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## News Media, Common Information, and Sectoral Comovement

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# News Media, Common Information, and Sectoral Comovement

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August 19, 2014

## Abstract

This paper investigates whether information complementarities can explain the strong patterns of sectoral comovement observed empirically. The theoretical model by Veldkamp and Wolfers (2007) suggests that firms base their output decisions on aggregate information rather than on sector-specific information because the former is less costly to acquire. Employing the connectedness index by Diebold and Yilmaz (2009, 2012) as a new comovement measure, we analyse two channels how news media as an important transmitter of macroeconomic information could influence sectoral comovement: the intensity of media coverage and its tone. While the volume of economy-wide news is found to be insignificant, our results suggest that sectoral business expectations assimilate stronger in reaction to a negative news tone shock. This sentiment shock is also reflected in a delayed—although small—increase of sectoral output comovement.

JEL classification: C32, D84, E32.

Keywords: Information complementarities, news, media coverage, sectoral comovement, connectedness, spillover index, expectation-driven business cycles.

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# 1 Introduction

It is one of the defining characteristics of business cycles that output and inputs move up and down together across most industries.<sup>1</sup> So investigating the sources of sectoral comovement can also shed light on the forces that drive the aggregate business cycle. According to Lucas (1977), the presence of strong patterns of sectoral comovement suggests that aggregate shocks determine the business cycle. While aggregate productivity shocks could play an important role, this is contested by the data; sectoral output is much more correlated than sectoral productivity (for the U.S., see Hornstein, 2000, and for Germany, see Lamla, Lein and Sturm, 2007). In light of this so-called excess comovement puzzle and due to the difficulty of identifying other sorts of common shocks that lead to a synchronised response across sectors, the literature has focused on spillovers of sector-specific shocks. Special attention has been given to production complementarities, that is, the fact that the output of one industry is used as an input for the production of another commodity (Hornstein and Praschnik, 1997; Horvath, 2000; Long and Plosser, 1983; Shea, 2002). Recently, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) provided a mathematical framework for analysing how the intersectoral network structure of the economy determines the role of idiosyncratic shocks in sectoral comovement and, accordingly, in aggregate fluctuations. Empirically, however, Foerster, Sartre, and Watson (2011) find in a structural factor analysis that changes in the variability of U.S. industrial production growth are mainly driven by changes in the importance of aggregate shocks.

As an alternative aggregate source of excess sectoral comovement, Veldkamp and Wolfers (2007) put forward information complementarities. The authors argue that firms have an incentive to acquire information on future aggregate productivity, which they use to make inference about their own sector's expected productivity. The reason is that information has high fixed costs of production and, due to its non-rivalry in consumption, low marginal

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<sup>1</sup>This was already emphasised by Burns and Mitchell (1946). For empirical evidence for the U.S., see Long and Plosser (1987), Christiano and Fitzgerald (1998), and Rebelo (2005); for Germany, see Lamla, Lein, and Sturm (2007).

costs of replication. Hence, the average costs of information and thus its price decline with rising demand (Romer, 1990). As there is more demand for general than for customised information, it is cheaper to retrieve information on macroeconomic aggregates than on sectoral quantities. When many firms form their expectations on the basis of common information and adjust their production decisions accordingly, sectoral comovement of output will be more pronounced.

Taking into account information costs in expectation formation was promoted by Mankiw and Reis (2002, 2006), whose sticky information model suggests that agents only occasionally update their information set. A microfoundation is given in the rational inattention model of Sims (2003), who emphasises costs of information processing rather than those of information acquisition. He establishes a crucial role of mass media in transmitting macroeconomic news since they fulfill an important information-processing service on which economic agents largely rely. But it is Carroll (2003) who explicitly models the impact of news media on expectations. In his epidemiologic model macroeconomic information spreads across the economy like a disease because households become “infected” by news reports. He shows that the rate of infection depends on the intensity of news coverage.

This paper analyses empirically whether the news media as a transmitter of aggregate information are a source of sectoral comovement. We first study the effect of media coverage on sectoral comovement of business expectations and then investigate whether the change in expectations is reflected in the level of output comovement across sectors. In contrast to Carroll (2003), we control for the macroeconomic environment to identify structural media shocks. These media shocks can be interpreted as “animal spirits” in the sense of Keynes (1936), that is, self-fulfilling beliefs. Akerlof and Shiller (2010) explicitly mention stories created by mass media as one of such psychological factors that drive the economy. According to the authors, news media tend to overinterpret economic facts, thereby influencing confidence so that, ultimately, the effects of real shocks can be amplified.

So far, only Lamla, Lein, and Sturm (2007) study empirically the question whether media coverage has an impact on sectoral comovement. Indeed,

the authors find that economy-wide news deploy a stronger effect on sectoral business climate indicators than sector-specific news. Since reported business expectations contain information about the firms' production plans, the authors conclude that common information can serve as a channel that amplifies sectoral comovement of production. Although this seems plausible, we aim at gaining more direct evidence. Does the effect of economic news on business expectations translate into a measurable impact on the real economy? Therefore, we analyse whether the dissemination of aggregate news leads to a higher degree of sectoral comovement of both business expectations and output.

The remainder of this paper is organised as follows. Section 2 develops the model and the estimation approach. Sections 3 and 4 present how we measure sectoral comovement, media coverage of business cycle news as well as the macroeconomic environment the media report about. Section 5 discusses the estimation results and Section 6 concludes.

## 2 Model

Does media coverage of macroeconomic news lead to a stronger comovement of business expectations and, accordingly, to a synchronisation of output across sectors? Which could be the mechanisms through which news media align sectoral expectations and production? We look at two potential channels, the intensity of media coverage and its content.

The first dimension, the intensity of media coverage, has been promoted by Carroll (2003). He finds that the intensity of news coverage influences the rate at which households acquire macroeconomic information. This result can be explained by the fact that greater news coverage lowers costs of information acquisition. But one can also draw on the logic of information-processing costs to justify the relevance of reporting intensity. As Sims (2003) points out, news media have an important information-processing function. An increase in news coverage of macroeconomic developments could thus signal that aggregate conditions have gained importance relative to firm-specific or sector-specific conditions. This is in line with agenda-setting theories, which

play an important role in media research, and which suggest that the primary function of media lies in influencing which issues people consider to be important.<sup>2</sup> No matter which cost argument applies, our hypothesis is that *the more macroeconomic news are disseminated by mass media, the more do business expectations assimilate across sectors because the latter share a greater common basis of information. As business expectations should contain information about production plans, output also comoves stronger across sectors.*

The second dimension of how media could influence the economy, the content of media coverage, has been emphasised by Doms and Morin (2004). They argue along the information-theoretic lines of Sims (2003) and stress that media convey (potentially erratic) signals about the state of the economy by the evaluative tone of news reports. Sheafer (2007) finds that the more negatively the media present the economy, the higher the perceived importance of economic issues among recipients. Apparently, people pay more attention to negative than to positive information. As an explanation, Lamla and Maag (2012) argue that agents have an asymmetric cost function when forecasting macroeconomic developments as they are more concerned about worsening than about improving economic conditions. When media put negative developments on the agenda, agents that normally do not care much about forming laborious forecasts now use more resources in their expectation formation process. Their information set converges towards the information employed by agents who form elaborate forecasts independently of media reporting. The results of Lamla and Maag (2012) confirm that disagreement of German households on future inflation reduces when the fraction of negative news (that is, news about rising inflation) increases. We apply these arguments to sectoral comovement of business expectations, which is, in a sense, an opposite concept to forecast disagreement. Our hypothesis is that *the more negatively media report about the economy, the larger is the common information set of sectors and, consequently, the more pronounced is sectoral comovement of business expectations and production.*

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<sup>2</sup>See McCombs and Shaw (1972) for seminal work. For a recent surveys of the agenda-setting literature see McCombs (2013).

To analyse whether news media have an independent effect on sectoral comovement, we use a two-stage estimation procedure inspired by Kilian (2009). In a first step, we identify structural media shocks and in a second step, we estimate the effect of such media shocks on both sectoral comovement of business expectations and sectoral comovement of output.

Following the literature on macroeconomic effects of media reports, we define media shocks as unexpected changes in media coverage of economic developments that are not reflected by incoming data on fundamentals. Veldkamp (2006), for instance, refers to news volume shocks with the term “media frenzies”, which are an abundance of information. Starr (2012) alludes to news tone shocks when speaking about “nonfundamental shocks to news coverage—that is, media portrayals of economic conditions more or less favorable than would be implied by the incoming economic data.” In fact, any aggregate shock could increase sectoral comovement if it is more important than sectoral shocks. To isolate the effect of news media, we have to control for the country’s current economic situation and its outlook. In the first stage we estimate the following autoregressive distributed lag (ADL) models:

$$\text{NEWS}_{k,t} = \alpha_k + \sum_{i=1}^p \beta_{k,i} \text{NEWS}_{k,t-i} + \gamma'_k \mathbf{ECON}_t + \varepsilon_{k,t}, \text{ with } k = 1, 2, \quad (1)$$

where  $\text{NEWS}_k$  is a measure of news volume ( $k = 1$ ) or a measure of the news tone ( $k = 2$ ), respectively.<sup>3</sup>  $\mathbf{ECON}$  is a vector of variables capturing information on the current and the expected state of the economy as available to media in month  $t$ .<sup>4</sup> The number of lags  $p$  of the respective news measure is determined by the Bayesian information criterion (BIC) from a maximum number of 12 lags, but the estimation results are robust to the use of the Akaike criterion.

Provided that the regressors are exogenous, the residuals from these regressions,  $\varepsilon_k$ , reflect structural media shocks that are not backed by actual

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<sup>3</sup>For details on the media data and the two measures of media coverage, please refer to Section 4.1.

<sup>4</sup>Details are given in Section 4.2.

economic developments and expectations. These media shocks can then be treated as predetermined with respect to sectoral comovement of business expectations and output. A change in comovement could have a contemporaneous effect on media coverage because the extent of sectoral comovement is related to the size of the aggregate quantity, which is then reported in the media. However, since we correct the news measures for information on aggregate developments, this channel can be excluded.

