SECTORAL MEDIA FOCUS AND AGGREGATE FLUCTUATIONS

a whole causes firms across all sectors to over- or underinvest in productive capacity. 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.

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 in-

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 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.

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 analyzes news based data sources and how they affect agents' expectations. Larsen, Thorsrud and Zhulanova (2019) document that news topics predict household inflation expectations, even after controlling for standard macro economic 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. Lamla, Lein and Sturm (2007) and Buchen (2014) both directly attempt to test Wolfers and Veldkamp's (2007) theory of sectoral co-movement 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 $i \in \{1, 2, \ldots, n\}$

where W is the wage, $L \quad \sum_{i=1}^{n} L_i$ and $\quad \sum_{i=1}^{n} \quad _i$. The consumption bundle C is an equal-shares Cobb-Douglas aggregate of goods

$$C = \prod_i C_i^{\frac{1}{n}} : \tag{2.6}$$

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.

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 before production takes place and before wages and prices are observed. In a second stage, firms choose how much intermediate inputs to use. The first stage of a firm's optimization problem is to solve

$$\max_{L_i} E \left[P_i Q_i \quad W L_i \quad \sum_j P_j X_{ij} \; j \quad _i \right] \tag{2.7}$$

where $\quad _i$ is the information set of a firm in sector i defined as

$$_i = f Z_i ; s ; r g : \tag{2.8}$$

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

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

$$L_i = (1 \quad) \frac{E [P_i Q_i \; j \quad _i]}{E [W \; j \quad _i]} : \tag{2.9}$$

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 s3.252 0.ouseho509(the)-352(re4d [(i)eem4.18855 0 Td [( )]TJ/F35 7.970

(12.9)
11.9552 Tf 1.9381 8.911 Td [(=)]TJ/437 11.9552 Tf 12.425 0 Td [(W)]TJ/F15 11.9552 Tf9524.062 0 Td [((11.9))]TJ -4 8.62321 3.258 Td [(and)-326p(b)-28io a=1

2.4. Determinants of sectoral labor demand. State-dependent reporting affects output in the model via the expectations in the labor input decision described by (2.9). In equilibrium, demand for labor in sector i depends on the expected gross sales of sector i goods and the expected cost of labor, W. As in Angeletos and La'o (2010, 2013), labor inputs are strategic complements among firms. If other firms hire more labor, the demand for intermediate good i goes up, increasing its price. Firms in sector i, anticipating higher prices for their output, hire more labor themselves. However, this effect is partly offset by the fact that an increase in labor demand by other sectors increases the market wage. The strength of the second effect depends on the labor supply elasticity .

In the appendix, we show that the labor demand function in (2.9) can be expressed as a function of expected aggregate output C and wages W,

$$L_i = (1 \quad) \ _i \frac{E[C \mid \ _i]}{E[W \mid \ _i]}; \tag{2.13}$$

where $_i$ is the Domar weight of sector i. The Domar weight of a sector captures the importance of the sector as a supplier of intermediate goods to other sectors and is a function of the parameters of the production function (2.1) and the consumption good aggregator (2.6).[2] Hence, equation (2.13) implies a unit elasticity of labor demand with respect to expected consumption for all sectors, and an elasticity with respect to expected wages of minus one.

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 $Z \in Z_1 \; Z_2 \; \cdots \; Z_n \; Z$. News media monitor the state of the economy and make state dependent decisions about which elements of Z are most newsworthy. We formalize this monitoring and reporting behavior using news selection functions

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

A news selection function S thus associates a pair $(s; r)$ with each state of the world $Z \in \mathcal{Z}$. The vector s indicates which sectors are reported on. An element of 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 r contains the realized values of productivity in the reported sectors. For instance, $s(Z) = (1; 0 \ldots; 0)$ means that in state $Z = (Z_1; \ldots; Z_n)$

indicator vector s. To the extent that these reporting decisions are state-dependent, they will also reveal information about the unreported sectors, i.e. sectors $1; 3; 5; 6; \ldots n$.

3.2. State-dependent reporting and beliefs. The rms in our model are Bayesian and understand the state-dependence of reporting decisions encoded in S. A rm that observes r and

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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 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.

