SECTORAL MEDIA FOCUS AND AGGREGATE FLUCTUATIONS

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Abstract. We formalize the editorial role of news media in a multi-sector economy and show that media can be an independent source of business cycle fluctuations, even when they report accurate information. Public reporting about a subset of sectoral developments that are newsworthy but unrepresentative causes firms across all sectors to hire too much or too little labor. We construct historical measures of US sectoral news coverage and use them to calibrate our model. Time-varying media focus generates demand-like fluctuations that are orthogonal to productivity, even in the absence of non-TFP shocks. Presented with historical sectoral productivity, the model reproduces the 2009 Great Recession.

1. Introduction

A fundamental question in macroeconomics regards the sources of aggregate fluctuations. Cochrane (1994) goes through a list of plausible candidates, including technology, monetary policy, government spending, oil price and credit shocks, and argues that these types of shocks are either too small, or imply counterfactual correlations between different macro economic variables. He summarizes this state of affairs, writing

> *"It would be nice to point to recognizable events, of the type that is reported by newspapers, as the source of economic fluctuations, rather than to residuals from some equations."*

In this paper, we argue not only that aggregate fluctuations can be generated by the type of events that are reported by newspapers, but, in fact, that some events generate aggregate fluctuations *because* they are reported by newspapers. We propose a model in which accurate public reporting about sectoral developments that are unrepresentative of the economy as a whole causes firms across all sectors to hire too much or too little labor. This creates the appearance of aggregate shocks that are orthogonal to productivity, even though the only source of exogenous variation are sector-specific productivity shocks.

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A recent literature has demonstrated that, under certain conditions, production networks can lead firm- or sector-specific shocks to generate aggregate fluctuations, e.g. Horvath (1999), Carvalho (2010), Acemoglu, Carvalho, Ozdaglar and Tahbaz-Saleh (2012), Carvalho and Gabaix (2013), Baqaee and Fahri (2019) and Carvalho and Grassi (2019). Shocks to a single sector or firm propagate to other sectors or firms through the trade of intermediate inputs. Foerster, Sartre and Watson (2011) and Atalay (2017) quantify these channels, and their results suggest that sector-specific shocks can explain a substantial portion of observed aggregate output fluctuations. However, trade in intermediate inputs by itself does not induce enough correlation in production across sectors to account for all of the observed volatility of aggregate output.

We show that news media can serve as a powerful additional source of sectoral comovement. A basic premise of our argument is that individual firms do not have the resources to directly observe every sector in the production network. Instead, firms rely on news media to monitor the economy on their behalf and to report the most newsworthy developments. However, even accurate reports provide only a partial picture of the economy. Such partial information, in turn, may lead firms to over- or underestimate how much of their product other firms will demand. As in Angeletos and La'o (2010, 2013), a firm that is overly optimistic about demand for its output hires too much labor. If firms across different sectors receive the same partial information via news media, over- or under-hiring of labor will be correlated across sectors. News media thus function as a coordination device for the economy, increasing the correlation of sectoral outputs beyond what would result from sectors' trading relationships alone.

We embed state-dependent news reporting in a modified version of the multi-sector model of Acemoglu *et al* (2012). In our model, news media act as information intermediaries that relay information about the state of the economy to firms. We argue that there are two aspects of this role that are particularly relevant for understanding business cycles. First, news organizations monitor the economy by collecting and producing information about a large number of events. Second, they make editorial decisions about which events are sufficiently newsworthy to be reported.[1] We formalize these editorial decisions using *news selection functions*, first introduced in Nimark and Pitschner (2019). A news selection function is a mapping from the state of the world to a vector of reported outcomes. News selection functions provide a flexible way to model state-dependent editorial decisions, thereby capturing the changing focus of news coverage over time.

By determining what gets reported in which states of the world, a news selection function implicitly defines a notion of *newsworthiness.* A given notion of newsworthiness, in turn, implies a specific selection bias of events that end up in the news. For instance, if extreme events are considered newsworthy, they will be over-represented in media reports relative to

[1]Our news selection functions represent what in the journalism and political science literature is referred to as the *gatekeeping process.* The former literature has studied where gatekeeping occurs, e.g. Shoemaker and Vos (2009) discusses whether the decision about what makes the news is made primarily at the news gathering (journalist) level, or at the news processing (copy-writing and editorial) level. The political science literature has focused mostly on how gatekeeping is affected by ideology and how it affects political opinion. Some of this literature has studied economic news directly, e.g. Soroka, Stecula and Wlezien (2015) who argue that news about future economic prospects affects public political opinion.

the unconditional frequency with which they occur. The effects of this selection bias increase with the number of sectors in the economy: The more potential events the news media has to report, the more extreme the reported outcome is likely to be.

The effect that news reports have on the economy depends on what criteria media organizations use to judge the newsworthiness of an event. To investigate empirically what these criteria may be in practice, we construct a measure of sectoral news coverage using articles from US newspapers. Using this new data set, we establish several facts. First, larger sectors receive more news coverage than smaller sectors. Second, after controlling for their size, some sectors receive a disproportionate amount of news coverage. Third, news coverage of individual sectors tends to increase when a sector experiences unusually large shocks.

We calibrate the model to match these features of the news data and the input-output structure of the US economy. For the production side, we choose parameters such that the model fits the data on intermediate input shares provided by the Bureau of Economic Analysis (BEA) aggregated to 29 sectors. In the calibrated model, state-dependent reporting decisions by news media contribute substantially to aggregate fluctuations. The variance of aggregate output is more than two times larger in the baseline model compared to the same model but without news media and one and a half times as large as in a model in which news media randomly chooses which sector to report. Moreover, when we feed actual sectoral TFP shocks into the model, it predicts a severe recession in 2009, while a full information version of the same model does not. The baseline model also generates fluctuations in aggregate labor that are substantially larger in magnitude, and more correlated with observed employment, than the alternative specifications do.

Using our model, we show that time-varying sectoral media focus can generate fluctuations in aggregate output and labor that are orthogonal to sectoral TFP. This is the case even though sectoral TFP shocks are the only exogenous source of variation in the model. Productivity in a given sector has a bigger impact on aggregate output when that sector is in the news, compared to when it is not. This type of state dependence cannot be captured by a constant linear relationship between sectoral productivity and aggregate output. Researchers applying a Foerster, Sartre and Watson (2011) or Atalay (2017)-style filter to data generated from our calibrated model would conclude that a common shock that is orthogonal to sectoral productivity accounts for about 17% of the total variance of aggregate output and about 38% of the total variance in aggregate labor.

The model we propose is stylized, which brings the benefits of tractability and transparency but imposes a lot of structure on the data. We therefore also present empirical evidence that supports the key mechanism but does not rely on the structure of our theoretical model. To this end, we first construct a sectoral news-weighted index of economic activity. When this index is above a corresponding unweighted aggregate reference index, the news are unrepresentatively good. When it is below the reference index, news are unrepresentatively bad. The difference between the news-weighted index and the reference index is thus an index of the "unrepresentativeness" of sectoral news reports.

According to our proposed mechanism, the unrepresentativeness index should predict how beliefs deviate from what is justified by fundamentals. As a second step, we therefore estimate a sign-restricted VAR as proposed by Enders, Kleeman and Mueller (*forthcoming*). This approach uses data on actual GDP growth and expectations of GDP growth to extract time series of mutually orthogonal shocks to beliefs and to fundamentals. Consistent with Enders *et al*, we find that positive shocks to beliefs that are orthogonal to fundamentals cause an increase in GDP growth. We then compute the correlations between the two shocks and our index of news unrepresentativeness. As our theory predicts, the index of news representativeness is positively and significantly correlated with the identified shocks to beliefs, but is approximately orthogonal to the identified aggregate fundamental shocks.

In our model, firms choose their production capacity in anticipation of demand for their products. This mechanism is consistent with the evidence presented by Gennaioli, Ma and Shleifer (2016), who show that firms' investment growth can be predicted by CFOs' expectations of sales growth, even after controlling for a plethora of other variables. Arif and Lee (2014) use information from firms' balance sheets to document that aggregate investment fluctuations are driven by firms' unduly optimistic expectations about future cash-flows that subsequently fail to materialize. Eisner (1978) and Greenwood and Hanson (2015) provide additional evidence that expectations about future sales drive investment decisions. Furthermore, Gennaioli *et al* (2016) document that expectation errors about sales growth are correlated across surveys and across different types of agents, suggesting that different agents may receive information from the same sources. In our model, news media provide the same partial information about the economy to firms in all sectors, thus providing a mechanism for why firms across different sectors make correlated prediction errors.

Our mechanism for translating changes in firms' beliefs into output decisions is similar to Angeletos and La'O (2013). In that paper, agents trade with randomly-matched trading partners and experience a sentiment shock that drives all firms to be optimistic about the production of their trading partner. In our paper, trading partners are fixed by the production structure, and news media reports on specific sectors drive optimism about production in other sectors. In both papers, firms produce more when they expect high demand for their product from other firms, i.e. when they expect more favorable terms-of-trade.

The idea that common but imperfect signals can generate demand-like disturbances is not new and was first formalized by Lorenzoni (2009). Both Nimark (2014) and Blanchard *et al* (2013) explore this idea empirically within fully specified structural models. Unlike in these earlier papers, however, consumers' expectations about future income plays no role in our model.

Chahrour and Ulbricht (2019) develop a flexible empirical framework for quantifying the importance of information frictions for business cycles and argue that undue optimism or pessimism can explain up to 51% of the variation in output. Angeletos, Collard and Dellas (2018) uses a semi-structural method, which is computationally simpler than a fully structural approach, to document that sentiment shocks can explain more than half of the variance of output, consumption and employment at business cycle frequencies. In a similar vein, but using a less structural approach, Angeletos, Collard and Dellas (2019) document that a single "main business cycle shock" appears to be driving most of the variation at business cycle frequencies of several aggregate variables. Time-varying sectoral media focus in our model generates aggregate fluctuations that share many of the properties of this shock, i.e. it generates positive comovement between output, employment and consumption through fluctuations that are orthogonal to productivity.

In this paper we propose a new approach to model incomplete information. Instead of noisy signals about variables of common interest, firms in our model receive perfectly accurate information about some sectors in the economy. But because this information only provides a partial picture of the economy, firms do not have complete information about all developments that could potentially affect their production decisions. Like us, Tian (2019) studies the role of input-output linkages when firms may be overly optimistic, but that paper models common belief fluctuations driven by exogenous noise in a public signal. Atolia and Chahrour (2020), by contrast, provide conditions under which such beliefs fluctuations have little or no impact on aggregate output.

One advantage of our approach to modeling incomplete information is that it avoids introducing exogenous informational shocks either at the firm or the aggregate level. This is more than an aesthetic advantage: Given a specific news selection function, beliefs are completely determined by the cross-sectional profile of productivity shocks. The model thus tightly links agents' beliefs to the real economy, and it makes specific predictions about what realizations of sector-specific shocks should be associated with undue optimism or pessimism. Macroeconomic models with incomplete information have mostly used survey data on expectations to discipline agents' beliefs, or inferred these beliefs indirectly from agents' decisions, e.g. Melosi (2016), Blanchard, L'Huillier and Lorenzoni (2013), Nimark (2014) and Angeletos *et al* (2018). By explicitly modeling news media as information intermediaries, we can exploit our novel data on news coverage to discipline agents' beliefs.

There is a large literature that studies news media markets from the perspectives of industrial organization and political economy, but there are surprisingly few papers that have incorporated an explicit role for news media in macroeconomic models. Two important exceptions are Carroll (2003), who shows that news coverage can explain how inflation expectations spread through a population, and Veldkamp and Wolfers (2007). Like we do, Veldkamp and Wolfers argue that a common information source can explain why sectoral output is more correlated than sectoral productivity. In their model, information providers exist to exploit economies of scale in information dissemination. In equilibrium, information about aggregate shocks relevant for every sector is cheaper for firms to acquire than information about their own sector. Information consumption is therefore tilted towards aggregate shocks and away from sector specific shocks, implying that sectoral output is more correlated than sectoral productivity.

A third paper that incorporates a role for news media in business cycles is Nimark (2014). That paper also considers state-dependent news reporting, but relative to the present paper, the selection of what to report is made over a different dimension. Here, the selection is across the sectoral cross-section of TFP while in Nimark (2014), the selection is between aggregate TFP vs (implicitly) non-economic news. There are also important differences in the implications of the two forms of news selection. In Nimark (2014) news media reports amplify the effect of an aggregate TFP shock. Here, accurate but unrepresentative news generate what appears to be aggregate shocks that are *orthogonal* to aggregate TFP, even though sectoral TFP shocks are the only source of exogenous variation. In Nimark (2014), exogenous noise shocks are necessary to make agents unduly optimistic or pessimistic. Here, beliefs are a deterministic function of the cross-section of productivity and no exogenous noise shocks are needed to generate fluctuations in beliefs that make them deviate from the true state.

Blinder and Krueger (2004) and Curtin (2007) document that a majority of households get most of their economic news from either TV news shows or newspapers. The samples of these studies include periods during which the internet was still in its infancy, and one may reasonably ask how much news consumption patterns have changed due to the increasing importance and popularity of online information sources. Based on browser history data of 50,000 US households, Flaxman *et al* (2016) report that "*the vast majority of online news consumption is accounted for by individuals simply visiting the home pages of their favorite, typically mainstream, news outlets*". Mainstream news outlets tend to cover the same news events online as in their print and broadcast editions, so the move of many news providers to an online format appears to be mostly a change in viewing technology rather than a change in the type of news content agents consume.

While there is relatively little theoretical work analyzing the role of news media in the macro economy, there exists a growing empirical literature that uses news-based data sources. For instance, Baker, Bloom and Davis (2016) construct a measure of economic policy uncertainty using dictionary methods and word counts from major US newspapers. They show that their measure of economic policy uncertainty can help explain implied volatility of stock prices for firms that are exposed to government policy decisions as well as help predict future industrial production and employment. Azzimonti (2018) constructs a measure of political partisan conflict using semantic searches of US newspapers. She shows that partisan conflict and the uncertainty it introduces about policy actions can explain about one quarter of the decrease in corporate investment over the period 2007-2009. Larsen, Thorsrud and Zhulanova (2019) document that news topics predict household inflation expectations, even after controlling for standard macroeconomic variables. They also document state dependence in the degree to which households update their expectations that is consistent with news media being the driving force behind this pattern. Shapiro, Sudhof and Wilson (2020) constructs a text-based measure of news sentiment and shows that it helps predict survey-based measures of consumer sentiment. Lamla, Lein and Sturm (2007) and Buchen (2014) both directly attempt to test Wolfers and Veldkamp's (2007) theory of sectoral comovement using German news coverage data.

2. A Multi-sector Economy

We study the role of state-dependent media focus in a simple multi-sector economy populated by two types of agents. A representative household decides how much labor to supply and how much to consume of each good. Firms decide how much labor and intermediate inputs to use in production. There are n sectors in the economy, and each sector consists of a continuum of firms that sell their goods in perfectly competitive markets. Sector $i \in \{1, 2, .., n\}$ is defined by how good i enters in the production function of other goods and by how goods produced by other sectors enter into the production function of a firm in sector i. The model structure is identical to that in Acemoglu *et al* (2012), with the exceptions that (i) aggregate labor supply is endogenous and (ii) firms choose labor inputs before demand for their product is known with certainty.

In the next sections, we embed news media in the model and then describe in detail how state-dependent reporting decisions determine what information is available to firms when they make their labor input decision. Here, we first describe agents' preferences and the production structure of the economy and discuss some of the properties of the model that are important for what follows.

2.1. **Sectors and firms.** A firm in sector i uses the Cobb-Douglas production function

$$Q_i = Z_i \left(\prod_j X_{ij}^{\alpha_{ij}} \right) L_i^{1-\alpha_i} \tag{2.1}$$

to produce good Q_i. The variable Z_i is a sector-specific productivity shock, X_{ij} is an intermediate input used by sector i that was produced by sector j, and L_i is the labor input used in sector i. The coefficients α_{ij} denote the share of good j used in the production of good i. The production function exhibits constant returns to scale so that $\sum_{j=1}^{n} \alpha_{ij} = \alpha_i$. The good Q_i produced by sector i can be used either for consumption C_i or as an intermediate input X_{ji} so that

$$C_i + \sum_j X_{ji} = Q_i. \tag{2.2}$$

Firms in sector i choose labor and intermediate inputs to maximize profits Π_i

$$\Pi_i = P_i Q_i - W L_i - \sum_j P_j X_{ij} \tag{2.3}$$

taking prices P_j of all goods as given.

2.2. **The representative household.** The representative household decides how much to work and how much to consume of each good. It solves the problem

$$\max_{X_1,\ldots,X_n,L} C - \frac{L^{1+1/\nu}}{1+1/\nu} \tag{2.4}$$

subject to the budget constraint

$$C = WL + \Pi \tag{2.5}$$

where W is the wage, $L \equiv \sum_{i=1}^{n} L_i$ and $\Pi \equiv \sum_{i=1}^{n} \Pi_i$. The consumption bundle C is a Cobb-Douglas aggregate of goods

$$C = \prod_i \left(C_i/\beta_i \right)^{\beta_i}, \tag{2.6}$$

where C_i denotes the amount of good i used for final consumption. We normalize the price of the aggregate consumption bundle C to 1.

For future reference, let A be the matrix describing the production network of the economy with typical element α_{ij}. We can then define Λ_i as the i^{th} element of the row vector $\boldsymbol{\Lambda}' \equiv \boldsymbol{\beta}'(I-A)^{-1}$ where $\boldsymbol{\beta}' \equiv (\beta_1, ..., \beta_n)$. The coefficient Λ_i is a measure of the Bonacich centrality of a sector, weighted by the sector's share of final consumption (see for instance Carvalho and Tahbaz-Salehi, 2019). It is the dot product of $\boldsymbol{\beta}$ and the i^{th} column of Leontief inverse $(I-A)^{-1} = I + A + A^2 + A^3 + ...$, in which element (i,j) captures the direct and indirect importance of sector j as a supplier for sector i.

