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ABSTRACT

We introduce information frictions into a tractable quantitative multi-country multi-sector model with global value chains. Producers in a sector do not perfectly observe contemporaneous shocks to other countries and sectors, and their output decisions respond to their idiosyncratic beliefs about worldwide productivity innovations. We discipline agents' information sets with new quarterly data containing the frequencies of country-industry-specific economic news reports by 11 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 that (i) greater news coverage is associated with smaller GDP forecast errors by professional forecasters; (ii) the dispersion of forecast errors shrinks with higher news coverage; and (iii) sectors more covered in the news exhibit stronger hours growth synchronization, and more so if they trade more with each other. We use these reduced form facts to discipline the key parameters in the new theory---the precision of the vectors of public and private signals about country-sector productivities. We find that (i) imperfect ``news" about economic fundamentals can be a quantitatively important source of international fluctuations and (ii) the effects of information frictions are amplified by the global production network. These information frictions appear as correlated labor wedges in standard models without dispersed information.

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1. Introduction

Global supply chains are increasingly important in shaping international trade and fluctuations. However, participating in this massive production network requires firms to acquire and process a large volume of information to coordinate with various suppliers and customers, and to respond to changes in sectors with which they are either directly and indirectly connected. This raises a number of questions. What are the micro and macro implications of such coordination being imperfect due to incomplete information about developments in other locations? Do these frictions disproportionately affect industries that are more involved in international trade? Can news media—the most important source of public information—alleviate informational frictions and facilitate shock transmission?

This paper makes three main contributions. Theoretically, we provide a framework that accommodates incomplete information in global value chains, in which we offer new analytical results on how information frictions interact with the production network. Empirically, we construct a new data set of global economic news coverage of individual countries and sectors, and document that higher news coverage is associated with smaller forecast errors, less forecast dispersion, and enhanced bilateral co-movement between country-sectors. Quantitatively, we evaluate the macroeconomic impact of information frictions, the contribution of noise shocks in the news to international fluctuations, and how micro shock transmission depends on news coverage intensity and its interplay with the production network.

Our theoretical framework combines the standard model of shock transmission through 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. Absent information frictions, rational expectations implies that firms from each country-sector perfectly observe the changes in productivities of all locations and can perfectly infer the equilibrium decisions of their suppliers and customers. The equilibrium outcomes are therefore uniquely determined by the underlying fundamentals. We deviate from this stringent assumption to accommodate the possibility that there may be doubts about other agents' fundamentals and responses. In particular, firms receive imperfect signals about other country-sectors' productivities, which could come from public sources such as news media or from their own idiosyncratic observations of economic conditions. Though news articles are informative, they also contain sentiments, fake information, or various kinds of media bias, which we collectively label "noise" (Bybee et al., 2021). This type of noise shifts aggregate beliefs about fundamentals, and are effectively non-technology shocks that can also propagate through global value chains.

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 no distinction between industries or between final vs. intermediate goods. In these first-generation models, information islands receive signals either about the aggregate economic fundamental (Lucas, 1972) or about their randomly encountered trading partner (Angeletos and La'O, 2013). By contrast, our framework incorporates the key heterogeneities that imply a rich pattern of strategic interactions. Firms know which sectors they are going to buy from and sell to, and receive public and private signals about the fundamentals in each country-sector in the world. The advantage of our environment is that it enables us to connect the theory with the data and provide a quantitative evaluation of the role of the information frictions.

Despite its richness, the model admits an analytical solution. It makes transparent the main consequences of informational frictions 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 completely sure whether it took place and whether other agents are aware of it. Further, agents' decisions depend on their expectations about both their trading partners' decisions and their partners' expectations. This dependence is summarized by a generalized Leontief inverse matrix, which can be conveniently derived from the observed input-output matrix. The indirect or general equilibrium feedback effects of the fundamental shocks are captured by these higher-order expectations, which we show are arrested by informational frictions as well.

Second, noise shocks transmit internationally. Innovations to the public signals about a country-sector's TFP, even if they are not driven by true TFP changes, induce changes in a country's trading partners' GDP. Agents choose to respond to the noisy news partly due to the fact that their trading partners are responding to it. Thus, this non-technology shock can be a source of international GDP synchronization. Third, the effect of the noise shock hinges on the production network structure. Following an upstream sector's shock, the relative importance of the public signal increases in the downstreamness of a sector. That is, sectors more remote from the shocked sector rely less on their private signal, and more on the public news signal to form expectations of the upstream sector's fundamental. This is because relative to first-order expectations, higher-order expectations are more important for the more downstream sector and news shocks are more effective in anchoring higher-order expectations.

Our empirical 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 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 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. They are also only modestly related to the sector's correlation with aggregate output growth.

Second, higher news coverage is associated with lower GDP forecast errors, and less disagreement among forecasters in their GDP projections. This empirical regularity not only reconfirms existing empirical findings that agents are subject to informational frictions, but also suggests that news coverage has informational content useful for predicting economic activity. In contrast with recent survey evidence on expectations (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020), in which the empirical tests stay agnostic about the source of information, our results connect the variations in the quality of forecasts with the news coverage intensity. Furthermore, existing work on survey evidence on expectations has focused on the consequences of noisy *private* information, while the idea of noise-driven business cycles (Lorenzoni, 2009; Angeletos and La'O, 2010; Barsky and Sims, 2012; Angeletos, Collard, and Dellas, 2018) require noisy *public* information or correlated noise. Our empirical results make it possible to discipline the role of public information based on micro evidence, as implemented in our quantitative exercise.

Third, greater news coverage is associated with higher business cycle synchronization. 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 in hours worked or output growth rates 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 synchronization. We also include an interaction effect between news coverage and bilateral trade. It turns out that sectors more covered in the news co-move even more if they trade more with each other. All in all, these reduced-form estimates, while not causal, support the idea that news coverage plays a role in international business cycle comovement.

Our final contribution is to quantify the magnitude of informational frictions and role of news media in shock transmission. We leverage the news data to discipline the key parameters governing the information structure. In particular, we impose the assumption that the precision of the public signal about a country-sector productivity is increasing in the news coverage of that country-sector. This assumption is guided by our reduced-form results, that show forecasts of GDP becoming more precise and less dispersed with greater news coverage. We use indirect inference via the theoretical analogs of the 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. The dispersion of the forecasts further helps identify the fraction of information that is in the public domain versus private domain.

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 labor inputs in all the countries, and by more in those more closely connected to the US, such as Canada. In the baseline imperfect information model, labor and GDP everywhere respond less to the same TFP shock than in a perfect information model. Thus, information frictions dampen the reactivity of the world economy to fundamental shocks. Cross-sectionally, we show that the reaction of the labor input in the rest of world 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 (e.g., US financial services) has a larger impact on world GDP. This is not the case in the perfect information economy.

Incomplete information in global value chains opens the door to international fluctuations driven by non-fundamental noise shocks. This is valuable because measured TFP shocks cannot successfully account for the observed level of cross-border comovement (Levchenko and Pandalai-Nayar, 2020; Huo, Levchenko, and Pandalai-Nayar, 2020b), necessitating a search for another driver of international business cycles. Relative to the perfect information setting, though the total volatility of hours is lower with information frictions, both TFP and noise shocks contribute to the fluctuations in hours. We also show that when the noise shocks in different country sectors are slightly correlated, the hours growth correlations increase substantially, allowing the model to easily reproduce the average correlations observed in the data. In addition, reduced-form international business cycle accounting exercises have found that labor wedges are correlated across countries and are quantitatively important in synchronizing GDP internationally (Huo, Levchenko, and Pandalai-Nayar, 2020a). With incomplete information, the noise shocks manifest themselves as labor wedges from the perspective of a perfect-information prototype model. Thus, noise shocks can be viewed as a micro-foundation for correlated labor wedges in reduced form.

Importantly, international comovement arises due to the responses of both first- and higher-order expectations. In a decomposition between direct effects and indirect effects of the shocks, the noise shocks play a more important role in driving the indirect effects, as the general equilibrium feedback primarily works through higher-order expectations interacting with the production network structure.

At the micro level, the model delivers patterns consistent with the empirical trade-comovement regression. In particular, when we increase the news coverage of a pair of sectors in the model, the covariance in hours worked between these sectors increases, and more so if these sectors trade more. These patterns mirror the findings of the trade-comovement regressions, and serve as external validation to our quantitative framework. The model also predicts that the relative importance of the noise shock is disciplined by the network structure. The generalized Leontief inverse matrix mentioned above provides a measure of the distance between a pair of sectors in the global value chain. When a sector is hit by TFP and noise shocks, other sectors that are more remote (roughly, these can be viewed as the more downstream sectors) will rely more on the news signals. For these sectors, the noise shock turns out to be the more important source of fluctuations. For less remote sectors, who rely more on private information, TFP shocks in an origin sector matter more. This interaction highlights the importance of taking into account the network structure and informational frictions jointly.

All in all, our findings suggest that information frictions can be amplified in a global value chain, and that the presence of such frictions can be important for understanding international shock transmission to real variables. The news media plays an important role in modulating the informational frictions, and can be used as a key source of discipline for quantitative models with these frictions.

Related literature. Our project connects two research programs that so far have had fairly limited contact. The first 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; Chahrour and Jurado, 2018; Acharya, Benhabib, and Huo, 2021; Hébert and La'O, 2020). Different from previous literature that quantifies the role of belief shocks by matching aggregate variables (Angeletos, Collard, and Dellas, 2018), we combine the cross-country expectations survey data with news share coverage to discipline the information frictions and shocks to beliefs. With the partial exception of Levchenko and Pandalai-Nayar (2020) and Baley, Veldkamp, and Waugh (2020), this literature has made little contact with the study of international shock transmission or international trade patterns.[1] Our contribution is to explore how information frictions affect shock transmission channels in the context of global supply chains.

The second 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; Huo, Levchenko, and Pandalai-Nayar, 2020a,b; Bonadio et al., 2021).[2]

Our paper is also related to a growing literature on network games with incomplete information

[1] 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).

[2] 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 perfect information global production networks from an international trade perspective. These frameworks cannot be used to study international transmission of shocks or related applications, even within a perfect information framework, 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.

(Bergemann, Heumann, and Morris, 2017; Angeletos and Huo, 2021; La'O and Tahbaz-Salehi, 2020; Auclert, Rognlie, and Straub, 2020; Lian, 2021). Closest to our work is the recent contribution by Chahrour, Nimark, and Pitschner (2021), that develops a framework with information frictions in a closed-economy production network, and shows that variations in news coverage can synchronize sectors' responses and amplify aggregate fluctuations. Our paper connects the news coverage with survey data on expectations formation, explores the interaction between international trade linkages and incomplete information, and quantifies the role of sectoral noise shocks in international business cycle fluctuations. The feature that the equilibrium outcome is shaped jointly by the network structure and information frictions resembles that in La'O and Tahbaz-Salehi (2020), though they focus on the implications for optimal monetary policy in a closed-economy and do not study the differential impacts between private signals and public signals.

