News Media and International Fluctuations*

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Abstract

We develop a multi-country multi-sector model with global value chains and informational frictions. Producers in a sector do not perfectly observe shocks to other countries and sectors, and their output decisions respond to beliefs about the productivity innovations worldwide. To discipline the agents' information sets, we collect new quarterly data containing the frequencies of country-industry-specific economic news reports by leading newspapers in the G7 plus Spain. Newspapers in each country publish articles on select events in both domestic and partner-country sectors, and not every event is reported worldwide. We show in reduced-form regressions that (i) greater news coverage is associated with smaller GDP forecast errors; and (ii) sectors more covered in the news exhibit greater business cycle comovement, even controlling for their trade intensity. We then use the news coverage data to discipline the key parameters in the quantitative model—the precision of the public and private signals about country-sector productivities. We find that noise shocks about TFP throughout the global value chain can be a quantitatively important source of international GDP comovement. Furthermore, these shocks would appear as correlated labor wedges in standard models without dispersed information.

Keywords: Information Frictions, Noise shocks, Global Value Chains, Business Cycle Comovement

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1. Introduction

Real GDP growth is positively correlated across countries. In spite of a large amount of research into the causes of international comovement, we still lack a full understanding of this phenomenon.[1] In particular, while a large closed-economy literature argues that most business cycle fluctuations are driven by non-technology ("demand") shocks (Angeletos, Collard, and Dellas, 2018), the international business cycle literature has predominantly relied on TFP shocks as drivers of comovement.

Quantification of the role of non-technology shocks in international comovement faces both modeling and measurement challenges. Quantitative frameworks with micro-founded demand shocks become intractable in multi-country settings, and data for many countries required to measure non-technology shocks are limited. The paper makes two main contributions. Our first contribution is to develop and solve a theoretical framework that features informational frictions and noise shocks in an international context. A successful recent literature in closed-economy macroeconomics has explored the possibility of generating aggregate fluctuations from non-technology shocks in models with informational frictions. In these types of environments, agents do not perfectly observe the fundamental shocks affecting their trading partners, and shocks to beliefs about those fundamentals can lead to aggregate fluctuations.[2] Theoretical treatments of these frictions typically rely on closed-economy frameworks not easily applied to a quantitative international setting. As a result, the consequences of imperfect information for the international business cycle are still unknown.

To model and quantify the impact of informational frictions and non-technology shocks on international comovement, we set up a theoretical framework that combines the standard model of business cycle shock transmission through the global supply chains (Huo, Levchenko, and Pandalai-Nayar, 2020a) with an environment characterized by dispersed information and sentiment shocks (Angeletos and La'o, 2010). In the model, there are multiple countries and sectors, connected with each other via trade in inputs and final goods. Informational frictions manifest themselves in imperfect knowledge of other country-sectors' productivity. In particular, each country-sector is populated by a continuum of "information islands." On each island, in the first stage workers must decide how much labor to supply, and firms how much labor to demand. In the second stage, after these labor decisions are set, all goods prices are revealed and intermediate input and final purchases are made, clearing goods markets. The second stage is thus simply an equilibrium in a standard global production network model with fixed sector-specific primary factors. In the first stage, each information island receives both a private and a public signal about productivities in every other country-sector. The public signal

[1]On the one hand, modern models of shock transmission through global supply chains do not endogenously generate the observed degree of comovement, and instead have to rely on correlated shocks if they are to replicate observed comovement successfully (Huo, Levchenko, and Pandalai-Nayar, 2020a). On the other hand, well-established candidates for such internationally correlated shocks are lacking. The predominant fundamental shock in international business cycle models – TFP – is essentially uncorrelated across countries (Huo, Levchenko, and Pandalai-Nayar, 2020b), suggesting we need a better understanding of the role of non-technology shocks for international comovement.

[2]There is abundant empirical evidence for the presence of such informational frictions (e.g. Coibion and Gorodnichenko, 2015).

is observed by every agent in this economy. Thus, disturbances to this public signal can be thought of as non-technology shocks, that we label "noise" (Angeletos and La'O, 2013; Huo and Takayama, 2015). They are aggregate shifts in beliefs about fundamentals.

As in the perfect-information international production literature, our framework is fully flexible about the configuration of domestic and international trade links. On the informational frictions side, early seminal contributions used highly stylized models, with islands meeting randomly to trade and no distinction between industries or between final vs. intermediate consumption. In these first-generation models, islands received signals only about the shocks to the randomly encountered island. By contrast, in our framework each island knows which sectors it is going to buy from and sell to, and receives two full vectors of signals about productivity in each country-sector in the world, one public and one private. The advantage of this environment is that it is more easily connected to data and quantified.

Despite its richness, the model admits an analytical solution. It makes transparent the main consequences of informational frictions and noise shocks for international shock transmission. First, relative to the perfect-information benchmark, introducing informational frictions reduces the impact of foreign TFP shocks on a country's GDP. This is sensible: agents do not fully react to the foreign TFP innovation as they are not fully sure it took place. Second, noise shocks transmit internationally. Innovations to the public signal about a country's TFP, even if they are not driven by true TFP changes, produce changes in a country's trading partners' GDP. Thus, we have provided a microfounded non-technology shock that can synchronize GDP internationally. Third, following an upstream sector's shock, the relative importance of the public signal increases in the downstreamness of a sector. That is, sectors more removed from the shocked sector rely less on their private signal, and more on the public signal to form expectations of the upstream sector's fundamental. This is because the higher-order expectations are more important for the more downstream sector. A more downstream sector must predict not so much an upstream sector's true TFP, but the beliefs of other sectors about the upstream sector's TFP. This also implies that noise shocks potentially contribute more to the fluctuations in more downstream sectors.

Our second contribution is to collect a large-scale dataset of economic news coverage of individual countries and sectors in the major newspapers of the G7 countries plus Spain (henceforth, "G7+"), and use it to quantify the model. Our dataset consists of the frequencies with which a particular country-sector – say, French pharmaceuticals, or the US auto industry – appears in the main newspapers throughout the G7+ countries. We record these frequencies quarterly from 1995 to 2020. We merge the newly collected data with standard production datasets such as KLEMS and the World Input-Output Database (WIOD); quarterly sectoral business cycle indicators such as industrial production and total hours worked; and GDP forecasts. This allows us, for the first time, to relate the intensity of news coverage to measures of real linkages, such as GVC participation, establish whether greater news coverage is associated with more precise forecasts, and investigate their role in international business cycle comovement at the quarterly frequency.

We document a three basic patterns about international economic news. First, there are pronounced differences in the intensity of news coverage across industries and countries. The coverage intensity differences are correlated with, but at best partly accounted for by the overall size, upstreamness, or downstreamness of a sector. Second, higher news coverage is associated with lower absolute GDP forecast errors, and less disagreement among forecasters in their GDP projections. This empirical regularity is suggestive that news coverage has informational content useful for predicting economic activity.

Third, greater news coverage is associated with higher business cycle comovement. We base this exercise on a textbook "trade-comovement" regression (Frankel and Rose, 1998), implemented at the country-sector-pair level. That is, we relate correlations between two country-sectors to input trade between those sectors, as well as the news coverage intensity of those sectors. We show that sectors more covered in the news tend to experience more business cycle comovement. We also include an interaction effect between news coverage and bilateral trade. It turns out that sectors more covered in the news comove even more if they trade more with each other. All in all, these reduced-form estimates provide evidence that news coverage plays a role in international business cycle comovement.

We then calibrate the model with the conventional data on the observed input-output relationships, and more importantly with key parameters governing the strength of information frictions estimated from our our novel news coverage data. Consistent with our empirical finding that the cross-sectional differences in business cycle comovement between country-sectors are significantly related to news coverage intensity, we use the news data to tightly discipline the variation in the precision of the public signal about each country-sector. That is, the more a sector is covered in the news, the higher is the precision of the public signal about its productivity. We use indirect inference via the theoretical analogs of our empirical forecast error regressions to translate news coverage in the data to the signal precision in the model. This exercise reveals that news coverage contributes strongly to making the public signal more precise.

To assess our model's performance, we estimate trade-comovement-news regressions in model generated data. We also estimate versions of network regressions in Acemoglu, Akcigit, and Kerr (2016) with news interactions both in the data and the model. While all of these data moments are untargeted, the model matches the empirical patterns very well.

We use the calibrated model to investigate the properties of the transmission of both TFP and noise shocks across countries. To start with, we compute impulse responses of the world economy to hypothetical shocks in individual countries. As is common in network models, a shock to US TFP increases GDP in all the countries, and by more in those more closely connected to the US, such as Canada. In the baseline imperfect information model, GDP everywhere responds less to the same TFP shock than in a perfect information model. Thus, introducing imperfect information dampens the reactivity of the world economy to fundamental shocks. Cross-sectionally, we show that the reaction of world GDP to a TFP shock in a particular sector depends strongly on the intensity of news coverage about that sector: productivity in country-sectors more covered in the news has a larger impact on world GDP. This is not the case for the perfect information economy.

More novel is the response of GDP to the public signal shocks. Following positive noise about US TFP, for example, GDP in all countries increases, generating an international "business cycle" driven by non-fundamental shocks. We then simulate the model with uncorrelated TFP and noise shocks. We find that relative to the perfect information setting, the volatility of hours is lower in the imperfect information model, and both shocks contribute to fluctuations in hours. While we do not identify TFP or noise shocks to provide a full quantification of international business cycles, we illustrate that very modestly correlated noise shocks can easily replicate average comovement across countries.

Finally, we show that noise shocks manifest themselves as fluctuations driven by the labor wedge in models without information frictions. This finding is relevant because reduced-form international business cycle accounting exercises find that labor wedges are correlated across countries and are quantitatively important in synchronizing GDP internationally (Huo, Levchenko, and Pandalai-Nayar, 2020a). Our theory provides a microfoundation for a shock that looks like a labor wedge in reduced form.

All in all, our findings suggest that noise shocks and imperfect information could be important for understanding international comovement.

Related literature. Our project connects two research programs that so far have had fairly limited contact. The first is the rapidly maturing literature on aggregate fluctuations in production networks (see, among others, Carvalho, 2010; Foerster, Sarte, and Watson, 2011; Acemoglu et al., 2012; Acemoglu, Akcigit, and Kerr, 2016; Barrot and Sauvagnat, 2016; Atalay, 2017; Grassi, 2017; Baqaee, 2018; Baqaee and Farhi, 2019a,b; Boehm, Flaaen, and Pandalai-Nayar, 2019a; Foerster et al., 2019; Bigio and La'O, 2019; Carvalho et al., 2016; vom Lehn and Winberry, 2021), as well as applications of these ideas and techniques to international shock transmission (e.g. Kose and Yi, 2006; Burstein, Kurz, and Tesar, 2008; Johnson, 2014; Eaton et al., 2016; Eaton, Kortum, and Neiman, 2016).[3]

The second is the closed-economy literature on the role of imperfect information and noise shocks in the business cycle (a very partial list includes Beaudry and Portier, 2006; Lorenzoni, 2009; Barsky and Sims, 2011; Blanchard, L'Huillier, and Lorenzoni, 2013; Angeletos and La'O, 2013; Nimark, 2014; Benhabib, Wang, and Wen, 2015; Huo and Takayama, 2015; Angeletos, Collard, and Dellas, 2018; Chahrour and Jurado, 2018; Acharya, Benhabib, and Huo, 2021). Closest to our work is the recent contribution by Chahrour, Nimark, and Pitschner (2021), that develops a framework with informational frictions in a closed-economy production network, and shows that incomplete news coverage can amplify aggregate fluctuations. The paper also collects frequencies of economic news coverage in

[3]Several papers, such as Baqaee and Farhi (2019c), Allen, Arkolakis, and Takahashi (2020), Adao, Arkolakis, and Esposito (2020), and Kleinman, Liu, and Redding (2020, 2021), provide theoretical treatments of the global production network from an international trade perspective. These frameworks cannot be used to study international transmission of business cycle shocks (and related applications) because they feature fixed within-period factor supply. As such, measured real GDP is not responsive to foreign shocks, and thus international transmission (to real GDP) is nonexistent by construction.

the US, by sector. With the partial exception of Levchenko and Pandalai-Nayar (2020), this literature has not made contact with the study of international business cycles.[4]

The rest of the paper is organized as follows. Section 2 sets up and solves a global network model of production and trade with informational frictions. Section 3 describes our data collection effort, and documents a number of basic patterns in international news coverage and business cycle comovement. Section 4 calibrates and quantifies the model. Section 5 concludes. The appendices collect additional details of the estimation and theoretical framework as well as robustness checks and further information on the data.

2. Theoretical Framework

This section develops a model with sufficiently rich production and information structures to quantify the role of informational frictions and non-fundamental shocks in the international business cycle.

2.1 Setup

There are N countries indexed by n and m and J sectors indexed by j and i. Each country n is populated by a representative household. The household consumes the final good available in country n and supplies labor and capital to firms. In each country-sector, there is a continuum of information islands indexed by ι, with a large number of competitive firms on each island.

Unlike the standard production network models, in our framework agents face informational frictions. In particular, each period is split into two stages. In the first stage, local labor markets open at each information island ι and the quantity of labor is determined. At this stage, firms may not have perfect knowledge about the fundamentals in other locations. In the second stage, all information becomes public. Firms choose their intermediate goods inputs and all goods markets clear at the equilibrium prices.

Households. The problem of the household is

$$\max \mathcal{F}_{n,t} - \sum_j \int H_{nj,t}(\iota)^{1+\frac{1}{\psi}} d\iota$$

subject to

$$P_{n,t}\mathcal{F}_{n,t} = \sum_j \int W_{nj,t}(\iota) H_{nj,t}(\iota) d\iota + \sum_j R_{nj,t} K_{nj},$$

where $\mathcal{F}_{n,t}$ is consumption of final goods, and $H_{nj,t}(\iota)$ is the total labor hours supplied to island ι in sector j. Labor collects a sector-island-specific wage $W_{nj,t}(\iota)$, $R_{nj,t}$ is the return to capital in each

[4]A smaller set of contributions introduces non-technology shocks in a reduced form, and shows that doing so improves the performance of international business cycle models (Stockman and Tesar, 1995; Wen, 2007; Bai and Ríos-Rull, 2015).

sector, and $P_{n,t}$ is the price of the final consumption bundle. For simplicity, we assume that final consumption is a Cobb-Douglas aggregate of goods coming from each country-sector:

$$\mathcal{F}_{n,t} = \prod_{m,i} \mathcal{F}_{mi,n,t}^{\pi_{mi,n}}.$$

Our formulation of the disutility of the labor supply extends GHH preferences (Greenwood, Hercowitz, and Huffman, 1988) to allow labor to be supplied separately to each sector and each island. In this formulation, labor is neither fixed to each sector nor fully flexible, and its responsiveness is determined by the Frisch elasticity ψ.