The majority of the time series from which the vector **ECON** is constructed are real-time data, which take into account publication lags. Due to this time structure, the exogeneity assumption holds automatically. But we also use financial market data, which are readily available, and we cannot exclude contemporaneous feedback effects from media coverage to financial markets. These feedback effects should lead to an underestimation of the media effects on comovement though; in fact, when we lag the financial data, the impulse responses become somewhat larger, so the true effects should lie in between.<sup>5</sup>

In the second stage we use a model along Kilian (2009) to examine whether news volume shocks and news tone shocks result in a change in sectoral comovement of business expectations (COMBE) and in sectoral comovement of output (COMIP):

$$\begin{aligned} \text{COMBE} &= \alpha_k + \sum_{h=0}^p \phi_{k,h} \hat{\varepsilon}_{k,t-h} + u_{k,t}, \quad k = 1, 2 \\ \text{COMIP} &= \beta_k + \sum_{h=0}^p \psi_{k,h} \hat{\varepsilon}_{k,t-h} + \nu_{k,t}, \quad k = 1, 2, \end{aligned} \quad (2)$$

where  $\hat{\varepsilon}_k$  are the residuals from Equation (1). The impulse response coefficients at horizon  $h$  correspond to  $\phi_h$  and  $\psi_h$ , respectively, and the number of lags  $p$ , which determines the maximum horizon of the impulse response function, is set to 12 months. Since the error terms  $u_t$  and  $\nu_t$  are potentially serially correlated, we use block-bootstrap confidence intervals to conduct

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<sup>5</sup>For a quantification, see Section 5.



inference on the response estimates.<sup>6</sup>

## 3 Measuring Sectoral Comovement

### 3.1 Connectedness Framework

When measuring sectoral comovement, most studies simply use pairwise sectoral correlations or correlations of the sectoral quantity with the aggregate quantity.<sup>7</sup> However, the correlation coefficients are conditional on market volatility and biased upward during volatile periods (Boyer, Gibson, and Loretan, 1997; Forbes and Rigobon, 2002; Loretan and English, 2000). They thus do not correct for the size of the shocks.

To overcome this flaw, we employ an alternative methodology developed by Diebold and Yilmaz (2009, 2012), which has been used for measuring interdependence between all sorts of markets: identical financial assets of different countries (Diebold and Yilmaz, 2009), various assets or asset classes within one country (Diebold and Yilmaz, 2011, 2012), and industrial production of several countries (Yilmaz, 2010). While the measure was initially presented as “spillover index”, it was later renamed into the somewhat broader term “connectedness measure” (Diebold and Yilmaz, 2011). In fact, the connectedness measure does not only capture spillovers of idiosyncratic shocks from one market to another, but also aggregate shocks. Furthermore, it takes into account that an aggregate shock does not necessarily impact all sectors exactly at the same time (Cooper and Haltiwanger, 1990). By covering responses to a shock up to a certain forecast horizon, the connectedness index accommodates such delayed reactions.

The connectedness measure is derived from the forecast error variance decomposition in a vector autoregressive (VAR) model, which splits the fore-

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<sup>6</sup>We choose 20,000 bootstrap replications and a block size of 4, but the results based on a block size of 8 are very similar. Note that the confidence intervals do not account for the fact that the residuals from the first-stage regression are generated regressors.

<sup>7</sup>Exceptions are Christiano and Fitzgerald (1998), and Hornstein (2000) who employ  $R^2$ -based measures of comovement, capturing the variation of the industry series explained by the variation of the aggregate series.

cast error variance of a variable into parts that are due to own shocks and parts that are due to shocks to the other variables in the system. While connectedness can be measured at different levels, we restrict ourselves to total or system-wide connectedness, which condenses all the information on the various interdependencies within the system into a single index. Total connectedness simply expresses the forecast error covariances shares, summed over all variables, as a percentage of total forecast error variation. While identification can rely on Cholesky decomposition, Diebold and Yilmaz (2012) exploit the generalised VAR framework developed by Koop, Pesaran, and Potter (1996), and Pesaran and Shin (1998). The advantage of generalised variance decompositions is that they are invariant to the ordering of the variables. So they are especially appealing when no *a priori* information for identification is available. Furthermore, Diebold and Yilmaz (2011) show that the total connectedness index derived from the generalised identification tends to follow the Cholesky-based measure very closely over time. As will be shown in Section 3.2, we also find this pattern for our data, which justifies using the generalised connected index. Details on the differences between the Cholesky-based and the generalised framework are laid out in Appendix A.

In a  $K \times K$  VAR model, the entries of the generalised forecast error variance decomposition are given by

$$w_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\text{MSE}[y_{i,t}(H)]} \text{ for } i, j = 1, \dots, K.$$

Each element  $w_{ij}^g(H)$  expresses the proportion of the  $H$ -step forecast error variance of some variable  $i$ ,  $\text{MSE}[y_{i,t}(H)]$ , which is accounted for by a standard deviation shock in variable  $j$  at time  $t$ .  $\sigma_{jj}$  is the variance of the shock to the  $j$ th equation,  $\Phi_h$  represent the  $K \times K$  MA-coefficient matrices for step  $h$ ,  $\Sigma_u$  is the variance-covariance matrix for the error vector  $u$ , and  $e_i$  and  $e_j$  are  $K \times 1$  selection vectors with unity as its  $i$ th or  $j$ th element, respectively, and zeros elsewhere.

Since the shocks are not orthogonalised, the row sums of the variance decomposition, that is, the sum of the contributions to the forecast error variance of variable  $i$ , are not necessarily equal to one,  $\sum_{j=1}^K w_{ij}^g(H) \neq 1$ .

Thus each element is normalised by the row sum,  $\tilde{w}_{ij}^g(H) = \frac{w_{ij}^g(H)}{\sum_{j=1}^K w_{ij}^g(H)}$ , so that  $\sum_{j=1}^K \tilde{w}_{ij}^g(H) = 1$  and  $\sum_{i,j=1}^K \tilde{w}_{ij}^g(H) = K$ .

Diebold and Yilmaz (2012) use these normalised entries of the generalised forecast error variance decomposition when deriving the total connectedness measure, which indicates the importance of covariance shares relative to own variances shares in the total forecast error variance. It is computed as the ratio of the sum of the off-diagonal elements to the sum of all elements in the  $H$ -step forecast error variance decomposition,

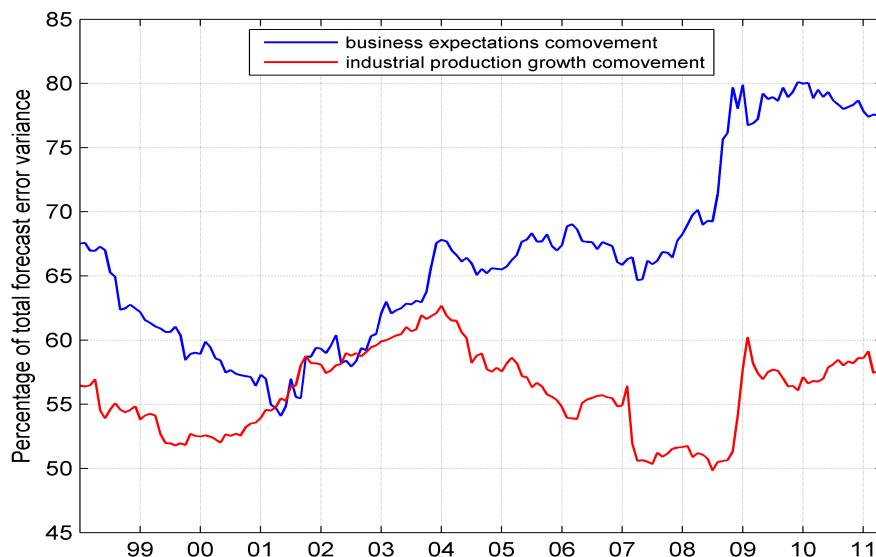
$$C^g(H) = \frac{\sum_{\substack{i,j=1, \\ i \neq j}}^K \tilde{w}_{ij}^g(H)}{\sum_{i,j=1}^K \tilde{w}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1, \\ i \neq j}}^K \tilde{w}_{ij}^g(H)}{K} \cdot 100. \quad (3)$$

Diebold and Yilmaz (2009, 2012) obtain a time-varying version,  $C_t^g(H)$ , by calculating the variance decomposition over a rolling window, which at each period only uses the most recent  $N$  periods. However, when using the connectedness measure as a dependent variable in a time series model, one needs to be aware of the fact that the rolling window produces a series based on overlapping observations. This creates a moving-average error term, and thus OLS estimates are inefficient and inference is biased (Harri and Brorsen, 2009). Furthermore,  $C_t^g(H)$  changes not only due to the new observation in  $t$ , but also due to the fact that observation  $(N+1)$  is dropped. To use COMBE and COMIP in Equation (2), we compute the connectedness measure over a recursive window, which uses all observations until  $t$ , and employ its first difference in order to capture the *change* of connectedness in  $t$ ,  $\Delta C_t^g(H)$ .

### 3.2 Sectoral Connectedness in German Manufacturing

We compute two time-varying measures of total connectedness, one reflecting sectoral comovement of business expectations, one capturing sectoral comovement of output. Our dataset contains seasonally adjusted monthly data from January 1991 to May 2011 for the German manufacturing industries, where the 24 2-digit sectors according to the European Classification of Economic Activities (NACE Rev.2; German version: WZ 2008) are aggregated to 14

Figure 1: Connectedness of sectoral business expectations and output (rolling window)



Notes: The shaded grey areas represent recessions as dated by the Economic Cycle Research Institute.

subdivisions.<sup>8</sup>

The connectedness measures are computed according to Equation (3) from two VAR models, one containing the monthly growth rates of the sectoral industrial production indexes and the other consisting of the sectoral Ifo business expectations indexes within the manufacturing industries.<sup>9</sup> For

<sup>8</sup>This middle category between the 1-digit and 2-digit level was abolished with the last revision of the NACE. It contains the following sectors: 1. food products, beverages and tobacco products; 2. textiles and wearing apparel; 3. leather and related products; 4. wood and products of wood and cork, except furniture; straw and plaiting materials; 5. paper and paper products; printing and reproduction of recorded media; 6. coke and refined petroleum products; 7. chemicals and chemical products; 8. rubber and plastic products; 9. other non-metallic mineral products; 10. basic metals and fabricated metal products, except machinery and equipment; 11. computer, electronic and optical products, and electrical equipment; 12. machinery and equipment; 13. motor vehicles, trailers, semi-trailers and other transport equipment; 14. furniture and other manufacturing.