2.3. **Optimality conditions and timing of actions.** To capture the notion that some production decisions are taken in anticipation of uncertain demand, firms choose the quantity of labor inputs in a first stage before production takes place and before equilibrium wages and prices are observed. In a second stage, firms choose how much intermediate inputs to use and pay a wage that induces the household to supply the quantity of labor inputs chosen by firms in the first stage. From the firms' perspective, labor inputs may be ex post suboptimal, while for the household, labor supply is optimal given the wage.

The first stage of a firm's optimization problem is to solve

$$\max_{L_i} E\left[P_i Q_i - W L_i - \sum_j P_j X_{ij} \mid \Omega_i\right] \tag{2.7}$$

where Ω_i, the information set of a firm in sector i, is defined as

$$\Omega_i = \{Z_i, \mathbf{s}, \mathbf{r}\}. \tag{2.8}$$

A firm thus observes its own productivity as well as $\mathbf{s}$ and $\mathbf{r}$, which summarize the information reported by news media. The vectors $\mathbf{s}$ and $\mathbf{r}$ are defined in the next section.

The optimal labor input decision equates the expected marginal product of labor with its marginal cost, i.e. the real wage. A firm's equilibrium labor demand can thus be described as the labor share $(1-\alpha_i)$ times the ratio of expected revenue and expected wage

$$L_i = (1-\alpha_i)\frac{E[P_i Q_i \mid \Omega_i]}{E[W \mid \Omega_i]}. \tag{2.9}$$

After firms choose labor inputs, production takes place, sectors trade intermediate inputs and the household decides how much of each good to use for final consumption. From the Cobb-Douglas structure, equating marginal product with marginal cost of intermediate input X_{ij} implies that firms in sector i spend share α_{ij} on intermediate input good j

$$X_{ij} = \alpha_{ij}\frac{P_i Q_i}{P_j}. \tag{2.10}$$

Households supply labor until the marginal utility of consuming the real wage equals the marginal disutility of working

$$L^{\frac{1}{\nu}} = W, \tag{2.11}$$

and spend a fraction β_i of their income on each good i

$$P_i C_i = \beta_i C. \tag{2.12}$$

2.4. **Expectations, network centrality and sectoral labor demand.** State-dependent reporting affects output in the model via the expectations in the labor input decision described by (2.9). Using market clearing and equation (2.12), we have $P_i Q_i = \Lambda_i C$, allowing us to rewrite the labor demand function (2.9) as a function of expected aggregate output C and wages W,

$$L_i = (1-\alpha_i)\Lambda_i\frac{E[C \mid \Omega_i]}{E[W \mid \Omega_i]}. \tag{2.13}$$

Demand for labor in sector i thus depends positively on the expected aggregate output and negatively on the expected cost of labor W.

Since labor inputs are chosen in the first stage, labor can be treated as a fixed factor in the second stage. In Appendix A, we show that conditional on first stage labor choices, the (log of) aggregate output can be expressed as

$$\log(C) = \mathbf{\Lambda}'(I - \boldsymbol{\alpha})\mathbf{l} + \mathbf{\Lambda}'\mathbf{z} + \kappa \tag{2.14}$$

where $\mathbf{l}$ and $\mathbf{z}$ are vectors with typical elements $\log(L_i)$ and $\log(Z_i)$, $\boldsymbol{\alpha}$ is the diagonal matrix with entries α_i along the diagonal, and κ is a constant that is independent of labor inputs and productivity.

First stage information sets Ω_i are incomplete and firms therefore make expectational errors resulting in ex post suboptimal labor inputs. We can define the *informational labor wedge* that these mistakes incur as follows.

Definition 1. *(Informational labor wedge) The sector i (log) informational labor wedge ϕ_i is the ratio*

$$\phi_i \equiv \log\left(\frac{L_i}{L_i^*}\right) \tag{2.15}$$

where L_i^* is the individually optimal labor input of a firm in sector i who knows every sectors' labor inputs and productivity,

$$L_i^* = (1 - \alpha_i)\Lambda_i \frac{C}{W}. \tag{2.16}$$

The wedge ϕ_i thus describes the percentage deviation of labor inputs in sector i from what would be optimal if the labor inputs and productivities of other sectors were known to firms in sector i.

The next proposition shows that the impact that an informational labor wedge has on aggregate output scales with the sector's weighted network centrality as measured by Λ_i.

Proposition 1. *The elasticity of aggregate output with respect to the wedge ϕ_i is proportional to the (weighted) Bonacich centrality Λ_i of sector i times that sector's labor share:*

$$\frac{\partial \log(C)}{\partial \phi_i} = (1 - \alpha_i)\,\Lambda_i. \tag{2.17}$$

Proof. Substitute the definition of ϕ_i into (2.14) to get

$$\log(C) = \mathbf{\Lambda}'(I - \boldsymbol{\alpha})\boldsymbol{\phi} + \mathbf{\Lambda}'(I - \boldsymbol{\alpha})\mathbf{l}^* + \mathbf{\Lambda}'\mathbf{z} + \kappa \tag{2.18}$$

where $\boldsymbol{\phi}$ and $\mathbf{l}^*$ are vectors with typical elements ϕ_i and l_i^*. The result then follows immediately from differentiating $\log(C)$ with respect to ϕ_i. □

When sector i employs more labor, it increases the supply of inputs to all sectors j with $\alpha_{ji} > 0$ who, in turn, produce more goods that can then be used as inputs by other sectors, and so on. Expectational errors in sectors that are more central in the network thus have a larger effect on aggregate output.

The importance of sector centrality for the impact of sectoral expectation errors closely resembles well-known results on the impact of sectoral productivity shocks, e.g. Acemoglu *et al* (2012). This is unsurprising since in the second stage, labor inputs are a fixed factor that differ from exogenous productivity only by exhibiting a decreasing marginal product. Proposition 1 also echoes results in Bigio and La'O (2020). They find that the impact of inefficient sectoral labor wedges on aggregate output also scales with the centrality of the sectors. The mechanism in our model, by which an expectational errors in one sector adds up as it propagates through the network, is the same as in full information models with similar production structures.

As in Angeletos and La'o (2010, 2013), labor inputs are strategic complements among firms in our model. The next proposition shows that weighted network centrality as measured by Λ_i also determines the strength of this strategic motive.

Proposition 2. *Near the full information equilibrium, individually optimal labor inputs* $\log(L_i^*)$ *are increasing in* $\log(L_j)$ *if* $\nu > 1$*, with a coefficient proportional to* $(1-\alpha_j)\Lambda_j$ *.*

Proof. In Appendix B. □

The proof follows from the fact that labor inputs in more central sectors have a bigger impact on C. Since optimal labor demand in sector i depends on other sector's labor demand only through their impact on C, firms then put more weight on more central sectors' labor inputs when predicting C. Hence, optimal labor demand in a given sector responds more strongly to labor inputs in relatively central sectors.[2]

Of course, if other firms hire more labor this increases the wage which, all else equal, reduces labor demand. However, the strength of this offsetting effect depends only on the Frisch-elasticity ν and not on the other sectors' centrality in the network. The condition $\nu > 1$ in the proposition ensures that the offsetting effect is not so strong as to make labor inputs strategic substitutes.

To sum up, expectations of firms in more central sectors are more important for aggregate output, and expectations about more central sector are more important for an individual sector's labor demand. As in the related full information models, the relevant measure of a sector's importance is its Bonacich centrality in the production network weighted by its share in final consumption.

3. The Editorial Role of News Media

In industrialized economies, firms are linked to each other through a complex network of trading relationships of intermediate goods. Shocks to a given sector propagate to other sectors through this network, and an individual firm's optimal production decisions partially depend on developments in other sectors. Given the complexity of a modern economy, arguably no individual firm has the resources to monitor every sector in the economy that could be relevant for its own production decision. Instead, many firms receive information about the economy via information intermediaries that monitor the economy and make state-dependent decisions about what to report. In this section, we describe how this editorial role of news media can be formalized within the multi-sector model presented above. This framework is based on the more abstract setting in Nimark and Pitschner (2019).

3.1. **Formalizing state dependent reporting.** The state of the economy is the n-dimensional vector of sector-specific productivity shocks $Z \in \mathcal{Z}_1 \times \mathcal{Z}_2 \times ... \times \mathcal{Z}_n \equiv \mathcal{Z}$. News media monitor the economy and make state dependent decisions about which elements of Z are

[2] A corresponding result applies to the relative importance of other sectors' productivity.

most newsworthy. We formalize this monitoring and reporting behavior using *news selection functions.*

Definition 2. (News selection function) *A news selection function* $\mathcal{S} : \mathcal{Z} \rightarrow (\mathbf{s}, \mathbf{r})$ *is a mapping from* n*-dimensional states of the world* $Z \in \mathcal{Z}$ *into pairs* $(\mathbf{s}, \mathbf{r})$, *where* $\mathbf{s} \in \{0, 1\}^n$ *is an* n*-dimensional indicator vector and* $\mathbf{r} \in \mathbb{R}^r$ *is an* r*-dimensional vector containing the elements* Z_i *of* Z *such that* $s_i = 1$.

A news selection function $\mathcal{S}$ thus associates a pair $(\mathbf{s}, \mathbf{r})$ with each state of the world $Z \in \mathcal{Z}$. The vector $\mathbf{s}$ indicates which sectors are reported on. An element of $\mathbf{s}$ equal to 1 indicates that the corresponding dimension of Z is reported, and a 0 indicates that the respective dimension is not reported. The vector $\mathbf{r}$ contains the realized values of productivity in the reported sectors. For instance, $\mathbf{s}(Z) = (1, 0 \ldots, 0)$ means that in state $Z = (Z_1, \ldots, Z_n)$ only the first dimension is reported so that $\mathbf{r}(Z) = Z_1$. Similarly, $\mathbf{s}(\widetilde{Z}) = (0, \ldots, 0, 1, 1)$ means that in state $\widetilde{Z} = (\widetilde{Z}_1, \ldots, \widetilde{Z}_n)$ only the last two dimensions are reported so that $\mathbf{r}(\widetilde{Z}) = (\widetilde{Z}_{n-1}, \widetilde{Z}_n)$. A news selection function $\mathcal{S}$ thus assigns a 1 to element i of $\mathbf{s}$ if the outcome Z_i is sufficiently newsworthy to be reported. Whether the element Z_i is reported or not generally depends on the entire state vector Z.

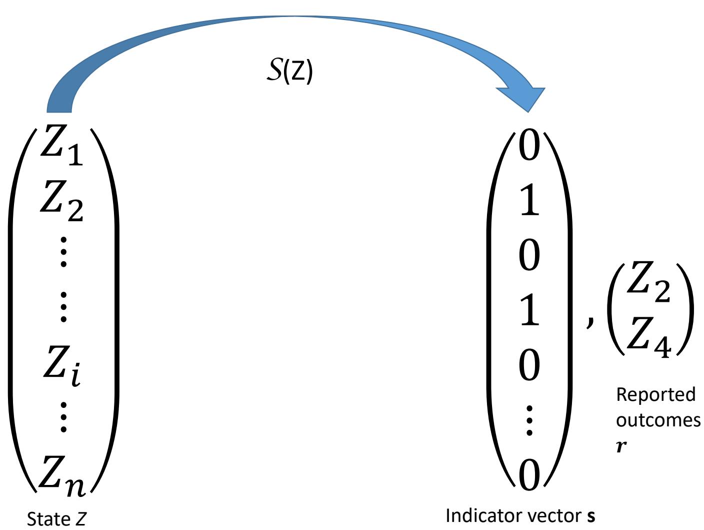

FIGURE 1. The news selection function $\mathcal{S}$ reports productivity in sector 2 and sector 4 in state Z.

The dimension of $\mathbf{r}$ (and the number of non-zero elements in $\mathbf{s}$) is r, so that all sector-specific shocks are reported if $r = n$. The elements in $\mathbf{r}$ are reported accurately by the information provider. However, if $r < n$ only a subset of the sector-specific productivity shocks are reported. The vector $\mathbf{r}$ then only provides a partial picture of the state of the economy.[3]

The mapping from realized states to reported sector-specific shocks is illustrated in Figure 1. There, the news selection function represented by $\mathcal{S}$ reports Z_2 and Z_4 in state Z. An agent who receives reports from an information provider characterized by $\mathcal{S}$ would then know the values of the productivity shocks in sector 2 and sector 4. This is the information contained in the vector $\mathbf{r}$. However, the agent would also know that the information provider chose to not to report about any of the other sectors. This information is contained in the indicator vector $\mathbf{s}$. To the extent that these reporting decisions are state-dependent, they will also reveal information about the unreported sectors, i.e. sectors $1, 3, 5, 6, ...n$.

3.2. **State-dependent reporting and beliefs.** The firms in our model are Bayesian and understand the state-dependence of reporting decisions encoded in $\mathcal{S}$. A firm that observes $\mathbf{r}$ and $\mathbf{s}$ has the posterior beliefs $p\left(Z \mid \mathbf{r}, \mathbf{s}\right)$. The posteriors are affected by the state-dependence of reporting decisions in two distinct ways. First, since some sectoral outcomes are considered more newsworthy than others, the distribution of reported sector-specific productivity shocks is different from the unconditional distribution of Z_i so that

$$p(Z_i \mid s_i = 1) \neq p(Z_i). \tag{3.1}$$

If not all outcomes in $Z_i \in \mathcal{Z}_i$ are equally newsworthy, the density $p(Z_i \mid s_i = 1)$ redistributes probability mass towards more newsworthy regions of the support of Z_i. Some types of outcomes may thus be over-represented in the news relative to their unconditional frequencies of occurring.

Second, state dependent reporting behavior implies that firms may also update their beliefs about non-reported sectors. Intuitively, this is because unreported sectoral outcomes that would have been reported had they occurred can be ruled out. More precisely, firms observing $s_j = 0$ can rule out any outcome Z_j that would have implied $s_j = 1$.

The selection bias introduced by news selection functions is related to, but conceptually distinct from the filtering biases that has been studied in the political economy literature. For instance, in the model of Stromberg (2004), media bias takes the form of giving more coverage to policy proposals that either affect larger groups of voters, or groups of voters that are more attractive from an advertising perspective. However, the editorial decision in that model is not state-dependent. Another form of filtering bias is proposed in Chan and Suen (2008). In their model, the state takes a continuous value in $(0, 1)$, but news media are restricted to reporting a binary signal. Like in our framework, news media thus provide a coarser signal than the true state of the world. However, in Chan and Suen (2008) news media do not make a decision about what events to report on.

More broadly, the political economy literature has mostly studied models in which reporting strategies relate to a single state variable, see for instance the survey by Gentzkow, Shapiro and Stone (2015). The news selection function framework presented here is more flexible and allows for the focus of what the news are about to depend on the state of the

[3]Nimark and Pitschner (2019) show that agents who are constrained in terms of how many stories they can observe can achieve a lower posterior entropy by delegating the choice of what to observe to an organization or mechanism that can condition on the realized state.

world. It can thus naturally capture the kind of crowding out effects generated by major news events that Eisensee and Stromberg (2007) as well as Nimark and Pitschner (2019) document empirically.

A key feature of our framework is that a news selection function classifies the sectoral outcomes in the state Z as either being newsworthy enough to be included in $\mathbf{r}$ or not. The criteria used for this classification determine how the indicator vector $\mathbf{s}$ depends on the state Z, and how the state-dependence of reporting decisions affects agents' beliefs. In the next section we discuss how three specific notions of newsworthiness, as encoded by different news selection functions, affect news selection biases and posterior beliefs.

4. Three notions of newsworthiness

News media monitor the world and report those events that are considered most newsworthy. What kind of events get reported thus depends on the criteria used to judge how newsworthy an event is. In this section we study three different notions of newsworthiness and how the implied selection biases affect firms' beliefs. The three notions are (i) extreme (or unusual) outcomes are more newsworthy, (ii) negative outcomes are more newsworthy, and (iii) some sectors are inherently more newsworthy. The journalism literature has identified certain characteristics as contributing to the newsworthiness of an event, e.g. Shoemaker and Vos (2009) and Harcup and O'Neill (2016). The three criteria we consider here correspond to the subset of these that most naturally applies to economic news reporting decisions.

The notions of newsworthiness we study here are highly stylized, which helps us illustrate clearly how the state-dependence of reporting decisions implied by each notion affect beliefs. In Section 5, we present empirical evidence on sectoral news coverage and discuss what makes sectoral developments more newsworthy in practice. To simplify the exposition, we here assume that Z_i are distributed as independent log standard normals so that $z_i \equiv \log Z_i \sim N(0,1)\,\forall i$ and $p(Z_j \mid Z_i) = p(Z_j) : j \neq i$. Neither of these assumptions are central to the mechanisms discussed here, and we relax the assumption of uncorrelated shocks when we solve and simulate the model.

4.1. Extreme outcomes are more newsworthy.

The first notion of newsworthiness we study considers extreme or unusual events more newsworthy than more commonplace events. Shoemaker and Vos (2009) survey the literature that studies which criteria news organizations use to judge whether an event is newsworthy. They argue that one such criterion is *deviance*, which can be either normative, social or statistical. They define normative or social deviance as deviations from norms, laws and social status quos. Statistical deviance is defined as the degree to which an "*event is out of the ordinary or unusual*" and is the notion of newsworthiness that we study here. We formalize it as follows.

Definition 3. (Extreme outcomes more newsworthy) *The news selection function $\mathcal{S}_{|z|}$ treats more extreme outcomes as more newsworthy if for each pair i and j such that $s_i = 1$ and $s_j = 0$ we have that $|z_i| \geq |z_j|$.*

The news selection function $\mathcal{S}_{|z|}$ thus orders outcomes $z_i : i = 1, 2, ...n$ in terms of their absolute deviations from their means and reports the values of shocks that had the r largest such deviations. Given that the normal distribution is single-peaked and symmetric, this corresponds to reporting the r least probable outcomes. The news selection function $\mathcal{S}_{|z|}$ thus captures the notion that more unusual events are considered more newsworthy.

