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Media Reporting and Business Cycles: Empirical Evidence based on News Data*

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Abstract

Recent literature suggests that news shocks could be an important driver of economic cycles. In this article, we use a direct measure of news sentiment derived from media reports. This allows us to examine whether innovations in the reporting tone correlate with changes in the assessment and expectations of the business situation as reported by firms in the German manufacturing sector. We find that innovations in news reporting affect business expectations, even when conditioning on the current business situation and industrial production. The dynamics of the empirical model confirm theoretical predictions that news innovations affect real variables such as production via changes in expectations. Looking at individual sectors within manufacturing, we find that macroeconomic news is at least as important for business expectations as sector-specific news. This is consistent with the existence of information complementarities across sectors.

JEL classification: E32, D82.

Keywords: Media reporting, news-driven business cycles, sectoral information complementarities.

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1 Introduction

The role of news as a driving force for business cycles has already been noted by Pigou (1927) and received renewed interest in recent years (see Beaudry and Portier, 2014, for a survey). In these models, favorable news about future demand causes increased activity because firms invest more to make their goods available once higher demand materializes, and because agents increase consumption as they feel richer. If many agents rely on the same news source, such as media reports, their behavior becomes coordinated, which means that news can generate business cycle fluctuations.

Empirical evidence suggests that news about future productivity is an important driver of macroeconomic fluctuations. There are two approaches to identify news shocks. The first is an indirect approach, which treats news as unobserved. Beaudry and Portier (2006), for example, exploit the fact that stock prices are a fast-moving variables, which readily incorporate information about future fundamentals immediately. They examine the joint behavior of total factor productivity (TFP) and stock prices. Looking at the correlation between the innovations that drive long-run movements in TFP and the innovations that are contemporaneously orthogonal to TFP, they find that these two are highly collinear. This suggests that news about future TFP is incorporated into expectations prior to the realization of the change in TFP.[1]

The second approach is a direct approach, which treats news as ex-post observable. Here, researchers use documents of past announcements of events, which are likely to have an impact on future outcomes (see, for example, Brückner and Pappa, 2015).

Our paper is related to the second approach. We use media reports about the business cycle as a measure of news instead of stock prices or other financial variables. In our data, media reports in the German-speaking media that are related to the current stance, or the outlook for, the business cycle are collected and evaluated by a media research institute. This allows us to measure whether media tend to report positively or negatively about the business cycle.[2]

[1]Extensions to higher-dimesional VARs include Beaudry and Lucke (2010) or Fan et al. (2016), for example. Additional approaches to identify news shocks includes Barsky and Sims (2011), Kurmann and Sims (2017), or Görtz and Tsoukalas (2017).

[2]The media research institute Medientenor, which provides us with the data, employs human coders, who read every article in the news and classify the information in these reports according to their topic (we look at business cycle, macroeconomic growth, sectoral information). In addition, they identify the tone of each statement in each article as 'good', 'bad' or 'neutral'. We aggregate this daily information for each month, which gives us a time series of media tonality. This approach is complementary to textual analysis approaches that have been used, for example, in accounting and finance, where written media reports are classified based on dictionaries and machine-learning techniques, see Loughran and McDonald (2016) and references therein. Shapiro et al. (2018) show that textual-analysis based news indicators correlate with the business cycle and have predictive power for future economic activity, which is consistent with the findings in this paper based on our Media Tenor data.

In a first step, we examine how media reporting influences firms' expectations about the future. Firms' expectations of the future business situation and their assessment of the current business situation is measured by two survey indicators from the German Ifo Institute. We document two regularities in the data. First, we show that the news indicator Granger-causes the assessment of firms about the current and future state of their business. Based on VAR estimates, we find that the news indicator has an economically important effect on expectations, conditional on the current business situation indicator. Since the effect of news on expectations conditions on the assessment of the current situation, there is information in media reports that is related to expectations beyond just reflecting the current business situation. Meanwhile, expectations about the future business situation are correlated with the assessment of the business situation six months later, confirming that firms on average make correct predictions. Furthermore, our findings show that the effect of news on expectations is, on impact, larger than the effect on current assessment. These findings are robust to including contemporaneous measures of industrial production data, suggesting that the information captured in the news variable is not just driven by media reflections on current data releases, which arguably also influence expectations. Even though we cannot directly measure a structural news shock, changes in the intensity of media reporting, conditional of the current stance of the business cycle, are arguably correlated with news shocks. The results presented here are thus consistent with the effects of news shocks, which influence firms' expectations and thereby their output in the future.

In a second step, we examine differences across sectors in the response to news related to the aggregate economy and sector-specific news. We find that in most sectors, news about the aggregate economy have on average a larger impact on sectoral business expectations than the sector-specific news. This finding lends support to the information-complementarities hypothesis put forward in Veldkamp and Wolfers (2007). If obtaining information on the driving forces behind output is costly, it is optimal for media to report more on the aggregate economy, which is relevant for all sectors, than producing sector-specific news, which is only relevant for a share of firms in the economy. If firms do not find it optimal to invest in obtaining sector-specific information, firms will base their decisions largely on news about the aggregate economy, which can be directly obtained from the media. This mechanism in turn amplifies the effects of common shocks relative to sectoral shocks.

The contribution of our paper is threefold. First, we use the tonality of media reports as a measure of news, which is an alternative to identifying news shocks using VARs including stock prices or innovations orthogonal to current total factor productivity. Second, we use indicators of business sentiment to measure firms business expectations and their assessment of the current situation, which complements the evidence based on consumer confidence indicators, as for example in Barsky et al. (2014). Third, we look at sectoral business expectations and disentangle sector-specific news reports from news reports about the aggregate economy. This relates to theoretical research suggesting that sectoral comovement originates from reliance of firms on information about the aggregate economy, rather than sector-specific information, which would be more costly to obtain. To our knowledge, this paper is the first that empirically analyses the response of firms expectations on sector-specific news and aggregate news.

The remainder of this paper is organized as follows. Section 2 presents our theoretical framework. Section 3 discusses the data and section 4 the empirical model. Section 5 reports our results and section 6 concludes.

2 Theoretical Framework

In this section, we outline a simple framework that explains how firms form their expectations and what information sets they can observe before turning to the description of the data and the empirical model in sections 3 and 4, respectively.

Business decisions are based on information they have about their own current situation and their own expectations for the future. We assume that the information gathered by a firm is reflected in media reports. Let Ω^i represent the information set for firm i. The information set contains advanced information that relates to future developments of the economy Ω_{fut} and it also contains information that reflects the current stance of the business cycle Ω_{cur}:

$$\Omega^i = \Omega_{fut} \cup \Omega_{cur}.$$

Thus, a firm i forms its future output decision based on its information set available in period t and responds to information about future developments:

$$\begin{aligned} E_t(y^i_{t+1}) &= E_t(y^i_{t+1}|\Omega^i) && (1)\\ \Leftrightarrow E_t(y^i_{t+1}) &= \alpha E_t(y^i_{t+1}|\Omega^i_{fut}) + \beta E_t(y^i_{t+1}|\Omega^i_{cur}). && (2) \end{aligned}$$

Our first testable hypothesis is therefore directly related to the literature on news and business cycles reviewed in the introduction. It suggests testing the relationship between media reporting and firms' business expectations to determine whether news reported in the media correlates with business expectations that are not explained by the current business situation or the current stance of the business cycle ($\alpha \neq 0$ in equation (2)):

H1: Media reporting affects firms' expectations of their future business situation, conditional on firms' assessment of the current business situation.

