Noisy Global Value Chains*

Ha Bui
University of Texas at Austin

Zhen Huo
Yale University

Andrei A. Levchenko
University of Michigan
NBER and CEPR

Nitya Pandalai-Nayar
University of Texas at Austin
and NBER

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Abstract

We study international propagation of both fundamental and non-fundamental shocks in a global production network model with information frictions. Producers in a sector do not perfectly observe other country-sector fundamentals, and their production decisions depend on their beliefs about worldwide exogenous states as well as other producers' behavior. In this environment, "noise" shocks – errors in the public signals about fundamentals – propagate internationally and generate aggregate fluctuations. Our key theoretical result is that noise shocks propagate relatively more powerfully to the more distant parts of the network, while TFP shocks propagate less powerfully. Using a novel panel dataset containing the frequencies of country-industry-specific economic news reports by 11 leading newspapers in the G7 plus Spain, we show that greater news coverage is associated with both smaller GDP forecast errors, and less disagreement among forecasters. We use these empirical regularities to discipline the parameters governing the severity of information frictions. We find that noise shocks are a quantitatively important source of international fluctuations.

Keywords: Information Frictions, Noise shocks, Global Value Chains, News Media, International Comovement

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1. Introduction

A long tradition going back to Keynes (1936) argues that aggregate fluctuations can arise from shocks to beliefs, such as animal spirits or sentiments. More recent work has indeed found that these types of non-fundamental shocks can be a quantitatively important source of domestic business cycle fluctuations (e.g. Lorenzoni, 2009; Angeletos, Collard, and Dellas, 2018). If non-fundamental shocks are a driver of the business cycle, it is a natural conjecture that they also propagate internationally.[1] However, the active literature on international shock transmission through trade and global value chains (GVCs) employs perfect information models. As a result, we currently lack a theoretical and quantitative framework to study the international propagation of non-fundamental shocks through GVCs.[2]

This paper makes three main contributions. Theoretically, we develop a new framework that accommodates incomplete information in global value chains, and present analytical results that characterize the propagation of both fundamental (TFP) and non-fundamental (noise) shocks through the production network. Empirically, we introduce a new panel data set on the intensity of economic news coverage of individual countries and sectors, and combine it with data on professional forecasts to discipline the key structural parameters of the theory. Quantitatively, we use the calibrated model to evaluate the impact of information frictions on international fluctuations at the macro level, and on shock transmission at the micro level.

Our main finding is that noise shocks and incomplete information are both quantitatively important in international business cycles, and generate qualitatively different fluctuations compared to the perfect information benchmark. At the macro level, noise shocks generate nearly a third of observed international comovement in hours, and aggregate fluctuations driven by noise shocks exhibit relatively stronger higher-order network effects. At the micro level, we show both theoretically and quantitatively that noise shocks propagate relatively more powerfully to the more distant parts of the network, while TFP shocks propagate less powerfully.

Theory. Our theoretical framework combines a standard model of shock transmission through GVCs with an environment characterized by dispersed information and noise shocks (Lorenzoni, 2009; Angeletos and La'O, 2010). As in the perfect-information international input network literature, our framework is fully flexible about the configuration of domestic and international trade links.

[1]There is both suggestive and formal evidence that non-fundamental shocks transmit internationally. To fix ideas, a "textbook" example of a non-fundamental shock is the dot-com boom in the United States in the late 1990s: a period of optimistic beliefs that generated an economic expansion (Angeletos, Lorenzoni, and Pavan, 2022). The expansion was broad-based globally, and spilled over to many countries that did not themselves experience a tech boom. World GDP growth rose from 2.6% in 1998 to a peak of 4.8% in 2000, falling back to 2.8% in 2001 after the dot-com bubble burst (International Monetary Fund, 2023). Additionally, Levchenko and Pandalai-Nayar (2020) provide econometric evidence that identified US sentiment shocks transmit to Canada and are an important source of Canadian fluctuations.

[2]In the closed-economy literature non-fundamental fluctuations arise from innovations to beliefs in incomplete information environments (Lorenzoni, 2009; Angeletos and La'O, 2013; Huo and Takayama, 2015). Indeed, there is abundant empirical evidence that managers are imperfectly aware of the global state (e.g. Candia, Coibion, and Gorodnichenko, 2023; Carstensen and Bachmann, 2023), attesting to the presence of information frictions in the GVCs.

There are multiple countries and sectors subject to productivity shocks, connected with each other via trade in inputs and final goods. Firms know the structure of the GVC, including which sectors they are going to buy from and sell to, and receive vectors of both public and private signals about the fundamentals in each country-sector in the world. The signals have heterogeneous precisions, allowing the severity of informational frictions to vary across country-sectors. The errors in the public signals, that we label "noise," shift aggregate beliefs about fundamentals, and are the non-fundamental shocks that can also propagate through the global value chains. Despite its richness, the model admits an analytical solution. The response of the world economy to the productivity and noise shocks is given by a generalized Leontief inverse, that is a function of the observed input-output matrix and structural parameters.

We use the model to characterize the transmission of shocks at the macro and micro levels. At the macro level, incomplete information in global value chains opens the door to international fluctuations driven by the non-fundamental noise shocks. When TFP cannot be perfectly observed, innovations to the public signals about a country-sector's TFP induce changes in its trading partners' production decisions, even if there is no change in true TFP. The noise shocks can thus be a source of aggregate fluctuations and international GDP synchronization. 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, 2024, 2023), necessitating a search for another driver of international business cycles. At the same time, introducing informational frictions dampens the fluctuations driven by TFP: agents do not fully react to foreign TFP innovations as they are not completely sure whether they took place and whether other agents are aware of them.

At the micro level, we show how information frictions affect shock propagation. As is common in input-output economies, the total impact of a shock in one sector on another sector is the sum of direct and indirect effects, the latter being transmission through input linkages with third sectors. We thus define *network distance* between two sectors as the fraction of indirect effects in the total impact of a shock: if propagation is mostly through indirect effects, network distance is greater.

Our main theoretical result is that an increase in network distance raises the impact of the noise shock, and lowers the impact of the TFP shock. That is, noise shocks propagate relatively more in sector pairs far from each other in the network. The intuition is as follows. Under incomplete information, the equilibrium outcomes are a function of infinitely many higher-order expectations, or beliefs about beliefs of others (Morris and Shin, 2002; Woodford, 2003). New in our theory, the order of expectations interacts with network distance. The first-order (in the network sense) impact of a shock on the economy is a function of first-order expectations, the second-order network impact is a function of second-order expectations, and so on. This property cannot be gleaned from the first-generation models that lack input-output relationships, but becomes evident when the input network and informational frictions are combined.[3]

[3]The early seminal contributions in the macroeconomics of dispersed information used highly stylized models with no distinction between industries or between final vs. intermediate goods. In these first-generation models, information

The public signal is relatively more useful than the private signal in forming higher-order expectations, as it is common knowledge in the economy. Since the noise shock lives in the public signal, it moves the higher-order expectations more than the first-order ones, and is thus relatively more important in higher-order network propagation that reaches the more distant parts of the network. At the same time, a TFP shock moves the higher-order expectations by less than first-order expectations because the common prior in the public information domain becomes increasingly important as the order increases, leaving the combined response to signals smaller. Since higher-order network propagation terms are tied to higher-order expectations, a given TFP shock decays faster as it moves through the network under informational frictions compared to perfect information.

Empirics. The key feature of the model is the presence of a vector of noisy public signals about each country-sector in the world economy. Our next goal is to assemble data that can be used to discipline the properties of these public signals. To do that, we use the major newspapers. Since news appearing in the major newspapers are public and highly visible, they are likely a strong correlate of the available public information about different country-sectors.

Our empirical contribution is to collect a large-scale dataset on the intensity of economic news coverage of individual countries and sectors in the major newspapers of the G7 countries plus Spain (henceforth, "G7+"). 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 these newly collected data with GDP forecasts; standard production datasets such as KLEMS and the World Input-Output Database (WIOD); and quarterly sectoral indicators such as industrial production and total hours worked. We document several basic patterns about international economic news coverage intensity. First, there are pronounced differences in the coverage intensity across industries and countries. These differences are correlated with, but at best partly accounted for by the overall size, upstreamness, or downstreamness of a sector.

Second, higher news coverage intensity is associated with lower GDP forecast errors and less disagreement among forecasters in their GDP projections. This empirical regularity suggests that more intense news coverage provides information useful for improving the accuracy of economic predictions. In contrast with recent survey evidence on expectations (e.g. Coibion and Gorodnichenko, 2015; Bordalo et al., 2020), in which the empirical tests stay agnostic about the source of information, our results connect the variation in the forecast quality to 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 require noisy *public* information or correlated noise (Lorenzoni, 2009; Angeletos and La'O, 2010; Barsky and Sims, 2012; Angeletos, Collard,

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 key heterogeneities in the production functions and information frictions. The main advantages of this environment are that (i) it leads to novel theoretical results on the interactions between the input network and information frictions; and (ii) the theory can be tightly connected with the data and used for a quantification of the role of the information frictions.

and Dellas, 2018). Our micro evidence makes it possible to discipline the role of public information, as implemented in our quantitative exercise.

Quantification. Our final contribution is to quantify the international propagation of noise shocks and the role of incomplete information in the international business cycle. We use the news coverage intensity data to pin down the key parameters governing the information structure. In particular, we posit that the precision of the public signal about a country-sector's productivity is increasing in the news coverage intensity of that country-sector. This assumption is guided by the reduced-form results, that show GDP forecasts becoming more precise and less dispersed with greater coverage intensity. We use indirect inference via the theoretical counterparts of the empirical forecast error regressions to translate coverage intensity in the data to the signal precision in the model. This exercise reveals that coverage intensity contributes strongly to making the public signal more precise. The unconditional dispersion of professional GDP forecasts further helps identify the fraction of information that is in the public versus private domain.

We simulate global fluctuations by feeding both TFP and noise shocks into our calibrated model world economy. The stochastic process for TFP is taken from the data. To be conservative, the noise shocks are assumed to be uncorrelated across countries and sectors. Noise shocks are quantitatively important: they can produce about one-fifth of the observed fluctuations in the aggregate hours worked, and about one-third of the observed international correlations in hours. At the same time, introducing information frictions reduces the standard deviation of hours generated by TFP shocks by 50%. 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, 2024). We show that incomplete information leads to correlated labor wedges in the quantitative model simulations. Thus, noise shocks provide a micro-foundation for internationally correlated labor wedges.

Informational frictions affect not only the relative importance of fundamental vs. non-fundamental shocks in the aggregate fluctuations, but also the underlying sources of aggregate volatility. We can write hours worked as a sum of the first- and higher-order network propagation terms. Introducing informational frictions reduces the importance of higher-order terms in the overall TFP-driven fluctuations. At the same time, higher-order terms are responsible for a greater share of the total hours volatility generated by noise shocks than by TFP shocks.

Next, we explore shock propagation at the micro level. We demonstrate the quantitative relevance of the main theoretical micro predictions. The relative importance of the noise shock rises in the network distance; and informational frictions dampen the propagation of TFP shocks relatively more to the more remote sectors. We also show that sectors more remote from others in the network exhibit more volatile labor wedges when fluctuations are driven by noise shocks.

Finally, we externally validate the quantitative model by examining the patterns of comovement in the cross-section of sector pairs. In the data, we document a link between news coverage and comovement in the context of a textbook "trade-comovement" regression (Frankel and Rose, 1998) at the country-sector-pair level. We relate correlations in hours or output between two country-sectors to input trade between those sectors, as well as the news coverage intensity of those sectors. In the data, sectors more covered in the news tend to experience more synchronization. We also include an interaction between news coverage intensity and bilateral trade. It turns out that sectors more covered in the news comove even more if they trade more with each other. These reduced-form correlations both serve as targets for external validation of the model, and more broadly provide statistical evidence that news coverage plays a role in international business cycle comovement. In the quantitative model, raising the news coverage intensity of a pair of sectors increases the covariance in hours worked between these sectors, and more so if these sectors trade more with each other. Thus, in contrast to a perfect information model, our model can successfully reproduce the qualitative patterns documented in the data.

In summary, the presence of informational frictions interacted with a complex production network can be quantitatively important for understanding the sources of international fluctuations and the transmission of different types of shocks. 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.

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; Bybee et al., 2023; Hébert and La'O, 2023). While previous literature quantified the role of belief shocks by matching aggregate variables (Angeletos, Collard, and Dellas, 2018), we combine novel news coverage data with cross-country expectations survey data 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.[4] Our contribution is to explore how information frictions affect shock transmission channels in the context of global supply chains.

The second is the literature on aggregate fluctuations in production networks under perfect information (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, 2019; Bigio and La'O, 2020; Carvalho et al., 2020; Foerster et al., 2022; vom Lehn and Winberry, 2022), as well as applications of these ideas and techniques to international shock transmission (e.g. Kose and Yi, 2006; Burstein,

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

Kurz, and Tesar, 2008; Johnson, 2014; Eaton et al., 2016; Eaton, Kortum, and Neiman, 2016; Bonadio et al., 2021; Huo, Levchenko, and Pandalai-Nayar, 2024, 2023; Kleinman, Liu, and Redding, 2020, 2023). We introduce and quantify the role of informational frictions and noise shocks in international comovement.

Our paper is also related to a growing literature on network games with incomplete information (Bergemann, Heumann, and Morris, 2017; Lian, 2021), especially in the context of input-output networks (Atolia and Chahrour, 2020; La'O and Tahbaz-Salehi, 2022; Pellet and Tahbaz-Salehi, 2023). The feature that the equilibrium outcome is shaped jointly by the network structure and information frictions resembles those in La'O and Tahbaz-Salehi (2022) and Pellet and Tahbaz-Salehi (2023). Building on these insights, we study the shock propagation across both sectors and borders beyond a closed-economy and we explore the differential impacts of private vs. public signals and how they interact with network remoteness. A recent contribution by Chahrour, Nimark, and Pitschner (2021) 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. In that paper the information structure is state-dependent, but there are only fundamental shocks. By contrast, in our framework the information structure is exogenous, but there are also noise shocks. Our paper also connects international news coverage data with data on expectations, quantifies the role of noise shocks in international business cycle fluctuations, and explores the interaction between the production network and incomplete information in shaping shock propagation.

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; Bianchi, Ludvigson, and Ma, 2022; Bordalo et al., 2020; Kohlhas and Walther, 2021; Angeletos, Huo, and Sastry, 2021; Fraiberger et al., 2021; Hassan et al., 2023; Bhandari, Borovička, and Ho, 2024). 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. Our paper contributes to this line of research by providing empirical evidence that greater news coverage is associated with improved quality of professional forecasts. For regular households, D'Acunto et al. (2021) shows that individuals' daily shopping experiences are informative when they forecast inflation rates. Closest to our empirical results, Carroll (2003), Lamla and Lein (2014) and Larsen, Thorsrud, and Zhulanova (2021) relate the gap in inflation forecasts between consumers and professional forecasters to the intensity of inflation news coverage. These papers focus on the regular consumers' acquisition of information that is available in the economy (i.e. possessed by the professional forecasters). In contrast, our results are about the relationship between news coverage and information available to the professional forecasters themselves.

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 some reduced-form patterns in international news coverage. Section 4 calibrates and quantifies the model. Section 5 concludes. The appendices collect proofs of propositions and additional details on theory, data, and robustness.

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.

Unlike in the standard production network models, in our framework agents face informational frictions. In each country-sector, there is a continuum of information islands indexed by ι, with a large number of competitive firms on each island. 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, households choose final consumption, and all goods markets clear at the equilibrium prices.[5]

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

[5]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, in contrast to the innovations to the public signals. Ours is the conventional timing assumption in the literature on belief shocks (e.g. Angeletos and La'O, 2013). Alternatively, firms could also choose a subset of their intermediate inputs in the first stage under incomplete information. In this case, more inputs in the production will be subject to informational frictions, which would strengthen our main results about the role of information frictions in shock propagation. We do not pursue this modeling approach for two reasons. First, it would further complicate the analysis. Second, these frictional intermediate inputs choices would manifest themselves as international trade wedges from a business cycle accounting perspective. As shown in Huo, Levchenko, and Pandalai-Nayar (2024), these trade wedges only play a secondary role in shaping international business cycles.

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 the $\pi_{mi,n}$'s capture the expenditure shares on various goods.

Our formulation of the disutility of the labor supply extends the GHH preferences (Greenwood, Hercowitz, and Huffman, 1988) to allow labor to be supplied separately to each sector and each island. It implies that the labor supply curve faced by each island is isoelastic in the real wage with 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 production. The total factor productivity shock $z_{nj,t}$ is the fundamental shock in the model economy. TFP shocks in sector (n,j) are distributed $z_{nj,t} \sim \mathcal{N}(0, \mathbb{V}(z_{nj,t}))$. For simplicity, this section assumes that these shocks are uncorrelated across sectors. We interpret K_{nj} as a fixed factor that does not change. It does not affect the substantive results but it will aid in calibrating the model to real production data.