The state dependence of reporting decision impled by $\mathcal{S}_{|z|}$ means that firms are more likely to observe extreme productivity outcomes. The next proposition proves this formally and shows that this selection effect grows with the number of sectors.

Proposition 3. *For a given $r < n$, the variance of productivity shocks conditional on being reported $var(z_i \mid s_i = 1)$ is larger than the unconditional variance $var(z_i)$ and increasing in the number of sectors n.*

Proof. In Appendix B. □

To prove the first part of the proposition, we use that in every state of the world, the squared value of every reported productivity shock is larger than the squared value of every unreported shock. The squared values of the reported shocks then state-wise dominates the squared values of the non-reported shocks, implying a higher expected squared value, i.e. a higher variance. To prove the second part, we use that adding dimensions to the state can only make the expected squared deviation of the r reported shocks larger.

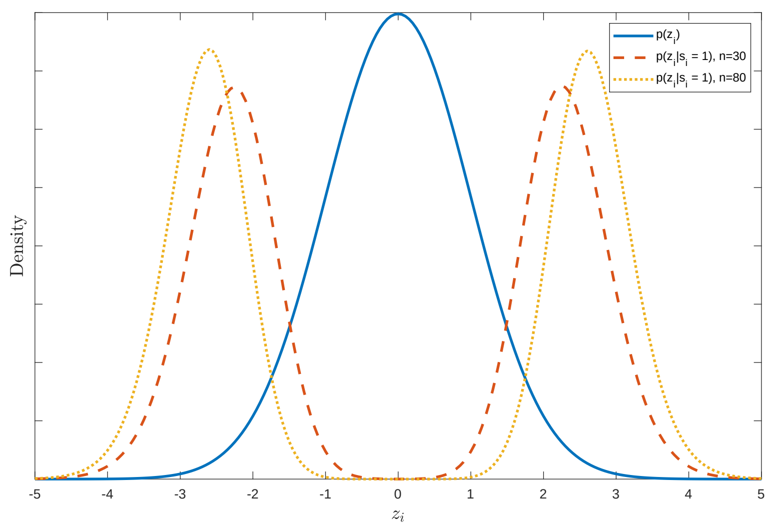

FIGURE 2. The distribution of z_i conditional on $s_i = 1$ for $n = 30$ and $n = 80$ implied by the news selection function $\mathcal{S}_{|z|}$.

Figure 2 illustrates the selection bias implied by $\mathcal{S}_{|z|}$. It shows the distribution of z_i conditional on $s_i = 1$ for $n = 30$ and $n = 80$ when news media reports a single sector (i.e. $r = 1$). For comparison, we also plot the unconditional distribution of z_i. The distribution $p(z_i \mid s_i = 1)$ depends on the number of sectors in the economy. With a larger number of sectors, the most extreme outcome is likely to be more extreme. This consequence of having a larger number of sectors is illustrated in Figure 2, where the distribution $p(z_i \mid s_i = 1)$ associated with $n = 80$ has more mass further from zero than the distribution that arises when $n = 30$.

The state-dependence of the news selection function thus affects what kind of events are more likely to be reported. This state-dependence also affects how firms update their beliefs about non-reported sectors, as summarized by the following proposition.

Proposition 4. *The conditional variance of unreported productivity shocks var* $(z_j \mid \mathbf{r}, \mathbf{s}, s_j = 0)$ *is increasing in the minimum value of the reported productivity shocks* $\min\{|z_i| : s_i = 1\}$.

Proof. In Appendix B. □

Proposition 4 implies that firms update their beliefs about the unreported sector shocks $\{z_j : s_j = 0\}$ when they observe the values of the reported sector shocks in $\mathbf{r}$, even if shocks are independent across sectors. The logic is as follows. If only the most extreme productivity outcomes are reported, any non-reported outcome must be less extreme than the least extreme among the reported outcomes. The conditional distribution of the unreported sector shocks are thus symmetrically truncated normal distributions where the truncation points are $-\min\{|z_i| : s_i = 1\}$ and $\min\{|z_i| : s_i = 1\}$. The proposition then follows from the fact that the variance of a symmetric truncated normal is increasing in the distance of the truncation points from the mean. In Figure 3, the shaded blue areas indicate the regions of the support of the unconditional distribution of z_j that have zero posterior probability conditional on $s_j = 0$ and $\min\{|z_i| : s_i = 1\} = 1.5$.

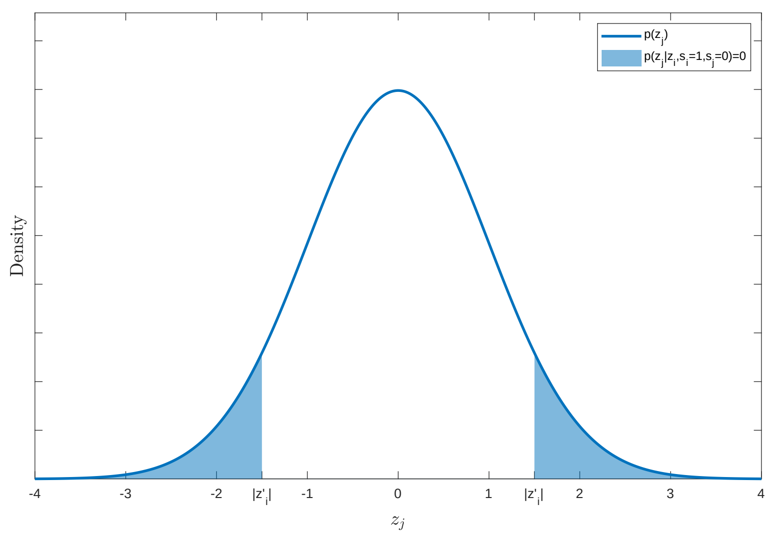

FIGURE 3. The distribution of z_j conditional on $s_j = 0$ and $min\{|z_i| : s_i = 1\}$ implied by the news selection function $\mathcal{S}_{|z|}$

Since firms can rule out outcomes more extreme than $\min\{|z_i| : s_i = 1\}$ for unreported sectors, their conditional uncertainty rises when more extreme events are reported. When something extreme (e.g. a financial crisis) occurs, it is always reported. Major, but less extreme events may then be crowded out of the news coverage and go unreported. However, if something mundane is in fact reported, firms can infer that whatever has occurred in the non-reported sectors must be even more mundane. In such cases, they can rule out large portions of the tail in the distributions of the non-reported sectors. State-dependent reporting decisions that treat extreme outcomes as more newsworthy thus generates time-varying conditional uncertainty about productivity in non-reported sectors.

4.2. **Negative outcomes are more newsworthy.** Another notion of newsworthiness that is potentially relevant is that negative events may be considered more newsworthy than positive ones. That negative economic news are indeed considered more newsworthy by news organizations is shown by Harrington (1989), who documents that network television news overemphasize bad economic news. Similarly, Soroka (2012) documents that bad news about unemployment, inflation and interest rates are more likely to be reported by the *New York Times* than good news about the same variables. In a recent survey of the news values literature, Harcup and O'Neill (2016) lists *bad news* as one characteristic that makes an event more newsworthy.

To formalize the notion that negative outcomes are considered more newsworthy, we can define a news selection function $\mathcal{S}_-$ that orders the newsworthiness of sectoral outcomes according to their relative position in $\mathbb{R}$.

Definition 4. (Negative outcomes more newsworthy) *More negative outcomes are considered more newsworthy according to the news selection function $\mathcal{S}_-$ for any pair $i, j \in \{1, 2, ..., n\}$ such that $s_i = 1$ and $s_j = 0$ we have that $z_i \leq z_j$.*

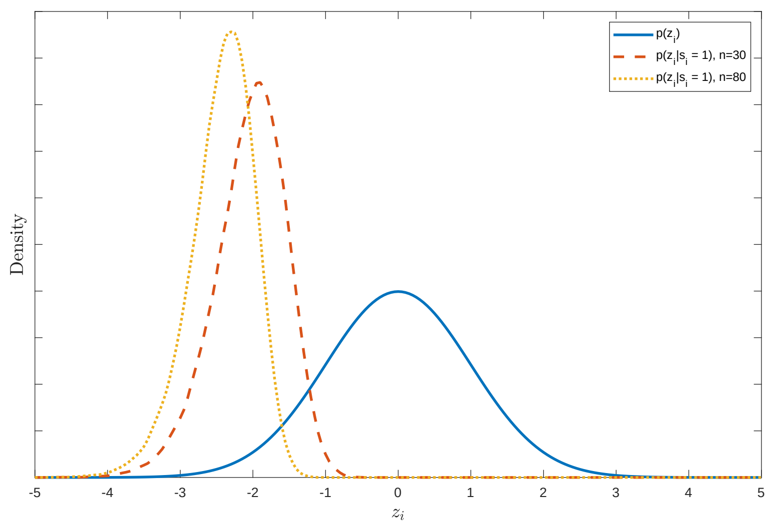

FIGURE 4. The distribution of z_i conditional on $s_i = 1$ for $n = 30$ and $n = 80$ implied by the news selection function $\mathcal{S}_-$.

The news selection function $\mathcal{S}_-$ thus reports the r lowest elements in z. The state dependence of $\mathcal{S}_-$ affects the conditional mean of both reported and unreported outcomes.

Proposition 5. *The mean of reported productivity shocks $E(z_i \mid s_i = 1)$ is lower than the unconditional mean of productivity shocks and decreasing in the number of sectors n.*

Proof. In Appendix B. $\square$

The proof uses that the values of reported sector shocks are lower than the unreported sector shocks in all states of the world, and that the weighted conditional means of reported and unreported shocks must equal the unconditional mean. The selection bias underlying Proposition 5 is illustrated in Figure 4. There, we plot the unconditional distribution of z_i together with the distributions of the same variable conditional on being reported for $n = 30$ and $n = 80$. Both the conditional mean and variance are decreasing in the number of sectors n. With a larger number of sectors, the most negative outcome is more likely to be far out in the left tail of the distribution, but the dispersion around that mean is also decreasing.

Again, the selection bias introduced by $\mathcal{S}_{-}$ affects the conditional distributions of unreported sector shocks.

Proposition 6. *The expected value of non-reported productivity shocks* $E\left(z_j \mid \mathbf{r}, \mathbf{s}, s_j = 0\right)$ *is increasing in the maximum value of the reported productivity shocks* $\max\left\{z_i : s_i = 1\right\}$.

Proof. In Appendix B. □

Since all non-reported sector shocks must be (weakly) more positive than the reported shocks, the conditional distribution of a non-reported shock is a left-truncated normal. The proposition then follows from observing that the truncation point is given by $\max\left\{z_i : s_i = 1\right\}$ and because the mean of a left truncated distribution is increasing in the truncation point. This is illustrated in Figure 5. If the most negative outcomes are reported, no unreported outcome can be smaller than the largest reported outcome. This means that realizations to the left of $\max\left\{z_i : s_i = 1\right\}$ in the support of the unreported shocks z_j can be ruled out. In the figure, this region is shaded in blue.

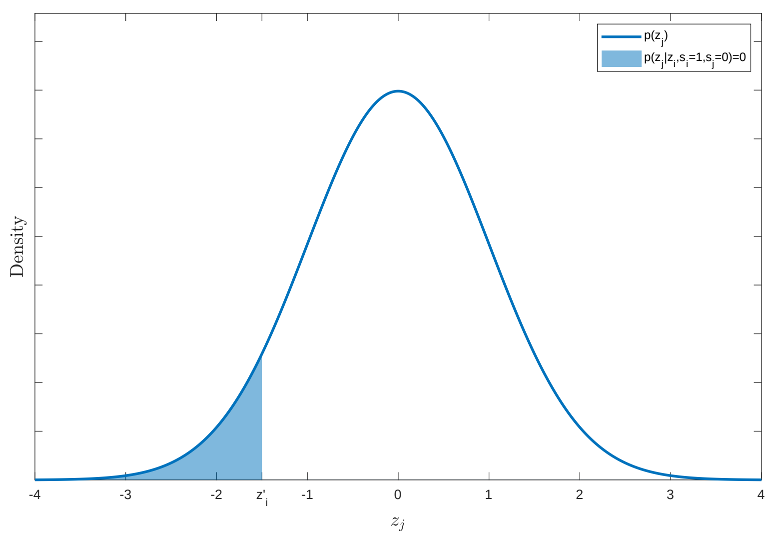

FIGURE 5. The distribution of a non-reported productivity shock $E\left(z_j \mid z^s, s, s_j = 0\right)$ implied by the news selection function $\mathcal{S}_{-}$.

4.3. **Unconditionally more newsworthy sectors.** The framework also allows for modeling some sectors as being inherently more newsworthy regardless of the realized state. For instance, some sectors may receive more news coverage because they are larger than others, or because they have trading relationships with a large number of other sectors. That this type of considerations may make a sector more newsworthy corresponds to what Harcup and O'Neill (2016) refer to as *magnitude.* In their terminology, magnitude describe the number of people affected by an event, and large magnitude events have been documented as being considered more newsworthy.

We define a sector as being inherently more newsworthy than another sector as follows.

Definition 5. (Unconditionally more newsworthy sectors) *Sector i is unconditionally more newsworthy than sector j if for each pair i and j whenever $z_i = z_j$ and $s_i \neq s_j$ we have that $s_i = 1$ and $s_j = 0$.*

Definition 5 does not specify a unique news selection function, since it only specifies whether sector i or j is reported when $z_i = z_j$. To construct a complete ordering of the newsworthiness of different outcomes, the criteria in Definition 5 needs to be combined with some additional criteria. For instance, a news selection function may always report z_i instead of z_j regardless of the state. Another possibility is that deviance or negativity determines newsworthiness, but that the newsworthiness of sectoral developments are also weighted based on the inherent relative newsworthiness of different sectors. Combining sector-specific weights with the previously discussed criteria can be done as follows.

Definition 6. (Weighted news selection functions) *For an n-dimensional vector ω with typical element $\omega_i \in \mathbb{R}_+$, the weighted composite news selection functions $\mathcal{S}_{|\omega|}$ and $\mathcal{S}_{-\omega}$ are constructed by defining their corresponding indicator vectors as $\mathbf{s}_{|\omega|} = \mathbf{s}_{||}(\omega \circ z)$ and $\mathbf{s}_{-\omega} = \mathbf{s}_{-}(\omega \circ [z - \max(z)])$, where $\circ$ denotes the n-dimensional Hadarmard (i.e. element-wise) product.*

The weights ω_i and ω_j in the definition regulate the relative newsworthiness of sectors. The larger ω_i is relative to ω_j, the more likely is sector i to be reported instead of sector j. Developments in a more newsworthy sector will therefore ceteris paribus have a bigger impact on the aggregate economy than a less newsworthy sector. In the next section, we present empirical evidence on sectoral news coverage in US newspapers and analyze what makes it more likely that a sector ends up in the news. When we calibrate the model, the vector of weights ω is used to match model moments of news coverage to the corresponding moments in the news coverage data.

5. Sectoral Coverage in U.S. Newspapers

How news reporting affects the economy depends on what kind of events are considered most newsworthy. In this section we present and analyze empirical measures of US sectoral news coverage that we will use below to calibrate the model. For our baseline measure, we take a company-sector matching approach where we first identify company names in news articles and assign each company to a sector. For each sector, we then compute the fraction of total firm mentions referring to companies in that specific sector. This approach allows us to compute a news coverage measure using sectoral definitions that are consistent with those of the BEA's production accounts. We can thus calibrate the production side and the news media side of the model using consistent sector definitions, and we can study how sectoral news coverage responds to sectoral developments as measured by the BEA. We also present some evidence using news coverage data based on articles that make explicit references to sectors or industries as a unit, rather than individual companies.

Our data is from Dow Jones Factiva. We use news articles from six major US outlets that covers the period from 1988 to 2018. The outlets in our sample are the Wall Street Journal, the New York Times, USA Today, the Boston Globe, the Charleston Gazette and the Atlanta Journal Constitution. The first three of these are the largest US newspapers by circulation. Importantly, for these six newspapers Factiva provides the entity tags that we use to match newspaper articles to company names and their respective sectors.

The tags assigned by Factiva to any given news article are names of entities that may or may not be US companies.[4] Our sample contains 996,025 such tags that correspond to 4,333 unique entities. To construct measures of sectoral news coverage from this data, we query Factiva for the NAICS code of each entity as well as its primary location. We also perform a name-based fuzzy-match to Compustat (which we verify manually) to obtain additional information on sector affiliation and country.[5] Finally, for the 200 most frequent entity tags for which neither Factiva nor Compustat contain sector and country information, we obtain it manually via web searches.

We keep all entities that represent US companies, and that we are able to assign to one of our sectors via their NAICS codes. We consider a company US-based if (i) Factiva lists its primary location as the US or (ii) Compustat lists both its postal address and its country of incorporation as the US or (iii) our web search yields that a company has substantial business activities in the US. Together, Factiva and Compustat allow us to identify 2,983 companies and their respective NAICS codes. These companies account for approximately 76% of the total number of entity tags in the sample. In addition, the 200 manually classified entities yield another 60 US companies and increase the fraction covered to approximately 82% percent of all tags. Finally, we find that most of the remaining 18% of tags refer to organizations that are not US companies (e.g. sports teams, government entities, or political institutions).

Based on the extracted NAICS code for each US company in our data, we group news coverage into 29 different sectors that approximately correspond to the definitions in Atalay (2017).[6] The sector labels are listed in Table 1. Most of the labels are self-explanatory, with perhaps the exception of *F.I.R.E.* which denotes the *Finance, insurance and real estate* sector. We then measure sectoral news coverage as the number of times US companies belonging to a given sector are mentioned in the news articles in our data set. This approach establishes a correspondence between the news coverage of the sectors that uses sector definitions that are consistent with those used by the BEA to construct sectoral output accounts.

[4]For instance, the European Union and ISIS are identified by Factiva as entity names in articles, but are neither companies nor US based.