Finally, our paper complements the empirical work on the properties of subjective beliefs at the business cycle frequency (recent contributions include Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Kohlhas and Walther, 2021; Bhandari, Borovička, and Ho, 2019; Bianchi, Ludvigson, and Ma, 2020; Angeletos, Huo, and Sastry, 2021). The literature has mostly focused on whether consensus and individual forecasts overreact or underreact to changes in economic conditions without identifying the sources of information. In contrast, D'Acunto et al. (2021) shows that individuals' daily shopping experiences are informative when forecasting inflation rates. Our paper contributes to this line of research by providing empirical evidence that greater news coverage is associated with improved quality of forecasts.

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 reduced-form patterns in international news coverage, forecast precision, and business cycle synchronization. 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 global value chains.

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.[3]

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 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:

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

where $\pi_{mi,n}$ captures the expenditure shares on various goods.

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) and $\omega_{mi,nj}$ determines its importance in the local production. 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, this

[3]The assumption of a continuum of islands within each country-sector helps ensure that innovations to the private signals do not have an impact on aggregate variables, which is in contrast to the innovations to the the public signals.

section assumes that the TFP shocks are i.i.d. across sectors.

This section assumes 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. We will relax these assumptions and allow for a more flexible specification in Section 4.

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.[4]

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 lowercase letters to denote variables in log deviations from steady state, 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 as encapsulated by the Leontief inverse $(\mathbf{I} - (\mathbf{I} - \boldsymbol{\eta})\boldsymbol{\omega})^{-1}$.

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 island ι. The local wage is determined by

[4] 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 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

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

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 ($\sum_{m,i} \pi_{mi,n} p_{mi,t}$).

Also note that when this equation holds exactly instead of in expectation, there is no labor wedge. The expectation error about the outcomes in the second-stage creates a wedge between marginal rate of substitution and marginal product of labor, which can be interpreted as the labor wedge. We shall revisit this observation in Section 4.

Information structure. We make the following assumptions on the information structure in the first stage. Agents receive two types of information: a private signal that is only observed by a subset of information islands and a public signal that is shared by all firms. In this section we do not need to specify the source of these signals. In the quantification below we will interpret the public signal as coming at least in part from news stories appearing in newspapers.

First, firms receive private information about other sectors' TFP shocks. On 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 $\tau_{nj,mi}$. Firms may have very accurate information about their own sector's TFP, which would be captured by a higher $\tau_{mi,mi}$.

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

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

As will become clear below, the innovation to the public signal $\varepsilon_{mi,t}$ will have aggregate consequences. This is the non-fundamental shock in our economy, and we label it "noise." We allow the precision of the public 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 (which receives the signal). 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 sectoral 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 worked is given by the aggregation across information islands within the 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

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

and

$$\mathbf{M} = \boldsymbol{\pi}(\mathbf{I} - (\mathbf{I} - \boldsymbol{\eta})\boldsymbol{\omega})^{-1}. \tag{2.6}$$

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

$$\boldsymbol{h}_t = \underbrace{\boldsymbol{\varphi}\boldsymbol{z}_t}_{\text{direct effect}} + \underbrace{\boldsymbol{\gamma}\boldsymbol{\varphi}\boldsymbol{z}_t + \boldsymbol{\gamma}^2\boldsymbol{\varphi}\boldsymbol{z}_t + \ldots}_{\text{indirect effect}}. \tag{2.7}$$

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 or shock transmission. 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), 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

$$
\begin{aligned}
h_{nj,t} = \varphi_{nj,mi}\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] + \sum_{k,\ell}\gamma_{nj,k\ell}\ \varphi_{k\ell,mi}\ \overline{\mathbb{E}}_{nj,t}\left[\overline{\mathbb{E}}_{k\ell,t}[z_{mi,t}]\right] + \\
+ \sum_{k,\ell}\sum_{o,q}\gamma_{nj,k\ell}\gamma_{k\ell,oq}\ \varphi_{oq,mi}\ \overline{\mathbb{E}}_{nj,t}\left[\overline{\mathbb{E}}_{k\ell,t}\left[\overline{\mathbb{E}}_{oq,t}\left[z_{mi,t}\right]\right]\right] + \cdots
\end{aligned}
\tag{2.8}
$$

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 γ is less than one, the optimal responses of sectoral hours satisfy*

$$
\boldsymbol{h}_t = \varphi\overline{\mathbb{E}}_t[\boldsymbol{z}_t] + \gamma\varphi\overline{\mathbb{E}}_t^2[\boldsymbol{z}_t] + \gamma^2\varphi\overline{\mathbb{E}}_t^3[\boldsymbol{z}_t] + \dots. \tag{2.9}
$$

where $\overline{\mathbb{E}}_t^k[\cdot]$ are higher-order expectations defined recursively as in (2.8).

Compared with the frictionless benchmark (2.7), 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

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

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*

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

In contrast to the frictionless solution in equation (2.7), the responses of hours are determined by a modified version of the Leontief inverse. Under 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 driven exclusively by fundamental shocks; rather they are influenced by the noise shocks as well. The presence of the imperfect signal not only provides information about the fundamentals, but also opens the 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

$$\boldsymbol{h}_t = (\mathbf{I} - \lambda_z \gamma)^{-1} \left\{ \varphi \lambda_z \boldsymbol{z}_t + (\mathbf{I} - \gamma)^{-1} \varphi \lambda_\varepsilon (\boldsymbol{z}_t + \boldsymbol{\varepsilon}_t) \right\} \tag{2.10}$$

where

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

Equation (2.10) 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 the true innovation in $z_{mi,t}$ is not fully 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 (2.10), instead of γ in the "Leontief inverse" in the perfect information setting. This expression also underscores that the noise shock contributes to international fluctuations, as actual hours depend not only on the fundamentals $\boldsymbol{z}_t$, but also on the noise in the public signal about those fundamentals $\boldsymbol{\varepsilon}_t$. The effect of $\boldsymbol{\varepsilon}_t$ on aggregate hours is 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, and sectors at different points in the supply chain react differently to the shocks. More downstream sectors react less to the TFP shocks in sector $(1,1)$. However, they react more to the noise shock in that sector. This result is best understood via the reliance on higher-order expectations. In particular, a sector nj production stages downstream from sector $(1,1)$ has the following equilibrium hours:

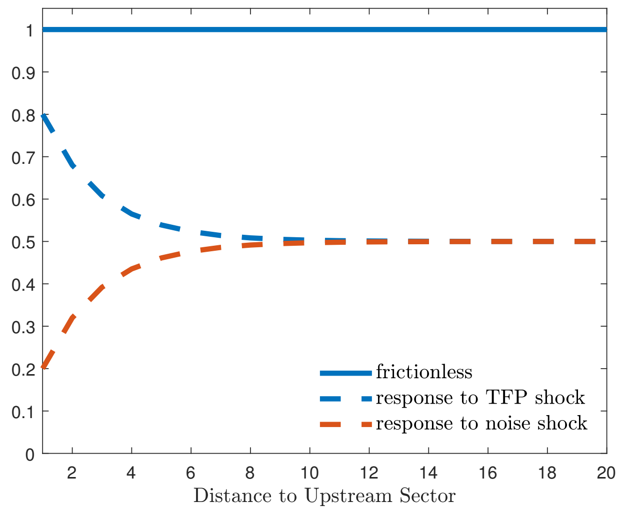
$$h_{nj,t} = \overline{\mathbb{E}}_{nj,t}^{(n-1)J+j}[z_{11,t}] = \left(\frac{\lambda_\varepsilon}{1-\lambda_z} + \frac{1-\lambda_z-\lambda_\varepsilon}{1-\lambda_z}\lambda_z^{(n-1)J+j}\right) z_{11,t} + \left(\frac{\lambda_\varepsilon}{1-\lambda_z} - \frac{\lambda_\varepsilon}{1-\lambda_z}\lambda_z^{(n-1)J+j}\right)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

Note that when the total precision is relatively small ($\lambda_z + \lambda_\varepsilon < 1$), 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.

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 in the global value chain for international fluctuations and comovement. To do this requires data that can be used to discipline not only the global production structure, but also the

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).

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.

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.[5] While we do not collect information on what is reported in the news – such information

[5]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,

would be challenging to gather systematically manually – we provide suggestive evidence on types of news content in Appendix B.1 below.

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.

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. 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 covers the entire private economy over the years 1972-2020, but is unbalanced. Appendix A.2 describes the the national data sources and their coverage for the underlying series used to construct our panel, as well as an overview of the data cleaning steps. We provide a detailed Online Handbook for constructing these series and assessing their quality on our websites.

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.

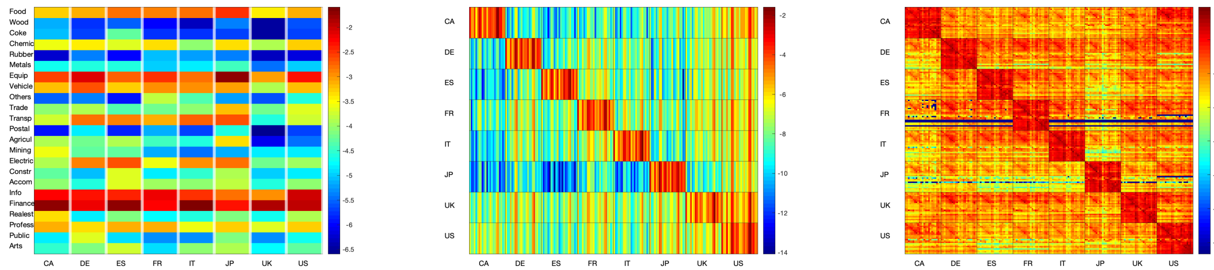
Forecast data. Monthly data on GDP forecasts come from Consensus Forecasts. This database provides current- and next-year real GDP growth forecasts for our sample of countries. The data are at the forecaster level, and includes professional forecasters from business, academia, and industry groups. To 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

automobiles×France, etc in 2020:Q2, and also account for overlaps where multiple countries or countries outside our sample are mentioned.

Figure 2: Sectoral GVC Position and News Coverage



A. Sectoral News Coverage B. Bilateral News Coverage C. Input-Output Matrix

Notes: This figure displays heatmaps of local news coverage shares. Panel A presenting local news coverage about the source country, by sector on the y-axis. Panel A displays the heat map of the bilateral news coverave of country-sectors on the x-axis in newspapers on the y axis. For reference, Panel C displays the heat map of the input-output matrix. 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. All non-zero shares are logged to improve legibility.

