Handling of Information in Forming Expectations

Inaugural-Dissertation
zur Erlangung des Grades
Doctor oeconomiae publicae (Dr. oec. publ.)
an der Ludwig-Maximilians-Universität München

2014

vorgelegt von

Teresa Buchen

Referent: Prof. Dr. Kai Carstensen
Korreferent: Prof. Dr. Timo Wollmershäuser
Promotionsabschlussberatung: 05.11.2014

Datum der mündlichen Prüfung: 24. Oktober 2014
Namen der Berichterstatter: Kai Carstensen, Timo Wollmershäuser, Benjamin Born

To Marta

Acknowledgements

Completing this thesis would not have been possible without the support of the people around me. First and foremost, I would like to express my gratitude to my supervisor Kai Carstensen. He granted me a great deal of freedom in my research and guided me with extremely helpful ideas and suggestions. Moreover, he always had an open door for questions and discussions. Besides, I would like to thank Timo Wollmershäuser and Benjamin Born, who kindly agreed to act as my second and third examiner.

I am indebted to my colleague Klaus Wohlrabe, co-author of the first and second chapter of my thesis. He took me under his wings and introduced me to the art of research. Sincere thanks are given to all my colleagues at the Ifo Center for Business Cycle Analysis and Surveys. From all the conferences and workshops I attended, I have profited most from the intense discussions during our internal seminars. I am much obliged to Steffen Henzel, Michael Kleemann and Christian Seiler, as well as to my former colleagues Steffen Elstner and Johannes Mayr, who helped me whenever I had a question. Special thanks go to my fellow graduate students Christian Beermann, Susanne Link and Gregor Tannhof for their encouragement and friendship. Acknowledgements are made to the Ifo Institute and the Faculty of Economics at the University of Munich for offering such an inspiring research environment.

My deepest gratitude goes to my family for giving me so much love and support. My parents, Magdalena and Bruno, have always backed my decisions and done everything to make my plans come true. I also appreciate the generous support of my parents-in-law, Bärbel and Herbert. In particular, I would like to thank my beloved husband Dominik for being so patient and for always believing in me. Finally, I am thankful to my little daughter Marta who cheers me up so many times. This work is dedicated to her.

Contents

List of Tables

List of Figures

Preface

For the past several decades, developed countries have become increasingly knowledge-driven economies, which rely more on information and knowledge than on physical inputs or natural resources. This process began in the late 1950s, and accelerated with the proliferation of personal computers and especially with the widespread use of the Internet (Powell and Snellman, 2004). Nowadays, economic agents have a large amount of information at their disposal to guide their expectations about the economy and their own prospects. However, this abundance of information poses new challenges on subjects. How shall they handle all the data? Which kind of information shall they use and how can they come to a conclusive interpretation? The answers to these questions crucially depend on the amount of resources devoted to the process of expectation formation. This dissertation addresses two different kinds of agents, professional forecasters and manufacturing firms, and their means of dealing with information in forming expectations.

The first two chapters consider state-of-the-art methods to cope with high-dimensional data when forecasting macroeconomic variables. Such techniques are commonly applied by professional forecasters since they require knowledge of statistics and programming as well as access to macroeconomic databases. They usually rely on the assumption that the true model of the economy is unknown. This is not only at odds with traditional econometrics, but also with the rational expectations hypothesis, which lies at the heart of classical macroeconomics. The focus of these chapters is on the performance of component-wise boosting, a data mining method that is relatively novel in macroeconomic forecasting.[1]

The third and fourth chapter deal with the expectation formation of firms. When forecasting is not the profession, people tend to rely on heuristics or simple rules of thumb when making predictions (Kahneman and Tversky, 1973). Thereby, they try to cut costs of information acquisition and processing, which are not taken into account by the rational expectations hypothesis either. The latter not only assumes that individuals are forward-looking and have knowledge of the true model of the economy, but that they are fully informed at every moment in time. On the contrary, Sims (2003), for instance, builds a rational inattention model to formalise the idea that individuals have finite capacities for processing information. Subjects only receive a noisy signal of a macroeconomic shock, so they face a signal extraction problem.[2] The author also establishes a crucial role of news media in the expectation formation process of economic agents. Their idiosyncratic coding errors do not average out, but have an aggregate effect because they rely to a large extent on the information-processing services provided by news media. Carroll (2003) develops an epidemiologic model to explain the influence of mass media on macroeconomic expectations; macroeconomic information spreads across the economy like a disease because households become "infected" by news reports, while the rate of infection depends on the intensity of news coverage. The effects of media coverage on business expectations as well as on their sectoral comovement are the topics of Chapter 3 and 4.