[5]The fuzzy match is based on the Levenshtein distance (Levenshtein 1966) between the name tag provided by Factiva and the company name as it appears in Compustat.

[6]We exclude the government sector from our analysis, since news coverage of government entities is dominated by reports that are unrelated to the economy, such as supreme court decisions and political debates. Sports teams are excluded as the related coverage typically focuses on the sport itself, not on economic aspects. Our sector classification is described in more detail in the Online Appendix.

Table 1. Sector Labels

Sector	Sector Name	Sector	Sector Name
1	agriculture & forestry	16	primary metals
2	mining	17	fabric. metal products
3	oil & gas extraction	18	non-electrical machinery
4	construction	19	electrical machinery
5	food & kindred products	20	motor vehicles
6	textile mill products	21	other transportation equipment
7	apparel & leather	22	instruments
8	lumber	23	misc. manufacturing
9	furniture & fixtures	24	transportation & warehousing
10	paper & allied products	25	communications
11	printing & publishing	26	electric & gas utilities
12	chemicals	27	wholesale & retail
13	petroleum refining	28	F.I.R.E.
14	rubber & plastics	29	other services
15	non-metallic minerals		

Notes: See Online Appendix for sector definitions.

For our baseline measure of sectoral news coverage, we use only articles from the Wall Street Journal and the New York Times. The reason for this is that it is only for these two news papers that Factiva entity tags are consistently available from 1988 onwards. In addition, the baseline specification excludes companies that are only mentioned by one of the two outlets in any given quarter. This filter excludes more minor events and thus brings the data closer to the notion of public news reports as implemented in the model. Below, we also discuss the implications of using two alternative measures. The first does not impose the filter that both the Wall Street Journal and the New York Times must report about a company. The second alternative measure also includes coverage from USA Today, the Boston Globe, the Charleston Gazette and the Atlanta Journal Constitution, but it starts only in 1997, the first year for which entity tags are available for these additional outlets.[7]

5.1. **Sample averages of sectoral news coverage.** One of the most salient facts in the data is the degree to which the average amount of news coverage received varies across sectors. Figure 6 plots the sectoral shares of total news coverage against their contributions to gross output, together with a 45 degree line. The sample correlation between sectoral news coverage and the sectoral shares of gross output is 0.64. Larger sectors thus tend to receive more coverage than smaller ones. The most widely featured sector in our news data is *Finance, insurance and real estate* followed by *Communications*, *Other services*, *Motor vehicles* and *Instruments*.

[7]The measures that reflect only the Wall Street Journal and the New York Times weight these two outlets equally. The measure that contains all six outlets assigns weights of 25% to The Wall Street Journal, The New York Times and USA Today, and it splits the remaining 25% equally between the Boston Globe, the Charleston Gazette, and the Atlanta Journal Constitution.

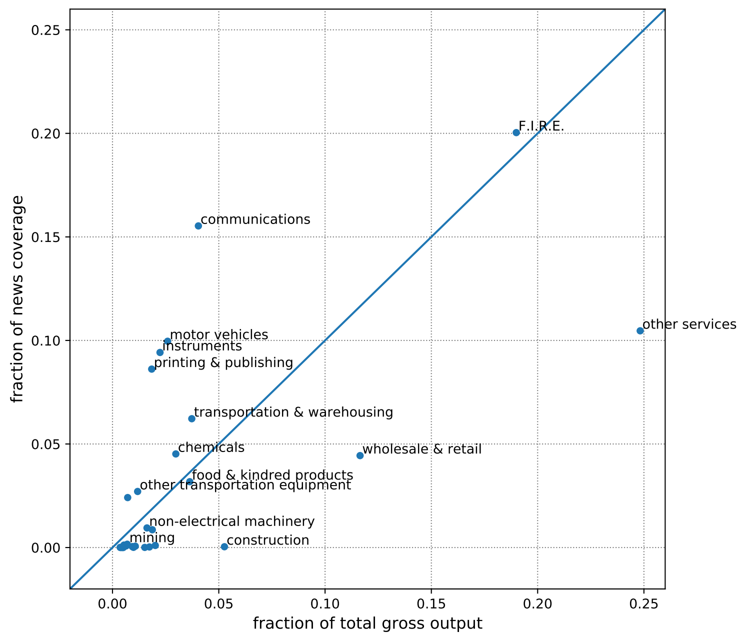

FIGURE 6. Sectoral news coverage and contribution to gross output. The horizontal axis measures the sector's sample average share of gross output, computed using the BEA/BLS multifactor productivity data set, while the vertical axis measures the corresponding sector's sample average share of news coverage.

Sectors that are above the 45 degree line in Figure 6 are over-represented in the news relative to their economic size. More specifically, the *Communications*, *Motor vehicles*, *Instruments* and *Printing & publishing* sectors all receive substantially more news coverage than their economic size alone would indicate. That these sectors are over-represented in the news relative to their economic size accords well with a casual reading of recent history. One of the major developments over this period was the rise of the Bay Area Tech industry. *Communications* include mobile phone and cable tv companies such as AT&T, Verizon and Comcast, but also newer companies such as Facebook, Ebay, Netflix and Twitter. The three most frequently mentioned companies in *Instruments* are Apple, Intel and Hewlett-Packard and news coverage of *Printing & publishing* is completely dominated by articles about Microsoft and (Google's parent company) Alphabet. Another major economic story over the sample period was the financial crisis and the resulting bailout of the Detroit-based auto industry. The most-frequently mentioned companies in the 10 sectors that receive the most coverage overall are reported in Figure 7.

Another finding is that about half of the sectors receive approximately zero news coverage. This is illustrated in Figure 8, where we plot the cumulative sum of the sectoral shares of news coverage together with the sectoral shares of gross output. While the 10 most reported on sectors together receive more than 90% of the total news coverage, the 15 least reported on sectors together receive less than 1% of the news coverage. This asymmetry is not as strong in terms of shares of gross output. The 15 smallest sectors produce about 10% of gross output. There are also some large sectors that are substantially under-represented in

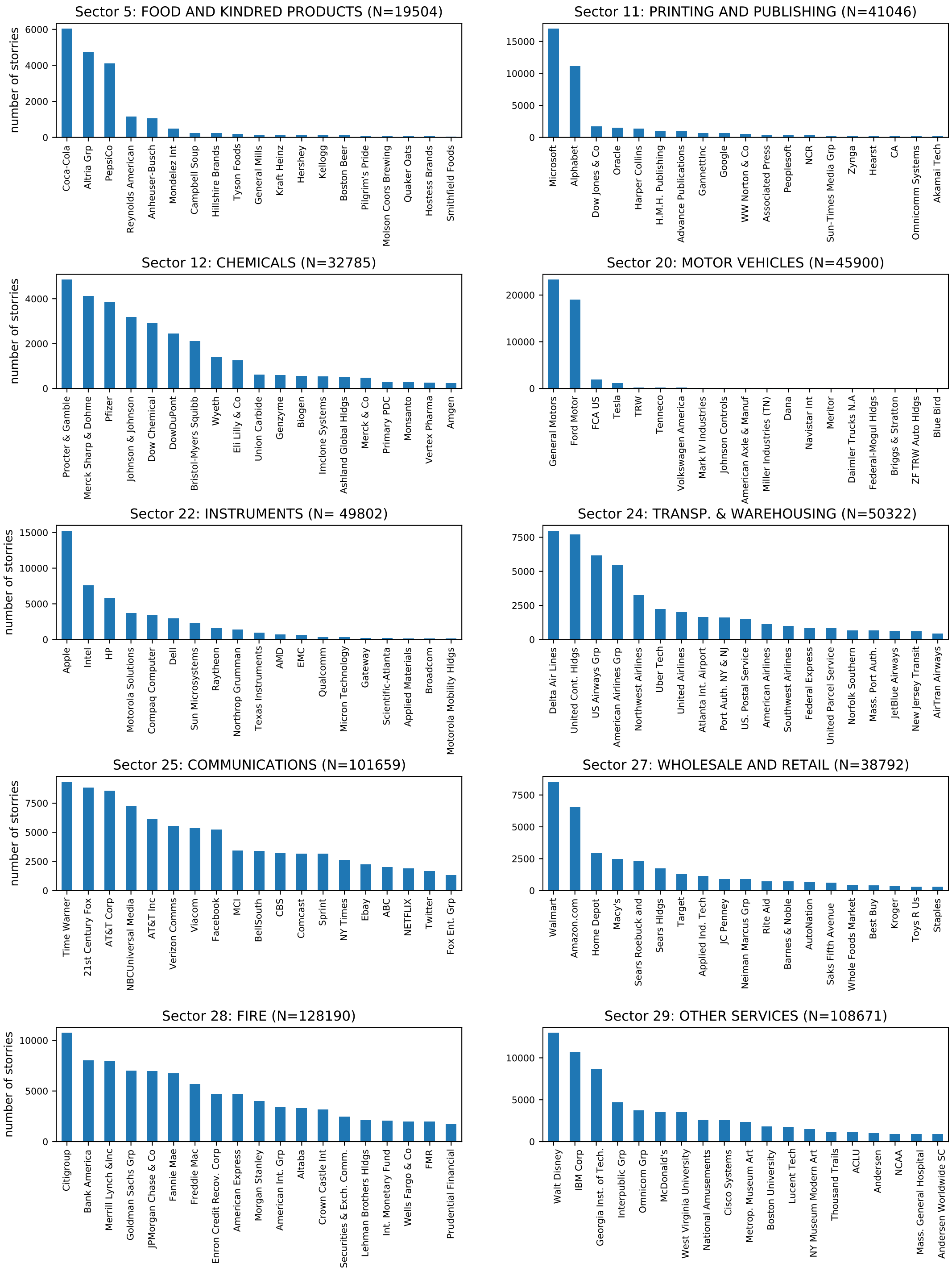

FIGURE 7. Most frequently mentioned company names for the 10 sectors that received the most coverage over the sample. Some company names have been abbreviated.

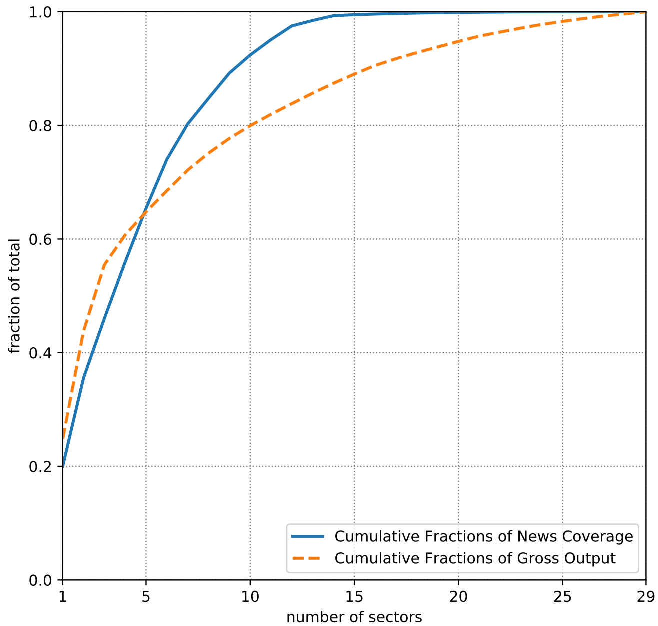

FIGURE 8. Cumulative sum of the sectoral shares of news coverage and gross output.

the news. For instance, the sector *Other services*, which includes companies as varied as IBM and Walt Disney, produces almost a quarter of GDP, but receives only about 10% of the news coverage. (IBM and Walt Disney are the most reported on companies within this sector, so these companies are not necessarily themselves under-represented in the news.)

Overall, the sample averages remain largely unchanged when we use the two alternative measures. *Finance, insurance and real estate* receives somewhat smaller share of the news coverage when we use all six newspapers, as both the Wall St Journal and the New York Times tend to cover these industries more than the other newspapers. Not imposing the filter that both the Wall St Journal and the New York Times must mention a company in a given quarter somewhat increases the fraction of news coverage received by the *Other services* industry, suggesting that a relatively large fraction of stories on this sector may not reflect large, nation-wide news.

5.2. **State dependence of sectoral news coverage.** In addition to its variation across sectors, news focus also varies substantially over time. This is illustrated in Figure 9 where we plot the time series of sectoral news coverage for the 10 sectors that receive the most news coverage on average over the sample period. The figure also illustrates that for most sectors and most time periods, the three alternative measures result in broadly similar time series.

The largest changes in news coverage occur during the financial crisis in 2008 and 2009. In this period, news coverage of the *Finance, insurance and real estate* sector increased from a pre-crisis average of around 20% to more than 50%. News coverage of the *Motor vehicle* sector increased from around 10% to more than 20%. Together, these two sectors thus accounted for about three quarters of all news coverage in 2009. Other sectors that normally

FIGURE 9. Sectoral news coverage over time for the 10 sectors that received the most coverage over the sample. Vertical axis is the number of name mentions referring to firms in that sector divided by the total of all firm mentions across our 29 sectors.

receive a substantial fraction of the news coverage naturally received a smaller share in this period. Both the *Printing and publishing* sector and the *Communications* sector saw their fraction of news coverage fall by approximately half during the crisis.

There are less dramatic movements of sectoral news coverage that are also likely to be driven by sectoral developments. The tech sectors discussed above experienced an increasing trend in news coverage in the 1990s and a sustained high level of news coverage in the decade since the financial crisis. The *Printing and publishing* sector, which includes Microsoft and Alphabet, saw a sharp and short-lived spike in news coverage during the dot-com boom of the late 1990s. We can also see that the *Transportation and warehousing* sector experienced a sharp spike in news coverage in 2016 - 2017. This is mostly driven by coverage of Uber, which while classified as a transportation company, may also be considered part of the tech industry.

The mirror image of the increase in news coverage of the tech sector in the last decade is also visible in Figure 9. Traditional sectors such as *Food and kindred products* and *Chemicals*, which both received substantial coverage throughout the 1990s, now receive a very small fraction of the total news coverage.

To investigate more formally if news coverage of a given sector is correlated with economic developments in that sector, we regress sectoral news coverage on observable economic outcomes in the same sectors. Table 2 displays the results of regressing news coverage on the log differences in sectoral gross output, TFP and hours worked, all of which come from the BEA/BLS multifactor productivity data set. These data, in turn, are based on the KLEMS accounting approach of Jorgensen, Ho and Samuels (2012). If a bad economic outcome in a sector is considered newsworthy, this should manifest itself as negative coefficients on these variables. We also include the absolute values of the same three variables. If extreme outcomes, either good or bad, in a sector are considered newsworthy, then this would result in a positive coefficient on these variables. The sample is annual and covers the period from 1988 to 2018, with annual news focus calculated as the simple average of the quarterly news focus in any given year. The table contains the result of these regressions for the ten sectors that receive the most coverage on average, i.e. the subset of sectors that typically receive at least some attention by the media.

Given that we have only 31 annual observations for each sector, many of the coefficients in Table 2 are not significant. Yet, the regression results confirm our interpretation of the more conspicuous fluctuations in Figure 9. The big spikes in news coverage of the *Motor vehicles* and *Finance, insurance and real estate* sectors during 2009 translate into large and significant coefficients on productivity growth and output growth, respectively. For the *Finance, insurance and real estate* sector, news coverage is also positively correlated with the absolute change in output, perhaps because the recovery of the financial sector was widely covered by the media. Changes in output are positively correlated with news coverage in the *Instruments* sector, which includes computer hardware companies. The results for the three sectors that receive the most coverage are thus both significant and consistent with news media making state dependent reporting decisions that emphasize both very positive and very negative sectoral outcomes.

For the remaining sectors, results are less straightforward to interpret in terms of well-known historical episodes. For instance, the regression of news coverage of the *Printing & Publishing* sector has a positive significant coefficient on productivity, and a negative significant coefficient on the absolute value of growth in hours. Thus, increases in news coverage are not always clearly associated with single instances of either good or bad news.

5.3. **Direct Media References to Specific Sectors.** The news measures shown so far reflect how frequently companies affiliated with specific sectors are mentioned in the articles in our database. Thus, a sector whose companies are discussed frequently is considered to receive a large amount of coverage. As discussed above, an important advantage of these

Table 2. Sectoral News Coverage and Observable Sector Properties

Sector	**Statistic**	**Const.**	Δl	Δy	Δz	$\lvert\Delta l\rvert$	$\lvert\Delta y\rvert$	$\lvert\Delta z\rvert$
FOOD & KINDRED PRODUCTS	coeff	0.04***	0.11	0.61	0.04	-1.23***	-0.01	0.57
	t-stat	3.17	0.5	1.14	0.15	-3.67	-0.01	1.41
PRINTING & PUBLISHING	coeff	0.1***	-0.28	-0.38	0.36**	-1.23**	0.23	0.39
	t-stat	4.3	-0.68	-0.68	2.07	-2.18	0.48	1.29
CHEMICALS	coeff	0.02**	-0.25	0.21	0.29	0.49*	-0.08	0.87**
	t-stat	2.41	-1.04	1.53	1.17	1.72	-0.54	2.3
MOTOR VEHICLES	coeff	0.09***	0.06	0.04	-0.68**	-0.15	0.11	0.38
	t-stat	10.05	0.44	0.27	-2.19	-0.93	0.93	1.32
INSTRUMENTS	coeff	0.11***	-0.24	0.15*	-0.62	-0.25	0.04	0.25
	t-stat	13.09	-1.3	1.94	-0.73	-1.01	0.58	0.25
TRANSP. & WAREHOUSING	coeff	0.05***	0.47	-0.35	0.77	0.33	-0.38	1.37
	t-stat	3.58	1.59	-1.43	1.21	0.82	-1.64	1.57
COMMUNICATIONS	coeff	0.05	-1.31*	7.27	-0.14	-0.19	-5.38	1.13
	t-stat	1.14	-1.75	1.14	-0.22	-0.33	-0.8	1.17
WHOLESALE & RETAIL	coeff	0.07***	0.17	-0.24	0.19	-1.33	0.39	-1.19
	t-stat	3.92	0.17	-0.43	0.24	-1.32	0.78	-1.24
F.I.R.E.	coeff	0.2***	0.33	-4.93***	1.2	-1.22	4.67***	2.36
	t-stat	3.96	0.52	-3.57	0.97	-1.2	3.58	1.02
OTHER SERVICES	coeff	0.11***	0.03	1.24	-2.9**	-1.2	-0.14	-1.75
	t-stat	5.14	0.02	1.13	-2.43	-0.88	-0.13	-0.99

Notes: The table shows results of multivariate regressions at the sector level. The sectors shown are the ten that received the most news coverage on average over the sample period. The independent variable is the fraction of news coverage received by a given sector. The dependent variables are a constant, log differences in labor, log differences in output, log differences in productivity as well as the corresponding absolute values. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively. Standard errors are robust to heteroscedasticity.

measures is that the sector definitions used are consistent with those applied by the BEA when constructing sectoral output accounts.

