.2): (i) the simple growth rate, (ii) its absolute value, (iii) its square, as well as (iv) an indicator for whether the period's productivity growth is negative. We use quarterly labor productivity as the underlying measure of productivity. The results are in Panel A of Table A4. The addition of these controls has a minimal impact on either the level of the coefficient of interest or its significance. Note that neither the premise that large shocks coincide with more coverage, nor that large shocks are easier to forecast appear supported by the data.[2]

Content of news. Productivity is not the only shock that might affect forecastability of GDP and news coverage. Closest to our conceptual framework, noise shocks also drive fluctuations (Angeletos and La'O, 2013; Angeletos, Collard, and Dellas, 2020) and may change forecastability of GDP. While it is very difficult to identify an empirical counterpart of the Angeletos-La'O-style noise/sentiment shock in the data, in the next set of robustness checks we control for "news sentiment" distilled from the news coverage data by Fraiberger et al. (2021). We apply the same 4 transformations to the news sentiment series as we do to productivity. Including the news sentiment variables has the additional benefit of controlling for the *direction/tone* of the news coverage, whereas our main variable of interest is the coverage *intensity*.[3] Panel B of Table A4 reports the results. Because of the imperfect overlap between our data and Fraiberger et al. (2021), the sample size falls by nearly 30%. Nonetheless, the coefficients and their level of significance are very similar to the baseline.

Monetary policy shocks. A growing literature finds that US monetary policy shocks are an important driver of the global financial cycle. It might be plausible that these shocks are correlated with news coverage intensity, and at the same time reduce forecast errors. While the time fixed effects in our regression control for the global financial cycle and the average effects of any monetary policy shocks on forecast errors, differential effects for countries more connected to the US might remain a concern. In Table A5 we therefore additionally control for monetary policy shocks in two ways. First, we use the absolute value of the US target rate, forward guidance, and quantitative easing shocks, constructed by Boehm and Kroner (2024) using the approach in Swanson (2021).[4] We interact these shocks with a country indicator to allow for country-specific effects of these shocks on the forecast errors. Second, we obtain a similar set of monetary policy shocks for the ECB and the Bank of England from Boehm and Kroner (2024), as well as a target rate and forward guidance shocks for the Bank of Japan from Kubota and Shintani (2022). We then control for the monetary policy shocks of

[2]We checked whether larger productivity shocks are associated with more news coverage by regressing news coverage on productivity growth conditional on country-sector and time effects. There is no significant relationship. We also checked whether larger deviations from the norm in GDP are easier to forecast. Forecast errors are actually larger when the realized GDP growth is exceptionally high or low. This is true whether exceptional is defined as below 25th percentile/above 75th percentile, or as below 5th percentile/above 95th percentile.

[3]The empirical news sentiment series reflect changes in sentiment due to true noise shocks (as in our model), but also any other shocks (e.g., productivity, future productivity, fiscal and monetary policy, financial shocks, etc.) that affect newspapers' views of the economy. Thus, including the empirical sentiment measures in the regressions controls for all shocks that might affect the tone/direction of news, not just the productivity shocks and noise shocks present in our theoretical framework. This aspect makes the empirical sentiment more attractive as a control variable, as it encompasses more potential confounders.

[4]Boehm and Kroner (2024) discuss the construction of these shocks in detail, and show they align well with the original measures in Swanson (2021) for the overlapping time frame.

all countries, and interact each with an own-country indicator to allow for a differential own effect. We lack identified monetary policy shocks for Canada, so we interact the US shocks with a Canada indicator as well. In this approach, the sample size shrinks substantially— ECB monetary policy shocks are only available after 2002 — so estimates are more noisy. However, with both approaches to controlling flexibly for heterogeneous effects of identified monetary policy shocks, the results remain similar.

Political cycle. Another potential confounder is the election cycle, if in election periods economic news coverage changes (up or down), while at the same time forecastability of GDP changes as well. We collected data on the dates of national elections in all the countries in the sample. Table A6 controls for an election-quarter dummy that might be correlated with news coverage intensity and forecast errors and finds similar results.

Re-weighting news coverage. Our baseline estimates of equations (4.1) and (4.2) use the total news coverage in each country and quarter. It could be that sectors important as input suppliers receive more attention from forecasters, and news coverage about them could better help predict aggregate outcomes. To account heuristically for this possibility, we weight news coverage in each sector by its Domar weight. In this way, the hypothesis is that news coverage of sectors with higher Domar weights reduces forecast errors by more than the same amount of news coverage in a sector with a low Domar weight. Appendix Table A7 displays the results. They are quite similar to Table 2.

Forecasts of unemployment. The active margin in the model is labor input, which is the main endogenous variable that reacts to news coverage. Unfortunately, to the best of our knowledge databases of forecasts of total hours worked do not exist for our countries. However, Consensus data do include forecasts for the unemployment rate. We thus estimate equations (4.1)-(4.2) for the forecast errors in the unemployment rate. The results are reported in Appendix Table A8. News coverage does reduce both the nowcast and one-year ahead forecast errors for unemployment, but the coefficients for the dispersion in the forecasts are not significant, albeit of the right sign.

Table A4: Global News Coverage and Forecast Errors: Controlling for Productivity and News Sentiment

	(1)	(2)	(3)	(4)
	Panel A: nowcast errors, productivity controls		Panel B: nowcast errors, productivity and sentiment controls	
Dep. Var.	|forecast error|	SD (forecast error)	|forecast error|	SD (forecast error)
$\log F_{n,t}$	-0.092***	-0.030***	-0.073***	-0.034***
	(0.010)	(0.011)	(0.013)	(0.011)
Observations	18,499	796	13,488	584
R^2	0.484	0.715	0.511	0.733
Time FE	yes	yes	yes	yes
$f \times n$ FE	yes		yes	
n FE		yes		yes
Prod. controls	yes	yes	yes	yes
Sent. controls			yes	yes

Notes: Standard errors clustered by country-forecaster (columns 1 and 3) and Driscoll-Kraay standard errors (columns 2 and 4) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 3 report the results of estimating equation (4.1). Columns 2 and 4 report the results of estimating equation (4.2). Panel A uses several transformations of labor productivity as additional controls. Panel B in addition uses several transformations of the news sentiments index from Fraiberger et al. (2021) as additional controls. Variable definitions and sources are described in detail in the text.