In this section, we 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, but they help simplify the exposition. 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 2. (Extreme outcomes more newsworthy) The news selection function $S_{|z|}$ 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 $S_{|z|}$ thus orders outcomes $z_i : z$

Proposition 1. *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 the Appendix.

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 shocks. 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.

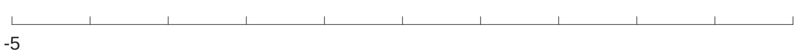

Figure 2. The distribution of Z_i conditional on $s_i = 1$ for $n = 30$ and $n = 80$ implied

Proof. In the Appendix.

Proposition 2 implies that rms update their beliefs about the unreported sector shocks $f z_j : s_j = 0g$ when they observe the values of the reported sector shocks in 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 $\min fj\, z_i j : s_i = 1g$ and $\min fj\, z_i j : s_i = 1g$. 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 $\min fj\, z_i j : s_i = 1g = 1{:}5$.

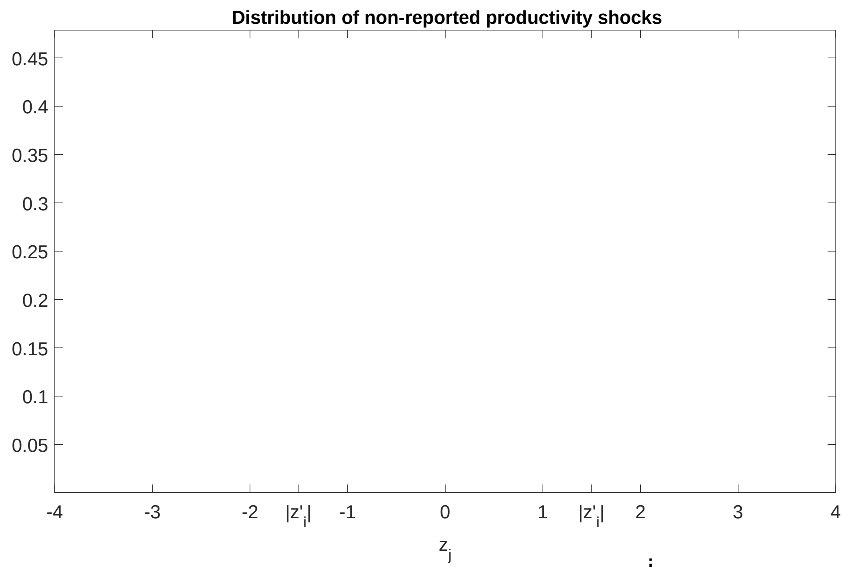

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Figure 3. The distribution of Z_j conditional on $s_j = 0$ and min

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 S that orders the newsworthiness of sectoral outcomes according to their relative position in R.

Definition 3. (Negative outcomes more newsworthy) More negative outcomes are considered more newsworthy according to the news selection function S for any pair $i,j \in \{1,2,\dots,n\}$ such that $s_i = 1$ and $s_j = 0$ we have that $z_i \leq z_j$.

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 S affects the conditional distributions of unreported sector shocks.

Proposition 4. *The expected value of non-reported productivity shocks* $E(z_j \mid r; s; s_j = 0)$ *is increasing in the maximum value of the reported productivity shocks* $\max\{z_i : s_i = 1\}$.

Proof. In the Appendix.

Since all non-reported sector shocks must be (weakly) more positive than the reported

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 4. (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 4 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 4 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

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 rst three of these are the largest US newspapers by circulation, and all six have consistent coverage by Factiva. Importantly, these six newspapers are the ones for which 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.[5] Our sample contains 1,178,716 such tags that correspond to 5,175 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

Table 1. Sector Labels

Sector	Sector Name	Sector	Sector Name

Figure 6.

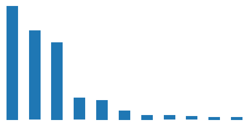

Figure 7. Most frequently mentioned company names for the 10 sectors that received the most coverage over the sample.

increases the fraction of news coverage received by the Motor vehicle industry, relative to the baseline.