<sup>9</sup>The business expectations index is computed by the Ifo Institute from data collected within its business survey, where nearly 7,000 firms (respectively sites) are asked about their appraisal of their current business situation as well as their short-term planning and expectations. The precise question used for the business expectations index is the following: “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

illustrative purposes, we first estimate the VAR models over a rolling window like in Diebold and Yilmaz (2009, 2012), where the lag length for each window is determined by the Bayesian information criterion (BIC). The window width of  $N = 83$  months has been chosen such that it is as large as possible, but that the resulting connectedness measures start in January 1998 at the latest. The forecast horizon has been set to  $H = 6$  months in order to capture delayed reactions to common shocks.<sup>10</sup> Figure 1 reveals that both sectoral output and business expectations exhibit strong comovement. On average, the sum of the covariances shares amount to 56 percent of total forecast error variation for industrial production growth and even to 67 percent for business expectations. The overall high level of connectedness can be explained by the fact that the sectors are not only affected by spillovers of industry-specific shocks, but also by economy-wide shocks. Both connectedness measures display cyclical behaviour and tend to rise in times of economic crises. The rise was especially pronounced in late summer 2008 at the beginning of the recent financial crisis. Until spring 2011, the comovement measures had not recovered.

While the level of connectedness depends on the forecast horizon, the pattern over time is merely affected. The upper panel of Figure 2 shows the percentage point change in connectedness, computed over a recursive window, which is the measure used in the subsequent analysis. The first window has again size  $N = 83$ , so that we can exploit the full data base later, and every following estimation window is increased by observation  $t$ . It can be seen that business expectations connectedness is characterised by larger movements than output comovement. This also holds—although to a smaller extent—for the qualitative measure of sectoral industrial production as captured by the same Ifo survey as the business expectations.<sup>11</sup> The biggest spikes of expectations connectedness are associated with the September 11 attacks<sup>12</sup>

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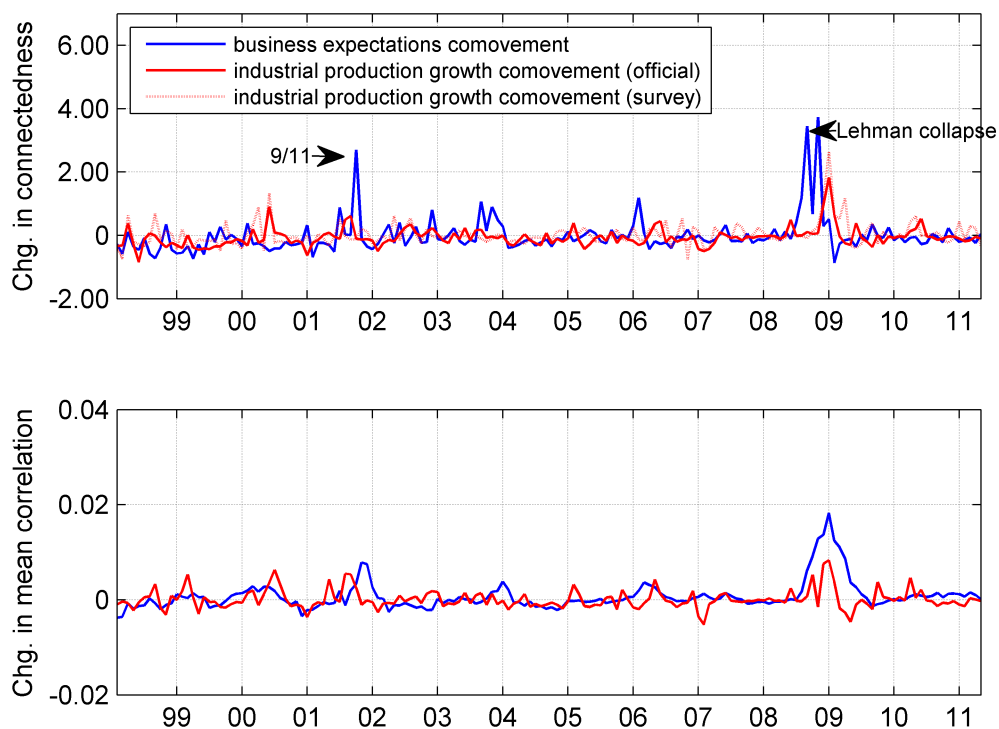
next six months.”

<sup>10</sup>We also tried forecast horizons of 1, 3 and 12 months, but the results merely change.

<sup>11</sup>The precise question is the following: “With respect to the business cycle, our domestic production activities concerning product group XY increased, roughly stayed the same, decreased in the last month.”

<sup>12</sup>In fact, the spike occurs one month later, in October 2001.

Figure 2: Change in comovement (recursive window)

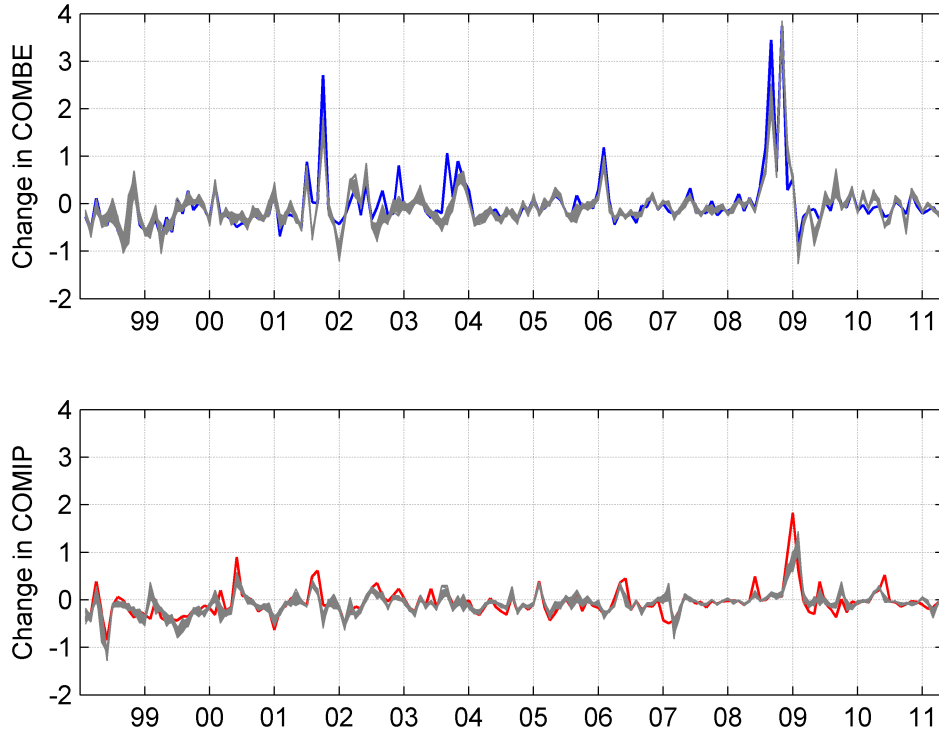


Notes: This figure displays the change in comovement measured by two alternative methods. The upper panel plots the percentage point change in the connectedness indexes, computed over a recursive window. The lower panel shows the difference of the average correlation of the sectoral quantities with the respective aggregate quantity, computed over a recursive window.

and the bankruptcy of Lehman Brothers, which marked the beginning of the recent financial crisis in September 2008. In contrast, the first difference of the average correlation of the sectoral business expectations indices and sectoral output with the respective aggregate quantity (computed over the same recursive window) seems less conclusive as a measure of comovement (see lower panel of Figure 2). Specifically, it tends to capture shocks later. For instance, the spark in business expectations comovement associated with 9/11 only appears in November 2001 and the one related to the outbreak of the recent financial crisis only in January 2009.

Finally, Figure 3 compares the change in the generalised connectedness

Figure 3: Comparison of generalised and Cholesky-based connectedness measures



Notes: The grey bands contains the (change in the) connectedness measures based on Cholesky decompositions with various orderings of the variables, while the red and the blue line are the (change in the) connectedness indices based on the generalised VAR model. COMBE: business expectations comovement; COMIP: industrial production growth comovement.

measures with the change in the Cholesky-based measures for various orderings of the variables. As there are as much as  $14!$  permutations of the 14 sectors variables, we choose a simple permutation scheme, leading to 93 different orderings: we put the first variable last, then the first two variables last, and so on. Subsequently, we put the second variable last, then the second and the third variable last, and so further and so on. It becomes clear that the generalised connectedness measures follow the pattern of the Cholesky-based measures closely. This allows us to proceed with the generalised connectedness measures and to avoid an *ad hoc* choice of variable

ordering.<sup>13</sup>

## 4 Measuring Aggregate Information

### 4.1 News Coverage

We retrieved data on news coverage from the media research institute Media Tenor, where humans conduct content analysis—without the use of a computer algorithm—of all economic news in a range of print and TV sources of at least five lines or five seconds, respectively. Our sample, which ranges from January 1998 to May 2011, contains macroeconomic reports from the most influential German media sources, among them six newspapers (DIE WELT, Frankfurter Allgemeine Zeitung, Süddeutsche Zeitung, Frankfurter Rundschau, BILD, BILD am Sonntag), four magazines (Focus, DER SPIEGEL, manager magazin, Wirtschaftswoche) and 17 TV broadcasts (Tagesthemen, Tagesschau, heute, heute journal, RTL aktuell, Sat.1 18:30, ProSieben Newstime, Fakt, Frontal 21, Kontraste, Monitor, Panorama, Plusminus, Report München, WISO and Berlin direkt).<sup>14</sup> As regards the content of the news reports, we do not only look at information on future aggregate productivity as in the theoretical model by Veldkamp and Wolfers (2007), but at any news about current and future cyclical developments in Germany and its most important export countries<sup>15</sup> that could be relevant to firms when forming their business expectations and when taking their production decisions. We include the following categories: Economic climate, gross domestic product and its components, Euro exchange rate, competitiveness, productivity, (un-)employment, labour costs, consumer confidence, insolvencies, start-ups,

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<sup>13</sup>In fact, the residuals are only weakly correlated, thus close to orthogonal. Tables A.1 and A.2 contain the residual correlation matrices when estimating the VAR models using the whole sample. The average (absolute) residual cross-correlation for the sectoral business expectation indices is 0.25 and for industrial production growth 0.28.