Production technology. Firms within sector j in country n operate the following production function

$$Y_{nj,t} = e^{z_{nj,t}} \left(K_{nj}^{1-\alpha_j} H_{nj,t}^{\alpha_j}\right)^{\eta_j} \left(\prod_{m,i} X_{mi,nj,t}^{\omega_{mi,nj}}\right)^{1-\eta_j} \tag{2.1}$$

where $X_{mi,nj}$ is the usage of inputs from country-sector (m,i) in (n,j). The total factor productivity shock $z_{nj,t}$ is the fundamental shock in the model economy. We interpret K_{nj} as a fixed factor that does not change. For simplicity, in this section, we assume that the TFP shocks are i.i.d across sectors.

We specify Cobb-Douglas functional forms for the preferences and the production technologies. This choice is to make the equilibrium representation more transparent and is not essential for the main insights on the effects of informational frictions. In Section 4, we will relax these assumptions and allow for a more flexible specification.

Second stage. In the second stage, primary inputs have already been fixed and firms only choose the amounts of intermediate goods. The problem of a firm in information island ι that has chosen $H_{nj,t}(\iota)$ is

$$\Omega_{nj,t}(H_{nj,t}(\iota)) = \max_{\{X_{mi,nj,t}(\iota)\}} P_{nj,t} e^{z_{nj,t}} \left(K_{nj}^{1-\alpha_j} H_{nj,t}(\iota)^{\alpha_j}\right)^{\eta_j} \left(\prod_{m,i} X_{mi,nj,t}(\iota)^{\omega_{mi,nj}}\right)^{1-\eta_j} - \sum_{m,i} P_{mi,n,t} X_{mi,nj,t}(\iota), \tag{2.2}$$

where $P_{nj,t}$ is the output price, and $P_{mi,n,t}$ is the price of input (m,i) in country n. This price can differ from the output price of (m,i), $P_{mi,t}$, due to trade costs.[5]

[5] We do not explicitly introduce trade costs in our framework. For our purposes, iceberg trade costs are isomorphic to taste shifters. To economize on notation, we thus conceive of the preference shifters $\pi_{mj,n}$ and $\omega_{mi,nj}$ as reflecting trade costs, an approach common in the IRBC literature (e.g. Backus, Kehoe, and Kydland, 1992).

The goods market clearing condition can be written as

$$\begin{aligned} P_{nj,t}Y_{nj,t} &= \sum_m P_{m,t}\mathcal{F}_{m,t}\pi_{nj,m} + \sum_{m,i}(1-\eta_i)P_{mi,t}Y_{mi,t}\omega_{nj,mi}, \\ &= \sum_{m,i}\eta_i P_{mi,t}Y_{mi,t}\pi_{nj,m} + \sum_{m,i}(1-\eta_i)P_{mi,t}Y_{mi,t}\omega_{nj,mi}, \end{aligned}$$

where the second equality is due to the trade balance condition.

Throughout, we use small letters to denote variables in log deviations from their steady states, and bold letters to denote vectors or matrices that collect the corresponding country-sector elements. The following lemma summarizes how changes in prices are related to changes in hours and fundamentals.

Lemma 1. *Given the predetermined hours, the prices that clear markets in the second stage are*

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

In turn, both output and input prices determine profits (2.2). The lemma highlights that in order to forecast the profits for a given choice of hours, a firm needs to forecast all other locations' fundamentals and hours, due to the linkages through the production network.

First stage. In the first stage, households send workers to each information island. We assume that all workers and firms share the same information within an information island ι. The local wage is determined by the labor market clearing on island ι.

The labor supply is determined by the expected real wage

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

where $\mathcal{I}_{nj,t}(\iota)$ denotes the information set on island ι, specified below. Meanwhile, firms choose their labor demand to maximize their expected profit

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

which leads to the following first-order condition

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

Equating local labor demand and supply leads to the following condition that characterizes the local equilibrium hours:

$$h_{nj,t}(\iota) = \left(1 + \frac{1}{\psi} - \alpha_j\right)^{-1}\mathbb{E}\left[\frac{1}{\eta_j}z_{nj,t} + \frac{1}{\eta_j}\ln p_{nj,t} + \left(1 - \frac{1}{\eta_j}\right)\sum_{m,i}\omega_{mi,nj}p_{mi,t} - \sum_{m,i}\pi_{mi,n}p_{mi,t}\middle|\mathcal{I}_{nj,t}(\iota)\right].$$

This equation shows that local hours are determined by the island's expectations of both exogenous and endogenous variables. Hours increase in both the island's expectation of its country-sector's TFP and output price. Hours decrease in the island's expectation of both the prices of inputs it needs in production (the $\left(1-\frac{1}{\eta_j}\right)\sum_{m,i}\omega_{mi,nj}p_{mi,t}$ term), and the prices of goods that households consume ($\sum_{m,i}\pi_{mi,n}p_{mi,t}$).

Information structure. We make the following assumptions on the information structure in the first stage. Firms receive two types of information: a private signal that is only observed by a subset of information islands and public signal that is shared by all firms. We will interpret the public information as news appearing in newspapers.

First, firms receive private information about other sectors' TFP shocks. In information island ι in sector (n, j), firms observe

$$x_{nj,mi,t}(\iota) = z_{mi,t} + u_{nj,mi,t}(\iota), \quad u_{nj,mi,t}(\iota) \sim \mathcal{N}(0, \tau_{nj,mi}^{-1}\mathbb{V}(z_{mi,t})) \qquad \forall m, i. \tag{2.3}$$

The private signal contains all other sources of information that is not common knowledge. The precision of the private signal is $\tau_{nj,mi}$. Particularly, firms may have very accurate information about their own sector's TFP.

Second, all firms observe public news about TFP in each country-sector (m, i):

$$s_{mi,t} = z_{mi,t} + \varepsilon_{mi,t}, \quad \varepsilon_{mi} \sim \mathcal{N}(0, \kappa_{mi}^{-1}\mathbb{V}(z_{mi,t})) \qquad \forall m, i. \tag{2.4}$$

We allow the precision of this signal to vary across country-sectors (m, i). The variation in the signal precision κ_{mi} will reflect the differences in the intensity of news coverage of the sector, as we will make explicit in the Section 4. To keep the scale of information heterogeneity manageable, we do not differentiate the public signals by country n. Note that the precisions of both public and private signals about TFP in sector (m, i) are scaled by the variance of the actual TFP that sector $\mathbb{V}(z_{mi,t})$, as in the quantification we will use actual sectoral data in which sector volatilities differ.

Taking stock, the information set of island ι is given by $\mathcal{I}_{nj,t}(\iota) = \{\{x_{mi,t}(\iota)\}, \{s_{mi,t}\}\}$. The presence of private signals implies that information is incomplete, and we discuss the implications of this for equilibrium outcomes in the next subsection.

2.2 Equilibrium Characterization

At the sectoral level, the total hours is given by the aggregation across information islands within the same country-sector

$$h_{nj,t} = \int h_{nj,t}(\iota)d\iota = \left(1+\frac{1}{\psi}-\alpha_j\right)^{-1}\overline{\mathbb{E}}_{nj,t}\left[\frac{1}{\eta_j}z_{nj,t} + \frac{1}{\eta_j}\ln p_{nj,t} + \left(1-\frac{1}{\eta_j}\right)\sum_{m,i}\omega_{mi,nj}p_{mi,t} - \sum_{m,i}\pi_{mi,n}p_{mi,t}\right].$$

Under incomplete information, the response of a sector's aggregate hours depends on the *average* expectations $\overline{\mathbb{E}}_{nj,t}[\cdot]$ about the prices that are determined in the second stage. Recall from Lemma 1 that all price changes are functions of the global vectors of changes in hours and fundamentals. It follows that the outcomes hinge on the expectations of other sectors' responses to shocks, and the fixed point problem can be represented as a beauty contest game.

Lemma 2. *The vector of country-sector changes in hours solves the following beauty contest game:*

$$\boldsymbol{h}_t = \boldsymbol{\varphi}\, \overline{\mathbb{E}}_t[\boldsymbol{z}_t] + \boldsymbol{\gamma}\, \overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right], \tag{2.5}$$

where $\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$ capture the effects of global value chains

$$\boldsymbol{\varphi} = \left(\frac{1+\psi}{\psi}\mathbf{I} - \boldsymbol{\alpha}\right)^{-1}(\boldsymbol{\eta}^{-1} + \mathbf{M}), \qquad \boldsymbol{\gamma} = \left(\frac{1+\psi}{\psi}\mathbf{I} - \boldsymbol{\alpha}\right)^{-1}\boldsymbol{\alpha}\boldsymbol{\eta}\,\mathbf{M},$$

and

$$\mathbf{M} = \left(\boldsymbol{\eta}^{-1} + (\mathbf{I} - \boldsymbol{\eta}^{-1})\boldsymbol{\omega} - \boldsymbol{\pi}\right)(\mathbf{I} - (\mathbf{I} - \boldsymbol{\eta})\boldsymbol{\omega})^{-1}.$$

The Lemma characterizes the solution to this global general equilibrium model conditional on a vector of fundamental and signal shocks. Knowing the change in hours implicitly given by (2.5) and the vector of TFP changes pins down GDP in every country (see Huo, Levchenko, and Pandalai-Nayar, 2020a, for the detailed derivations). The result highlights the respective roles of GVCs and imperfect information. The cross-country linkages through trade are encapsulated by the matrices $\boldsymbol{\varphi}$ and $\boldsymbol{\gamma}$. These matrices are functions of only various observable shares, such as labor and intermediate input intensities in production, and final and intermediate expenditure shares. These matrices can be computed using widely available world input-output datasets. The role of information frictions is encapsulated by the fact that agents set hours based on *expectations* of the log changes in productivity and hours in all countries and sectors worldwide, as highlighted in the discussion of the frictionless benchmark that follows next.

Frictionless benchmark. Consider momentarily the frictionless benchmark ($\boldsymbol{\tau} = \infty$), in which case the outcomes are uniquely pinned down by the fundamentals alone. Particularly, we can take off the expectation operator from (2.5) and simplify to obtain:

$$\boldsymbol{h}_t = (\mathbf{I} - \boldsymbol{\gamma})^{-1}\boldsymbol{\varphi}\, \boldsymbol{z}_t.$$

This is a special case of the analytical solution to the global network model in Huo, Levchenko, and Pandalai-Nayar (2020a), under Cobb-Douglas preferences. It resembles the Leontief inverse, and the change in hours can be decomposed into direct and indirect effects

$$\boldsymbol{h}_t = \underbrace{\boldsymbol{\varphi} \boldsymbol{z}_t}_{\text{direct effect}} + \underbrace{\boldsymbol{\gamma}\boldsymbol{\varphi}\boldsymbol{z}_t + \boldsymbol{\gamma}^2\boldsymbol{\varphi}\boldsymbol{z}_t + \dots}_{\text{indirect effect}} \tag{2.6}$$

As in conventional production network models, the fundamental shocks $\boldsymbol{z}_t$ uniquely determine the outcomes. A strong implication of perfect information and rationality is that agents have no difficulty in inferring the beliefs, and therefore the decisions, of other firms. As a result, news coverage plays no role in shaping international fluctuations. However, the feature that agents can perfectly infer others' beliefs is at odds with abundant empirical evidence that beliefs are heterogeneous (e.g. Coibion and Gorodnichenko, 2015; Bordalo et al., 2020), and it will be modified once we allow for incomplete information.

Incomplete information. With incomplete information, an important deviation from the frictionless benchmark above is that the equilibrium outcomes now depend on both first-order and higher-order expectations. To see this, consider the response of hours in sector (n, j) to a TFP shock that takes place in sector (m, i). Repeatedly iterating condition (2.5) leads to

$$\begin{aligned} h_{nj,t} = {} & \varphi_{nj,mi}\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] + \sum_{k,\ell} \gamma_{nj,k\ell}\ \varphi_{k\ell,mi}\ \overline{\mathbb{E}}_{nj,t}\left[\overline{\mathbb{E}}_{k\ell,t}[z_{mi,t}]\right] + \\ & + \sum_{k,\ell}\sum_{o,q} \gamma_{nj,k\ell}\gamma_{k\ell,oq}\ \varphi_{oq,mi}\ \overline{\mathbb{E}}_{nj,t}\left[\overline{\mathbb{E}}_{k\ell,t}\left[\overline{\mathbb{E}}_{oq,t}\left[z_{mi,t}\right]\right]\right] + \cdots \end{aligned}$$

When the shock is not common knowledge, the law of iterated expectations does not apply and higher-order expectations start to differ from first-order expectations. Firms need to forecast the forecasts of their suppliers and customers, and the forecasts of their suppliers' suppliers, and so on. In fact, in equilibrium firms' decisions will depend on an infinite number of different higher-order expectations. The following proposition summarizes this discussion.

Proposition 2.1. *If the norm of the leading eigenvalue of $\boldsymbol{\gamma}$ is less than one, the optimal responses of sectoral hours satisfy*

$$\boldsymbol{h}_t = \boldsymbol{\varphi}\overline{\mathbb{E}}_t[\boldsymbol{z}_t] + \boldsymbol{\gamma}\boldsymbol{\varphi}\overline{\mathbb{E}}_t^2[\boldsymbol{z}_t] + \boldsymbol{\gamma}^2\boldsymbol{\varphi}\overline{\mathbb{E}}_t^3[\boldsymbol{z}_t] + \dots \tag{2.7}$$

where $\overline{\mathbb{E}}_t^k[\cdot]$ are higher-order expectations in order k.

Compared with the frictionless benchmark (2.6), Proposition 2.1 shows that the direct effect is arrested by the first-order uncertainty about the underlying fundamental, since the expectation of the shock is less volatile than the shock itself. Further, the indirect effect is arrested by the higher-order uncertainty. Proposition 2.1 also reveals that the relative importance of higher-order expectations depends on the position of a sector in the production network, a point we will illustrate via examples below.

Given the assumption on the information structure, it is straightforward to specify sector (n,j)'s first-order expectations about sector (m,i)'s shocks

$$\overline{\mathbb{E}}_{nj,t}\begin{bmatrix} z_{mi,t} \\ \varepsilon_{mi,t} \end{bmatrix} = \begin{bmatrix} \frac{\tau_{nj,mi}+\kappa_{mi}}{1+\tau_{nj,mi}+\kappa_{mi}} & \frac{\kappa_{mi}}{1+\tau_{nj,mi}+\kappa_{mi}} \\ \frac{1}{1+\tau_{nj,mi}+\kappa_{mi}} & \frac{1+\tau_{nj,mi}}{1+\tau_{nj,mi}+\kappa_{mi}} \end{bmatrix}\begin{bmatrix} z_{mi,t} \\ \varepsilon_{mi,t} \end{bmatrix} \equiv \mathbf{\Lambda}_{nj,mi}\begin{bmatrix} z_{mi,t} \\ \varepsilon_{mi,t} \end{bmatrix}.$$

The equilibrium outcomes, however, depend on the shocks in a more involved way because of all the higher-order expectations. The following proposition provides the closed-form solution.

Proposition 2.2. *In response to shocks about sector (m,i), the equilibrium outcomes respond to both the fundamental shock and the noise in the news*

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

The 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

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

Different from the frictionless solution in equation (2.6), the responses of hours are determined by a modified version of the Leontief inverse. In the case with information frictions, it is the interaction between the uncertainty about the underlying shocks and the production network that shapes aggregate fluctuations.