Chapter 1 assesses the macroeconomic forecasting accuracy of component-wise boosting. This is a variable selection device that iteratively adds to the model the predictors with the largest contribution to the fit. It has demonstrated excellent prediction performance in many other areas such as biomedicine and informatics. In macroeconomic forecasting, results are also promising (Bai and Ng, 2009; Kim and Swanson, 2014; Ng, 2014; Robinzonov et al., 2012; Shafik and Tutz, 2009). But most

[1] Hand et al. (2001) define data mining as "the science of extracting useful information from large data sets or databases." For a critical view on traditional statistics compared to data mining methods, see Breiman (2001).

[2] For a recent overview on models of information choice, see Veldkamp (2011).

studies use U.S. data and are confined to just a few target variables. We evaluate whether the predictive qualities of boosting are confirmed when using data for three different regions, the United States, Germany and the euro area, and when forecasting a wide range of macroeconomic variables. Furthermore, we study to what extent its forecasting performance depends on the method used to determine its main regularisation parameter, the number of iterations. We find that boosting outperforms the autoregressive benchmark in most cases and that the relative forecasting accuracy of boosting improves with increasing forecasting horizon. What is more, K-fold cross-validation as stopping criterion dominates the commonly used information criteria. In summary, boosting is shown to be a valid method for macroeconomic forecasting. However, as for every data mining method, thoughtful choice of the model selection criterion is one of the core challenges to achieve useful forecasts (Hand, 2009).

Chapter 2 complements the analysis of Chapter 1. Instead of comparing boosting only to a simple autoregressive benchmark model, the study also includes a range of forecast combination schemes and factor models, which are currently the most commonly applied practices when using many predictors in macroeconomic forecasting. We directly compare our results to the ones obtained by Stock and Watson (2006), who predict U.S. industrial production as a key macroeconomic variable. Our results confirm the findings of Chapter 1; boosting is a serious competitor, not only relative to an autoregressive model, but also in comparison to other state-of-the-art forecasting methods such as forecast averaging and factor models. Furthermore, the forecast accuracy of boosting is best when using a resampling method (here bootstrapping) as stopping criterion. Finally, the relative forecasting performance of boosting compared to the benchmark ameliorates with increasing forecasting horizon.

Chapter 3 discusses the role of news media in the expectation formation process of firms. Akerlof and Shiller (2010) suggest that the stories created by mass media around macroeconomic facts are one of the psychological factors—or animal spirits—that drive the ups and downs of an economy. By influencing the confidence of economic agents, media reporting can lead to feedback effects on the economy. We investigate empirically on a micro level whether news coverage indeed has an effect on the expectation formation process of enterprises that exceeds the impact of actual economic developments. Thereby, we look at two channels how media can influence firms: the intensity of news coverage and its evaluative tone. Our findings suggest that a firm's propensity to update business expectations increases when media coverage becomes more intense. This volume effect is the stronger the more unusual the economic situation is, so news media amplify the effect of fundamentals. Furthermore, the influence of media coverage is more pronounced in economic downturns than in upswings. The overall tone of news reporting, however, does not play a role for a firm's decision whether or not to update its business expectations.

Finally, *Chapter 4* analyses on the macro level whether mass media as a common source of information can impact sectoral comovement. Comovement is referred to when "agents take similar actions or aggregate variables behave similarly without an apparent motive to coordinate" (Veldkamp, 2011). The study is inspired by Veldkamp and Wolfers (2007) whose theoretical model explains excess sectoral comovement—the fact that sectoral output is much more correlated than sectoral productivity—by information complementarities across sectors. They argue that due to lower costs of aggregate information, firms base their output decisions on these rather than on sector-specific information. We examine empirically whether mass media as an important transmitter of aggregate news affect comovement of sectoral business expectations as well as of sectoral production. Again, we consider the two channels mentioned above, intensity and tone of news coverage. We do not find evidence for the hypothesis that the more intense media coverage of economy-wide news is, the more do business expectations or production comove across sectors because the latter share a greater common basis of information. However, our results suggest that the tone of media coverage does play a role for the extent to which sectors comove. We find that sectoral business expectations become more synchronised in reaction to a negative news tone shock, which is also reflected in a delayed increase of sectoral output comovement. Apparently, the larger the fraction of negative news, the more attention do firms pay to media reports, so sectors have more similar information sets. As a consequence, firms adapt their expectations and their production decisions in a more similar vein across sectors.