Table A5: Global News Coverage and Consensus Forecast Errors: Controlling for Monetary Shocks

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	|forecast error|	|forecast error|	|forecast error|	|forecast error|
$\log F_{n,t}$	-0.124***	-0.050***	-0.198***	-0.105***
	(0.012)	(0.018)	(0.032)	(0.037)
Observations	12,883	9,874	12,203	9,413
R^2	0.547	0.588	0.721	0.804
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes	yes	yes	yes
Productivity, Sentiment Controls	yes	yes	yes	yes
US MP shocks×country FE	yes		yes	
All MP shocks×own-country FE		yes		yes
Dep. Var	SD (forecast error)	SD (forecast error)	SD (forecast error)	SD (forecast error)
$\log F_{n,t}$	-0.037***	0.0051	-0.060***	-0.026
	(0.012)	(0.014)	(0.018)	(0.028)
Observations	558	420	546	408
R^2	0.748	0.810	0.626	0.638
Time FE	yes	yes	yes	yes
Country FE	yes	yes	yes	yes
Productivity, Sentiment Controls	yes	yes	yes	yes
US MP shocks×country FE	yes		yes	
All MP shocks×own-country FE		yes		yes

Notes: Standard errors clustered by country-forecaster in parentheses for top panel and Driskoll-Kraay standard errors for bottom panel.. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 3 report the results of estimating equation (4.1) (top panel) or (4.2) (bottom panel) with non-linear functions of productivity, sentiment, as well as US monetary policy shocks interacted with an indicator for each country. Columns 2 and 4 report the results of estimating equation (4.1) (top panel) or (4.2) (bottom panel) with non-linear functions of productivity, sentiment, as well as monetary policy shocks for the US, ECB, U.K. and Japan as controls. The monetary policy shocks in these columns are additionally interacted with an indicator for the central bank of the country. US monetary policy shocks are interacted with a Canada indicator as well. Variable definitions and sources are described in detail in the text.

Table A6: Global News Coverage and Consensus Forecast Errors: Controlling for Elections

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	|forecast error|	SD (forecast error)	|forecast error|	SD (forecast error)
$\log F_{n,t}$	-0.072***	-0.033**	-0.269***	-0.071***
	(0.013)	(0.011)	(0.030)	(0.019)
Observations	13,488	584	12,774	572
R^2	0.512	0.733	0.701	0.611
Election-quarter indicator	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes		yes	
Country FE		yes		yes
Prod. controls	yes	yes	yes	yes
Sent. controls	yes	yes	yes	yes

Notes: Standard errors clustered by country-forecaster (columns 1 and 3) and Driscoll-Kraay standard errors (columns 2 and 4) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 3 report the results of estimating equation (4.1). Columns 2 and 4 report the results of estimating equation (4.2). The independent variable is the news frequency share. All columns include an election-quarter control. All columns include controls for non-linear functions of productivity and news sentiment. Variable definitions and sources are described in detail in the text.

Table A7: Global News Coverage and Consensus Forecast Errors: Domar-Weighted News Coverage

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	|forecast error|	SD (forecast error)	|forecast error|	SD (forecast error)
$\log F_{n,t}$	-0.077***	-0.025**	-0.287***	-0.054***
	(0.010)	(0.011)	(0.028)	(0.016)
Observations	18,562	800	17,326	768
R^2	0.470	0.703	0.696	0.537
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes		yes	
Country FE		yes		yes

Notes: Standard errors clustered by country-forecaster (columns 1 and 3) and Driscoll-Kraay standard errors (columns 2 and 4) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 3 report the results of estimating equation (4.1). Columns 2 and 4 report the results of estimating equation (4.2). The independent variable is the Domar-weighted news frequency share. Variable definitions and sources are described in detail in the text.

Table A8: Global News Coverage and Consensus Forecast Errors: Unemployment

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	$\lvert$forecast error$\rvert$	SD (forecast error)	$\lvert$forecast error$\rvert$	SD (forecast error)
$\log F_{n,t}$	-0.169***	-0.007	-0.262***	-0.005
	(0.035)	(0.007)	(0.033)	(0.012)
Observations	16,334	700	15,262	672
R^2	0.655	0.642	0.513	0.567
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes		yes	
Country FE		yes		yes

Notes: Standard errors clustered by country-forecaster (columns 1 and 3) and Driscoll-Kraay standard errors (columns 2 and 4) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 3 report the results of estimating equation (4.1). Columns 2 and 4 report the results of estimating equation (4.2). The dependent variable is the forecast error of the unemployment rate. Variable definitions and sources are described in detail in the text.

C.3 External Validation: News Coverage and Sectoral Comovement

Data. Panel data on sectoral macroeconomic variables at the quarterly frequency are not readily available for many countries. We gather this information from national statistical sources and create concordances to build a new panel dataset of industrial production and hours worked by sector for the 8 countries in our sample. As the national sources vary in sectoral classifications and in levels of disaggregation, we concord each individual data source to our 23 ISIC-Revision 4 sectors for each country. The panel covers the entire private economy over the years 1972-2020, but is unbalanced. A detailed Online Handbook describes the the national data sources and their coverage for the underlying series used to construct our panel, and the steps for data cleaning and constructing these variables.