For maximum expositional simplicity and transparency, we assume Cobb-Douglas functional forms for the preferences and the production technologies. This is not essential for any of the main insights on the effects of informational frictions. A CES specification of preferences and technology leads to a more involved expression for equilibrium prices than the one in Lemma 1 below, but the main theoretical results (Propositions 2.1 and 2.2 below) continue to hold. Appendix D.2 replicates the quantitative results under non-unitary substitution elasticities.

Second stage. In the second stage, the primary factors 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 $H_{nj,t}(\iota)$ in the first stage 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.[6]

[6]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

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. Thus, $\boldsymbol{\omega}$ is the $NJ \times NJ$ matrix of input coefficients/expenditure shares $\omega_{nj,mi}$, and $\boldsymbol{\eta}$ and $\boldsymbol{\alpha}$ are the $NJ \times NJ$ diagonal matrices of value added coefficients/shares η_i, and labor coefficients/shares α_i. Vectors of prices $\boldsymbol{p}_t$, productivities $\boldsymbol{z}_t$, and hours $\boldsymbol{h}_t$ are $NJ \times 1$, stacking country-sectors. As customary, $\mathbf{I}$ is the identity matrix of the appropriate dimensions. 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*

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

Proof. See Appendix A.1. □

In turn, both output and input prices determine profits (2.2).

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 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

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

costs, an approach common in the IRBC literature (e.g. Backus, Kehoe, and Kydland, 1992).

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

$$h_{nj,t}(\iota) = \left(1 + \frac{1}{\psi} - \alpha_j\right)^{-1} \mathbb{E}\left[\frac{1}{\eta_j} z_{nj,t} + \frac{1}{\eta_j} p_{nj,t} + \left(1 - \frac{1}{\eta_j}\right) \sum_{m,i} \omega_{mi,nj} p_{mi,t} - \sum_{m,i} \pi_{mi,n} p_{mi,t} \middle| \mathcal{I}_{nj,t}(\iota)\right]. \tag{2.3}$$

Equation (2.3) highlights that in order to decide on the optimal hours in stage 1, island ι must form expectations of what its output, input, and consumption prices will be at stage 2. 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 ($\sum_{m,i} \pi_{mi,n} p_{mi,t}$). In turn, Lemma 1 shows that forecasting these prices can be done by means of forecasting all other locations' fundamentals and hours, due to the linkages through the production network as encapsulated by the Leontief inverse $(\mathbf{I} - (\mathbf{I} - \boldsymbol{\eta})\boldsymbol{\omega})^{-1}$.

Also note that when (2.3) 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 will 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 particular information island and a public signal that is shared by all firms. First, all firms observe a public signal about TFP in each country-sector (m, i):

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

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). To keep the scale of information heterogeneity manageable, we do not differentiate the public signals by receiving country n.

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

$$x_{nj,mi,t}(\iota) = z_{mi,t} + u_{nj,mi,t}(\iota), \quad u_{nj,mi,t}(\iota) \sim \mathcal{N}(0, \tau_{nj,mi}^{-1} \mathbb{V}(z_{mi,t})) \qquad \forall m, i, \iota. \tag{2.5}$$

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 high $\tau_{mi,mi}$. 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 of that sector $\mathbb{V}(z_{mi,t})$, as in the quantification we will use actual sectoral data in which sectoral volatilities differ.

In this section we do not need to specify the source of these signals. In Section 4 below, we will interpret the public signal as coming at least in part from news stories appearing in newspapers, and the variation in the signal precision κ_{mi} will reflect the differences in the intensity of news coverage of the sector. In Section 4 we also explore a specification in which the precision of private signals falls in the network distance, in the spirit of rational inattention.[7]

Taking stock, the information set of island ι is given by $\mathcal{I}_{nj,t}(\iota) = \left\{x_{nj,mi,t}(\iota), s_{mi,t}\right\}_{i=1,\dots,J}^{m=1,\dots,N}$. The presence of private signals implies that information is dispersed, 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

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

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:*

$$\boldsymbol{h}_t = \boldsymbol{\varphi}\, \overline{\mathbb{E}}_t[\boldsymbol{z}_t] + \boldsymbol{\gamma}\, \overline{\mathbb{E}}_t\left[\boldsymbol{h}_t\right], \tag{2.6}$$

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

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

where

$$\mathbf{M} = \boldsymbol{\pi}(\mathbf{I} - (\mathbf{I} - \boldsymbol{\eta})\boldsymbol{\omega})^{-1} \tag{2.7}$$

[7] We acknowledge that to keep the framework tractable, information structure is exogenously given and non state-dependent. For example, we do not model the possibility that larger shocks, or negative shocks, are better understood by agents than smaller or positive shocks (e.g. Nimark, 2014; Chahrour, Nimark, and Pitschner, 2021). Our theory and quantification do allow for rich (albeit exogenous) cross-sectional heterogeneity in the precision of information available about different country-sectors. This heterogeneity is disciplined in the quantification with the news coverage data.

and $\boldsymbol{\pi}$ is an $NJ \times NJ$ matrix whose $(nj, mi)^{th}$ element is the final consumption share in country n on goods from country-sector (m, i).

Proof. See Appendix A.2. □

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 (2.6) and the vector of TFP changes pins down GDP in every country (see Huo, Levchenko, and Pandalai-Nayar, 2024, 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 (2.6) 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 (2024), under Cobb-Douglas preferences. It resembles the Leontief inverse, and the change in hours can be decomposed into direct and indirect effects:

$$\boldsymbol{h}_t = \underbrace{\boldsymbol{\varphi} \boldsymbol{z}_t}_{\text{direct effect}} + \underbrace{\boldsymbol{\gamma} \boldsymbol{\varphi} \boldsymbol{z}_t + \boldsymbol{\gamma}^2 \boldsymbol{\varphi} \boldsymbol{z}_t + \ldots}_{\text{indirect effect}}. \tag{2.8}$$

The direct (also called "first-order," in the network sense) effect captures the changes in hours resulting from the change in own productivity and in the world vector of prices following a vector of productivity changes, but holding every other sector's hours response fixed. The second-order effect adds the first-round change in hours. The third-order effect adds the response of hours to the first-round change in hours, and so on. All the indirect effects together encapsulate the infinite-round adjustment of hours to changes in other sectors' hours.

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 (2.6) leads to

$$
\begin{aligned}
h_{nj,t} &= \varphi_{nj,mi}\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] + \sum_{k,\ell}\gamma_{nj,k\ell}\ \varphi_{k\ell,mi}\ \overline{\mathbb{E}}_{nj,t}\left[\overline{\mathbb{E}}_{k\ell,t}[z_{mi,t}]\right] + \\
&+ \sum_{k,\ell}\sum_{o,q}\gamma_{nj,k\ell}\gamma_{k\ell,oq}\ \varphi_{oq,mi}\ \overline{\mathbb{E}}_{nj,t}\left[\overline{\mathbb{E}}_{k\ell,t}\left[\overline{\mathbb{E}}_{oq,t}\left[z_{mi,t}\right]\right]\right] + \cdots
\end{aligned}
\tag{2.9}
$$

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*

$$
\boldsymbol{h}_t = \boldsymbol{\varphi}\overline{\mathbb{E}}_t[\boldsymbol{z}_t] + \boldsymbol{\gamma}\boldsymbol{\varphi}\overline{\mathbb{E}}_t^2[\boldsymbol{z}_t] + \boldsymbol{\gamma}^2\boldsymbol{\varphi}\overline{\mathbb{E}}_t^3[\boldsymbol{z}_t] + \ldots . \tag{2.10}
$$

where $\overline{\mathbb{E}}_t^k[\cdot]$ are higher-order expectations defined recursively as in (2.9).

Proof. See Appendix A.3. ◻

Compared with the frictionless benchmark (2.8), 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 highlights the interaction between the order of expectations and the position of sectors in the production network. In particular, the order of the expectations increases together with the order of the network effect. For the direct effect, agents only need to forecast the vector of world TFP. For that forecast, they use the first-order expectations. For the second order effect, they need to forecast the endogenous response of hours to the change in TFP. For that they rely on second-order expectations, as they need to forecast what the other agents believe. For the third round effect, they need to forecast yet other agents' response to the first round change in hours, for which third-order expectations are required, and so on. So the relative importance of higher-order expectations depends on the relative positions of sectors in the production network, a point we elaborate below.

With Cobb-Douglas aggregators the elements in γ are positive in the quantitative exercise, which implies that the interactions among country-sectors are strategic complements, and the direct and indirect effects have the same sign. With CES aggregators, the signs of the elements of γ depend on the substitution elasticities and need not be positive, implying that strategic complementarity/substitutability varies by sector pair. That said, relative to the perfect information case, fluctuations will still be driven by noise shocks.

It is worth noting that the assumption that the leading eigenvalue of γ is less than 1 is only needed for the representation (2.10) of the equilibrium outcome as an infinite expansion of higher-order expectations. This assumption is sufficient but not necessary for the existence and uniqueness of the equilibrium.

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

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

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

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

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

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

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

Proof. See Appendix A.4. □

In contrast to the frictionless solution in equation (2.8), 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).

Benchmark with common precision. To see the underlying forces in a more transparent way, it is useful to explore the case in which the signal precision is homogeneous across locations.

Corollary 2.1. *Assume common precision across locations: $\tau_{nj,mi} = \tau$ and $\kappa_{mi} = \kappa$. The equilibrium outcome can be expressed as*

$$\boldsymbol{h}_t = (\mathbf{I} - \lambda_z \boldsymbol{\gamma})^{-1} \left\{ \varphi \lambda_z \boldsymbol{z}_t + (\mathbf{I} - \gamma)^{-1} \varphi \lambda_\varepsilon (\boldsymbol{z}_t + \boldsymbol{\varepsilon}_t) \right\}, \tag{2.11}$$

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

Proof. See Appendix A.5. □

We unpack Corollary 2.1 by inspecting two extreme cases. When there is only private information ($\lambda_\varepsilon = 0$), the first-order uncertainty results in a weaker response to the fundamental, $\overline{\mathbb{E}}_{nj,t}[z_{mi,t}] = \lambda_z z_{mi,t}$, as 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 with $\overline{\mathbb{E}}^k_{nj,t}[z_{mi,t}] = \lambda_z^k z_{mi,t}$. At the macro level, the response of hours can be written as $\boldsymbol{h}_t = (\mathbf{I} - \lambda_z \gamma)^{-1} \varphi \lambda_z \boldsymbol{z}_t$, which is as if the network dependence becomes $\lambda_z \boldsymbol{\gamma}$ in the "Leontief inverse" and the fundamental shock itself is attenuated by λ_z. When there is only public information ($\lambda_z = 0$), inference is still imperfect but the first-order and higher-order expectations coincide with each other, $\overline{\mathbb{E}}^k_{nj,t}[z_{mi,t}] = \lambda_\varepsilon (z_{mi,t} + \varepsilon_{mi,t})$. The response of hours becomes $\boldsymbol{h}_t = (\mathbf{I} - \gamma)^{-1} \varphi \lambda_\varepsilon (\boldsymbol{z}_t + \boldsymbol{\varepsilon}_t)$. This expression 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 $\boldsymbol{\varepsilon}_t$. In this case, the impacts of the noise shocks on the economy are uniform across lower- and higher-order network effects, as the "Leontief inverse" remains the same as in the perfect information benchmark. Finally, when both private and public information are present, the equilibrium outcome is a mixture of the two extreme cases.

2.3 Informational Frictions and Network Propagation

To capture the interaction between information frictions and shock propagation through the network in a more precise way, we proceed to define a notion of bilateral network distance.

Definition 1. *The **network distance** between (n,j) and (m,i) is:*

$$d_{nj,mi} \equiv 1 - \frac{\mathcal{T}^{(1)}_{nj,mi}}{\mathcal{T}_{nj,mi}} = \frac{\sum_{k=2}^{\infty} \mathcal{T}^{(k)}_{nj,mi}}{\sum_{k=1}^{\infty} \mathcal{T}^{(k)}_{nj,mi}}, \tag{2.12}$$

where $\mathcal{T}^{(k)}_{nj,mi}$ is the k-th order impact of productivity in (m,i) on (n,j)'s hours absent information frictions (see

2.9):

$$\mathcal{T}^{(1)}_{nj,mi} = \varphi_{nj,mi}, \qquad \mathcal{T}^{(2)}_{nj,mi} = \sum_{k,\ell} \gamma_{nj,k\ell}\, \varphi_{k\ell,mi}, \qquad \mathcal{T}^{(3)}_{nj,mi} = \sum_{k,\ell}\sum_{o,q} \gamma_{nj,k\ell}\gamma_{k\ell,oq}\, \varphi_{oq,mi}, \ldots,$$

and $\mathcal{T}_{nj,mi} \equiv \sum_{k=1}^{\infty} \mathcal{T}^{(k)}_{nj,mi}$ *is the corresponding total effect.*

Network distance is the fraction of the total impact of a shock in (m,i) on (n,j)'s hours that is due to the indirect effects when there are no information frictions. The more indirect the impact, the higher is network distance. As is clear from Lemma 2, $d_{nj,mi}$ is a function of model primitives such as the input-output matrix and consumption and factor shares, plus the Frisch elasticity. Loosely, $d_{nj,mi}$ can be thought of as a bilateral sector-pair version of the "upstreamness" indicators such as Antràs et al. (2012). In our case, $d_{nj,mi}$ is stated in terms of the sensitivity of (n,j)'s hours, and reflects distance to a production sector rather than distance to final consumption as in Antràs et al. (2012).

We now state the key proposition that describes the impact of information frictions on shock propagation through the network. Recall from Proposition 2.2 that $G^s_{nj,mi}$ is the impact of a 1-unit shock $s = \{z, \varepsilon\}$ in (m,i) on hours in (n,j).

Proposition 2.3. *Assume firms observe labor market outcome in their own country-sector. Consider an increase of the network distance via the following perturbation indexed by the sequence* $\{\delta_k\}$ *with positive elements*

$$\widetilde{\mathcal{T}}^{(k)}_{nj,mi} = \mathcal{T}^{(k)}_{nj,mi}(1+\delta_k), \quad \textit{for} \quad k > 1$$
$$\widetilde{\mathcal{T}}^{(1)}_{nj,mi} = \mathcal{T}_{nj,mi} - \sum_{k=2}^{\infty} \widetilde{\mathcal{T}}^{(k)}_{nj,mi}.$$

1. *With perfect information, the response* $G^z_{nj,mi}$ *to the TFP shock remains unchanged.*
2. *With incomplete information, the response* $G^\varepsilon_{nj,mi}$ *to the noise shock becomes larger and the response* $G^z_{nj,mi}$ *to the TFP shock becomes smaller.*

Proof. See Appendix A.6. □

The proposition describes a perturbation of the network in which the network distance $d_{nj,mi}$ increases while the total sum of the $\mathcal{T}_{nj,mi}$ impact coefficients stays constant. It states two results. When information is perfect, the network distance in and of itself is irrelevant for (n,j)'s hours response to (m,i)'s shocks, conditional on a fixed total elasticity $\mathcal{T}_{nj,mi}$. By contrast, with informational frictions a higher network distance lowers the importance of fundamental shocks, and raises the importance of the noise shocks, even holding $\mathcal{T}_{nj,mi}$ constant.

Under incomplete information shock propagation is jointly determined by the network properties and higher-order expectations. The proof of Proposition 2.3 proceeds to show that higher-order expectations react progressively less to innovations in true TFP, and react progressively more to the noise shocks. The intuition is that the common prior and the public signals are more useful in forecasting the beliefs of others. Thus agents rely on them increasingly more to form higher-order expectations, in the process becoming more susceptible to the noise shocks. The increasing reliance on the common prior leads to a reduction in the response to the sum of private and public signals, and therefore to the TFP shocks that appear in both signals. The network distance measures the weight put on those higher-order expectations (Proposition 2.1). An increase in the network distance in Proposition 2.3 shifts more weight to those higher-order expectations, reducing the overall response to the fundamental and increasing the response to noise.[8]

Illustration. In the general case, the k-th order response is a complicated function of the full network, as encapsulated by the impact matrix $\gamma^k\varphi$ (see 2.10). To illustrate the interaction between the production network and incomplete information, we consider a stylized vertical network. We begin by arbitrarily ordering all country-sectors by their upstreamness, where the most upstream sector is 1 and the most downstream sector is NJ. To make the results as transparent as possible, we assume that only the most upstream sector is subject to the fundamental shock $z_{1,t}$, all other sectors' TFP shocks are muted, and consider a vertical network such that

$$h_{1,t} = \mathbb{E}_{1,t}[z_{1,t}], \qquad h_{k,t} = \mathbb{E}_{k,t}[h_{k-1,t}] \quad \text{for } k > 1.$$

That is, only sector 1 has a first-order reaction to its own TFP shock. All the other sectors react only to expected hours changes in the sector directly upstream, with a unitary elasticity. This implies that sector k's total impact coefficient on beliefs about $z_{1,t}$ is given by the k-th order coefficient: $\mathcal{T}_{k,1} = \mathcal{T}_{k,1}^{(k)} = 1$. That is, the transmission is via higher-order network effects for more downstream sectors.

