Noisy Global Value Chains*

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June 2026

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 – transmit 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

JEL Codes: F41, F44

*We are grateful to the editor (Guido Lorenzoni), anonymous referees, Marios Angeletos, Chris Boehm, Ryan Chahrour, Oli Coibion, Steve Davis, Doireann Fitzgerald, Chen Lian, Kris Nimark, Dennis Novy, Todd Walker, Shang-Jin Wei, Sifan Xue, and seminar participants at Basel, Bocconi, Brown, BU, Chicago, College of William and Mary, Colorado, CUHK, Duke, Federal Reserve Board, Fudan, Harvard/MIT, HKU, Indiana, Lausanne, LSE CFM International Macro Conference, Maastricht, Montreal, Northwestern, NBER IFM, NYU, Paris School of Economics, Richmond Fed, SciencesPo, SF Fed, SED 2021 (Minnesota), Stanford, Tsinghua University, UCLA, UT Austin, University of Macau, Yale, the Virtual Conference on Imperfect Information in Macroeconomics, 2nd International Economic Joint Conference at HKU Shenzhen, and the 5th International Macro/Finance/Trade/Sovereign Debt Workshop for helpful comments, George Cui and Elliot Kang for superb research assistance, and our team of RAs from the University of Michigan and UT Austin for the multi-year effort in gathering our international news coverage data. Previously circulated as "Information Frictions and News Media in Global Value Chains." Email: buithuha@grinnell.edu, zhen.huo@yale.edu, alev@umich.edu and npnayar@utexas.edu.

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 state 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 indirect 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, the setup is fully flexible about the configuration of domestic and international trade links. There are multiple countries and sectors subject to productivity shocks, connected with each other via trade in

[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 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 dot-com boom. Section 2.4 revisits the dot-com period evidence in greater detail, using econometric estimates of the international transmission of identified US noise shocks from Levchenko and Pandalai-Nayar (2020).

[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.

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, 2023, 2025), 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-degree (in the network sense) impact of a shock on the economy is a function of first-order expectations, the second-degree 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 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

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-degree 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-degree 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 requires noisy *public* information or correlated noise (Lorenzoni, 2009; Angeletos and La'O, 2010; Barsky and Sims, 2012; Angeletos, Collard, and Dellas, 2018). Our micro evidence makes it possible to discipline the role of public

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 quantification of the role of the information frictions.

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, 2025). 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 direct and indirect network propagation terms. Introducing informational frictions reduces the importance of the direct terms in the overall TFP-driven fluctuations. At the same time, indirect 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.

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., 2024; Hébert and La'O, 2023; Nikolakoudis, 2025). While previous literature quantified the role of belief shocks by matching the macro aggregates (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. This research program has had relatively few applications in the international context. Exceptions include Levchenko and Pandalai-Nayar (2020) on the international transmission of sentiment shocks; Candian (2019) and Candian and De Leo (2025) on dispersed information and distorted beliefs in exchange rate determination; and Baley, Veldkamp, and Waugh (2020) on the impact of uncertainty on international trade levels. Our contribution is to explore how information frictions affect the shock transmission mechanisms in the context of global supply chains.[4]

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; Rubbo, 2023), as well as applications of these ideas and techniques to international shock transmission (e.g. Kose and Yi, 2006; Burstein, Kurz, and Tesar, 2008; Johnson, 2014; Eaton et al., 2016; Eaton, Kortum, and Neiman, 2016; Bonadio et al., 2021, 2025; Huo, Levchenko, and Pandalai-Nayar, 2023, 2025; Kleinman, Liu, and Redding, 2023, 2024). 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; Atolia and Chahrour, 2020; Chahrour, Nimark, and Pitschner, 2021; Lian, 2021; La'O and Tahbaz-Salehi, 2022; Pellet and Tahbaz-Salehi, 2023; Nikolakoudis, 2024; Hajdini et al., 2025; Fang et al., 2025), especially in the context of input-output networks. A common theme in this literature is that the equilibrium outcome is shaped jointly by the network structure and information frictions. Building on these insights, we explore the differential impacts of private vs. public signals and how they interact with network remoteness. In addition we explore the international propagation of both fundamental and noise shocks. We use news coverage data to discipline the informativeness of noisy public signals.

[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).

Finally, our paper complements the empirical work on the properties of subjective beliefs at the business cycle frequency (recent contributions include Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Kohlhas and Walther, 2021; Angeletos, Huo, and Sastry, 2021; Fraiberger et al., 2021; Bianchi, Ludvigson, and Ma, 2022; Hassan et al., 2024; Bhandari, Borovička, and Ho, 2025). 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.[5,6] Appendix Figure A1 depicts the model timing.[7]

Households. The problem of the household is

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

subject to

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

where $\mathcal{F}_{n,t}$ is consumption of final goods, and $H_{nj,t}(\iota)$ is the total labor hours supplied to island ι in sector j. Labor collects a sector-island-specific wage $W_{nj,t}(\iota)$, $R_{nj,t}$ is the return to capital in each sector, and $P_{n,t}$ is the price of the final consumption bundle. For simplicity, we assume that final consumption is a Cobb-Douglas aggregate of goods coming from each country-sector:

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

where 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.

[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).

[6]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 (2025), these trade wedges only play a secondary role in shaping international business cycles.