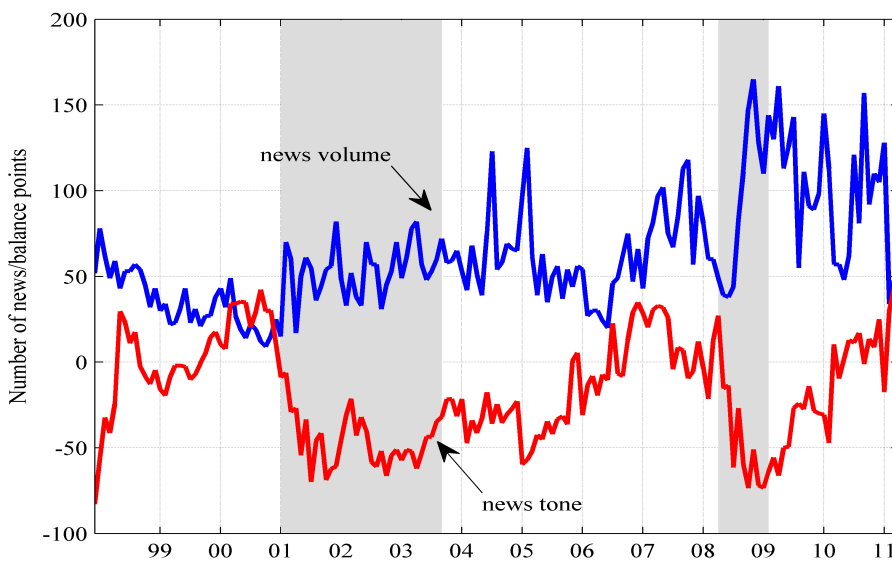
<sup>14</sup>For numbers on the scope of these media, see Table B.1.

<sup>15</sup>In 2012, the ten most important export countries for Germany were the following. France, USA, UK, the Netherlands, China, Austria, Italy, Switzerland, Belgium and Poland. We also include reports about the business cycle in the EU as well as the euro zone.



capital resources and bank lending, and future prospects. To make sure that we capture those news that could potentially influence the business expectations as reported in the Ifo Business Survey, we only use those reports published between the first and the 20th day of each month, which is the period during which firms fill out the questionnaires.

Figure 4: News indexes



Notes: The shaded grey areas represent recessions as dated by the Economic Cycle Research Institute.

From the media data we construct two measures of news coverage. Firstly, we capture the extent to which aggregate information is available by “news volume”, that is, the number of macroeconomic news reports per month.<sup>16</sup> The higher the number of news, the cheaper is any piece of macroeconomic information. Obviously, the price of a newspaper or TV access hardly varies over time. But as Veldkamp (2006) puts it, the number of stories in a mass medium is a proxy for the extent to which certain information is easily accessible from any number of high-demand, low-cost source of information. The more the media report about macroeconomic developments, the easier it is

<sup>16</sup>For the news volume index we could only use those media sources that are available for the whole time span: Tagesthemen, Tagesschau, heute journal, heute, RTL aktuell, SAT.1 18:30, Focus, and DER SPIEGEL.

to be well-informed without making an effort. Secondly, we quantify how journalists evaluate current economic developments by constructing a “news tone index”, which is a balance index of the proportion of positive and negative news per month. Media Tenor codes news reports as positive or negative if they contain either an explicit judgement or an implicit valuation from the context.

Figure 4 displays both news measures from 1998 to mid 2011. The news volume ranges between 9 and 165, with an average of around 60 reports per month. The news tone, which by construction can vary between -100 and 100 balance points, has an average of about -18. At the beginning of the recessions in 2001 and 2008, the news tone became considerably more negative. Overall, there is a negative relationship between news tone and news volume, with a correlation coefficient of -0.3. Thus, on average, an increase in the volume of media coverage is driven by a hike in the share of negative news.

## 4.2 Macroeconomic Environment

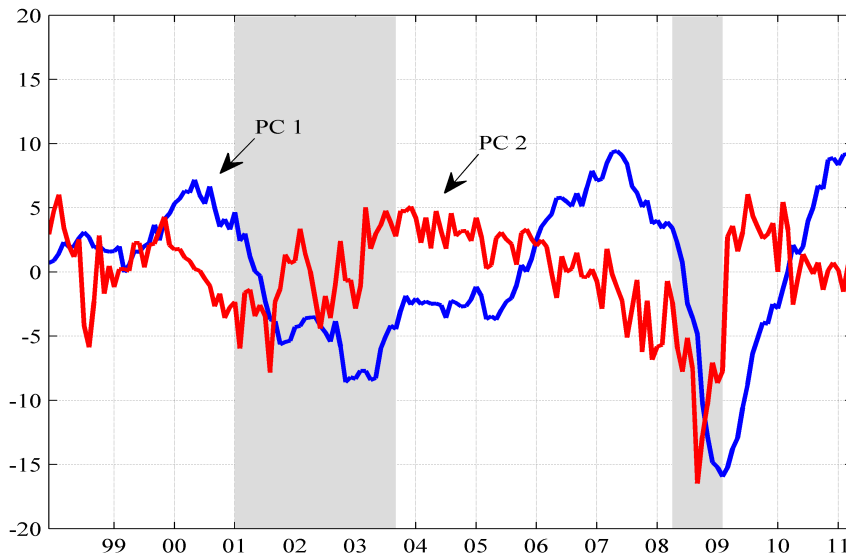
Macroeconomic events that are reported by news media stem from a variety of fields. Our media dataset already contains 13 broad categories, and each of them can be represented by numerous variables. To obtain a comprehensive picture of the present state of the economy as well as expectations regarding future economic developments in Germany, we compiled a large dataset consisting of 103 monthly time series. The choice of variables was driven by real-time considerations; to reproduce the information set that was available to media at the time of reporting, we have to take into account publication lags and revisions of macroeconomic data. The first group of time series covers the real economy and includes production, orders received, and employment. It is retrieved from the real-time database of the German Bundesbank, from which we also obtained real-time information on prices.<sup>17</sup> Another big bloc of time series are business surveys (most notably the Ifo Business Survey), consumer surveys, and composite indicators. These

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<sup>17</sup>[http://www.bundesbank.de/statistik/statistik\\_realtime.php](http://www.bundesbank.de/statistik/statistik_realtime.php)

time series are lagged one month, since they are usually not revised, but are not available before the end of the month. The next group covers financial markets and includes variables such as interest rates, term spreads, credit spreads, equity indices, and exchange rates. These data are readily available and are not revised. Finally, we also use surveys, composite indicators and equity indices of Germany's most important trading partners. As far as available, all data are adjusted for seasonal variations and for calendar working days variations. Also, they are standardised and transformed to stationarity. The list of variables as well as the respective stationarity transformation can be seen in Table C.1.

Figure 5: Principal components



Notes: The shaded grey areas represent recessions as dated by the Economic Cycle Research Institute.

Including all these variables into our models is impossible since we would run into dimensionality problems. So we performed a factor analysis, which is a popular data-reduction method in macroeconomics. The idea of a factor analysis is that a small number of latent factors,  $F_t$ , drive the comovements of an  $N$ -dimensional vector of time-series variables,  $X_t$ :

$$X_t = \Lambda F_t + e_t,$$

where  $e_t$  is an  $N \times 1$  vector of idiosyncratic disturbances and  $\Lambda$  represents the factor loadings that determine the contribution of each variable to the factor. These latent factors thus condense the information in our large dataset into one or few variables that proxy the macroeconomic situation and outlook. Stock and Watson (2002) show that when the number of time series  $N$  and the time dimension  $T$  are large, the factors can be consistently estimated using a simple method such as principal components (PC), and that the factors are estimated precisely enough to be treated as proper variables in subsequent regressions. We use the first two principal components that represent those linear combinations explaining the largest and second largest part of variance in the data. In fact, the number of factors that replace the information in a large number of time series is a crucial issue, and there are many different criteria that can be used. We primarily look at the fraction of variance which is accounted for by the factors. Table C.2 lists the estimation results for the first ten principal components. It can be seen that the first two principal components capture the bulk of variance in the data; the first accounts for 31% and the second for 13%. The variance contribution of all other principal components is below 10%. Figure 5 gives a graphical representation of the first two principal components, which are used in the baseline specifications ( $\mathbf{ECON}'_t = (\text{PC1}_t, \text{PC2}_t)$ ). As a robustness check, we also include the third and the fourth principal component in the regressions, and the results are nearly unchanged.

## 5 Empirical Results

After having described how the variables are measured, we can now present our results when estimating models (1) and (2). Table 1 reports the first-stage regression results with news volume as dependent variable. With an  $R^2$  of 57%, model fit is reasonably high. Time-dependence of news volume seems to be low; the Bayesian information criterion chose just one lag. Furthermore, the coefficients of the first two principal components of the macroeconomic dataset are significant and have the expected sign. Since news volume includes negative as well as positive (and neutral) news reports, we compute

the absolute deviation of the principal components from the respective mean (a.d.). So the more unusual the macroeconomic situation is, the more intense is the news coverage. Figure 6 gives a graphical impression of the results. The upper panel compares the actual number of news reports with its fitted value, and the lower panel plots the corresponding residual, the news volume shock.<sup>18</sup> News volume shocks seem to be especially pronounced whenever a new cyclical phase begins; at the outbreak of the recession in 2001, in the beginning of the recovery mid 2004 to early 2005, as well as in the beginning and in the aftermath of the recent financial and economic crisis.

Table 1: First-stage regression for news volume

<i>Dependent variable: news volume</i>			
Variable	Coefficient	<i>t</i> -statistic	<i>t</i> -probability
CONSTANT	10.30	2.81	0.01
NEWS VOLUME(-1)	0.57	7.05	0.00
PC1 (a.d.)	2.14	3.34	0.01
PC2 (a.d.)	2.40	3.04	0.00
$R^2$	0.57	Durbin-Watson	2.21
$\bar{R}^2$	0.56	Nobs	159
$\sigma^2$	504.96	Nvars	4

Notes: a.d. - absolute deviation from the mean. Inference is based on robust standard errors.