Trade, news coverage and comovement in the data. As an empirical setting, we use one of the best-known reduced-form relationships linking international trade and comovement – the "trade-comovement" regression (Frankel and Rose, 1998). We extend the standard regression to include bilateral news coverage and its interaction with bilateral trade intensity. In particular, we fit the following relationship in the cross-section of country-sector pairs:

$$\rho^H_{nj,mi} = \beta_1 \ln \mathrm{Trade}_{nj,mi} + \beta_2 \ln \mathrm{Trade}_{nj,mi} \times F_{nj,mi} + \beta_3 F_{nj,mi} + \boldsymbol{\delta} + \nu_{nj,mi}, \tag{C.7}$$

where $\rho^H_{nj,mi}$ is the correlation of hours worked growth rates between country-sector (n, j) and country-sector (m, i). Our hours data are quarterly, and we use 4-quarter growth rates as the baseline.

While the majority of trade-comovement regressions are estimated at the country-pair level, it is somewhat less straightforward to define bilateral trade intensity at the sector-pair than at the aggregate level, since generically sectors are simultaneously upstream and downstream from each other. We define the sector-pair version of the traditional trade intensity variable ($\mathrm{Trade}_{nj,mi}$) as:

$$\mathrm{Trade}_{nj,mi} = \frac{1}{4}\left(\omega_{mi,nj} + \omega_{nj,mi} + \theta_{mi,nj} + \theta_{nj,mi}\right), \tag{C.8}$$

where $\omega_{mi,nj} = \frac{X_{mi,nj}}{\sum_{l,k} X_{lk,nj}}$ is the share of input (m, i) in the total input spending of (n, j). Thus, it captures the importance of (m, i) as a supplier of inputs to sector (n, j). The share $\theta_{nj,mi} = \frac{X_{mi,nj}}{\sum_{l,k} X_{mi,lk}}$ is the sales share of (n, j) in (m, i)'s total sales. Thus, it captures the importance of (m, i) as a destination of (n, j)'s sales. Our measure of trade intensity averages the directional bilateral upstream and downstream intensities ω's and θ's.

The new regressor is the news intensity, computed as the average of the frequencies with which the country-sectors are covered in the news:

$$F_{nj,mi} = \frac{1}{2}\left(F_{nj} + F_{mi}\right), \tag{C.9}$$

where F_{nj} is the frequency share of sector (n, j) in the global news. We include $F_{nj,mi}$ both as a main effect, and also as an interaction with trade intensity. The latter explores the possibility that greater news coverage is associated with disproportionately greater comovement in sectors linked more intensively via trade relationships.

Table A9 reports the results. The columns differ in the fixed effects included. As highlighted in many studies, greater bilateral trade intensity is associated with higher comovement. In our specification, this is true even controlling for country-pair effects and thus exploiting variation within a pair of countries across sector pairs. The novel result is that both news coverage intensity by itself, and the news intensity interacted with trade are highly statistically significant. Even controlling for

Table A9: International Comovement, Trade, and News Coverage

Dep. Var.: $\rho^H_{nj,mi}$	(1)	(2)	(3)	(4)	(5)
	All country-sector pairs				International
$\ln \text{Trade}_{nj,mi}$	0.014***	0.009***	0.021***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.868***	0.487***	0.604***	0.261***	0.510***
	(0.117)	(0.092)	(0.121)	(0.101)	(0.151)
$F_{nj,mi}$	9.686***		5.335***		
	(1.016)		(1.056)		
Observations	16,032	16,032	16,032	16,032	14,030
R-squared	0.052	0.448	0.152	0.464	0.454
Country-sector FE	no	yes	no	yes	yes
Country pair FE	no	no	yes	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (C.7). The dependent variable is the correlation in 4-quarter growth rates of total hours worked between country-sectors (n, j) and (m, i). The dependent variables are log trade intensity as in (C.8) and news coverage intensity as in (C.9). Throughout, we restrict the sample to country-sector pairs where a minimum of 10 years of data are available for computing correlations. Columns 1-4 use all country-sector pairs. Column 5 restricts the sample to pairs where $m \neq n$.

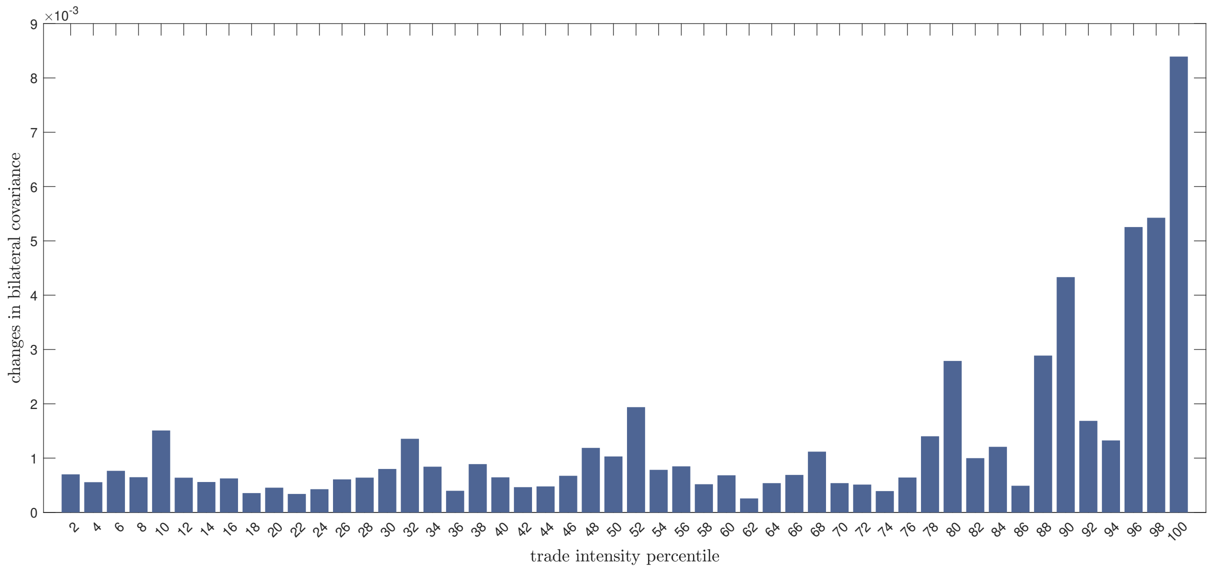
both sets of country-sector effects, sector pairs that are more covered in the news comove more. Once we include country pair effects we cannot estimate the main effect of news coverage, but even in this case we can estimate the interaction of news coverage with bilateral trade. Sectors more covered in the news exhibit more pronounced comovement the more they trade with each other. Finally, column 5 restricts the sample to sector-pairs located in different countries. If anything, the coefficient on the interaction between news coverage and trade intensity becomes larger. This is *prima facie* evidence that news coverage intensity plays a role in conditioning the extent of cross-border comovement.[5]