Figure 1 displays the responses of hours to TFP and noise shocks as a function of the sector's downstreamness k. With perfect information, the equilibrium outcome in this stylized economy is simple: all country-sectors k respond one-for-one to the fundamental shock:

$$h_{k,t} = z_{1,t} \quad \forall k \in \{1, \dots, NJ\}.$$

That is, the shock transmits to other country-sectors perfectly. This is depicted by the solid blue line. By contrast, with information frictions the transmission is imperfect, and sectors at different points in the supply chain react differently to the same shock. The following proposition characterizes this stylized economy's responses to shocks under imperfect information.

Proposition 2.4. *Assume the precision of the public signal is $\kappa_1 = \kappa$ and the precisions of the private signals are $\tau_{k,1} = \tau$ for all k. A sector k production stages downstream from sector 1 has the following equilibrium*

[8] We stress that the results in Proposition 2.3 are not due to any systematic variation in the precision of information with network distance. They hold even if the information precision about different country-sectors is identical.

hours:

$$h_{k,t} = \overline{\mathbb{E}}^{k}_{k,t}[z_{1,t}] = G^z_k z_{1,t} + G^\varepsilon_k \varepsilon_{1,t},$$

where G^z_k is decreasing in k and G^ε_k is increasing in k:

$$G^z_k = \frac{1}{1+\kappa}\left(\kappa + \left(\frac{\tau}{1+\kappa+\tau}\right)^k\right), \qquad G^\varepsilon_k = \frac{\kappa}{1+\kappa}\left(1 - \left(\frac{\tau}{1+\kappa+\tau}\right)^k\right). \tag{2.13}$$

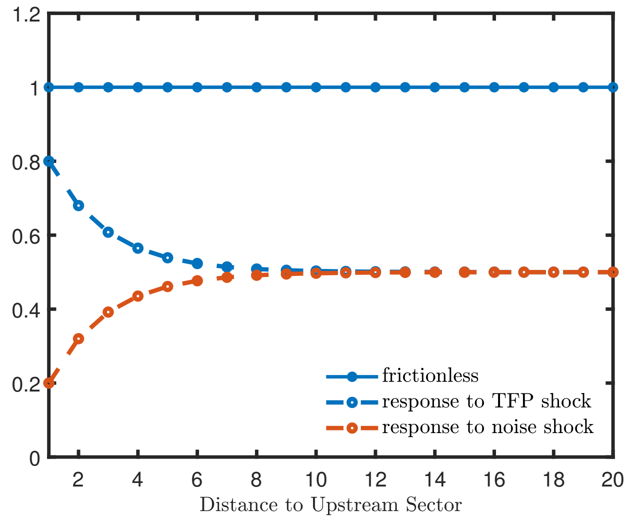
Proof. See Appendix A.7. □

This proposition states two basic properties of the interaction between informational frictions and the network structure. First, the response to the fundamental shock $z_{1,t}$ is smaller for more downstream sectors (higher k). This is depicted by the dashed blue line in Figure 1. Note that this is in contrast to the response to the exact same fundamental shock under perfect information, where the response does not decay downstream. Second, the hours response to the noise shock $\varepsilon_{1,t}$ is stronger in the more downstream sectors, as depicted by the dashed red line in Figure 1. To describe the result differently, an island's policy function translates the private and public signals into the hours response. As one moves further downstream, the higher is the responsiveness of sectoral hours to the public signal and the lower is the responsiveness to the private signal. Since in the policy function the coefficient on the public signal is the coefficient on the noise shock $\varepsilon_{1,t}$, noise plays a bigger role in the fluctuations of hours in more downstream sectors. For the TFP shock $z_{1,t}$, the reduced response to the private signal dominates the increased response to the public signal, attenuating the total response to the TFP shock in sectors further downstream.

Proposition 2.4 is best understood via the role of higher-order expectations. Each sector needs to forecast the hours of the sector immediately upstream from it. Take the sector immediately downstream from sector 1. By assumption, its hours do not depend directly on its expectation of $z_{1,t}$, but do depend on the sector 1 hours $h_{1,t}$. Thus, the downstream sector needs to forecast the endogenous response of $h_{1,t}$. To do that requires evaluating a second-order expectation, namely sector 2's belief about sector 1's beliefs. For that, the public signal is more useful than the private signal, as it is common knowledge that both sector 1 and sector 2 are observing the same public signal. The public signal is a better window into the beliefs of others than the private signal. Then sector 3 has to forecast the hours of sector 2. Since 3 is further downstream from the fundamental shock than 2, it is even less important to 3 what the true fundamental is. To forecast 2's hours, it needs to form expectations about 2's beliefs about sector 1's hours. Because the public signal is common to sectors 1, 2, and 3, it is relatively more important in evaluating the third-order expectation, and thus sector 3 relies even more on the public signal than sector 2.

Since the public signal is simply true TFP plus noise, putting progressively more weight on the public signal has the direct consequence that the noise shock has a greater effect on hours. Indeed,

Figure 1: Hours Response in a Vertical Network



Notes: This figure displays the response of hours in a vertical network to a shock in the most upstream sector as a function of sector downstreamness. The solid line displays the response to a TFP shock in the environment without information frictions. The dashed lines display the hours responses to a TFP shock (blue) and noise shock (red) under incomplete information. The calibration uses $\lambda_z = 0.6$ and $\lambda_\varepsilon = 0.2$.

by about sector 12, the responses of hours to true TFP and to the noise shock coincide. This means that from sector 12 onwards, it is as if sectors only rely on the public signal to make its hours supply decision. Meanwhile, the same fundamental shock $z_{1,t}$ moves higher-order expectations by less than lower-order ones, attenuating the transmission of the TFP shocks further downstream.

This section defines a vertical network directly in terms of impact matrices, rather than the structural parameters such as input-output coefficients. This is done for maximum clarity in conveying the key intuition. Appendix A.8 presents the results of a vertical network example in which the "snake" network is defined more conventionally by the coefficients of the input-output matrix. In this case, responses to all shocks under all informational structures decay further downstream. However, it is still the case that the public signal matters relatively more in the 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. To do this requires data that can be used to discipline not only the global production structure, but also the informational frictions.

3. Data

The calibration of our model uses several sources of data.

Global sectoral news data. Our key empirical contribution is to assemble a novel database of international economic news coverage. Our data collection spans the main national newspapers in the G7 countries plus Spain over the period 1995-2020. 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 in a particular quarter.

The information is sourced from Dow Jones Factiva, a news database. 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.[9] 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 A2 displays the concordance between Factiva sectors and ISIC Rev. 4. All in all, there are 131 country-sectors. In principle data are available daily, but to merge with the other economic time series we aggregate to quarters.

There are a number of nuances in this process, discussed in detail in Appendix B.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. While we do not collect information on what is reported in the news – such information would be challenging to gather systematically manually – we provide suggestive evidence on types of news content in Appendix C.1.[10]

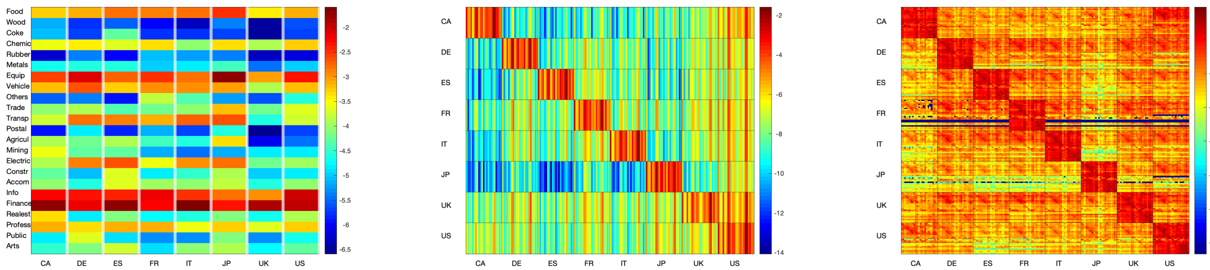
Basic patterns in economic news data. We document some patterns in these novel data, highlighting that country-sector news coverage is cross-sectionally heterogeneous, and only weakly correlated with observables.

As a visual illustration of the cross-sectional heterogeneity, Panel A of Figure 2 plots the domestic sector shares in local news coverage. 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

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

[10] Our data are related to but distinct from the approach in Baker, Bloom, and Davis (2016), who collect the frequency of newspaper articles with certain keywords and use the time variation in the frequency to construct a policy uncertainty index. In contrast, we emphasize news coverage frequency *shares* for any country-sector instead of time variation in total coverage. As we show below, this captures most of the variation in our news coverage intensity data.

Figure 2: News Coverage and Input-Output Heat Maps



A. Sectoral News Coverage

B. Bilateral News Coverage

C. Input-Output Matrix

Notes: This figure displays heatmaps of local news coverage shares. Panel A presents the news coverage about the sector on the y-axis in newspapers in countries on the x-axis. Panel B displays the heat map of the bilateral news coverage of country-sectors on the x-axis in newspapers in countries on the y-axis. The colors code the share of the y-axis country news coverage about the x-axis country-sector in the y-axis country's total news. For reference, Panel C displays the heat map of the input-output matrix. The colors code the share of the y-axis country-sector's sales to the x-axis country-sector in the x-axis country-sector's total sales. In panels B and C sector labels are suppressed due to lack of space. All non-zero shares are logged to improve legibility.

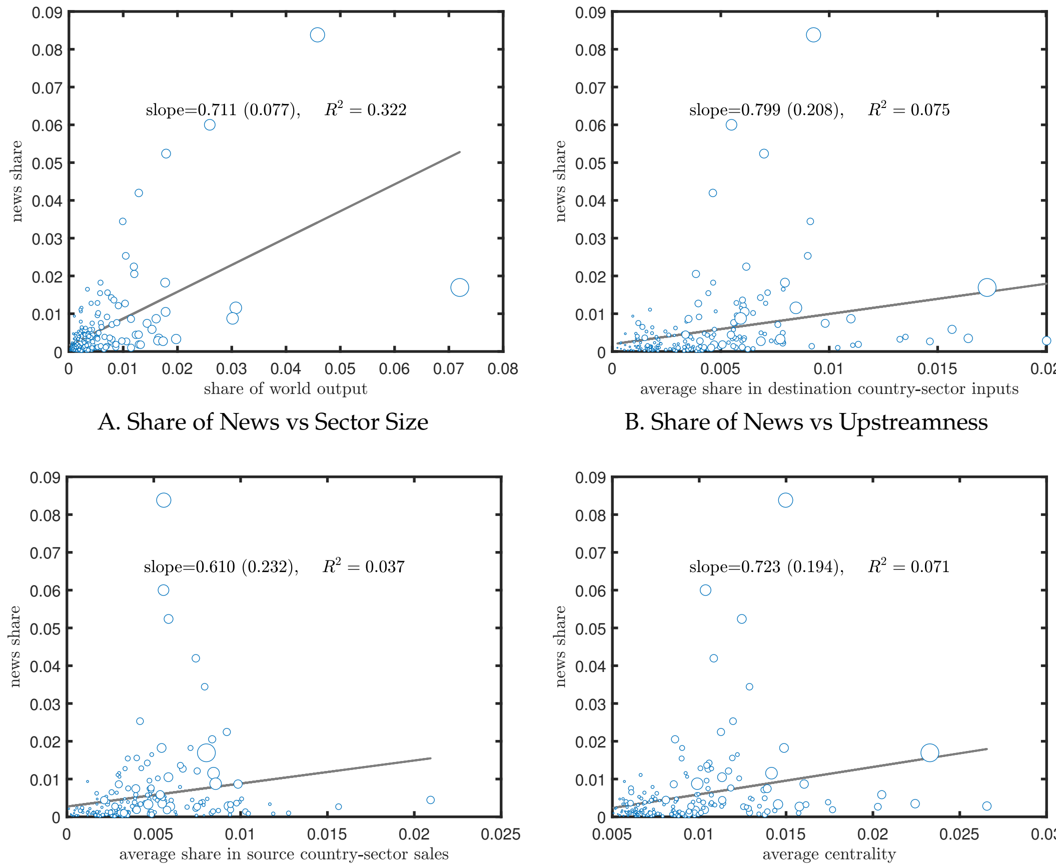
countries. Panel B of Figure 2 depicts a heatmap of local news coverage shares (averaged over time), and contrasts it to a standard input-output heatmap in Panel C (e.g. Huo, Levchenko, and Pandalai-Nayar, 2024). While both news coverage shares and input shares are higher for domestic sectors, as evident 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). As documented for the U.S. by Chahrour, Nimark, and Pitschner (2021), there is indeed a positive association. However, for our sample 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.[11] Finally, Panel D considers the Bonacich network centrality as a single summary measure of how important the sector is in the global 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 C.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

[11] Upstreamness and downstreamness are defined in Appendix C.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. The size of the circles corresponds to the country-sector's share in world output.

news coverage and sectoral TFP growth, and news coverage and sectoral comovement with aggregate GDP (Appendix Figure A5). None of these observables systematically explain a majority of news coverage.

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 include professional forecasters from business, academia, and industry groups. To compute forecast errors, we combine Consensus Forecasts with the actual GDP growth from the IMF World Economic Outlook database. Appendix B.2 describes these data in detail.

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 classifications and in levels of disaggregation, we concord each individual data source to our 23 ISIC-Revision 4 sectors for each country. The panel covers the entire private economy over the years 1972-2020, but is unbalanced. Appendix B.3 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.

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.

4. Quantification

This section begins by describing how we use the news coverage intensity data to discipline the key parameters of our model. We then study the calibrated model's quantitative properties. We first present the macro implications, that quantify the roles of TFP and noise shocks in aggregate volatility and international comovement. We then turn to the micro implications, and show how TFP and noise shocks propagate through the network. Next, we externally validate the model by documenting the relationship between news coverage and comovement in real variables, both in the data and in the model. Finally, we develop several extensions: (i) varying the precision of the public signal contained in the news coverage; (ii) exploring the differential implications of public vs. private information, and (iii) allowing for the private signal precision to decay in network distance, capturing the notion that agents might have better information about neighboring sectors than more distant ones.

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 calibrate the Frisch elasticity to 2, a common value in the business cycle literature. 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 $\pi_{mi,n}$ and input expenditure shares $\omega_{mi,nj}$ are taken from WIOD. The top panel of Table 1 summarizes these calibration choices. While the main text presents the results under Cobb-Douglas functional forms for the final and intermediate input bundles, Appendix D.2 replicates the quantitative results under non-unitary substitution elasticities.

The more novel aspect of our quantitative framework is the information frictions. Recall from (2.4) and (2.5) that these frictions are pinned down by two vectors of parameters, the private signal precision $\tau_{nj,mi}$ and the public signal precision κ_{mi}. To complete the calibration of the model, we must set values to these parameters. Since news appearing in the major country newspapers are public and highly visible, our approach is to use the news coverage intensity data to discipline the variation

Table 1: 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. The indirect inference procedure for calibrating χ_0 and χ_1 is described in detail in the text.

in the public signal precision about different country-sectors. The challenge is that while we observe news coverage frequencies, we do not directly observe agents' public signals obtained from the news coverage. Thus, we need to establish a connection between the news coverage intensity and agents' information sets. We do that by estimating an empirical relationship between news coverage and forecast errors and forecast dispersion. We then use indirect inference to pin down the $\tau_{nj,mi}$'s and κ_{mi}'s by running the same regressions inside the model.

News coverage and information frictions: empirical results. We begin by establishing that greater news coverage is associated with smaller absolute forecast errors using the following specification:

$$\left|\text{forecast error}\right|_{f,n,t} = \beta_0 + \beta_1 \log F_{n,t} + \delta_{f,n} + \delta_t + \nu_{f,n,t}, \tag{4.1}$$

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.[12]

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

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

Table 2 reports the results for nowcasts in Panel A, and one-year ahead forecasts in Panel B. Estimates of equation (4.1) 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:

$$SD\left(\text{forecast error}_{f,n,t}\right)_{n,t} = \beta_0 + \beta_1 \log F_{n,t} + \delta_n + \delta_t + \varepsilon_{n,t}, \tag{4.2}$$

where the dependent variable is the standard deviation across forecasters of GDP forecasts for 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. Panels A-B, columns 2 and 4 of Table 2 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.

Robustness. Appendix C.2 presents a series of robustness checks that control in a flexible way for a variety of confounders that could potentially affect both forecast precision and news coverage intensity. The baseline fixed effects absorb some potential confounders, for instance, forecaster-country specific factors that affect forecast precision independent of news coverage, and global shocks that could raise the level of news coverage and change forecast precision at the same time. Conditional on these fixed effects, a potential concern that there is some other variable that creates time series variation in the forecastability of GDP and at the same time is correlated with news coverage intensity. The appendix adds controls for nonlinear transformations of productivity and news sentiment indices; monetary policy; and the political cycle.[13] It also contains additional checks, such as using expectations of the unemployment rate instead of GDP, and alternative weighting for sectoral news coverage.