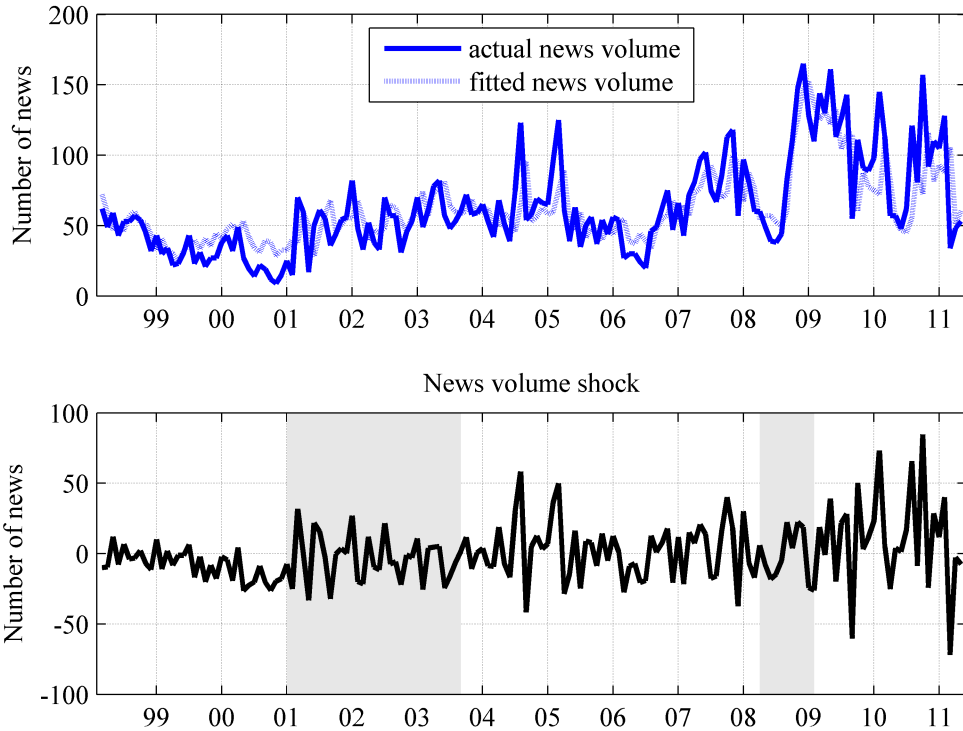
Table 2: First-stage regression for news tone

<i>Dependent variable: news tone</i>			
Variable	Coefficient	<i>t</i> -statistic	<i>t</i> -probability
CONSTANT	-8.61	-4.98	0.00
NEWS TONE(-1)	0.48	6.68	0.00
PC1	2.31	6.00	0.00
PC2	0.59	1.83	0.07
$R^2$	0.77	Durbin-Watson	2.12
$\bar{R}^2$	0.77	Nobs	159
$\sigma^2$	216.60	Nvars	4

Table 2 shows the first-stage regression results when using the news tone index as dependent variable. Model fit is even higher here with an  $R^2$  of 77%. The news tone also changes rather quickly; again, the BIC selected only one lag. Here, the second principal component (PC2) is only significant

<sup>18</sup>Apparently, the residuals are heteroskedastic, so we use robust standard errors when estimating the first stage for news volume.

Figure 6: First-stage regression for news volume

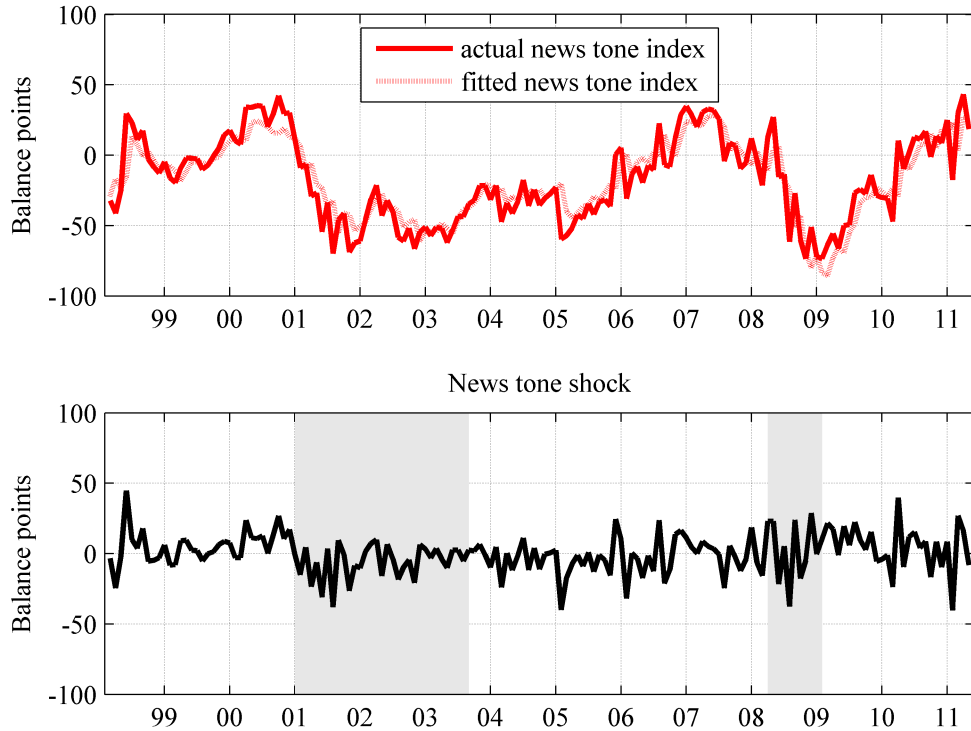


Notes: The shaded grey areas represent recessions as dated by the Economic Cycle Research Institute.

at the 10%-level, but both variables have the expected sign; the more positive the macroeconomic environment becomes, the more positive is the tone of media reports. But as can be seen in Figure 7 news media tend to exaggerate the fundamental data; in a positive (negative) macroeconomic environment the news tone tends to be even more positive (negative). This leads to predominantly negative news tone shocks during the recession between 2001 and autumn 2003 and during the Great Recession in 2008 (shaded grey areas), and predominantly positive news tone shocks in periods of economic recovery.

Finally, Figure 8 summarises the cumulated responses of the level of business expectations comovement (COMBE) as well as of output growth comovement (COMIP) among sectors to a positive news volume shock and a negative news tone shock, respectively. The shocks have been standardised

Figure 7: First-stage regression for news tone

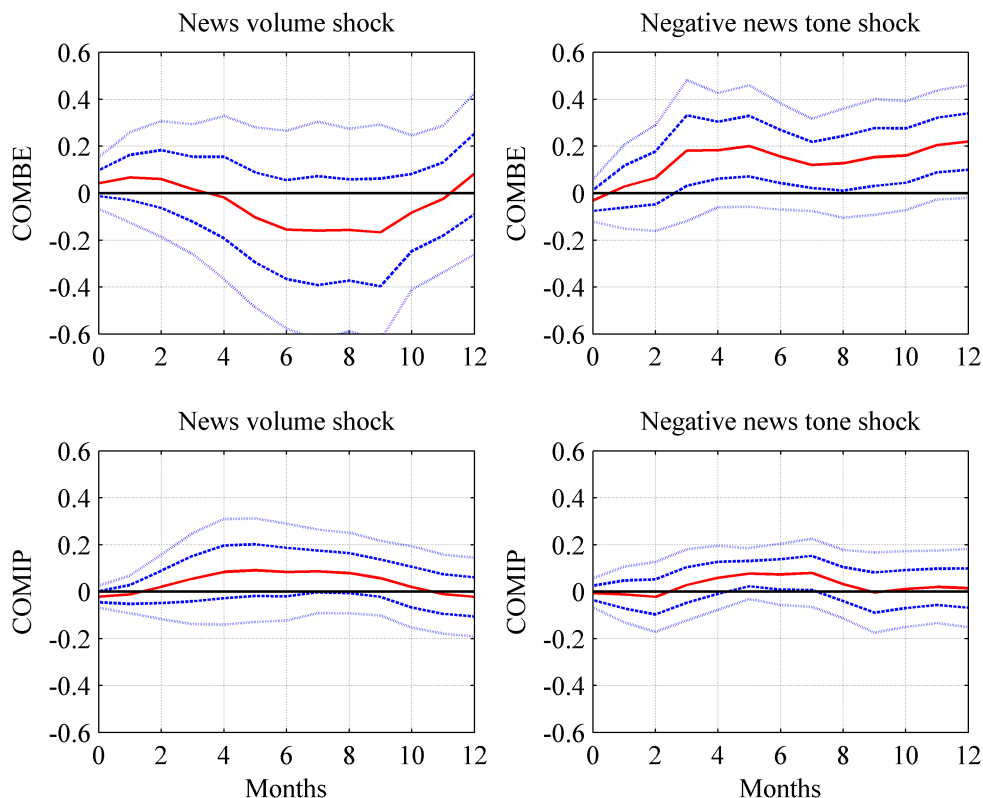


Notes: The shaded grey areas represent recessions as dated by the Economic Cycle Research Institute.

in order to be comparable. It can be seen that an innovation in news volume does not have a significant effect, neither on sectoral business expectations comovement, nor on output comovement. A negative news tone shock, however, has a positive impact on comovement of sectoral business expectations. The effect becomes significant after three months and reaches its maximum at month 12, when comovement has risen by 0.22 percentage points. There is also a delayed positive response of production comovement, which becomes significant after five months. However, the effect fades quickly and its size is much smaller with a cumulative increase of 0.08 percentage points after seven months.<sup>19</sup>

<sup>19</sup>When lagging the financial data one month, comovement of business expectations rises by 0.25 percentage points after 12 months, and comovement of output by 0.10 percentage points after seven months in response to a negative news tone shock. The true effects

Figure 8: Responses of sectoral comovement to media shocks



Notes: The plots show the cumulated responses estimated from models (9) and (10). The one and two standard deviation confidence bands are computed with a block bootstrap, using 20,000 bootstrap replications and a block size of 4. COMBE: business expectations comovement; COMIP: industrial production comovement.

As a robustness check, we run the regressions for a restricted sample excluding the recent financial and economic crisis, where its beginning is dated on the bankruptcy of Lehman Brothers in September 2008. Appendix D shows that the results only hold partly; the effect of a news tone shock on sectoral comovement of output remains significant, whereas the response of business expectations comovement does not.