At first sight, the findings of Chapters 3 and 4 contradict each other. Firstly, the volume of media coverage influences the probability of a firm revising its business expectations, but it does not influence sectoral comovement of business expectations. This can be explained by the fact that companies could interpret news reports differently across sectors. So while more firms adapt their business expectations in response to more intense news coverage, they do not necessarily update in the same direction and to the same extent across sectors.

Secondly, the tone of news reports does not impact the propensity of a firm to update business expectations, but it affects sectoral comovement of business expectations. The findings from Chapter 4 suggest that the more negatively the media present the economy, the more attention do firms pay to macroeconomic issues, so that sectors share a greater common basis of information. Why is this result not confirmed on the micro level?

In fact, it could simply be due to the different nature of data used in both studies. In Chapter 3, we examine the expectation updating behaviour of firms using Ifo Business Survey data. These are qualitative data, from which we can only infer whether or not a firm updates its expectations, but not to what extent. In Chapter 4, comovement is computed from sectoral business cycle indicators. These are constructed from Ifo Business Survey data, but constitute quantitative measures of sectoral business expectations, from which we can derive how strongly expectations vary. So while the tone of news coverage does not influence the decision whether to update expectations at all, it could still have an effect on the size of adjustment. Unfortunately, the latter question could not be tackled due to data limitations.

Yet, the results of the last two chapters also exhibit commonalities. Altogether, we find only moderate media effects on the expectation formation of firms and on comovement of sectors. Chapter 3 suggests that in "normal" times, media coverage does not affect expectations updating of firms, but only becomes relevant when the macroeconomic situation changes more dramatically, especially to the downside. Chapter 4 indicates that sectoral comovement is also affected more strongly in unusual economic times. When excluding the recent financial and economic crisis from the sample, the effect of a news tone shock on sectoral comovement of business expectations does no longer hold. The effect on sectoral comovement of output is robust, but it is only small and fades fairly quickly.

Chapter 1

Assessing the Macroeconomic Forecasting Performance of Boosting: Evidence for the United States, the Euro Area, and Germany*

The use of large datasets for macroeconomic forecasting has received a great deal of interest recently. Boosting is one possible method of using high-dimensional data for this purpose. It is a stage-wise additive modelling procedure, which, in a linear specification, becomes a variable selection device that iteratively adds the predictors with the largest contribution to the fit. Using data for the United States, the euro area and Germany, we assess the performance of boosting when forecasting a wide range of macroeconomic variables. Moreover, we analyse to what extent its forecasting accuracy depends on the method used for determining its key regularisation parameter: the number of iterations. We find that boosting mostly outperforms the autoregressive benchmark, and that K-fold cross-validation works much better as stopping criterion than the commonly used information criteria.

*This chapter is based on Wohlrabe and Buchen (2014).

1.1 Introduction

There has been a recent upswing of interest using large datasets for macroeconomic forecasting. An increasing number of time series describing the state of the economy are available that could be useful for forecasting. Also, computational power to handle an immense amount of data has steadily risen over time. Thus researchers now attempt to improve their forecasting models by exploiting a broader information base.

Conventional econometric methods are not well suited for incorporating a large number of predictors; depending on the number of time-series observations, it is either impossible or inefficient to estimate the respective forecasting model. To overcome these problems without losing relevant information, new forecasting methods have been developed. Eklund and Kapetanios (2008) classify the methods for forecasting a time series into three broad, partly overlapping, categories. The first group includes methods that use the whole dataset for forecasting, such as Bayesian regression and factor methods. The second group consists of forecast combination methods that use subsets of the data to produce multiple forecasts, which are then averaged. Component-wise boosting belongs to the third category. The latter assembles variable selection methods (LASSO and least angle regression are other examples) that also use subsets of the data, but produce only one forecast based on the optimal set of variables. More specifically, component-wise boosting is a stage-wise additive modelling procedure, that sequentially adds the predictor with the largest contribution to the fit without adjusting the previously entered coefficients.