Calibration of information friction parameters. These estimation results cannot be used to calibrate unrestricted vectors of $\tau_{nj,mi}$'s and κ_{nj}'s. Therefore, we must shrink the parameter space of the signal precisions. We make the following assumptions. The public signal precision in the theory has an

[13]Note that these robustness results do not address the possibility that agents learn about the public signal shocks through non-newspaper sources such as social media. Our indirect inference procedure will calibrate the signal precision parameters under the assumption that greater news coverage of a country-sector is correlated with the availability of public information. We do not require that agents literally get all of their public signal from newspapers.

Table 2: Global News Coverage and Forecast Errors

	(1)	(2)	(3)	(4)
	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
Dep. Var.	$\lvert$forecast error$\rvert$	SD (forecast error)	$\lvert$forecast error$\rvert$	SD (forecast error)
$\log F_{n,t}$	-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	0.470	0.645	0.696	0.408
Time FE	yes	yes	yes	yes
$f \times n$ FE	yes		yes	
n FE		yes		yes

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

affine relationship to the observable news coverage intensity:

$$\kappa_{nj} = \chi_0 + \chi_1 F_{nj}, \tag{4.3}$$

where F_{nj} is the average frequency share of sector (n, j) in the global news coverage as in (4.1)-(4.2). 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 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 (4.1) and (4.2) 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 (4.1) and (4.2) 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 (n, j).[14] And third, while the theoretical model is static, the empirical regressions rely on within-forecaster variation in forecast quality and news coverage over

[14] Since our news coverage data are at the country-sector-time level, it would have been desirable to relate news coverage to forecasts of sectoral output/value added, rather than of GDP. Regrettably, we could not find a dataset of sectoral forecasts that covers our countries and sectors.

time. There is no viable alternative to this, as forecaster fixed effects are essential in the empirics in order to absorb confounding factors. To align the model environment more tightly with the data and the empirical variation we use, we make the following auxiliary assumptions.

Let there be forecasters, who have no role in any real outcomes in the economy, but who also extract signals about the economy. Similar to firms in the model, the forecasters receive a private signal and a public signal about each country-sector (n, j). To better connect with the empirical regressions, we assume the forecasters differ from firms in the model in two ways. First, the forecasters do not observe any sector's fundamental perfectly. And second, instead of fixing the precision of public signals based on the average news share, we allow the precision to change with the news share over time as in the data, i.e, for the forecasters, $\kappa_{nj,t} = \chi_0 + \chi_1 F_{nj,t}$. While our model is static, this approach allows us to exploit the longitudinal variation in the data for the purposes of calibrating these critical parameters.[15] The forecasters assume that the firms' and workers' signal precision for all country-sectors is given by (4.3) 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 run the following regressions on model-generated data:

$$\mathbb{E}\left[\left|v_{nt} - \mathbb{E}_{f,t}[v_{nt}]\right|\right] = \beta_{01}^{M} + \beta_1^{M} \log F_{n,t} + \delta_n + \nu_{nt} \tag{4.4}$$

$$\text{SD}\left(v_{nt} - \mathbb{E}_{f,t}[v_{nt}]\right) = \beta_{02}^{M} + \beta_2^{M} \log F_{n,t} + \delta_n + \nu_{nt}. \tag{4.5}$$

These are the model counterparts to the empirical specifications (4.1) and (4.2). In equation (4.4), 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 (4.5), the dependent variable is the theoretical standard deviation of the cross-sectional forecast error in every period.

Table 3 displays the moments generated by the model and compares them to the data counterparts. The calibrated model matches well the empirical relationships between the forecast levels and dispersion and news coverage, as well as the unconditional dispersion. The bottom panel of Table 1 lists the implied values of τ, χ_0, and χ_1.

Identification. It is not always transparent in indirect inference procedures which of the three data moments "identify" which structural parameter. Relatedly, while the empirical regressions control for a large variety of confounders, we cannot rule out all potential omitted variables. Thus, there remains a possibility that the coefficient estimates targeted by the indirect inference procedure are biased. We use the approach proposed by Andrews, Gentzkow, and Shapiro (2017) to address these two issues.

[15]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.

Table 3: Information Friction Parameter Calibration: Model vs. Data

	Data	Model
Indirect inference		
Slope, $\lvert$forecast error$\rvert$	-0.082	-0.082
Slope, SD (forecast error)	-0.030	-0.034
Unconditional moment		
SD (forecast error)	0.072	0.069

Notes: This table reports the fit of the calibration procedure for the information frictions parameters. The targets are (i) the slope coefficient in the forecast error regressions (4.1) (Slope, $\lvert$forecast error$\rvert$), (ii) the slope coefficient in the forecast dispersion regression (4.2) (Slope, SD ($\lvert$forecast error$\rvert$)), and (iii) the cross-country average of the unconditional standard deviation of the nowcast error of the GDP growth rate. The column labeled "Model" displays the same moments in the model, namely the slope coefficients from estimating regressions (4.4) and (4.5) and the unconditional dispersion of the forecast errors, under the best-fit values of $\{\tau, \chi_0, \chi_1\}$.

Andrews, Gentzkow, and Shapiro (2017) advocate reporting a measure of *sensitivity*, which in the context of our indirect inference procedure amounts to the matrix of derivatives of the model-implied coefficients with respect to the structural parameters. Appendix Table A13 reports the full 3×3 matrix (3 moments × 3 structural parameters). Figure 4 displays the relationship between each moment on the y-axis and the structural parameter that to which it is most closely related. The forecast error coefficient is most sensitive to the slope of the precision of the public signal with respect to news coverage χ_1 (left panel). The forecast dispersion coefficient is most sensitive to the precision of the private signal τ (middle panel).

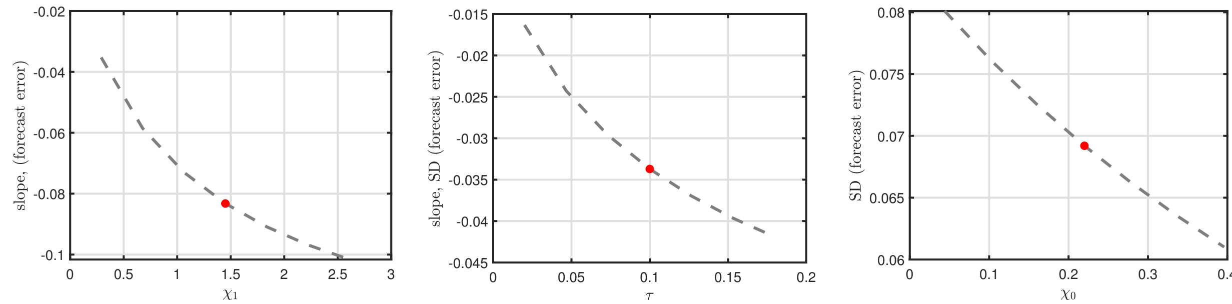
To build intuition for how the empirical estimates inform the model parameters, Appendix D.1 shows that under some simplifying assumptions, the coefficient in equation (4.4) is related to the slope χ_1, and the coefficient in equation (4.5) is related to the product of χ_1 and the precision of private signal τ:

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

The intuition is as follows. The slope of the relationship between the news coverage intensity and the quality of the forecasts (4.1)/(4.4) contains information on how much the public signal precision improves with more news coverage. Because the forecasters rely on both private and 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 (4.2)/(4.5) is informative about both the private signal precision and the slope of the news-public signal precision relationship.

Finally, the unconditional forecast dispersion is in theory affected by all 3 parameters. Since χ_1 and τ are most closely tied to the other two moments both theoretically and in the data, the right panel of Figure 4 plots the unconditional forecast dispersion against the remaining parameter, the intercept χ_0.

Figure 4: Sensitivity and Identification



Notes: This figure plots the sensitivity of model moments to the parameters uncovered by indirect inference. The left panel illustrates how the coefficient β_1^M in (4.4) varies with χ_1. The center panel illustrates how the coefficient β_2^M in (4.5) varies with τ. The right panel illustrates how the model analog of the unconditional dispersion of forecasts varies with χ_0.

Figure 4 also speaks to the potential impact of biases in the empirical regression coefficients targeted by the procedure. Going from the y- to the x-axis conveys how much the structural parameters would change if they were targeting a different coefficient. The y-axis scale is set to approximately ±1 standard error of the estimates in Table 2. The figure shows that any bias in the estimated coefficients that is within 1 standard error of the baseline estimate would result in a range of χ_1 from about 1 to 2 (our baseline value is 1.45). Over this entire range, it is still the case that news coverage is positively associated with public signal precision.

Shock processes. 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 (2023). 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.

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.[16] This assumption helps ease the computation burden, though our main results remain valid when we impose full rationality. 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 (2.10).

[16] A similar form of bounded rationality is assumed in Gabaix (2014) and Lian (2021).

4.2 Macro Implications

Section 2 establishes that under incomplete information, international fluctuations can arise from both fundamental and non-fundamental shocks, and that the shock transmission channels are modified relative to the perfect information benchmark. This subsection explores the quantitative implications of incomplete information for macro volatility and international comovement.

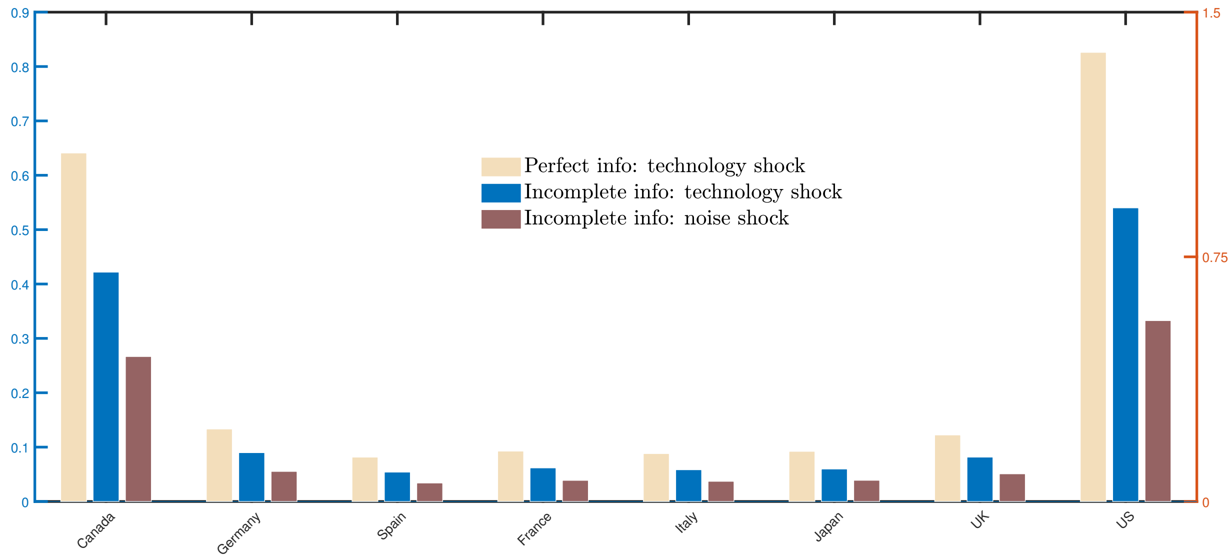
We start with some impulse response exercises. Figure 5 shows the changes in hours in response to a one standard deviation TFP shock in all sectors in the US. (Because the response of the US hours to a US shock is by far the highest in the sample, it is displayed on the right scale.) The beige bars display the hours changes in the perfect information model. As is common in network propagation models, the impact is uneven, with by far the largest hours change in the US itself, and the second-largest change in the economy most closely connected to it, Canada. The blue bars depict the hours 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. This is intuitive: when agents do not perfectly know the TFP shock, they will not react fully to it. When facing such uncertainty about the fundamentals, agents also rely on signals when making their production decisions. It follows that the noise shocks in the public signal contribute to international fluctuations. The brown bars in Figure 5 show the changes in hours in response to a one standard deviation noise shock in all sectors in the US. World output goes up following a positive noise shock about US TFP. The impact is once again strongest in the US itself (right axis), and second-strongest in Canada.

Table 4 displays the business cycle statistics of hours growth, aggregated at the country level. The first row illustrates the two basic implications of incomplete information: it attenuates the response to the fundamental shocks while opening the door for non-fundamental fluctuations. Column 1 presents the standard deviation of hours growth under perfect information and only TFP shocks. Column 2 instead feeds in the same TFP shocks, but under informational frictions. The standard deviation of growth in hours worked coming from TFP shocks falls by half compared to the perfect information case. On the other hand, fluctuations generated by noise shocks are about 65% of those driven by fundamental shocks. Putting the TFP and noise shocks together in column 4, the model generates around one-third of the average volatility of hours observed in the data (last column).[17]

Direct vs. indirect effects. Informational frictions affect not only the relative importance of fundamental vs. non-fundamental shocks in the aggregate fluctuations, but also the underlying channels through which the shocks propagate in the economy. Recall from Section 2 that hours are driven

[17]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 several other dimensions, including inability to match empirical evidence on the international transmission of noise shocks (Levchenko and Pandalai-Nayar, 2020), and inability to match the observed international comovement with TFP shocks (Huo, Levchenko, and Pandalai-Nayar, 2024); and (ii) neither model aims to match empirical hours growth volatility, which would require more shocks and possibly correlated shocks.

Figure 5: Response to US TFP and Noise Shocks



Notes: This figure displays the change in hours worked in each country following a 1-standard deviation TFP or noise shock in the US. The beige bars show the hours change due to a TFP shock without informational frictions. The blue bars show the hours change due to a TFP shock in the baseline model with imperfect information. The brown bars show the hours change in response to a noise shock in the US. 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.

by both direct (changes in expected fundamentals) and indirect effects (changes in other sectors' expected hours).[18] With incomplete information, the direct effects are arrested by first-order uncertainty about the fundamental while indirect effects are arrested by higher-order uncertainty. A fundamental shock moves higher-order expectations by less than the first-order expectations, which implies that firms' beliefs about their upstream suppliers' and downstream customers' changes in hours are less important in production decisions. It follows that informational frictions weaken the indirect effects of TFP shocks, relative to the perfect-information benchmark. The second row in Table 4 confirms this intuition. It reports the ratio of the standard deviation of hours due to the indirect effects to the standard deviation of hours due to direct effects. The relative volatility of indirect to direct effects declines from 0.47 to 0.40 when going from perfect to imperfect information (column 1 vs. column 2).

Turning to the noise shocks, public signals are more useful than private ones in forming expectations about others' beliefs. Because noise shocks live in the public signals, noise is more important in shaping higher-order expectations than first-order expectations. Since the indirect effects are a function of higher-order expectations, the volatility due to indirect effects relative to direct effects is higher for noise-driven fluctuations compared to TFP-driven fluctuations, as evident in Table 4 (0.56 vs. 0.4).

[18]The direct effects are often referred to as "first-order" (in the network sense), and the indirect effects are often referred to as "higher-order" (again in the network sense).

Table 4: Business Cycle Statistics

	(1) Perfect Information	(2) Incomplete Information	(3)	(4)	(5) Data
	TFP	TFP	noise	both	
Hours volatility	0.99	0.50	0.30	0.59	1.55
indirect vs direct effects: $\frac{\sigma_{\text{indirect}}}{\sigma_{\text{direct}}}$	0.47	0.40	0.56	0.44	
Bilateral hours correlation					
uncorrelated noise	0.09	0.11	0.06	0.10	0.19
correlated noise	0.09	0.11	0.30	0.17	
Bilateral labor wedge correlation					
uncorrelated noise	—	0.06	0.03	0.05	
correlated noise	—	0.06	0.24	0.12	

Notes: For hours volatility, this table reports the mean across the G7+ countries of the standard deviation of aggregate hours. For bilateral correlation, this table reports the mean of bilateral correlation of aggregate hours or the labor wedge between all possible G7+ country pairs. The Data column reports the volatility or bilateral correlation of four-quarter growth rates of aggregate hours, excluding the years 2008 and 2009 from the sample.

Comovement. The noise shocks also induce international comovement. In our baseline model, 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 4 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 nearly a third of this correlation, 0.06. We next relax the assumption that noise shocks are uncorrelated internationally. To discipline this exercise, we turn to the identified sentiment shocks in the US and Canada in Levchenko and Pandalai-Nayar (2020), which yields a country-level noise shock correlation of 0.18. Thus, we impose a covariance matrix for the noise shock such that the bilateral correlation of noise shocks at the country level matches this estimate. The results are reported in the row labeled "correlated noise." The bilateral hours correlations increase significantly. The model correlation with both TFP and noise shocks is quite close to the observed hours correlation.[19]

Labor Wedge. With incomplete information, the marginal rate of substitution (MRS) and the marginal product of labor (MPL) are equalized only in expectation ex ante, but not necessarily ex post. As a result, a noise shock produces a divergence between MRS and MPL, and appears as a labor wedge, as discussed in Angeletos and La'O (2010). What is unique in our setting is that

[19] Incorporating information frictions and a new source of aggregate fluctuations need not in general increase international comovement. Whether comovement increases or decreases relative to perfect information will depend on the production network, the nature of information frictions, and the properties of the shock processes, and is thus a quantitative question.

the fluctuations in the labor wedges help understand international comovement. Huo, Levchenko, and Pandalai-Nayar (2024) show in an international business cycle accounting exercise that labor wedges are correlated internationally, and that the labor and the efficiency (TFP) wedges are the two most important ones when it comes to accounting for observed international comovement. Our incomplete-information model generates internationally correlated labor wedges, as reported in the bottom panel of Table 4. The modest correlation in the noise shocks we consider in the table generates a notable correlation in the labor wedge, 0.12.