An alternative approach to quantifying sectoral news focus is to consider articles that contain direct references to specific sectors. For example, a newspaper may directly refer to the conditions in the "auto sector" or the "motor vehicle industry". Because such industry definitions primarily reflect how news editors tend to partition the economy in their reporting, they do not coincide exactly with the sector definitions used by economists and the BEA. Therefore, we would expect them to differ somewhat from the NAICS-based measures shown above. Nevertheless, explicit references to specific sectors may be an important part of sectoral news coverage and, to the extent possible, it is worth comparing sectoral news coverage measured using this approach to our baseline measure as a robustness check.

To identify and measure direct references to specific sectors consists, we first systematically search for word-pairs (2-grams and 3-grams) that contain the terms "industry" or "sector". This allows us to construct a comprehensive list of expressions newspapers commonly use for direct references to sectors. Second, we group these expressions into meaningful categories and then quantify how frequently they occur. We find that the resulting sector definitions are not entirely consistent with their NAICS-based counterparts, but a number of sectors with frequent coverage are closely related and thus allow for a direct comparison. For example, we find that newspapers commonly make direct references to the auto sector, the food and tobacco industry, and the financial sector.

Figure 10 shows the time series for these three sectors. Blue lines reflect fractions based on NAICS codes, and orange lines reflect fractions computed from direct references to the sectors.[8] Our principal finding here is that, while the behavior is not exactly identical, the key features are consistent. In terms of the ordering, the financial sector receives the most coverage under both definitions, followed by the auto sector and the food/tobacco industry, respectively. In terms of the time-series behavior, we also observe clear similarities. While the food and tobacco sector receives relatively stable coverage over the sample period, both the auto sector and the financial industry are mentioned significantly more in the context of the 2008-2009 crisis.

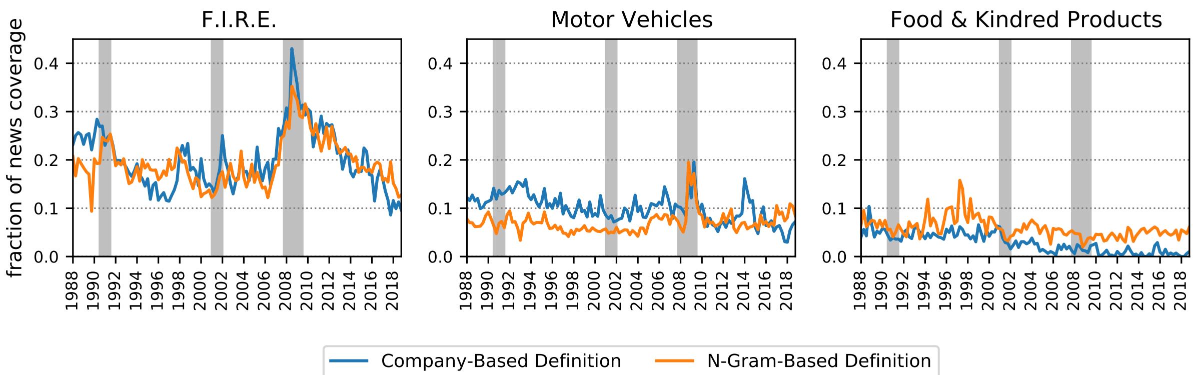

Figure 10. Time series of fractions of news coverage received by three different sectors. Blue lines are fractions based on NAICS codes. Orange lines reflect fractions computed based on direct references to sectors.

6. Aggregate Fluctuations and State-dependent Reporting

The empirical evidence presented above shows that sectoral news coverage reflects the size of sectors, and that it responds to sectoral developments. In this section we analyze the implications of these systematic reporting decisions for aggregate fluctuations. We calibrate the model to match several key unconditional moments of sectoral news coverage and the input-output structure of the US economy. We then study the model's implications for several non-targeted unconditional and conditional moments.

6.1. **Calibrating production functions and preferences.** The intermediate input share parameters in the production function (2.1) are calibrated to be consistent with the BEA input-output tables, aggregated to the 29 sectors defined in Table I. We compute α_{ij} as the ratio of sector-i's input use of sector-j goods, relative to the total use of inputs by sector i. Finally, the consumptions shares β_i, are calibrated by calculating each sector's share in

[8]The terms we use to identify each of these sectors are shown in the Online Appendix.

final good absorption in the economy. The online Data Appendix provides additional details regarding how these shares were computed.

The log of sectoral productivity shocks are normally distributed white noise processes. The covariance matrix of sectoral TFP shocks in the model is set to equal the covariance of the (linearly detrended) log of sectoral TFP constructed from the BEA/BLS multifactor productivity tables for the years 1987-2018. The average cross-sector correlation of TFP in this sample, and hence in the calibrated model, is 0.06.

Beyond the input-output structure and the processes for exogenous productivities, the only remaining parameter to calibrate is the aggregate labor elasticity, ν. This parameter determines both the firm's direct labor response to its own productivity and, as described in Proposition 2, the strength of strategic complementarities in labor choices among firms. Authors have used a wide range of values for this parameter (see for instance discussion in Peterman, 2016). In our baseline specification, we select a value for ν that equates the standard deviation of aggregate labor growth in the model and data, implying $\nu = 2.4$ which is lower than what is used in many calibrated business cycle models, e.g. King and Rebelo (1999) but higher than what is typically found in micro econometric studies of the labor market, e.g. Altonji (1986). Below, we discuss how the value of ν affects the importance of the key mechanism in the model and its ability to match the data.

6.2. **Calibrating the news selection function.** To calibrate the news selection function we need to specify (i) what makes a sector newsworthy and (ii) how many sectors news media report about in each period. In the baseline model, we use the weighted composite news selection function $\mathcal{S}_{|\omega|}$, which reports the largest weighted deviations of the log of sectoral productivity shocks, with $r = 1$ so that news media report on one sector in each period. The sector weights in the vector ω are chosen such that the average fraction of news coverage received by each sector in the model matches that in the news coverage data from Section 5.[9] The news selection function also captures that sectors are more likely to be in the news when they experience large shocks. The calibrated model is solved using an iterative algorithm that is described in detail in Appendix A.5.

6.3. **Aggregate fluctuations with and without news media.** Below, we present model simulations based on historical sectoral productivity shocks from the years 1987 - 2018. This allows us to use the realized cross-section of productivity both to illustrate the mechanism through which news media affects aggregate outcomes and to discuss specific historical episodes. To analyze how news media affect aggregate fluctuations on average, we also compare unconditional population moments under different assumptions about what information is available to firms.

To quantify the importance of news media for aggregate fluctuations, we first compute the logs of aggregate output and hours in the baseline model generated by the historical cross-section of productivity shocks. In the model, aggregate value added output is equal to final consumption C as defined by (2.6). The deviation of the log of aggregate output from its mean is plotted in the left panel of Figure 11. Comparing the fluctuations in the baseline

[9]The weights in ω are thus a function both of the average fraction of news coverage a sector receives and of the standard deviation of sectoral productivity shocks.

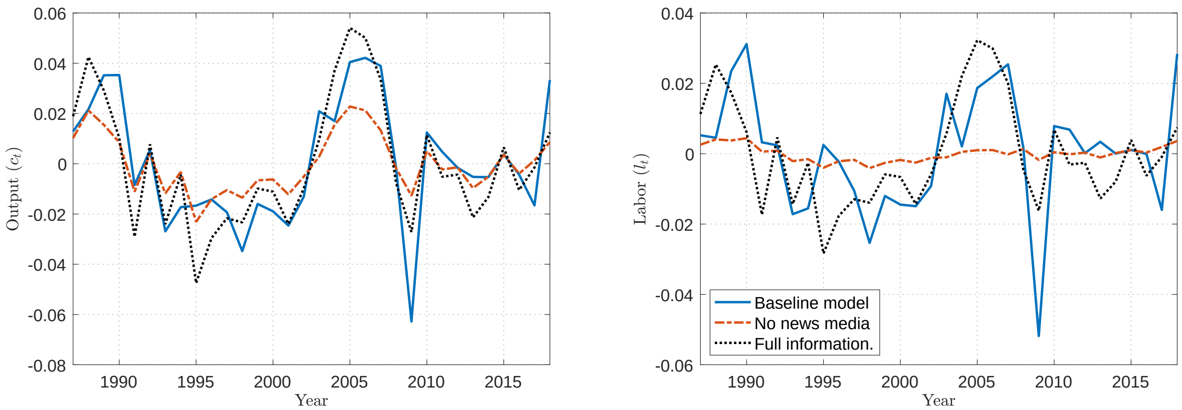

FIGURE 11. Output (left panel) and labor (right panel) fluctuations in baseline, no news media, and full information models.

model (solid blue line) to those in the model without news media where firms only observe their own sector's productivity (dashed red line), output fluctuations are visibly larger in the baseline model relative to the model without news media.

The right panel of Figure 11 shows that the differences between the models with and without new media is even larger for labor. The fact that aggregate labor moves so little in the model without news media emphasizes that nearly all of the output fluctuations in that model are driven by the direct effects of changing productivity, rather than changes in the amount of labor inputs used by firms. By contrast, the model with news media exhibits large fluctuations in total labor inputs, which serve to amplify the direct effects of changing productivity.

The population moments of the calibrated model also show that news media reporting contributes substantially to output and labor volatility. The standard deviation of aggregate output is 2.5% when firms have access to reports by news media, but only 1.2% when they do not. For aggregate labor fluctuations, the difference is even larger: the standard deviation of labor is 1.7% in the baseline model relative to 0.2% in the model without news media. News media affect output fluctuations not only by providing more information that individual firms respond to, but also by increasing coordination of labor input decisions across sectors. The average cross-sector correlation in labor inputs is 0.98 in the baseline model compared to 0.08 in the model without news media.

6.4. **Unrepresentative news and the Great Recession.** The period of the Great Recession provides a particularly stark example of how news reporting can change the aggregate consequences of sectoral shocks. The baseline model predicts a severe recession in 2009, with aggregate output 6.3 % below steady state. This compares to a decline in output of only 1.3% below its steady state level in the model without news media. The difference between the model with and without news media is also larger in terms of the response of labor. In the baseline model, aggregate labor inputs falls to 5.2% below its mean in 2009, while it is only 0.2% below average in the model without news media.

Since both versions of the model experience the same sequence of productivity shocks, these differences must be driven by differences in firms' beliefs about the demand for their product. What news media report, and hence what firms in the baseline model believe, is completely determined by the cross-section of sectoral productivity. We illustrate this cross-section in the left panel of Figure 12.

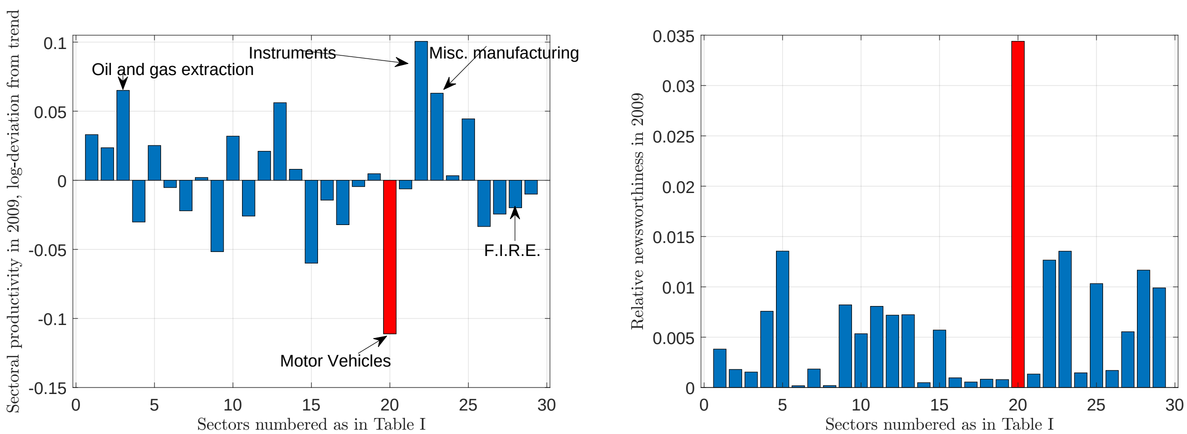

FIGURE 12. The left panel illustrates the cross-sectional profile of sector-specific log productivity z in 2009. The right panel illustrates the cross-sectional newsworthiness of sectoral productivity $|\omega \circ z|$.

The unweighted mean deviation from trend of sectoral productivity in 2009 is 0.16%. However, as shown in the figure, the *Motor vehicles* sector experienced a very large negative productivity shock in that year (red bar). This shock is also what was reported on by news media in the model. Other sectors, such as *Instruments, Oil and gas extraction* and *Miscellaneous manufacturing* experienced substantial positive productivity shocks in the same period. However, these were not reported by the news media. The sector that news media did report on, and therefore the one that firms in all sectors therefore knew about, experienced a large negative shock. Firms across all sectors therefore hired less labor than they would have, had they observed only their own productivity. Moreover, the effect of this common pessimism is amplified by the strategic complementarity embedded in the labor demand function (2.13). As firms anticipate lower demand for labor by the *Motor vehicles* sector, they also anticipate lower demand for their own output, hence lowering their own demand for labor as well. Since all sectors get the same information from the news media, firms in all sectors know that all other sectors will reduce their labor demand because of what was reported. This will in turn make them reduce their labor demand even further, and so on. Thus it is strategic complementarity in labor inputs combined with firms' common knowledge of media reports that make the negative shock to the *Motor vehicles* sector disproportionately influential.

Figure 12 also illustrates the relative newsworthiness of the different sectors in 2009 according to the calibrated news selection function. The right panel of the figure shows the absolute values of the cross-section of productivity shocks weighted by ω. It is clear that not only is the sectoral productivity shock hitting the *Motor vehicles* industry the largest in absolute terms, it is also by far the most newsworthy. The right panel also illustrates a limitation of the simple model, in which newsworthiness is based only on productivity outcomes, and where the vector of weights ω are calibrated using only unconditional moments. We know from the data that *Finance, insurance and real estate* actually received more news coverage than *Motor vehicles* in 2009. However, in the model, the finance sector is not the most newsworthy sector in that period.

The model's predictions for the 2009 episode thus highlight both one of its strengths and a dimension in which it is too simple. The mechanism is strong enough to replicate the depth of the Great Recession without additional exogenous shocks to household preferences or to financial frictions, e.g. Christiano, Eichenbaum and Trabant (2015). Given what we know about the importance of the financial sector during this episode, we certainly do not want to claim that our model provides a complete accounting of the Great Recession. However, our results do suggest that unduly pessimistic expectations about demand, caused by unrepresentative sectoral media coverage, may have contributed substantially to the severity of the recession.

6.5. **Aggregate fluctuations in baseline and full information model.** One reason why the baseline model generates a large recession in 2009, while the model without news media does not, is that in the former model firms in every sector know about the fall in productivity in the motor vehicle sector. In the model without news media, only firms in the *Motor vehicles* sector are aware of this. If firms could observe productivity in every sector, they would also all know about the motor vehicle sector. As reported above, the unweighted cross-section of productivity in 2009 was slightly positive. However, some of the larger sectors experienced negative shocks, which result in a mild recession in the full information model. This is illustrated by the dotted grey lines in Figure 11.

In the full information model, output falls to 2.7% below average. This is less than half of the response of the baseline model. The difference between the response of labor in the full information and the baseline model is even larger. Labor inputs is only 1.6% below average in the full information model but 5.2% below in the baseline model. That all firms know about the negative shock to the *Motor vehicles* sector is thus not sufficient to generate a severe recession. The reason why the baseline model generates a strong recession in 2009 is because the sector shock reported by news media in 2009 is both common knowledge and unrepresentative of the cross-section of shocks affecting other sectors.[10]

6.6. **GDP and hours worked in the model and in the data.** Figure 13 compares model predictions with actual outcomes of (demeaned) growth of output (left panel) and hours worked (right panel). In terms of magnitudes, the baseline model slightly over-predicts the actual fall in output of 5.0%, but underpredicts the actual fall in hours worked of 8.2%. Due

[10]We set the labor elasticity parameter $\nu = 1.48$ in the full information model which implies an unconditional standard deviation of aggregate output equal to that of the baseline model.