A second influence of media reporting on economic outcomes is related to the information complementarities model (Veldkamp and Wolfers, 2007) and compares the response of sectoral output expectations to news related to the aggregate economy to news related to the own sector. In principle, if a firm receives perfect information about the future outlook of its own sector, macroeconomic news should be irrelevant (since all effects of the aggregate economy on the own sector should also be incorporated in the perfect information about the own sector). As outlined in the introduction, the information complementarities framework assumes that information is not freely available and that macroeconomic news is more accurate and cheaper than sector-specific news. This suggests that sectoral expectations may respond more strongly to news about the aggregate economy.

To provide a simple framework for this model, we decompose the information set for firm i, Ω^i, into two parts: Information for the economy as a whole (macroeconomic information) (mac) and sector-specific information about the industry to which the firm belongs (sec),

$$\Omega^i = \Omega^i_{mac} \cup \Omega^i_{sec}. \tag{3}$$

The information firm i has on the aggregate economy and on its own sector is a subset of the entire information available for the aggregate, Ω_{mac}, and the sector, Ω_{sec}, respectively:

$$\Omega^i_{mac} \subset \Omega_{mac}, \tag{4}$$

$$\Omega^i_{sec} \subset \Omega_{sec}. \tag{5}$$

The sector-specific information set Ω_{sec} consists of a part Ω_o that can be observed by all firms in the sector, and an unobservable part, Ω_u,

$$\Omega_{sec} = \Omega_o \cup \Omega_u. \tag{6}$$

Since aggregate developments are the sum of all sectoral developments, information about the aggregate economy contains sectoral information, therefore $\Omega_{mac} \cap \Omega_{sec}$ and macroeconomic information reveals something about the unobservable part of the sectoral information set, $\Omega_{mac} \cap \Omega_u$. If firms in a sector use the available information on macroeconomic developments to 'guestimate' the sector-specific unobservable part, then this implies

$$\Omega_{sec} = \Omega_o \cup \Omega_{mac}. \tag{7}$$

Thus, a firm i forms its future output decision based on its own information set about sector-specific and aggregate economic developments:

$$\begin{aligned} E_t(y^i_{t+1}) &= \gamma E_t(y^i_{t+1}|\Omega^i_{mac}) + \delta E_t(y^i_{t+1}|\Omega^i_{sec}) & (8) \\ \Leftrightarrow E_t(y^i_{t+1}) &= \tilde{\gamma} E_t(y^i_{t+1}|\Omega^i_{mac}) + \tilde{\delta} E_t(y^i_{t+1}|\Omega^i_{o}). & (9) \end{aligned}$$

To sum up, both sector-specific as well as macroeconomic information are important for making output decisions at the firm level. Although the 'true' sector-specific information is more important for firms' production plans, this information is costly to obtain and the observable part might be incomplete, imprecise or simply too costly to be collected at a high frequency.

Meanwhile, economy-wide information is made available at low or no costs as several research institutes provide accurate and reliable macroeconomic forecasts to various media agencies. This means that firms' production decisions are influenced by aggregated information provided by the media.

The second hypothesis directly follows from the information complementarities framework outlined above:

H2: Information about the aggregate economy has a significant impact on a firm's expectation, conditional on sector-specific information.

3 Data

Our analysis requires two types of data. On the one hand, we use data on firms' expectations and perceptions based on survey data as published by the Ifo Institute for Economic Research. On the other hand, we need data that capture information about sectoral and aggregated developments that is disseminated through the media. For this, we employ information contained in news magazines, newspapers and TV news broadcasts. All measures are available at the aggregate and the sector-specific level.

Data on the state of the business cycle. Each month, the Ifo institute sends a survey to approximately 7,000 firms in the sectors manufacturing, construction and (retail and wholesale) trade all over Germany.[3] In general, this Ifo Business Tendency Survey intends to capture the firms' appraisals of the business situation and their expectations about short-term developments. For instance, it asks firms to judge their current business situation and their business expectations for the upcoming six months.[4]

Firms are invited to answer most of the questions on a three-category scale: 'good/better', 'satisfactorily/same' or 'bad/worse'. When aggregating, the replies are weighted according to the importance of each firm and its sector. The percentage shares of the positive and negative responses to each question are balanced (ignoring the answer 'satisfactorily'). In this way each qualitative question is converted into a single Ifo indicator.

The Ifo business climate indicator combines two questions: the assessment of the current business situation and the business expectations for the next six months.[5] We will use the same two questions—labeled *Ifo Situation* and *Ifo Expectations* in the remainder of this paper— individually to see whether news reports in the media affect the way in which firms assess the current business situation and whether these news reports change their expectations about future developments of the business climate of their own product line.[6] In our analysis, we concentrate on

[3]See Nerb (2004) for a description.

[4]For more detailed information, we refer to Oppenländer (1997) or Sturm and Wollmerhäuser (2004). See Theil (1955) or Strigel (1990) for earlier work.

[5]More precisely, it is the geometric mean of the indicators derived from the balances to the question: 'We judge our current business situation for product group `XY` to be good, satisfactorily, or bad', and the question: 'With respect to the business cycle, our business situation for product group `XY` is expected to be somewhat better, more or less the same, or somewhat worse in the next six months.' Note that both questions refer to the 'business climate' of the firm and do not explicitly ask for developments in profits, or production. How the term 'business climate' should be interpreted is left open to the individual firms. Nevertheless, it is generally acknowledged that these qualitative results give a good indication of how actual industrial production evolves over the time.

[6]Hence, rather than focusing on the forecasting ability of Ifo Business Tendency Survey indicators, as is often done in literature (see, e.g. Fritsche and Stephan, 2002 and Hüfner and Schröder, 2002), this paper uses these indicators as direct measures for firms' sentiment and assessments of their own future development.

the manufacturing sector, which takes up by far the largest part of the Ifo Business Tendency Survey.[7]

Data on media reports. The media data captures the number of statements regarding the economic development on a daily frequency from 01/1999 to 09/2007. These statements cover both the German economy as a whole as well as on specific sectors individually. According to the standard of so-called media content analysis, Media Tenor captures news which are at least five lines long in case of printed media or last at least five seconds in the case of television reports. We rely on news reports stemming from 26 newspapers, weekly magazines and TV broadcasts.[8] Overall, our dataset consists of 109,023 statements on the aggregate economy and 218,192 sector-specific statements on the six sectors employed in our analysis.

Besides the number of reports, Media Tenor captures its content. Trained coders identify whether each report contains a positive message for the sector or the aggregate economy or whether there is rather bad news attached to it. Inter-coder reliability tests guarantee that coding the same article twice leads to an identical outcome.[9] To allow comparison with the Ifo indicator, we calculate the balance between the share of positive and the share of negative news in a given period. If all news in a given period are positively toned, the balance is set to $+100$, while it is -100 if all news are negatively toned. If, for example, 10 reports are positively toned and 5 negatively, the balance is $+50$.[10]

The classification used in the media data allows us to focus on developments of six sectors: Chemistry, Electrics, Cars, Machinery, Food and Textiles. The appearance of these sectors in the media relative to the amount of news on the aggregate economy is shown in Figure 1. It shows that some sectors are more often mentioned in the media than others. Furthermore, relative to each individual sector, the amount of news on aggregate developments is substantially larger.

[7] We do not consider retail and wholesale trade and the construction sector, because we do not have data from Media Tenor on news reports covering these sectors.

[8] The following news sources are analysed: Daily press: Frankfurter Allgemeine Zeitung, Welt, Süddeutsche Zeitung, Frankfurter Rundschau, Tageszeitung, Bild, Neue Zürcher Zeitung, Berliner Volksstimme, Sächsische, Westdeutsche Allgemeine Zeitung, Kölner Stadt-Anzeiger, Rheinischer Merkur; daily TV-News: ARD Tagesschau, Tagesthemen, ZDF Heute, Heute Journal, RTL Aktuell, SAT.1 18:30, ProSieben Nachrichten; Weekly Press: Spiegel, Focus, Die Woche, Wochenpost, Welt am Sonntag, Bild am Sonntag, Die Zeit.