[7]All decisions in the model are static within a period. Our previous work (Huo, Levchenko, and Pandalai-Nayar, 2023, 2025; Bonadio et al., 2025) analyzed in detail the consequences of dynamics on GDP comovement, and found them to be limited. Relative to a static setting, the key difference introduced by allowing persistent noise shocks is that they generate additional dynamic effects, whose persistence depends on the speed of learning—specifically, on how quickly agents' forecast errors about the noise shock dissipate (Huo and Takayama, 2025). Moreover, compared with a standard signal-extraction environment, the analysis becomes substantially more complex because dynamic higher-order expectations interact with input-output linkages. This interaction amplifies the role of informational frictions, generating additional inertia in responding to noise shocks, but at the same time makes the characterization of equilibrium dynamics considerably more challenging, given the high-dimensional structure of the model.

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

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

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

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

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.[8]

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, which requires that final consumption expenditure equals total factor income $\forall\, m$: $P_{m,t}\mathcal{F}_{m,t} = \sum_i \eta_i P_{mi,t}Y_{mi,t}$.

[8] In our framework, when the model is formulated in changes expressed as a function of expenditure shares, iceberg costs are isomorphic to taste shifters. To economize on notation, we thus conceive of the preference shifters $\pi_{mj,n}$ and $\omega_{mi,nj}$ as reflecting trade costs, an approach common in the IRBC literature (e.g. Backus, Kehoe, and Kydland, 1992). By the same token, the international borders can be reflected in iceberg costs of shipping internationally as in the trade literature, or in home bias in preferences as in the international macro literature.

Throughout, lowercase letters denote variables in log deviations from steady state, and bold letters denote vectors or matrices that collect the corresponding country-sector elements. Thus, $\boldsymbol{\pi}$ is an $NJ \times NJ$ matrix whose $(mi, nj)^{th}$ element corresponds to $\pi_{mi,n}$;[9] $\boldsymbol{\omega}$ 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 operator $\mathbb{E}[\cdot|\mathcal{I}]$ denotes the expectation based on information set $\mathcal{I}$.

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.2. □

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

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

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

[9] Since this is final goods consumption, the (mi, nj) element is invariant to the destination sectoral dimension j.

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 agents. First, all agents observe a public signal about TFP in each country-sector (m, i):

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

where the precision of the public signal about (m, i) is $\kappa_{mi} \mathbb{V}(z_{mi,t})^{-1}$. 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 $\tau_{nj,mi} \mathbb{V}(z_{mi,t})^{-1}$. 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 parameter κ_{mi} will reflect the differences in the intensity of news coverage of the sector. In Appendix D.3 we also explore a specification in which the precision of private signals falls in the network distance, in the spirit of rational inattention.

Taking stock, the information set of island ι is given by $\mathcal{I}_{nj,t}(\iota) = \left\{x_{nj,mi,t}(\iota), s_{mi,t}\right\}_{i=1,\ldots,J}^{m=1,\ldots,N}$. The presence of private signals implies that information is dispersed, and we next discuss the implications of this feature of the environment for the equilibrium outcomes.

2.2 Equilibrium Characterization

At the sectoral level, the total hours worked is given by the aggregation of (2.3) 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 prevail 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

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

where

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

Proof. See Appendix A.3. □

The Lemma characterizes the solution to this global general equilibrium model conditional on a

vector of fundamental and signal shocks.[10] 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, 2025, 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 φ and γ. 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 perfect information benchmark that follows next.

Perfect information benchmark. Consider momentarily the perfect information benchmark ($\tau = \infty$), 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:

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

This is a special case of the analytical solution to the global network model in Huo, Levchenko, and Pandalai-Nayar (2025), under Cobb-Douglas preferences. It resembles the Leontief inverse, and the change in hours can be decomposed into direct and indirect effects:

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

The direct (also called "first-degree," 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-degree effect adds the first-round change in hours. The third-degree 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. 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).

[10] Note that both prices and hours are log-normally distributed. Hence, the expressions in Lemmas 1 and 2 hold exactly up to constant terms, rather than being first-order approximations. Lemma 2 would hold to a first order approximation if preferences and technologies were CES. Appendix A.3 contains further theoretical discussion.

Incomplete information. With incomplete information, the equilibrium outcomes 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

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

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*

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

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

Proof. See Appendix A.4. □

Compared with the perfect information 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 degree 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 round 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 assumptions on the information structure, Bayes' rule implies that sector (n, j)'s first-order expectations about sector (m, i)'s shocks are

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

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

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

Proof. See Appendix A.5. □

In contrast to the perfect information 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).

Special case 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*

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

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.6. □

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 $\boldsymbol{h}_t = (\mathbf{I} - \lambda_z \boldsymbol{\gamma})^{-1} \boldsymbol{\varphi} \lambda_z \boldsymbol{z}_t$, 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 $\boldsymbol{h}_t = (\mathbf{I} - \boldsymbol{\gamma})^{-1} \boldsymbol{\varphi} \lambda_\varepsilon (\boldsymbol{z}_t + \boldsymbol{\varepsilon}_t)$. 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" is 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.