Apparently, the impact of media coverage was especially strong during the recent recession. To assess the economic relevance of news tone shocks in that period, we implement a counterfactual analysis, where we set all news should lie somewhere in between.



tone shocks equal to zero and compare the counterfactual time series with the actual change in comovement. Figure 9 plots both time series for business expectations and industrial production from April 2008, the beginning of the recession, to March 2009. The pronounced increase of sectoral business expectations comovement by 3.5 percentage points in September 2008 and by 3.7 percentage points in November 2008 would have been around 0.3 and 0.5 percentage points lower, respectively. This corresponds to a contribution of 8% and 13% of the news tone shocks in these months to the rise in business expectations comovement. Output comovement rose somewhat later, in January 2009 with an increase by 1.8 percentage points, where the effect of the news tone shock also amounts to 13%.<sup>20</sup>

Taken together, our results put the importance of a common information base as source of sectoral comovement into perspective. Most importantly, we do not find evidence for the hypothesis that the more abundant media coverage of macroeconomic news is, the more do business expectations or production align across sectors because the latter share a greater common basis of information. In fact, we find the news volume effects to be insignificant. Contrarily, the tone of news coverage seems to be more decisive for sectoral comovement. The larger the fraction of negative news, the more do firms adapt their expectations in a similar vein across sectors. This effect was especially important in the recent recession. Finally, the impact of a news tone shock on comovement of sectoral output—while robust to sample choice—is only small and short-lived.

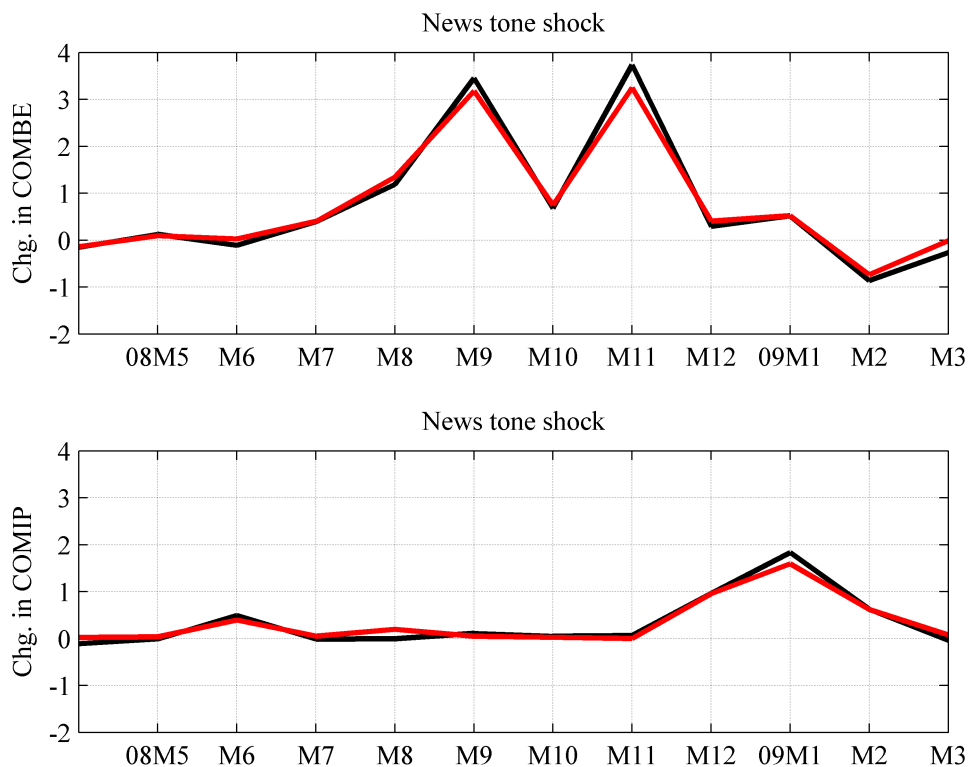
## 6 Conclusion

The synchronised up and down of output across sectors is a stylised fact of the business cycle. Yet, it is unclear why output is more correlated across sectors than productivity. Veldkamp and Wolfers (2007) build a model of information complementarities as a new explanation for this excess comovement puzzle. They suggest that since information of general interest is cheaper

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<sup>20</sup>Figure E.1 displays the counterfactual analysis for the whole sample and both media shocks.

Figure 9: Counterfactual analysis



Notes: The black lines represent the actual change in sectoral business expectations comovement (COMBE) and output comovement (COMIP). The red lines depict the corresponding counterfactual time series, where all news tone shocks are set equal to zero.

than tailored information, firms rely on information about future aggregate productivity, from which they draw conclusions about their own sector's productivity. As the production decisions of many firms are based on similar information, sectoral output becomes more correlated.

Carroll (2003) and Sims (2003), rooted in the sticky information and rational inattention literature, suggest that mass media are an important transmitter of macroeconomic information that can influence economic agents' expectations. We study empirically whether the intensity of news coverage and its overall tone have an impact on how strongly both business expectations and output comove across sectors. Thereby, we employ the connectedness measure by Diebold and Yilmaz (2009, 2012) as a new measure of sectoral

comovement and use a detailed dataset on media coverage of macroeconomic news for Germany.

Overall, the evidence for aggregate information that is transmitted by news media as a source of sectoral comovement is moderate. In particular, the news volume channel, which refers to arguments of information costs, does not significantly affect sectoral comovement, neither for business expectations nor for production. The news tone, on the contrary, seems to be of importance. A negative news tone shock has a significant effect on sectoral comovement of business expectations; the larger the fraction of negative news reports, the more do the sectors adjust their expectations in a similar vein. But the response of sectoral output is relatively small and fades out quickly. Finally, excess comovement remains a puzzle.

## **Acknowledgements**

I am indebted to Johannes Mayr who introduced me to the connectedness framework. Moreover, I would like to thank Kai Carstensen and Steffen Elstner for helpful comments and suggestions. Many thanks also go to Media Tenor for providing data.

## Appendix

### A Cholesky and Generalised Forecast Error Variance Decompositions

Consider a covariance-stationary  $K$ -variable VAR( $p$ ),

$$y_t = \sum_{i=1}^p A_i y_{t-i} + u_t,$$

where  $A_i$  are  $K \times K$  coefficient matrices and  $u_t$  is a disturbance term with  $u \sim (0, \Sigma_u)$ . The moving average (MA) representation is given by

$$y_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i}. \quad (4)$$

The traditional impulse response function is defined as the difference between two realisations of  $y_{t+h}$  that are identical up to time  $t-1$ . In time  $t$ , one realisation is hit by a shock of size  $\delta$  ( $u_t = \delta$ ), whereas the other is not. Furthermore, it is assumed that no other shocks occur between time  $t$  and  $t+h$ . It is given by

$$\begin{aligned} I_y(h, \delta, \Omega_{t-1}) &= \mathbb{E}[y_{t+h} | u_t = \delta, u_{t+1} = \dots = u_{t+h} = 0, \Omega_{t-1}] \\ &\quad - \mathbb{E}[y_{t+h} | u_t = 0, u_{t+1} = \dots = u_{t+h} = 0, \Omega_{t-1}]. \end{aligned} \quad (5)$$

The traditional impulse response function is independent of  $\Omega_{t-1}$ , the history of the economy up to time  $t-1$ , but it depends on the composition of the shocks defined by the vector  $\delta$ , since the innovations are typically correlated contemporaneously. In order to identify the shocks, a common solution is to orthogonalise the error terms. The model is transformed using a Cholesky decomposition of the variance-covariance matrix  $\Sigma_u$ ,  $PP' = \Sigma_u$ , where  $P$  is a  $K \times K$  lower triangular matrix. Equation (4) can now be written

as

$$y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i}, \quad (6)$$

where  $\Theta_i := \Phi_i P$ , and the components of the new error vector  $w_t := P^{-1}u_t$  are uncorrelated and have unit variance,  $\Sigma_w = I_K$ . Using Equations (5) and (6), the orthogonalised impulse response function of a unit shock to the  $j$ th equation on  $y_{t+h}$  is given by

$$I_j^o(h) = \Phi_h P e_j, \text{ with } h = 0, 1, 2, \dots,$$

where  $e_j$  is a  $K \times 1$  selection vector with unity as its  $j$ th element and zeros elsewhere.

Yet, the Cholesky-based impulse responses and forecast error variance decompositions depend on the ordering of the variables. In order to avoid this shortcoming, the generalised VAR framework follows a different approach. Instead of shocking all elements of  $u_t$  and orthogonalising them, only one element  $u_{jt}$  is shocked. The effects of other shocks at time  $t$  are averaged out using the typical correlation observed historically between the errors. Hence, the generalised impulse response function represents the average response to a shock to  $u_{jt}$ , given the variance-covariance matrix  $\Sigma_u$  as observed in the history  $\Omega_{t-1}$ ,

$$I_j^g(h, \delta_j, \Omega_{t-1}) = \mathbb{E}[y_{t+h} | u_{jt} = \delta_j, \Omega_{t-1}] - \mathbb{E}[y_{t+h} | \Omega_{t-1}]. \quad (7)$$

Koop, Pesaran, and Potter (1996) show that under the assumption that  $u_t$  has a multivariate normal distribution, its conditional expectation is given by

$$\mathbb{E}[u_t | u_{jt} = \delta_j] = \Sigma_u e_j \sigma_{jj}^{-1} \delta_j. \quad (8)$$

Using Equations (4), (7) and (8), the unscaled  $h$ -step generalised impulse response to a shock in the  $j$ th equation at time  $t$  can be expressed as

$$\left( \frac{\Phi_h \Sigma_u e_j}{\sqrt{\sigma_{jj}}} \right) \left( \frac{\delta_j}{\sqrt{\sigma_{jj}}} \right).$$

By setting  $\delta_j = \sqrt{\sigma_{jj}}$ , we get the  $h$ -step generalised impulse response function to a standard deviation shock to the  $j$ th equation in time  $t$ ,

$$I_j^g(h) = \sigma_{jj}^{-1/2} \Phi_h \Sigma_u e_j, \text{ with } h = 1, 2, \dots \quad (9)$$

The generalised impulse response function reduces to the Cholesky-based impulse response function when the covariance matrix  $\Sigma_u$  is diagonal.