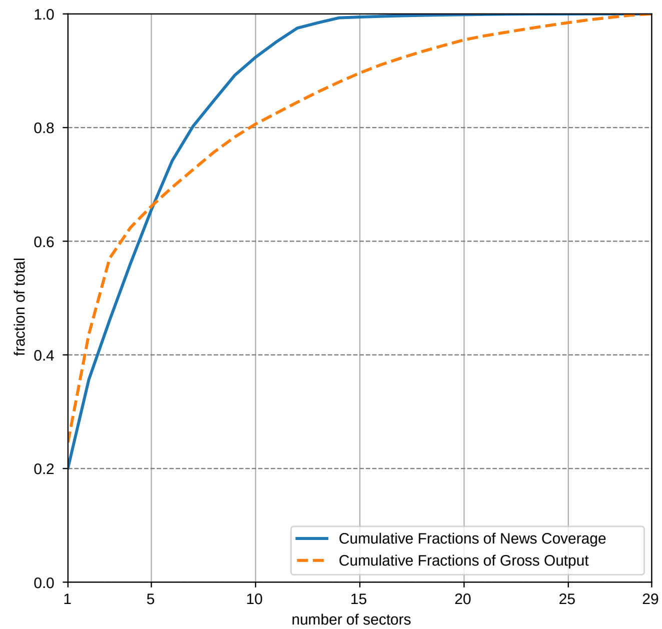

Figure 8. Cumulative sum of the sectoral shares of news coverage and gross output.

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 (expressed as fractions of total coverage) for the 10 sectors that receive the most news coverage on average over the sample period. The gure 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 nancial 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 accounted for about three quarters of all news coverage in 2009. Other sectors that normally 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 nancial 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 Uber, which while classi ed as a transportation company, may also be considered part of the tech industry.

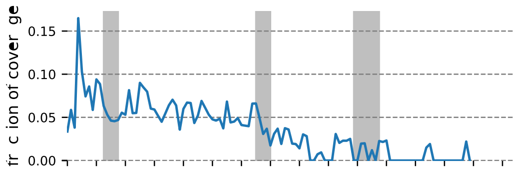

Figure 9. Sectoral news coverage over time for the 10 sectors that received the most coverage over the sample. Vertical axis measures fraction of news coverage the sector received.

The mirror image of the increase in news coverage of the tech sector in the last decade is outcomes, either good or bad, in a sector are considered newsworthy, then this would result in a positive coe cient on these variables. The sample is annual and covers the period from 1988 to 2016, 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.

The results show that news focus is systematically related to economic variables at the sector level. As an example, consider the Finance, insurance and real estatesector. For this sector, news focus is negatively correlated with changes in gross output and positively with the corresponding absolute value. Changes in output are positively correlated with news coverage in the Instruments sector, which includes computer hardware companies. We also nd evidence for a relationship between sectoral news focus and productivity. For the Transportation and warehousing

Table 2. Sectoral News Coverage and Observable Sector Properties

Sector	Statistic	Const.	l	y	z	j lj	j yj	j zj
FOOD & KINDRED PRODUCTS	coe	0.04***	0.21	1.06	-0.08	-1.34**	-0.71	0.76
	t-stat	3.82	0.65	1.35	-0.2	-2.64	-0.72	1.4
PRINTING & PUBLISHING	coe	0.1***	-0.25	-0.34	0.27	-0.92	-0.02	0.33
	t-stat	3.96	-0.57	-0.5	0.92	-1.31	-0.04	0.75
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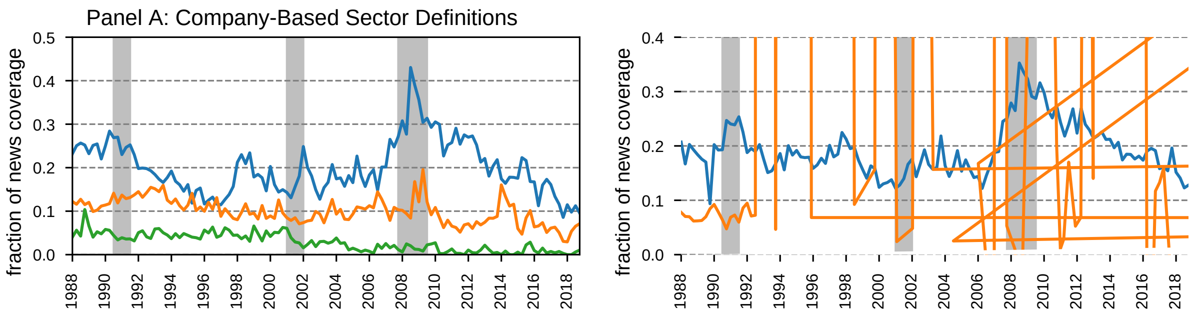
terms of the time-series behavior, we also observe clear similarities. While the food and tobacco sector receives relatively stable coverage over the sample period, both the auto sector and the nancial industry are mentioned signi cantly more in the context of the 2008-2009 crisis.[9]