Note that these results should be interpreted as conditional correlations and not a causal relationship (as is the case with the entirety of the trade-comovement empirical literature). This is in contrast to the model exercise described below, where we can assess the causal effect of an increase in bilateral news coverage. Eliminating all sources of confounding variation is possible in a model environment, but not in the empirical regressions.

Trade, news coverage and comovement in the model. To explore the interaction between news coverage and trade intensity in the model, we implement the following local perturbation exercise: fixing a pair of country-sectors, the news share for these two country sectors is increased by 25% and the global influence matrix is recomputed. We then compare the covariance between these two sectors' hours worked with that in the baseline economy. We perform this local perturbation for all the country-sector pairs. This exercise is intended to mimic the empirical trade-comovement regression, but in the model we have the added benefit of being able to implement a fully controlled experiment in which nothing changes except for news coverage intensity/signal precision. This exercise is of course not attainable in empirical analysis, which must worry about confounding factors.

[5]The results are robust to various alternatives: using industrial production instead of hours correlations; using 1-quarter instead of 4-quarter growth rates; using covariances instead of correlations; and using alternative news and trade intensity variables. Results available upon request.

Figure A5: Quantitative Model: Changes in Bilateral Comovement and Trade Intensity



Notes: This figure displays the change in bilateral covariance in the model due to a sector-pair specific increase in the news coverage intensity, against percentile of sector-pair bilateral trade intensity.

Figure A5 displays the changes in covariance relative to the baseline counterparts in this model exercise. In the figure, the "shocked" country-sector pairs are ranked according to their bilateral trade intensity. The changes in covariance are positive overall, consistent with the intuition that more news coverage facilitates shock transmission. Furthermore, this increase tends to be greater for the pairs that exhibit a greater trade intensity – the model counterpart of the interaction coefficient between news coverage and trade intensity in the empirical regressions. The reason is simple: when the trade linkages between two country sectors are weak, whether they are aware of each others' fundamental or not is nearly irrelevant. On the other hand, sectors that trade intensively with each other must form expectations about the productivity of their trading partners, and thus increasing news precision about that productivity leads to higher comovement.

D. Quantification Appendix

D.1 Indirect Inference

To illustrate the basic logic of the identification, consider a simple case where labor is inelastically supplied ($\psi = 0$). In this case, the change in a country's GDP is simply due to the changes in TFP

$$v_{nt} = \sum_j \mathcal{D}_{nj} z_{nj,t},$$

where $\mathcal{D}_{nj}$ is the corresponding Domar weight. Denote the individual forecast error as

$$e_{f,n,t} \equiv v_{nt} - \mathbb{E}_f[v_{nt}] = \sum_j \mathcal{D}_{nj} \left(\frac{1}{1+\tau+\kappa_{nj,t}} z_{nj,t} - \frac{\kappa_{nj,t}}{1+\tau+\kappa_{nj,t}} \varepsilon_{nj,t} - \frac{\tau}{1+\tau+\kappa_{nj,t}} u_{nj,f,t} \right).$$

Note that here we allow the news coverage share to vary with time and $\kappa_{nj,t}$ is therefore indexed by t as well. The individual noise $u_{nj,f,t}$ is associated with the individual forecaster f, which wash out in aggregate, $\int_f u_{nj,f,t} df = 0$. The variance of the individual forecast error at time t can be expressed as

$$\mathbb{V}_t(e_{f,n,t}) = \sum_j \mathcal{D}_j^2 \mathbb{V}(z_{nj,t}) \frac{1}{1+\tau+\kappa_{nj,t}}.$$

Under the assumption that $\kappa_{nj,t} = \chi_0 + \chi_1 F_{nj,t}$, the first-order approximation of $\mathbb{V}_t(e_{f,n,t})$ around the average news coverage $\overline{F}$ can be written as

$$\begin{aligned}
\mathbb{V}_t\left(e_{f,n,t}\right) &\approx \text{const} - \chi_1 \frac{\overline{F}}{(1+\tau+\chi_0+\chi_1\overline{F})^2} \sum_j \mathcal{D}_{nj}^2 \mathbb{V}(z_{nj,t})(F_{nj,t} - \overline{F}) \\
&\approx \text{const} - \chi_1 \frac{\overline{F}^2}{(1+\tau+\chi_0+\chi_1\overline{F})^2} \sum_j \mathcal{D}_{nj}^2 \mathbb{V}(z_{nj,t}) \ln F_{nj,t}.
\end{aligned}$$

The loading on the news coverage is a function of χ_1, which is increasing in χ_1 when χ_1 is below certain threshold. Note that absolute value of the forecast error $|e_{f,n,t}|$ follows a folded normal distribution, and the mean of it is proportional to the standard deviation of $|e_{f,n,t}|$. As a result, the coefficient β_1^M in equation (4.4) is directly related to χ_1.