4.3 Micro Implications

Beyond generating aggregate fluctuations, our framework delivers a rich set of implications at the micro level on the patterns of propagation of different shocks through the input network.

Interaction between noise shocks and network effects. Proposition 2.3 highlights that following a shock to (m, i), the responses of the country-sectors more remote from (m, i) in the network distance tend to put a higher weight on higher-order expectations and therefore respond more to the noise shock and less to the TFP shock. The theoretical result is stated holding constant the total perfect-information impact encapsulated by $\mathcal{T}_{nj,mi}$. In the real input-output data, sector pairs differ widely in their physical input linkages. To control for this, we examine relative impact of TFP and noise shocks as the network distance varies, by fitting the following relationship in the model's simulation:

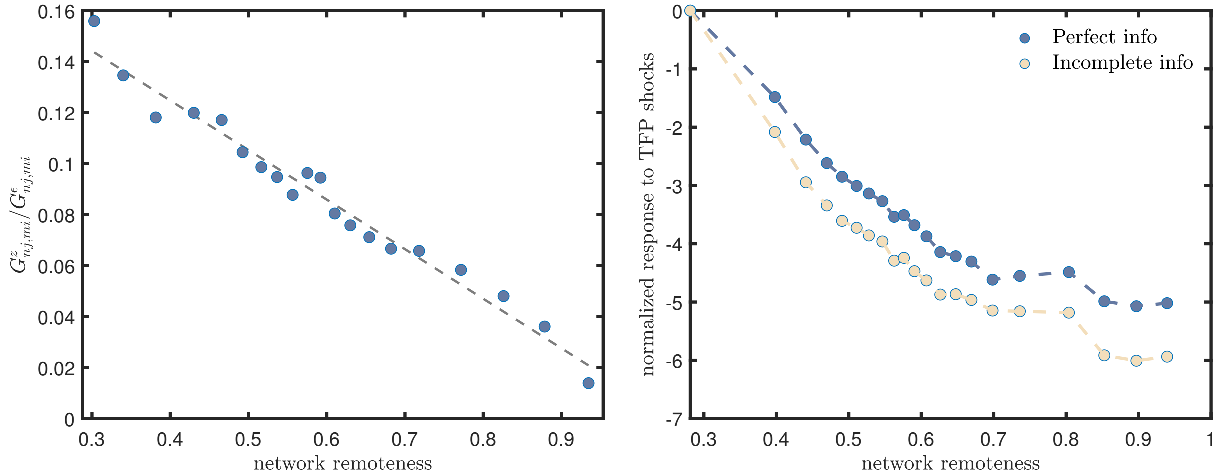
$$\frac{G^z_{nj,mi}}{G^\varepsilon_{nj,mi}} = \beta_0 - \underset{(0.001)}{0.195}\, d_{nj,mi} + \delta_{mi} + \nu_{nj,mi}, \tag{4.6}$$

where δ_{mi} controls for the variance of (m, i)'s TFP shock and the precision of the public signal. The negative coefficient on $d_{nj,mi}$ shows that agents are relatively less susceptible to the TFP shocks compared to noise shocks as the network remoteness increases. (The standard error is reported in parentheses below the coefficient.) Panel A of Figure 6 visualizes this relationship via a binscatter plot.

Interaction between TFP shocks and network effects. Proposition 2.3 also contrasts how TFP shocks propagate through the network with and without informational frictions. With incomplete information, the response of (n, j)'s hours depends on both first-order and higher-order expectations of (m, i)'s TFP. Higher-order expectations respond less to true TFP innovations than lower-order expectations. When (m, i) is more remote from (n, j), the relative importance of higher-order expectations increases, attenuating the response of (n, j)'s hours. Of course, even with perfect information, country-sector (n, j)'s response to a TFP shock in (m, i) falls in network distance between them. However, the response decays faster in network distance under informational frictions compared to the perfect information benchmark.

Panel B of Figure 6 illustrates this graphically in our quantitative model. It plots the log response

Figure 6: Shock Transmission and Network Distance



A. Reliance on public signals

B. Decay of TFP shocks

Notes: Panel A displays the ratio of hours responses to TFP relative to noise shocks, $G^z_{nj,mi}/G^\varepsilon_{nj,mi}$, as function of the network distance $d_{nj,mi}$. This is the binscatter plot of the regression (4.6) controlling for variances of the TFP and the noise shocks. Panel B displays the binscatters of the normalized responses to TFP shocks as a function of the network distance for the complete (blue) and incomplete (beige) information models.

of hours in (n, j) to a TFP shock in sector (m, i) normalized by the response of (m, i) to its own shock, $\ln G^z_{nj,mi} - \ln G^z_{mi,mi}$, under perfect information (blue dots) and with informational frictions (beige dots), as a binscatter in network distance. We can establish that the decay is significantly faster under imperfect information by fitting slopes through the full sample of country pairs summarized by the two binscatters in Figure 6. It turns out that the difference in slopes is highly statistically significant.[20]

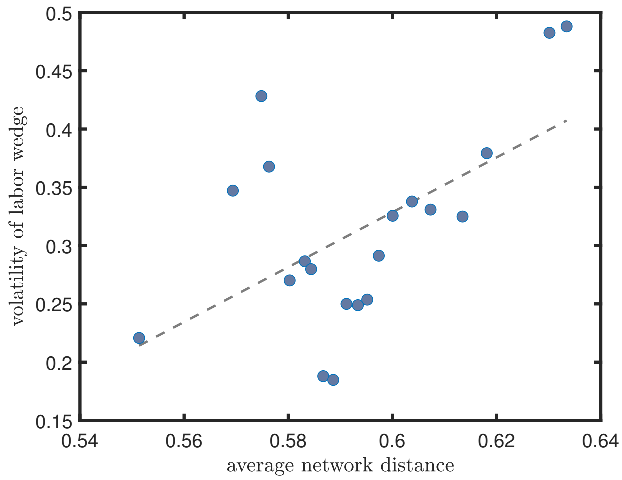
Interaction between labor wedge and network effects. Above we discussed the model implications with respect to the overall labor wedge volatility. Our framework also has cross-sectional implications for labor wedge fluctuations. Higher network distance increases the relative importance of public signals and noise shocks in overall fluctuations. Intuitively, it should also mean that sectors more remote from others in the network exhibit more volatile labor wedges. Since the labor wedge is a country-sector level object, whereas $d_{nj,mi}$ is bilateral, we first define the average bilateral network distance of country-sector (n, j) as $\overline{d}_{nj} \equiv \frac{1}{NJ-1} \sum_{m,i \neq n,j} d_{nj,mi}$. A larger $\overline{d}_{nj}$ implies that the interaction between (n, j) and other sectors is on average more indirect – the sector is "more remote" overall.

[20]We fit the following relationship in the sample of country-sector pairs and information friction assumptions:

$$\ln G^{z,q}_{nj,mi} - \ln G^{z,q}_{mi,mi} = \beta_1 d_{nj,mi} + \beta_2 d_{nj,mi} \mathbb{I}\left\{q = Incomplete\right\} + \delta^q_{mi} + \nu^q_{nj,mi},$$

where $q = \{Complete, Incomplete\}$ indexes the information structure. That is, we fit the slopes in panel (b) of Figure 6 separately for both the complete and incomplete information models, including mi fixed effects specific to the information structure, so that we can test for the difference in slopes by means of the coefficient β_2. Standard errors are clustered by mi. The β_2 is highly significantly different from zero, with a point estimate of -0.42 and a standard error of 0.14, implying a $p-$value of 0.004.

Figure 7: Labor Wedge and Network Remoteness



Notes: The figure displays the binscatters of the labor wedge volatility as a function of the average network distance of a country sector.

Figure 7 displays the relationship between the volatility of the labor wedge and the average network distance at the country-sector level conditional on the noise shocks, controlling for a country-sector's labor volatility. When fluctuations are driven by noise shocks, the volatility of the labor wedge is increasing in the network distance. This pattern echoes the discussion above: the reliance of public signals increases in the network distance, and a stronger response to noise shocks yields more volatile labor wedges.

4.4 External Validation: News Coverage and Sectoral Comovement

Relative to perfect information GVC models, our framework better matches patterns in the data such as the role of non-fundamental shocks in domestic business cycles (Angeletos, Collard, and Dellas, 2018), the transmission of an identified US sentiment shock to Canada (Levchenko and Pandalai-Nayar, 2020), and the importance of correlated labor wedges in international comovement (Huo, Levchenko, and Pandalai-Nayar, 2024). This section additionally validates the model by showing that it can replicate non-targeted relationships between news coverage, bilateral trade, and output comovement at the sector level. In the process, we document a novel correlation between news coverage and bilateral comovement, that further highlights the relevance of news coverage to the real economy.

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

Table 5: International Comovement, Trade, and News Coverage

Dep. Var.: $\rho^H_{nj,mi}$	(1)	(2)	(3)	(4)	(5)
	All country-sector pairs				International
$\ln \text{Trade}_{nj,mi}$	0.014***	0.010***	0.021***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.857***	0.455***	0.575***	0.222**	0.452***
	(0.118)	(0.093)	(0.122)	(0.101)	(0.152)
$F_{nj,mi}$	9.493***		4.993***		
	(1.025)		(1.058)		
Observations	16,032	16,032	16,032	16,032	14,030
R-squared	0.051	0.448	0.152	0.464	0.454
Country-sector FE	no	yes	no	yes	yes
Country pair FE	no	no	yes	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (4.7). The dependent variable is the correlation in 4-quarter growth rates of total hours worked between country-sectors (n, j) and (m, i). The dependent variables are log trade intensity as in (C.7) and news coverage intensity as in (4.8). Throughout, we restrict the sample to country-sector pairs where a minimum of 10 years of data are available for computing correlations. Columns 1-4 use all country-sector pairs. Column 5 restricts the sample to pairs where $m \neq n$.

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

$$\rho^H_{nj,mi} = \beta_1 \ln \text{Trade}_{nj,mi} + \beta_2 \ln \text{Trade}_{nj,mi} \times F_{nj,mi} + \beta_3 F_{nj,mi} + \boldsymbol{\delta} + \nu_{nj,mi}, \tag{4.7}$$

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

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

$$F_{nj,mi} = \frac{1}{2}\left(F_{nj} + F_{mi}\right), \tag{4.8}$$

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

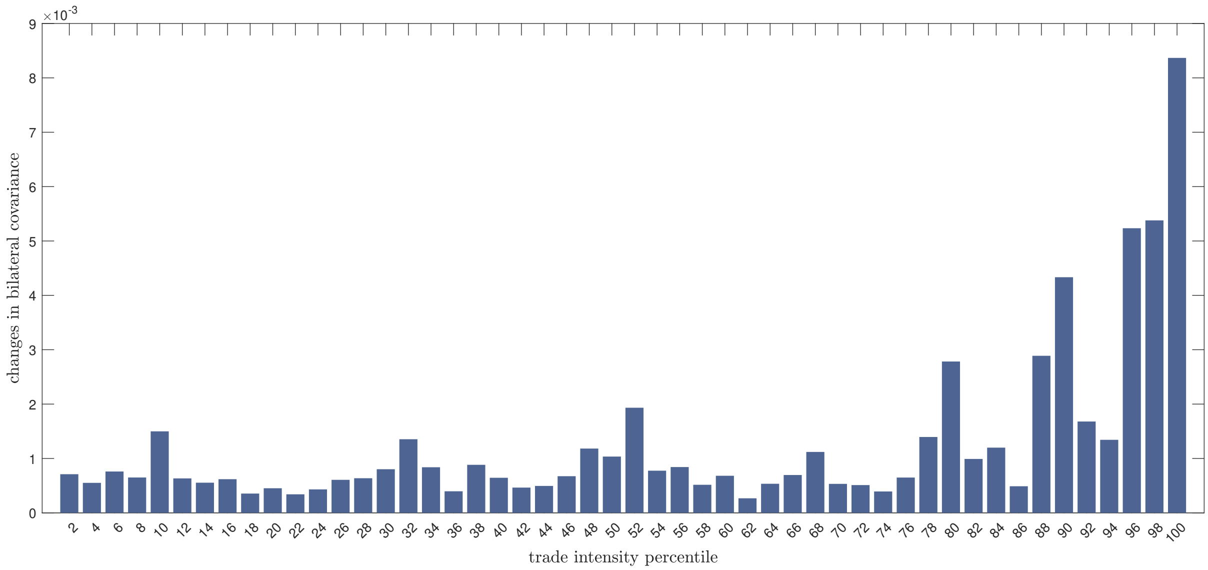
Table 5 reports the results. The columns differ in the fixed effects included. As highlighted in many studies, greater bilateral trade intensity is associated with higher comovement. In our specification, this is true even controlling for country-pair effects and thus exploiting variation within a pair of countries across sector pairs. The novel result is that both news coverage intensity by itself, and the news intensity interacted with trade are highly statistically significant. Even controlling for both sets of country-sector effects, sector pairs that are more covered in the news comove more. Once we include country pair effects we cannot estimate the main effect of news coverage, but even in this case we can estimate the interaction of news coverage with bilateral trade. Sectors more covered in the news exhibit more pronounced comovement the more they trade with each other. Finally, column 5 restricts the sample to sector-pairs located in different countries. If anything, the coefficient on the interaction between news coverage and trade intensity becomes larger. This is *prima facie* evidence that news coverage intensity plays a role in conditioning the extent of cross-border comovement.

Appendix C.3 provides further details and presents a number of robustness checks. Note that these results should be interpreted as conditional correlations and not a causal relationship (as is the case with the entirety of the trade-comovement empirical literature). This is in contrast to the model exercise described below, where we can assess the causal effect of an increase in bilateral news coverage. Eliminating all sources of confounding variation is possible in a model environment, but not in the empirical regressions.

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

Figure 8 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. Furthermore, this increase tends to be greater for the pairs that exhibit a greater trade intensity – the model counterpart of the interaction coefficient between news coverage and trade intensity in the empirical regressions. The reason is simple: when the trade linkages between two country sectors are weak, whether they are aware of each others' fundamental or not is nearly irrelevant. On the other hand, sectors that trade intensively with each other must form expectations about the productivity of their trading partners, and thus increasing news precision about that productivity leads to higher comovement.

Figure 8: Changes in Bilateral Comovement and Trade Intensity



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

4.5 Additional Exercises

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 the public signal precision to news coverage χ_1. The answer is no. Consider two extreme cases: if $\chi_1 \approx 0$, the news coverage is not informative at all and firms will ignore it when making decisions. Consequently, the noise contained in the news coverage is irrelevant. At the opposite extreme, suppose $\chi_1 \approx \infty$ and the news coverage is very informative. In this case, the variance of the noise shock approaches zero and agents know the fundamental state perfectly after observing the public signal. In this case, the model converges to perfect information and noise shocks also cannot play a significant role in shaping the aggregate fluctuations. Appendix Figure A9 displays the hours volatility driven by the noise shock as a function of the slope of the precision-news coverage relationship χ_1. According to our assumptions, signal precision increases one-for-one with χ_1. The vertical line displays the value of χ_1 that emerges from our indirect inference procedure.

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

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

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

where δ measures the extent with which the precision varies with the network distance. Our baseline model corresponds to $\delta = 0$; when $\delta > 0$, (n, j) has more precise private signals about sectors close to it in the network. Thus, this formulation implements the basic idea of rational inattention in a reduced-form way.[21]

The left panel of Figure A10 in Appendix D.4 shows how the volatility of hours changes with the parameter δ. As expected, a larger δ reduces firms' needs to rely on public news in general, and therefore the contribution of noise shocks decreases and that of TFP shocks increases. However, even for relatively large values of δ, the noise shock remains an important source of international fluctuations. At the micro level, the precision of private information is lower when country sectors are further away from each other, which reinforces our result on the relationship between the network remoteness and the reliance of public signals. With common precision, the network remoteness only shifts the relative importance between first-order and higher-order expectations; with heterogeneous precision, first-order expectations will also rely more on public information when network remoteness increases. The right panel of Figure A10 confirms this intuition.

Finally, Appendix D.3 discusses two additional exercises that describe how news coverage affects shock propagation across sectors under alternative assumptions on informational frictions: no informational frictions, and only private signals.

5. Conclusion

This paper studies the importance of information frictions in complex global value chains. We develop a quantitative framework in which non-technology shocks (noise in the public signal) 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

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

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 a microfoundation, empirical evidence, and quantification of international shock transmission of non-technology shocks, and of the role of production networks in modulating the effect of information frictions.