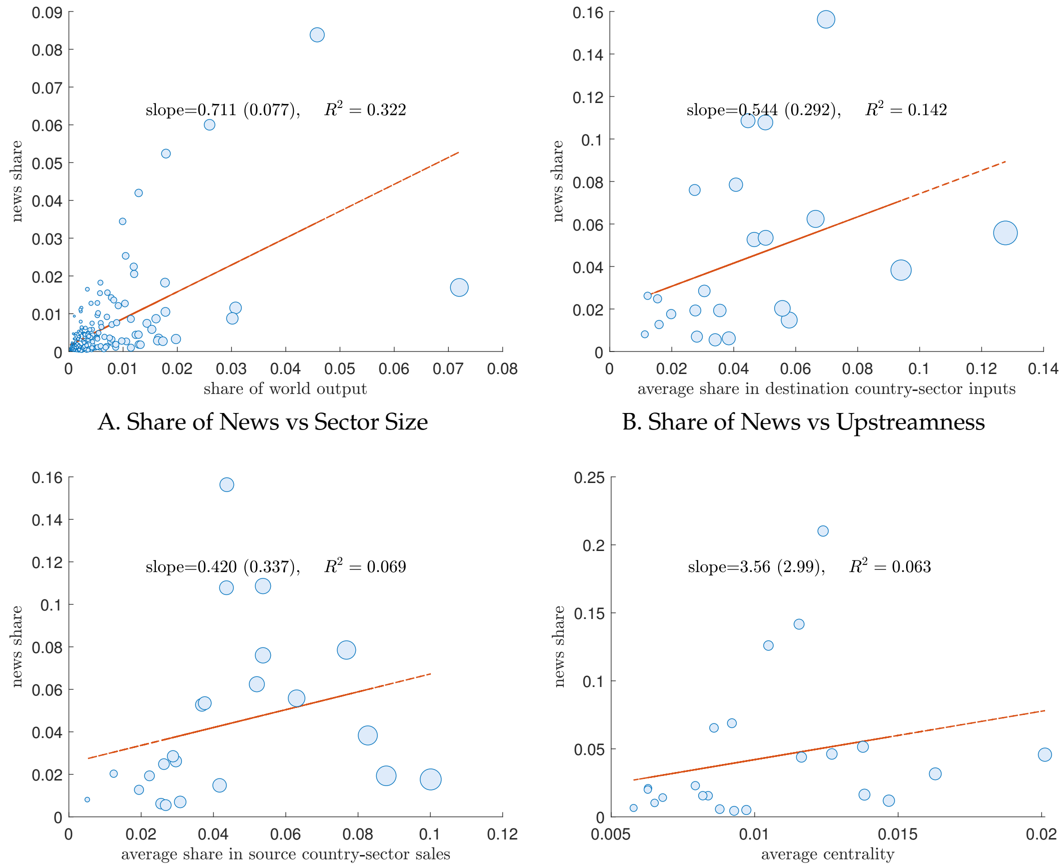
explicitly to the precision of information available to agents, by combining it with forecast error data. The third connects news coverage to comovement in real activity.

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 plots the 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. Panel B 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 C (e.g. Huo, Levchenko, and Pandalai-Nayar, 2020a). While both news coverage shares and input shares are higher for domestic sectors, as evident from the more saturated block diagonals in Panels B and C, 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 B and C that the patterns of news coverage are not highly correlated with input usage.

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.[6] Finally, Panel D considers the Bonacich network centrality as a single summary measure of how important the sector is in the global

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

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.

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. We also assess the correlation between news coverage and sectoral TFP growth, and news coverage and sectoral comovement with aggregate GDP (Appendix Figure A4). None of these observables systematically explain a majority of news coverage.

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

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

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.[7] 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,

[7] 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.

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.

Correlation vs. causation. The regression estimates relating news coverage to absolute forecast errors and dispersion should not be viewed as causal. The fixed effects absorb a variety of confounders, for instance, forecaster-country specific factors that affect forecast precision independent of news coverage, and aggregate business cycle shocks that could raise the level of news coverage and change forecasters' forecasts of GDP at the same time. However, not all confounding variation can be absorbed by the available fixed effects. It is possible that a country or country-sector specific shock in period t raises news coverage, and forecasters improve their forecasts of GDP because they are aware of the shock. Indeed, without controlling for every other possible source of agents' information, we could never be sure that that it is news coverage that improves the precision of the signal, rather than some other source of invormation correlated with the news coverage. Thus, we would not want to interpret the improved forecasts as caused only by the news.

However, such confounding variation is not problematic when we use these regressions to calibrate our model in Section 4. To anticipate what comes below, we will posit that greater news coverage of a country-sector is associated with greater public signal precision about that sector's fundamentals. We will then use these regressions as a disciplining device for the calibration of this relationship. For this purpose, it is not crucial that the regression coefficient identifies the causal relationship, only that the news coverage is correlated with precision. That is, in the calibration we will use the regression as a forecasting device (no pun intended), rather than a structural estimate of a causal effect.

For example, it may be that the pattern uncovered in the regressions is driven by the distinction between large and small shocks. In particular, if large shocks are accompanied by increases in news coverage, and large deviations of GDP from the norm are easier to forecast, then whether a country is experiencing a large or a small shock in a given quarter can be viewed as an omitted variable. Note that even in this case, the mechanism fits with our notion that greater news coverage coincides with greater signal precision about the state of the economy. Only that in this case the news coverage is a correlate, rather than the causal driver, of the changes in the signal precision.[8]

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

[8]Neither the premise that large shocks coincide with more coverage, nor that large shocks are easier to forecast appear supported by the data. We checked whether larger TFP shocks are associated with more news coverage by regressing news coverage on TFP shocks conditional on country-sector and time effects. There is no significant relationship. We also checked whether larger deviations from the norm in GDP are easier to forecast. Forecast errors are actually larger when the actual GDP growth is exceptionally high or low. This is true whether exceptional is defined as below 25th percentile/above 75th percentile, or as below 5th percentile/above 95th percentile

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.

include bilateral news coverage and its interaction with bilateral trade intensity. In particular, we fit the following relationship in the cross-section of country-sector pairs:

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

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

Table 2: International Comovement, Trade, and News Coverage

Dep. Var.: $\rho_{nj,mi}$(hours)	(1)	(2)	(3)	(4)	(5)	(6)
	All country-sector pairs				Domestic	International
ln $\text{Trade}_{nj,mi}$	0.014***	0.009***	0.021***	0.008***	0.016***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)
ln $\text{Trade}_{nj,mi} \times F_{nj,mi}$	0.867***	0.480***	0.603***	0.257**	0.863**	0.498***
	(0.117)	(0.092)	(0.121)	(0.101)	(0.424)	(0.150)
$F_{nj,mi}$	9.721***		5.354***			
	(1.018)		(1.058)			
Observations	16,032	16,032	16,032	16,032	2,002	14,030
R-squared	0.052	0.448	0.152	0.464	0.610	0.454
Country-sector FE	no	yes	no	yes	yes	yes
Country pair FE	no	no	yes	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). 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). Columns 1-4 use all country-sector pairs. Column 5 restricts the sample to pairs where $m = n$, and column 6 to pairs where $m \neq n$. Throughout, we restrict the sample to country-sector pairs where a minimum of 10 years of data are available for computing correlations.

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

Further, as columns (5) and (6) show, this result is holds both for the relationship between trade intensity and news coverage with the comovement of sectors located within a country and in different countries.[9] Appendix B.3 provides further details and presents a number of robustness checks. Note that, similar to the forecast regressions above, these results should be interpreted as conditional correlations and not a causal relationship (as is the case with the entirety of the trade-comovement empirical literature).

4. Quantification

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

[9]This decomposition is sensitive to whether sector-pairs with short time series are included in computing correlations. For sector pairs with minimum time-series length of 12 years, the magnitude of the coefficients in column (6) increases and those in column (5) become insignificant.

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), but the main theoretical results (Propositions 2.1 and 2.2) continue to hold.[10]

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 time path of 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.

To simulate the model, we also need the covariance structure of the TFP shocks. At quarterly frequency, estimates of TFP shocks are not available at the country-sector level. We instead employ the covariance matrix of the Solow residual at the yearly frequency. We use the Solow residuals for all sectors of the G7+ countries computed in Huo, Levchenko, and Pandalai-Nayar (2020b). As that paper computes the Solow residuals for sectors at an ISIC-Rev 3 level of disaggregation, we concord these sectors to the 23 sectors in our baseline dataset.

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 signals about other sectors' TFP, $\tau_{nj,mi} = \tau$. Under these assumptions on the public and private

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

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.

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

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.

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.[11] 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 quarter-to-quarter variation in news coverage.

We then implement the following regressions using model-generated observations

$$\mathbb{E}\left[\left|v_{nt} - \mathbb{E}_{f,t}[v_{nt}]\right|\right] = \beta_{01}^M + \beta_1^M \log F_{n,t} + \delta_n + \nu_{nt} \tag{4.2}$$

$$\text{SD}\left(\left|v_{nt} - \mathbb{E}_{f,t}[v_{nt}]\right|\right) = \beta_{02}^M + \beta_2^M \log F_{n,t} + \delta_n + \nu_{nt}, \tag{4.3}$$

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 (as 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 D.1 shows that the coefficient in equation (4.2) is related to the slope χ_1 and the

[11]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.

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.

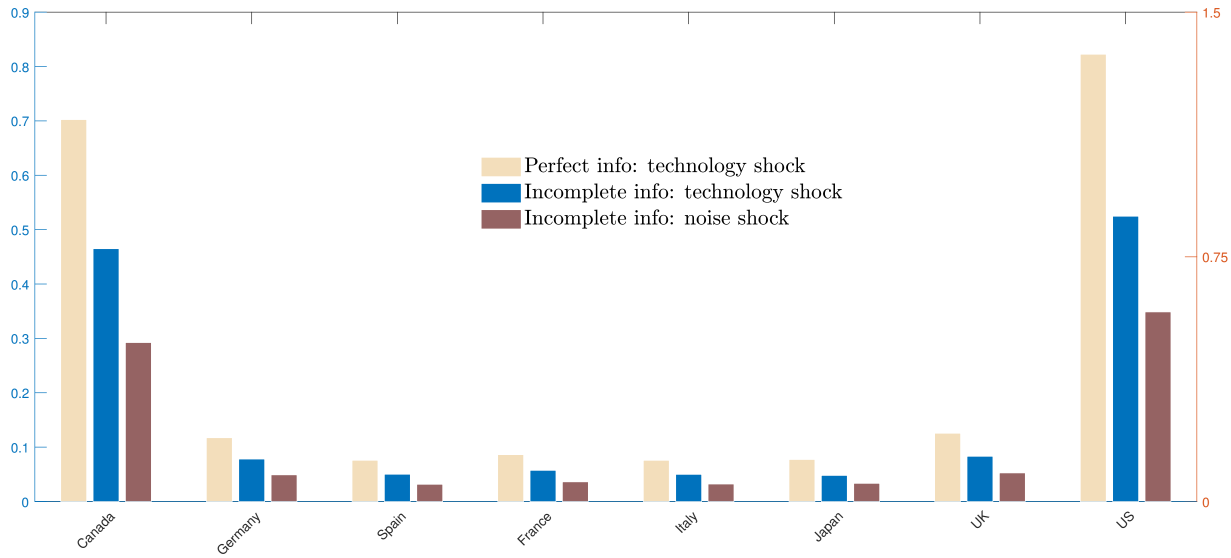
Computation. When solving the model, we make two additional assumptions. First, we assume that firms' subjective beliefs do not internalize the fact that the TFP shocks are slightly correlated. Without this assumption, solving for the equilibrium strategy requires inverting a matrix of size 90000×90000, which is very costly. Due to the low correlation of TFP shocks across countries in the data, our quantitative results are not likely to be significantly affected by this assumption. Second, we assume that firms can observe their own sector's hours, but do not use this information to infer other locations' shocks. Whether we make this assumption or not has a negligible impact on our quantitative results, but allows us to implement the decomposition in equation (2.9).