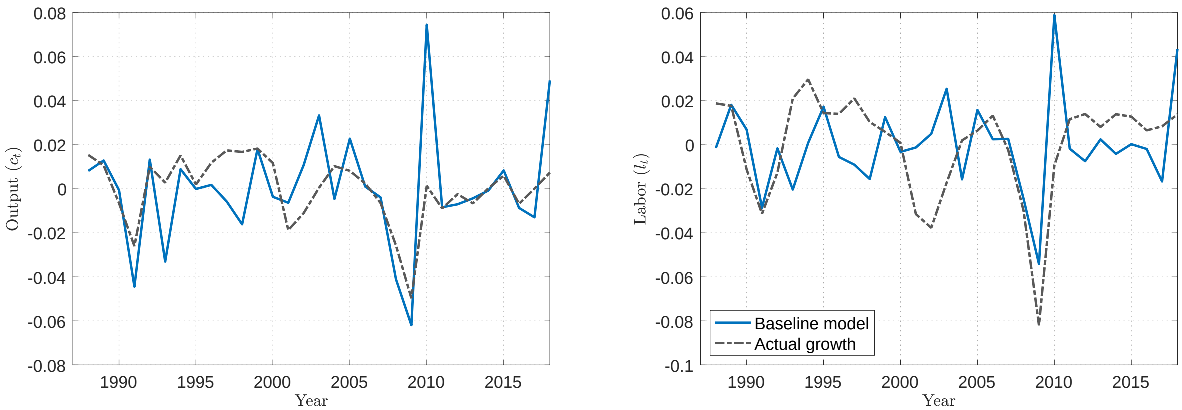

FIGURE 13. Output growth (left panel) and labor growth (right panel) in baseline model together with actual demeaned historical growth rates.

to the lack of endogenous persistence in the model, it over-predicts the speed of the recovery in both output and labor after the recession in 2009. The correlations between aggregate output and labor growth in the model and the data is, respectively, 0.57 and 0.35. The corresponding correlations for the full information model are 0.57 and 0.21. This suggests that our model mechanism, which works through firms' labor demand, does help the baseline model explain observed fluctuations in hours worked relative to the full information model.

6.7. **Time varying media focus as aggregate non-productivity shocks.** Atalay (2017) uses a multi-sector model that, unlike our model, includes capital as a production factor and allows for a richer specification of consumption and production elasticities. Using a filter implied by his model and realistic values of elasticities of substitution, he estimates that sectoral productivity shocks explain approximately 80% of the variance of aggregate output. The remaining 20% of the variance of aggregate output is attributed to common non-productivity shocks.

Here, we show that in spite of sectoral productivity shocks being the only source of exogenous variation, the time-varying focus of news media creates the appearance of an aggregate non-productivity shock in our model. The mechanism is as follows. When a sector is in the news, productivity in that sector has a disproportional impact on aggregate output. This creates a relationship between sectoral productivities and output that is strongly non-linear. A researcher applying a filter that imposes a constant (log-) linear relationship between sectoral productivity and output would therefore conclude that sectoral productivity shocks cannot explain all of the variation in aggregate output.

To quantify how much of aggregate output fluctuations in our model would be attributed to common non-productivity shocks by a linear filter, we first generate a long (100,000 periods) artificial sample from our baseline model. We then run the regressions

$$c_t = \gamma^c + \sum_{i=1}^{n} \delta_i^c z_{i,t} + \epsilon_t^c \tag{6.1}$$

and

$$l_t = \gamma^l + \sum_{i=1}^{n} \delta_i^l z_{i,t} + \epsilon_t^l \tag{6.2}$$

on the generated sample, where c_t is the simulated time-series of the log of aggregate value added C and l_t is log of aggregate labor L. The fitted values from these regressions are the linear projection of the variables onto the log of sectoral productivity shocks. They therefore represent the best possible fit that can be achieved by any linear model.

The variance of the residuals, which by construction are orthogonal to all linear combinations of sectoral productivity shocks, corresponds to the lower bound for the variance attributed to a common non-productivity shock by an Atalay-style filter.[11] In our baseline calibration, this residual accounts for 17% of variance of aggregate output, which is close to the 20% found by Atalay (2017). The corresponding share of the of aggregate labor variance accounted for by the residual is even larger at 38%. The apparent aggregate non-productivity shock generated by the time-varying focus of news media can thus account for a substantial fraction of aggregate fluctuations. By contrast, both the full information and the no news version of the model imply a constant log-linear relationship between sectoral productivity and aggregate output and, hence, that the residual variance would be zero.

The regression coefficients from (6.1) and (6.2) are based on the population moments of the model, but can also be used to decompose the model's predictions of aggregate output and labor conditional on the historical productivity shocks. This decomposition is illustrated in Figure 14. More than half of the fall in output during the Great Recession can be explained by the residual, which also explains more than two-thirds of the fall in labor in the same period.

This exercise also demonstrates that time-varying sectoral media focus produces demand-driven business cycle fluctuations that share qualitative properties with the *Main Business Cycle* (MBC) shock identified by Angeletos, Collard and Dellas (2019). They find that a shock that is orthogonal to productivity, but increases output, employment and consumption is responsible for a large fraction of business cycle fluctuations. Our model can thus account for the findings of both Atalay (2017) and Angeletos *et al* (2019), in spite of sectoral productivity shocks being the only source of exogenous variation.

6.8. **Selection bias and inference from state-dependent reporting decisions.** State-dependent reporting decisions affect aggregate output through two distinct channels. First, the selection bias towards more extreme shocks increases the standard deviation of firms' labor input decisions. Second, as shown in Section 4, the state dependence of reporting decisions allows firms to make inference not only about the shocks that are reported by news media, but also about those that news media chose not to report.

To quantify the importance of the state-dependent news reporting in the model, we solve the model under the assumption that reporting decisions are random. The population standard deviation of output in this version of the model is 1.6%, or about one-third less than in the baseline model.

[11]This represents a lower bound because any additional restrictions implied by a model-based filter beyond the restriction of linearity can only reduce the fit of the model and increase the amount of variance attributed to the common non-productivity shock.

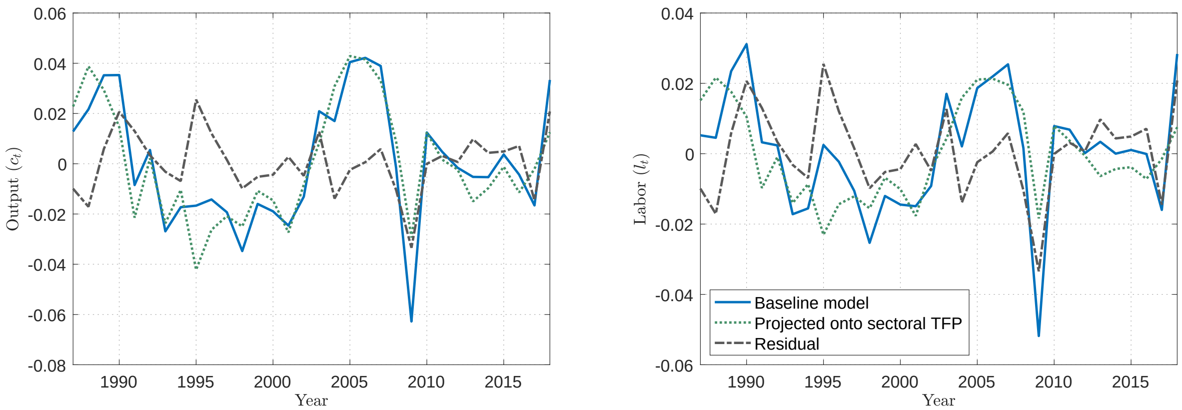

FIGURE 14. Decomposing fluctuations in log of aggregate output and labor. The dotted grey line is the projection of c_t and l_t onto the sectoral productivity shocks. The residual is the component of aggregate output and labor that cannot be expressed as a linear function of the cross-section of productivity shocks.

The news selection function in the baseline version also weighs larger sectors more when evaluating newsworthiness. The effect on output of this systematic bias towards reporting on larger sectors is substantial: The standard deviation of output in the model when news media simply report the productivity shock with the largest (unweighted) absolute deviation from its mean is around 2.0%, about halfway between the baseline and random-news versions of the model.

We also compute how much output would change if firms did not take into account the state dependence of reporting decisions when forming beliefs about non-reported sectors. The effect of time-variation in conditional beliefs on output through this channel accounts for about 0.4 percentage point of the standard deviation of output.

6.9. **Labor elasticity and aggregate fluctuations.** News media reports affect outcomes in the model via firms' choices of labor inputs. How much firms' labor demand responds to news reports depend on the Frisch elasticity parameter ν. When this elasticity is high, wages need to increase by a relatively small amount in order to induce households to supply additional labor. Larger values of ν thus imply a stronger response of labor demand to both productivity shocks and to reports indicating that demand for intermediate inputs will increase.

As an example, consider when news media report on a sector with high productivity. All other sectors then infer that the high productivity sector will hire more labor, produce more and therefore demand more intermediate inputs. This in turn creates an incentive for firms in other sectors to also hire more labor. As can be seen in equation (2.9) this incentive is tempered if the hiring by the high productivity sector is expected to drive up wages. However, when labor elasticity ν is large, firms can attract additional labor supply without a sharp increase in wages. A large value for ν thus increases the strategic complementarity in labor inputs across sectors.

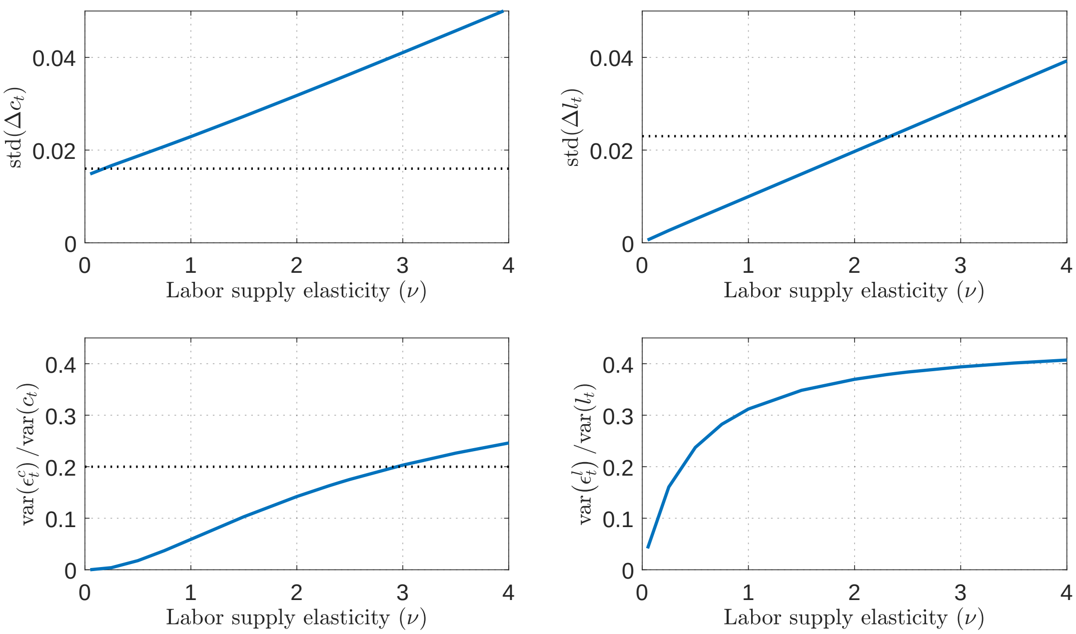

FIGURE 15. Model quantities for different values of the labor elasticity parameter ν. Top panels shows that the standard deviation of output and labor is increasing in the value ν. Dotted lines indicate standard deviations of GDP growth and employment growth in the data. Bottom panels display the relative variance of the residual from projecting aggregate output and labor onto sectoral productivity shocks for different values of ν.

The dependence of key model outcomes on the value of ν is illustrated in Figure 15. The two top panels show that the standard deviation of growth in both aggregate output (c_t) and labor (l_t) are increasing in ν. The horizontal dotted lines indicate the corresponding sample standard deviations of growth of GDP and in hours worked. In the baseline calibration used for the simulations above, we set $\nu = 2.4$, which makes the model match the standard deviation of growth in hours worked. However, at that value for ν the model over-predicts the standard deviation of output growth. That the model cannot match both output and labor volatility at the same time is partly due to the absence of capital in firms' production functions, combined with the assumption of constant returns to scale. Without capital, the share, and hence the marginal productivity of labor, is necessarily higher than in a model that would also include capital. This makes output respond stronger to changes in labor inputs in the baseline model than it would in a model with capital.

The bottom two panels of the figure illustrate how ν influences the quantitative importance news media in the model. The variance of the residual from the projections in (6.1) and (6.2) relative to the variance of output and labor are also increasing in ν. As explained above, the complementarity of labor inputs across sectors, as well as the aggregate response to news reports, are increasing in ν. Large values of this parameter thus also increase the difference between the response to a sectoral shock when it is reported compared to when it is not.

Large values of ν thus strengthen the nonlinearities generated by time-varying sectoral news media focus and makes it contribute more to aggregate fluctuations in output and labor.

7. Sectoral news and beliefs: Time series evidence

Above, we analyzed how media reports that are unrepresentative of the economy as a whole can influence beliefs and aggregate output in a simple and stylized model. While simplicity brings the benefits of tractability and transparency, it also imposes a lot of structure on the data. In this section we therefore present empirical evidence that supports the key mechanism, but does not rely on the structure of our theoretical model.

The main argument we make in this paper is straightforward: When the news are unrepresentatively good, economic agents will be unduly optimistic. When the news are unrepresentatively bad, they will be unduly pessimistic. To test this theory directly, we here first construct a sectoral news-weighted index of economic activity. When this index is above a corresponding unweighted aggregate reference index, the news are unrepresentatively good. When it is below the reference index, news are unrepresentatively bad. We refer to the difference between the news-weighted index and the reference index as our *unrepresentativeness index* of news reports.

As a second step, we estimate a sign-restricted VAR as in Enders, Kleeman and Mueller (*forthcoming*). This allows us to extract time series of mutually orthogonal shocks to beliefs and to fundamentals from data on GDP growth and GDP growth expectations. Our theory predicts that our index of news unrepresentativeness should be able to explain changes in beliefs that cannot be accounted for by fundamentals.

7.1. A news-weighted index of economic activity.

In Section 5 we documented that the amount of news coverage a sector receives varies across sectors and across time. That data by itself does not tell us how good or bad the news are, only which sectors were prominent in the news coverage at different points in time. To construct a news-weighted index of economic activity that will allow us to address whether the news are unrepresentatively good or bad, we need to combine the sectoral news coverage data with some corresponding sectoral data on economic activity.

Time series on sectoral economic activity available at a higher than annual frequency are scarce. However, monthly sectoral employment data is available from the Establishment Survey of the BLS for all of our sectors other than agriculture, starting in 1990. We use the sub-sample that overlaps with our news data, i.e. 1990:Q1-2018:Q4, to construct a news-weighted index of employment growth Δl_t^{news} as

$$\Delta l_t^{news} \equiv \sum_{i=1}^{n} \frac{1}{2} \left(f_{i,t} + f_{i,t-1}\right) \left(l_{i,t} - l_{i,t-1}\right). \tag{7.1}$$

where $l_{i,t}$ is (log) employment in sector i in period t. The weight $f_{i,t}$ is the fraction of news coverage received by sector i at time t. The deviation Δl_t^{unrep} of the news-weighted index and unweighted aggregate employment growth Δl_t is then given by

$$\Delta l_t^{unrep} \equiv \Delta l_t^{news} - \Delta l_t, \tag{7.2}$$

where Δl_t is the change in the log of total employment between periods $t-1$ and t. When Δl_t^{unrep} is positive, sectors receiving more news coverage than the average sector are also experiencing faster employment growth than the economy as a whole, indicating that the news are unrepresentatively good. The opposite holds when Δl_t^{unrep} is negative.

Our news coverage shares do not take into account that the total amount of news coverage devoted to economic news may vary over time. To account for time-variation in the volume of economic news, we scale Δl_t^{unrep} by the *News Heard Index* from the *Michigan Survey of Household Expectations*. The *News Heard Index*, which we normalize to have mean one, captures variations in the fraction of the population that reports having heard news about changes in business conditions in a given quarter. The top panel of Figure 16 illustrates both the scaled and unscaled index. The two series are highly correlated, and the scaling makes only a small differences for our results, which we report below.

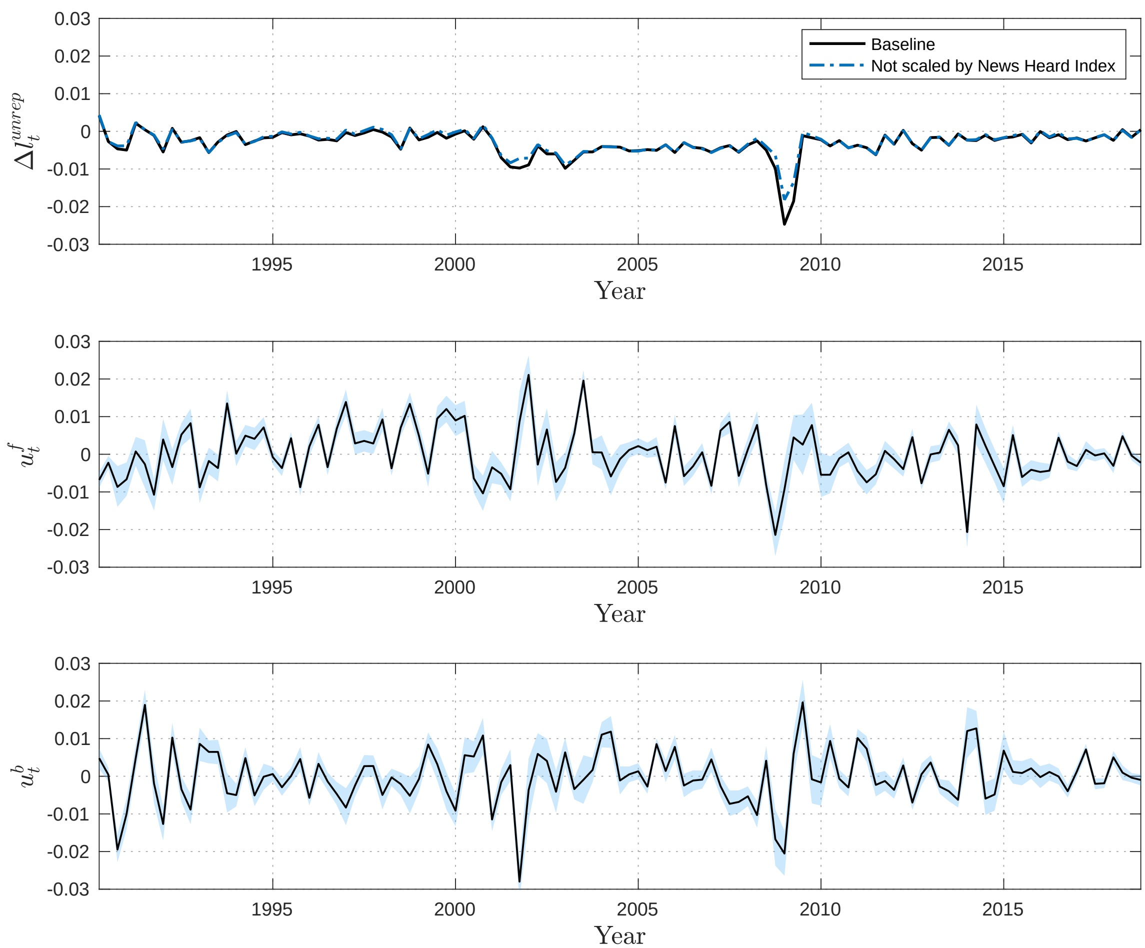

FIGURE 16. Time series of News Unrepresentativeness Index Δl_t^{unrep} (top), posterior of VAR shock to fundamentals u_t^f (middle), and posterior of VAR shock to beliefs u_t^b (bottom). Light blue shaded areas indicate 95% posterior probability intervals.