Proposition 2.2 makes it explicit that the aggregate fluctuations are no longer a result of only fundamental shocks; rather they are influenced by the noise in the signal as well. The presence of the imperfect signal not only provides information about the fundamentals, but also opens door to fluctuations that are orthogonal to the fundamentals. The basic logic is similar to the closed-economy models without production networks such as Lorenzoni (2009) or Angeletos and La'O (2013).

Example: Homogenous Signal Precision. To see the underlying forces in a more transparent way, we explore a special case in which the signal precision is homogeneous across locations: $\tau_{nj,mi} = \tau$ and $\kappa_{mi} = \kappa$. In this case, the equilibrium outcomes can be expressed as

$$\boldsymbol{h}_t = (\mathbf{I} - \lambda_z\gamma)^{-1}\left\{\varphi\lambda_z\boldsymbol{z}_t + (\mathbf{I}-\gamma)^{-1}\varphi\lambda_\varepsilon(\boldsymbol{z}_t + \boldsymbol{\varepsilon}_t)\right\} \tag{2.8}$$

where

$$\lambda_z = \frac{\tau}{1+\tau+\kappa} \in (0,1), \qquad \lambda_\varepsilon = \frac{\kappa}{1+\tau+\kappa} \in (0,1).$$

Condition (2.8) makes it clear that the information friction dampens the response to the fundamental shock. The first-order uncertainty results in a weaker response to the fundamental itself, since

$\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] = (\lambda_z + \lambda_\varepsilon)z_{mi,t} + \lambda_\varepsilon \varepsilon_{mi,t}$, and so a true innovation in $z_{mi,t}$ is not reflected in the agents' expectations. Higher-order uncertainty further dampens the propagation mechanism through trade linkages. Here, it is as if the network dependence becomes $\lambda_z \gamma$ in the "Leontief inverse" pre-multiplying the curly brackets in equation (2.8), instead of γ in the "Leontief inverse" in the perfect information setting. This expression also underlines that the noise in news contributes to international fluctuations, as actual hours depend not only on the fundamentals z_t, but also on the noise in the public signal about those fundamentals ε_t. The effects of ε_t on aggregate hours are decreasing in the precision of the private signals τ.

Example: Vertical Network. To highlight the interaction between the production network and the role of noise, we consider a stylized vertical network. We begin by arbitrarily ordering all country-sectors by their upstreamness, where the most upstream sector is $(n, j) = (1, 1)$ and the most downstream sector is (N, J). We assume that each sector only purchases inputs from the sector directly before it in the production chain (a "snake" network). Therefore, for country-sector $(1, 1)$, its input shares from any country-sector $(n, j) \neq (1, 1)$ are zero. Each country-sector $(n, j) > (1, 1)$ has a unitary input share from the country-sector $(n-1)J + j - 1$, and zero from all other country-sectors. This implies that

$$\gamma = \begin{bmatrix} 0 & 0 & \dots & 0 & 0 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}.$$

We assume that only the most upstream sector is subject to the fundamental shock $z_{11,t}$, and all other sectors' TFP shocks are muted. We normalize $\varphi_{11,11} = 1$ and all other country-sector pairs (mi, nj), $\varphi_{nj,mi} = 0$

Figure 1 displays the responses of hours to TFP shocks and to noise shocks. With perfect information, the equilibrium outcome in this economy is simple: all country-sectors (n, j) respond one-for-one to the fundamental shock:

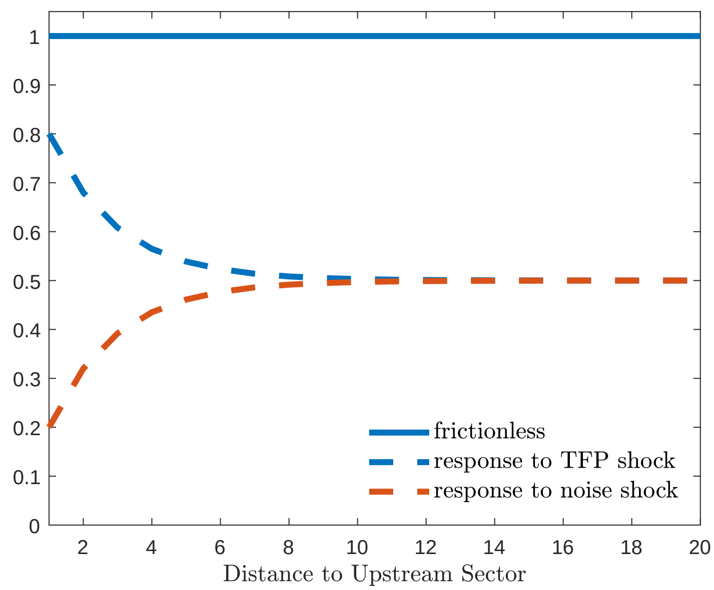
$$h_{nj,t} = z_{11,t}.$$

That is, the shock transmits to other country-sectors perfectly.

In contrast, with information frictions, the transmission is imperfect, a result best understood via the reliance on higher-order expectations

$$\begin{aligned} h_{nj,t} =& \overline{\mathbb{E}}_{nj,t}^{(n-1)J+j}[z_{11,t}] \\ =& \left\{ \lambda_z^{(n-1)J+j} + \lambda_\varepsilon \left(1 + \lambda_z + \ldots + \lambda_z^{(n-1)J+j-1}\right) \right\} z_{11,t} + \lambda_\varepsilon \left(1 + \lambda_z + \ldots + \lambda_z^{(n-1)J+j-1}\right) \varepsilon_{11,t}. \end{aligned}$$

Figure 1: Hours Response in a Vertical Network



Notes: This figure displays the response of hours in a vertical network to a TFP shock in the most upstream sector and to a pure noise shock in a frictionless environment (solid line) and with information frictions (dashed lines).

Note that the more downstream is a sector, the smaller is the response to the fundamental shock $z_{11,t}$. The transmission is dampened via the production chain, as the term in curly brackets multiplying the fundamental shock is decreasing in downstreamness.

Meanwhile, the more downstream is a sector, the higher is its dependence on the public news $s_{mi,t}$ relative to the private signal. The downstream firms need to think about higher-order expectations, and public news is more informative about those than private signals. As a byproduct, since the coefficient on the public signal is the coefficient on the noise shock, this shock plays a bigger role in the fluctuations of hours in more downstream sectors.

Our next goal is to quantify this model and explore the importance of imperfect information and noise shocks for fluctuations and international comovement. To do this requires data that can be used to discipline not only the global production structure, but also the informational frictions.

3. Data and Basic Patterns

3.1 Data

Global sectoral news data. We construct a novel database of international economic news coverage. The information is sourced from Dow Jones Factiva, a news aggregator. Our data collection spans the main national newspapers in the G7 countries plus Spain. The newspapers are: the Wall Street Journal (US), the New York Times (US), USA Today (US), Financial Times (UK), the Globe and Mail (Canada), Süddeutsche Zeitung (Germany), Corriere della Sera (Italy), El País (Spain), Le Figaro

(France), Mainichi Shimbun (Japan), and Sankei Shimbun (Japan). For each of these newspapers, we tabulate the frequency with which each sector from each country in the sample is mentioned in a particular time window. That is, one observation in our data would be how many articles about the German automotive sector appear in the New York Times. All in all, there are 131 country-sectors, and we compile the frequency of their coverage in each of the major newspapers in the G7 in our sample. In principle data are available daily, but to merge with the other economic time series we aggregate to quarters. Our sample period spans 1995-2020. Factiva does not employ commonly used sectoral classifications, so we concord Factiva sectors to ISIC-Rev 4 to merge these data with other sources. Appendix Table A1 displays the concordance between Factiva sectors and ISIC Rev-4.

Similar to Chahrour, Nimark, and Pitschner (2021), our approach relies on a set of "tags," which are standardized content identifiers applied to each news article in Factiva. The tags can range from sector or country names to the names of celebrities. We restrict attention to articles tagged as "economic," and within them, search manually for sector×country tags in each newspaper in a particular time window.[6] While we do not collect information on what is reported in the news – such information would be challenging to gather systematically manually – we provide suggestive evidence on types of news content in Appendix B.1 below.

There are a number of nuances in this process, discussed in detail in Appendix A.1. One worth mentioning is that revisions to Factiva's tagging algorithm around the year 2000 resulted in an increase in the number of tags applied to each article. This creates a level shift in the number of tags, as the algorithm does not appear to have been applied to articles prior to 2000 retroactively. For the purposes of our analysis, we will either use frequency shares (share of tags about a country-sector in total tags) or time fixed effects, and so this aspect of the data will not drive our results.

Sectoral macro 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. Our data cover 23 sectors in each country, spanning the entire economy. Appendix A.2 describes the the national data sources and their coverage for the underlying series used to construct our panel, as well as the data cleaning steps. As the national sources vary in sectoral classification and in level of disaggregation, we concord each individual data source to our 23 ISIC-Revision 4 sectors for each country. The panel is unbalanced, and covers years 1972-2020.

For the global trade and input-output linkages, we use the World Input Output Database (WIOD). Basic sectoral output data for calibrating our model come from KLEMS 2019. We use the year 2006 to compute production and input shares.

[6] As we search for the interaction of a sector and country, the dimensionality of our manual search is orders of magnitude higher than in Chahrour, Nimark, and Pitschner (2021). That is, we cannot simply download all tags in all newspapers in, say, 2020:Q2 and then sort by sector to count "automobile" tags. We must search for automobiles×Germany, automobiles×France, etc in 2020:Q2, and also account for overlaps where multiple countries or countries outside our sample are mentioned.

Forecast data. Monthly data on GDP forecasts come from Consensus Forecasts. This database provides current- and next-year real GDP growth forecasts for our sample of countries. The data are at the forecaster level, and includes professional forecasters from business, academia, and industry groups. To compute forecast errors, we combine these data with the actual GDP growth from the IMF World Economic Outlook database. Appendix A.3 describes these data in detail.

3.2 Basic Patterns

This section documents three basic patterns in the economic news data. The first highlights the heterogeneity in the news coverage across countries and sectors. The second relates news coverage explicitly to the precision of information available to agents, by combining it with forecast error data. The third connects news coverage to comovement in real activity.

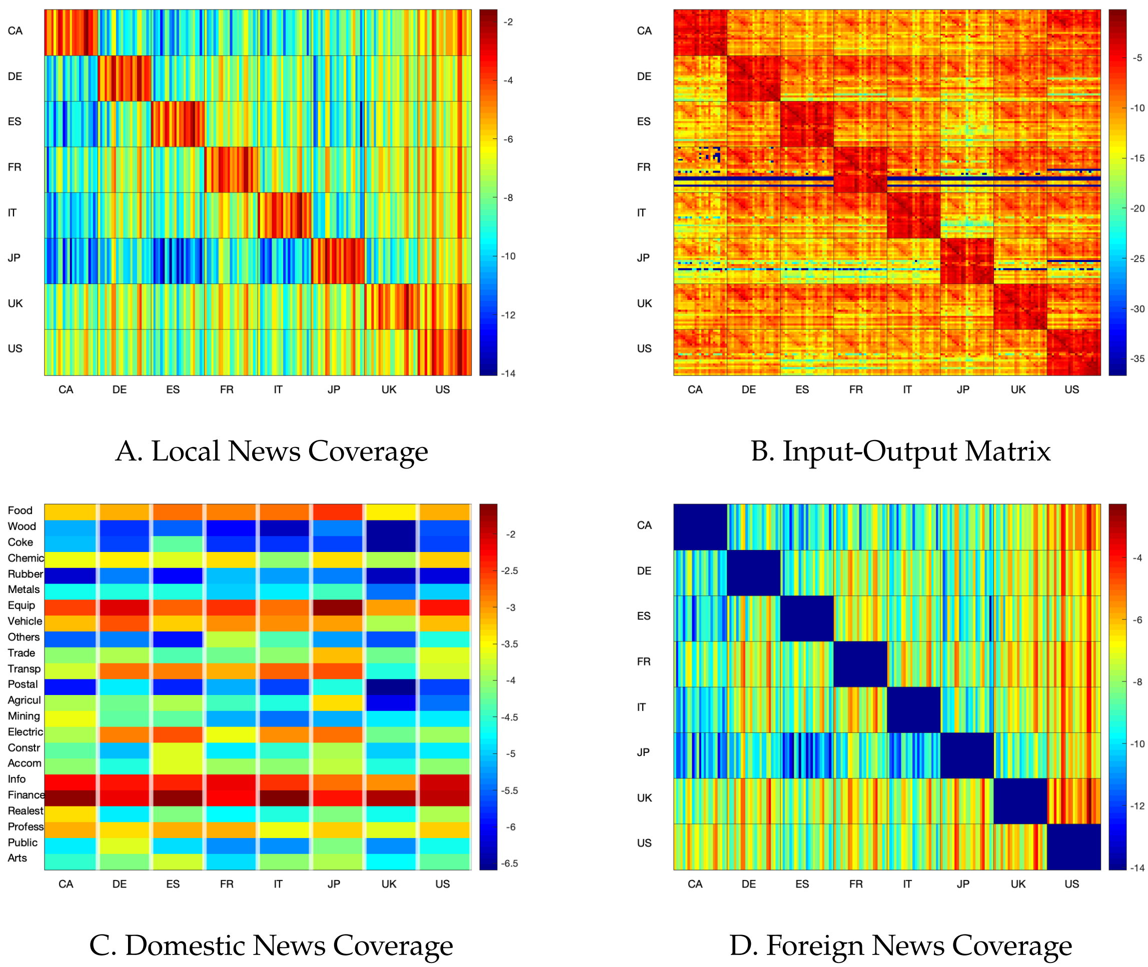
Fact 1: news coverage is heterogeneous, and positively but weakly correlated to sector size or GVC participation. As a visual illustration of the cross-sectional heterogeneity, Panel A of Figure 2 depicts a heatmap of local news coverage shares (averaged over time), and contrasts it to a standard input-output heatmap in Panel B (e.g. Huo, Levchenko, and Pandalai-Nayar, 2020a). While both news coverage shares and input shares are higher for domestic sectors, as is evident from the more saturated block diagonals in Panels A and B, there is significant variation off-diagonal. For instance, some US sectors receive a relatively large share of news coverage in all countries in our sample. Newspapers in Japan and Canada do not tend to cover European countries. It is immediately evident when comparing Panels A and B that the patterns of news coverage are not highly correlated with input usage.

The large difference in domestic news coverage shares and foreign news coverage shares makes it challenging to pick up the heterogeneity in domestic coverage from Panel A. Panel C therefore plots only domestic sector shares in local news coverage. It illustrates that while some domestic sectors (e.g. financial services) always receive a large share of news coverage, coverage of other sectors varies by country. For instance, German news outlets report on equipment and automobile sectors more frequently than many other countries. Finally Panel D "blacks out" the diagonal of the news coverage shares heat map to better illustrate the off-diagonal variation. It highlights both the predominance of US sectoral coverage in foreign news in most countries, but also other patterns (such as high coverage of other EU country-sectors in EU countries).