Noise-driven volatility. Corollary 2.1 also illustrates that the importance of noise-driven aggregate fluctuations is non-monotonic in the precision of the public signals. When the public signals are uninformative ($\kappa = 0$), $\lambda_\varepsilon = 0$ and agents put no weight on the public signals in forming their expectations. As a result, the coefficient on $\boldsymbol{\varepsilon}_t$ in (2.11) is 0: there are no noise-driven fluctuations. By contrast, if $\kappa = \infty$ public signals are perfectly precise and agents know the true fundamentals. In that case, $\lambda_z = 0$ and $\lambda_\varepsilon = 1$, and the hours change in (2.11) coincides with the perfect information benchmark. In this case there is also no role for the private signals or noise-driven volatility. The exact fraction of noise-driven volatility in the quantitative model depends on the calibrated precision of the public signals, as we explore in Appendix D.3.

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 degree 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 the 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.7. □

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, holding fixed the 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.[11]

Illustration. In the general case, the k-th degree 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-degree 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 degree coefficient: $\mathcal{T}_{k,1} = \mathcal{T}_{k,1}^{(k)} = 1$. That is, the transmission is via higher-degree network effects for more downstream sectors.

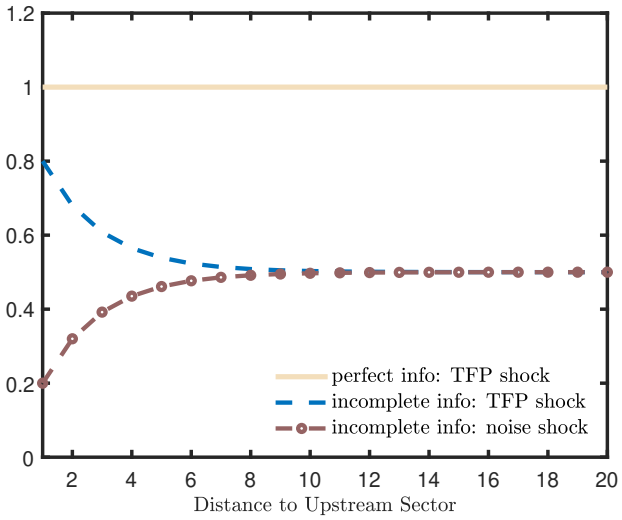
Figure 1 displays the responses of hours to TFP and noise shocks as a function of the sector's downstreamness k. With perfect information, the equilibrium outcome in this stylized economy is simple: all country-sectors k respond one-for-one to the fundamental shock:

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

That is, the shock transmits to other country-sectors perfectly. This is depicted by the solid beige line.

[11] 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.

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/beige 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 (simple dash, blue) and noise shock (circle dash, brown) under incomplete information. The calibration uses $\lambda_z = 0.6$ and $\lambda_\varepsilon = 0.2$.

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 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.8. □

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 circle-dashed brown 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, 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.9 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.

2.4 Anecdotal and Historical Evidence

To provide a concrete illustration of the mechanisms operating in the model, we turn to a "textbook" example of a non-fundamental shock: the dot-com boom in the United States in the 1990s, a period of optimistic beliefs that generated an economic expansion (Angeletos, Lorenzoni, and Pavan, 2022). The

basic empirical challenge is identifying noise shocks separately from productivity and other shocks. Levchenko and Pandalai-Nayar (2020) develop a strategy to extract US noise as shocks orthogonal to both surprise and news TFP that maximize the forecast error variance of an expectational variable, such as GDP forecasts or consumer confidence. They then examine the propagation of noise and technology shocks to the US and Canada.

Both the experience of the 1990s dot-com period and the full sample support the predictions of our theory. First, the US noise shocks during the 1990 are responsible for a substantial fraction of the overall economic expansion in the 1990s (Figure 7 of Levchenko and Pandalai-Nayar, 2020, p. 329). In the full sample, US noise shocks are an important source of aggregate fluctuations in both US and Canada (Figures 3 and 6 and Tables 1 and 2 of that paper, pp. 317-324). Together, these results support Proposition 2.2/Corollary 2.1: noise shocks generate aggregate fluctuations and propagate internationally.

Second, the comparison of the impact of US noise shocks on the US vs. Canada supports Proposition 2.3: noise shocks are relatively more important in the more distant parts of the network. The Canadian economy has a greater network distance to the US than the US economy to itself: the average network distance (2.12) between a Canadian sector and a US sector is 57% larger than the average network distance between a US sector and another US sector.

Proposition 2.3 would then predict that US noise shocks are relatively more important for Canada than for the US, compared to technology shocks. Figure 2, based on results from Levchenko and Pandalai-Nayar (2020) supports this proposition. Panel A reports the results for GDP, and Panel B for hours worked. The left-most bars in each panel illustrate the experience of the 1990s expansion. They display the shares of the US noise and technology shocks in the total change in GDP and hours accounted for by those shocks combined. As predicted by Proposition 2.3, the relative importance of the US noise in Canada is higher than in the US itself for both GDP and hours during the dot-com boom.