Similarly, consider the across-sectional dispersion of the forecast error, which corresponds to the variance of $e_{f,n,t}$ due to the idiosyncratic noise.

$$\mathbb{V}_t(e_{f,n,t} - \overline{e}_{f,n,t}) = \sum_j \mathcal{D}_{nj}^2 \mathbb{V}(z_{nj,t}) \frac{\tau}{(1+\tau+\kappa_{nj,t})^2}.$$

Its first-order approximation is

$$\mathbb{V}_t(e_{f,n,t} - \overline{e}_{f,n,t}) \approx \text{const} - 2\chi_1\tau \frac{\overline{F}^2}{(1+\tau+\chi_0+\chi_1\overline{F})^3} \sum_j \mathcal{D}_{nj}^2 \mathbb{V}(z_{nj,t}) \ln F_{nj,t}.$$

Notice in this case, the product of χ_1 and τ appears in the loading on the news share. The variance of the absolute value of $e_{f,n,t} - \overline{e}_{f,n,t}$ is proportional to $\mathbb{V}_t(e_{f,n,t} - \overline{e}_{f,n,t})$, and is also directly related to

Table A10: Sensitivity Matrix

	Slope, | forecast error |	Slope, SD(forecast error)	SD (forecast error)
τ	-0.074%	0.385%	0.424%
χ_0	-0.149%	-0.213%	-0.166%
χ_1	0.385%	0.273%	-0.218%

Notes: Each column of this table reports the percentage change in the model moment (column) with respect to a 1% change in the parameter identified by indirect inference (row). Taken together, the elements of this table correspond to the sensitivity matrix for indirect inference suggested by Andrews, Gentzkow, and Shapiro (2017).

$\chi_1 \tau$.

Finally, the unconditional variance of the individual forecast error is

$$\frac{1}{T}\sum_{t=1}^{T}\mathbb{V}_t(e_{f,n,t}) = \frac{1}{T}\sum_{t=1}^{T}\sum_{j}\mathcal{D}_{nj}^2\mathbb{V}(z_{nj,t})\frac{1}{1+\tau+\chi_0+\chi_1 F_{nj,t}},$$

which helps to determine the magnitude of χ_0.

With elastic labor supply, one needs to replace the Domar weights with the influence matrix, but the derivation applies in a similar way.

In the quantitative model, the corresponding matrix that measures the sensitivity of the indirect inference procedure according to Andrews, Gentzkow, and Shapiro (2017) is given by Table A10.

D.2 CES Model Results

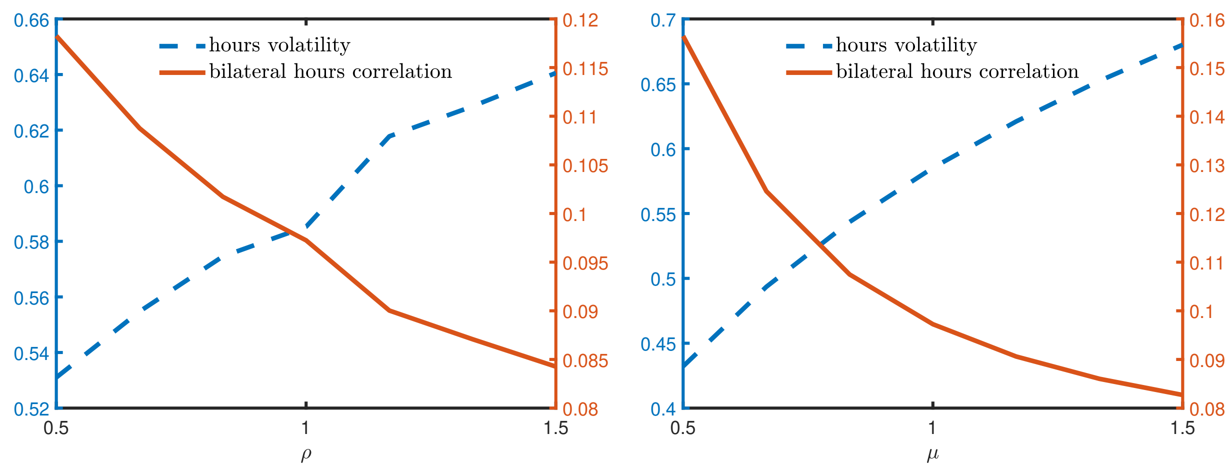
This appendix presents the quantitative results under non-unitary elasticities of substitution. We extend the model in Section 2 to allow for CES preferences in consumers' final goods and firms' intermediate goods composite bundles:

$$\mathcal{F}_n = \left(\sum_{m,i} \vartheta_{mi,n} \mathcal{F}_{mi,n}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \qquad X_{nj} = \left(\sum_{m,i} \zeta_{mi,nj} X_{mi,nj}^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}.$$

The elasticities of substitution are ρ and μ, respectively. We choose $\rho = 1.2$ and $\mu = 0.7$, both of which are standard values used in the literature (see, among others, Boehm, Flaaen, and Pandalai-Nayar, 2019; Boehm, Levchenko, and Pandalai-Nayar, 2023; Huo, Levchenko, and Pandalai-Nayar, 2025). Table A11 replicates the main quantitative results (Table 4 in the main text), and shows that the magnitudes are similar.

We further explore how the business cycle statistics vary with these elasticities. Figure A6 shows that when increasing the final goods elasticity ρ or the intermediate goods elasticity μ, the hours volatility increases, but the bilateral correlation decreases. With lower elasticities, the shock transmission is amplified as firms in different locations comove with each other. This pattern has been discussed in Huo, Levchenko, and Pandalai-Nayar (2025) in an economy with perfect information, and here we verify this insight extends to models with informational frictions. Quantitatively, our main results are robust to alternative parameterization.

Figure A6: Business Cycle Statistics under Different Elasticities of Substitution



A. Varying ρ B. Varying μ

Notes: The figure displays how the average standard deviation of hours and bilateral correlation of hours vary with elasticities of substitution. The left panel varies the final goods elasticity ρ when fixing $\mu = 1$, and the right panel varies the intermediate goods elasticity μ when fixing $\rho = 1$.