Panel A of Figure 3 illustrates that the average frequency share of a sector in global news is positively correlated with the sector's size (measured by sector sales share in global sales). While there is an association, it is far from perfect, with an R^2 of only 32%. The panels B and C of Figure 3 highlight that coverage is also positively correlated with a sector's importance as an input for downstream sectors, and as a sales destination for upstream sectors.[7] Finally, Panel D considers the Bonacich network centrality as a single summary measure of how important the sector is in the global

[7] Upstreamness and downstreamness are defined in Appendix B.1.

Figure 2: Sectoral GVC Position and News Coverage



A. Local News Coverage

B. Input-Output Matrix

C. Domestic News Coverage

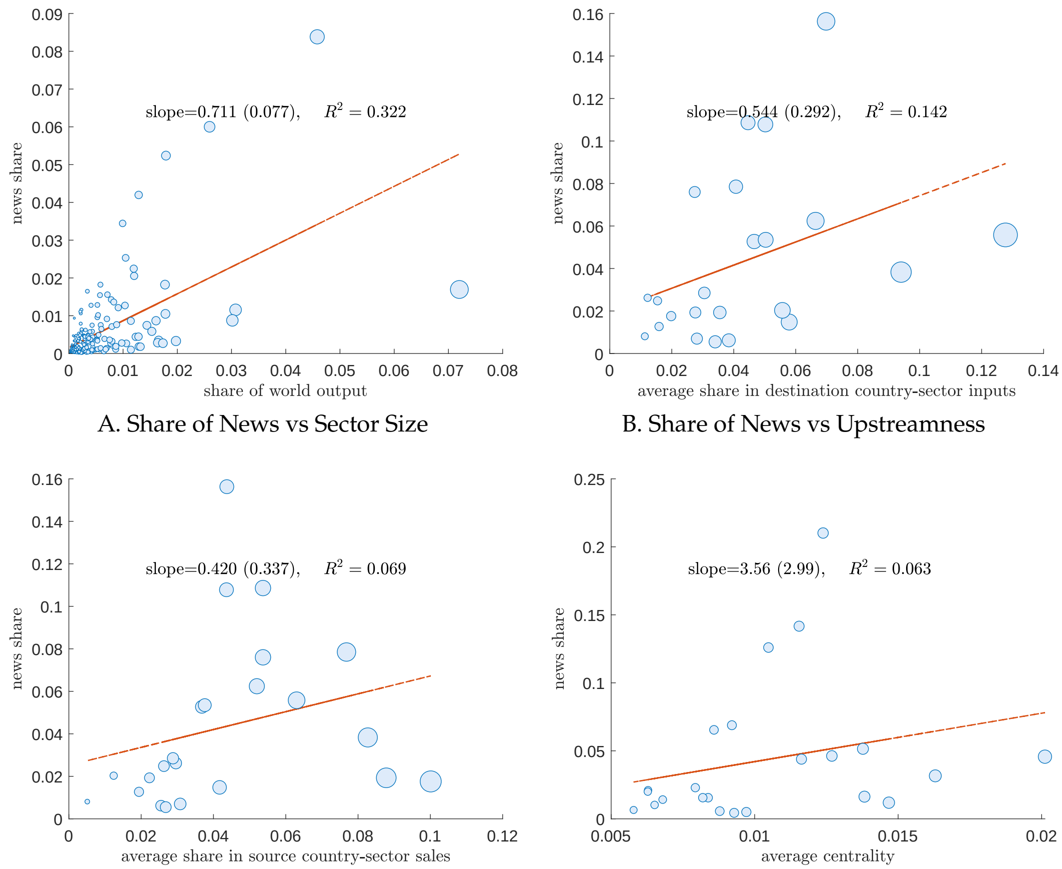
D. Foreign News Coverage

Notes: This figure displays heatmaps of local news coverage shares (Panel A) and the input-output matrix (Panel B). Panel C highlights the diagonal of the news coverage matrix, presenting local news coverage about the source country. Panel D eliminates the diagonal to better highlight heterogeneity in foreign news shares in local news. The local coverage share is the share of source country's (y-axis) news coverage about destination country-sector (x-axis) in source country's total news. The input-output share is the share of source country-sector's (y-axis) sales to destination country-sector (x-axis) in source country-sector's total sales. In Panel D, we set domestic news shares to 0. All non-zero shares are logged to improve legibility.

production network. As with the overall size, this measure of GVC position has the expected positive correlation with the share of a sector in global news coverage, but the relationship is far from close.

Appendix B.1 explores these correlations between sector size, GVC position, and news coverage intensity more systematically by projecting news coverage on multiple indicators jointly, as well as exploiting the bilateral country patterns in news coverage.

Figure 3: News Coverage, Size, and Sectoral GVC Position



A. Share of News vs Sector Size

B. Share of News vs Upstreamness

C. Share of News vs Downstreamness

D. Share of News vs Bonacich Centrality

Notes: This figure displays the scatterplots of the share of global news coverage on the y-axis (all 4 panels) against the share of the sector in world output (panel A), upstream intensity (panel B), downstream intensity (panel C), and Bonacich centrality, which here is equivalent to the Leontief inverse (panel D). All plots report the bivariate regression slope coefficient, robust standard error, and the R^2.

Fact 2: greater news coverage is associated with smaller forecast errors. The first empirical regularity we establish is between absolute forecast errors and news intensity coverage:

$$\left|\text{forecast error}\right|_{f,n,t} = \beta_0 + \beta_1 \log F_{n,t} + \delta_{f,n} + \delta_t + \varepsilon_{f,n,t}, \tag{3.1}$$

where f indexes forecasters, n countries, and t quarters. The dependent variable is the absolute error in either the prediction of current (nowcast) or the next year's country n GDP, by forecaster f in quarter t. The news coverage variable $F_{n,t}$ is the share of global news coverage of country n in period t, that is, the total news coverage in all newspapers from all source countries of country n in period t divided by total news coverage in all newspapers in period t. We control for forecaster×country and time effects. The inclusion of time effects absorbs the level of economic news coverage in a period.[8]

[8]Note that as more information comes to light, forecasts later in the calendar year should be more precise than forecasts at the beginning of the year. Time effects take care of this regularity.

All standard errors are clustered at the forecaster×country level to account for autocorrelation in the residuals.

Table 1 reports the results for nowcasts in Panel A, and one-year ahead forecasts in Panel B. Estimates of equation (3.1) are in columns 1 and 3. The news coverage intensity has a strong negative and statistically significant relationship with forecast errors. The magnitude of the coefficient is economically significant. A one-standard deviation change in the news intensity is associated with absolute nowcast errors that are 0.16 standard deviations lower, and 1-year forecast errors that are 0.22 standard deviations lower.

News coverage is also associated with less disagreement among forecasters. We relate the cross-sectional standard deviation of the forecasts for each country and date to news coverage as follows:

$$SD\left(\left|\text{forecast error}\right|_{f,n,t}\right)_{n,t} = \beta_0 + \beta_1 \log F_{n,t} + \delta_n + \delta_t + \varepsilon_{n,t}, \tag{3.2}$$

where the dependent variable is the standard deviation across forecasters regarding the GDP of country n at time t. Since the forecaster dimension is collapsed in this regression, we can only include country and time fixed effects. Because the cross-sectional dimension is small (only 8 countries), we use Driscoll-Kraay standard errors instead of clustering by country. Columns 2 and 4 of Table 1 report the results. There is indeed significantly less disagreement among forecasters when news coverage increases. The slope is high in magnitude. A one-standard deviation change in news coverage intensity is associated with forecast dispersion that is 0.24 standard deviations lower for nowcasts, and 0.36 standard deviations lower one year ahead.

Our baseline estimates of equations (3.1) and (3.2) use 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 A4 displays the results. They are quite similar to Table 1. 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 (3.1)-(3.2) for the forecast errors in the unemployment rate. The results are reported in Appendix Table A5. 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.

Fact 3: greater news coverage is associated with higher business cycle comovement. To establish this stylized fact, we use one of the best-known reduced-form relationships linking international trade and comovement – the "trade-comovement" regression. We extend the standard regression to include bilateral news coverage and its interaction with bilateral trade intensity. In particular, we fit

Table 1: Global News Coverage and Consensus Forecast Errors

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	$\lvert$forecast error$\rvert$	SD ($\lvert$forecast error$\rvert$)	$\lvert$forecast error$\rvert$	SD ($\lvert$forecast error$\rvert$)
$\log F_{n,t}$	-0.0817***	-0.0295***	-0.290***	-0.0609***
	(0.0099)	(0.0107)	(0.0272)	(0.0157)
Observations	18,582	800	17,338	768
R^2	0.379	0.706	0.668	0.543
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 (3.1). Columns 2 and 4 report the results of estimating equation (3.2). Variable definitions and sources are described in detail in the text.

the following relationship in the cross-section of country-sector pairs:

$$\rho_{nj,mi} = \beta_1 \ln \text{Trade}_{nj,mi} + \beta_2 \ln \text{Trade}_{nj,mi} \times F_{nj,mi} + \beta_3 F_{nj,mi} + \boldsymbol{\delta} + \varepsilon_{nj,mi}, \tag{3.3}$$

where $\rho_{nj,mi}$ is the correlation of hours worked (or industrial production) growth rates between country-sector (n, j) and country-sector (m, i). Our hours and industrial production data are quarterly, and we use 4-quarter growth rates as the baseline. The traditional regressor is trade intensity $\text{Trade}_{nj,mi}$, defined in Appendix B.3.

The new regressor is the news intensity, computed as the average of the frequencies with which countries are covered in each other's news:

$$F_{nj,mi} = \frac{1}{2}\left(F_{nj} + F_{mi}\right), \tag{3.4}$$

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 input relationships.

Table 2 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 both sets of country-sector effects and country pair effects, sectors pairs that are more covered in the

Table 2: International Comovement, Trade, and News Coverage

Dep. Var.: $\rho_{nj,mi}$(hours)	(1)	(2)	(3)	(4)
$F_{nj,mi}$	4.528***	29.85***	6.881***	27.07***
	(1.088)	(7.290)	(1.142)	(7.510)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.688***	0.0715	0.989***	0.271**
	(0.134)	(0.112)	(0.136)	(0.114)
$\ln \text{Trade}_{nj,mi}$	0.0217***	0.0140***	0.0250***	0.0105***
	(0.00126)	(0.00106)	(0.00175)	(0.00149)
Observations	10,235	10,235	10,235	10,235
R^2	0.067	0.622	0.182	0.638
Country-sector FE	no	yes	no	yes
Country pair FE	no	no	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). 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 (B.7) and news coverage intensity as in (3.4).

news comove more, and this higher comovement is even more pronounced when sectors also trade with each other. This is *prima facie* evidence that news coverage intensity plays an important role in conditioning the extent of cross-border comovement. Appendix B.3 provides further details and presents a number of robustness checks.

4. Quantication

4.1 Calibration

On the real side the model is quite parsimonious. It requires only the Frisch elasticity and the various production function parameters. 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. This more general specification of preferences and technology leads to a different expression for how prices respond to shocks and hours (Lemma 1),[9] but the main theoretical results (Propositions 2.1 and 2.2) continue to hold.

We calibrate the Frisch elasticity to 2, a common value in the business cycle literature. We choose $\rho = 1.5$ and $\mu = 0.7$, both of which are standard values used in the literature (see for instance the estimates of the input elasticity in Boehm, Flaaen, and Pandalai-Nayar (2019b), or the timepath of

[9]The Appendix contains the detailed derivations under the CES specification.

trade elasticity estimates in Boehm, Levchenko, and Pandalai-Nayar (2020)). The labor and value added intensities α_j and η_j come from KLEMS, and are average shares of labor in value added and shares of value added in gross output across countries and years. The final consumption shares and input expenditure shares $\pi_{mi,n}$ and $\omega_{mi,nj}$ are taken from WIOD. The top panel of Table 3 summarizes these calibration choices.

Table 3: Parameterization

Param.	Value	Source	Related to
Fundamental Economy Parameters			
ψ	2		Frisch elasticity
α_j	[.38, .69]	KLEMS 2019	labor and capital shares
η_j	[.33, .65]	KLEMS 2019	intermediate input shares
$\pi_{mi,n}$		WIOD 2016	final use trade shares
$\omega_{mi,nj}$		WIOD 2016	intermediate use trade shares
Information Friction Parameters			
τ	0.11	dispersion of forecasts errors	private signal precision
χ_0	0.22	indirect inference	public signal precision, intercept
χ_1	1.45	indirect inference	private signal precision, elasticity to news coverage

Notes: This table summarizes the model calibration. We describe the indirect inference procedure for calibrating χ_0 and χ_1 in the text.

The more novel aspect of our quantitative framework is the information frictions. Recall from (2.3) and (2.4) that these frictions are pinned down by two sets of parameters, the private signal precision $\tau_{nj,mi}$ and the public signal precision κ_{mi}. We would like to use the news coverage intensity data described above to discipline the variation in the precision of the public signal about different country-sectors. The challenge is that we observe frequency shares of news coverage, but do not directly observe agents' public signals obtained from news coverage. Therefore, we posit the following affine functional form that connects the public signal precision in the theory to the news coverage intensity:

$$\kappa_{nj} = \chi_0 + \chi_1 F_{nj}, \tag{4.1}$$

where F_{nj} is the average frequency share of sector (n, j) in the global news coverage as in Section 3.2. Here, χ_0 captures the minimum amount of information in the public domain, while χ_1 captures the sensitivity of the precision to news coverage intensity. For the private signals, we assume that firms perfectly observe their own sector's TFP, i.e., $\tau_{nj,nj} = \infty$, and set a common precision for the private

Table 4: Internal Calibration: Model vs. Data

Indirect inference				
	Data		Model	
	(1)	(2)	(1)	(2)
Dep. Var	$\lvert\text{FE}\rvert$	SD ($\lvert\text{FE}\rvert$)	$\lvert\text{FE}\rvert$	SD ($\lvert\text{FE}\rvert$)
$\log F_{n,t}$	-0.0817***	-0.0295***	-0.0820***	-0.0336***
	(0.0099)	(0.0107)	(0.0044)	(0.0019)
Observations	18,582	800	816	816
R-squared	0.379	0.706	0.668	0.543
Time FE	yes	yes		
Country-forecaster FE	yes			
Country FE		yes	yes	yes
Unconditional moment				
SD ($\lvert$forecast error$\rvert$)	0.077		0.0690	

Notes: The unconditional moment is the cross-country average of the standard deviation of the nowcast error of GDP growth rate.

signals about other sectors' TFP, $\tau_{nj,mi} = \tau$. Under these assumptions on the public and private signals, the calibration requires finding three values: τ, χ_0, and χ_1.

We calibrate $\{\tau, \chi_0, \chi_1\}$ via indirect inference, by fitting three data moments. The first two are the slope coefficients of the reduced-form relationships (3.1) and (3.2) that capture how the forecast errors and the cross-sectional belief dispersion vary with the news intensity. The third targeted data moment is the unconditional cross-sectional dispersion of the absolute forecast error in the Consensus Forecast data.