Our analysis is parsimonious, and can be enriched in several dimensions. The news coverage varies across newspapers located in different countries. At the same time, it is possible to infer whether forecasters in the Consensus data are local or foreign. These two pieces of information open the door to modeling and quantifying finer information structures, in which the public signals received by agents differ by country, and thus noise shocks are country-specific. The analysis above sidesteps the financial channel of international transmission of noise shocks. While Angeletos, Lorenzoni, and Pavan (2022) model the interaction of belief shocks and the financial system in the closed economy setting, little is currently known about international transmission of noise shocks through the financial markets, and the role of belief shocks in the global financial cycle more generally. These open questions are a fruitful avenue for future research.

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Online Appendix

A. Proofs

A.1 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

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

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

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

A.2 Proof of Lemma 2

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

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

The labor demand solves firms' problem

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

which leads to the following FOC

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

Combining demand and supply leads to

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

In terms of log-deviation from the pre-shock equilibrium,

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

At the country-sector level, we have

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

In matrix form,

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

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

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

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

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

which leads to

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

A.3 Proof of Proposition 2.1

It follows from the main text directly.

A.4 Proof of Proposition 2.2

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

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

The best response requires that

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

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 $\mathbf{G}_{mi} \equiv \begin{bmatrix} \mathbf{G}_{11,mi} & \mathbf{G}_{12,mi} & \dots & \mathbf{G}_{NJ,mi} \end{bmatrix}'$ is given by

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

A.5 Proof of Corollary 2.1

Suppose that the policy function takes the following form:

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

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

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

The best response requires that

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

Matching the coefficients leads to

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

The policy functions are thus given by

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

A.6 Proof of Proposition 2.3

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

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

$$\begin{aligned}
\overline{\mathbb{E}}_{m(1),t}[z_{mi,t}] &= g_1^z z_{mi,t} + g_1^\varepsilon s_{mi,t}, \\
\overline{\mathbb{E}}_{m(1),t}[\overline{\mathbb{E}}_{m(2),t}[z_{mi,t}]] &= g_2^z z_{mi,t} + g_2^\varepsilon s_{mi,t}, \\
&\vdots \\
\overline{\mathbb{E}}_{m(1),t}[\ldots[\overline{\mathbb{E}}_{m(k),t}[z_{mi,t}]\ldots] &= g_k^z z_{mi,t} + g_k^\varepsilon s_{mi,t}.
\end{aligned}$$

For j-th order expectation, the total response to the technology shock is $g_j^z + g_j^\varepsilon$ and the response to the noise shock is g_j^ε. We will prove that: (1) $g_j^z + g_j^\varepsilon < g_{j-1}^z + g_{j-1}^\varepsilon$; (2) $g_j^\varepsilon > g_{j-1}^\varepsilon$.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.7 Proof of Proposition 2.4

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

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

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

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

Rearranging, we get:

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

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

A.8 Alternative Vertical Network

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

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

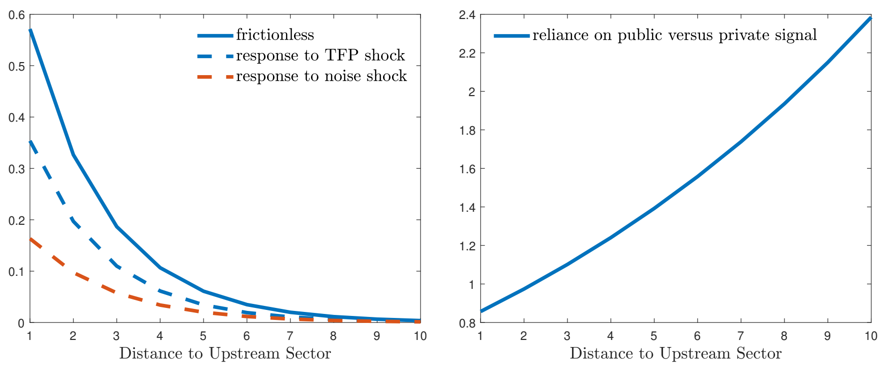
In this economy, each country will respond to their own productivity shock and the productivity shocks in their upstream countries. Under perfect information, the hours response to a country 1 TFP shock as a function of network distance is depicted by the solid line in the left panel of Figure A1. Without information frictions, the response of hours in country i is:

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

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

The dashed lines in Figure A1 display the responses under information frictions. As we found elsewhere, information frictions attenuate the impact of TFP shocks, but introduce transmission of noise shocks. The responses to both shocks decay in network distance. However, the noise shock becomes relatively more important as we move downstream. The right panel plots the ratio of the responses to the public signal compared to the private signal. As in the main text, the relative response to the public signal increases with downstreamness.

Figure A1: Hours Response in a Vertical Network



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

B. Data Appendix

B.1 International News Data

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

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

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

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

B.2 Forecast Data

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

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

B.3 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 compiling these data involves non-harmonized national sources, approaches vary by country and sometimes by sector, we provide a data construction Online Handbook that should be consulted for further details. The Handbook also contains all the country-specific concordances into the sectoral classification used in the paper.

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

B.3.1 United States

US Industrial Production. The US industrial production data are from the Federal Reserve Board for the manufacturing sector.[22] 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.[23] Services PPI information is also obtained from the Census Bureau. We seasonally adjusted the time series using X-11-ARIMA. In some cases we imputed industry growth rates from available subindustries.

US hours. The US hours worked data are from the US Bureau of Labor Statistics.[24] We compute total hours worked by multiplying the average weekly hours worked with employment. 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.

B.3.2 Canada

Canadian sectoral GDP. There is no industrial production data for Canada. Instead, it has been supplanted by monthly sectoral GDP series compiled by Statistics Canada.[25] The data start in 1997. We aggregate the months into quarters.

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

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

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

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

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:[26]

1. Extract the average weekly hours of hourly-paid employees,[27] and the standard work week hours for salaried employees.[28]

2. Download the employment of salaried and hourly-paid employees.[29]

3. Combine them into a monthly time series of the average total hours worked:

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

   where $Hours_{mt}$ is the aggregate working hours of sub-industry m in month t; $HrHrly_{mt}$ is the "average weekly hours for employees paid by the hour, by sub-industry, monthly, unadjusted for seasonality" (hour/week); $HrSalary_{mt}$ is the "standard work week for salaried employees, by sub-industry, monthly, unadjusted for seasonality" (hour/week); $EmpHrly_{mt}$ and $EmpSalary_{mt}$ are "employment by industry, monthly, unadjusted for seasonality" for "Employees paid by the hour" and "Salaried employees paid a fixed salary".

These data are monthly and start from 2001. We aggregate up to quarterly frequency to match the rest of our data.

B.3.3 Japan

Japanese Industrial Production. The Japanese industrial production data are from the Ministry of Economy, Trade and Industry.[30]

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).[31]

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.[32] We seasonally adjust the final series using X-12ARIMA-SEATS.

B.3.4 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.[33]

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

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

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

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

[30] 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.

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

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

[33] 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 Industrial Production. For each series, we download information on production, turnover and prices. 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.

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 break in the series.

Table A2: 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 A2 – *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 A2 – *Factiva - ISIC Rev-4 Sector Concordance (Cont.)*

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

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Table A2 – *Factiva - ISIC Rev-4 Sector Concordance (Cont.)*

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

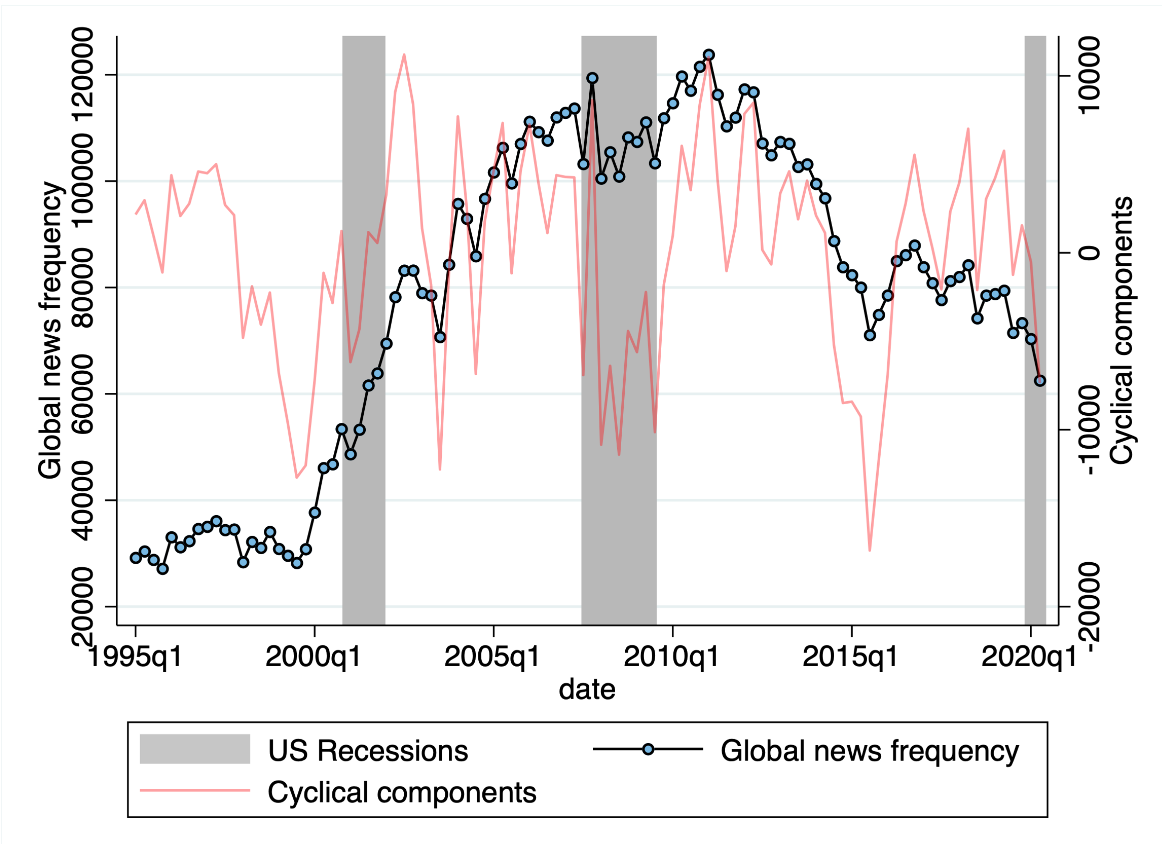
C. Empirical Appendix

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

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

Heterogeneity and variation. The frequency of *total* economic news varies over time, but appears to be at best modestly correlated with recessions. Figure A2 plots global economic news coverage (the sum of the raw frequencies of news about all country-sectors in all of our newspaper sources in each quarter), along with the NBER recession dates for our sample. To minimize the effect of the level changes in tags caused by Factiva's algorithm change detailed discussed in Appendix B, we also plot the HP-filtered global economic news coverage series. Economic news coverage varies over time, and increased relative to trend at the start of the Great Recession. A clear pattern is not discernible for the 2002 recession, perhaps as it corresponds to a period with other aggregate shocks (e.g. China's WTO accession in December 2001).

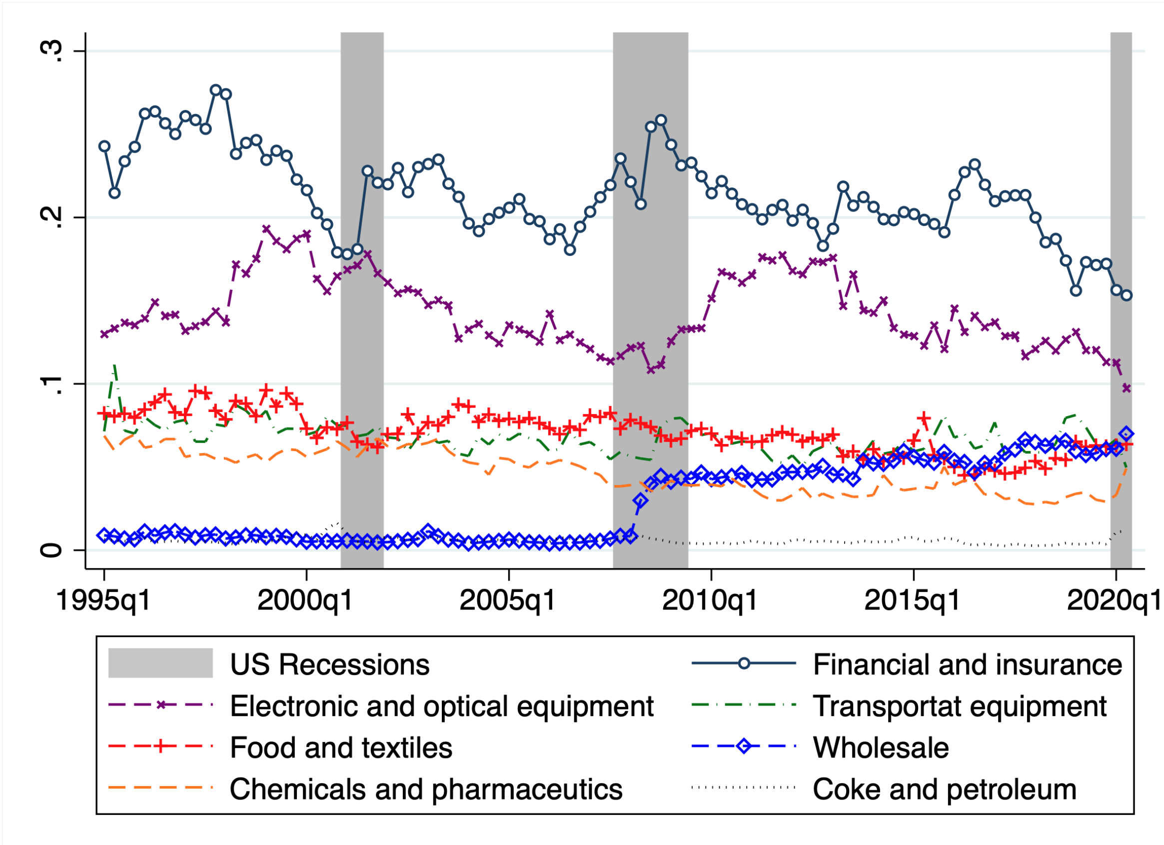
Figure A2: Economic News Frequency, 1995-2020



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

Figure A3 plots the shares of several large sectors in total global news coverage over time. While there is some time variation, the ordering of sectors in terms of news coverage shares in the cross-section remains quite stable. This suggests that within-sector variation over time is less important than cross-sectional variation. To make this more precise, we estimate a simple within-across decomposition to illustrate that average cross-sectional

Figure A3: 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.

variation is much more important than time-series variation within a sector over time:

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

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

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

Upstreamness and downstreamness indicators. For Figure 3, we define sector i's importance as an input as the average expenditure share on sector i's inputs in other sectors:

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

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

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

Table A3: Correlates of Global News Coverage, Country-Sector Level

Dep. Var.: F_{mi}	(1)	(2)	(3)	(4)
S_{mi}	0.880*	0.487	0.940**	0.525
	(0.458)	(0.469)	(0.376)	(0.403)
UP_{mi}	0.730**	0.715**	1.138**	0.892*
	(0.290)	(0.264)	(0.571)	(0.474)
DN_{mi}	-0.742*	-0.480	-0.899	-0.602
	(0.431)	(0.426)	(0.702)	(0.654)
Observations	184	184	184	184
R^2	0.205	0.251	0.605	0.642
Country FE	NO	YES	NO	YES
Sector FE	NO	NO	YES	YES

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

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

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

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

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

Table A3 reports the results. Sector size and upstream intensity are significant and some with the expected sign. Overall, even these three variables together explain less than 20% of the variation in the global news coverage across countries and sectors (column 1).

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

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

where s indexes country of the source of the news, m and i index country and sector about which news is reported, and $F_{s,mi}$ is the news coverage frequency share about (m, i) in the newspapers printed in source country s ("local news"). For this equation, we use the bilateral versions of upstream and downstream indicators, that reflect how important is sector (m, i) for producers in country s. These are defined analogously, but at the country level.[34] We also added to the specification the indicator for whether the country of the

[34]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 A4: Correlates of Local News Coverage, Country-Pair-Sector level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.: $F_{s,mi}$								
S_{mi}	0.261**	0.261**	0.169*	0.287***	0.168*	0.173*	0.167*	0.170
	(0.0958)	(0.0959)	(0.0869)	(0.0959)	(0.0870)	(0.0883)	(0.0980)	(0.0962)
$UP_{s,mi}$	0.408***	0.408***	0.407***	0.381***	0.407***	0.409***	0.379***	0.382***
	(0.118)	(0.118)	(0.118)	(0.101)	(0.118)	(0.117)	(0.101)	(0.100)
$DN_{s,mi}$	-0.0416	-0.0413	-0.0352	-0.0128	-0.0349	-0.0445	-0.0108	-0.0210
	(0.102)	(0.102)	(0.102)	(0.0947)	(0.102)	(0.103)	(0.0946)	(0.0943)
$1\{s = m\}$	0.0159***	0.0159***	0.0157***	0.0159***	0.0157***		0.0159***	
	(0.00328)	(0.00329)	(0.00328)	(0.00283)	(0.00329)		(0.00284)	
Observations	1,472	1,472	1,472	1,472	1,472	1,472	1,472	1,472
R^2	0.373	0.373	0.374	0.489	0.375	0.338	0.491	0.504
Country s FE	NO	YES	NO	NO	YES	NO	YES	NO
Country m FE	NO	NO	YES	NO	YES	NO	YES	NO
Country pair FE	NO	NO	NO	NO	NO	YES	NO	YES
Sector FE	NO	NO	NO	YES	NO	NO	YES	YES

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

newspaper is the same as the country of the sector, $1\{s = m\}$, to pick up the strength of the home bias in news coverage.