Boosting has attracted much attention in machine learning and statistics because it can handle large datasets in a computationally efficient manner and because it has proven excellent prediction performance in a wide range of applications (Bühlmann and Hothorn, 2010). However, only recently has the method found its way into the macroeconometric literature. Apart from several financial applications (Andrada-Félix and Fernández-Rodríguez, 2008; Audrino and Barone-Adesi, 2005; Gavrishchaka, 2006; Audrino and Trojani, 2007), there are only few macroeconometric studies on the forecasting performance of boosting (Bai and Ng, 2009; Buchen and Wohlrabe, 2011;

Kim and Swanson, 2014; Ng, 2014; Robinzonov et al., 2012; Shafik and Tutz, 2009). Results with respect to the predictive accuracy of boosting are promising. However, most of these studies are confined to U.S. data and use only few target variables.[1]

We add to this literature by analysing the performance of boosting when forecasting a wide range of macroeconomic variables using three datasets for the United States, the euro area, and Germany. Moreover, we investigate to what extent the forecasting performance of boosting depends on the specification of the boosting algorithm concerning the stopping criterion for the number of iterations.

Careful choice of the stopping criterion of boosting is crucial since the number of iterations M is the key parameter regularising the trade-off between bias and variance, on which the forecasting performance hinges. Small values of M yield a parsimonious model with a potentially large bias. The larger M becomes, the more one approaches a perfect fit, increasing the variance of the forecasting model. There are several methods for estimating the optimal number of iterations. Information criteria proposed by Bühlmann (2006) are wide-spread because they are computationally attractive,[2] but they tend to lead to overfitting (Hastie, 2007). Alternatively, resampling methods such as K-fold cross-validation can be applied. We evaluate whether the various stopping criteria result in relevant differences in the predictive performance of boosting when forecasting macroeconomic aggregates.

The remainder of this paper is organised as follows. The next section explains the boosting algorithm, especially how it handles the trade-off between bias and variance. Section 1.3 sums up our empirical analysis and Section 1.4 concludes.

[1] An exception is Carriero et al. (2011) who compare different methods that can be used in a VAR framework for forecasting the whole dataset consisting of 52 macroeconomic variables, including several reduced-rank models, factor models, Bayesian VAR models, and multivariate boosting. The latter is an extension of the standard boosting method developed by Lutz and Bühlmann (2006), where the predictors are selected according to a multivariate measure of fit. The results indicate that the forecasting performance of multivariate boosting is somewhat worse than that of the standard boosting approach.

[2] They are used, for instance, by Bai and Ng (2009), Kim and Swanson (2014), Robinzonov et al. (2012), and Shafik and Tutz (2009).

1.2 The Boosting Algorithm

Boosting was originally designed as a classification scheme (Freund and Schapire, 1995, 1996) and later extended to regression problems (Friedman, 2001; Friedman et al., 2000).[3] It is based on the machine learning idea, meaning that it is a computer programme that "learns from the data" (Hastie et al., 2009). Instead of estimating a "true" model, as is traditionally done in statistics and econometrics, it starts with a simple model that is iteratively improved or "boosted" based on the performance with training data. As Bühlmann and Yu (2003) put it, "for large dataset problems with high-dimensional predictors, a good model for the problem is hard to come by, but a sensible procedure is not."

1.2.1 Forward Stage-wise Modelling

Boosting estimates a sequence of nested models, resulting in an additive model:

$$\hat{f}_M(\boldsymbol{x}_t) = \bar{y} + \sum_{m=1}^{M} b(\boldsymbol{x}_t; \hat{\boldsymbol{\beta}}_m),$$

where $m = 1, 2, ..., M$ denote the iteration steps, y_t is the dependent variable and $b(\boldsymbol{x}_t; \hat{\boldsymbol{\beta}}_m)$ is called *learner*, which is a simple function of the input vector $\boldsymbol{x}_t$ depending on the parameter vector $\hat{\boldsymbol{\beta}}_m$. The fitting method used to determine $b(\boldsymbol{x}_t; \hat{\boldsymbol{\beta}}_m)$ is also part of the learner.