In mapping the model to the heuristic regressions (3.1) and (3.2) we face three challenges. First, we only have data on professional forecasters, not firms or workers. Second, the forecasts are of GDP, and not of individual country-sectors (m, i). And third, while the theoretical model is static, the empirical regressions rely on within-forecaster variation in forecast quality and news coverage over time. There is no viable alternative to this, as forecaster fixed effects are essential in the empirics in order to absorb confounding factors. To map the model environment more tightly to the data and the empirical variation we use, we make the following auxiliary assumptions.

Let there be forecasters, who have no role in any real outcomes in the economy, but who also extract signals about the economy. Similar to firms in the model, the forecasters receive a private signal and a public signal about each country-sector (n, j). To better connect with the empirical regressions, we assume the forecasters differ from firms in the model in two ways. First, the forecasters do not observe any sector's fundamental perfectly. And second, instead of fixing the precision of public signals based on the average news share, we allow the precision to change with the news share over time as in the data, i.e, for the forecasters, $\kappa_{nj,t} = \chi_0 + \chi_1 F_{nj,t}$. While our model is static, this approach allows us to exploit the longitudinal variation in the data for the purposes of calibrating these critical parameters.[10] The forecasters assume that the firms and workers' signal precision for all country-sectors is given by (4.1) in which F_{nj} is *average* news share of sector (n, j) over time. Thus, we obtain the influence matrix that describes how country n's GDP growth, v_{nt}, depends on the underlying TFP and noise shocks under the average F_{nj} rather than the news coverage in each quarter.

We then implement the following regressions using model-generated observations

$$\mathbb{E}\left[\left|v_{nt} - \mathbb{E}_{f,t}[v_{nt}]\right|\right] = \beta_{01}^{M} + \beta_{1}^{M} \log F_{n,t} + \delta_n + \varepsilon_{nt} \tag{4.2}$$

$$\mathrm{SD}\left(\left|v_{nt} - \mathbb{E}_{f,t}[v_{nt}]\right|\right) = \beta_{02}^{M} + \beta_{2}^{M} \log F_{n,t} + \delta_n + \varepsilon_{nt}, \tag{4.3}$$

which are the model counterparts to the empirical specifications (3.1) and (3.2). In equation (4.2), the dependent variable is the theoretical mean of the individual absolute nowcast error of GDP. Since this is a theoretical moment, there is no need to include the time fixed effect (since confounding time-varying factors are not present in this repeated static model) or the individual forecaster fixed effect. Similarly, in equation (4.3), the dependent variable is the theoretical standard deviation of the cross-sectional forecast error in every period.

Appendix XX shows that the coefficient in equation (4.2) is proportional to the slope χ_1 and the coefficient in equation (4.3) is related to the product of χ_1 and the precision of private signal τ:

$$\beta_1^M \propto -\chi_1, \qquad \beta_2^M \propto -\chi_1 \tau.$$

The intuition for this procedure is as follows. The slope of the relationship between the news coverage intensity and the quality of the forecasts (3.1)-(4.2) contains information on how much the public signal precision improves with more news coverage. Because the forecasters rely on both private vs. public signals, the relative strength of the public and private signals manifests itself in the dispersion across forecasts. Thus, the slope of the news coverage-dispersion relationship (3.2)-(4.3) is informative about both the private signal precision and the slope of the news-public signal precision relationship. Finally, the unconditional cross-sectional belief dispersion together with the slope of (3.2)-(4.3) helps pin down the level parameter χ_0.

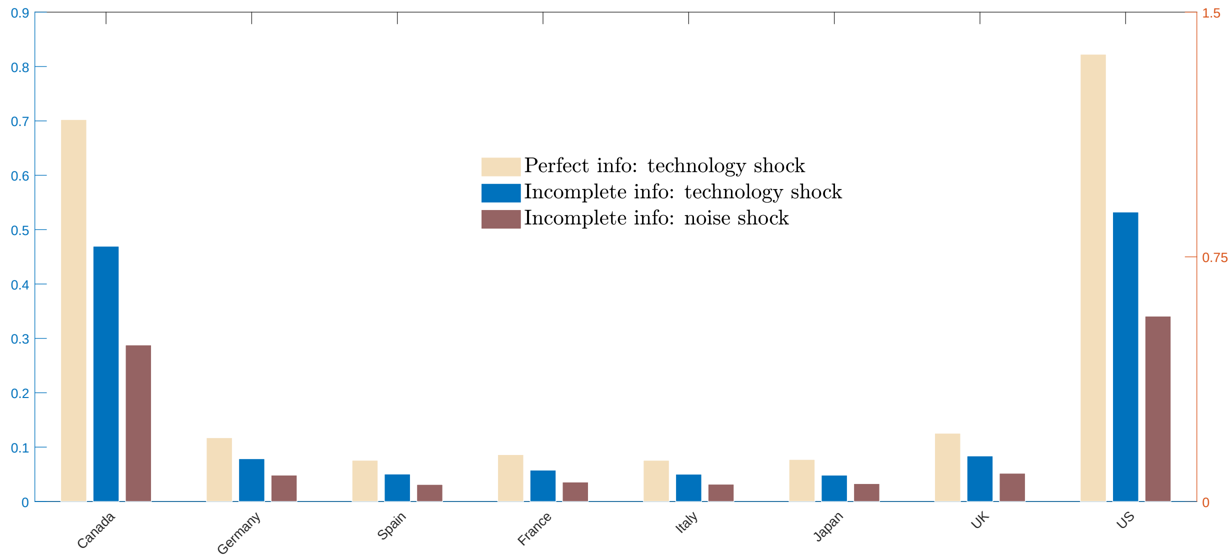
Table 4 displays the moments generated by the model and compares them to the data counterparts. The calibrated model matches the empirical relationships between the forecast levels and dispersion and news coverage, as well as the unconditional dispersion well.

4.2 Aggregate Implications

Section 2 derives two basic properties of the economy with incomplete information: the effects of fundamental shocks are dampened and the international fluctuations are driven by both fundamental

[10]The alternative would be to use the average news shares $\kappa_{nj} = \chi_0 + \chi_1 \bar{F}_{nj}$, but we would lose statistical power for estimating these parameters.

Figure 4: Response to US TFP and Noise Shocks



Notes: This figure displays the change in hours worked of each country following a TFP shock in the US. The beige bars show the hours change without informational frictions. The blue bars show the hours change in the baseline model with imperfect information. The brown bars show the hours change in response to a noise shock in the US. The magnitude of the shocks are adjusted to equal their standard deviations. The scale of the response in US is on the right y-axis, and the scale of all other countries is listed on the left y-axis.

and non-fundamental shocks. In this subsection, we explore these effects quantitatively.

We start with some impulse response exercises. Figure 4 shows the changes in hours in response to a 1 unit TFP shock in all sectors in the US. The beige bars display the real GDP changes in the perfect information model. As is common in network propagation models, the impact is uneven, with by far the largest GDP change in the US itself, and the second-largest change in the economy most closely connected to it, Canada. The blue bars depict the GDP changes following the same TFP shock, but in our baseline imperfect information model. The world economy is uniformly less reactive to TFP shocks when there are informational frictions. In our calibration, the informational frictions are sufficiently severe that the response of the US GDP is 34% smaller than in the frictionless benchmark. Other countries also react less to the US TFP shock under imperfect information. This is intuitive: when agents do not perfectly know the extent of the TFP shock, they will not react fully to it.

The brown bars in Figure 4 show the changes in hours in response to a 1 unit noise shock in all sectors in the US. World output goes up following positive noise shock about US TFP. The impact is once again strongest in the US itself (right axis), and second-strongest in Canada. The response to noise shocks is smaller than to fundamental shocks, as noise shocks do not affect private signals. We return to this point in Section 4.4.

Table 5 displays the business cycle statistics of hours aggregated at the country level. Column 1 presents the log standard deviation of hours under the perfect information and only TFP shocks. As a shorthand for TFP shocks, we feed in the log difference between industrial production and total

Table 5: Business Cycle Statistics

Hours volatility	(1) Perfect Information TFP	(2) Incomplete Information TFP	(3) Noise	(4) Total	(5) Data
Canada	1.42	0.78	0.49	0.92	1.15
Germany	2.90	1.57	0.35	1.61	0.91
Spain	3.39	1.46	0.61	1.58	2.98
France	2.64	1.27	0.41	1.33	1.43
Italy	2.75	1.28	0.42	1.34	1.52
Japan	2.73	1.60	0.64	1.72	1.26
UK	2.87	1.45	0.51	1.54	1.09
US	1.29	0.80	0.36	0.88	2.06
Bilateral hours correlation					
Uncorrelated noise	0.085	0.104	0.098	0.104	0.187
Correlated noise ($\rho = 0.025$)	0.085	0.102	0.344	0.207	
Bilateral labor wedge correlation					
Uncorrelated noise	—	0.046	0.034	0.040	
Correlated noise	—	0.057	0.287	0.125	

Notes: For volatility, this table reports the standard deviation of aggregate hours in each country. For bilateral correlation, this table reports the mean of bilateral correlation of aggregate hours between possible 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.

hours in each sector.[11] Column 2 instead feeds in the same TFP shocks, but under informational frictions. In this case, the total volatility of hours coming from TFP shocks is lower that under perfect information. This confirms the intuition developed in Section 2 that incomplete information dampens the responses to fundamental shocks.

At the same time, since firms rely on news when making their production decisions, now the noise shocks in news contribute to international fluctuations. In the end, noise shocks generate about the same amount aggregate fluctuations as fundamental shocks. Also note that the noise-driven fluctuations are more important in UK and US, as the sectors in these two countries are heavily covered in the news, and it induces firms in these two countries to pay additional attention to news as all other countries are responding the news as well.

The noise in news also induces international comovement. So far, we have maintained the assumption that noise shocks are independent across countries and across sectors. The average bilateral correlations between different country pairs are reported in Table 5 under "Uncorrelated noise." We

[11] We are not aware of any estimates of quarterly sectoral TFP for multiple countries.

next check how much correlation in the noise shocks is required to match the observed correlation in hours, which is about 0.21 in our data. Thus, we induce a correlation across countries and sectors in the noise shocks ε_{mi}. The results are reported in the row labeled "Correlated noise." We match the observed correlation in aggregate hours across countries with the correlation in the noise shocks of only 0.025. Thus, even a modest correlation in the noise shocks translates into a significant level of observed hours correlation.

With incomplete information, the marginal rate of substitution (MRS) and the marginal product of labor (MPL) are equalized only under their expected values in the first-stage of a period. As a result, any unexpected changes of the fundamental in all other country sectors will result in a wedge between MRS and MPL, which can be driven by both the TFP shock and the common noise shock. This type of wedge can interpreted as the labor wedge, as discussed in Angeletos and La'o (2010). What is unique in our setting is that the fluctuations in the labor wedges help understand international comovement. Huo, Levchenko, and Pandalai-Nayar (2020a) show that in a perfect-information economy, the efficiency (TFP) wedge and the labor wedge are the two most important wedges that account for observed international comovement and that these two wedges are correlated with each other. Through the lens of our incomplete-information model, the implied labor wedges are correlated across countries, as reported in the bottom panel of Table 5. Even the modest correlation in the noise shocks we induce leads to a much larger correlation in the labor wedge, 0.155. The labor wedge is also positively correlated with the TFP wedge, with a mean correlation of 0.04 across different country pairs.

4.3 Micro Implications and External Validation

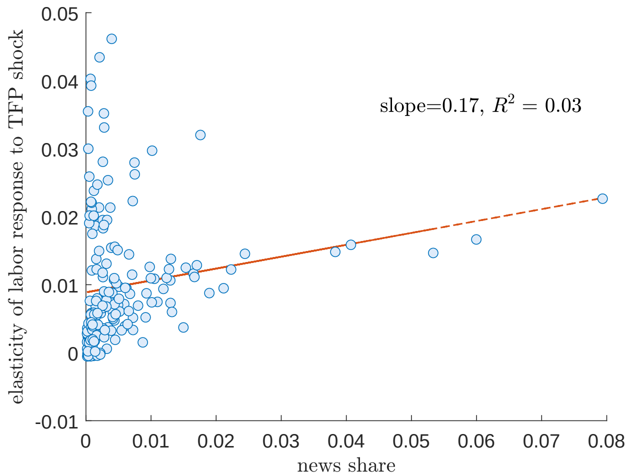
Intuitively, if a sector (n, j) is covered in the news more intensively, other sectors are more likely to respond to a shock originating from sector (n, j), since firms have more information and they also understand that other firms are more aware of the shock. To highlight the role of news coverage in the shock transmission, we define the average elasticity of hours response to a TFP or a noise shock in sector (n, j) as follows:

$$\varrho_{nj}^{s} = \frac{1}{NJ-1} \sum_{mi \neq nj} G_{mi,nj}^{s} \qquad s = z, \varepsilon. \tag{4.4}$$

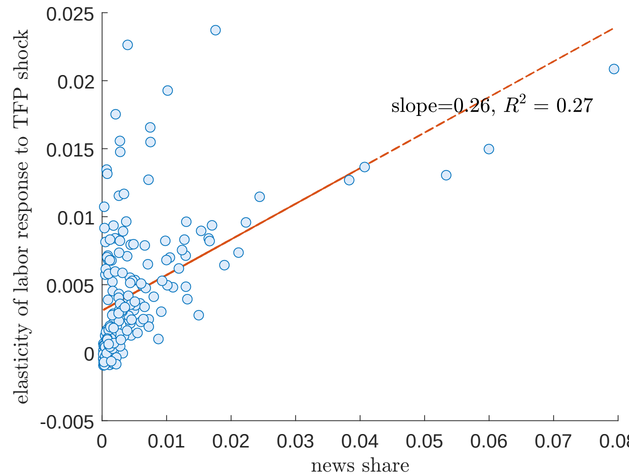
That is, ϱ_{nj}^{z} is the average log change in hours across all countries and sectors following a 1-unit log change in TFP in sector (n, j), and similarly for the noise shock ε.

Figure 5 displays the relationship between ϱ_{nj}^{z} and the news frequency share of sector (n, j). The left panel presents this relationship under perfect information. In this case, the average elasticity is only weakly correlated with the news share, which is expected as firms do not rely on news. Any positive correlation between the news share and ϱ_{nj}^{z} is simply due to the fact that in the news data, larger and more connected sectors tend to be covered more. The right panel presents this relationship under incomplete information. Here, the average elasticity is strongly correlated with the news share.

Figure 5: News Share and TFP Shock Transmission



A. Perfect Information Model



B. Incomplete Information Model

Notes: The figure displays scatterplots of the average elasticity of total hours change in other sectors following a TFP shock in a particular sector, (4.4), against the sector's share of the global news coverage. The left panel depicts the perfect information model, while the right panel the baseline model with informational frictions.

Greater news coverage increases the shock propagation from sector (n, j) to the rest of the world economy.

Appendix Figure A6 displays the elasticity $\varrho^{\varepsilon}_{nj}$ of hours with respect to the noise shock in sector (n, j) 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.

External Validation. As external validation, we examine two sets of non-targeted moments that are informative about the role of news coverage in shock transmission. The first is the trade-comovement regression (3.3) run in Section 3.2. We implement the same regression with the model implied bilateral correlation between different country-sector pairs. Table 6 compares the model generated results with their data counterparts. With incomplete information, our baseline model with incomplete information reproduces the basic pattern, and the correlation of hours is significantly increasing in the news coverage. In contrast, with perfect information, the correlation is not significantly related in news, and if anything, the slope coefficient is negative.