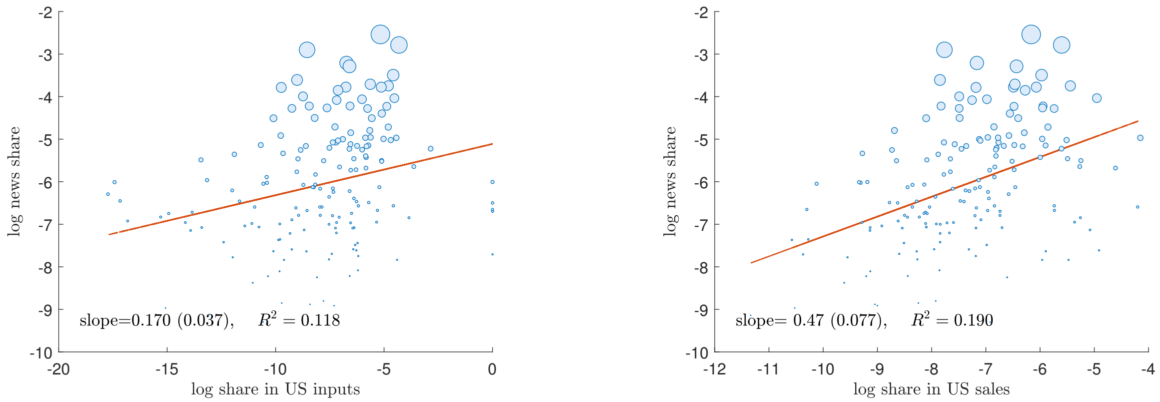
Table A4 reports the results. Overall, the coefficients have the expected sign, and the explanatory power of these regressors at the bilateral level is higher than at the global level, explaining 40% of the variation (column 1). There is clear home bias in news coverage, with shares on average 1.5% higher 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 A4 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 A5 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 A6-A7 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

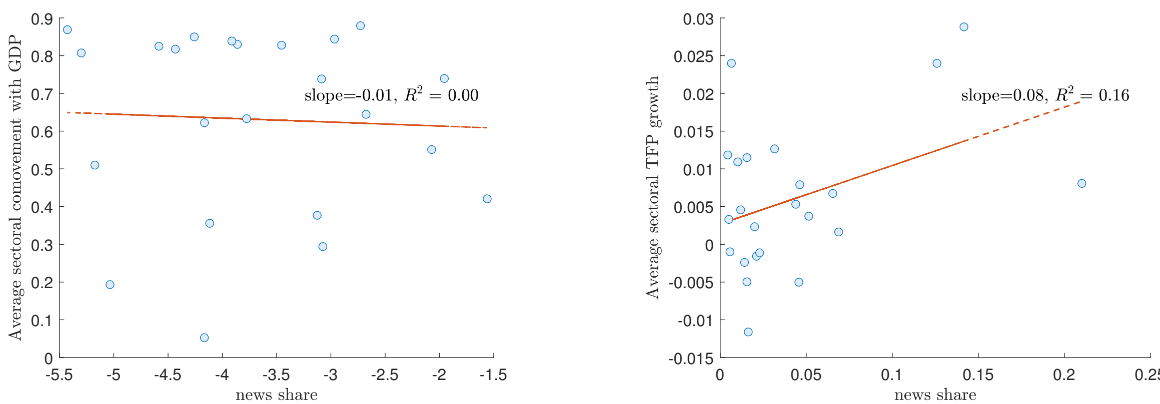
Figure A4: Importance in US GVC and US News Coverage



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 A5: News Coverage, Sector Comovement and TFP Growth



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

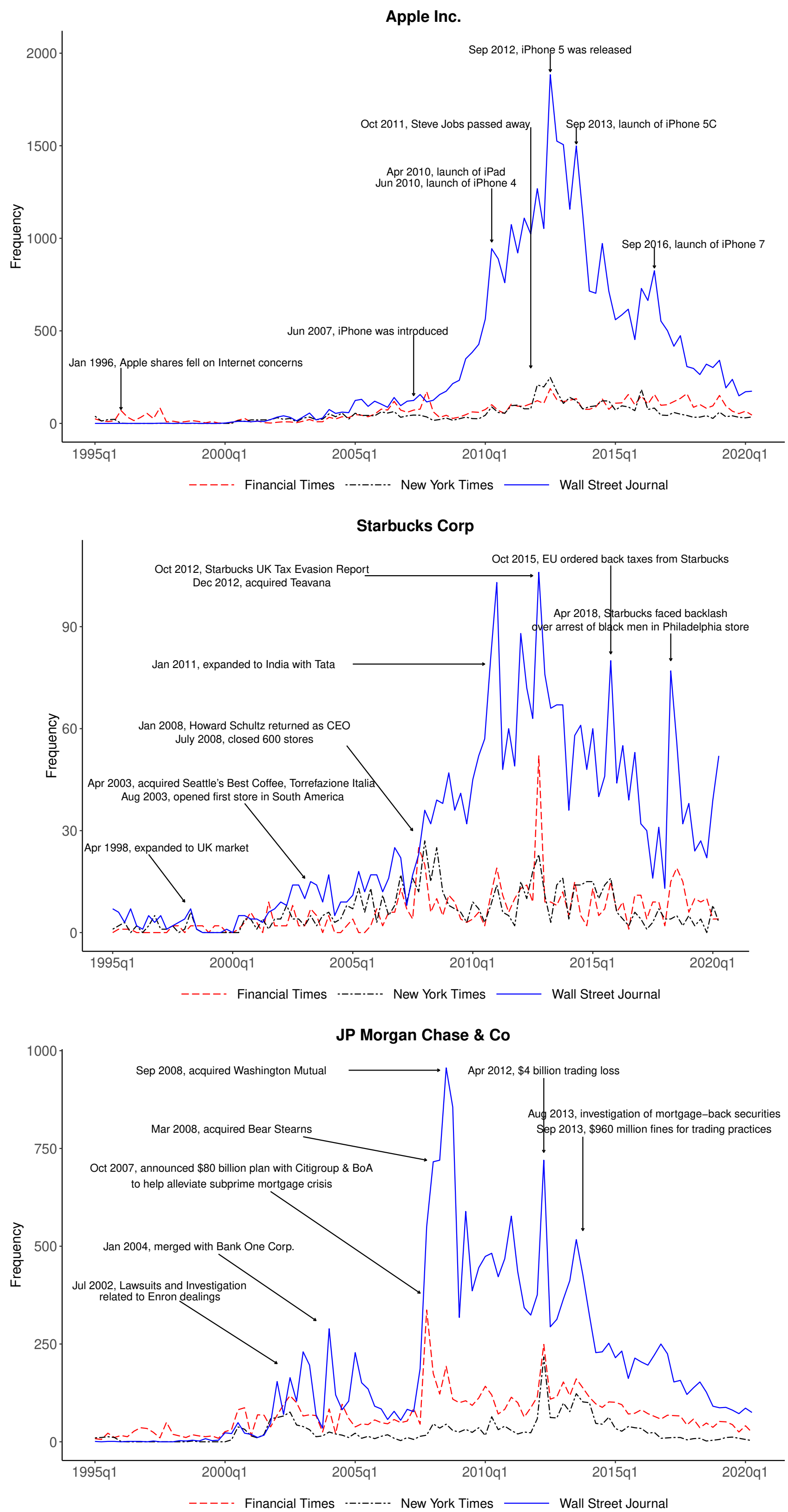
B. Share of Global News vs Average Sectoral TFP (Solow Residual) Growth

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.

in a spike in the coverage about Apple Inc.[35] The bottom panel of Figure A7 plots the news coverage of key Japanese industries in global news around the time of the 2011 Tohoku earthquake, together with some control industries for comparison. There is a spike in coverage of the industries that were most severely affected by the natural disaster.

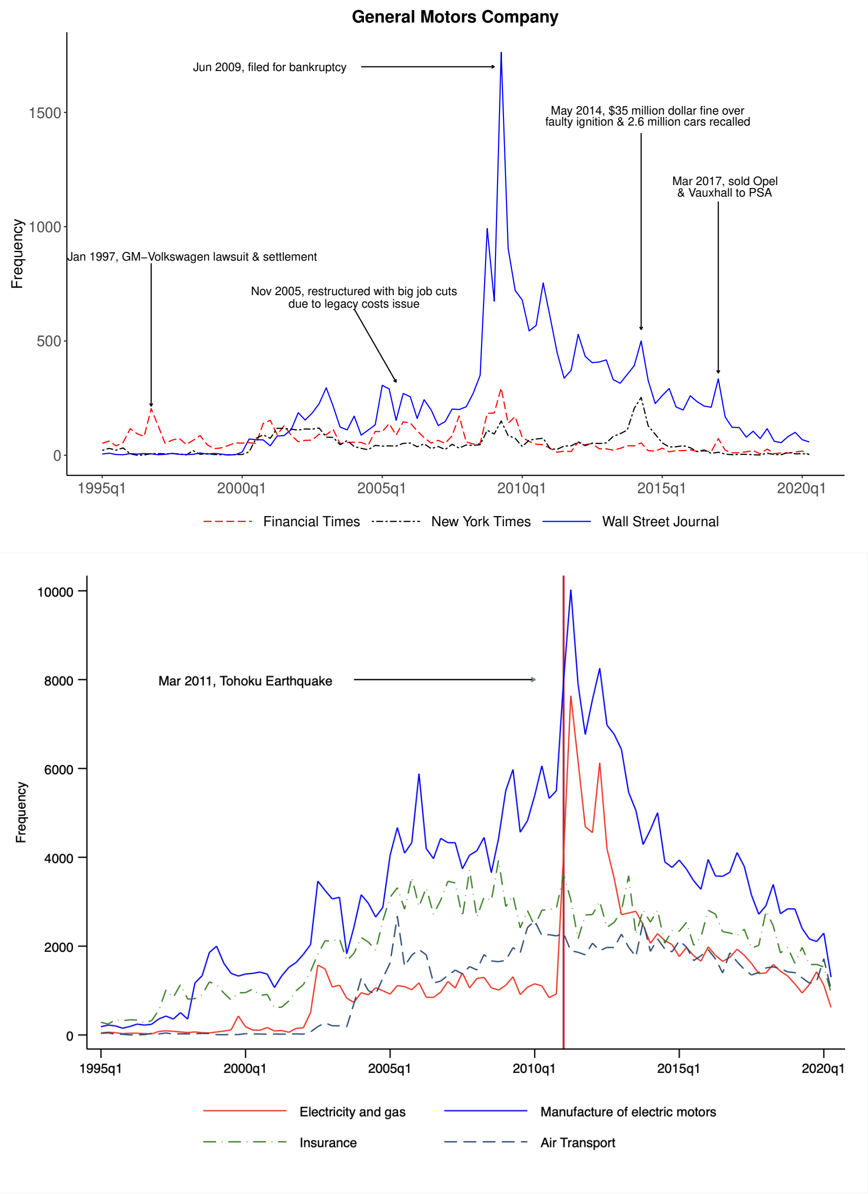
[35]The news coverage of Apple varies in levels across the three US newspapers plotted, but is positively correlated across the newspapers, suggesting the news media focuses on similar events in reporting. The levels variation reflects the number of articles in the typical newspaper. For instance the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

Figure A6: Company-Specific Figures: Apple, JP Morgan Chase, Starbucks



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

Figure A7: 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.

C.2 Forecast Error Regressions: Robustness

Productivity shocks. Suppose that an upward deviation in productivity growth made GDP easier to forecast, while at the same time was associated with more intense news coverage. Then, omitting productivity growth from the regression would lead to a spurious coefficient on the news coverage intensity. Of course, there are many possibilities. It could actually be that *downward* deviations in productivity growth improve forecast precision/increase coverage, or *absolute* deviations. Thus, we add controls for a variety of transformations of productivity growth to equations (4.1) and (4.2): (i) the simple growth rate, (ii) its absolute value, (iii) its square, as well as (iv) an indicator for whether the period's productivity growth is negative. We use quarterly labor productivity as the underlying measure of productivity. The results are in Panel A of Table A5. The addition of these controls has a minimal impact on either the level of the coefficient of interest or its significance. Note that neither the premise that large shocks coincide with more coverage, nor that large shocks are easier to forecast appear supported by the data.[36]

Content of news. Productivity is not the only shock that might affect forecastability of GDP and news coverage. Closest to our conceptual framework, noise shocks also drive fluctuations (Angeletos and La'O, 2013; Angeletos, Collard, and Dellas, 2020) and may change forecastability of GDP. It is notoriously difficult to identify an empirical counterpart of the Angeletos-La'O-style noise/sentiment shock. This is because shifts in empirical measures of agents' expectations (such as GDP forecasts, consumer confidence indices, etc.) can be driven by any shock, not just the truly exogenous shifts in beliefs. Thus, identifying the correct noise shock in the data requires orthogonalizing shifts in agents' expectations with respect to all the other (plausible) shocks that can move expectations: not only current and expected future productivity, but fiscal policy, monetary policy, commodity price and financial shocks, etc. While this can be done to some extent (Levchenko and Pandalai-Nayar, 2020), orthogonalizing shifts in empirically measured sentiment with respect to all other shocks is a tall order.

With that caveat, in the next set of robustness checks we control for "news sentiment" distilled from the news coverage data by Fraiberger et al. (2021). We apply the same 4 transformations to the news sentiment series as we do to productivity. Including the news sentiment variables has the additional benefit of controlling for the *direction/tone* of the news coverage, whereas our main variable of interest is the coverage *intensity*.[37] Panel B of Table A5 reports the results. Because of the imperfect overlap between our data and Fraiberger et al. (2021), the sample size falls by nearly 30%. Nonetheless, the coefficients and their level of significance are very similar to the baseline.

Monetary policy shocks. A growing literature finds that US monetary policy shocks are an important driver of the global financial cycle. It might be plausible that these shocks are correlated with news coverage intensity, and at the same time reduce forecast errors. While the time fixed effects in our regression control for the global financial cycle and the average effects of any monetary policy shocks on forecast errors, differential effects for countries more connected to the US might remain a concern. In Table A6 we therefore additionally control for monetary policy shocks in two ways. First, we use the absolute value of the US target rate, forward guidance, and quantitative easing shocks, constructed by Boehm and Kroner (2023) using the approach in Swanson (2021).[38] We interact these shocks with a country indicator to allow for country-specific effects of these shocks on the forecast errors. Second, we obtain a similar set of monetary policy shocks for the ECB and the Bank of England from Boehm and Kroner (2023), as well as a target rate and forward guidance shocks for the Bank of Japan from Kubota and Shintani (2022). We then control for the monetary policy shocks of

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

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

[38]Boehm and Kroner (2023) discuss the construction of these shocks in detail, and show they align well with the original measures in Swanson (2021) for the overlapping time frame.

Table A5: Global News Coverage and Forecast Errors: Controlling for Productivity and News Sentiment

	(1)	(2)	(3)	(4)
	Panel A: nowcast errors, productivity controls		Panel B: nowcast errors, productivity and sentiment controls	
Dep. Var.	$\lvert$forecast error$\rvert$	SD (forecast error)	$\lvert$forecast error$\rvert$	SD (forecast error)
$\log F_{n,t}$	-0.0924***	-0.0298***	-0.0734***	-0.0335***
	(0.0102)	(0.0107)	(0.0127)	(0.0109)
Observations	18,517	796	13,488	584
R^2	0.484	0.715	0.511	0.733
Time FE	yes	yes	yes	yes
$f \times n$ FE	yes		yes	
n FE		yes		yes
Prod. controls	yes	yes	yes	yes
Sent. controls			yes	yes

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

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

Political cycle. Another potential confounder is the election cycle, if in election periods economic news coverage changes (up or down), while at the same time forecastability of GDP changes as well. We collected data on the dates of national elections in all the countries in the sample. Table A7 controls for an election-quarter dummy that might be correlated with news coverage intensity and forecast errors and finds similar results.

Re-weighting news coverage. Our baseline estimates of equations (4.1) and (4.2) use the total news coverage in each country and quarter. It could be that sectors important as input suppliers receive more attention from forecasters, and news coverage about them could better help predict aggregate outcomes. To account heuristically for this possibility, we weight news coverage in each sector by its Domar weight. In this way, the hypothesis is that news coverage of sectors with higher Domar weights reduces forecast errors by more than the same amount of news coverage in a sector with a low Domar weight. Appendix Table A8 displays the results. They are quite similar to Table 2.