More specifically, boosting performs forward stage-wise modelling: it starts with the intercept and in each iteration m adds to the model the learner that most improves the fit, without modifying the parameters of those previously entered. The learners are selected according to a loss function $L(y_t, \hat{f}_m(\boldsymbol{x}_t))$, given the current model $\hat{f}_{m-1}(\boldsymbol{x}_t)$. Since in each iteration, only the parameters of the last learner need to be estimated, the algorithm is computationally feasible even for high-dimensional data. Generally, a forward stage-wise modelling procedure can be summarised as follows.

[3] For an overview of boosting methods, see Bühlmann and Hothorn (2007a).

1. Initialise $\hat{f}_0(\boldsymbol{x}_t) = \bar{y}$.

2. For $m = 1$ to M:

   (a) Compute
   $$\hat{\boldsymbol{\beta}}_m = \underset{\hat{\boldsymbol{\beta}}}{\text{argmin}} \sum_{t=1}^{T} L(y_t, \hat{f}_{m-1}(\boldsymbol{x}_t) + b(\boldsymbol{x}_t; \hat{\boldsymbol{\beta}})).$$

   (b) Set
   $$\hat{f}_m(\boldsymbol{x}_t) = \hat{f}_{m-1}(\boldsymbol{x}_t) + b(\boldsymbol{x}_t; \hat{\boldsymbol{\beta}}_m).$$

1.2.2 Component-wise L_2-Boosting

Generally, boosting can accommodate all sorts of nonlinearities, but for high-dimensional datasets, it is advisable to engage in variable selection so as to reduce the complexity of the learner (Bühlmann and Yu, 2003). This can be achieved by estimating a (generalised) linear model. With so-called component-wise boosting, instead of a function of predictors, one variable x_t is chosen and fitted in each step. In regression problems with the random variable $Y \in \mathbb{R}$, squared error loss (L_2-loss) is a common choice for the loss function,[4]

$$L(y_t, \hat{f}_m(\boldsymbol{x}_t)) = \frac{1}{2}(y_t - \hat{f}_m(\boldsymbol{x}_t))^2.$$

With L_2-loss, the boosting algorithm repeatedly fits the learner to the current residuals u_t:

$$\begin{aligned} L(y_t, \hat{f}_m(\boldsymbol{x}_t)) &= L(y_t, \hat{f}_{m-1}(\boldsymbol{x}_t) + b(x_t; \hat{\beta})) \\ &= \frac{1}{2}(y_t - \hat{f}_{m-1}(\boldsymbol{x}_t) - b(x_t; \hat{\beta}))^2 \\ &= \frac{1}{2}(u_t - b(x_t; \hat{\beta}))^2. \end{aligned}$$

[4] The loss function is scaled by the factor $\frac{1}{2}$ in order to ensure a convenient representation of the first derivative.

Note that in a time-series context the predictor vector $\boldsymbol{x}_t$ contains p lags of the target variable y_t as well as p lags of the exogenous variables $z_{j,t}$, where $j = 1, ..., N$:

$$\boldsymbol{x}_t = (y_{t-1}, y_{t-2}, ..., y_{t-p}, z_{1,t-1}, z_{1,t-2}, ..., z_{1,t-p}, ..., z_{N,t-1}, z_{N,t-2}, ..., z_{N,t-p}).$$

Hence, component-wise boosting simultaneously selects variables and lags. From all potential predictor variables $x_{k,t}$, where $k = 1, ..., p(1 + N)$, it selects in every iteration m one variable $x_{k^*_m,t}$—but not necessarily a different one for each iteration—which yields the smallest sum of squared residuals (SSR).

The algorithm for component-wise boosting with L_2-loss can be summarised as follows.

1. Initialise $\hat{f}_0(\boldsymbol{x}_t) = \bar{y}$.

2. For $m = 1$ to M:

   (a) Compute the residual $u_t = y_t - \hat{f}_{m-1}(\boldsymbol{x}_t)$.

   (b) For $k = 1, ..., p(1 + N)$, regress the residual u_t on $x_{k,t}$ to obtain $\hat{\beta}_k$ and compute $\text{SSR}_k = \sum_{t=1}^{T}(u_t - x_{k,t}\hat{\beta}_k)^2$.

   (c) Choose $x_{k^*_m,t}$ such that $\text{SSR}_{k^*_m} = \min \text{SSR}_k$.