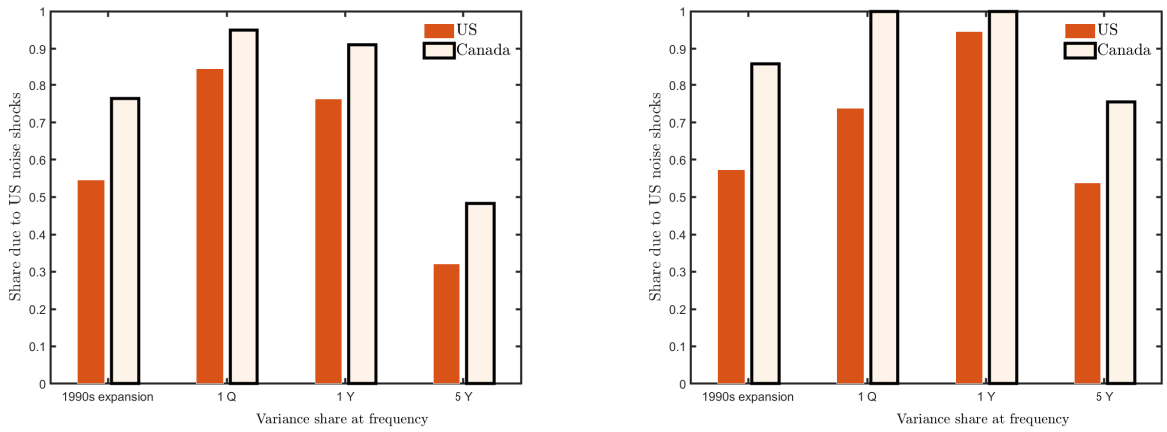
The remaining bars in both panels examine the full sample (1968-2010 in that paper). They report the shares of variance in GDP and hours accounted for by the US noise shocks, relative to the combined variance accounted for by the US noise and technology shocks.[12] Across multiple frequencies, the variance share accounted by the US noise shocks is higher in Canada than the US. All in all, these results suggest that both during the dot-com expansion and more broadly, US noise shocks are relatively more important than US technology shocks for the more distant part of the production network – Canada.

3. Data

Road map. Our next goal is to quantify the model and explore the importance of imperfect information and noise shocks in the global value chain for international fluctuations. Quantification of the

[12]The underlying inputs are in Tables 1-3 of Levchenko and Pandalai-Nayar (2020), pp. 319-321.

Figure 2: Relative Importance of US Noise Shocks for the US and Canada



A. GDP B. Hours

Notes: The bars labeled "1990s expansion" display the share of the cumulative change in GDP and hours that is due to the US noise shock, in the total change in GDP and hours explained by the US noise and US technology shocks combined, during the 1990s expansion (1992Q1 to 2000Q2). The rest of the bars display the share of the variance at different frequencies accounted for by the US noise shocks, as a fraction of the variance accounted for by the US noise and US technology shocks combined. In all cases, "technology" shocks refers to the combination of identified surprise US TFP and US news TFP shocks.

model above faces one main hurdle: disciplining the parameters governing the private and public signal processes (2.4) and (2.5). (The rest of the calibration, such as the input-output matrices and basic elasticities is more common and straightforward.) We proceed as follows. First, we collect a dataset on the economic news coverage in several countries spanning more than 2 decades. Second, we combine this dataset with information on forecast errors by country, and document empirical relationships between forecast errors, forecaster disagreement, and news coverage. Third, we posit a parsimonious specification for the signal processes (2.4) and (2.5), that relates the precision of the public signal in a country-sector (a model object) to the intensity of news coverage (a data object). We use indirect inference to pin down the 3 parameters governing the parsimonious signal process by targeting the reduced-form empirical relationships between news coverage and forecaster errors and disagreement estimated in the second step. Finally, we use the resulting parameters governing signal precision to simulate the model and quantify the relative importance of noise shocks in aggregate fluctuations and their transmission through the network.

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. Examples of sector tags include "Banking/Credit" or "Construction," and examples of region tags include "Canada" or "United States." 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. Factiva does not employ commonly used sectoral classifications, so we concord Factiva sectors to ISIC Rev. 4 to merge these data with other sources. Appendix Table A1 displays the concordance between Factiva sectors and ISIC Rev. 4. 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.[13]

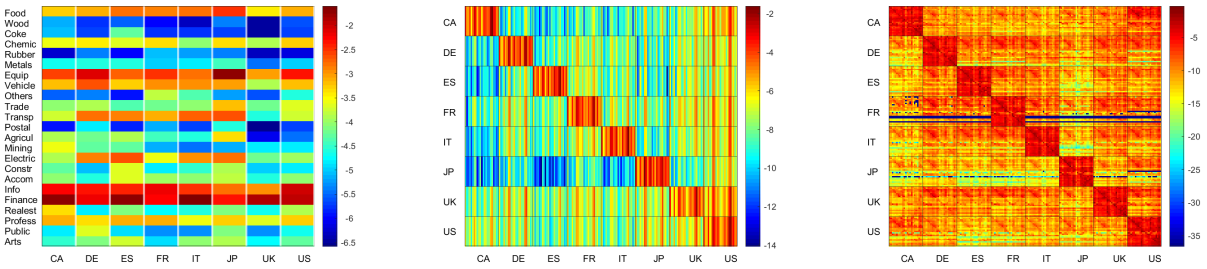
We use these data to define a country-level news coverage variable $F_{n,t}$ as the share of global news coverage dedicated country n in period t. That is, $F_{n,t}$ is the total news coverage in all newspapers from all source countries of country n in period t divided by total news coverage in all newspapers in period t. Analogously, we define $F_{nj,t}$ as the share of global news coverage of country n sector j in period t.

Basic patterns in economic news data. We document some patterns in these 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 3 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,

[13]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 3: 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.