Forecasts of unemployment. The active margin in the model is labor input, which is the main endogenous variable that reacts to news coverage. Unfortunately, to the best of our knowledge databases of forecasts of total hours worked do not exist for our countries. However, Consensus data do include forecasts for the unemployment rate. We thus estimate equations (4.1)-(4.2) for the forecast errors in the unemployment rate. The results are reported in Appendix Table A9. News coverage does reduce both the nowcast and one-year ahead forecast errors for unemployment, but the coefficients for the dispersion in the forecasts are not significant, albeit of the right sign.

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

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	|forecast error|	|forecast error|	|forecast error|	|forecast error|
$\log F_{n,t}$	-0.124***	-0.0495***	-0.198***	-0.105***
	(0.0123)	(0.0179)	(0.0323)	(0.0371)
Observations	12,883	9,874	12,203	9,413
R^2	0.547	0.588	0.721	0.804
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes	yes	yes	yes
Productivity, Sentiment Controls	yes	yes	yes	yes
US MP shocks×country FE	yes		yes	
All MP shocks×own-country FE		yes		yes

Dep. Var	SD (forecast error)	SD (forecast error)	SD (forecast error)	SD (forecast error)
$\log F_{n,t}$	-0.0373***	0.00513	-0.0598***	-0.0262
	(0.0120)	(0.0097)	(0.0180)	(0.0281)
Observations	558	420	546	408
R^2	0.748	0.810	0.626	0.638
Time FE	yes	yes	yes	yes
Country FE	yes	yes	yes	yes
Productivity, Sentiment Controls	yes	yes	yes	yes
US MP shocks×country FE	yes		yes	
All MP shocks×own-country FE		yes		yes

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

Table A7: Global News Coverage and Consensus Forecast Errors: Controlling for Elections

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	$\lvert$forecast error$\rvert$	SD (forecast error)	$\lvert$forecast error$\rvert$	SD (forecast error)
$\log F_{n,t}$	-0.0718***	-0.0334**	-0.269***	-0.0711***
	(0.0127)	(0.011)	(0.0301)	(0.0191)
Observations	13,488	584	12,774	572
R^2	0.512	0.733	0.701	0.611
Election-quarter indicator	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes		yes	
Country FE		yes		yes

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

Table A8: 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 (forecast error)	$\lvert$forecast error$\rvert$	SD (forecast error)
$\log F_{n,t}$	-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	0.470	0.703	0.696	0.537
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes		yes	
Country FE		yes		yes

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

Table A9: Global News Coverage and Consensus Forecast Errors: Unemployment

	Panel A: nowcast errors		Panel B: one-year ahead forecast errors	
	(1)	(2)	(3)	(4)
Dep. Var	$\lvert$forecast error$\rvert$	SD (forecast error)	$\lvert$forecast error$\rvert$	SD (forecast error)
$\log F_{n,t}$	-0.1690***	-0.0069	-0.2620***	-0.0054
	(0.0349)	(0.0066)	(0.0327)	(0.0117)
Observations	16,334	700	15,262	672
R^2	0.655	0.642	0.513	0.567
Time FE	yes	yes	yes	yes
Country-forecaster FE	yes		yes	
Country FE		yes		yes

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

C.3 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:

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

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 A10 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 A11 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 A12 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 A10: International Comovement, Trade, and News Coverage, Industrial Production

Dep. Var.: $\rho^{IP}_{nj,mi}$	(1)	(2)	(3)	(4)	(5)
	All country-sector pairs				International
$\ln \text{Trade}_{nj,mi}$	0.027***	0.013***	0.038***	0.011***	0.009***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	-0.421***	0.060	0.164	0.075	0.614***
	(0.162)	(0.117)	(0.169)	(0.134)	(0.167)
$F_{nj,mi}$	0.217		7.170***		
	(1.393)		(1.474)		
Observations	11,475	11,475	11,475	11,475	10,088
R-squared	0.088	0.638	0.179	0.645	0.646
Country-sector (n,j) FE	no	yes	no	yes	yes
Country-sector (m,i) FE	no	yes	no	yes	yes
Country pair FE	no	no	yes	yes	yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table reports the results of estimating (4.7). The dependent variable is the correlation in 4-quarter growth rates of industrial production between country-sectors (n,j) and (m,i). The regressors are log trade intensity as in (C.7) and news coverage intensity as in (4.8). Columns 1-4 use all country-sector pairs in computing correlations. Column 5 only 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 A11: 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)
$\ln \text{Trade}_{nj,mi} \times F_{nj,mi}$	0.122*	0.066	0.556***	0.703***	0.174**	0.173
	(0.073)	(0.124)	(0.098)	(0.126)	(0.087)	(0.120)
$F_{nj,mi}$			1.907***	1.852***		
			(0.432)	(0.511)		
Observations	16,653	11,627	16,032	11,475	16,032	11,475
R-squared	0.321	0.582	0.465	0.646	0.465	0.645
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 (4.7). The dependent variable is the correlation between country-sectors (n, j) and (m, i) of, alternatively, 1-quarter growth rates of hours in column 1; 1-quarter growth rate of industrial production in column 2; 4-quarter growth rates of hours in columns 3 and 5; 4-quarter growth rates of industrial production in columns 4 and 6. The regressors are log trade intensity as in (C.7) in columns 1-4 and a final sales based measure of trade intensity in columns 5-6, and news coverage intensity as in (4.8). 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 A12: 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) $Cov^{H}_{nj,mi}$ International
	4Q Growth Rates		1Q Growth Rates		4Q Growth Rates
ln Trade$_{nj,mi}$	0.0260***	0.0629***	0.000265	0.0707***	0.0239***
	(0.00448)	(0.00464)	(0.00513)	(0.00504)	(0.00516)
ln Trade$_{nj,mi}$ $\times$ News$^{global}_{nj,mi}$	0.728**	2.465***	0.942**	1.445***	1.861***
	(0.342)	(0.539)	(0.378)	(0.428)	(0.509)
Observations	16,032	11,475	16,653	11,627	14,030
R-squared	0.567	0.744	0.417	0.646	0.558
Country-sector FE	yes	yes	yes	yes	yes
Country pair FE	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 (4.7), with the dependent variables 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 considers only pairs of sectors in where $m \neq n$. The regressors are log trade intensity as in (C.7) and news coverage intensity as in (4.8). All covariances are computed on samples with a minimum of 10 years of data.

D. Quantification Appendix

D.1 Indirect Inference

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

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

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

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

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

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

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

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

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

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

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

Its first-order approximation is

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

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

Finally, the unconditional variance of the individual forecast error is

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

Table A13: Sensitivity Matrix

	Slope, | forecast error |	Slope, SD(forecast error)	SD (forecast error)
τ	-0.07%	0.39%	0.42%
χ_0	-0.15%	-0.21%	-0.17%
χ_1	0.39%	0.27%	-0.22%

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

which helps to determine the magnitude of χ_0.

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

In the quantitative model, the corresponding matrix that measures the sensitivity of the indirect inference procedure according to Andrews, Gentzkow, and Shapiro (2017) is given by Table A13.

D.2 CES Model Results

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

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

The elasticities of substitution are ρ and μ, respectively. We choose $\rho = 1.2$ and $\mu = 0.7$, both of which are standard values used in the literature (see, among others, Boehm, Flaaen, and Pandalai-Nayar, 2019; Huo, Levchenko, and Pandalai-Nayar, 2024; Boehm, Levchenko, and Pandalai-Nayar, 2023). Table A14 replicates the main quantitative results (Table 4 in the main text), and shows that the magnitudes are similar.

D.3 Information, News Coverage and Shock Propagation

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

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

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

Panel A of Figure A8 displays the relationship between ϱ_{mi}^z and the news frequency share of sector (m, i) in the baseline model, after partialling out the country-sector size measured by the sales value in the steady state. The average elasticity is strongly correlated with the news share, with a slope of 0.19 and R^2 of 0.60. Greater news coverage increases the shock propagation from sector (m, i) to the rest of the world economy. Panel B displays the elasticity ϱ_{mi}^ε of hours with respect to the noise shock in sector (m, i) against the news share. The

Table A14: Business Cycle Statistics, CES Model

	(1) Perfect Information	(2) Incomplete Information	(3) Incomplete Information	(4) Incomplete Information	(5) Data
	TFP	TFP	noise	both	
Hours volatility	0.92	0.44	0.30	0.53	1.55
indirect vs direct effects: $\frac{\sigma_{\text{indirect}}}{\sigma_{\text{direct}}}$	0.48	0.44	0.53	0.47	
Bilateral hours correlation					
uncorrelated noise	0.10	0.12	0.06	0.10	0.19
correlated noise	0.10	0.12	0.31	0.19	
Bilateral labor wedge correlation					
uncorrelated noise	—	0.06	0.03	0.05	
correlated noise	—	0.06	0.24	0.12	

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

correlation with the news share is even stronger than for the TFP elasticity. Noise shocks to sectors well-covered in the news transmit more strongly.

Panel C of Figure A8 displays ϱ^z_{mi} under perfect information. In this case, there is not much of a discernible relationship, with both the slope and the R^2 near zero.

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

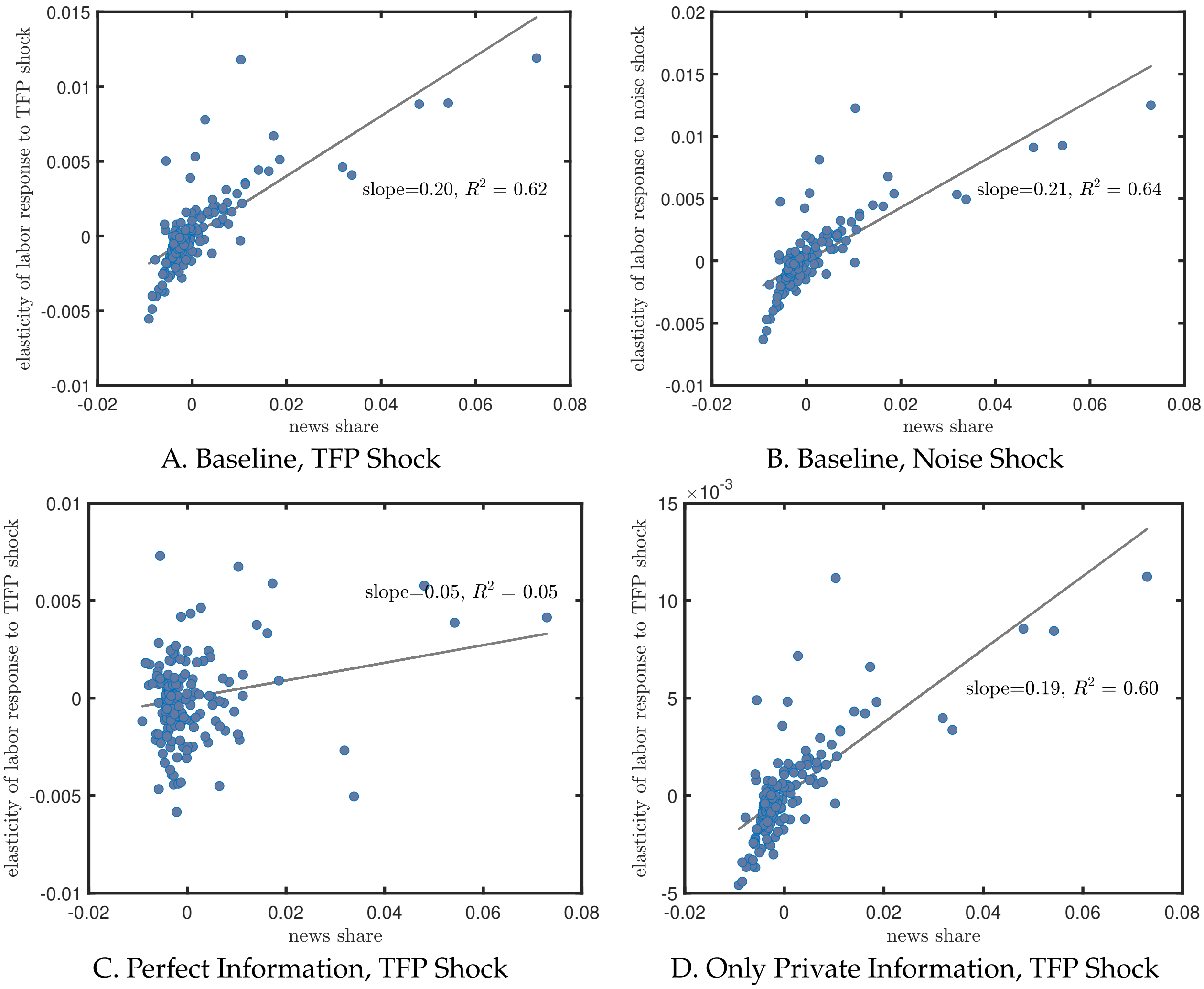
$$\tilde{\tau}_{nj,mi} = \tau + \chi_0 + \chi_1 F_{mi}.$$

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 A15 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

Figure A8: News Share and TFP Shock Transmission



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

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. Panel D of Figure A8 displays the relationship between news share and the strength of shock propagation in this model. Comparing to the baseline model in Panel A, find that the two economies are similar to each other. The particular information structure discussed in this subsection could be viewed as an extreme case that maximizes the information in the private domain.

In short, the distinction between private and public information matters for the equilibrium allocations.

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

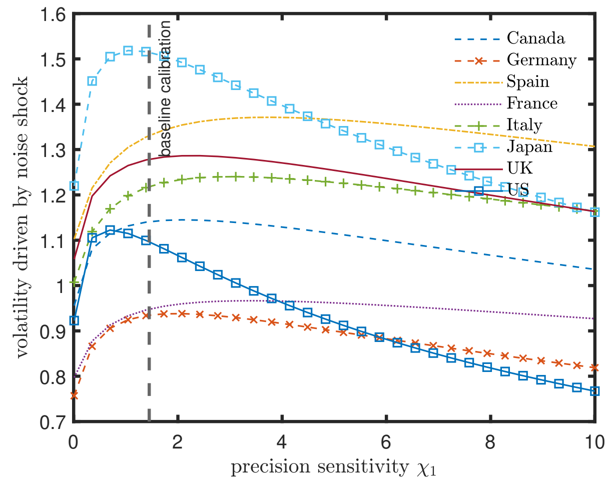
Table A15: Business Cycle Statistics

	(1)	(2)	(3)	(4)
	Private-Info Economy	Baseline Economy		
	TFP	TFP	Noise	Total
Hours volatility	0.56	0.50	0.30	0.59

Notes: This table reports the mean across the G7+ countries of the standard deviation of aggregate hours, in the model with only private information (column 1) and the baseline model (columns 2-4).

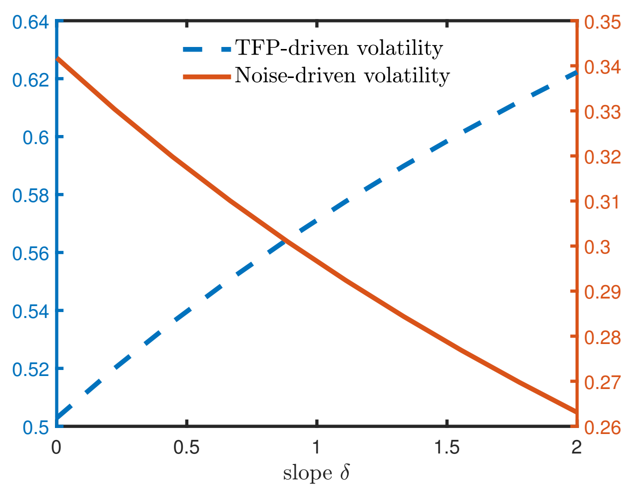
D.4 Additional Figures

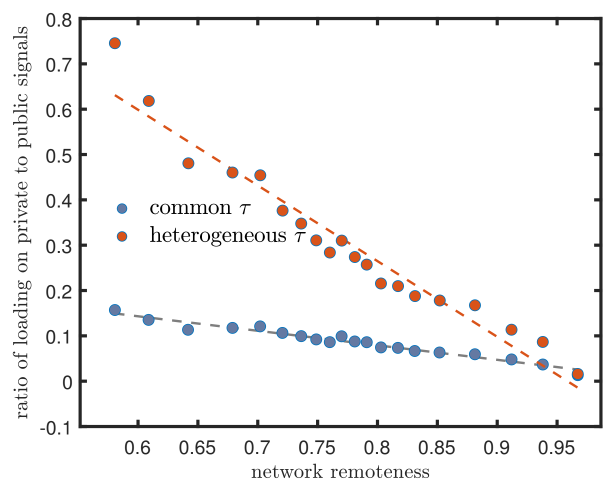
Figure A9: Precision Sensitivity and Volatility Driven by Noise Shocks



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

Figure A10: Heterogeneous Private Information Precision





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