Table A11: Business Cycle Statistics, CES Model

	(1) Perfect Information	(2) Incomplete Information	(3)	(4)	(5) Data
	TFP	TFP	noise	both	
Hours volatility	0.957	0.459	0.306	0.552	1.550
indirect vs direct effects: $\frac{\sigma_{\text{indirect}}}{\sigma_{\text{direct}}}$	0.504	0.459	0.564	0.491	
Bilateral hours correlation					
uncorrelated noise	0.104	0.122	0.060	0.103	0.190
correlated noise	0.104	0.122	0.307	0.193	
Bilateral labor wedge correlation					
uncorrelated noise	—	0.062	0.028	0.055	
correlated noise	—	0.062	0.243	0.121	

Notes: This table presents the business cycle statistics for the model with CES final and intermediate demand. For hours volatility, this table reports the mean across the G7+ countries of the standard deviation of aggregate hours. For bilateral correlation, this table reports the mean of bilateral correlation of aggregate hours or the labor wedge between all possible G7+ country pairs. The Data column reports the volatility or bilateral correlation of four-quarter growth rates of aggregate hours, excluding the years 2008 and 2009 from the sample.

D.3 Additional Quantitative Exercises

News coverage and shock propagation in the cross-section of sectors. Intuitively, if a sector (m, i) is covered in the news more intensively, other sectors are more likely to respond to a shock originating from sector (m, i), even conditional on the origin sector's size. This is because firms have more information and they also understand that other firms are more aware of the shock. To highlight the role of news coverage in the shock transmission, we define the average elasticity of hours response to a TFP or a noise shock in sector (m, i) as follows:

$$\varrho^s_{mi} = \frac{1}{NJ-1} \sum_{mi \neq nj} G^s_{nj,mi} \qquad s = z, \varepsilon. \tag{D.1}$$

That is, ϱ^z_{mi} is the average log change in hours across all countries and sectors following a 1-unit log change in TFP in sector (m, i), and similarly for the noise shock ε.

Panel A of Figure A7 displays the relationship between ϱ^z_{mi} and the news frequency share of sector (m, i) in the baseline model, after partialling out the country-sector size measured by the sales value in the steady state. The average elasticity is strongly correlated with the news share, with a slope of 0.19 and R^2 of 0.60. Greater news coverage increases the shock propagation from sector (m, i) to the rest of the world economy. Panel B displays the elasticity ϱ^ε_{mi} of hours with respect to the noise shock in sector (m, i) against the news share. The correlation with the news share is even stronger than for the TFP elasticity. Noise shocks to sectors well-covered in the news transmit more strongly.

Panel C of Figure A7 displays ϱ^z_{mi} under perfect information. In this case, there is not much of a discernible relationship, with both the slope and the R^2 near zero.

Heterogeneous precision for private signals. So far, we have imposed that firms receive private information about other country-sectors with the same precision. This is of course a simplifying assumption. In reality, firms are more willing to acquire information about locations that are more relevant for their own profits, a key insight from the rational inattention literature (Sims, 2003; Maćkowiak and Wiederholt, 2009). We accommodate this type of endogenous information structure by allowing country sector (n, j)'s private signal precision about (m, i)'s TFP shock to decay in network distance. In particular, we assume that

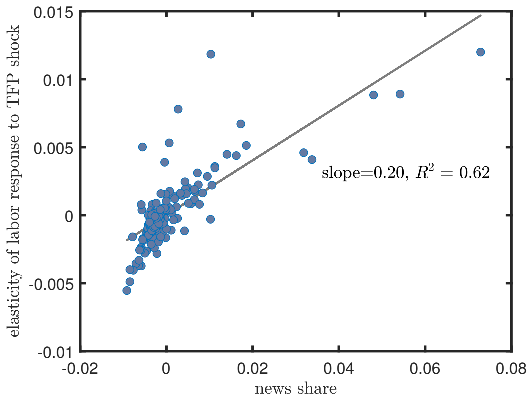
$$\tau_{nj,mi} = \tau + \delta(1 - d_{nj,mi}),$$

where δ measures the extent with which the precision varies with the network distance. Our baseline model corresponds to $\delta = 0$; when $\delta > 0$, (n, j) has more precise private signals about sectors close to it in the network. Thus, this formulation implements the basic idea of rational inattention in a reduced-form way.[6]

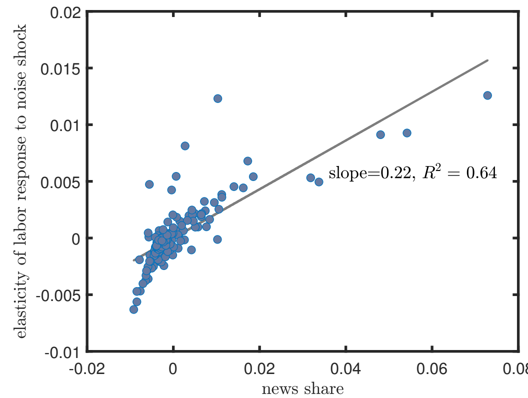
The left panel of Figure A8 shows how the volatility of hours changes with the parameter δ. As expected, a larger δ reduces firms' needs to rely on public news in general, and therefore the contribution of noise shocks decreases and that of TFP shocks increases. However, even for relatively large values of δ, the noise shock remains an important source of international fluctuations. At the micro level, the precision of private information is lower when country sectors are further away from each other, which reinforces our result on the relationship between the network remoteness and the reliance of public signals. With common precision, the network remoteness only shifts the relative importance between first-order and higher-order expectations; with heterogeneous precision, first-order expectations will also rely more on public information when network remoteness increases. The right panel of Figure A8 confirms this intuition.