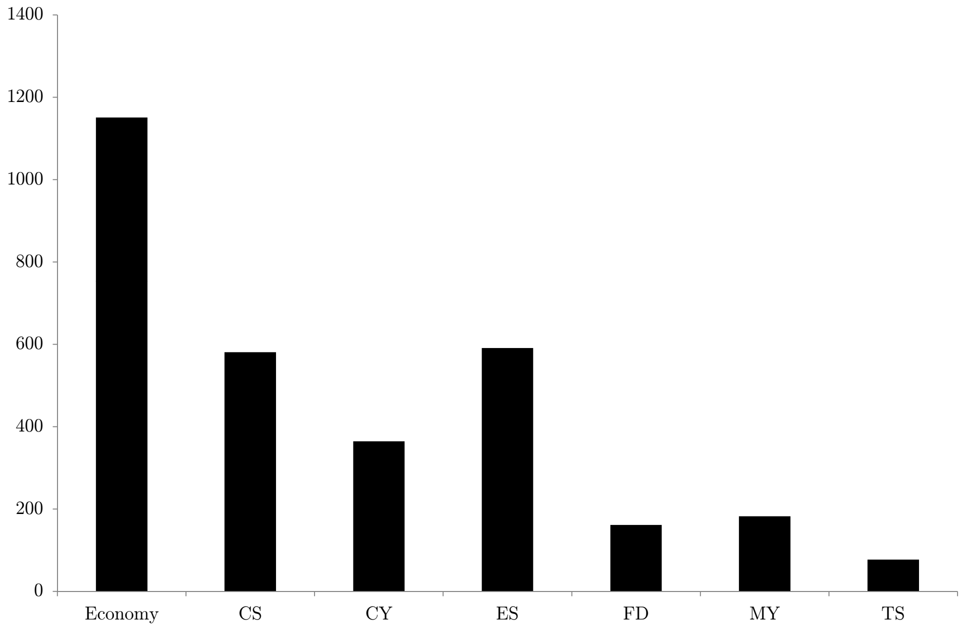
[9] See Appendix A for a more detailed description. Similar data for inflation perceptions and expectations was used in Lamla and Lein (2014) and Lamla and Lein (2015) for Germany or in Dräger (2015) for Sweden. For more information on media content analysis see also Holsti (1969).

[10] Although our variables are bounded between $+100$ and -100 there is little merit in applying the log-odds transformation, as the mass of observations is concentrated and more than two standard deviations away from the bounds.

Whereas there is basically twice as much reporting on the aggregate economy as compared to the automobile and electricity sectors, it is even tenfold the amount of news on the textile industry.[11]

This implies that, if we would abstract from the tone or quality of these reports, it should be easier to obtain detailed information on the performance of the aggregate economy relative to information on developments of individual sectors. One obvious reason is that there are several institutions and research departments providing information on the current and future outlook of the economy. Another reason is the above-mentioned scarcity of data at the sectoral level.

Figure 1: Average number of reports per month for the aggregate economy and individual sectors

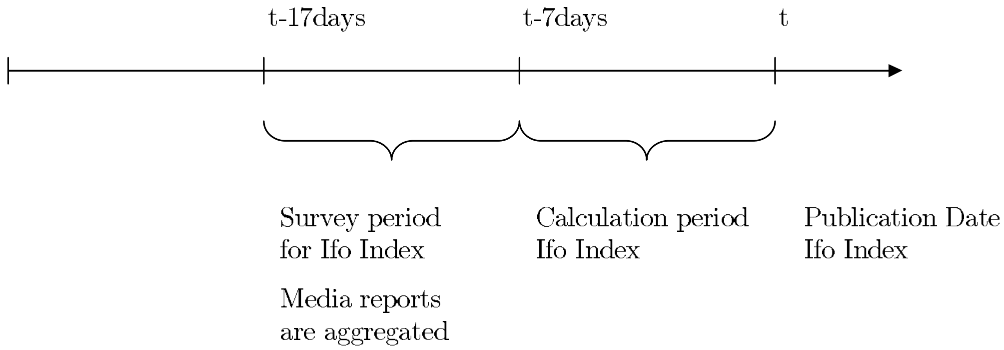


Notes: This figure shows the average number of media reports per month. Economy refers to news related to the aggregate economy, all others to news about individual sectors: Cars (CS), Chemistry (CY), Electrics (ES), Food (FD), Machinery (MY) and Textiles (TS).

Figure 2 illustrates the construction of the media indicator with respect to its aggregation in time. The Ifo Business Climate Indicator is made public between the 18th and the 24th of a month. Since it takes several days for the Ifo institute to construct it, we assume the firms have

[11]Note that our measure of macroeconomic news is *not* the average or aggregate of the sector-specific news items, but instead contains the assessment of news focusing on the German economy as a whole. Moreover, the manufacturing sector accounts for less than 25% of German GDP and our six sectors are only part of that. Consequently, the information contained in our sector-specific variable relative to our news measure on the economy as a whole basically does not overlap.

Figure 2: Timeline of the Construction of the Media Indices and the Ifo Index



Notes: This figure illustrates the construction of the monthly media data used in the estimation. To avoid including media reports about the Ifo Index for the same time period, we aggregate media reports from 17 days before the release of the Ifo data to 7 days before the release. t denotes the publication date of the Ifo Index.

already submitted the questionnaire a week before publication. For the same ten days during which firms fill out the Ifo Business Tendency Survey, we accumulate the media reports and construct our media indicators. Hence, we assume that survey participants are especially affected by news reports released during the period in which they fill out the surveys.[12] Because the Ifo Business Climate Indicator is made public one week later, by construction there cannot be any contemporaneous impact running from the publication of this indicator to our constructed news indicator.

In Table 1, we present summary statistics of our variables. Table 1 shows the sectoral time series characteristics.[13] Media reporting on the aggregate economy has, with an average value of -23.7, a rather pessimistic tone. This is not the case when looking at the Ifo indicators for the situation and expectations in the manufacturing sector as a whole over the same period: here, positive and negative responses seem to average out over the time. In contrast, media reports on sector-specific developments do not reveal such a negative average tone. With the exception of the food sector, all reports have on average a rather positive tone. Ifo Situation and Expectations for sector-specific developments look more similar to the media data for the same sector, where the average tends to be positive, again with the exception of the food sector and also the textiles

[12]As a robustness check, we also construct media indicators using data covering the full month. However, this does not alter the results qualitatively.
[13]In Table 4 in the Appendix, we show summary statistics for the stacked series covering the six sectors used in the panel VAR analysis.