   (d) Update $\hat{f}_m(\boldsymbol{x}_t) = \hat{f}_{m-1}(\boldsymbol{x}_t) + \nu b(x_{k^*_m,t}; \hat{\beta}_{k^*_m})$, where $0 < \nu < 1$.

The parameter ν was introduced by Friedman (2001) who showed that the prediction performance of boosting is improved when the learner is shrunk toward zero. The final function estimate is then the sum of the M learners multiplied by the shrinkage parameter ν:

$$\hat{f}_M(\boldsymbol{x}_t) = \bar{y} + \sum_{m=1}^{M} \nu b(x_{k^*_m,t}; \hat{\beta}_{k^*_m}).$$

1.2.3 Controlling the Bias-Variance Trade-off

Both the number of iterations M and the shrinkage parameter ν regulate the trade-off between bias and variance that emerges when fitting a model and that influences its forecasting performance. Suppose the data arise from the true but unknown model $Y = f(\boldsymbol{X}) + \varepsilon$, where Y is a random target variable and $\boldsymbol{X}$ is the vector of random predictors. Under the assumption that the error has $\mathrm{E}(\varepsilon) = 0$ and $\mathrm{Var}(\varepsilon) = \sigma_\varepsilon^2$, we can derive the expected forecast error $\mathrm{Err}(\boldsymbol{x_t})$ at an arbitrary predictor vector $\boldsymbol{x}_t$ of a forecasting model $\hat{f}(\boldsymbol{x}_t)$ using squared error loss:

$$\begin{aligned}
\mathrm{Err}(\boldsymbol{x}_t) &= \mathrm{E}[(Y - \hat{f}(\boldsymbol{x}_t))^2 | \boldsymbol{X} = \boldsymbol{x}_t] \\
&= \sigma_\varepsilon^2 + [\mathrm{E}[\hat{f}(\boldsymbol{x}_t)] - f(\boldsymbol{x}_t)]^2 + \mathrm{E}[\hat{f}(\boldsymbol{x}_t) - \mathrm{E}[\hat{f}(\boldsymbol{x}_t)]]^2 \\
&= \sigma_\varepsilon^2 + \mathrm{Bias}^2(\hat{f}(\boldsymbol{x}_t)) + \mathrm{Var}(\hat{f}(\boldsymbol{x}_t)).
\end{aligned}$$

The first term of this decomposition of the expected forecast error is the noise, that is, the variance of the target series around its true mean $f(\boldsymbol{x_t}) = \mathrm{E}(Y|\boldsymbol{X} = \boldsymbol{x}_t)$. It is irreducible, even if we knew the true model. The second term is the squared bias, the amount by which the average model estimate differs from the true mean. In contrast to simple OLS regression, where you assume that the true model is known, thus $\mathrm{E}[\hat{f}(\boldsymbol{x}_t)] = f(\boldsymbol{x}_t)$, this term is not zero but depends on model complexity. Typically, it will be larger if the model is not complex enough so that we omit important variables. The third term is the variance of the forecasting model, the expected squared deviation of $\hat{f}(\boldsymbol{x}_t)$ around its mean. This term increases with model complexity. If we fit the training data harder, the model will generalise less well to unseen data and the forecasting performance deteriorates. Thus the model must be chosen such that bias and variance are balanced to minimise the expected forecast error (Hastie et al., 2009).

One way of avoiding overfitting with boosting is to employ a *weak* learner, i.e., one that involves few parameters and has low variance relative to bias (Bühlmann and Yu, 2003). This can be achieved, for instance, by shrinking the learner toward zero because doing so reduces its variance. The other way of controlling the bias-variance trade-off is to restrict the number of boosting iterations. The shrinkage parameter ν and the number of iterations M are connected; the smaller ν, the more iterations are needed to achieve a given prediction error (Hastie et al., 2009). Empirical work finds that the exact size of the shrinkage parameter is of minor importance, as long as it is "sufficiently small", i.e., $0 < \nu \leq 0.1$ (Bühlmann and Hothorn, 2007a; Friedman, 2001; Hastie et al., 2009). Consequently, the optimal number of iterations M^* is the main regularisation parameter of boosting.