In the second exercise, we explore how the observed hours worked at the country-sector level is conditioned by the intensity of news coverage of upstream and downstream sectors. We run the

Table 6: International Comovement: Model vs. Data

Dep. Var.: $\rho_{nj,mi}$(hours)	Data (1)	Data (2)	Model: Incomplete Info (3)	Model: Incomplete Info (4)	Model: Perfect Info (5)	Model: Perfect Info (6)
$F_{nj,mi}$	4.528***	29.85***	3.454**	2.814*	-0.124	-0.264
	(1.088)	(7.290)	(1.582)	(1.638)	(1.750)	(1.847)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.688***	0.0715	0.634***	0.696***	0.299	0.346*
	(0.134)	(0.112)	(0.174)	(0.164)	(0.193)	(0.185)
$\ln \text{Trade}_{nj,mi}$	0.0217***	0.0140***	0.0477***	0.0661***	0.0541***	0.0740***
	(0.00126)	(0.00106)	(0.00119)	(0.00119)	(0.00129)	(0.00128)
Observations	10,235	10,235	16,836	16,836	16,836	16,836
Country-sector FE	no	yes	no	yes	no	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3) in the data (columns 1-2), and in the model (columns 3-6). 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 (B.7) and news coverage intensity as in (3.4). Note the number of observations in the model regressions differ from the empirical counterpart as hours growth correlation for some country-pairs are missing in the data.

following heuristic regression in the model and in the data:

$$\Delta \ln H_{nj,t} = \beta^{up} \underbrace{\left(\sum_{m,i;mi \neq nj} \omega_{mi,nj} \Delta \ln H_{mi,t} \right)}_{\texttt{true upstream hours}} + \beta^{up}_{news} \underbrace{\left(\sum_{m,i;mi \neq nj} F_{mi,t} \omega_{mi,nj} \Delta \ln H_{mi,t} \right)}_{\texttt{news of upstream hours}} \tag{4.5}$$

$$+ \beta^{dn} \underbrace{\left(\sum_{m,i;mi \neq nj} \theta_{nj,mi} \Delta \ln H_{mi,t} \right)}_{\texttt{true downstream hours}} + \beta^{dn}_{news} \underbrace{\left(\sum_{m,i;mi \neq nj} F_{mi,t} \theta_{nj,mi} \Delta \ln H_{mi,t} \right)}_{\texttt{news of downstream hours}} + \boldsymbol{X}_{nj,t} + \boldsymbol{\delta} + u_{nj,t}.$$

This type of regression is closely related to to the network shock propagation specifications in Acemoglu, Akcigit, and Kerr (2016). We extend it to allow for news-adjusted network effects. The left-hand side variable, $\Delta \ln H_{nj,t}$ is the log change in hours worked in sector j, country n, in quarter t. As above, $F_{mi,t}$ is the share of sector (n, j) in the global news coverage in quarter t. The matrix of fixed effects $\boldsymbol{\delta}$ includes time and country-sector effects, and the country-sector controls $\boldsymbol{X}$ include own news shares and own input and sales shares and the interactions with news coverage. These controls soak up time-varying aggregate shocks, as well as country-sector specific time-invariant productivity growth. Further, the own-news and own-input and sales controls help mitigate any effects of current period deviations in sectoral productivity from its average growth rate.

The input expenditure shares $\omega_{mi,nj} = \frac{x_{mi,nj}}{\sum_{l,k} x_{lk,nj}}$ are defined as the share of input mi in the total input spending of nj. Thus, they capture the importance of mi as a supplier of inputs to sector nj. The downstream sales shares $\theta_{nj,mi} = \frac{x_{mi,nj}}{\sum_{l,k} x_{mi,lk}}$ are the sales shares of nj in mi's total sales. Thus, they

Table 7: Hours Responses to Upstream and Downstream: Model v.s. Data

	Data		Model: Incomplete Info		Model: Perfect Info	
Dep. Var.: $\ln H_{nj,t}$	(1)	(2)	(3)	(4)	(5)	(6)
β_{up}	0.39***	0.44***	0.358***	0.278***	0.511***	0.542***
	(0.08)	(0.10)	(0.0394)	(0.0560)	(0.0339)	(0.0468)
β_{dn}	0.52***	0.33***	0.682***	0.451***	0.563***	0.596***
	(0.07)	(0.09)	(0.0382)	(0.0916)	(0.0316)	(0.0650)
$\boldsymbol{\beta}_{up,news}$		-0.09		0.0667		-0.0285
		(0.09)		(0.0439)		(0.0290)
$\boldsymbol{\beta}_{dn,news}$		0.30***		0.262***		-0.0424
		(0.11)		(0.0897)		(0.0612)
Observations	10,947	10,947	18,400	18,400	18,400	18,400
R-squared	0.43	0.43	0.638	0.640	0.798	0.798
Country-sector FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes				

Notes: This table reports the results of estimating versions of equation 4.5 in the data (columns 1 and 2), in the model with information frictions (columns 3 and 4) and with perfect information (columns 5 and 6). Columns (1), (3) and (5) do not include interactions with news shares, while columns (2),(4) and (6) include such interactions. The variation in observation count across columns reflects missing hours growth series at the country-sector level in the data.

captures the importance of mi as a destination of nj's sales.

The regressor labeled `true upstream hours` thus reflects the usual upstream propagation: it is a input-share weighted change in hours of sectors supplying inputs to (n, j). The regressor labeled `news of upstream hours` instead reweights upstream hours by the news coverage intensity. The regressors labeled `true downstream hours` and `news of downstream hours` do the same for downstream transmission. In an environment where news coverage is orthogonal to comovement in hours, any transmission through real input linkages would be picked up by the non-news weighted regressors. The "news" regressors will be significant if sectors more covered in the news are characterized by more comovement that would be expected simply based on a sector's up- and down-stream linkages.

Table 7 reports the results. In the data, in turns out that the news adjusted downstream hours is positive and significant. Even though we do not directly target this moment, our model matches the data closely (column 4). When information is perfect, it is not surprising that the coefficient involving the news is insignificant and the sign is opposite to that in the data.

4.4 Private vs. Public 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 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 $\tilde{x}_{nj,mi,t}(\iota)$

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

where

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

That is, we fix the the total precision to be 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 A11 in Appendix C.2 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 their 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 is high. In this case, higher news coverage still implies greater transmission, but now it is through the private information channel. In Figure A7, we compare the role of news share in the shock transmission, and the two economies are similar to each other. The particular information structure discussed in this subsection could be viewed as an extreme case in which we maximize the information in the private domain.

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

5. Conclusion

Most shocks driving the business cycle are not TFP, and TFP shocks are not correlated across countries. This limits the usefulness of TFP as a driver of international comovement. In this paper, we develop a quantitative framework in which non-technology shocks transmit internationally through the production network. Our theory features both a flexible international input-output structure, and a rich informational structure, while at the same time admitting an analytical solution. We calibrate this framework using novel data on international economic news coverage disaggregated by country and sector. Both in reduced-form heuristic regressions, and in our quantitative model, sectors more covered in the news (i) exhibit more precise and less dispersed forecasts; and (ii) generate more international comovement. Our paper thus provides empirical evidence and quantitative support for a microfoundation for international comovement driven by non-technology shocks.

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Appendix

A. Data Appendix

A.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 result, so we can avoid duplicate articles across different editions of the same newspapers.

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 very granular 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 granular categories such as citrus groves and non-citrus fruit/tree nut farming. We use the second granularity level 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 develops into Dow Jones Intelligent Identifiers Codes. Therefore, we observe an increase in frequency of sectors across newspapers and countries after 2000.

A.2 Macroeconomic Data: Sectoral Hours Worked and Industrial Production

We collect quarterly information on total hours worked by sector, and on industrial production by sector or the best available substitute from national sources. Table A1 summarizes the sources briefly. The rest of the section describes the data in detail.

Table A1: Quarterly Sectoral Data Sources

Country	Sources
US	Federal Reserve Board; US Census Bureau; US Bureau of Labor Statistics
Canada	Statistics Canada
Japan	Japanese Ministry of Economy, Trade and Industry; Statistics Japan
Germany, France, Italy, Spain, UK	Eurostat

A.2.1 United States

US Industrial Production. The US industrial production data are from the Federal Reserve Board.[12] The IP data are index numbers, and reflect the amount of gross output produced by an industry. The IP database covers industrial sectors going back to 1972. We seasonally adjusted the time series for the construction industry (ISIC4 industry F) which exhibited a clear seasonal pattern. There is no directly comparable real output series for services. The US Census Bureau has conducted a Quarterly Services Survey since 2003, though many service categories were not added until later years. The database collects data on total revenues.[13]

US hours. The US working hour data are from the US Bureau of Labor Statistics [14]. There are two series of the US working hours: all employees' working hours (AE) and production and non-supervisory employees' working hours (PNE). The AE hours worked are not available before February 2006. Our final hours series uses the AE working hours while it is available, and PNE hours prior to February 2006. We splice the two series based on the ratios between AE and PNE hours in March, April and May, 2006.

A.2.2 Canada

Canadian sectoral GDP. There is no industrial production data for Canada. Instead, it has been supplanted by monthly sectoral GDP series in 1997 compiled by Statistics Canada.[15] We aggregate the months into quarters.

Canadian hours. There is no readily available series for total hours worked by sector for Canada. We can construct it by combining information on average weekly hours and total employment. measurement of Canadian working hours is based on SEPH (Survey of Employment Payroll and Hours) data. There is not a total number of hours directly provided in this data, but we construct one with the data provided by StatCan by means of the following steps:[16]

1. Extract the average weekly hours of hourly-paid employees [17], and the standard work week hours for salaried employees [18].
2. Download the employment of salaried and hourly-paid employees [19].
3. Combine them into a monthly time series of the average total hours worked:

$$Hours_{mt} = HrHrly_{mt} * 4 * EmpHrly_{mt} + HrSalary_{mt} * 4 * EmpSalary_{mt}, \tag{A.1}$$

   where $Hours_{mt}$ is the aggregate working hours of sub-industry m in month t; $HrHrly_{mt}$ is the "average weekly hours for employees paid by the hour, by sub-industry, monthly, unadjusted for seasonality" (hour/week); $HrSalary_{mt}$ is the "standard work week for salaried employees, by sub-industry, monthly, unadjusted for seasonality" (hour/week); $EmpHrly_{mt}$ and $EmpSalary_{mt}$ are "employment by industry, monthly, unadjusted for seasonality" for "Employees paid by the hour" and "Salaried employees paid a fixed salary". These data are monthly and starts from 2001. We aggregate up to quarterly frequency to match the rest of our data. We aggregate the sub-industry-level working hours into industry-level working hours and seasonally adjust the resulting working hours series using X-13ARIMA-SEATS.

A.2.3 Japan

The Japanese industrial production data are from the Ministry of Economy, Trade and Industry.[20] The Japanese working hours data are from Statistics of Japan.[21] We seasonally adjust the series using X-13ARIMA-SEATS.

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[12] https://www.federalreserve.gov/datadownload/Choose.aspx?rel=G17

[13] https://www.census.gov/services/qss/historic_data.html

[14] https://www.bls.gov/ces/data/

[15] https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=3610043401

[16] We are grateful to Xing Guo for giving us this procedure.

[17] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410025501

[18] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410021101

[19] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410020101

[20] Manufacturing: https://www.meti.go.jp/english/statistics/tyo/iip/b2015_result-2.html; other industries: https://www.meti.go.jp/english/statistics/tyo/sanzi/result-2.html#past.

[21] https://www.e-stat.go.jp/en/dbview?sid=0003031520

We linearly interpolate the missing values.

A.2.4 European Countries

We have five European countries in the data: Germany, Spain, France, Italy, and the UK. The five countries' industrial production data and total hours worked data are from Eurostat. [22]

A.3 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.

[22] IP: https://ec.europa.eu/eurostat/web/main/data/database?p_p_id=NavTreeportletprod_WAR_NavTreeportletprod_INSTANCE_nPqeVbPXRmWQ&p_p_lifecycle=0&p_p_state=normal&p_p_mode=view; hours: https://ec.europa.eu/eurostat/web/main/data/database?p_p_id=NavTreeportletprod_WAR_NavTreeportletprod_INSTANCE_nPqeVbPXRmWQ&p_p_lifecycle=0&p_p_state=normal&p_p_mode=view.

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

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
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

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**
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

B. Empirical Appendix

B.1 Further Stylized Facts on News Coverage, Size, and GVC Participation

Section 3.2 presented some broad stylized facts on 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 A1 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 above and discussed in Appendix A, 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 A1: Economic News Frequency, 1995-2020