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 $S_{j!\,j}$

Output fluctuations are visibly larger in the baseline model relative to the model without news media. The population moments of the calibrated model also show that news media reporting contributes substantially to output volatility. The standard deviation of aggregate output is 2.3% when firms have access to reports by news media, but only 0.5% when they do not. 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 correlation of sectoral output in the baseline model is 0.82 compared to 0.10 in the model without news media.

The period of the Great Recession provides a particularly clear example of how news reporting changes the aggregate consequences of sectoral shocks. The baseline model predicts a severe recession in 2009, with aggregate output 5 percent below steady state. However, in the model without news reporting, output barely falls below its steady state level in the same period. Aggregate output in both models is conditional on the same sequence of productivity shocks, so this difference must be driven by differences in firms' beliefs, which themselves are entirely determined by the cross-section of sectoral productivity. This cross-section is illustrated 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 $|\omega z|$.

The average sectoral productivity in 2009 is only slightly negative, but 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 *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 that firms across 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 labor demand, and therefore lower demand for their output, in other sectors. Hence, media reporting drives an aggregate contraction both directly because it affects all firms' information and, indirectly, because what is reported is common knowledge among firms.

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 productivity shocks weighted by ! . It is clear that not only is the sectoral productivity shock hitting the Motor vehicle 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 where news media report on a single sector, and where newsworthiness is based only on productivity outcomes. 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, but it is somewhat unsatisfying to have a model that does so without any special role for the financial sector. However, given that the mechanism in the model relies on news media reporting unrepresentatively bad news in 2009, a richer model that implied additional reporting on the financial sector in that period would likely generate a recession at least as deep as in the baseline model.

6.4. Output fluctuations in baseline and full information model. One reason that the baseline model generates a large recession in 2009 while the model without news media does not is that firms in every sector know about the bad news coming out of the motor vehicle sector. In the model without news media, only firms in the motor vehicle sector are aware of this. If firms could observe productivity in every sector, they would also all know about the motor vehicle sector. However, since the cross-section of productivity in 2009 was not particularly bad overall, the full information model does not generate a strong recession in that period. This is illustrated in Figure 13. The full information model generates only a mild recession in 2009, with output about 1.5% below average. The reason the partial information model generates a strong recession and the full information does not is that the sector shock reported by news media in 2009 is unrepresentative of the shocks the economy experienced as a whole.[12]

In Figure 13 we also plot actual (demeaned) output growth for the same period. Both models are simple and highly stylized, and we should not expect either of them to fit actual data closely. The correlation between actual output growth and output in the full information model is 0.24 and improves only marginally in the baseline partial information model.

6.5. Time varying media focus and common 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

[12]We set the labor elasticity parameter equal to 0.65 in the full information model. The baseline model and the full information model then has the same unconditional standard deviation of aggregate output.