[6]In a similar manner, it would also be straightforward to model a dependence of the signal precision on the volatility of the TFP shocks.

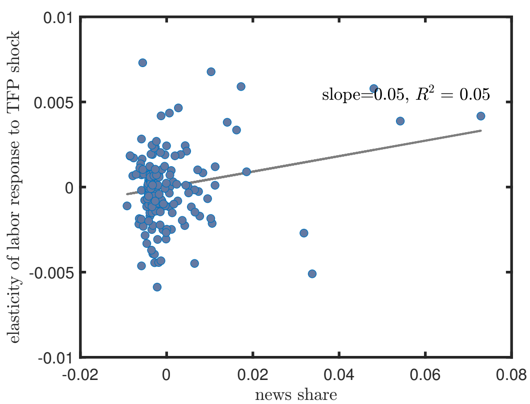
Figure A7: News Share and TFP Shock Transmission



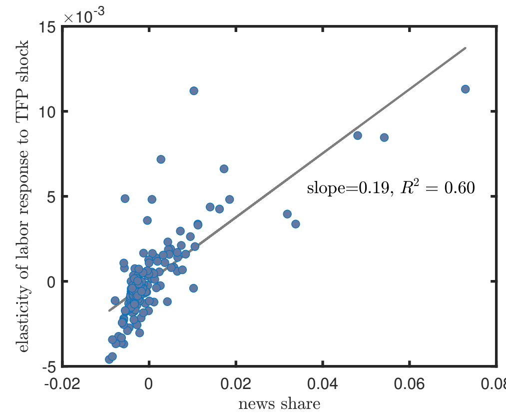
A. Baseline, TFP Shock



B. Baseline, Noise Shock



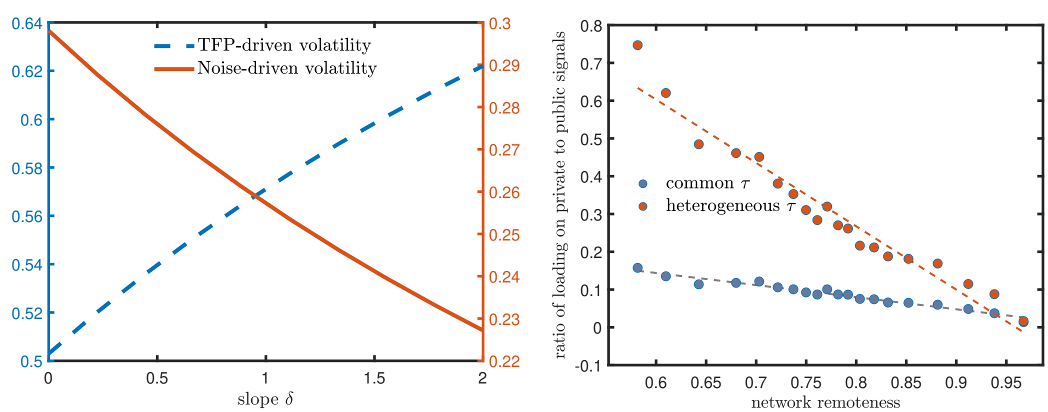
C. Perfect Information, TFP Shock



D. Only Private Information, TFP Shock

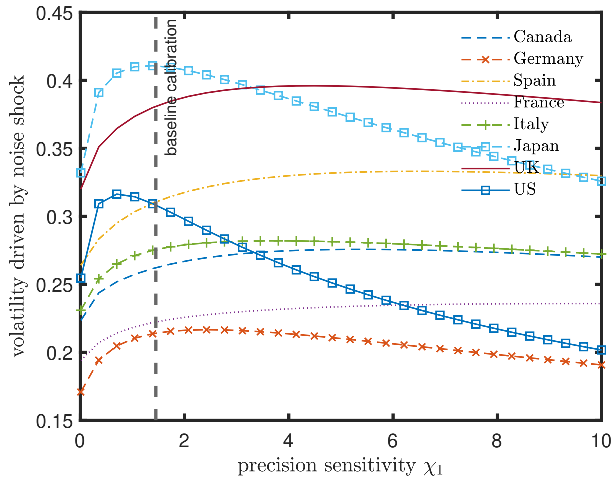
Notes: The figure displays scatterplots of the average elasticity of total hours change in other sectors following a shock in a particular sector (D.1) on the y-axis against that sector's share of the global news coverage on the x-axis. Panels A and B display the ϱ^z_{mi} and ϱ^ε_{mi} in the baseline model. Panel C displays ϱ^z_{mi} in the perfect information model, and Panel D ϱ^z_{mi} in the alternative economy in which all information is private. The OLS fit and the slope coefficients and R^2's are added to each panel. The plots partial out sector size as measured by total sales.

Figure A8: Heterogeneous Private Information Precision



Notes: The left panel displays the average standard deviation of hours across countries driven by TFP shocks (blue dashed line) and noise shocks (red dashed line) as a function of the elasticity of private information precision with respect to network remoteness. The right panel displays the ratio of responses to private signals to responses to news signals as a function of the network distance. This is the binscatter plot of the regression (4.6) controlling for variances of the TFP and the noise shocks. The blue dots correspond to the baseline model with common private information precision, and the red dots correspond to the heterogeneous precision case where δ is set to 1.

Figure A9: Precision Sensitivity and Volatility Driven by Noise Shocks



Notes: The figure displays the non-monotonicity of noise-driven fluctuations in the model as a function of χ_1.