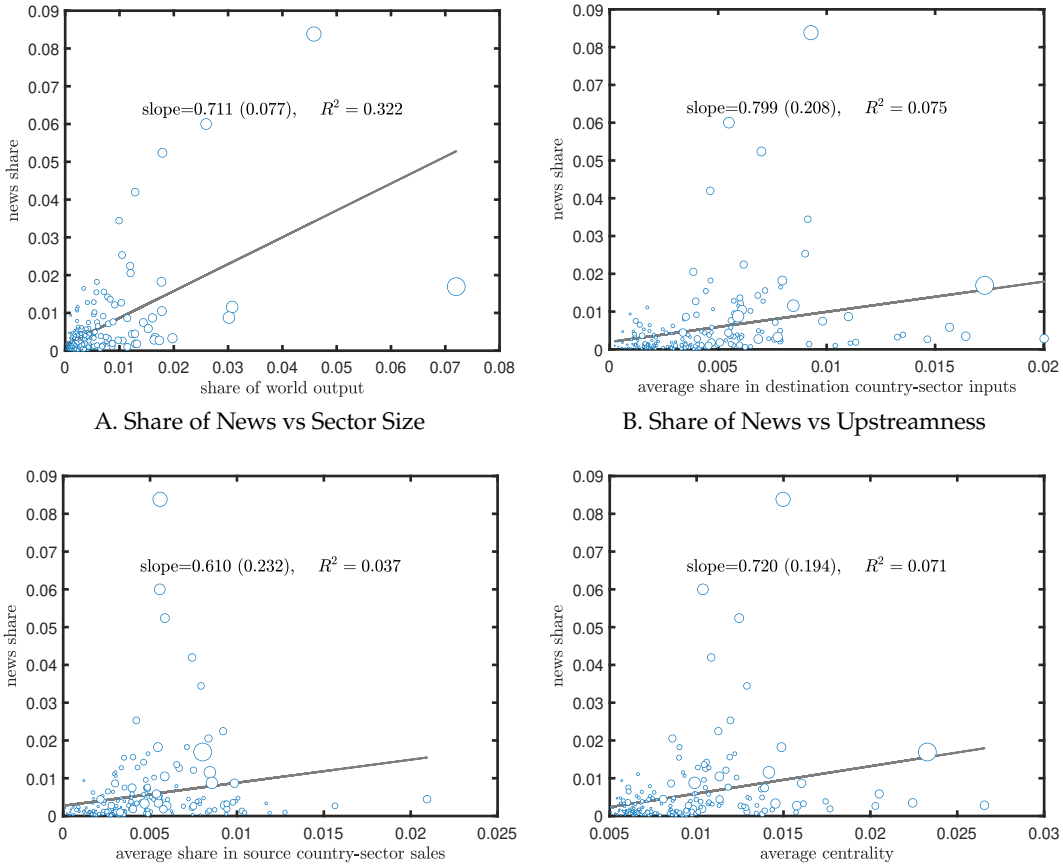
German news outlets report on equipment and automobile sectors more frequently than many other countries. Panel B of Figure 3 depicts a heatmap of local news coverage shares (averaged over time), and contrasts it to a standard input-output heatmap in Panel C (e.g. Huo, Levchenko, and Pandalai-Nayar, 2025). 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 4 plots the average frequency share of a sector against 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 4 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.[14] 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.

[14]Upstreamness and downstreamness are defined in Appendix C.1.

Figure 4: News Coverage, Size, and Sectoral GVC Position



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.

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. 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.

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	public 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.

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.

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, governing 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 in the public signal precision about different country-sectors. We assume news coverage is associated with the public signals agents receive, and therefore contains information both about the true productivity shocks and noise.

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. Importantly, our calibration strategy does not use news coverage to back out noise *shocks*.[15] Our approach is to discipline the *parameters* governing the public and private signal processes.

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 as defined in Section 3. We control for forecaster×country and time effects. The inclusion of time effects absorbs the level of economic news coverage in a period, and implies that the coefficient estimate β_1 is invariant to whether $F_{n,t}$ is the news share, or the absolute level of news coverage.[16] We log $F_{n,t}$ to interpret β_1 in terms of the effect of a percent change in the share of news coverage. 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

[15] 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 conceptually 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 for a single country (Levchenko and Pandalai-Nayar, 2020), orthogonalizing shifts in empirical expectations variables with respect to all other shocks is infeasible in our multi-country setting, in part because identified fiscal, monetary, financial, and all other candidate shocks affecting expectations are not available on a consistent basis for many countries.

[16] 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.

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.

Interpretation and robustness. The OLS coefficients may be biased as estimates of the causal effect of exogenous shifts in news coverage on forecastability of GDP. One broad possibility is that omitted variables drive both forecastability of GDP and news coverage. 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 is 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. 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. It adds controls for nonlinear transformations of productivity and news sentiment indices to take into account the possibility that positive vs. negative shocks result in different news coverage intensity; monetary policy; and the political cycle.[17] It also contains additional checks, such as using expectations of the unemployment rate instead of GDP, and alternative weighting for sectoral news coverage. All in all, these exercises alleviate the concern that our coefficient is spurious, and driven by the fact that certain developments in the economy move both the forecastability of GDP and news coverage.