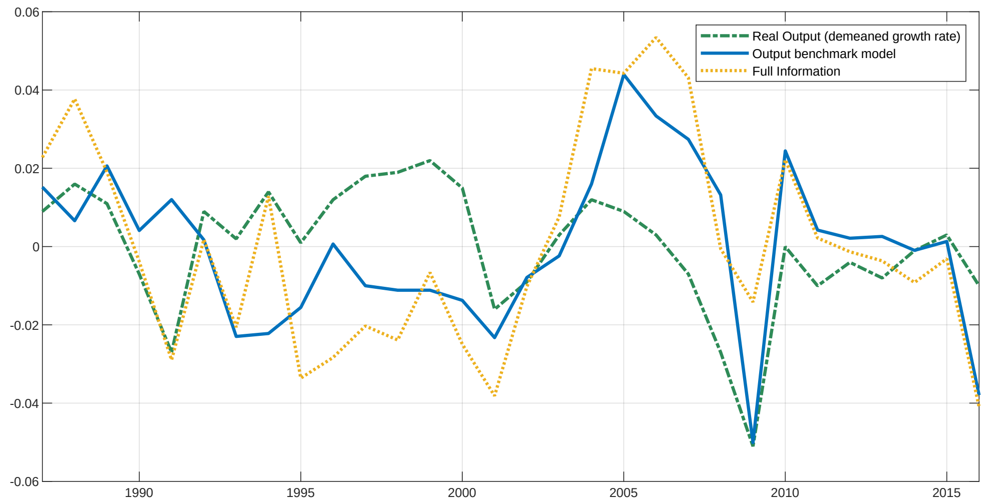


Figure 13. Output uctuations around steady state in baseline model (blue solid line), full information model (yellow dotted line) and historical demeaned GDP growth (green dash-dot line).

implied by a log-linearized equation from his model, he estimates that for realistic values of elasticities of substitution, sectoral productivity shocks explain approximately 80% of the variance of aggregate output. The remaining variance is attributed to common non-productivity shocks.

In our model, sectoral productivity is the only source of exogenous variation, but the relationship between sectoral productivities and output is strongly non-linear: When a sector is in the news, productivity in that sector has a bigger impact on aggregate output than it does when that sector is not in the news. Since the hon othe sectoral seocks-367(sdep-305(iXad-265(noo2f6 explain sectorall aggregate output.

imep-30osningy noo-835dataoo-835generautedy our moder wrsneact to cncludet aggregate output (pro)-27(ductivit)27(e))-735(sho)-27(c)27(ks.-876(T)82(oy)4764equnc)27u(i)1f(y)4764h(o)27(productivity shocksy lter,s wimp(s)-364(,000y)3374dep-305rirose) frms our baseline modes.questio

the selection bias towards more extreme shocks increases the standard deviation of firms' labor input decisions. Second, as shown in Section 2, the state dependence of reporting decisions allows firms to make inference not only about those shocks that are reported by news media, but also about those shocks 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 news media randomly choose which sector to report on. The population standard deviation of output in this version of the model is 1.3%, or about one half of that in the baseline model. The news selection function in the baseline version also weighs larger sectors more when evaluating newsworthiness. However, the effect on output of this systematic bias towards reporting on larger sectors is relatively small. The standard deviation of output in the model when sectors simply report the productivity shock with the largest (unweighted) absolute deviation from its mean is only marginally lower than in the baseline 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 is very small, accounting for less than 0.1 percentage point of the standard deviation of output. This is due to both the weak sectoral correlations in the model and the absence of strong

6.7.1. News coverage and sectoral correlations. If the mechanism in the model is relevant in reality, we would expect that output in sectors that are over-represented in the news are more strongly correlated with aggregate output relative to less-reported sectors of the same size. We therefore rst run a regression of average sectoral news coverage on Domar weights

$$\frac{1}{T}\sum_{t=1}^{T} f_{i;t} = {}_{f} + {}_{f}\;{}_{i} + "^{f}_{i} \tag{6.2}$$

where $f_{i;t}$ denotes the fraction of news coverage received by sector i in period t. A positive residual $"^{f}_{i}$ implies that the sector is over-represented in the news relative to its economic size. (The same information is contained in Figure 6.) We then run the regression

$${}_{i;y} = \; + \; {}_{i} + "_{i} \tag{6.3}$$

where ${}_{i;y}$ denotes the correlation between gross output growth in sector i and aggregate output growth. A positive residual $"_{i}$ indicates that sector i is more strongly correlated with aggregate output than what would be implied by its economic size alone.

The correlation of the residuals from the two regressions is 0.21, suggesting that sectors that are over-represented in the news are indeed also more strongly correlated with aggregate output, as predicted by our model.