Table 1: Summary Statistics – Individual Sectors and the Economy

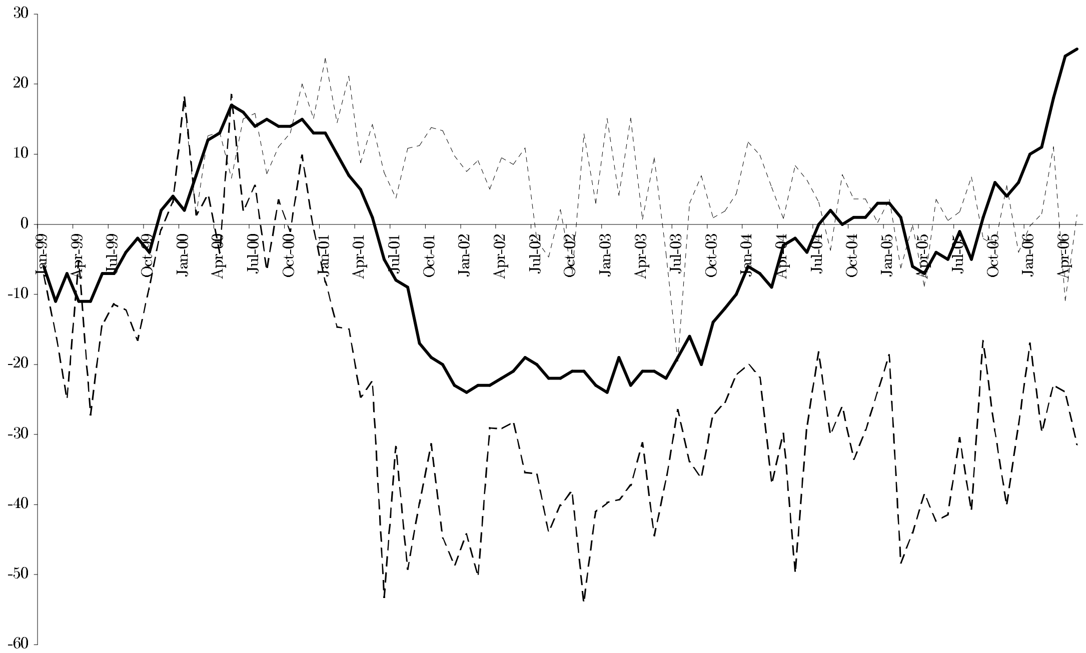
Variable	Mean	Std. Dev.	Min.	Max.	Observations
News Economy (n^{mac})	-23.7	18.1	-64.2	21.0	103
News Cars	6.1	11.1	-27.3	30.5	89
News Chemistry	6.9	12.2	-28.1	34.8	89
News Electronics	5.6	11.4	-23.5	33.6	89
News Food	-1.0	15.4	-53.3	27.0	89
News Machinery	4.9	14.8	-55.1	33.3	89
News Textiles	15.3	17.8	-20.0	66.7	89
Ifo Situation Aggregate Manufacturing	-2.2	13.9	-24.0	28.0	103
Ifo Expectations Aggregate Manufacturing	3.3	11.5	-31.0	24.0	103
Ifo Situation Cars	16.3	15.0	-10.0	47.0	103
Ifo Situation Chemistry	9.9	15.1	-18.0	47.0	103
Ifo Situation Electronics	-3.4	18.8	-35.0	32.0	103
Ifo Situation Food	-9.2	7.2	-29.0	9.0	103
Ifo Situation Machinery	1.7	17.3	-30.0	45.0	103
Ifo Situation Textiles	-23.0	14.7	-48.0	6.0	103
Ifo Expectations Cars	7.0	19.6	-35.0	58.0	103
Ifo Expectations Chemistry	10.4	13.7	-26.0	35.0	103
Ifo Expectations Electronics	6.4	15.5	-35.0	38.0	103
Ifo Expectations Food	-2.6	8.0	-29.0	17.0	103
Ifo Expectations Machinery	4.1	13.7	-33.0	27.0	103
Ifo Expectations Textiles	-6.3	12.3	-40.0	16.0	103

Notes: This table provides summary statistics for the data used in estimation. The upper panel summarizes the media data, the lower panel the Ifo Survey data.

sector. Looking at both the extreme values and the standard deviations, all series face similar degrees of volatility.

Figure 3 illustrates the movement of the Ifo Situation indicator in comparison to our macroeconomic news measure and the average of the six sector-specific news measures. The three series are positively correlated. The macroeconomic media indicator seems to be somewhat more volatile than the sector-average news indicator. Moreover, both indicators show a low degree of persistence in comparison to the Ifo Situation indicator for the manufacturing sector.

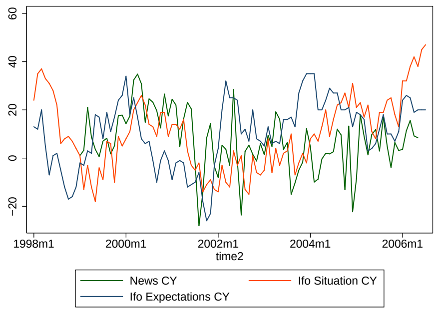
Figure 3: Media tone and the Ifo Situation indicator for the aggregate economy



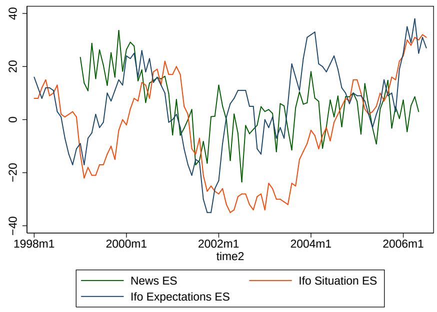
Notes: This figure illustrates the measure of the tonality in media reports (balance between positive and negative news) and the Ifo survey data for the aggregate economy. The solid line shows the aggregate Ifo Situation indicator for manufacturing as a whole, the dashed thick line shows the media indicator for the macroeconomy (News Economy), the dashed thin line shows the average of the sector-specfic media indicators (News Sector).

In Figure 4 we show the three time series for each sector. While most display a cyclical pattern, the food sector seems to be less cyclical, which is consistent with earlier findings that durable-goods industries are much more cyclical than nondurable-goods industries (Petersen and Strongin, 1996). For most sectors, the media indicators and the Ifo Situation indicators are positively correlated, with a correlation coefficient of 0.18 (Table 2). Several additional observations can be made. First, the average of sector-specific news reports and economy-wide news has a correlation coefficient of

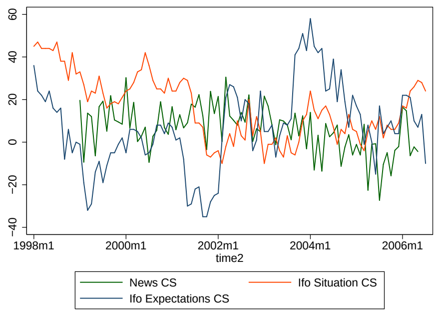
Figure 4: Sector-specific media tone and Ifo indicators



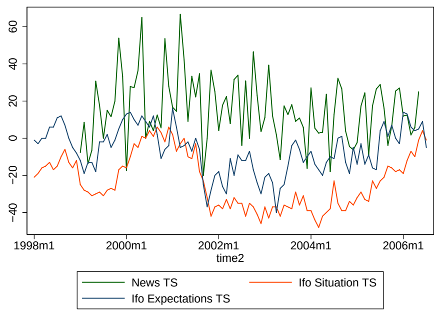
(a) Chemistry



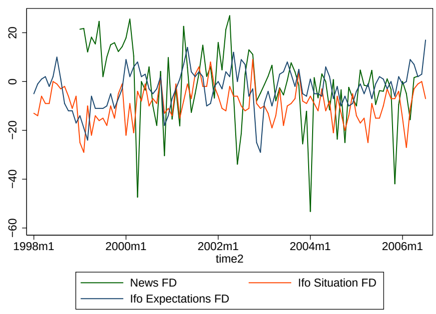
(b) Electronics



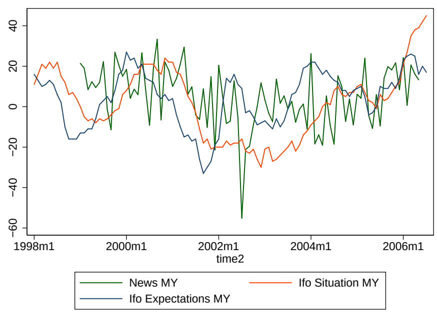
(c) Cars



(d) Textiles



(e) Food



(f) Machinery

Notes: This figure illustrates the media tone (balance between positive and negative news) and the Ifo survey data for each sector. The tone of media reports is shown as green line, the Ifo Situation and Expectations as red and blue lines, respectively.

about 0.5. As the industrial sector is a relevant part of the total economy a positive correlation is expected. However, as economy-wide news is not simply the average of sector-specific news, the correlation is indeed well below 1. Second, the news measure of the aggregate economy shows a substantially stronger correlation with the aggregate sector-specific Ifo indexes than the sector-specific news measure. This indicates that companies might be more influenced by economy-wide news than by sector-specific news. Third, most news seems to be related to the present economic situation as both the economy-wide news measure and the sector-specific news measure are more strongly correlated with Ifo Situation indicator than the Ifo Expectations indicator. Finally, given the differences in correlation coefficients with Ifo Expectations, there appears to be more forward-looking information contained in the macroeconomic news than in sector-specific news. This might raise the value of macroeconomic news for firms.