7.2. **Extracting belief shocks using a sign-restricted VAR.** Enders, Kleeman and Mueller (*forthcoming*) propose a VAR-based method to extract belief shocks from data on nowcast errors and GDP growth. The method proceeds in two steps. First, it constructs a time series of nowcast errors as the difference between current GDP growth and the median GDP growth nowcast from the *Survey of Professional Forecasters.* These nowcast errors are not available in real time and hence are not part of any agent's information set at time t.

In a second step, we estimate a bivariate VAR in median nowcast errors and GDP growth, while imposing two sign restrictions: (i) A fundamental shock contemporaneously affects GDP growth and nowcast errors in the same direction, and (ii) a belief shock affects the two variables with opposed signs. Assumption (i) implies that fundamental shocks cause a (weakly) larger change in actual GDP growth than they do in expectations, i.e. median expectations under-react to fundamental shocks. Assumption (ii) implies that belief shocks cause (weakly) smaller changes in actual output than in expected output.

These identifying restrictions hold across a very broad class of models with potentially very different information structures, including those of Lorenzoni (2009), Blanchard et al (2013), and Angeletos and La'o (2010, 2013). There is also substantial empirical evidence supporting the assumption of under-reaction of average beliefs to fundamental shocks, e.g. Coibion and Gorodnichenko (2012, 2015).[12]

We closely follow both the estimation and identification approach of Enders *et al* , with two minor exceptions: We extend the sample period to include the most recent data, and we estimate the model using Bayesian methods that allow us to take into account parameter uncertainty when making inference. We thus estimate the following VAR(4) using the sample from 1968:Q4-2020:Q1.

$$\begin{bmatrix} nce_t \\ \Delta y_t \end{bmatrix} = \sum_{p=1}^{4} A_p \begin{bmatrix} nce_{t-p} \\ \Delta y_{t-p} \end{bmatrix} + B \begin{bmatrix} u_t^f \\ u_t^b \end{bmatrix}. \tag{7.3}$$

The variable nce_t is the nowcast error, defined as $nce_t \equiv \Delta y_t - \overline{E}_t^{med} (\Delta y_t)$ where $\overline{E}_t^{med}$ denotes the median expectation from the *Survey of Professional Forecasters.* The measure of actual output growth, Δy_t, is based on the third-release of GDP from the BEA. The structural innovations u_t^f and u_t^b are, respectively, the shocks to fundamentals and beliefs and are uncorrelated white noise processes.

We impose the sign restrictions

$$B = \begin{bmatrix} + & - \\ + & + \end{bmatrix}$$

on the impact matrix B implied by assumption (i) and (ii) as one-sided (improper) uniform priors. The posterior distribution of the parameters in A_p and B is simulated using 10 million

[12]The evidence on individual forecasts is more mixed, and some author have found that these may overreact to new information and/or extrapolate from recent data, e.g. Bordalo, Gennaioli, Ma and Shleifer (2020), Broer and Kohlhas (2019) and Kohlhas and Walther (forthcoming).

draws from a Metropolis-Hastings algorithm and we use (improper) uniform priors for all coefficients in A_p.[13]

After estimating the posterior distribution of A_p and B, we can compute the impulse responses of real GDP growth to both fundamental and belief shocks and these are similar to those obtained by Enders *et al.* As can be seen in Figure 17, the median response to a one standard deviation fundamental shock is an increase in GDP growth of about 2.7 percentage points. A one standard deviation belief shock increases GDP growth by about 0.8 percentage points at the median. The 95 percent probability intervals are bounded away from zero for both type of shocks. The posterior distributions of the time series of u_t^f and u_t^b are plotted in the bottom two panels of Figure 16.

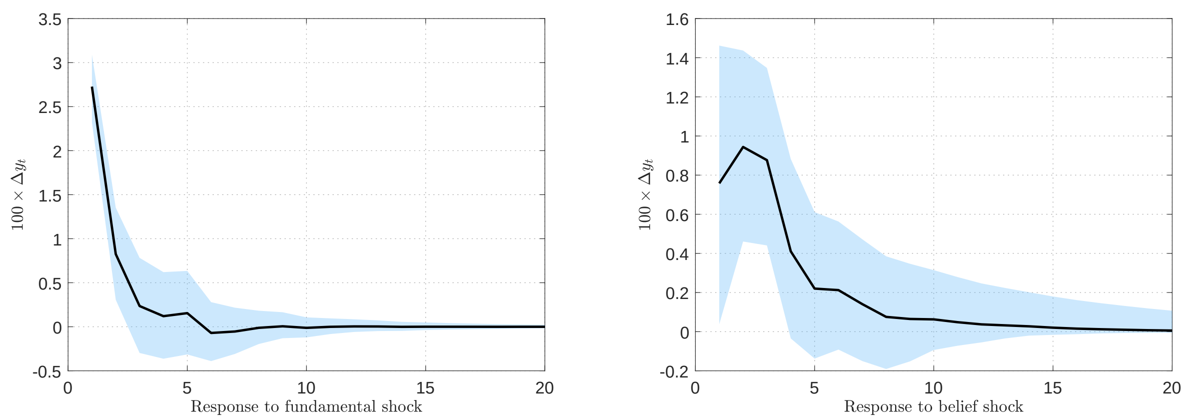

FIGURE 17. Impulse response functions of real GDP to fundamental (left panel) and belief (right panel) shock identified by the VAR with sign restrictions.

7.3. **Unrepresentative news and beliefs.** If the mechanism we have proposed in this paper is important in practice, the news-weighted index should be positively correlated with the belief shock extracted using the VAR. Figure 18 illustrates the posterior correlation between the index Δl_t^{unrep} and the two shock processes u_t^f and u_t^b.

As the theory predicts, the unrepresentative index is strongly correlated with the belief shocks u_t^b. The median correlation is 0.27 and the 95% probability interval ranges from 0.19 to 0.35. The posterior distribution is also clearly bounded away from 0. The median correlation between fundamental shocks and Δl_t^{unrep} is lower at 0.096, and the posterior distribution has substantial probability mass (4.5%) below zero. The fact the correlation between u_t^f and

[13]Baumeister and Hamilton (2019) argue that imposing sign restrictions directly on the impact matrix using Bayesian priors may be more numerically more robust than relying on OLS estimates and rotations of reduced form covariance matrices.

Δl_t^{unrep} is approximately zero suggest that Δl_t^{unrep} indeed captures the degree to which the sectoral news are unrepresentative of the economy as a whole.[14]

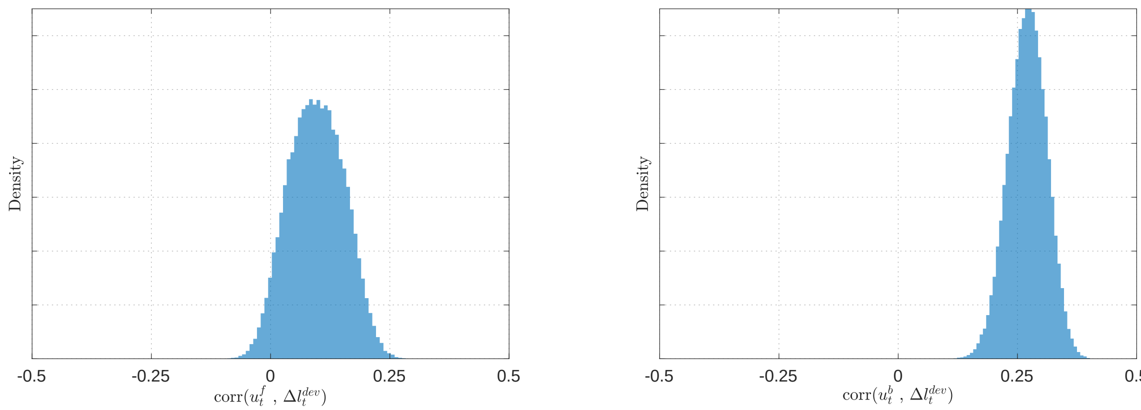

FIGURE 18. Posterior distributions of correlations between shocks identified from the SVAR model and the index of news unrepresentativeness. The left panel illustrates the correlation between fundamental shocks and the index, and the right panel the correlation between belief shocks and the index.

One might be concerned with a potential reverse causality channel, in which a change in beliefs drive news coverage instead of the reverse. Such a channel, however, could not easily explain both the positive correlation of our unrepresentativenes index with belief shocks and the fact that the index is approximately uncorrelated with fundamental shocks.

To account for these patterns, an alternative story would require three key elements. First, it would require the existence of fluctuations in beliefs that are correlated across individuals, but unrelated to either economic fundamentals or reports in the news media. Many existing models introduce correlated fluctuations in beliefs through exogenous common noise shocks, e.g. Lorenzoni (2009), Angeletos and La'O (2013) and Blanchard, L'Huillier and Lorenzoni (2013). However, these papers do not explain why economy-wide beliefs fluctuate, but instead study the consequences of such fluctuations. By contrast, our theory explains the source of correlated mistakes and makes additional testable predictions that are borne out by the data.

Second, such an account would require that news media can distinguish between (e.g) booms driven by fundamentals from those driven by beliefs. We find it hard to believe that news media have the ability to do this, while at the same time having no role in generating those beliefs.

Finally, the media would have to condition the nature of their reporting on this knowledge, reporting only representative sectors in response to fundamental shocks but reporting sectors

[14]The results are qualitatively unchanged when we do not scale by the News Heard index from the Michigan survey. The median correlation between the unrepresentativeness index and the belief shocks decreases somewhat to 0.23 with the 95% posterior probability interval ranging from 0.15 to 0.30 The median correlation with the fundamental shocks is virtually unchanged.

with extreme outcomes in response to belief-driven fluctuations. Even if the media had the ability to condition their reporting in this way, we think there is little reason (and no evidence) to presume that news media have an incentive to report in this manner.

8. Conclusions

Since the early 1990s, many authors have documented that aggregate output fluctuations are largely orthogonal to contemporaneous productivity. Hall (1993), Blanchard (1993) and Cochrane (1994) all argue that some form of a consumption shock is needed to account for the business cycle. However, no consensus has emerged about the theoretical underpinnings of such a shock. In a recent paper, inspired by Lucas' (1977) observation that "business cycles are all alike", Angeletos, Collard and Dellas (2019) document the properties of what they label the *main business cycle* (MBC) shock. This shock, which is approximately orthogonal to productivity, appears to be responsible for most business cycle fluctuations in several key macroeconomic variables.

In this paper we have demonstrated that time varying sectoral media focus can generate aggregate fluctuations that are orthogonal to productivity, even in a model where the only source of exogenous variation is sectoral TFP shocks. While our model is too stylized to account for all of the dynamics associated with MBC shocks, many of our findings are consistent with them. Like that shock, time varying sectoral media focus generates fluctuations that are orthogonal to aggregate productivity and positively correlated with output, consumption and employment.

Angeletos *et al* (2019) argue that the facts they document are consistent with fluctuations in firms' beliefs about the demand for their products. We have proposed a theory that can explain not only why firms' demand expectations vary over time, but also why the demand expectations of firms across different sectors move together. Discussing financial markets, Shiller (2001) writes that *"Significant market events generally occur only if there is similar thinking among large groups of people, and the news media are essential vehicles for the spread of ideas."* We argue that the same logic applies to business cycles. News media are essential vehicles for spreading information about specific sectoral developments to the rest of the economy. To the extent that this information only provides a partial picture of the economy, firms across many different sectors will take actions based on the same partial information and thereby causing fluctuations in aggregate variables. We also presented time series evidence documenting that unrepresentative sectoral news coverage can help explain fluctuations in beliefs that cannot be accounted for by shocks to fundamentals. This evidence does not rely on the model structure directly, but provides independent support for its key mechanism.

In this paper we have also proposed a conceptually new approach to model incomplete information. Firms in our model receive accurate but partial information from news media, and what media report depends deterministically on the cross-section of productivity shocks. By constructing a novel data set of sectoral news coverage, we are able to discipline the reporting decisions of news media in the model. This approach avoids introducing exogenous noise shocks and provides a tight link between beliefs, developments in the real economy, and observable patterns in news coverage.

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Appendix A. Solving the model

In this appendix we describe how to solve the model. We first present the primitives of the model and the optimality conditions of firms and households. We then derive the expressions that we use to solve the model numerically and describe an algorithm for doing so. Throughout, we use the notation convention that lower case letters denote the log of the corresponding uppercase letter. Bold letters and symbols denote vectors.

A.1. **Model primitives.** Households maximize the utility function

$$\max_{X_1,\ldots,X_n,L_i} C - \frac{L^{1+1/\nu}}{1+1/\nu} \tag{A.1}$$

where L is labor supply and C is the final consumption good. The final good C is a Cobb-Douglas aggregate of sector-specific goods C_i given by

$$C = \prod_i \left(C_i/\beta_i\right)^{\beta_i}. \tag{A.2}$$

Sector i produces quantity Q_i of good i using the Cobb-Douglas production function

$$Q_i = Z_i \left(\prod_j X_{ij}^{\alpha_{ij}}\right) L_i^{1-\alpha_i} \tag{A.3}$$

where Z_i is a sector-specific productivity shock and $\alpha_i = \sum_j \alpha_{ij}$. Total output in sector i can be used either for the final consumption C_i or as an intermediate input X_{ij} in sector j so that

$$C_i + \sum_j X_{ji} = Q_i. \tag{A.4}$$

Sector specific labor demand L_i adds up to total labor demand L, i.e.

$$\sum_i L_i = L. \tag{A.5}$$

Households spend the income they receive from working and from owning the firms so that

$$C = WL + \Pi, \tag{A.6}$$

reflecting the normalization of the aggregate price $P = 1$. Under full information, profits Π are zero of course. When firms face information frictions, however, informational errors may lead Π to be non-zero.

A.2. **Optimality conditions.** Households supply labor until marginal disutility of working equals marginal utility of consuming wage

$$W = L^{\frac{1}{\nu}}. \tag{A.7}$$

The intermediate goods are combined into the final consumption good using Cobb-Douglas aggregator (A.2). The optimal expenditure on good i, holding total expenditure C fixed, is then given by

$$P_i C_i = \beta_i C. \tag{A.8}$$

Labor markets are competitive, so households earn the same wage in every sector. Since firms choose labor before observing all prices, firm choose labor inputs so that expected marginal cost equals expected marginal product

$$E[W \mid \Omega_i] = (1 - \alpha_i)\,\frac{E[P_i Q_i \mid \Omega_i]}{L_i}. \tag{A.9}$$

Marginal product of intermediate input j equals its marginal cost so that

$$P_j = \frac{\alpha_{ij}}{X_{ij}} P_i Q_i \tag{A.10}$$

holds in equilibrium. Using (A.8) and (A.10), the market clearing condition (A.4) can be rewritten as

$$P_i Q_i = \sum_j \alpha_{ji} P_j Q_j + \beta_i C. \tag{A.11}$$

A.3. **Solving for prices as a function of aggregate output, labor inputs and productivity.** The only decision taken under incomplete information is a firm's decision of how much labor to employ. To solve the model, we need to be able to express that choice as a function of a firm's expectations about the exogenous sector-specific productivity shocks Z_i and the labor input choices of firms in other sectors. The first step towards this goal involves solving for prices as a function of aggregate output, labor inputs and productivity. What follows, are tedious but straightforward algebraic manipulations of the equilibrium conditions above.

Start by substituting in the optimal demand for intermediate inputs X_{ij} into the production function (A.3) using (A.10) to get

$$Q_i = Z_i \left(\prod_j \left(\alpha_{ij} \frac{P_i Q_i}{P_j} \right)^{\alpha_{ij}} \right) L_i^{1-\alpha_i}. \tag{A.12}$$

Use that $\sum_{j=1}^{n}\alpha_{ij}=\alpha_i$ to compute $\Pi_j(P_iQ_i)^{\alpha_{ij}}=(P_iQ_i)^{\alpha_i}$ and move this term outside the product in the parenthesis, so that

$$Q_i = Z_i\left(P_iQ_i\right)^{\alpha_i}\left(\prod_j\left(\frac{\alpha_{ij}}{P_j}\right)^{\alpha_{ij}}\right)L_i^{1-\alpha_i}. \tag{A.13}$$

Divide both sides by $Q_i^{\alpha_i}$

$$Q_i^{1-\alpha_i} = Z_iP_i^{\alpha_i}\left(\prod_j\left(\frac{\alpha_{ij}}{P_j}\right)^{\alpha_{ij}}\right)L_i^{1-\alpha_i} \tag{A.14}$$

and multiply by $P_i^{1-\alpha_i}$

$$\left(P_iQ_i\right)^{1-\alpha_i} = Z_iP_i\left(\prod_j\left(\frac{\alpha_{ij}}{P_j}\right)^{\alpha_{ij}}\right)L_i^{1-\alpha_i}. \tag{A.15}$$

Define gross sales V_i as

$$V_i \equiv P_iQ_i, \tag{A.16}$$

take logs of both sides of (A.15)

$$\left(1-\alpha_i\right)v_i = z_i + p_i + \left(1-\alpha_i\right)l_i + \sum_j\alpha_{ij}\left(\log\left(\alpha_{ij}\right)-p_j\right). \tag{A.17}$$

and rearrange the resulting expression to get

$$\left(1-\alpha_i\right)\left(v_i-l_i\right) - z_i - \sum_j\alpha_{ij}\log\left(\alpha_{ij}\right) = p_i - \sum_j\alpha_{ij}p_j. \tag{A.18}$$

Define the input-output matrix A so that the typical i^{th} row and j^{th} element is α_{ij}. We can then write the r.h.s. of (A.18) as

$$p_i - \sum_j\alpha_{ij}p_j = p_i - A_i\mathbf{p} \tag{A.19}$$

where we use bold-face to denote vectors (i.e. $\mathbf{p}\equiv(p_1,p_2,...,p_n)'$) and A_i is the i^{th} row of A.