6.7.2. News coverage-weighted productivity and aggregate output. Our model predicts that productivity in a given sector has a bigger impact on aggregate output when the sector in question is in the news. We therefore compute two news-weighted aggregate productivity series as follows

$$z^{f}_{t} \quad \sum_{i=1}^{n} f_{i;t}\, z_{i;t}\,; \quad z^{f;}_{t} \quad \sum_{i=1}^{n} f_{i;t} \quad \frac{{}_{i}}{\sum_{i=1}^{n} {}_{i}} \quad z_{i;t}\,: \tag{6.4}$$

The measure z^{f}_{t} simply weighs sectoral productivity in period t by the fraction of news coverage a sector received in that period. The correlation between z^{f}_{t} and aggregate output growth is 0.46. Given the strong correlation between news coverage and the size of a sector, this positive correlation is unsurprising. The second measure, $z^{f;}_{t}$ therefore weighs sectoral productivity by the fraction of news coverage in period t that is not simply a re ection of the
11.9552 Tf 179.,

7. Conclusions

In this paper we have demonstrated that time varying sectoral media focus can generate aggregate uctuations that are orthogonal to productivity, even in a model where the only source of exogenous variation are sectoral TFP shocks. That aggregate output uctuations are partially orthogonal to productivity has been well-documented at least since the early 1990s, e.g. Hall (1993), Blanchard (1993) and Cochrane (1994). However, no consensus has emerged regarding the causes of the non-productivity related uctuations. Inspired by Lucas' (1977) statement that \business cycles are all alike", Angeletos, Collard and Dellas (2019) use exible VAR methods to document the properties of what they label the Main Business Cycle(MBC) shock. This shock appears to be responsible for most of the business cycle variation in several key macroeconomic variables.

While our model is too stylized to account for all of the dynamics associated with MBC shocks, many of our ndings are consistent with them. Like that shock, time varying sectoral media focus generates uctuations that are orthogonal to aggregate productivity and positively correlated with output, consumption and employment. Angeletos et al (2019) further argue that the facts they document are consistent with uctuations in rms' beliefs about the demand for their products. We have provided a theory that can explain why the demand expectations of rms across di erent sectors move together. Discussing nancial markets, Shiller (2001) writes that \Signi cant 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 thus argue here that the same logic applies to macroeconomic uctuations.

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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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

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

Under full information, profits are zero of course. When firms face information frictions, however, informational errors may lead to be non-zero.

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

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

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 PC fixed, is then given by

$$P_i C_i = \frac{1}{n} PC \tag{A.8}$$

We normalize the price of the aggregate good to 1 and use (A.2) to replace C to get

$$P_i = \frac{1}{n}\frac{1}{C_i}\prod_j C_j^{\frac{1}{n}}. \tag{A.9}$$

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

$$E[W \mid {}_i] = (1 -)\frac{E[P_i Q_i \mid {}_i]}{L_i}. \tag{A.10}$$

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

$$P_j = \frac{{}_{ij}}{X_{ij}} P_i Q_i \tag{A.11}$$

holds in equilibrium.

A.3. Solving for L_i as function of L and Z. 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 firms expectations about the exogenous sector-specific productivity shocks Z_i and the labor input choices of firms in other sectors.

Start by substituting in the optimal demand for intermediate inputs X_{ij} into the production function (A.3) using (A.11) to get

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

Use that $\sum_{j=1}^{n} {}_{ij} = \quad$ to compute $\prod_j (P_i Q_i)^{_{ij}} = (P_i Q_i)$ and move this term outside the product in the parenthesis, so that

$$Q_i = Z_i (P_i Q_i) \left(\prod_j \frac{_{ij}}{P_j}^{\;_{ij}} \right) L_i^{1} \quad : \qquad \text{(A.13)}$$

Divide both sides by Q_i

$$Q_i^{1} = Z_i P_i \left(\prod_j \frac{_{ij}}{P_j}^{\;_{ij}} \right) L_i^{1} \qquad \text{(A.14)}$$

and multiply by P_i^{1}

$$(P_i Q_i)^{1} = Z_i P_i \left(\prod_j \frac{_{ij}}{P_j}^{\;_{ij}} \right) L_i^{1} \quad : \qquad \text{(A.15)}$$