The second generic possibility is pure reverse causality: perhaps there are periods of exogenously high GDP forecastability vs. low GDP forecastability. And perhaps news coverage responds en-

[17]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.	|forecast error|	SD (forecast error)	|forecast error|	SD (forecast error)
$\log F_{n,t}$	-0.082^{***}	-0.030^{***}	-0.290^{***}	-0.061^{***}
	(0.010)	(0.011)	(0.027)	(0.016)
Observations	18,562	800	17,326	768
R^2	0.470	0.706	0.696	0.543
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.

dogenously, changing in intensity depending on whether GDP is highly forecastable or not. One could imagine news coverage either expanding or contracting when GDP is (exogenously) highly forecastable, depending on the underlying model of how news coverage is formed. Thus, the bias from this type of direct reverse causality is difficult to sign ex ante. We acknowledge this possibility and note that signing these biases and convincingly establishing causality would be useful for future research in this area. In the meantime, below we implement the sensitivity analysis following Andrews, Gentzkow, and Shapiro (2017). This exercise quantifies the consequences of potential bias in the coefficients. To preview the results, over reasonable ranges of regression coefficients in (4.1)-(4.2), the calibration remains reliable.

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 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).[18] Here, χ_0 captures the minimum amount of information in the public domain, while χ_1 captures the

[18]Note that κ_{nj} and τ are shifters in the precisions of the signals, and the actual signal precisions are scaled by the variance of the country-sector productivity shocks (see 2.4 and 2.5). Under this specification, a given change in any country's news coverage has the same effect on the responsiveness of the expectations to a signal. In the hypothetical alternative in which the signal precision itself is affine in news coverage, the signal-to-noise ratio will differ across country-sectors in arbitrary ways, which we view as undesirable.

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.[19]

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).[20] And third, while the theoretical model is static, the empirical regressions rely on within-forecaster variation in forecast quality and news coverage over time. There is no viable alternative to this, as forecaster fixed effects are essential in the empirics in order to absorb confounding factors. To 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.[21] 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.

[19] If there was a trend increase in the amount of information in the public domain – i.e. an increase in the public signal precision κ_{nj} over time – that would imply different properties of the business cycle late in the period relative to earlier. Our data do not point to a strong trend. There is no pronounced secular rise in the total amount of economic news coverage in our data from 2000 to 2020 (Figure A3). Note that an upward trend in the amount of publicly available information would imply falling unconditional dispersion in forecast errors. There is only a modest decrease in the unconditional forecast error dispersion over time in our data, and the quantitative properties of our model are insensitive to this trend (results available upon request).

[20] 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.

[21] 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, |forecast error|	-0.082	-0.083
Slope, SD (forecast error)	-0.030	-0.035
Unconditional moment		
SD (forecast error)	0.077	0.072

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, $|\text{forecast error}|$), (ii) the slope coefficient in the forecast dispersion regression (4.2) (Slope, SD $(|\text{forecast error}|)$), 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 $\{\tau, \chi_0, \chi_1\}$.

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 sources of endogeneity. 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.

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 A10 reports the full 3×3 matrix (3 moments × 3 structural parameters). Figure 5 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:

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

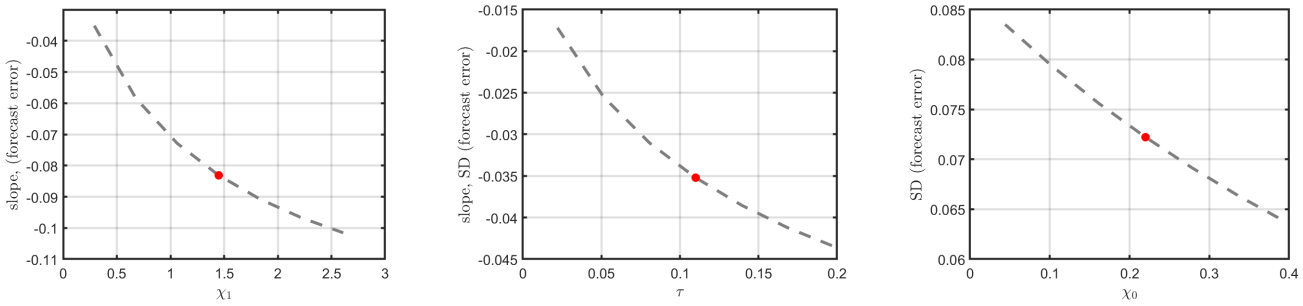
The intuition is as follows. The slope of the relationship between the news coverage intensity and the quality of the forecasts (4.1)/(4.4) contains information on how much the public signal precision improves with more news coverage. Because the forecasters rely on both private and public signals, the 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 5 plots the unconditional forecast dispersion against the remaining parameter, the intercept χ_0.

Figure 5 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.

Figure 5: 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.

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.[22] 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).

4.2 Quantitative Implications

4.2.1 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. Panel A in Figure 6 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.