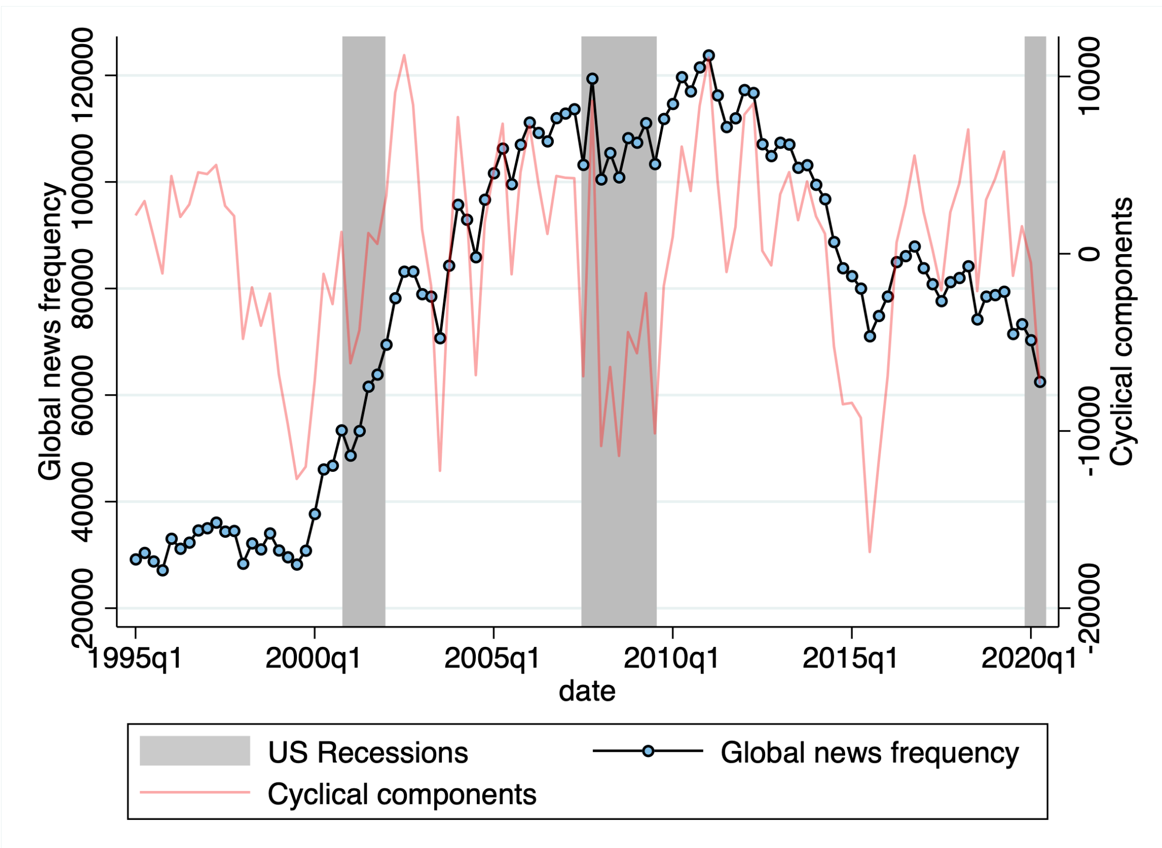
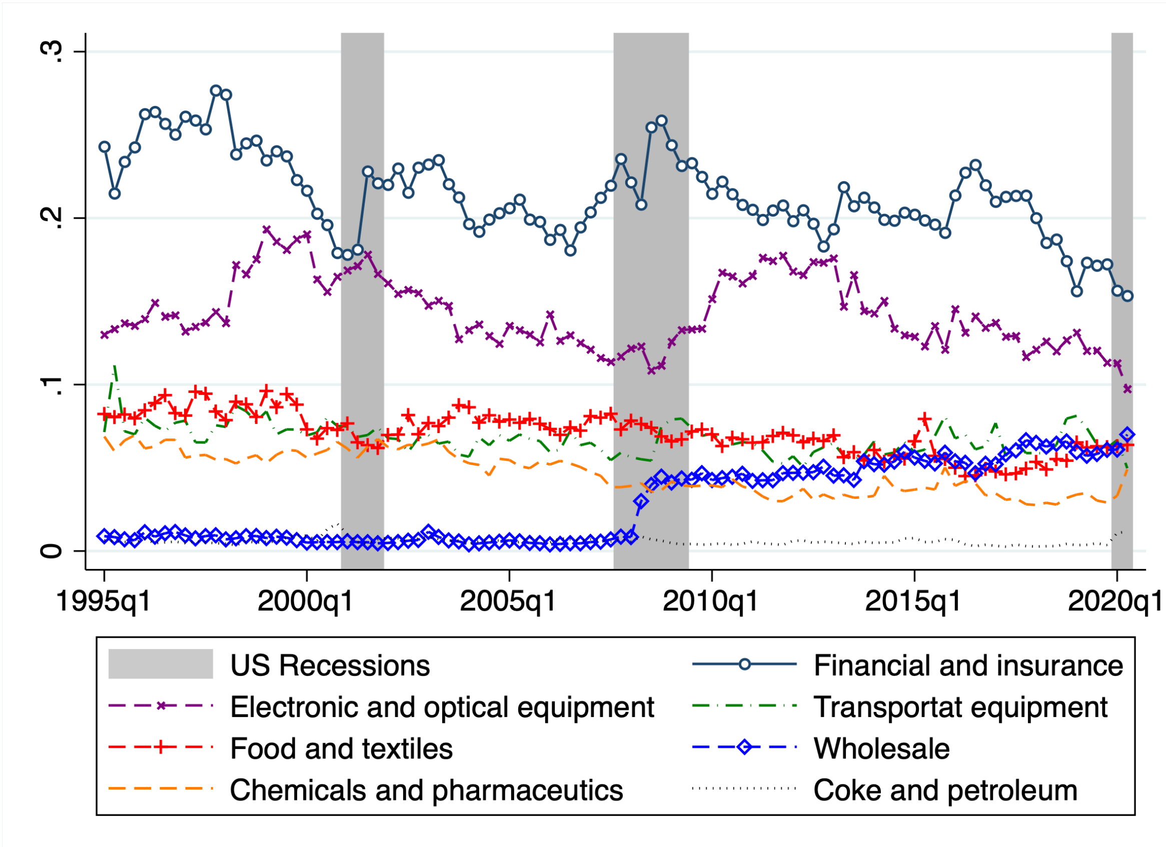


Figure A2 plots the frequency of news reports in global news coverage for several large sectors. It is immediately clear that, while there are some changes over time, the ordering of sectors in terms of news coverage in the cross-section remains quite consistent. This suggests that within-sector variation over time is less important than cross-sectional variation. To make this more precise, we estimate a simple within-across decomposition to illustrate that average cross-sectional variation is much more important than time-series variation within a sector over time:

$$F_{nj,t} = \delta_{nj} + u_{nj,t}, \tag{B.1}$$

where F_{njt} is either the total frequency (number of mentions), or the frequency share of sector j in country n

Figure A2: 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.

reported in total economic news coverage in quarter t, and δ_{nj} 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_{nj} 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 3, we define sector i's importance as an input as the average expenditure share on sector i's inputs in other sectors:

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

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 of upstream sectors to i:

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

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

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

share of global coverage on these characteristics simultaneously:

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

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:

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

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:

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

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 downstream indicators, that reflect how important is sector (m, i) for producers in country s. These are defined analogously, but at the country level.[23] 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.

[23] These indicators are:

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

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

Dep. Var.: $F_{s,mi}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S_{mi}	0.226**	0.226**	0.111	0.273***	0.111	0.116	0.139	0.142
	(0.0983)	(0.0985)	(0.0903)	(0.0998)	(0.0905)	(0.0909)	(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)
$DN_{s,mi}$	0.0661	0.0664	0.0741	0.0855	0.0744	0.0647	0.0877	0.0773
	(0.115)	(0.115)	(0.114)	(0.106)	(0.115)	(0.115)	(0.106)	(0.105)
$1\{s = m\}$	0.0152***	0.0152***	0.0150***	0.0154***	0.0150***		0.0154***	
	(0.00338)	(0.00339)	(0.00337)	(0.00293)	(0.00338)		(0.00294)	
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: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This Table reports the results of estimating equation (B.6). Variable definitions and sources are described in detail in the text.

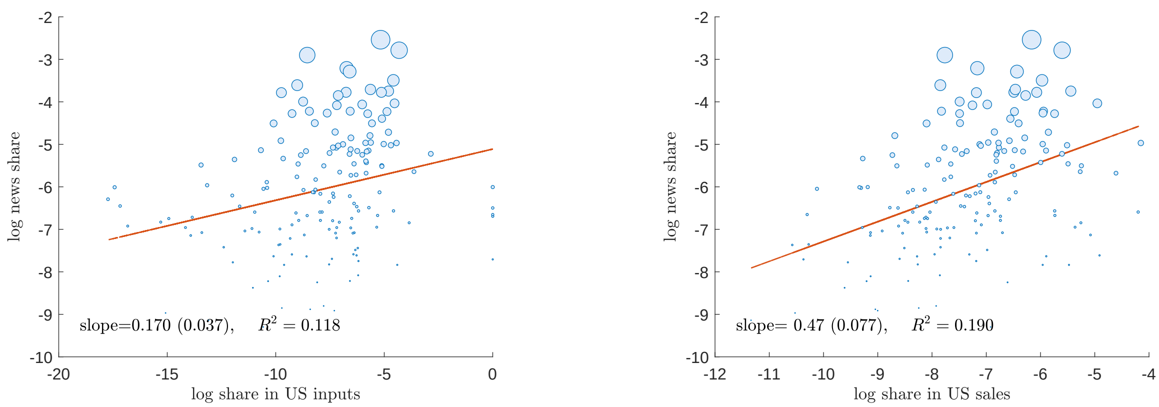
Table A3 reports the results. Overall, the coefficients have the expected sign, and the explanatory power of these regressors at the bilateral level is higher than at the global level, explaining 40% of the variation (column 1). There is clear home bias in news coverage, with shares on average 1.5% higher 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.

To further illustrate these patterns, Figure A3 plots the log share of US coverage of country-sector (m, i) against the the upstream importance $UP_{US,mi}$ (panel A) and downstream importance $DN_{US,mi}$ (panel B) in the US economy. The positive correlations are evident, but so is the large amount of variation of actual around the predicted values.

What is in the news?. Appendix Figures A4-A5 plot the time series of US news coverage for several prominent global companies, labeling large events. At the company level, there is a great deal of time variation in the intensity of news coverage, both at short and long frequencies. Spikes in news coverage can be identified with important events for these companies, but cannot always be mapped to company innovations. For instance, the introduction of the original iPhone received very little news coverage, but the launch of the iPhone 5 resulted in a spike in the coverage about Apple Inc.[24] The bottom panel of Figure A5 plots the news coverage of key Japanese industries in global news around the time of the 2011 Tohoku earthquake, together with some control industries for comparison. There is a spike in coverage of the industries that were most severely affected by the natural disaster.

[24] The news coverage of Apple varies in levels across the three US newspapers plotted, but is positively correlated across the newspapers, suggesting the news media focuses on similar events in reporting. The levels variation reflects the number of articles in the typical newspaper. For instance the Wall Street Journal published around 64000 articles in 2012:Q3, while the New York Times published around 15000 articles a month in this period.

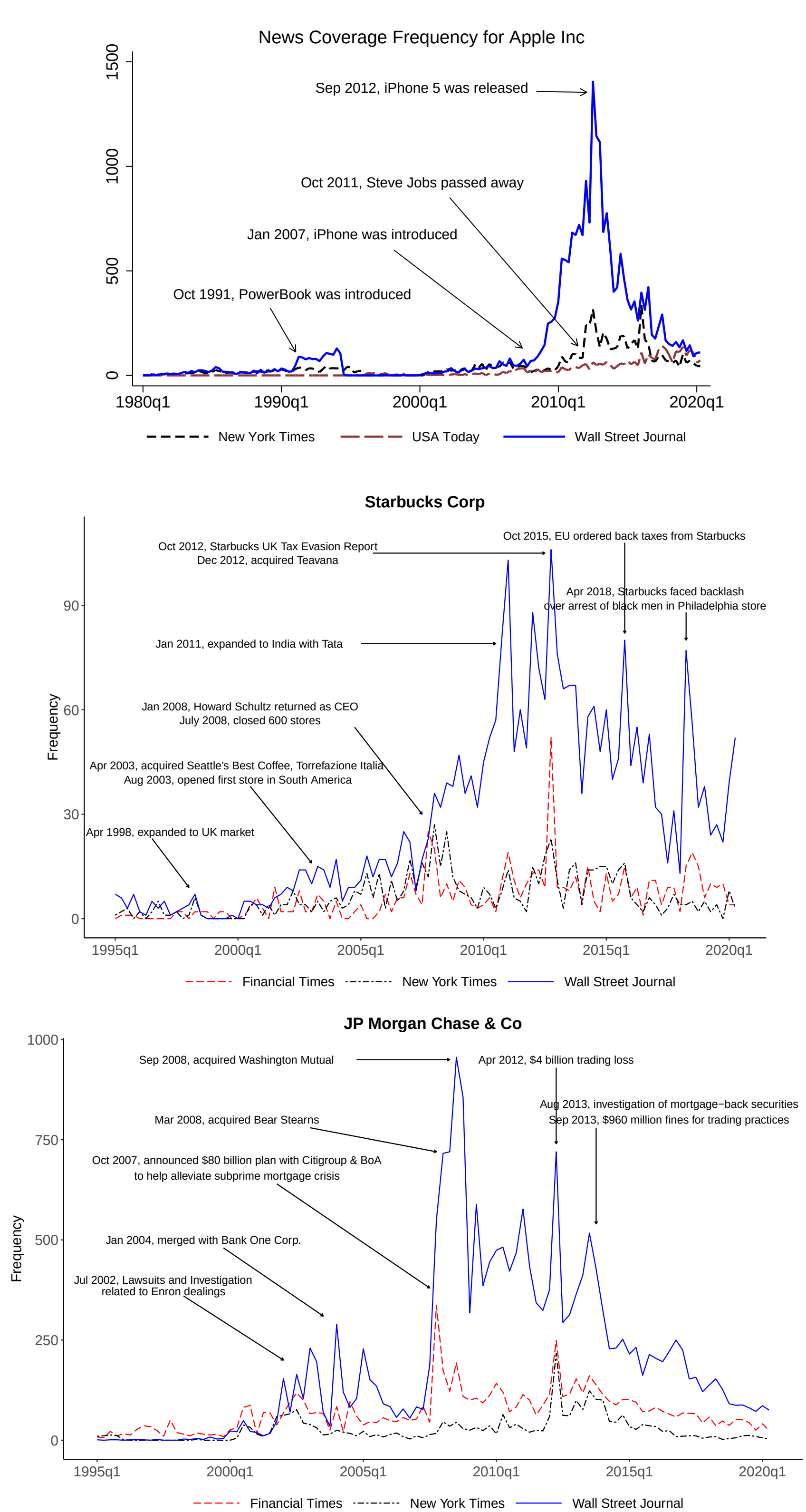
Figure A3: Importance in US GVC and US News Coverage



A. Share of US News vs Share in US Inputs B. Share of US News vs Share of US Downstream Sales

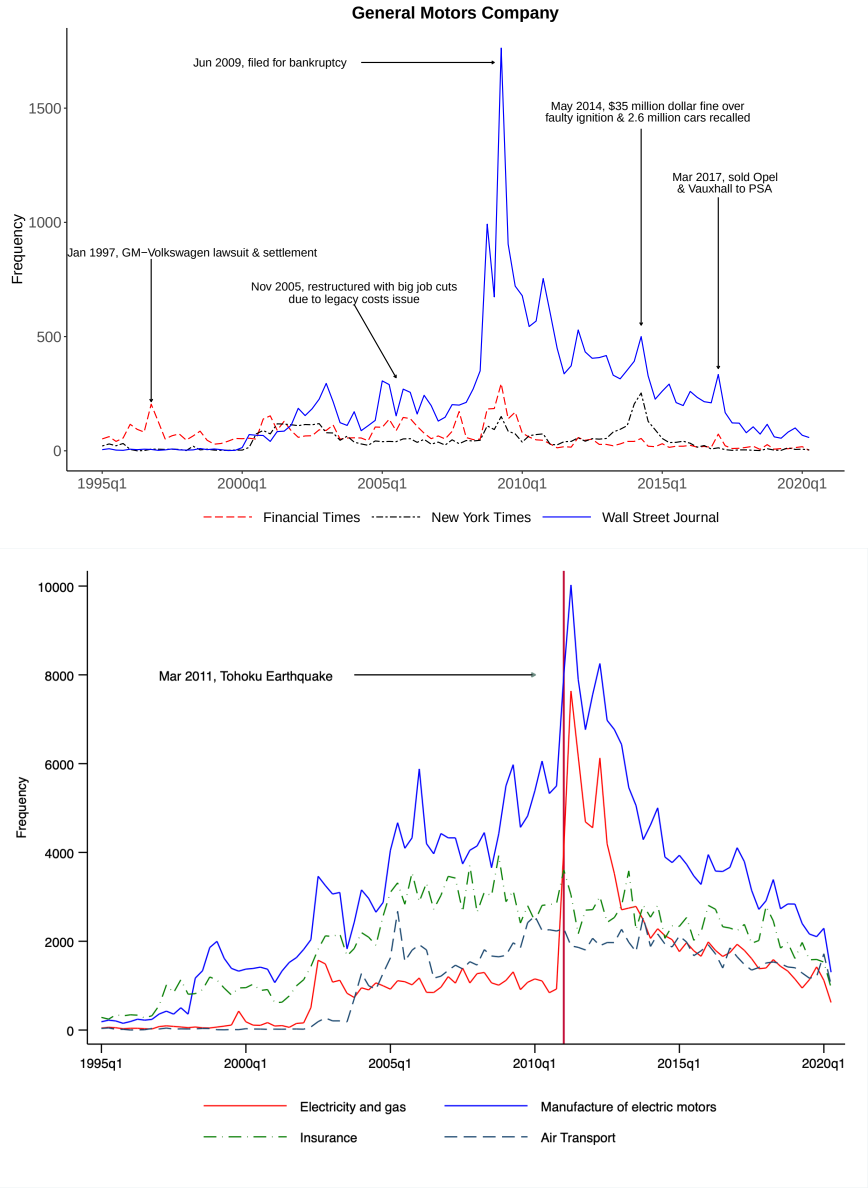
Notes: This figure displays the scatterplots of the log share of US news coverage on the y-axis (both panels) against the intensity with which US uses the sector as an input (panel A), and downstream intensity (panel B). Both plots report the bivariate regression slope coefficient, robust standard error, and the R^2.