4.2 Aggregate Implications

Section 2 derives two basic properties of the economy with incomplete information: the transmission of fundamental shocks is dampened and the international fluctuations are driven by both fundamental and non-fundamental shocks. This subsection explores 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. (Because the response of the US GDP to a US shock is by far the highest in the sample, it is displayed on the right scale.) 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

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.

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 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 growth, aggregated at the country level. Column 1 presents the log standard deviation of hours growth under perfect information and only TFP shocks. We simulate the TFP shocks based on the country-sector Solow residuals computed from Huo, Levchenko, and Pandalai-Nayar (2020b). Column 2 instead feeds in the same TFP shocks, but under informational frictions. In this case, the standard deviation of growth in hours worked coming from TFP shocks falls to about one half of what was under perfect information. This confirms the intuition developed in Section 2 that incomplete information dampens the responses to fundamental shocks.

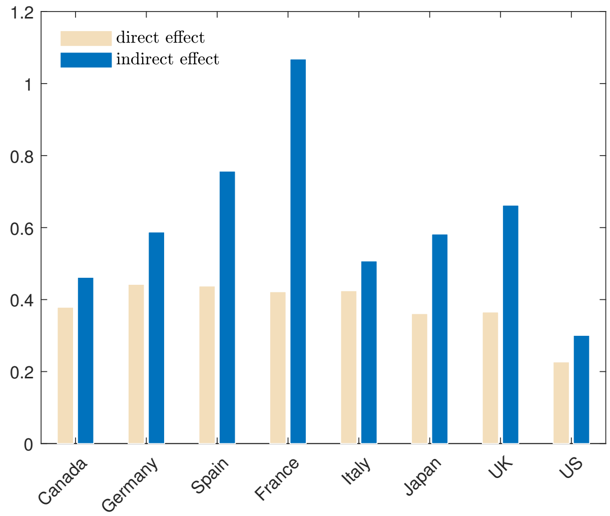
At the same time, since firms rely on news when making their production decisions, now the noise shocks in news contribute to international fluctuations. In the end, fluctuations generated by noise shocks are about 65% of those driven by fundamental shocks. Putting the TFP and noise shocks

Table 5: Business Cycle Statistics

Hours volatility	(1) Perfect Information TFP	(2) Incomplete Information TFP	(3) Incomplete Information Noise	(4) Incomplete Information Total	(5) Data
Canada	0.85	0.42	0.27	0.49	1.15
Germany	0.69	0.33	0.23	0.40	0.91
Spain	1.23	0.45	0.33	0.56	2.87
France	0.77	0.31	0.23	0.39	1.43
Italy	1.07	0.44	0.30	0.54	1.52
Japan	1.12	0.66	0.43	0.79	1.26
UK	1.18	0.59	0.39	0.71	1.09
US	0.96	0.64	0.32	0.71	1.43
Mean	0.98	0.48	0.31	0.57	1.55
Bilateral hours correlation					
Uncorrelated noise	0.094	0.113	0.054	0.096	0.187
Correlated noise ($\rho = 0.024$)	0.094	0.113	0.329	0.187	
Bilateral labor wedge correlation					
Uncorrelated noise	—	0.056	0.024	0.049	
Correlated noise	—	0.056	0.268	0.118	

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.

Figure 5: Relative Contribution of Noise Shocks



Notes: The figure displays the fraction of volatility driven by the noise shocks in the direct effect (beige bars) and indirect effect (blue bars) according to the decomposition in equation (2.7). Across different countries, the contribution of the noise shocks is larger in the indirect effects.

together in column 4, we get to around one-third of the average volatility of hours observed in the data for most countries (last column).[12]

As stated in condition (2.7), the labor input fluctuations can be decomposed into direct effects due to changes of the fundamentals and indirect effects due to changes in hours in other country sectors. With incomplete information, the relative contribution of the noise shocks tends to be larger for the latter: the indirect effects are tied to the general equilibrium considerations modulated by the interaction between the production network and the higher-order expectations, and the news signals are more useful in anchoring the higher-order expectations than private ones. In Figure 5, the beige bars display the fraction of total volatility due to the noise shocks in the direct effects, and the blue bar display the same in the indirect effects. Clearly, noise shocks play a larger role in the indirect effects.

The noise shocks also induce 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." In the data, the correlation in aggregate hours worked is about 0.19 in our sample of countries. Uncorrelated noise shocks alone generate over a quarter of this correlation, 0.054. We next check how much correlation in the noise shocks is required to match the observed correlation in hours. 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

[12]The perfect information model generates hours volatility closer to the data for most countries. However, we note that (i) the perfect information model has counterfactual implications in other dimensions as highlighted throughout this paper and (ii) neither model aims to match empirical hours growth volatility, which would require more shocks and possibly correlated shocks.

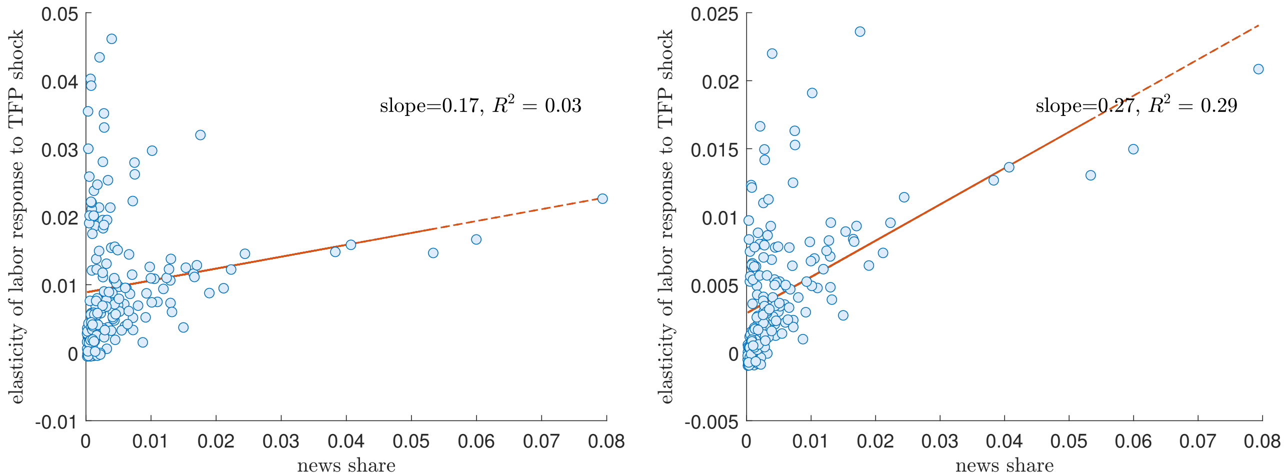
countries with the correlation in the noise shocks of only 0.024. Thus, even a modest correlation in the noise shocks translates into a significant level of observed hours correlation.

Labor Wedge. With incomplete information, the marginal rate of substitution (MRS) and the marginal product of labor (MPL) are equalized only in expectation in the first stage of a period. As a result, any unexpected changes of the fundamentals 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, 0.118. The labor wedge is also positively correlated with the TFP wedge, with a mean correlation of 0.024 across country pairs.

Non-Monotonicity in Noise-Driven Fluctuations. Given the role of the public signal noise in international fluctuations, a natural question is whether the magnitude of the fluctuations generated by the noise shocks is monotonic in the news coverage intensity or equivalently, the sensitivity of precision to news coverage χ_1. The answer is no. Consider two extreme cases: if $\chi_1 \approx 0$, the news signals are not informative at all and firms will ignore them when making decisions. Consequently, the noise contained in the news signals is irrelevant. At the opposite extreme, suppose $\chi_1 \approx \infty$ and the news signals are very informative. In this case, the variance of the noise shock approaches zero and agents know the fundamental state perfectly after observing the public signal. In this case, the model converges to perfect information and noise shocks also cannot play a significant role in shaping the aggregate fluctuations. Appendix Figure A8 displays the hours volatility driven by the noise shock as a function of the slope of the precision-news coverage relationship χ_1. According to our assumptions, signal precision increases one-for-one with χ_1. The vertical line displays the value of χ_1 that emerges from our indirect inference procedure.

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

Figure 6: 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.

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

Appendix Figure A9 displays the elasticity $\varrho_{nj}^{\varepsilon}$ 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.

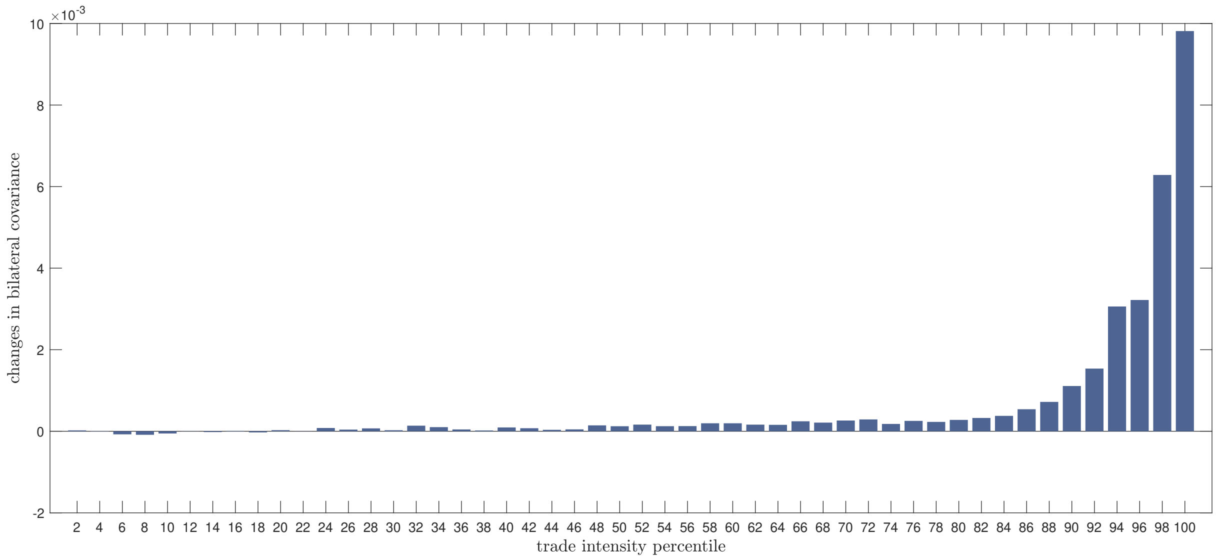
Interaction between News and Trade Intensity. The trade-comovement regressions in Section 3.2 suggest that the impact of greater news coverage on shock transmission should be stronger when a pair of country-sectors is more closely connected with each other through trade. To explore the interaction between news coverage and trade intensity, we implement the following local perturbation exercise in our model economy: fixing a pair of country-sectors, the news share for these two country sectors is increased by 25% and the global influence matrix is recomputed. We then compare the covariance of between these two sectors' hours worked with that in the baseline economy. We perform this local perturbation for all the country-sector pairs. This exercise is intended to mimic the empirical trade-comovement regression, but in the model we have the added benefit of being able to implement a fully controlled experiment in which nothing changes except for news coverage intensity/signal precision. This exercise is of course not attainable in empirical analysis, which must worry about confounding factors.