Non-monotonicity in noise-driven fluctuations. As discussed in Section 2, the fluctuations generated by the noise shocks are non-monotonic in the precision of the public signals or equivalently, in the sensitivity of the public signal precision to news coverage χ_1. Consider two extreme cases: if $\chi_1 \approx 0$ and $\chi_0 = 0$, the news coverage is not informative at all and firms will ignore it when making decisions. Consequently, the noise contained in the news coverage is irrelevant. At the opposite extreme, suppose $\chi_1 \approx \infty$ and the news coverage is very informative. In this case, the variance of the noise shock approaches zero and agents know the fundamental state perfectly after observing the public signal. In this case, the model converges to perfect information and noise shocks also cannot play a significant role in shaping the aggregate fluctuations. The importance of noise-driven volatility is a therefore quantitative question, and depends on the estimates of χ_1.

Figure A9 displays the hours volatility driven by the noise shock as a function of the slope of the precision-news coverage relationship χ_1. According to our assumptions, signal precision increases one-for-one with χ_1. The vertical line displays the value of χ_1 that emerges from our indirect inference procedure.

It is evident that the fluctuations are indeed non-monotonic in signal precision over the relevant range of χ_1. But there is no clear pattern across countries. While for Japan our calibrated values imply that the noise-driven volatility is close to the maximum, the peak volatility obtains for lower χ_1 in the US, and higher χ_1 in several other countries. In a number of cases, the volatility is quite flat above our preferred value of χ_1.

Economy with homogeneous public information precision within a country. Another exercise we have experimented is to impose that the precision of public signals within a country is common, that is

$$\kappa_{nj} = \chi_0 + \chi_1 F_n.$$

It turns out that our main business cycle statistics remain similar to the baseline case. Table A12 displays the results.

Economy with only private information. In our baseline model agents have access to both public and private signals. One may wonder to what extent this distinction has real consequences for the equilibrium allocations, relative to a counterfactual informational structure in which all signals are

Table A12: Business Cycle Statistics, Common Precision within a Country

	(1) Perfect Information	(2) Incomplete Information	(3)	(4)	(5) Data
	TFP	TFP	noise	both	
Hours volatility	0.986	0.536	0.404	0.672	1.550
indirect vs direct effects: $\frac{\sigma_{\text{indirect}}}{\sigma_{\text{direct}}}$	0.464	0.401	0.576	0.464	
Bilateral hours correlation					
uncorrelated noise	0.094	0.087	0.049	0.075	0.190
correlated noise	0.094	0.087	0.266	0.163	
Bilateral labor wedge correlation					
uncorrelated noise	—	0.066	0.020	0.050	
correlated noise	—	0.066	0.205	0.138	

private but the informativeness about other country-sectors' fundamental remains the same. To answer this question, we consider the following alternative information structure: firms only receive modified private signals $\tilde{x}_{nj,mi,t}(\iota)$

$$\tilde{x}_{nj,mi,t}(\iota) = z_{mi,t} + \widetilde{u}_{nj,mi,t}(\iota), \quad \tilde{u}_{nj,mi,t}(\iota) \sim \mathcal{N}(0, \tilde{\tau}_{nj,mi}^{-1}\mathbb{V}(z_{mi,t})) \qquad \forall m, i,$$

where

$$\tilde{\tau}_{nj,mi} = \tau + \chi_0 + \chi_1 F_{mi}.$$

That is, the total precision is identical to the baseline model, but all the information is now in the private domain.

In these two environments, the first-order expectations conditional on TFP shocks are identical. Crucially, the higher-order expectations are different, as public signals are more useful than private ones for forecasting others' beliefs. As shown in Section 2, the equilibrium outcome hinges on the interaction between the production network and all the higher-order expectations, which makes the distinction between complete and incomplete information relevant. Table A13 reports the business cycle statistics in this alternative economy. Relative to the baseline model, the overall volatility is smaller, but it turns out that there is no uniform amplifying or dampening effects for TFP-driven fluctuations in the private-information-only economy, which highlights the importance of calibrating the network structure and the informational friction jointly.

Another important difference is that when information is all private, aggregate fluctuations can only be driven by TFP shocks. The noise-driven fluctuations require common or correlated aggregate noise shocks. In our baseline economy, we assume that the news are publicly observed by all agents and agents interpret the signals in the same way. This assumption could be violated if some agents do not pay full attention to the news or they have idiosyncratic interpretations of the news.

In addition, one may interpret the regression evidence on the correlation between forecast quality and news coverage as indicating that agents do not directly obtain information from public signals, but instead pay more attention to their private information about the fundamental when news coverage

Table A13: Business Cycle Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline economy			No-info economy			Private-info economy		
	TFP	noise	both	TFP	noise	both	TFP	noise	both
Hours volatility	0.503	0.298	0.585	0.106	0.000	0.106	0.446	0.000	0.446
Bilateral hours correlation	0.111	0.056	0.097	-0.005	—	-0.005	0.092	—	0.092

Notes: This table reports the mean across the G7+ countries of the standard deviation of aggregate hours and the bilateral hours correlation, in the baseline model (columns 1-3), the model with no signals (columns 4-6), and the model with only private information (columns 7-9).

is high. In this case, higher news coverage still implies greater transmission, but now it is through the private information channel. Panel D of Figure A7 displays the relationship between news share and the strength of shock propagation in this model. Comparing to the baseline model in Panel A, find that the two economies are similar to each other. The particular information structure discussed in this subsection could be viewed as an extreme case that maximizes the information in the private domain.

In short, the distinction between private and public information matters for the equilibrium allocations. The fraction of non-fundamental driven fluctuations depends on the exact split of the information between public and private, but the role of news in facilitating shock transmission is robust to this variation.

Economy with no information. We also explore an alternative environment where firms have neither private nor public signals about other country-sectors' TFP shocks except that they perfectly observe the productivity in their own country sector. As a result, when firms choose their labor inputs, they are unaware of changes in other locations and only respond to their own shocks. As a result, except for their own shocks, both the direct and indirect effects of shock transmission will be muted. Under this extreme assumption, the volatility of hours is much lower, as shown in Table A13. In addition, the comovement of hours across countries is only due to the shock correlation and much lower, as the internal shock propagation along the production network ceases to exist.

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