Table 2: Correlation Table

Correlations-Observations	News Economy	News Sector	Ifo Situation	Ifo Expectations
News Economy	1.000	89	103	103
News Sector	0.487	1.000	89	89
Ifo Situation	0.502	0.182	1.000	103
Ifo Expectations	0.185	0.003	0.410	1.000

Notes: This table reports correlation coefficients of our variables, where the sector-specific media indicators are averaged across the six sectors. The lower triangular shows the pairwise correlation coefficients while the upper triangular contains the number of observations.

4 Empirical Framework

We employ Granger causality analysis to investigate the relationships between media information and the assessments of current and expected business situations. In that way, we can provide evidence regarding the information complementarity hypothesis. We analyze Granger causality in a VAR to overcome simultaneity problems. Hypothesis H1 is confirmed when news 'Granger cause' firms' business expectations. This is the case when the time series prediction of the Ifo indicators from their own past can be improved by adding lags of news balances to the equation. Using our four variables of interest—Media Tenor news balances concerning sector-specific news (n_t^{sec}) and news addressing the stance of the macroeconomy (n_t^{mac}), the Ifo Situation indicator (i_t^s) and the Ifo Expectations indicator (i_t^e)—gives the following VAR(p) model:

$$\begin{pmatrix} n_t^{mac} \\ n_t^{sec} \\ i_t^e \\ i_t^s \end{pmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \\ a_{40} \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) & A_{14}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) & A_{24}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) & A_{34}(L) \\ A_{41}(L) & A_{42}(L) & A_{43}(L) & A_{44}(L) \end{bmatrix} \begin{pmatrix} n_{t-1}^{mac} \\ n_{t-1}^{sec} \\ i_{t-1}^e \\ i_{t-1}^s \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{pmatrix}, \quad (10)$$

where, for $j, k = 1, \ldots, 4$, a_{j0} are the constants, A_{jk} are polynomials of order p in the lag operator L, and e_{jt} are independent and identically distributed disturbance terms such that the covariance matrix $\Sigma = E(e_{jt}e_{kt})$ is not necessarily zero for $j \neq k$. For now, we just use an average of sector-specific news for n^{sec}. Below, we extend our analysis and estimate the VAR for each sector.

The Granger-causality testing procedure does not generally give us an estimate of the sign of the overall effect. In order to test whether there exists a positive or negative effect of one variable on another, we apply the neutrality test, in which we calculate the sum of the lagged values of an explanatory variable and test whether it significantly differs from zero (Zarnowitz, 1992, pp. 365–379).

Hence, in this setting the analysis of a Granger-causal relation from news balances on the assessment of the (future) business climate (hypothesis H1) boils down to testing whether each of the coefficients of the lag polynomials $A_{jk}(L) = A_{jk}^1, \ldots, A_{jk}^p$, specifically A_{31} and A_{41}, (A_{32} and A_{42}) in equation (10) differ from zero. If furthermore the sum of these elements is significantly different from zero, we know that news does have a long-run impact on the two Ifo indicators. We apply likelihood ratio tests to carry out these test, i.e. we estimate both the constrained and unconstrained systems. We also use likelihood ratio tests to determine the optimal lag length (p) of the system.[14]

As robustness check and further refinements of the baseline VAR described above, we consider two modifications. First, we remove the effect of current real economic events reported in the media. Although we have included the Ifo Situation indicator in our baseline VAR, we might capture demand or supply shocks that are reported in the media and affect the business situation

[14]We use the Choleski factorization to identify the primitive innovations. In our case the ordering is largely predetermined by the construction (timing) of the media variables—as depicted in Figure 2—and the reference in time of the two Ifo survey questions. By construction, we cannot have a contemporary feedback effect from the two Ifo indicators on media as the media coverage of these indicators has been excluded. Hence, we can clearly separate between these two shocks. With respect to the two Ifo indicators, we assume that the Situation indicator can have a contemporaneous effect on the Ifo Expectations, but not vice versa. Because the Ifo Situation indicator reflects the current actual situation, which then might feed into the calculation of the outlook of the firm, this appears to be a sensible assumption. Only with respect to the macroeconomic and the sector-specific media indicators, it is less obvious which ordering is theoretically more plausible. We hypothesise the contemporaneous effect of macroeconomic news on sector-specific news to be negligible. Hence, the ordering from most exogenous to most endogenous is the two Ifo indicators—Ifo Situation and Ifo Expectations—followed by the two media variables—sector-specific and macroeconomic news. None of the qualitative conclusions depend upon this assumption, or in general upon the ordering chosen. Results are available upon request.

at the same time. Therefore, in a first stage, the media indicators are regressed on both macroeconomic and sector-specific (ex-post) industrial production growth.[15] The resulting residual is a media indicator that is orthogonal to industrial production in the economy/the sector. It should therefore not include contemporaneous demand or supply shocks that are included in the 'hard data' and be interpreted as a shock to news itself. Within the VAR framework, we then replace the original news indicators by these residuals. It turns out that the results are very similar to the baseline VAR. The results of this robustness check are presented in Appendix B.

Second, in the VAR described above, the sectoral news impact is related to the sectoral expectation and situation assessment by imposing the same coefficient for each sector. To extend the VAR to a sectoral VAR, which allows for different coefficients for each sector and the constants in Equation (10) are replaced by sector dummies. We basically estimate a VAR for each sector, not allowing for dynamic interdependencies across sectors.

5 Results

Table 3 reports the results of the Granger causality and Neutrality tests.[16] There is clear evidence that Ifo Expectations subsequently Granger cause changes in the Ifo Situation indicator and not the other way around. This is as expected and demonstrates that expectations are consistent with future assessments of the situation. Confirming hypothesis H1, we find that a positive innovation in the macroeconomic news variable Granger-causes firms' business expectations. Confirming hypothesis H2, we observe that macroeconomic news has a significant impact on business expectations whereas sector-specific news does not Granger-cause business expectations. In addition, as the neutrality test cannot reject the null that the sum of the estimated coefficients equals zero, the effect of macroeconomic news on business expectations appears to be rather short-lived.

While this analysis provides us with information concerning the significance and the direction of the impact of one variable on another, the neutrality tests only give an imperfect picture on how a shock evolves over time. We therefore calculate the implied impulse-response functions. Figure 5 shows that a one standard deviation shock in Ifo Expectations will, with some delay, have a significant impact on the actual business assessment by firms, i.e. the Ifo Situation indicator.[17] The maximum impact is reached after about six months, the time horizon over which firms are

[15]Besides the contemporaneous values we include up to three lags of macroeconomic and sector-specific industrial production growth.