Figure 7 displays the changes in covariance relative to the baseline counterparts. In the figure, the "shocked" country-sector pairs are ranked according to their bilateral trade intensity. The changes in covariance are positive overall, consistent with the intuition that more news coverage facilitates shock transmission. The magnitude of the changes is also increasing in the trade intensity. Furthermore, this increase tends to be greater for those pairs that exhibit a greater trade intensity. The reason is simple: when the trade linkages between two country sectors are weak, whether they are aware of each others' fundamental or not is nearly irrelevant. On the other hand, sectors that trade intensively with each other must form expectations about the productivity of their trading partners, and thus increasing news precision about that productivity leads to higher comovement.

In Appendix Table A8, we further elaborate on this point by showing that the trade comovement type of regression with covariance as dependent variables display similar results empirically. In the specifications with the richest set of fixed effects for confounding factors (source-country-sector, destination-country-sector and country-pair) higher bilateral news coverage is always associated with increased bilateral hours growth covariance and industrial production growth rates covariances for sectors that trade more with each other.

Interaction between News and Network Effects. Section 2 highlighted that following a shock in country m sector i, the responses of the country-sectors more remote from (m, i) tend to put a higher weight on higher-order expectations and therefore rely more heavily on public news. To see the meaning of remoteness in our setting more clearly, recall that in condition (2.8), the importance of first-order effects in country-sector (n, j) is captured by $\varphi_{nj,mi}$, and the importance of the second-order effects depends on how other country-sectors respond to the shock, $\sum_{k,\ell} \gamma_{nj,k\ell}\varphi_{k\ell,mi}$. Without going to even higher-order terms, the remoteness can be captured by the ratio of these two: the more remote (n, j) is relative to (m, i), the more important are the second order effects.

Figure 7: Changes in Bilateral Comovement and Trade Intensity



Notes: This figure displays the change in bilateral covariance after a local increase of the news share.

Taking advantage of Lemma 2, this ratio can be approximated by

$$d_{nj,mi} \equiv \frac{\mathbf{M}\sum_{k,\ell}\mathbf{M}_{nj,k\ell}}{\mathbf{M}_{nj,mi}+\mathbf{M}\sum_{k,\ell}\mathbf{M}_{nj,k\ell}},$$

where $\mathbf{M}$ (given by (2.6)) is related to the observed expenditure shares. The numerator captures the second-order effects, and the denominator captures the sum of first- and second-order effects. We expect that a higher $d_{nj,mi}$ implies that country-sector (n,j)'s fluctuations in response to (m,i)'s shocks is driven more by the noise shock than the TFP shock. The following test in the model's simulation confirms this conjecture

$$\frac{\mathbb{V}(G^{\varepsilon}_{nj,mi}\varepsilon_{mi,t})}{\mathbb{V}(G^{\varepsilon}_{nj,mi}\varepsilon_{mi,t})+\mathbb{V}(G^{z}_{nj,mi}z_{mi,t})} = \beta_0 + \underset{(0.004)}{0.164}\, d_{nj,mi} + \delta_{mi} + v_{nj,mi},$$

where δ_{mi} controls for the precision of the signal for (m,i). The positive coefficient of $d_{nj,mi}$ shows that the importance of noise shocks is increasing in the measured remoteness.

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 $\tilde{x}_{nj,mi,t}(\iota)$

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

where

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

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

In these two environments, the first-order expectations conditional on TFP shocks are identical. Crucially, the higher-order expectations are different, as public signals are more useful than private ones for forecasting others' beliefs. As shown in Section 2, the equilibrium outcome hinges on the interaction between the production network and all the higher-order expectations, which makes the distinction between complete and incomplete information relevant. Table A9 in Appendix D.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 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 that maximizes the information in the private domain.

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

5. Conclusion

We live in the information age, in which news media is readily accessible, but often the news contains information that is not factual. This noise in the news might lead agents to incorrect inference about economic fundamentals, with consequences for their real behavior. This is particularly plausible when firms make decisions in complex global value chains, which requires them to forecast the fundamentals and decisions of all direct and indirect links in their network.

In this paper, we study the importance of information frictions in complex global value chains, with an emphasis on the role of the news media in disciplining the strength of the frictions. We develop a quantitative framework in which non-technology shocks (noise in the news) can also 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 or countries more covered in the news (i) exhibit more precise and less dispersed forecasts; and (ii) generate more international synchronization. Our paper thus provides empirical evidence and quantitative support for a microfoundation for international shock transmission of non-technology shocks, and for the role of production networks in amplifying information frictions.

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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 summarizes the data cleaning procedures. As constructing these data series are very involved and the approach varies by country and sometimes by sector, we provide a very detailed quarterly data construction handbook online.

A.2.1 United States

US Industrial Production. The US industrial production data are from the Federal Reserve Board for the manufacturing sector.[13] 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 use the concordance tables 17 and 18 in the Online Handbook to aggregate the IP data.

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.[14] Services PPI information is also obtained from the Census Bureau.

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

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

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

We seasonally adjusted the time series using X-11-ARIMA. In some cases we impute subindustry growth rates from available subindustries, which is documented in the Online Handbook. The cleaned data series are summarized in Table 22 of the Online Handbook.

US hours. The US working hours data are from the US Bureau of Labor Statistics [15]. We compute total working hours by multiplying the average weekly working hours with employment. We aggregate the total hours series to our 23 sector classification using the concordance in Table 3 of the Online Handbook.

There are two series of the US average weekly working hours and employment: all employees' (AE) and production and non-supervisory employees'(PNE). The AE series 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 2006. The final cleaned US hours data is summarized in tables 8 and 9 of the Online Handbook.

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.[16] We aggregate the months into quarters.

We use the concordance Table 15 in the Online Handbook to aggregate Canadian sectoral GDP into our ISIC-based classification. Due to data availability, we partially impute the series for two industries (10-15 and M-N) before 2007. We provide details on the imputation process in Section 5.2 of the Online Handbook. The final cleaned data is summarized in Table 20 of that document.

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:[17]

1. Extract the average weekly hours of hourly-paid employees [18], and the standard work week hours for salaried employees [19].
2. Download the employment of salaried and hourly-paid employees [20].
3. Combine them into a monthly time series of the average total hours worked:

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

[15] https://www.bls.gov/ces/data/
[16] https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=3610043401
[17] We are grateful to Xing Guo for giving us this procedure.
[18] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410025501
[19] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410021101
[20] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410020101

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".

There are several additional steps necessary to clean each sector in the Canadian data, as some of the series are inconsistent with each other. We provide detailed information on the cleaning procedures (and imputation, where necessary) in Sections 1.3-1.6 of the Online Handbook. Our aggregate hours data almost perfectly matches offical Canadian aggregate total working hours (Figure 1 of the Online Handbook).

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 using the concordance in Table 1 of the Online Handbook and seasonally adjust the resulting working hours series using X-11ARIMA-SEATS. The cleaned data are summarized in Table 6 of the Online Handbook.

A.2.3 Japan

Japanese Industrial Production. The Japanese industrial production data are from the Ministry of Economy, Trade and Industry.[21]

We use the concordance between these data and ISIC-Rev 4 in Table 16 of the Online Handbook. Three industries require some imputation (16-18, 26-28 and R-S) due to missing subindustries in early years. We provide the details in the Online Handbook Section 6.2, and summarize the data in Table 21 of that document.

Japanese Hours. The Japanese working hours data are from Statistics of Japan. There are two series provided here: Average/Aggregated weekly hours of work by industry and status in employment and Weekly hours of work by industry and status in employment. However, the series begin at different dates varying from Q1 2000 to Q1 2011, and they also vary in their sectoral classification (either the 10,11, 12 or 13th Japanese Standard Industrial Classification).[22]

As the data encompass two revisions of the JSIC codes in 2002 and 2007, we use the official concordance tables to reclassify all the series into ISIC-4.[23] There are a number of nuances specific to individual sectors in applying these concordances. We document these in detail, sector by sector, in Section 2.2 of the Online Handbook.

We seasonally adjust the final series using X-12ARIMA-SEATS. The cleaned data are summarized in Table 7 and the implied aggregate hours worked is compared to official statistics in Figure 2 of the Online Handbook.

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. [24]

European Industrial Production. For each series, we download information on production, turnover and prices. For aggregation, we use the concordance table 19 in the Online Handbook. We prioritize the series as follows. First, we use the deflated production series where available. When not available, we use industrial PPI to deflate the nominal turnover series. If industrial PPI is not available, we use the growth rates of nominal turnover and flag the data. If there are gaps in the deflated production series or it is very short, we impute/backcast it using the deflated nominal turnover. We flag and document all such instances in Section 8.2 of the Online Handbook. The cleaned data are summarized in Tables 23-28 of that document.

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[21] 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.

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

[23] Note that some of these concordance tables are only available in Japanese.

[24] 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.

European Working Hours. We use two complementary sources of working hours from Eurostat: quarterly industry actual working hours (calculated by multiplying quarterly industry employment by average weekly working hours in the industry times 12) and quarterly industry working hours index. When possible, we use the actual working hours (seasonally adjusted using X-11-Arima-SEATS). For the manufacturing sector, as the average weekly working hours are not broken down by subsector, we use the working hours index. There is a classification revision during our sample – we only use series where despite the reclassification there is no obvious issue in the series. Figures 5-9 of the Online Handbook illustrate the comparison between our total hours for each country and official national hours. The series line up very well. The cleaned data are summarized by country and sector in Tables 10-14 of that document.

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.