Pesaran and Shin (1998) show how the generalised impulse responses from Equation (9) can be used to derive the forecast error variance decomposition, which lies at the heart of the connectedness measure. When using a Cholesky factorisation, the proportion of the  $H$ -step forecast error variance of some variable  $i$  which is accounted for by shocks in variable  $j$ , is given by<sup>21</sup>

$$w_{ij}^o(H) = \frac{\sum_{h=0}^{H-1} (e_i' \Phi_h P e_j)^2}{\text{MSE}[y_{i,t}(H)]} \text{ for } i, j = 1, \dots, K.$$

Analogously, the entries of the generalised forecast error variance decomposition are given by<sup>22</sup>

$$w_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\text{MSE}[y_{i,t}(H)]} \text{ for } i, j = 1, \dots, K.$$

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<sup>21</sup>See Lütkepohl (2005) for the derivation.

<sup>22</sup>Pesaran and Shin (1998) scale the numerator with the variance of the variable to be decomposed,  $\sigma_{ii}$ . However, since the numerator should contain the sum of the squared impulse responses,  $\sigma_{ii}$  should in fact be replaced by  $\sigma_{jj}$ , the variance of the shock to the  $j$ th equation as in Diebold and Yilmaz (2011).

Table A.1: Residual correlation matrix for business expectations

	food	text	leath	wood	paper	coke	chem	rubb	n-met	metal	comp	mach	vehic	furn
food	1	0.12	0.03	0.07	0.03	0.00	0.10	0.17	0.26	0.16	0.10	0.06	0.01	0.12
text	0.12	1	0.22	0.17	0.21	0.16	0.15	0.31	0.23	0.25	0.25	0.22	0.20	0.18
leath	0.03	0.22	1	0.15	0.12	0.03	0.12	0.13	0.14	0.09	0.06	0.17	0.07	0.11
wood	0.07	0.17	0.15	1	0.07	0.04	0.06	0.20	0.25	0.23	0.11	0.08	0.08	0.22
paper	0.03	0.21	0.12	0.07	1	0.09	0.26	0.24	0.11	0.35	0.36	0.35	0.21	0.24
coke	0.00	0.16	0.03	0.04	0.09	1	0.20	0.03	0.05	0.12	0.20	0.12	0.09	0.11
chem	0.10	0.15	0.12	0.06	0.26	0.20	1	0.26	0.25	0.46	0.42	0.40	0.25	0.18
rubb	0.17	0.31	0.13	0.20	0.24	0.03	0.26	1	0.36	0.33	0.32	0.39	0.26	0.31
n-met	0.26	0.23	0.14	0.25	0.11	0.05	0.25	0.36	1	0.28	0.19	0.28	0.12	0.22
metal	0.16	0.25	0.09	0.23	0.35	0.12	0.46	0.33	0.28	1	0.48	0.57	0.31	0.34
comp	0.10	0.25	0.06	0.11	0.36	0.20	0.42	0.32	0.19	0.48	1	0.50	0.34	0.32
mach	0.06	0.22	0.17	0.08	0.35	0.12	0.40	0.39	0.28	0.57	0.50	1	0.30	0.25
vehic	0.01	0.20	0.07	0.08	0.21	0.09	0.25	0.26	0.12	0.31	0.34	0.30	1	0.25
furn	0.12	0.18	0.11	0.22	0.24	0.11	0.18	0.31	0.22	0.34	0.32	0.25	0.25	1

Notes: This table reports the residual correlations for the sectoral business expectations indices resulting from a VAR model when estimated over the whole sample. The sectors within German manufacturing are the following. 1. food products, beverages and tobacco products; 2. textiles and wearing apparel; 3. leather and related products; 4. wood and products of wood and cork, except furniture; straw and plaiting materials; 5. paper and paper products; printing and reproduction of recorded media; 6. coke and refined petroleum products; 7. chemicals and chemical products; 8. rubber and plastic products; 9. other non-metallic mineral products; 10. basic metals and fabricated metal products, except machinery and equipment; 11. computer, electronic and optical products, and electrical equipment; 12. machinery and equipment; 13. motor vehicles, trailers, semi-trailers and other transport equipment; 14. furniture and other manufacturing.

Table A.2: Residual correlation matrix for industrial production

	food	text	leath	wood	paper	coke	chem	rubb	n-met	metal	comp	mach	vehic	furn
food	1	-0.03	-0.08	0.02	0.17	0.03	0.03	-0.02	-0.03	-0.10	-0.08	0.05	-0.09	0.00
text	-0.03	1	0.24	0.22	0.27	0.01	0.18	0.11	0.17	0.41	0.38	0.29	0.31	0.48
leath	-0.08	0.24	1	0.23	0.09	0.04	0.16	0.20	0.11	0.31	0.19	0.03	0.33	0.24
wood	0.02	0.22	0.23	1	0.37	0.09	0.34	0.25	0.58	0.51	0.39	0.25	0.31	0.44
paper	0.17	0.27	0.09	0.37	1	0.03	0.18	0.35	0.29	0.35	0.34	0.17	0.23	0.20
coke	0.03	0.01	0.04	0.09	0.03	1	0.07	0.06	0.15	0.02	0.14	0.02	0.03	-0.02
chem	0.03	0.18	0.16	0.34	0.18	0.07	1	0.19	0.35	0.38	0.22	-0.03	0.27	0.18
rubb	-0.02	0.11	0.20	0.25	0.35	0.06	0.19	1	0.33	0.45	0.35	0.21	0.39	0.21
n-met	-0.03	0.17	0.11	0.58	0.29	0.15	0.35	0.33	1	0.40	0.30	0.10	0.18	0.24
metal	-0.10	0.41	0.31	0.51	0.35	0.02	0.38	0.45	0.40	1	0.55	0.35	0.40	0.57
comp	-0.08	0.38	0.19	0.39	0.34	0.14	0.22	0.35	0.30	0.55	1	0.47	0.41	0.46
mach	0.05	0.29	0.03	0.25	0.17	0.02	-0.03	0.21	0.10	0.35	0.47	1	0.31	0.21
vehic	-0.09	0.31	0.33	0.31	0.23	0.03	0.27	0.39	0.18	0.40	0.41	0.31	1	0.27
furn	0.00	0.48	0.24	0.44	0.20	-0.02	0.18	0.21	0.24	0.57	0.46	0.21	0.27	1

Notes: This table reports the residual correlations for sectoral industrial production growth resulting from a VAR model when estimated over the whole sample. The sectors within German manufacturing are the following. 1. food products, beverages and tobacco products; 2. textiles and wearing apparel; 3. leather and related products; 4. wood and products of wood and cork, except furniture; straw and plaiting materials; 5. paper and paper products; printing and reproduction of recorded media; 6. coke and refined petroleum products; 7. chemicals and chemical products; 8. rubber and plastic products; 9. other non-metallic mineral products; 10. basic metals and fabricated metal products, except machinery and equipment; 11. computer, electronic and optical products, and electrical equipment; 12. machinery and equipment; 13. motor vehicles, trailers, semi-trailers and other transport equipment; 14. furniture and other manufacturing.



## B Scope of Media Coverage

Table B.1: Media scope

<b>Newspapers</b> (sold issues as of 4/2013)	BILD	2,438,684
	BILD am Sonntag	1,259,622
	Süddeutsche Zeitung	400,647
	Frankfurter Allgemeine Zeitung	329,705
	DIE WELT	222,722
	Frankfurter Rundschau	no data
<b>Magazines</b> (sold issues as of 4/2013)	DER SPIEGEL	842,322
	Focus	509,983
	Wirtschaftswoche	154,261
	manager magazin	107,950
<b>TV broadcasts</b> (mio. viewers as of 2012)	Tagesschau	8.79
	Report München	3.74
	RTL aktuell	3.54
	heute-journal	3.53
	Fakt	3.53
	heute	3.52
	Berlin direkt	2.97
	Panorama	2.87
	Kontraste	2.71
	Monitor	2.67
	Plusminus	2.65
	Frontal 21	2.57
	Tagesthemen	2.51
	WISO	2.5
	Sat.1 Nachrichten	1.79
ProSieben Newstime	0.8	

The data are retrieved from the following websites. [http://www.ard.de/home/intern/fakten/ard-mediendaten/Zuschauer\\_und\\_Marktanteile\\_der\\_Fernsehnachrichten/409020/index.html](http://www.ard.de/home/intern/fakten/ard-mediendaten/Zuschauer_und_Marktanteile_der_Fernsehnachrichten/409020/index.html), [http://www.ard.de/home/intern/fakten/ard-mediendaten/Zuschauer\\_und\\_Marktanteile\\_von-Informationssendungen/409102/index.html](http://www.ard.de/home/intern/fakten/ard-mediendaten/Zuschauer_und_Marktanteile_von-Informationssendungen/409102/index.html), and <http://daten.ivw.eu>

## C Macroeconomic Data and Principal Components

Table C.1: List of macroeconomic variables

Series	Transformation
<b>REAL ECONOMY</b>	
Orders received, industry, constant prices, cadj, sadj	1
Orders received, intermediate goods, constant prices, cadj, sadj	1
Orders received, capital goods, constant prices, cadj, sadj	1
Orders received, consumer goods, constant prices, cadj, sadj	1
Production, industry, constant prices, cadj, sadj	1
Production, intermediate goods, constant prices, cadj, sadj	1
Production, capital goods, constant prices, cadj, sadj	1
Production, consumer goods, constant prices, cadj, sadj	1
Production, durable consumer goods, constant prices, cadj, sadj	1
Production, non-durable, constant prices, cadj, sadj	1
Production, energy, constant prices, cadj, sadj	1
Employed persons, overall economy, sadj	1
<b>PRICES</b>	
Consumer price index, all categories, sadj	1
<b>FINANCIAL MARKETS</b>	
Day-to-day money market rate, Frankfurt, monthly avg.	2
Three-month money market rate, Frankfurt, monthly avg.	2
Discount rate/short term euro repo rate, monthly avg.	2
Long-term government bond yield, 9-10 yrs, monthly avg.	2
Yields on fully taxed bonds outstanding, public bonds, monthly avg.	2
Yields on fully taxed bonds outstanding, corporate bonds, monthly avg.	2
Yields on listed federal bonds outstanding, 3-5 yrs, monthly avg.	2
Yields on listed federal bonds outstanding, 5-8 yrs, monthly avg.	2
term spread (10 yrs - Policy instrument), monthly avg.	0
term spread (10 yrs - 1 day, monthly avg.	0
term spread (10 yrs - 3 months), monthly avg.	0
1 Day - policy rates, monthly avg.	0
Corporate - treasury Bond, monthly avg.	0
Spread AA - gov, monthly avg.	0
Spread BBBnf - gov, monthly avg.	0