[16]We opt for the Likelihood-Ratio test. However, Wald tests lead to qualitatively identical results.

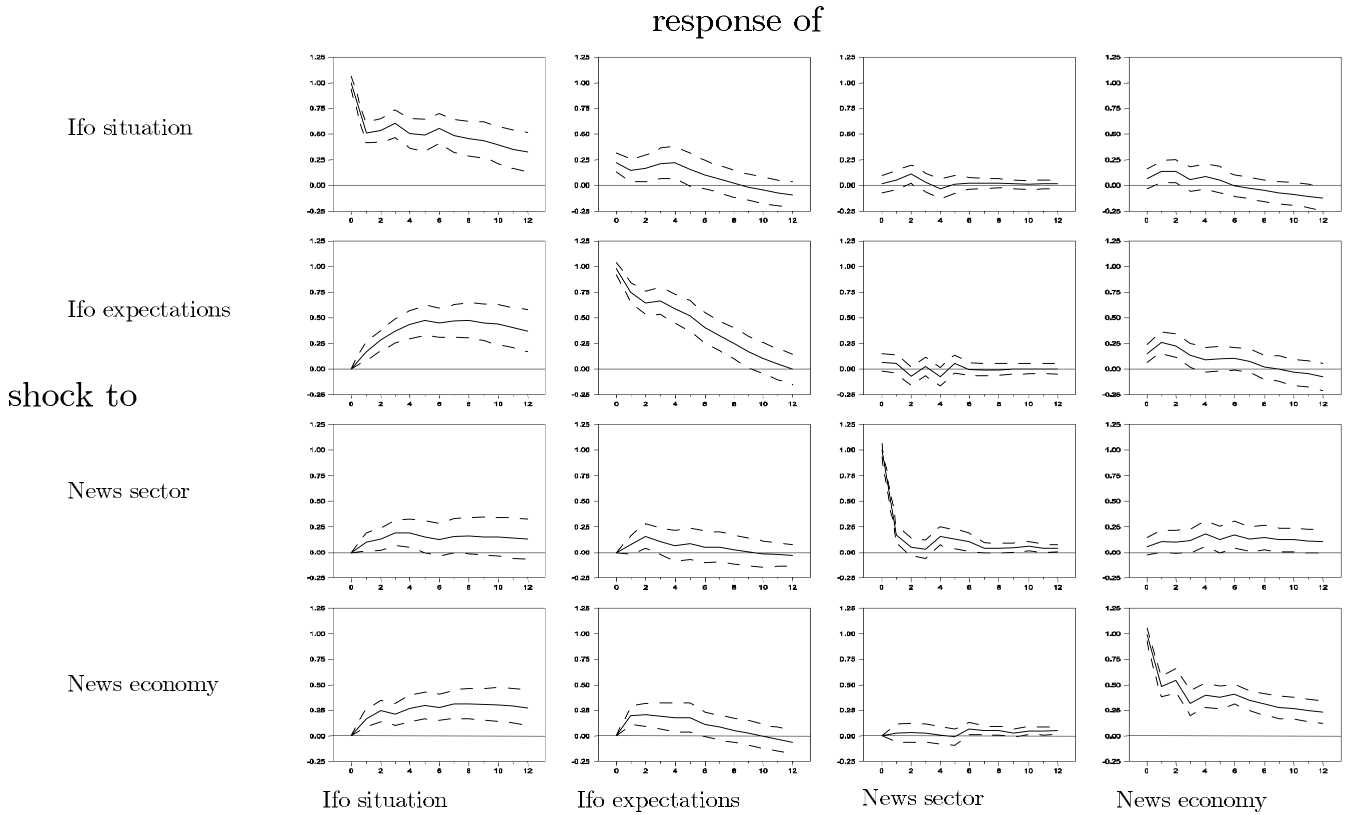
[17]The impulse-response functions are scaled by the standard deviation of the response variable and each shock equals one standard deviation of the impulse variable.

Table 3: Neutrality and Granger Causality Tests

Variable \ Equation	**Ifo Situation**		**Ifo Expectations**		**News Sector**		**News Economy**	
	Neutrality	Granger	Neutrality	Granger	Neutrality	Granger	Neutrality	Granger
Ifo Situation	0.000	0.000	0.393	0.748	0.454	0.332	0.004	0.0139
	(567.73)	(580.94)	(0.72)	(3.47)	(0.56)	(6.88)	(8.10)	(15.97)
Ifo Expectation	0.000	0.000	0.000	0.000	0.115	0.060	0.782	0.005
	(29.28)	(42.81)	(375.10)	(462.32)	(2.29)	(12.07)	(0.07)	(18.31)
Sector-specific News	0.539	0.124	0.958	0.228	0.000	0.000	0.008	0.105
	(0.36)	(9.99)	(0.00)	(8.14)	(28.88)	(37.98)	(6.69)	(10.48)
Economy-wide News	0.005	0.000	0.816	0.000	0.031	0.374	0.000	0.000
	(7.73)	(24.73)	(0.05)	(23.46)	(4.66)	(6.44)	(471.07)	(496.53)

Notes: This table reports Granger causality and neutrality test results. The reported p-values (and χ^2 statistics) are based on Likelihood-Ratio tests. Six lags of each endogenous variable are selected and included in each equation ($p = 6$). Columns labeled 'Neutrality' show p-values of tests on the significance of the sum of the coefficients. Columns labeled 'Granger' report p-values for tests on joint significance. The associated χ^2 statistics are shown in parentheses. The results are based on 498 observations.

Figure 5: Panel VAR



Notes: This figure reports impulse-response functions for the Panel VAR specified in equation (10). The first to fourth rows indicate responses of each variable to a shock in the business situation indicator, the business expectation indicator, the sectoral news variable and the macroeconomic news variable, respectively. Columns show the responses of each of these variables. The impulse-response functions are plotted together with their 95% bootstrapped confidence intervals based on Giannini (1992).

asked to assess future developments. This implies that firms, on average, give coherent answers, and are able to quite accurately describe their economic standing six months in advance.

Furthermore, we can confirm H1 that media reporting affects the business expectations after controlling for the current assessment of the business situation. This suggests, that media reporting contains information beyond the information included in the current business situation assessment. Overall, a shock in macroeconomic news exhibits a stronger impact on the Ifo indicators than sector-specific news. This affirms the importance of information complementarities in hypothesis H2. Companies rely on macroeconomic news in order to infer sector-specific information.

It is generally found that the Ifo indicators capture movements in the real economy quite well (see Nierhaus and Sturm, 2007). This suggests that information transmission via the media has indeed an impact on the real economy and thereby drives business cycles and amplifies sector comovement.[18]

As Figure 7 in Appendix B reveals hardly any changes emerge when we conduct the first robustness check in which we use the news data that is orthogonal to industrial production growth in the economy and per sector. Hence, information as distributed by the media still appears to affect the firms' assessments of current and future developments.