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

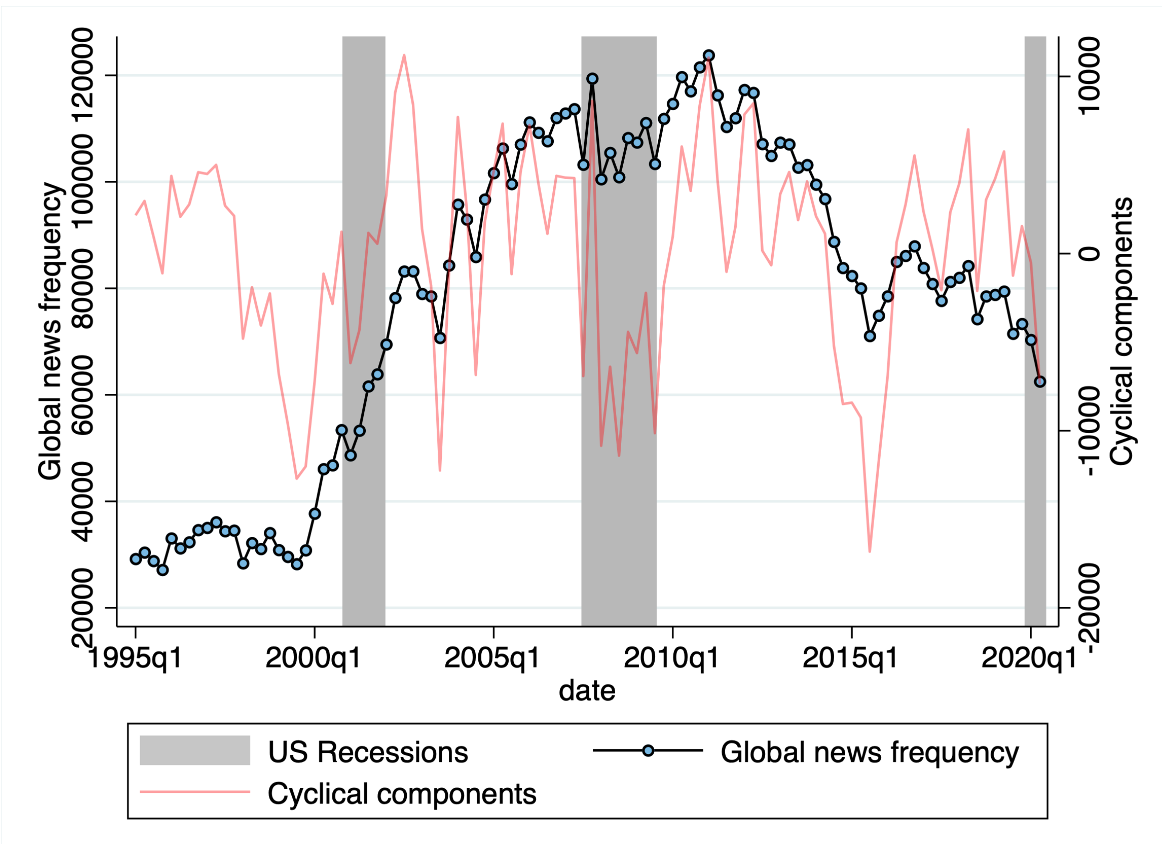
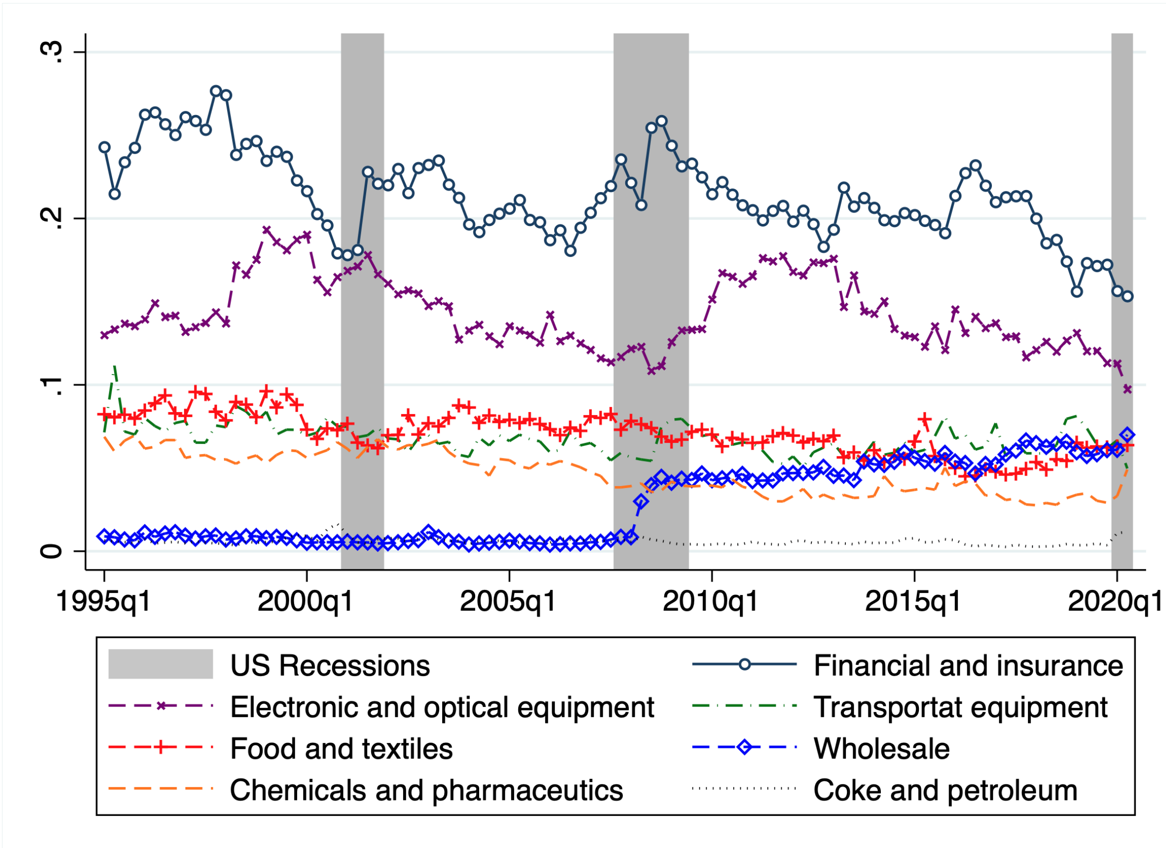


Figure A2 plots the frequency of news reports in global news coverage for several large sectors. It is immediately clear that, while there are some changes over time, the ordering of sectors in terms of news coverage in the cross-section remains quite consistent. This suggests that within-sector variation 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.[25] 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.

[25]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.

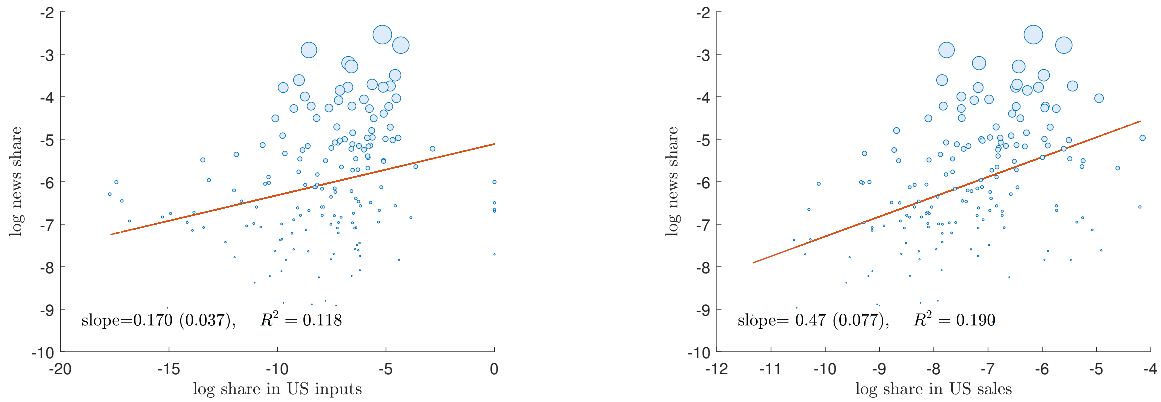
To further illustrate these patterns, Figure A3 plots the log share of US coverage of country-sector (m, i) against the the upstream importance $UP_{US,mi}$ (panel A) and downstream importance $DN_{US,mi}$ (panel B) in the US economy. The positive correlations are evident, but so is the large amount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

Finally, Figure A4 plots the share of news coverage of sector (i) in global news against the average correlation of industrial production growth in m, i with GDP growth in m (panel A) and against the average TFP growth of m, i across all m (panel B). News coverage is more strongly related to average TFP growth, and has no obvious relationship with sectoral correlations with own GDP growth.

What is in the news?. Appendix Figures A5-A6 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.[26] The bottom panel of Figure A6 plots the news coverage of key

[26]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

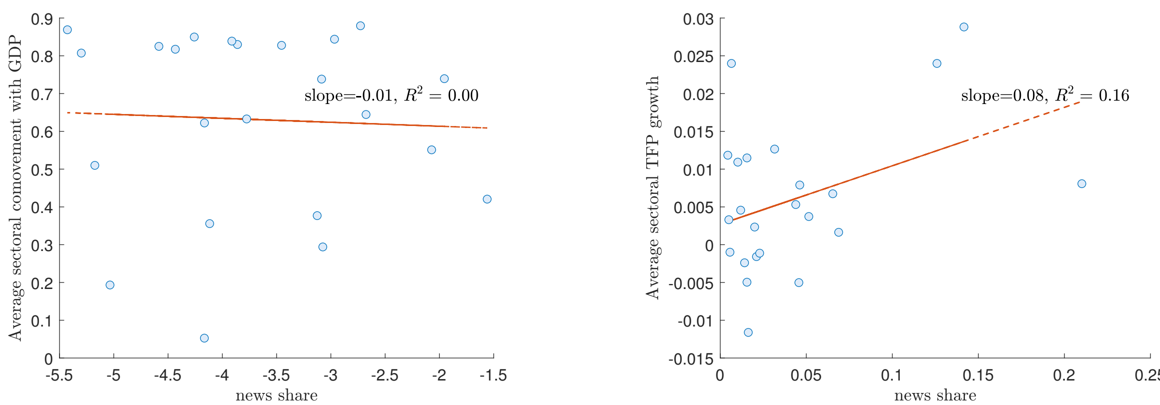
Figure A3: Importance in US GVC and US News Coverage



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: News Coverage, Sector Comovement and TFP Growth



A. Share of Global News vs Average Sectoral Comovement with Country GDP

B. Share of Global News vs Average Sectoral TFP (Solow Residual) Growth

Notes: This figure displays the scatterplots of the log share of global news coverage on the y-axis (both panels) against average comovement of the sector with country GDP (panel A), and the average growth rate of the sector's TFP shocks (panel B). Both plots report the bivariate regression slope coefficient and the R^2.

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.