<b>Series</b>	<b>Transformation</b>
Spread BBF - gov, monthly avg.	0
DAX share price index, monthly avg.	1
Nominal effective exchange rate, monthly avg., sadj	1
VDAX - new volatility index, monthly avg.	1
VDAX - old volatility index, monthly avg.	1
Corporate non-financial AA, monthly avg.	1
Corporate non-financial BBB, monthly avg.	1
Corporate financial BBB, monthly avg.	1
<b>SURVEYS AND COMPOSITE INDICATORS</b>	
ZEW present economic situation	0
ZEW economic sentiment indicator	0
Ifo business climate index, sadj.	0
Ifo business expectations, sadj.	0
Ifo assessment of business situation, sadj.	0
Ifo business climate index, manufacturing, sadj.	0
Ifo business expectations, manufacturing, sadj.	0
Ifo assessment of business situation, manufacturing, sadj.	0
Ifo business climate index, construction, sadj.	0
Ifo business expectations, construction, sadj.	0
Ifo assessment of business situation, construction, sadj.	0
Ifo business climate index, wholesale trade, sadj.	0
Ifo business expectations, wholesale trade, sadj.	2
Ifo assessment of business situation, wholesale trade, sadj.	2
Ifo business climate index, retail trade, sadj.	0
Ifo business expectations, retail trade, sadj.	0
Ifo assessment of business situation, retail sale, sadj.	0
GfK business cycle expectations, sadj.	0
GfK income expectations, sadj.	0
GfK willingness to buy, sadj.	0
GfK prices next 12 months, sadj.	0
GfK prices last 12 months	0
GfK unemployment next 12 months, sadj.	0
GfK financial situation last 12 months	2
GfK financial situation next 12 months	0
GfK economic situation last 12 months	0
GfK economic situation next 12 months	0
GfK major purchases at present, sadj.	0
GfK major purchases over next 12 months	0

<b>Series</b>	<b>Transformation</b>
GfK savings at present, sadj.	2
GfK savings over next 12 months, sadj.	0
GfK consumer confidence index, sadj.	0
GfK consumer confidence climate (balance), sadj.	0
DG ECFIN consumer confidence indicator, sadj.	0
DG ECFIN unemployment over next 12 months, sadj.	0
DG ECFIN statement on financial situation of household, sadj.	2
DG ECFIN industrial confidence indicator	0
DG ECFIN services confidence indicator	2
DG ECFIN retail confidence indicator	2
DG ECFIN construction confidence indicator	2
DG ECFIN economic sentiment indicator	0
EarlyBird	0
<b>INTERNATIONAL INDICATORS</b>	
DG ECFIN, France, economic sentiment indicator	0
DG ECFIN, UK, economic sentiment indicator	0
DG ECFIN, Netherlands , economic sentiment indicator	0
DG ECFIN, Austria, economic sentiment indicator	0
DG ECFIN, Italy, economic sentiment indicator	0
DG ECFIN, Belgium, economic sentiment indicator	0
DG ECFIN, Poland, economic sentiment indicator	0
DG ECFIN, EU, economic sentiment indicator	0
DG ECFIN, Eurozone, economic sentiment indicator	0
OECD, US, CLI, amplitude adj., sadj.	0
OECD, China, CLI, amplitude adj., sadj.	0
OECD, Switzerland, CLI, amplitude adj., sadj.	0
US Univ. of Michigan consumer sentiment, expectations	0
EM Euro-Coin real time estimates, sadj.	1
France, CAC 40, monthly avg.	1
US, Dow Jones Composite Average, monthly avg.	1
UK, FT30 Index, monthly avg.	1
Netherlands, AEX Index, monthly avg.	1
China, SSE Composite Index, monthly avg.	1
Austria, ATX, monthly avg.	1
Italy, FTSE MIB, monthly avg.	1
Switzerland, SMI, monthly avg.	1
Belgium, BEL20, monthly avg.	1
Poland, WIG, monthly avg.	1

<b>Series</b>	<b>Transformation</b>
EURO STOXX 50, monthly avg.	1

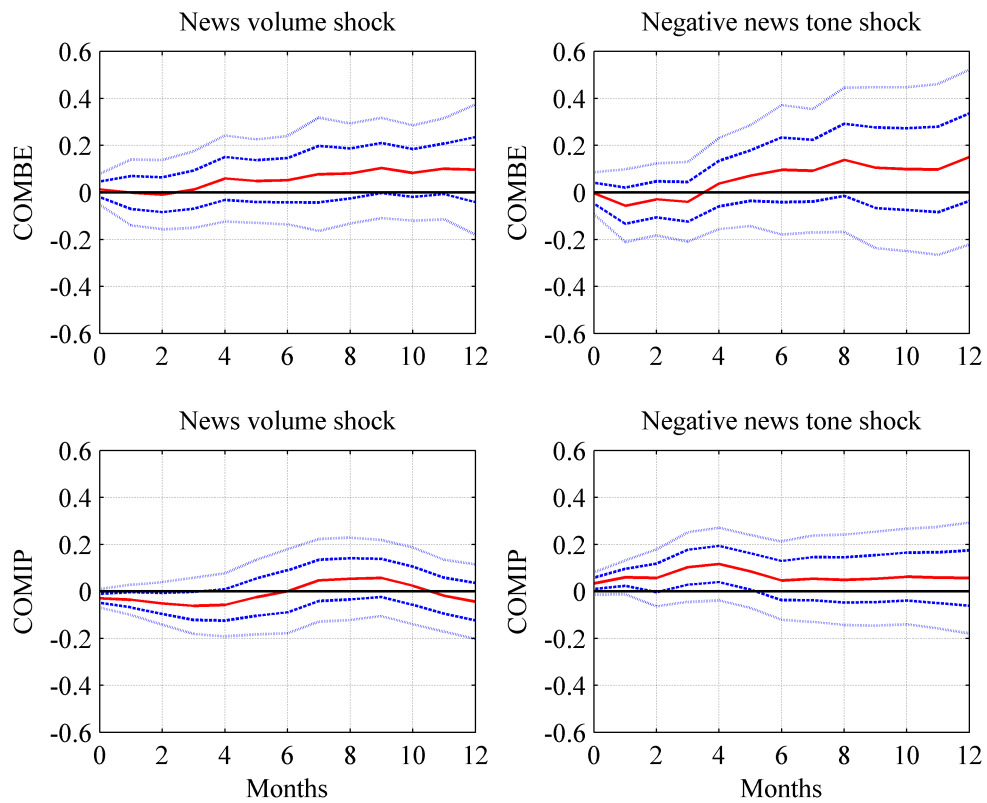
Transformation - 0:  $x_t$ , 1:  $\ln(x_t/x_{t-1})$ , 2:  $x_t - x_{t-1}$ .

Table C.2: Principal components analysis

Principal component	Eigenvalue	Variance proportion	Cumulative variance proportion
PC 1	31.86	0.31	0.31
PC 2	13.63	0.13	0.44
PC 3	9.62	0.09	0.53
PC 4	6.33	0.06	0.59
PC 5	4.93	0.05	0.64
PC 6	4.56	0.04	0.68
PC 7	3.56	0.03	0.72
PC 8	2.16	0.02	0.74
PC 9	1.99	0.02	0.76
PC 10	1.79	0.02	0.77

## D Results for Restricted Sample (01/1998-08/2008)

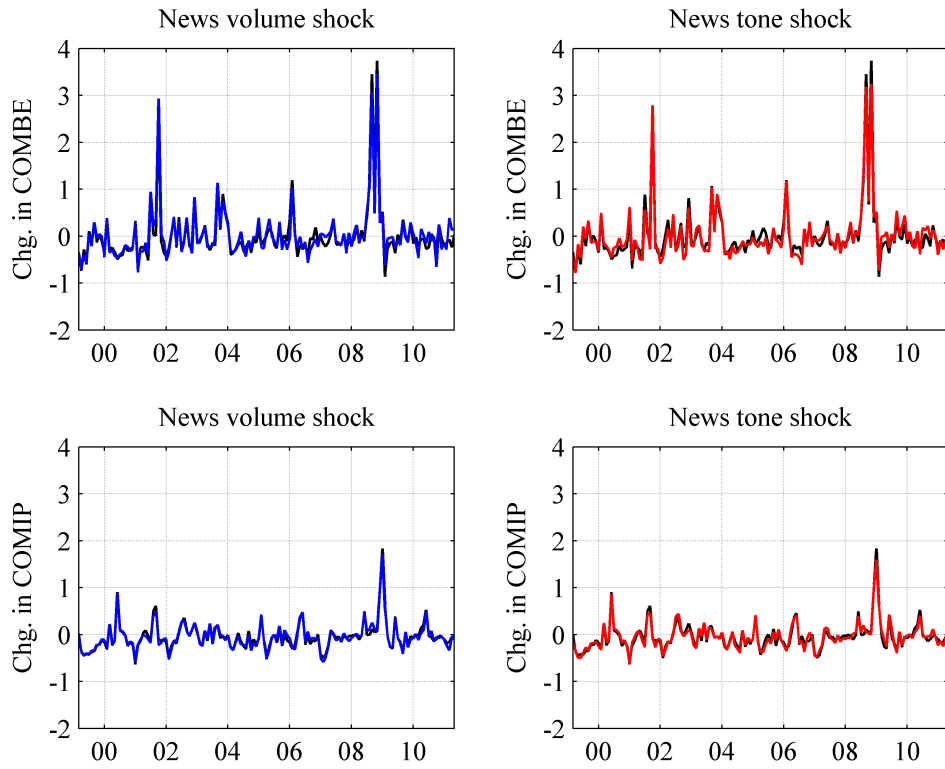
Figure D.1: Responses of sectoral comovement to media shocks (restricted sample)



Notes: The plots show the cumulated responses estimated from models (9) and (10). The one and two standard deviation confidence bands are computed with a block bootstrap, using 20,000 bootstrap replications and a block size of 4. COMBE: business expectations comovement; COMIP: industrial production comovement.

## E Counterfactual Analysis

Figure E.1: Counterfactual analysis (complete)



Notes: The black lines represent the actual change in sectoral business expectations comovement (COMBE) and output comovement (COMIP). The blue (red) lines depict the corresponding counterfactual time series, where all news volume (tone) shocks are set equal to zero.

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