De ne gross sales V_i as

$$V_i \quad P_i Q_i ; \qquad \text{(A.16)}$$

take logs of both sides of (A.15)

$$(1 \quad) v_i = z_i + p_i + (1 \quad) l_i + \sum_j {}_{ij} (\log ({}_{ij}) \quad p_j) : \qquad \text{(A.17)}$$

and rearrange the resulting expression to get

$$(1 \quad) (v_i \quad l_i) \quad z_i \quad \sum_j {}_{ij} \log ({}_{ij}) = p_i \quad \sum_j {}_{ij}\, p_j : \qquad \text{(A.18)}$$

De ne the input-output matrix IO so that the typical i^{th} row and j^{th} element is ${}_{ij}$. We

Since this has to hold for each i we get

$$V = (I \quad IO^0)^{\ 1} \frac{C}{n} \quad 1 \tag{A.24}$$

De ne the vector as

$$= (I \quad IO^0)^{\ 1} \frac{1}{n} \quad 1 \tag{A.25}$$

and = log( ) with typical element $_i$. We then have

$$p = (I \quad IO)^{\ 1}[(1 \quad)(\quad + c \quad 1 \quad l) \quad z \quad] \tag{A.26}$$

or equivalently

$$p = (I \quad IO)^{\ 1}[(1 \quad)(\quad l) \quad z \quad] + (I \quad IO)^{\ 1}[(1 \quad) c \quad 1] \tag{A.27}$$

so that

$$P_i = \exp(\ _i [(1 \quad)(\quad l) \quad z \quad] + \ _i (1 \quad) c \quad 1) \tag{A.28}$$

where $_i$ is the i^{th} row of the Leontief inverse $(I \quad IO)^{\ 1}$:

A.4. Final expressions. To solve the model we need to compute the optimal labor demand

L[(8.]TJ/F7 8.4755 Tf 8.455 -1.793 Td [(i)]TJ/F8 11.9552 Tf 13.344 1.793 Td [(=

$$L_i = (1 \quad) \frac{E[P_i Q_i \, j \quad _i]}{E[W \, j \quad _i]} \tag{A.29}$$

as a function of expected labor inputs and productivity in every sector $L_j : j \ 2 \ f\, 1; 2; :::; n g; z$: To that end, rst use that

$$P_i Q_i = \ _i C$$

$$W = \ \sum \ L_i^{\ \frac{1}{}} :$$

We then need to nd an expression of C as a function of L_i and z: Combining and rearranging the following three equations

$$C = \prod_i$$

Substitute into (A.30) to get

$$C = \prod_i \left(\frac{1}{n} \frac{C^{1 \ (1 \ \ ) \ _i \ \ 1}}{\exp(\ _i[(1 \ \ )(\ \ l) \ \ z \ \ ])} \right)^{\frac{1}{n}} \tag{A.34}$$

$$= \prod_i \left(\frac{1}{n^{\frac{1}{n}}} \frac{C^{(1 \ (1 \ \ ) \ _i \ \ 1)\frac{1}{n}}}{\exp(\ _i[(1 \ \ )(\ \ l) \ \ z \ \ ])^{\frac{1}{n}}} \right) \tag{A.35}$$

$$= C^{(1 \ \frac{1}{n}(1 \ \ ) \ _i \ _j \ _{ij})} \prod_i \left(\frac{1}{n^{\frac{1}{n}}} \frac{1}{\exp(\ _i[(1 \ \ )(\ \ l) \ \ z \ \ ])^{\frac{1}{n}}} \right) \tag{A.36}$$

so that

$$C = \prod_i \left(\frac{1}{n^{\frac{1}{n}} \exp(\ _i[(1 \ \ )(\ \ l) \ \ z \ \ ])^{\frac{1}{n}}} \right)^{\frac{n}{(1 \ \ ) \ _i \ _j \ _{ij}}} : \tag{A.37}$$