We can now rewrite the relationships in (A.18) as the matrix equation

$$\left[\left(I-\boldsymbol{\alpha}\right)\left(\mathbf{v}-\mathbf{l}\right)-\mathbf{z}-\boldsymbol{\tau}\right] = \left(I-A\right)\mathbf{p} \tag{A.20}$$

where $\boldsymbol{\alpha}$ is a diagonal matrix with the i^{th} diagonal element $\alpha_i=\sum_j\alpha_{ij}$, $\boldsymbol{\tau}$ is a vector with the i^{th} element given by $\sum_j\alpha_{ij}\log\left(\alpha_{ij}\right)$.

Using the definition (A.16), the market clearing condition (A.11) can be rewritten as

$$V_i = \sum_j\alpha_{ji}V_j + \beta_iC. \tag{A.21}$$

Since this has to hold for each i, we can solve for $\mathbf{V}$

$$\mathbf{V} = C\left(I-A'\right)^{-1}\boldsymbol{\beta}. \tag{A.22}$$

Solve (A.20) for $\mathbf{p}$ and eliminate $\mathbf{v}$ using (A.22) to get

$$\mathbf{p} = \left(I-A\right)^{-1}\left[\left(I-\boldsymbol{\alpha}\right)\left(\boldsymbol{\gamma}+c\times\mathbf{1}_n-\mathbf{l}\right)-\mathbf{z}-\boldsymbol{\tau}\right], \tag{A.23}$$

where $\boldsymbol{\gamma} \equiv \log\left((I-A')^{-1}\boldsymbol{\beta}\right)$ is a vector. Separating out the terms associated with c, we have

$$\mathbf{p} = (I-A)^{-1}\left[(I-\boldsymbol{\alpha})(\boldsymbol{\gamma}-\mathbf{l}) - \mathbf{z} - \boldsymbol{\tau}\right] + c \times (I-A)^{-1}(I-\boldsymbol{\alpha})\mathbf{1}_n. \tag{A.24}$$

This expression can in turn be simplified as

$$\mathbf{p} = (I-A)^{-1}\left[(I-\boldsymbol{\alpha})(\boldsymbol{\gamma}-\mathbf{l}) - \mathbf{z} - \boldsymbol{\tau}\right] + c \times \mathbf{1}_n. \tag{A.25}$$

by observing that $(I-A)^{-1}(I-\boldsymbol{\alpha})\mathbf{1}_n = \mathbf{1}_n$. To see this last point, note that

$$(1-A)\mathbf{1}_n = \begin{pmatrix} 1-\alpha_1 \\ 1-\alpha_2 \\ \vdots \\ 1-\alpha_n \end{pmatrix} \tag{A.26}$$

implying

$$\mathbf{1}_n = (1-A)^{-1}\begin{pmatrix} 1-\alpha_1 \\ 1-\alpha_2 \\ \vdots \\ 1-\alpha_n \end{pmatrix} = (1-A)^{-1}(I-\boldsymbol{\alpha})\mathbf{1}_n.$$

A.4. **Output and labor demand as functions of productivity and labor inputs.** To solve the model, we need to compute the optimal labor demand as a function of expected labor inputs and productivity in every sector $L_j : j \in \{1, 2, ..., n\}, \mathbf{z}$. To that end, first use (A.8) and (A.25) to write

$$\begin{aligned}\mathbf{c} &= c + \log(\boldsymbol{\beta}) - \mathbf{p} \\ &= (I-A)^{-1}(\mathbf{z}+\boldsymbol{\tau}) + (I-A)^{-1}(I-\boldsymbol{\alpha})(\mathbf{l}-\boldsymbol{\gamma}) + \log(\boldsymbol{\beta}).\end{aligned} \tag{A.27}$$

Expressing the consumption aggregator (A.2) in logs, we have

$$c = \sum_i \beta_i(c_i - log(\beta_i)) = \boldsymbol{\beta}'\mathbf{c} - \boldsymbol{\beta}'\log(\boldsymbol{\beta}). \tag{A.28}$$

Combing (A.27) and (A.28), we conclude

$$c = \boldsymbol{\Lambda}'(I-\boldsymbol{\alpha})\mathbf{l} + \boldsymbol{\Lambda}'\mathbf{z} + \kappa \tag{A.29}$$

where $\boldsymbol{\Lambda}' \equiv \boldsymbol{\beta}'(I-A)^{-1}$ and $\kappa \equiv \boldsymbol{\Lambda}'\boldsymbol{\tau} - \boldsymbol{\Lambda}'(I-\boldsymbol{\alpha})\boldsymbol{\gamma}$. We then have an expression of the desired form

$$L_i = (1-\alpha_i)\Lambda_i \frac{E\left[\exp\left(\boldsymbol{\Lambda}'(I-\boldsymbol{\alpha})\mathbf{l} + \boldsymbol{\Lambda}'\mathbf{z} + \kappa\right) \mid \Omega_i\right]}{E\left[(\sum L_i)^{\frac{1}{\nu}} \mid \Omega_i\right]}. \tag{A.30}$$

A.5. **Numerical solution algorithm.** We solve the model by evaluating the conditional expectations in (A.30) using a simulation-based parameterized expectations method. The simulation is initialized by solving the model under full information for a history $\{L_1, L_2, ..., L_T\}$ based on draws, $\{\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_T\}$, from the process for log sectoral productivities.

To start, define the two key terms in expectations in (A.30):

$$T^1 = \exp\left(\mathbf{\Lambda}'\left(I - \boldsymbol{\alpha}\right)\mathbf{l} + \mathbf{\Lambda}'\mathbf{z} + \kappa\right) \tag{A.31}$$

$$T^2 = \left(\sum L_i\right)^{\frac{1}{\nu}} \tag{A.32}$$

The algorithm is then described by the following steps.

(1) For each possible reporting outcome, $s \in \mathbf{s}$, isolate all the periods, $\{t\}$, such that $\mathbf{s}(\mathbf{z}_t) = s$. Then, for each sector $i = 1, ..., N$,
  (a) approximate the conditional expectations terms $E[T_t^1|\Omega_{it}]$ and $E[T_t^2|\Omega_{it}]$ by evaluating the realizations $\{T_t^1\}$ and $\{T_t^2\}$ and regressing these on a constant, own-sector productivity, and the reported productivity series, i.e. on $\{1, z_{it}, \mathbf{r}(\mathbf{z}_t)\}$.
  (b) Using the fitted values $\{\hat{T}_t^1\}$ and $\{\hat{T}_t^2\}$ from these regressions in place of expectations, update the policy choices $\{L_{it}\}$ according to (A.30)

(2) Check if the history $\{L_1, L_2, ..., L_T\}$ has converged. If not, return to Step 1.

For the results in the paper, we set $T = 100,000$, which was sufficient to ensure our results do not depend on how we seed the random number generator. We also experimented with more general functional forms for the regression step in (1.a) but found these had no affect on the equilibrium. For the graphs in the paper, we added the history of observed productivity shocks to the end of the random draws of $\mathbf{z}_t$.

Appendix B. Proofs of Propositions

Proof of Proposition 2. The proposition states that (log of) optimal labor inputs L_i^* is increasing in (the log of) L_j and in proportion to the centrality Λ_j of sector j. We thus need to show that

$$\frac{\partial \log L_i^*}{\partial \log L_j^*} > 0 \tag{B.1}$$

and can be written in a form

$$\frac{\partial \log L_i^*}{\partial \log L_j^*} = \Lambda_j \kappa_L. \tag{B.2}$$

where κ_L is a constant given by model parameters.

Proof. Evaluating (A.30) under full information, the log of optimal labor inputs l_i^* is given by

$$l_i^* = const. + \sum_{k=1}^{n}\left(1 - \alpha_k\right)\Lambda_k l_k - \log\left(\left(\sum_{k=1}^{n}\exp\left(l_k\right)\right)^{\frac{1}{\nu}}\right) \tag{B.3}$$

where all terms that are independent of labor inputs are collected in the constant. Taking derivatives with respect to l_j gives

$$\frac{\partial l_i^*}{\partial l_j^*} = (1-\alpha_j)\,\Lambda_j - \frac{1}{\nu}\frac{\exp(l_j)}{\sum_{k=1}^{n}\exp(l_k)}. \tag{B.4}$$

Using that in the full information equilibrium

$$\frac{\exp(l_j)}{\sum_{k=1}^{n}\exp(l_k)} = \frac{(1-\alpha_j)\Lambda_j}{\sum_{k=1}^{n}(1-\alpha_k)\Lambda_k} \tag{B.5}$$

and the fact that

$$\sum_{k=1}^{n}(1-\alpha_k)\Lambda_k = \Lambda'(I-\boldsymbol{\alpha})\mathbf{1}_n = \boldsymbol{\beta}'^{-1}(I-\boldsymbol{\alpha})\mathbf{1}_n = \boldsymbol{\beta}'\mathbf{1}_n = 1, \tag{B.6}$$

we can simplify (B.4) to get

$$\frac{\partial l_i^*}{\partial l_j^*} = (1-\alpha_j)\Lambda_j\left(1-\frac{1}{\nu}\right), \tag{B.7}$$

which is of the desired form and positive if $\nu > 1$. □

Proof of Proposition 3. The proposition states that for a given $r < n$, the variance of productivity shocks conditional on being reported $var(z_i \mid s_i = 1)$ is larger than the unconditional variance $var(z_i)$ and increasing in n.

Proof. We start by proving that $var(z_i \mid s_i = 1) > var(z_i)$. Define the variable $x_i \equiv z_i^2$. Since $E(z_i) = 0$, $E(x_i) = var(z_i)$. Denote the k^{th} order statistic of $\{x_1, x_2, ..., x_n\}$ as $x_{(k)}$ so that

$$x_{(1)} \equiv \min\{x_1, x_2, ..., x_n\} \tag{B.8}$$

$$x_{(2)} \equiv \min\left\{\{x_1, x_2, ..., x_n\} \setminus x_{(1)}\right\} \tag{B.9}$$

$$\vdots$$

$$x_{(k)} \equiv \min\left\{\{x_1, x_2, ..., x_n\} \setminus \left\{x_{(1)}, x_{(2)}, ..., x_{(k-1)}\right\}\right\} \tag{B.10}$$

Note that $s_i = 1$ implies that

$$x_i \in \left\{x_{(n)}, x_{(n-1)}, ..., x_{(n-r+1)}\right\}. \tag{B.11}$$

Since $x_{(k)} \geq x_{(k-j)}$ for any $j > 0$, $x_{(k)}$ first order dominates $x_{(k-j)}$, and hence

$$E\left(x_{(k)}\right) \geq E\left(x_{(k-j)}\right) \tag{B.12}$$

so that

$$var(z_i \mid s_i = 1) \geq var(z_j \mid s_j = 0). \tag{B.13}$$

Combining (B.13) with the fact that

$$var(z_i) = p(s_i = 1)var(z_i \mid s_i = 1) + p(s_i = 0)var(z_j \mid s_j = 0) \tag{B.14}$$

gives the desired result

$$var(z_i) = var(z_i \mid s_i = 1) - p(s_i = 0)\left[var(z_i \mid s_i = 1) - var(z_j \mid s_j = 0)\right] \tag{B.15}$$

$$\leq var(z_i \mid s_i = 1). \tag{B.16}$$

To prove the second part of the proposition, we also need to show that $var(z_i \mid s_i = 1)$ is increasing in n. Using the same notation as above, consider $n = l$, so that the squared values of the reported sectors is the set $\left\{x_{(l)}, x_{(l-1)}, ..., x_{(l-r+1)}\right\}$. Now, consider adding one dimension to the state so that $n = l + 1$. If $x_{l+1} > x_{(l-r+1)}$ the value of one element in the random vector $\left\{x_{(l)}, x_{(l-1)}, ..., x_{(l-r+1)}\right\}$ is replaced by a larger value. The elements in the vector $\left(x_{(l+1)}, x_{(l)}, ..., x_{(l-r+2)}\right)$ are then larger than or equal to the corresponding elements in the vector $\left(x_{(l)}, x_{(l-1)}, ..., x_{(l-r+1)}\right)$. The former vector thus first order dominates the latter vector, implying that $E\left(x_{(l+1)}, x_{(l)}, ..., x_{(l-r+2)}\right) > E\left(x_{(l)}, x_{(l-1)}, ..., x_{(l-r+1)}\right)$. The desired result then follows from the fact that the definition of x_i implies that $E(x_i) = var(z_i)$. □

Proof of Proposition 4. The proposition states that the conditional variance of unreported productivity shocks $var\left(z_j \mid \mathbf{s}, \mathbf{r}, s_j = 0\right)$ is increasing in the minimum value of the reported productivity shocks $\min\left\{|z_i| : s_i = 1\right\}$.

Proof. The news selection function $\mathcal{S}_{|z|}$ implies that

$$p\left(|Z_j| > \min\left\{|Z_i| : s_i = 1\right\} \mid s_j = 0\right) = 0. \tag{B.17}$$

The distribution $p\left(Z_j \mid \mathbf{r}, \mathbf{s}, s_j = 0\right)$ is therefore a truncated normal with density function

$$p\left(Z_j \mid \mathbf{r}, \mathbf{s}, s_j = 0\right) = \begin{cases} 0 \text{ if } Z_j < -\min\left\{|Z_i| : s_i = 1\right\} \\ \\ \frac{\phi(Z_j)}{\Phi(\min\{|Z_i|:s_i=1\}) - \Phi(-\min\{|Z_i|:s_i=1\})} \\ \\ 0 \text{ if } Z_j > \min\left\{|Z_i| : s_i = 1\right\} \end{cases}. \tag{B.18}$$

where ϕ and Φ are the pdf and cdf of the unconditional distribution of Z_j.

A zero mean symmetric two-sided truncated normal distribution with truncation points $-a$ and a is a mean preserving spread of any zero mean symmetric two-sided truncated normal distribution with truncation points $-b$ and b such that $a > b$. The proposition then follows from that a mean preserving spread increases the variance of a distribution. □

Proof of Proposition 5. The proposition states that the mean of reported productivity shocks $E\left(z_i \mid s_i = 1\right)$ is lower than the unconditional mean of productivity shocks and decreasing in the number of sectors n.

Proof. Denote the k^{th} order statistic of the vector z as $z_{(k)}$. Then $z_{(k)}$ state-wise dominates $z_{(k-j)}$ for any $j > 0$ so that $E\left(z_{(k)}\right) > E\left(z_{(k-j)}\right)$. To prove the first part of the proposition, note that the elements in $\mathbf{r}$ consists of the first r order statistics of z, so that

$$E\left(z_i \mid s_i = 1\right) < E\left(z_j \mid s_j = 0\right). \tag{B.19}$$

The result then follows from that

$$\begin{aligned} E\left(z_i\right) &= p(s_i = 1)E\left(z_i \mid s_i = 1\right) + p(s_j = 0)E\left(z_j \mid s_j = 0\right) && \text{(B.20)} \\ &= 0 && \text{(B.21)} \end{aligned}$$

To prove the second part of the proposition, set the dimension of the state $n = l$. The reported sector shocks in the set $\left\{z_{(1)}, z_{(2)}, ..., z_{(r)}\right\}$ then consists of the first r order statistics of an l dimensional vector. Now, consider adding one dimension to the state so that $n = l+1$.

If $z_{l+1} < z_{(r)}$ the value of one element in the random vector $\left(z_{(1)}, z_{(2)}, ..., z_{(r)}\right)$ is replaced by a smaller value. If $z_{l+1} > z_{(r)}$ the vector is unchanged. The values of the first r order statistics drawn from l sectors thus first order stochastically dominates the first r order statistics drawn from $l+1$ sectors. The conditional mean $E\left(z_i \mid s_i = 1\right)$ is thus decreasing in the number of sectors n. $\square$

Proof of Proposition 6. The proposition states that the expected value of non-reported productivity shocks $E\left(z_j \mid \mathbf{s}, \mathbf{r}, s_j = 0\right)$ is increasing in the maximum value of the reported productivity shocks $\max\left\{z_i : s_i = 1\right\}$.

Proof. The news selection function $\mathcal{S}_-$ implies that

$$p\left(Z_j < \max\left\{Z_i : s_i = 1\right\} \mid s_j = 0\right) = 0. \tag{B.22}$$

The conditional distribution of a non-reported sector shocks is thus normal but left-truncated at $\max\left\{Z_i : s_i = 1\right\}$ with expected value given by

$$E\left(Z_j \mid s_j = 0, \max\left\{Z_i : s_i = 1\right\}\right) = \frac{\phi\left(\max\left\{Z_i : s_i = 1\right\}\right)}{1 - \Phi\left(\max\left\{Z_i : s_i = 1\right\}\right)} \tag{B.23}$$

which is increasing in $\max\left\{Z_i : s_i = 1\right\}$. $\square$