To document the responses of different sectors and as a further robustness check, we estimate our model for each sector separately (sector-specific VAR). For the sake of brevity, Figure 6 only shows the impulse-response functions of one standard deviation news shocks on the two Ifo indicators for each of the six sectors.[19]

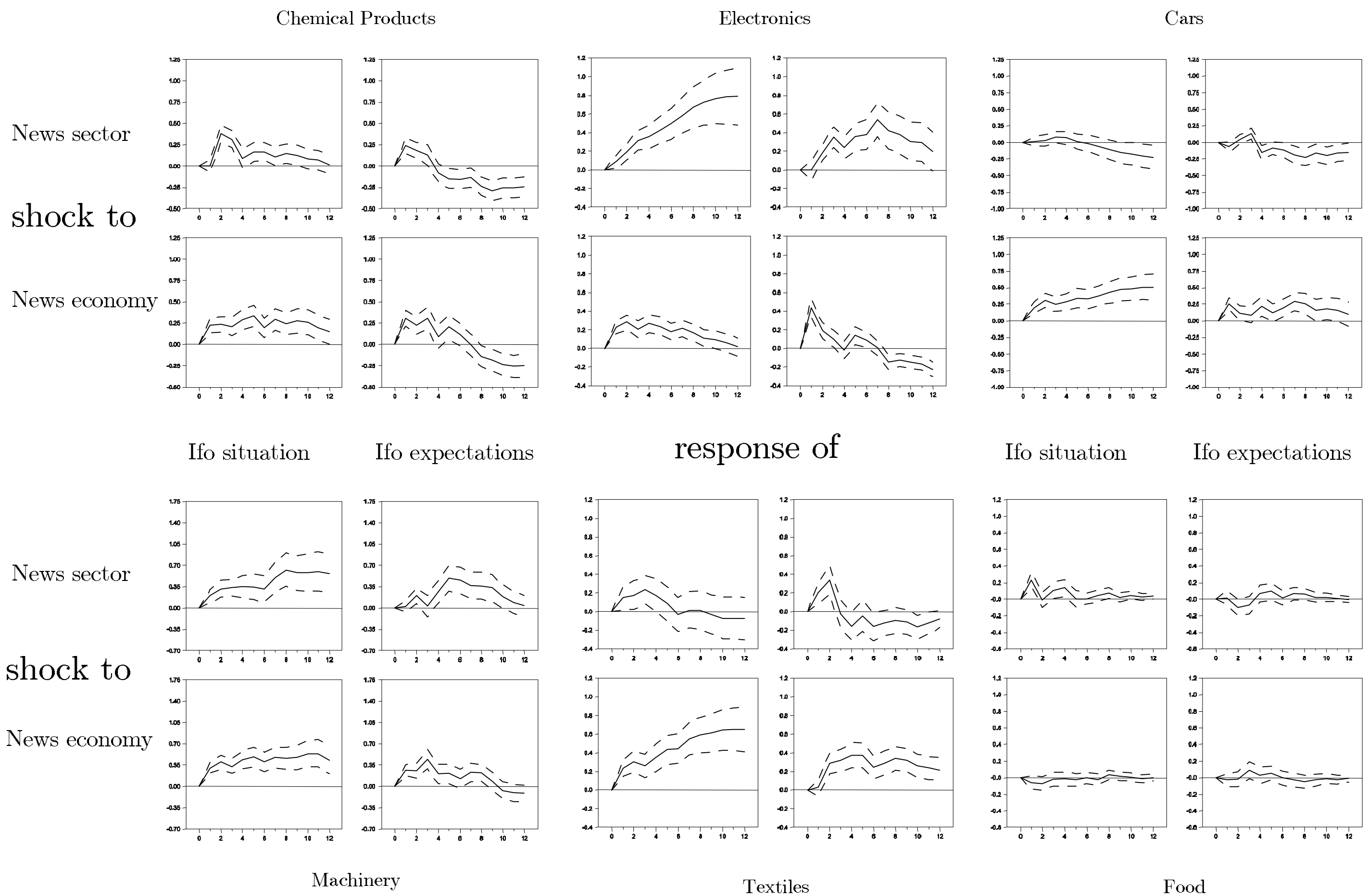
While on average there is compelling evidence in favor of our proposition that macroeconomic information has a strong impact, there is some degree of heterogeneity in the responses across sectors. For instance, the food sector is neither influenced by macroeconomic nor sector-specific news. Sectors like textiles, chemistry, cars and machinery exhibit a clear pattern that matches our ex-ante considerations and the general picture that emerged from Figure 5.

The different impact across sectors can be explained by different needs for sector-specific information. That would be consistent with the theoretical framework presented here and in the spirit of Veldkamp and Wolfers (2007). Firms make rational choices when deciding between buying

[18] Other evidence supporting the view that news is highly relevant for economic outcomes is provided by Mora and Schulstad (2007). They find that the information agents have about current GNP, i.e. first releases on these, have a larger impact on their own actions than the true ex-post figures of GNP. The authors study the degree to which expectations affect the evolution of the economy. They find that once GNP first releases are taken into account, the true (revised) value of GNP growth at time t has no predictive power in explaining future growth rates at any time. Thus, all the predictive power lies in the unexpected part of the announcements, and not in the true level of growth.

[19] That is, we concentrate on the A_{31}, A_{41}, A_{32} and A_{42} polynomials in equation (10). The full set of results is available upon request.

Figure 6: Sector-specific VARs



Notes: This figure reports impulse-response functions for the Sector-specific VARs. It reports the responses of the business situation and business expectations indicators to sector-specific and macroeconomic news for each of the six sectors. The impulse-response functions are plotted together with their 95% bootstrapped confidence intervals based on Giannini (1992).

sector-specific information (for a relatively high price) or obtaining only macroeconomic information (for a relatively low price) and trying to infer the sectoral development from that. If a firm in a given sector knows that sectoral productivity developments are closely related to macroeconomic productivity developments, the loss of making decisions based on macroeconomic information is relatively small. The reverse holds when sector-specific productivity developments are less synchronized with those of the rest of the economy. Hence, the loss of making decisions based on macroeconomic information is higher, the higher the difference between macroeconomic and sector-specific productivity developments. Furthermore, if the volatility of productivity growth is high, then there are higher costs associated with a mismatch between the actual and the optimal output decision. Hence, if this loss outweighs the costs firms face for acquiring sector-specific information, it is rational for them to obtain this relatively costly information.

This is consistent with the empirical results presented here. For example, the necessity of the food sector to base their decisions on external information is low as food consumption patterns are usually quite stable over time and productivity growth in this sector is in general low.[20] Hence, the incentives to react to new developments (macroeconomic or sectoral shocks) is much lower than in other sectors.[21] Furthermore, the evidence presented supports that sectors underlying rapid productivity growth and low correlation with the macroeconomy have more incentives to gather sector-specific information. For electronics, for example, with an average TFP growth of six percent and the lowest correlation between sector and macroeconomic productivity, we observe that sector-specific information has a more pronounced impact than macroeconomic news. The other sectors react more strongly to macroeconomic news.

6 Conclusions

Using indicators of firms assessment and expectations regarding their business situation, as well as an extensive data set on economic news in the media, we find that media coverage Granger causes companies' business expectations, but not vice versa. This indicates that information provided by the media goes beyond what is included in the companies' assessment of the current business situation and is thus included in the companies' expectation formation. Although we cannot directly identify news shocks, changes in the intensity of media coverage, conditional on

[20]TFP growth in the food sector is basically zero. The average unweighted TFP growth across all sectors is about one percent.

[21]This is underlined by the low degree of volatility in this sector relative to the other sectors in our sample. See Table 1.

the current state of the business cycle, is likely to be correlated with such news shocks. Our empirical results therefore confirm theoretical models in which news shocks play an important role in explaining business cycles.

In addition, our contribution provides empirical evidence for theoretical models on information complementarities. Looking at the sectoral responses to macroeconomic news and news about a particular sector, we find that those on macroeconomic developments have a much stronger impact on companies' business expectations than those on their own sector. This result is in line with the strategic complementarity in information acquisition across sectors as developed by, for instance, Veldkamp and Wolfers (2007). When sectoral information is scarce and costly to accumulate, it makes sense for companies to forecast the future development of their industry based on aggregated information available at much lower cost. The complementarity of this information varies from sector to sector. It may be more important for some sectors to have up-to-date sector-specific information than for others. For example, sectors that rely on large and potentially irreversible investments face greater volatility or competition might be more responsive to sectoral as compared to macroeconomic news. This heterogeneity is also reflected in our empirical analysis.