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

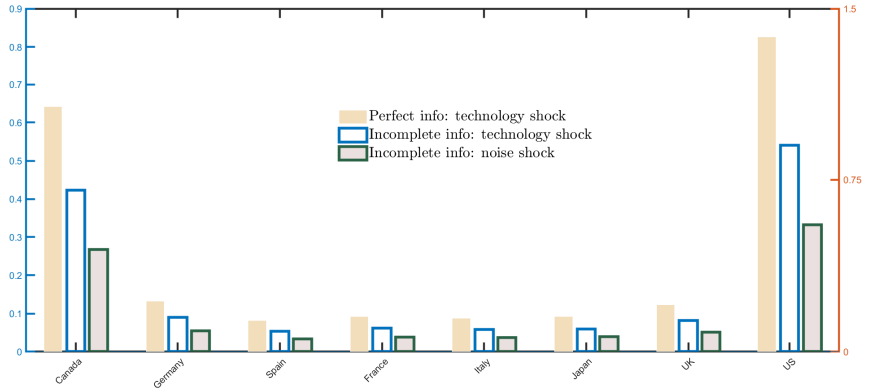
When facing such uncertainty about the fundamentals, agents also rely on signals when making their production decisions. It follows that the noise shocks in the public signal contribute to international fluctuations. The brown bars in Figure 6 show the changes in hours in response to a one standard deviation 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.

Panel B of Figure 6 shows the average global hours response to a shock originating in each country, excluding that country's own response. This provides a measure of the strength of international spillovers generated by each country's shock. The magnitudes are highly uneven, reflecting differences in country size. Conversely, Panel C of Figure 6 displays the hours response to shocks to the rest of the world, excluding the country itself. Here, smaller economies such as Canada exhibit the largest responses, whereas the United States reacts the least to shocks originating abroad. In all cases, the noise shocks have an impact similar to TFP shocks under incomplete information.

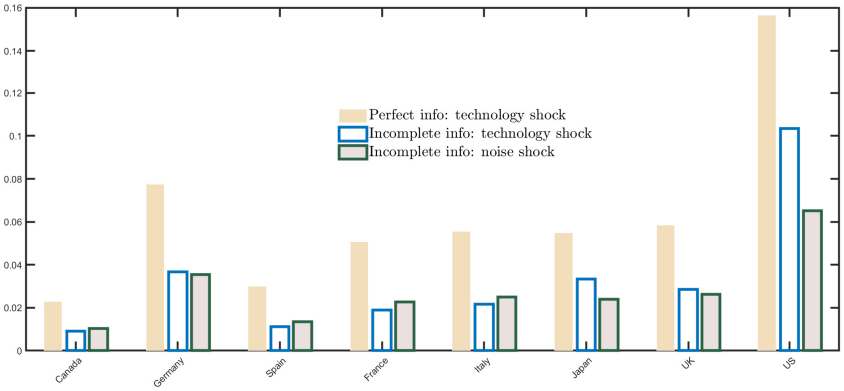
Table 4 displays the business cycle statistics of hours growth, aggregated at the country level. The first row illustrates the two basic implications of incomplete information: it attenuates the response to the fundamental shocks while opening the door for non-fundamental fluctuations. Column 1 presents 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 60% of those driven by fundamental shocks.[23] 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).

[23] In Columns 2-3, we use the model with information frictions and simulate the TFP or noise shocks one at a time. Recall that the TFP and noise shocks are orthogonal to each other.

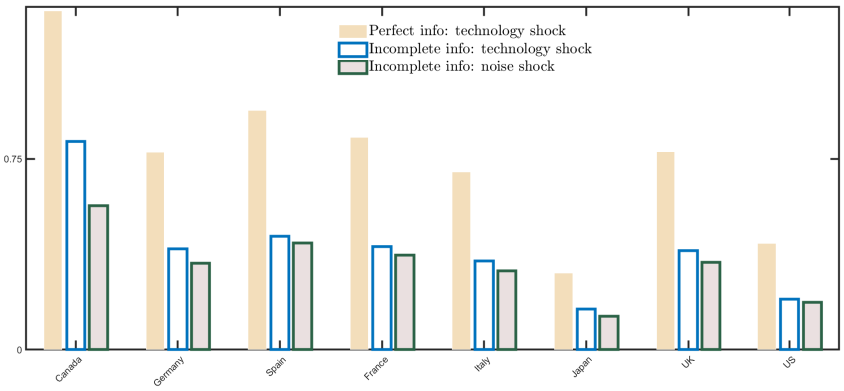
Figure 6: Impulse Responses to TFP and Noise Shocks



A. Response to US TFP and Noise Shocks



B. World Average Response to A Country's TFP and Noise Shocks



C. Responses to Rest-of-World Shocks

Notes: Panel A displays the change in hours worked in each country following a 1-standard deviation TFP or noise shock in the US. Panel B displays the average change in hours worked in the world (excluding the shock-originating country) following a 1-standard deviation TFP or noise shock in each country. Panel C displays the change in hours worked in a country following a 1-standard deviation TFP or noise shock in the rest of the world (excluding that country). The beige bars show the hours change due to a TFP shock without informational frictions. The blue empty bars show the hours change due to a TFP shock in the baseline model with imperfect information. The brown bars with a blue outline show the hours change in response to a noise shock in the US. In Panel A, 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.

Table 4: Business Cycle Statistics

	(1) Perfect Information	(2)	(3)	(4)	(5)
		Incomplete Information			Data
	TFP	TFP	noise	both	
Hours volatility	0.986	0.503	0.298	0.585	1.550
indirect vs direct effects: $\frac{\sigma_{\text{indirect}}}{\sigma_{\text{direct}}}$	0.464	0.395	0.561	0.437	
Bilateral hours correlation					
uncorrelated noise	0.094	0.111	0.056	0.097	0.190
correlated noise	0.094	0.111	0.298	0.172	
Bilateral labor wedge correlation					
uncorrelated noise	—	0.058	0.027	0.051	
correlated noise	—	0.058	0.239	0.116	

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.