Figure A4: Company-Specific Figures: Apple, JP Morgan Chase, Starbucks



Notes: This figure displays the frequencies of news coverage of Apple Inc, Starbucks Corp., and JPMorgan Chase & Co. in the Financial Times, the New York Times, and the Wall Street Journal. Recognizable events in the company history are labeled.

Figure A5: The Auto Sector and the 2011 Tohoku Earthquake



Notes: This figure displays the frequencies of news coverage of pf General Motors Company, and the frequency of the coverage of key sectors around the time of the 2011 Tohoku earthquake in the Financial Times, the New York Times, and the Wall Street Journal. Recognizable events in the company history are labeled.

B.2 Forecast Error Regressions: Robustness

Table A4: 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	$\lvert$forecast error$\rvert$	SD ($\lvert$forecast error$\rvert$)	$\lvert$forecast error$\rvert$	SD ($\lvert$forecast error$\rvert$)
$\log F_{n,t}$	-0.0772***	-0.0254**	-0.287***	-0.0540***
	(0.0097)	(0.0111)	(0.0272)	(0.0157)
Observations	18,582	800	17,338	768
R^2	0.378	0.703	0.668	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 (3.1). Columns 2 and 4 report the results of estimating equation (3.2). The independent variable is the Domar-weighted news frequency share. Variable definitions and sources are described in detail in the text.

Table A5: 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 ($\lvert$forecast error$\rvert$)	$\lvert$forecast error$\rvert$	SD ($\lvert$forecast error$\rvert$)
$\log F_{n,t}$	-0.1690***	-0.0069	-0.2620***	-0.0054
	(0.0349)	(0.0066)	(0.0327)	(0.0117)
Observations	16,348	700	15,271	672
R^2	0.111	0.642	0.233	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 (3.1). Columns 2 and 4 report the results of estimating equation (3.2). The dependent variable is the forecast error of the unemployment rate. Variable definitions and sources are described in detail in the text. Variable definitions and sources are described in detail in the text.

B.3 Trade-Comovement Regressions: Details and Robustness

The trade intensity variable. 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 trade intensity variable as:

$$\text{Trade}_{nj,mi} = \frac{1}{4}\left(\omega_{mi,nj} + \omega_{nj,mi} + \theta_{mi,nj} + \theta_{nj,mi}\right), \tag{B.7}$$

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.

Robustness. Table A6 confirms the findings with correlations in industrial production instead of hours worked. Appendix Tables A7 and A8 use correlations based on 1-quarter growth rates in hours and IP, respectively. We also consider a local news coverage regressor, that is an average of the local coverage frequencies of sectors (n,j) and (m,i) in the newspapers of m and n respectively, $F_{m,nj}$ and $F_{n,mi}$. Appendix Tables A9, A10 use local news instead of global news to compute bilateral coverage intensitities. Throughout, there is a consistently positive association between news coverage and news coverage interacted with trade intensity and international comovement.

Table A6: International Comovement, Trade, and News Coverage, Industrial Production

Dep. Var.: $\rho^{IP}_{nj,mi}$	(1)	(2)	(3)	(4)
$F_{nj,mi}$	-0.927	48.12***	3.745***	45.04***
	(0.993)	(6.153)	(1.178)	(6.585)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.0822	0.279**	0.547***	0.324***
	(0.115)	(0.112)	(0.132)	(0.117)
$\ln \text{Trade}_{nj,mi}$	0.0221***	0.00979***	0.0388***	0.00985***
	(0.00104)	(0.000830)	(0.00151)	(0.00118)
Observations	12,090	12,090	12,090	12,090
R^2	0.062	0.707	0.145	0.709
Country-sector (n,j) FE	no	yes	no	yes
Country-sector (m,i) FE	no	yes	no	yes
Country pair FE	no	no	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). The dependent variable is the correlation in 4-quarter growth rates of industrial production between country-sectors (n,j) and (m,i). The dependent variables are log trade intensity as in (B.7) and news coverage intensity as in (3.4).

Table A7: International Comovement, Trade, and News Coverage, Correlations in 1-Quarter Hours Growth

Dep. Var.: $\rho^{Hours}_{nj,mi}$	(1)	(2)	(3)	(4)
$F_{nj,mi}$	0.906	71.43***	3.657***	61.52***
	(1.153)	(5.308)	(1.062)	(5.332)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.369***	0.195**	0.563***	0.185**
	(0.138)	(0.0968)	(0.123)	(0.0924)
$\ln \text{Trade}_{nj,mi}$	0.0229***	0.0105***	0.0202***	0.00297**
	(0.00133)	(0.000861)	(0.00164)	(0.00121)
Observations	10,245	10,245	10,245	10,245
R^2	0.054	0.784	0.274	0.796
Country-sector (n, j) FE	no	yes	no	yes
Country-sector (m, i) FE	no	yes	no	yes
Country pair FE	no	no	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). The dependent variable is the correlation in 1-quarter growth rates of total hours worked between country-sectors (n, j) and (m, i). The dependent variables are log trade intensity as in (B.7) and news coverage intensity as in (3.4).

Table A8: International Comovement, Trade, and News Coverage, Correlations in 1-Quarter Industrial Production Growth

Dep. Var.: $\rho^{IP}_{nj,mi}$	(1)	(2)	(3)	(4)
$F_{nj,mi}$	0.895	36.49***	3.735***	30.67***
	(0.966)	(3.741)	(1.151)	(4.053)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.371***	0.291***	0.665***	0.301***
	(0.113)	(0.0808)	(0.129)	(0.0829)
$\ln \text{Trade}_{nj,mi}$	0.0190***	0.00694***	0.0320***	0.00564***
	(0.00115)	(0.000673)	(0.00165)	(0.00101)
Observations	12,090	12,090	12,090	12,090
R^2	0.044	0.846	0.120	0.849
Country-sector (n, j) FE	no	yes	no	yes
Country-sector (m, i) FE	no	yes	no	yes
Country pair FE	no	no	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). The dependent variable is the correlation in 1-quarter growth rates of total hours worked between country-sectors (n, j) and (m, i). The dependent variables are log trade intensity as in (B.7) and news coverage intensity as in (3.4).

Table A9: International Comovement, Trade, and News Coverage, Local News

Dep. Var.: $\rho^{Hours}_{nj,mi}$	(1)	(2)	(3)	(4)
$F^{local}_{nj,mi}$	-1.748***	3.064***	1.261**	2.567***
	(0.598)	(0.494)	(0.563)	(0.505)
$\ln \text{Trade}_{nj,mi} \times F^{local}_{nj,mi}$	-0.0354	0.571***	0.377***	0.634***
	(0.126)	(0.110)	(0.117)	(0.113)
$\ln \text{Trade}_{nj,mi}$	0.0290***	0.0118***	0.0286***	0.0101***
	(0.00115)	(0.000999)	(0.00160)	(0.00140)
Observations	10,235	10,235	10,235	10,235
R^2	0.069	0.624	0.179	0.638
Country-sector (n, j) FE	no	yes	no	yes
Country-sector (m, i) FE	no	yes	no	yes
Country pair FE	no	no	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). 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 (B.7) and news coverage intensity as in (3.4). News coverage intensity is computed based on local news.

Table A10: International Comovement, Trade, and News Coverage, Local News, Industrial Production

Dep. Var.: $\rho^{IP}_{nj,mi}$	(1)	(2)	(3)	(4)
$F^{local}_{nj,mi}$	0.716	1.418***	1.341**	1.447***
	(0.499)	(0.432)	(0.553)	(0.448)
$\ln \text{Trade}_{nj,mi} \times F^{local}_{nj,mi}$	0.745***	0.409***	0.450***	0.489***
	(0.109)	(0.0970)	(0.114)	(0.0993)
$\ln \text{Trade}_{nj,mi}$	0.0270***	0.0109***	0.0402***	0.00994***
	(0.000968)	(0.000782)	(0.00137)	(0.00111)
Observations	12,090	12,090	12,090	12,090
R^2	0.075	0.707	0.145	0.710
Country-sector (n, j) FE	no	yes	no	yes
Country-sector (m, i) FE	no	yes	no	yes
Country pair FE	no	no	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). The dependent variable is the correlation in 4-quarter growth rates of industrial production between country-sectors (n, j) and (m, i). The dependent variables are log trade intensity as in (B.7) and news coverage intensity as in (3.4). News coverage intensity is computed based on local news.

C. Quantication Appendix

C.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. The variance of the individual forecast error can be expressed as

$$\mathbb{V}_t \left(v_{nt} - \mathbb{E}_f[v_{nt}] \right) \approx \text{const} - \chi_1 \frac{\overline{F}}{(1+\tau+\chi_0+\chi_1\overline{F})^2} \sum_j \mathcal{D}_{nj}^2 \mathbb{V}(z_{nj,t}) \ln F_{nj,t}$$

$$\mathbb{V}_t \left(v_{nt} - \mathbb{E}_f[v_{nt}] \middle| \text{news} \right) \approx \text{const} - \chi_1 \tau \frac{2\overline{F}}{(1+\tau+\chi_0+\chi_1\overline{F})^3} \sum_j \mathcal{D}_{nj}^2 \mathbb{V}(z_{nj,t}) \ln F_{nj,t}$$

$$\mathbb{V} \left(v_{nt} - \mathbb{E}_f[v_{nt}] \middle| \text{news} \right) = \sum_j \mathcal{D}_{nj}^2 \frac{\mathbb{V}(z_{nj,t})\tau}{(1+\tau+\chi_0+\chi_1 F_{nj})^2}$$

C.2 Economy with only private information

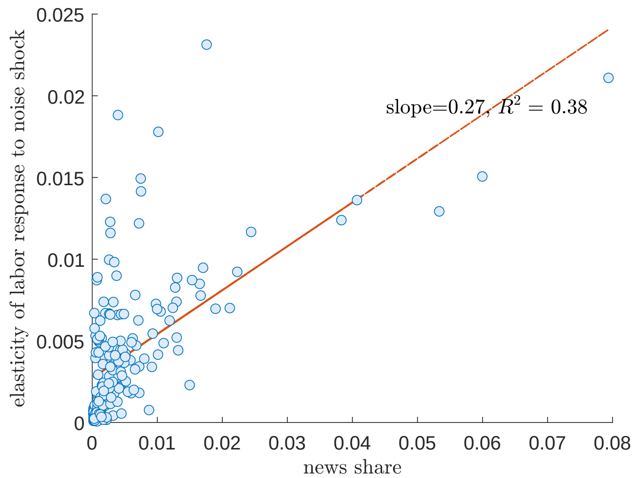
In this part, we report the results in the economy where there is no public signal but the information about the fundamentals is as accurate as in the baseline model as described in subsection 4.4. The following table reports the business cycle statistics under the private-information economy. Comparing with the baseline economy, the changes in the volatility of hours driven by TFP shocks display sizable heterogeneity across countries.

Table A11: Business Cycle Statistics

Hours volatility	(1) Private-Info Economy	(2) Baseline Economy	(3)	(4)
	TFP	TFP	Noise	Total
Canada	0.30	0.28	0.23	0.36
Germany	0.21	0.19	0.13	0.23
Spain	0.43	0.39	0.41	0.56
France	0.22	0.19	0.17	0.26
Italy	0.25	0.22	0.23	0.32
Japan	0.53	0.50	0.36	0.62
UK	0.36	0.32	0.29	0.43
US	0.29	0.28	0.16	0.32

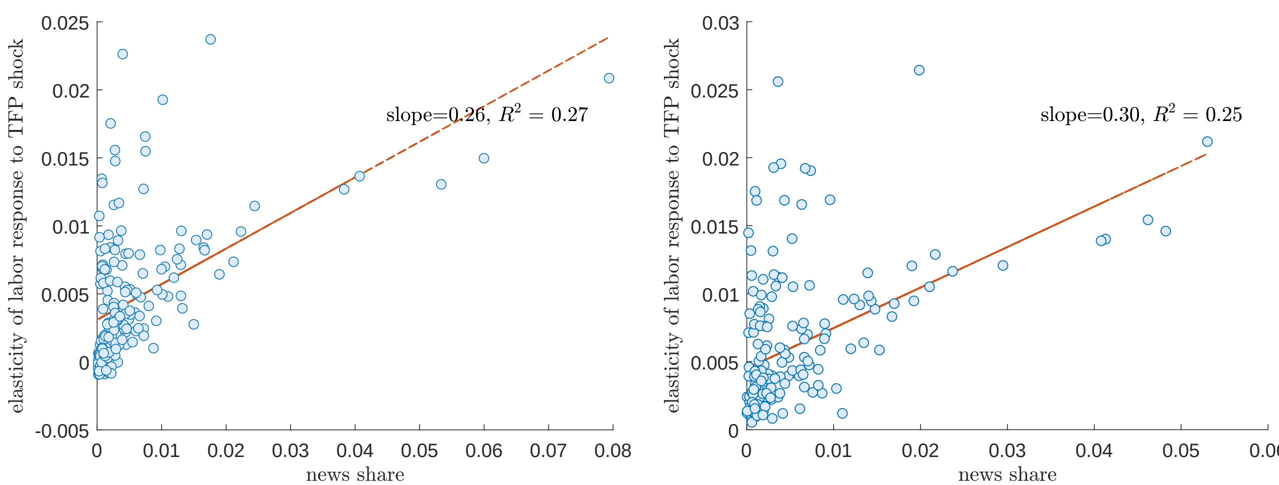
Figure A7 compares the role of news share in TFP shock transmission between the baseline economy and that in the economy with only private information. The patterns are quite similar to each other, though the R-square is slightly higher in the baseline economy.

Figure A6: News Share and Noise Shock Transmission



Notes: The figure displays the scatterplot of the average elasticity of total hours change in other sectors following a noise shock in a particular sector, (4.4), against the sector's share of the global news coverage, in the baseline model with informational frictions.

Figure A7: News Share and TFP Shock Transmission



A. Baseline economy B. Private-info only economy