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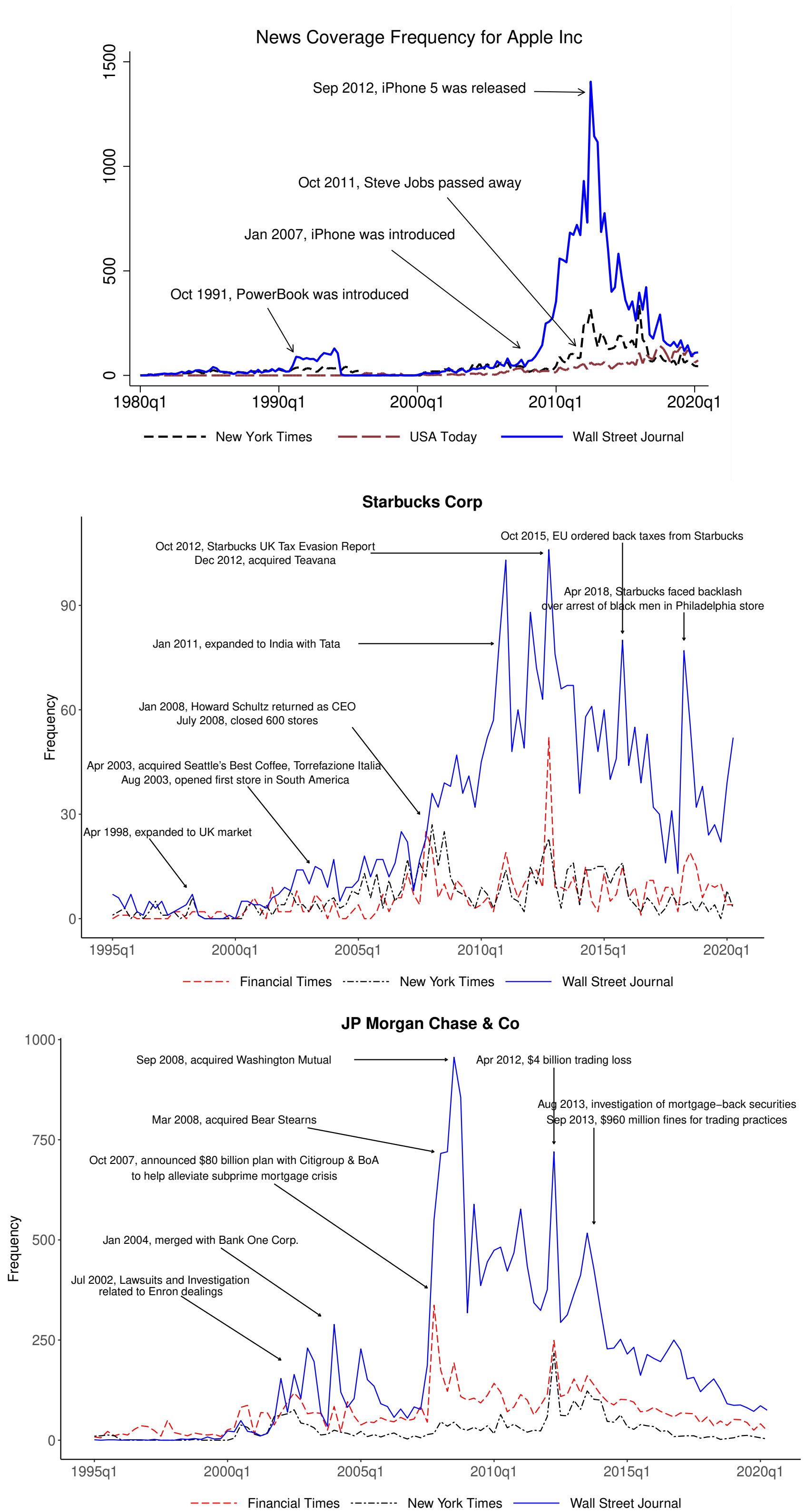
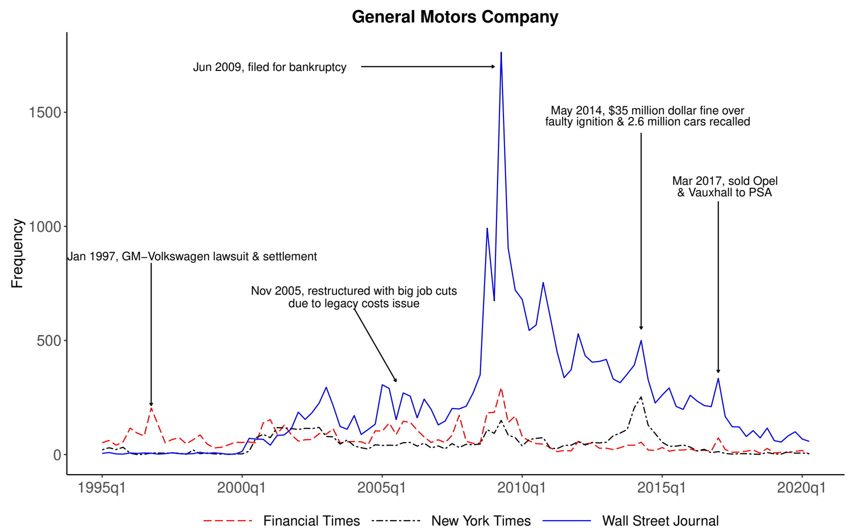
the New York Times published around 15000 articles a month in this period.

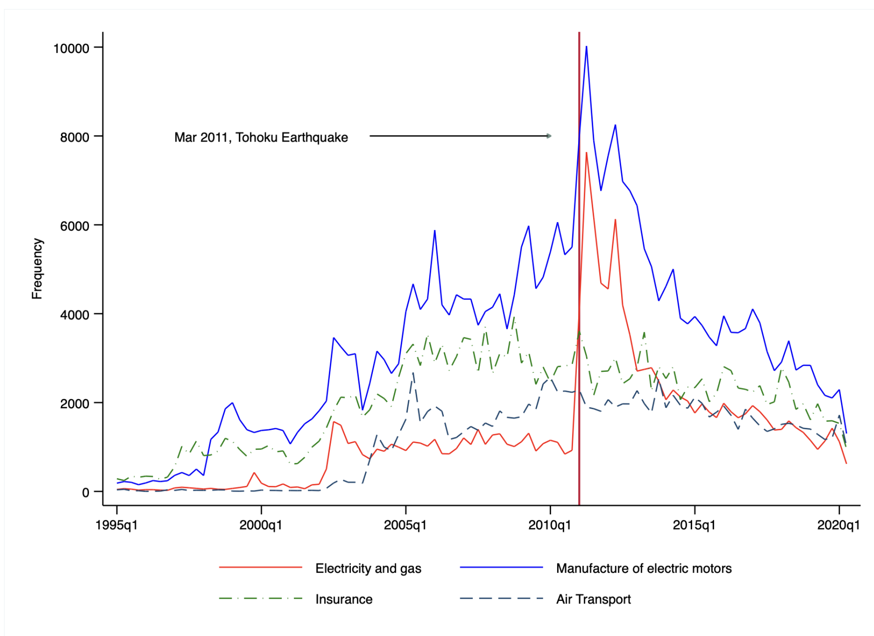
Figure A5: Company-Specific Figures: Apple, JP Morgan Chase, Starbucks



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

Figure A6: 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. While the interaction terms with news coverage are not significant in all specifications, they are strongly significant for country-sector pairs in different countries. Appendix Table A7 performs further robustness checks assessing 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 $F_{n,mi}$. Finally we also assess robustness using a sales based measure of trade intensity, where $\text{Trade}_{nj,mi} = \frac{1}{2}\left(\theta_{mi,nj} + \theta_{nj,mi}\right)$.

Our external validation exercise in the model centers on the relationship between trade intensity, news coverage, and sectoral covariances (Section 4.3). Table A8 assesses this relationship in the data and finds that the interaction between trade intensity and news coverage is positively associated with increased sector-pair covariance in a wide range of specifications.

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

Dep. Var.: $\rho^{IP}_{nj,mi}$	(1)	(2)	(3)	(4)	(5)	(6)
	All country-sector pairs				Domestic	Foreign
ln $\text{Trade}_{nj,mi}$	0.028***	0.013***	0.038***	0.011***	0.032***	0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.006)	(0.001)
ln $\text{Trade}_{nj,mi} \times F_{nj,mi}$	-0.166	0.152	0.508***	0.184	1.222	0.704***
	(0.165)	(0.111)	(0.170)	(0.129)	(0.782)	(0.161)
$F_{nj,mi}$	1.266		9.436***			
	(1.423)		(1.487)			
Observations	11,175	11,175	11,175	11,175	1,352	9,823
R-squared	0.090	0.653	0.190	0.659	0.734	0.659
Country-sector (n, j) FE	no	yes	no	yes	yes	yes
Country-sector (m, i) FE	no	yes	no	yes	yes	yes
Country pair FE	no	no	yes	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). The dependent variable is the correlation in 4-quarter growth rates of industrial production between country-sectors (n, j) and (m, i). The regessors are log trade intensity as in (B.7) and news coverage intensity as in (3.4). Columns 1-4 use all country-sector pairs in computing correlations. Column 5 uses only pairs where $m = n$ and Column 6 uses pairs where $m \neq n$. In all cases, the sample is restricted to pairs where a minimum of 10 years of data is available for computing correlations.

Table A7: International Comovement, Trade, and News Coverage, Robustness

Dep. Var.:	(1) $\rho^{H}_{nj,mi}$	(2) $\rho^{IP}_{nj,mi}$	(3) $\rho^{H}_{nj,mi}$	(4) $\rho^{IP}_{nj,mi}$	(5) $\rho^{H}_{nj,mi}$	(6) $\rho^{IP}_{nj,mi}$
	1Q Growth Rates		4Q Growth Rates			
			Local News		Sales Intensity	
$\ln \text{Trade}_{nj,mi}$	0.003***	0.010***	0.007***	0.010***	0.009***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.138*	0.127	0.517***	0.583***	0.201**	0.239**
	(0.073)	(0.111)	(0.094)	(0.117)	(0.087)	(0.113)
$F_{nj,mi}$			1.793***	1.471***		
			(0.417)	(0.494)		
Observations	16,653	11,325	16,032	11,175	16,032	11,175
R-squared	0.320	0.612	0.465	0.660	0.465	0.659
Country-sector FE	yes	yes	yes	yes	yes	yes
Country pair FE	yes	yes	yes	yes	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (3.3). The dependent variable is the correlation between country-sectors (n, j) and (m, i) of, alternatively, 4-quarter growth rates of hours in columns 3 and 5, 4-quarter growth rates of industrial production in columns 4 and 6, 1-quarter growth rates of hours in column 1 and 1-quarter growth rate of industrial production in column 2. The regessors are log trade intensity as in (B.7) in columns 1-4 and a final sales based measure of trade intensity in columns 5-6, and news coverage intensity as in (3.4). The news coverage is assumed to be global in columns 1,2,5 and 6, and is assumed to be local in columns 4 and 5. In all cases, the sample is restricted to pairs where a minimum of 10 years of data is available for computing correlations.