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 by both direct (changes in expected fundamentals) and indirect effects (changes in other sectors' expected hours).[24] 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 0.464 to 0.395 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

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

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 (0.561 vs. 0.395).

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, 0.056. 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.

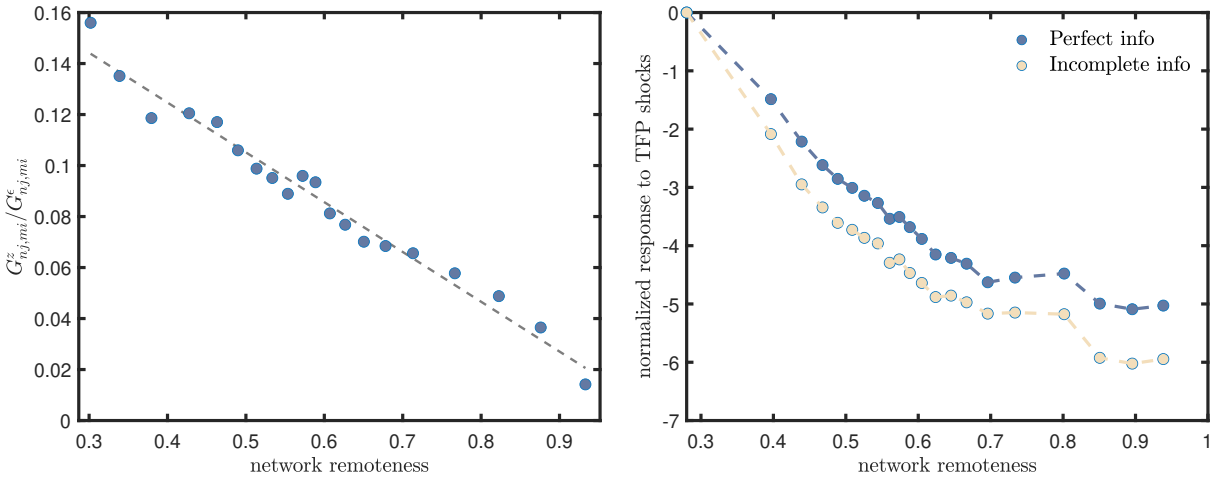
Labor Wedge. With incomplete information, the marginal rate of substitution (MRS) and the marginal product of labor (MPL) are equalized only in expectation ex ante, but not necessarily ex post. As a result, a noise shock produces a divergence between MRS and MPL, and appears as a labor wedge, as discussed in Angeletos and La'O (2010). What is unique in our setting is that the fluctuations in the labor wedges help understand international comovement. Huo, Levchenko, and Pandalai-Nayar (2025) 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, 0.116.

4.2.2 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

Figure 7: 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.

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 7 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 7 illustrates this graphically in our quantitative model. It plots the log response

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. The rate of decay of the impulse response is notably faster in the incomplete information model.[25]

External validation. 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 Section 2.4 above), and the importance of correlated labor wedges in international comovement (Huo, Levchenko, and Pandalai-Nayar, 2025). Appendix C.3 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.

Additional exercises. The baseline quantification uses Cobb-Douglas aggregators for both final and intermediate goods, which implicitly regulates the degree of strategic complementarity in the underlying network game. Appendix D.2 shows that the main macro implications are robust to a more general CES aggregator and elasticities of substitution that are closer to recent empirical estimates. Appendix D.3 reports a number of additional results. First, it shows that shocks to sectors more covered in the news propagate more strongly to the rest of the economy. Next, it allows for the possibility that firms have more precise private signals about sectors close to them in the network. This is a reduced-form way of capturing endogenous information acquisition, as agents are more likely to seek information about sectors on which they depend more heavily. As sectors further away in the network are lower in importance for a given country-sector, private signal precision about these sectors is low, which reinforces our result on the relationship between the network remoteness and the reliance of public signals. Next, Appendix D.3 shows that the magnitude of fluctuations generated by noise shocks is non-monotonic in news coverage intensity. It also considers an alternative specification in which the precision of public signals is common across sectors within a country. The resulting business cycle statistics are similar to those in our baseline. Finally, it discusses the consequences of alternative assumptions on informational frictions: only private information and no information. With only private information, public signals are removed and the precision of private signals is adjusted so that the average first-order expectations remain the same as the baseline model conditional on TFP shocks. We show that lessons on the fundamental shock transmission are still valid though the the noise-driven fluctuations are muted. In the no-information economy, agents receive no signals about

[25]For instance, at the network distance of 0.5 (about the 25th percentile in the network distance distribution across country–sector pairs), in the perfect information model, the average relative impulse is $\frac{G^z_{nj,mi}}{G^z_{mi,mi}} \approx 0.058$ (exp(−2.85)). In the incomplete information model, the average relative impulse is 0.027 (exp(−3.60)), or about 50% the value of the perfect information model.

other locations' TFP shocks, and both the volatility and bilateral correlation of hours are reduced.

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. We find that noise shocks are both a quantitatively important source of international fluctuations, and that informational frictions generate qualitatively different fluctuations.

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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