We then have the desired expression

$$L_i = (1 \ \ ) \ _i \frac{E_i\left[\prod_i \left(\frac{1}{n^{\frac{1}{n}} \exp(\ _i[(1 \ \ )(\ \ l) \ \ z \ \ ])^{\frac{1}{n}}} \right)^{\frac{n}{(1 \ \ ) \ _i \ _j \ _{ij}}} \ _j \ \ _i \right]}{E_i \left[\sum (\ \ L_i)^{\frac{1}{}} \ _j \ \ _i \right]} : \tag{A.38}$$

A.5. Numerical solution algorithm. We solve the model by evaluating the conditional expectation in (A.38) using a simulation based MCMC method. The simulation is initialized by solving the model under full information for T draws from the process for sectoral productivities.

The algorithm is described by the following steps.

(1) Take S draws from the distribution of the vector of sectoral productivity shocks z:
(2) For the rst T draws of z nd the full information equilibrium vector L:
(3) For draw $T + s$
  (a) Apply the news selection function S to nd the vectors $r(z_{T+s}); s(z_{T+s})$:
  (b) Compute $L_{i;T+s}$ for every i by evaluating the conditions expectation (A.38) where $\ _i = f \ z_{i;T+s}; r(z_{T+s}); s(z_{T+s}) g$:
(4) Repeat steps 2-4 until convergence.

The conditional expectation in Step 4 is computed by rst identifying the set of indices in the chain up to draw $T + s$ such that $s(z_{T+s}) = s(z_{T+t}) : t < s;$ i.e the set of draws for which the news selection function chose the same sector to report on as in draw $T + s$. Within this set, nd the K draws that minimizes the distance $(z_{i;T+s} \ \ z_{i;T+t})^2 + (z_{j;T+s} \ \ z_{j;T+t})^2$: Over these K draws compute the average of expression (A.38) over the vectors $L_{T+s}; Z_{T+s}$.

As the simulated time series grows, the distribution lls out and becomes dense so that the distance in Step 2 shrinks. The algorithm thus use a discretized state space, but the bin-size shrinks over time. For the simulations used in the paper, we set $T = 1000$, $S = 200000$ and $K = 10$. Increasing S or K increase computational time, but does not increase precision in a meaningful way. For the graphs in the paper, we added the BEA productivity shocks to the end of the random draws of z.

Appendix B. Proofs of Propositions

B.1. Proof of Proposition 1. 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

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

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

$$\vdots$$

$$x_{(k)} \equiv \min\left(\{x_1, x_2, ..., x_n\} \setminus \{x_{(1)}, x_{(2)}, ..., x_{(k-1)}\}\right) \tag{B.3}$$

Note that $s_i = 1$ implies that

$$x_i \in \left\{x_{(n)}, x_{(n-1)}, ..., x_{(n-r+1)}\right\}. \tag{B.4}$$

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

$$E\left[x_{(k)}\right] \geq E\left[x_{(k-j)}\right] \tag{B.5}$$

so that

$$var(z_i \mid s_i = 1) \geq var(z_j \mid s_j = 0). \tag{B.6}$$

Combining (B.6) with the fact that

$$var(z_i) = p(s_i = 1)var(z_i \mid s_i = 1) + p(s_i = 1)var(z_j \mid s_j = 0) \tag{B.7}$$

gives the desired result

$$var(z_i) = var(z_i \mid s_i = 1) - p(s_i = 1)\left[var(z_i \mid s_i = 1) - var(z_j \mid s_j = 0)\right] \tag{B.8}$$

$$< var(z_i \mid s_i = 1). \tag{B.9}$$

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

B.2. Proof of Proposition 2. The proposition states that the conditional variance of unreported productivity shocks $var(z_j \; j \; s; r; s_j = 0)$ is increasing in the minimum value of the reported productivity shocks $\min fj \, z_i j : s_i = 1g$:

Proof. The news selection function S_{jzj} implies that

$$p(jZ_j j > \min fj \, Z_i j : s_i = 1g \; j \; s_j = 0) = 0:$$

The distribution $p(Z_j \; j \; r; s; s_j = 0)$ is therefore a truncated normal with density function

$$p(Z_j \; j \; r; s; s_j = 0) =$$