Table A8: International Comovement, Trade, and News Coverage: Covariances

Dep. Var.:	(1) $Cov^{H}_{nj,mi}$	(2) $Cov^{IP}_{nj,mi}$	(3) $Cov^{H}_{nj,mi}$	(4) $Cov^{IP}_{nj,mi}$	(5) $Cov^{H}_{nj,mi}$ Domestic	(6) $Cov^{H}_{nj,mi}$ Foreign
	4Q Growth Rates		1Q Growth Rates		4Q Growth Rates	
$\ln \text{Trade}_{nj,mi}$	0.0256***	6.96e-06	0.0629***	0.0700***	0.0548**	0.0236***
	(0.00448)	(0.00513)	(0.00458)	(0.00507)	(0.0254)	(0.00516)
$\ln \text{Trade}_{nj,mi} \times \text{News}^{global}_{nj,mi}$	0.753**	0.968**	1.897***	0.971**	5.415***	1.787***
	(0.340)	(0.376)	(0.517)	(0.429)	(1.865)	(0.505)
Observations	16,032	16,653	11,175	11,325	2,002	14,030
R-squared	0.568	0.416	0.752	0.653	0.707	0.558
Observations	12,090	12,090	10,731	10,731	1,480	10,610
R-squared	0.626	0.606	0.780	0.761	0.746	0.619
Country-sector FE	yes	yes	yes	yes	yes	yes
Country pair FE	yes	yes	yes	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) with sector-pair covariances as the dependent variables. The dependent variables are the covariances in 4-quarter growth rates of hours and industrial production between country-sectors (n, j) and (m, i) (columns 1 and 2), or the covariances in 1-quarter growth rates of hours and industrial production between country-sectors (n, j) and (m, i) (columns 3 and 4). Column 5 restricts attention to the covariance in 4Q growth rates of hours between pairs of domestic sectors, while column 6 considers only pairs of sectors in different countries. The regressors are log trade intensity as in (B.7) and news coverage intensity as in (3.4). All covariances are computed on samples with a minimum of 10 years of data.

C. Proofs

Proof of Lemma 1. The market clearing condition for the sales in country n sector j in levels is

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

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

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

The market clearing condition is then

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

The log-linearized version is

$$p_{nj,t} + y_{nj,t} = \sum_m\sum_i \frac{\pi_{nj,m}P_m\mathcal{F}_m}{P_{nj}Y_{nj}}\frac{\eta_i P_{mi}Y_{mi}}{P_m\mathcal{F}_m} + \sum_m\sum_i \frac{(1-\eta_i)\omega_{nj,mi}P_{mi}Y_{mi}}{P_{nj}Y_{nj}}(p_{mi,t}+y_{mi,t}).$$

It is easy to verify that $p_{nj,t} = -y_{nj,t}$ satisfies the equilibrium condition.

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

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

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

$$x_{nj,t} = y_{nj,t} + p_{nj,t} - p^x_{nj,t} = y_{nj,t} + p_{nj,t} - \sum_{mi}\omega_{mi,nj}p_{mi,t}.$$

The production technology implies that

$$y_{nj,t} = z_{nj,t} + \eta_j\alpha_j h_{nj,t} + (1-\eta_j)x_{nj,t}.$$

Using the expression for $p_{nj,t}$ and $x_{nj,t}$ derived earlier, we reach the following expression for the output changes in matrix form

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

Solving for $\boldsymbol{y}_t$ leads to

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

Proof of Lemma 2. In the first stage, the local labor supply condition at island (n, j, ι) is

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

The labor demand solves firms' problem

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

which leads to the following FOC

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

Combining demand and supply leads to

$$H_{nj,t}(\iota)^{1+\frac{1}{\psi}-\alpha_j}\mathbb{E}\left[P^c_{n,t}\middle|\mathcal{I}_{nj,t}(\iota)\right] = \alpha_j\eta_j(1-\eta_j)^{\frac{1}{\eta_j}-1}\mathbb{E}\left[(P^x_j)^{1-\frac{1}{\eta_j}}P^{\frac{1}{\eta_j}}_{nj}\exp(z_{nj,t})^{\frac{1}{\eta_j}}\middle|\mathcal{I}_{nj,t}(\iota)\right]K^{1-\alpha_j}_{nj}.$$

In terms of log-deviation from the trend,

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

At the country-sector level, we have

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

In matrix form,

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

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

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

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

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

which leads to

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

Proof of Proposition 2.1. It follows from the main text directly.

Proof of Proposition 2.2. Consider the response to shocks take place in country-sector (m, i). The aggregate response of firms in country-sector (n, j) takes the following form

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

The best response requires that

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

In equilibrium, it requires that

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

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

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

D. Quantification Appendix

D.1 Indirect Inference

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

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

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

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

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

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

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

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

The loading on the news coverage is a function of χ_1, which is increasing in χ_1 when χ_1 is below certain threshold. Note that absolute value of the forecast error $|e_{f,n,t}|$ follows a folded normal distribution, and the mean of it is proportional to the standard deviation of $|e_{f,n,t}|$. As a result, the coefficient β_1^M in equation (4.2) is directly related to χ_1.

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

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

Its first-order approximation is

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

Notice in this case, the product of χ_1 and τ appears in the loading on the news share. The variance of the absolute value of $e_{f,n,t} - \overline{e}_{f,n,t}$ is proportional to $\mathbb{V}_t(e_{f,n,t} - \overline{e}_{f,n,t})$, and is also directly related to $\chi_1\tau$.

Finally, the unconditional variance of the individual forecast error is

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

which helps to determine the magnitude of χ_0.

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

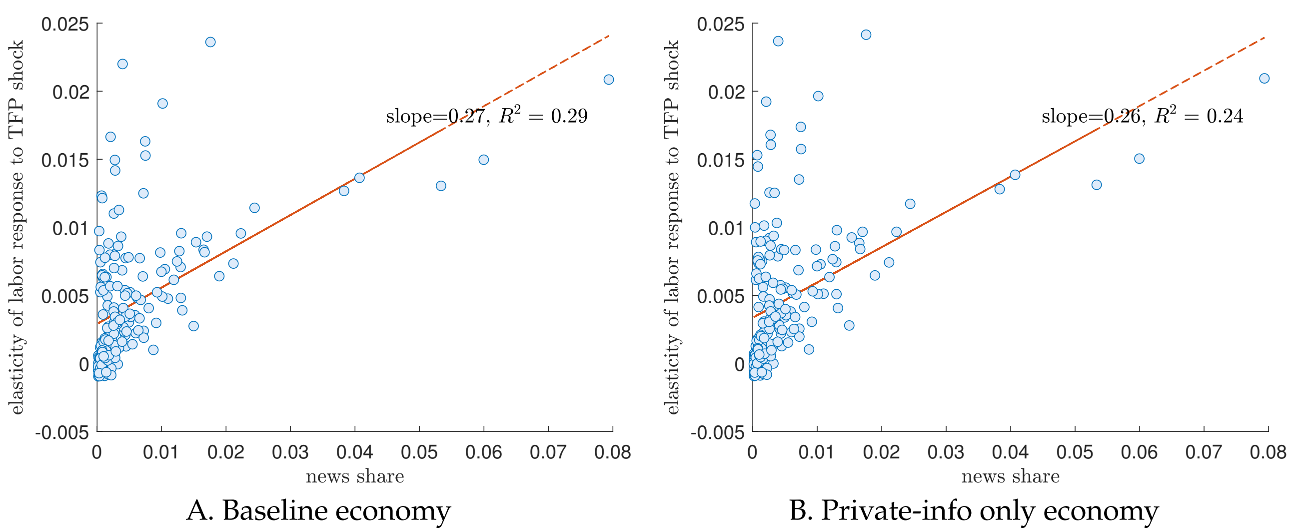
D.2 Economy with Only Private Information

This subsection reports the results in the economy where there is no public signal but the information about the fundamentals is 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. 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^2 is slightly higher in the baseline economy.

Table A9: Business Cycle Statistics

Hours volatility	(1) Private-Info Economy	(2) Baseline Economy	(3)	(4)
	TFP	TFP	Noise	Total
Canada	0.47	0.42	0.27	0.49
Germany	0.37	0.33	0.23	0.40
Spain	0.54	0.45	0.33	0.56
France	0.36	0.31	0.23	0.39
Italy	0.52	0.44	0.30	0.54
Japan	0.72	0.66	0.43	0.79
UK	0.66	0.59	0.39	0.71
US	0.68	0.64	0.32	0.71

Figure A7: News Share and TFP Shock Transmission

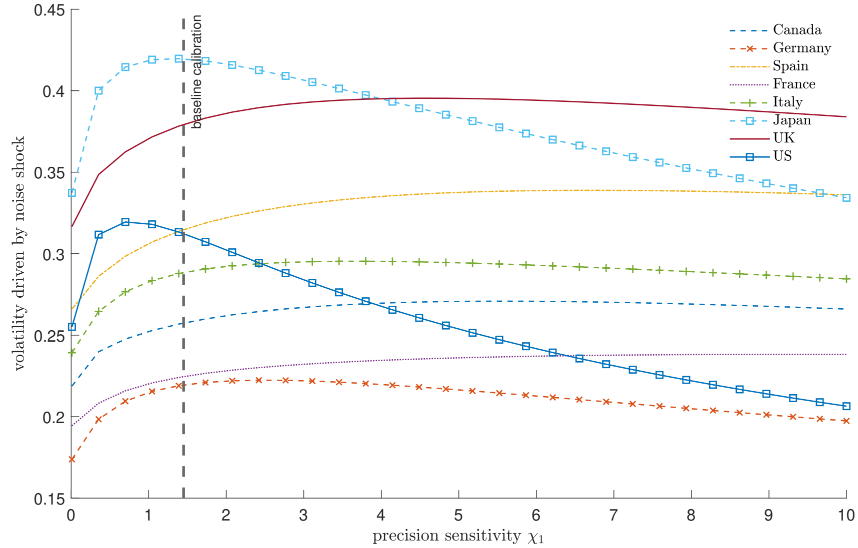


Notes: The figure displays the scatterplot of the average elasticity of total hours change in other sectors following a noise shock in a particular sector, (4.4), against the sector's share of the global news coverage, in the baseline model with informational frictions (left panel), and in the alternative economy in which all information is private (right panel).

D.3 Additional Figures

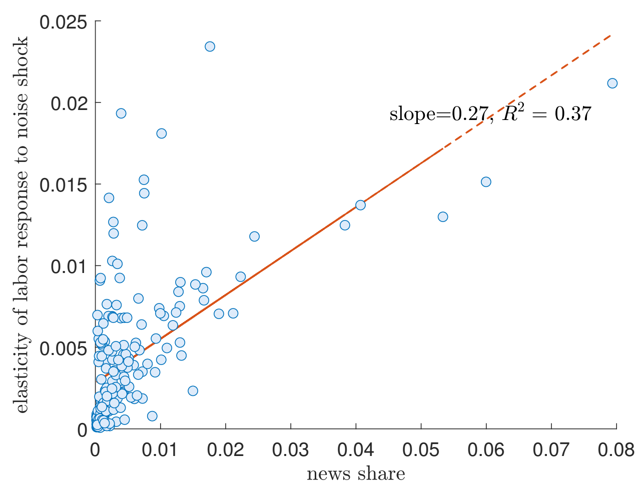
This part contains additional figures that complement the analysis in the main text.

Figure A8: Precision Sensitivity and Volatility Driven by Noise Shocks



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

Figure A9: 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.