Overall, our paper provides additional insights into the relevance of news shocks. It also highlights the sectoral dynamics due to the complementarity of information, an area that requires further attention.

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A Media Data

The media data employed in this paper is collected and created by Media Tenor, a provider of media intelligence. Here, we describe in more detail how the data is collected and created and how it compares to other datasets used in the literature that reflect the content of media reporting.

Media Tenor first collects all articles from major newspapers and media broadcasts in Germany that are at least five lines long in case of printed media or last at least five seconds in the case of television reports. We rely on news reports stemming from 26 newspapers, weekly magazines and TV broadcasts.[22]

Then, trained coders read every newspaper article and watch every television report that talks about the economic situation or expected economic development. This may be related to the German economy as a whole or to one or more specific sectors. The coders have to evaluate every statement related to the key topic (economic situation or expected economic developments) on whether it is toned neutral, good, or bad.

The resulting data includes for every article that is related to the German aggregate economy or a specific sector in the German economy the following information: i) a sectoral identifier, which indicates which sector the article is related to. If the article is related to the aggregate economy, we have an identifer for the aggregate economy. ii) the date when the article appeared in the media. iii) three variables that indicate whether a statement are toned good, bad, and neutral, respectively.

From this information, we construct measures of the frequency and tone of news media per month, which is described in the main body of this paper.

This approach is complementary to other approaches based on textual analysis of media data as described by Loughran and McDonald (2011), Bodnaruk et al. (2015), and in the survey on applications in accounting and finance of Loughran and McDonald (2016). The advantage of using textual analysis is that with a given codebook, there is a unique algorithm that classifies media reports based on dictionaries and sentiment word lists. That means, conditional on the provided media reports, the algorithm would always come up with the same classification. Human coders might come up with two different classifications when reading the same text. To control for this, Media Tenor asks two different coders to code each text independently of each other. Only if

[22]The following news sources are analysed: Daily press: Frankfurter Allgemeine Zeitung, Welt, Süddeutsche Zeitung, Frankfurter Rundschau, Tageszeitung, Bild, Neue Züricher Zeitung, Berliner, Volksstimmer, Sächsische, Westdeutsche Allgemeine Zeitung, Kölner Stadt-Anzeiger, Rheinischer Merkur; daily TV-News: ARD Tagesschau, Tagesthemen, ZDF Heute, Heute Journal, RTL Aktuell, SAT.1 18:30, ProSieben Nachrichten; Weekly Press: Spiegel, Focus, Die Woche, Wochenpost, Welt am Sonntag, Bild am Sonntag, Die Zeit.

Table 4: Summary Statistics – Panel of six sectors

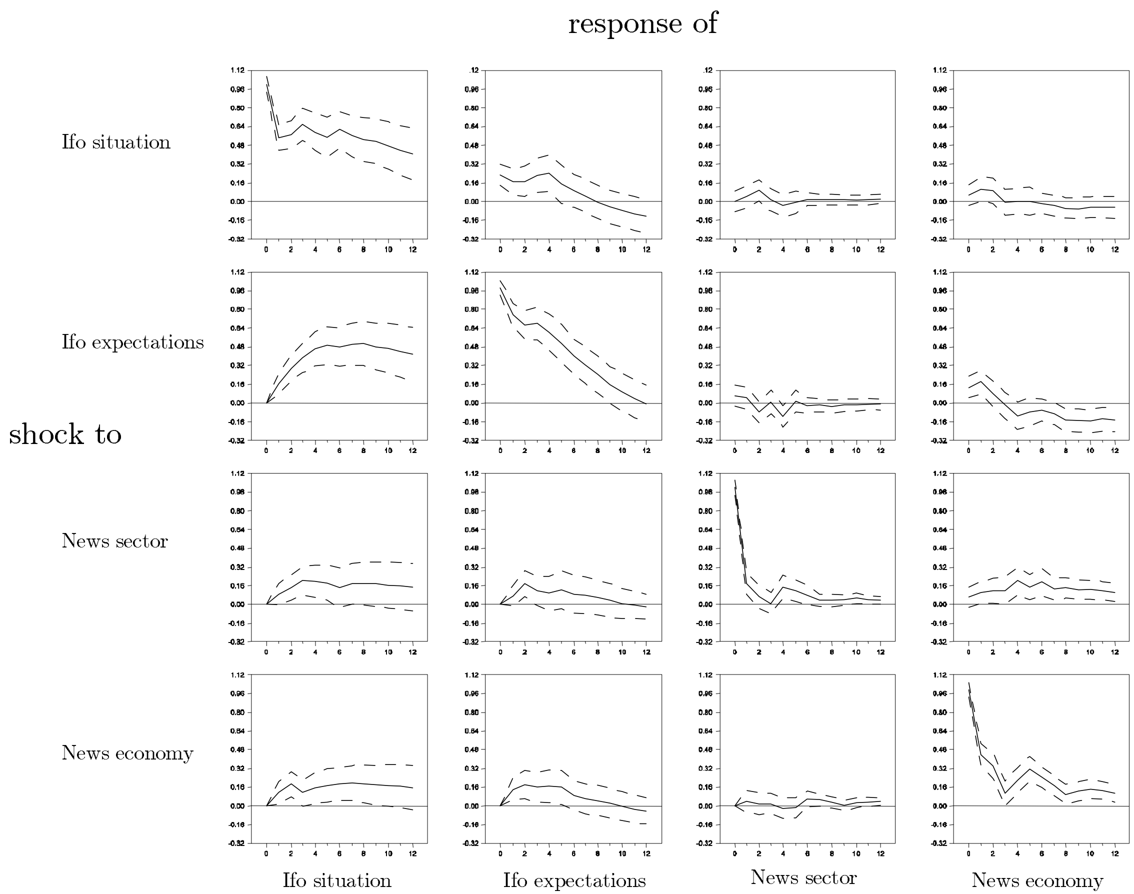
Variable	Mean	Std. Dev.	Min.	Max.	Observations
News Economy (n^{mac})	-23.7	18.1	-64.2	21.0	618
News Sector (n_t^{sec})	6.3	14.7	-55.1	66.7	534
Ifo Situation (i^s)	-1.3	19.8	-48.0	47.0	618
Ifo Expectations (i^e)	3.2	15.3	-40.0	58.0	618

Notes: This table reports summary statistics for the average of all sectoral data.

the two coders come up with the same classification, the data is final. If not, the coders have to re-read the text or further coders have to classify the same text until they achieve convergence. Since the textual analysis codebook described in Loughran and McDonald (2016) is only available in English, and the media data we use is solely in German, we cannot easily replicate our analysis based on their dictionaries, since simple translations are often not capturing all the different words available in another language. Furthermore, our data includes also TV broadcasts, which are not readily available in electronic text formats, that we could quantify.

B Additional Tables and Figures

Figure 7: Two-Step VAR



Notes: This figure reports impulse-response functions for the Panel VAR specified in equation (10). Here, news variables are the residuals of a regression of the news variables used in the main body of the paper on aggregate and sectoral industrial production and three lags thereof. The residual thus captures news that are orthogonal to current industrial production and therefore should capture news related to future economic developments. The first to fourth row indicate responses of each variable to a shock in the business situation indicator, the business expectation indicator, the sectoral news variable and the macroeconomic news variable, respectively. Columns show the responses of each of these variables. The impulse-response functions are plotted together with their 95% bootstrapped confidence intervals based on Giannini (1992).