There are several ways of estimating M^*, the most prominent being resampling methods and information criteria. Resampling methods estimate the expected forecast error directly by running the boosting algorithm multiple times with datasets drawn randomly from the original dataset.[5] K-fold cross-validation, for instance, randomly allocates the data into K roughly equal-sized parts. For the kth part, the model is fit to the other $K-1$ parts and the forecast error with respect to the kth part is calculated. After repeating this for all K parts, the average forecast error yields the cross-validation estimate for the expected forecast error. With information criteria, on the other hand, the estimated forecast error is composed of two parts, one term capturing model fit and the other term penalising model complexity, measured by the degrees of freedom.

For a linear model estimated by OLS, the degrees of freedom are simply the number of fitted parameters (Hastie et al., 2009). For boosting, the degrees of freedom must be determined as a function of the number of iterations. With growing m, the complexity of the fitted procedure does not increase by constant amounts, but by exponentially decreasing amounts. This is largely due to the nature of forward stage-wise fitting; the learner that is added to the model in each iteration depends on the performance of the current model (Bühlmann and Yu, 2003). In fact, there is no exact expression for the degrees of freedom of boosting (Bühlmann and Hothorn, 2007b). But Bühlmann (2006) develops an approximation for L_2-boosting, which defines the degrees of freedom of boosting in iteration m as the trace of the boosting hat matrix $\mathcal{B}_m$:

$$\mathrm{df}(m) = \mathrm{trace}(\mathcal{B}_m), \tag{1.1}$$

[5] To be valid for time-series data, the mboost package implemented in R uses a model-based approach, assuming i.i.d. residuals. The idea is to fit the model first, and to subsequently resample from the residuals. For details about how to construct the new samples from the residuals, see Efron and Tibshirani (1986).

where $\mathcal{B}_m$ is a projection matrix that yields the fitted function $\hat{f}_m(\boldsymbol{x}_t)$ when post-multiplied by the realisations y_t:

$$\hat{f}_m(\boldsymbol{x}_t) = \mathcal{B}_m y_t.$$

Bühlmann (2006) proposes to insert (1.1) into the corrected Akaike criterion:

$$\text{cAIC}(m) = \log(\hat{\sigma}^2) + \frac{1 + \text{df}(m)/T}{(1 - \text{df}(m) + 2)/T}\ , \text{ where}$$
$$\hat{\sigma}^2 = T^{-1}\sum_{t=1}^{T}(y_t - \hat{f}_m(\boldsymbol{x}_t))^2.$$

An alternative method is to use the gMDL criterion (Minimum Description Length criterion using a g-prior), which bridges the AIC and the BIC in a data-driven manner and adaptively selects the better among the two (Bühlmann and Hothorn, 2007a):[6]

$$g\text{MDL}(m) = \log(S) + \frac{\text{df}(m)}{T}\log(F), \text{ where}$$
$$S = \frac{T\hat{\sigma}^2}{T - \text{df}(m)},\ F = \frac{\sum_{t=1}^{T} y_t^2 - T\hat{\sigma}^2}{\text{df}(m)S}.$$

Finally, the estimate for the optimal number of boosting iterations is given by:

$$\hat{M}^* = \underset{1 \leq m \leq M^{max}}{\text{argmin}}\ \text{IC}(m),$$

where M^{max} is a large upper bound for the candidate number of boosting iterations and IC is one of the information criteria.

These information criteria are computationally attractive, but they tend to lead to overfitting. Hastie (2007) shows that the trace of the boosting hat matrix is only a poor approximation since it treats the model at stage m as if it was computed by a predetermined sequence of linear updates.[7] However, the sequence of updates is adaptively chosen, and the cost of searching for the variable with the best fit is ignored.

[6] For details, see Hansen and Yu (2001).

[7] In that case, Equation (1.1) would be an exact measure of the degrees of freedom (Hastie et al., 2009).

Hence, the penalty term of the information criteria tends to be too small, resulting in the procedure being stopped too late. As an alternative, Hastie (2007) suggests approximating the degrees of freedom of boosting by the size of the active set, that is, the number of selected variables until iteration m, or using K-fold cross-validation to estimate the expected forecast error. In the following empirical application, we evaluate whether the various methods of determining the stopping criterion result in relevant differences in the macroeconomic forecasting performance of boosting.

1.3 Empirical Analysis

1.3.1 Data

For our empirical analysis, we use three large-scale datasets with monthly frequency—one each for the United States, the euro area, and Germany. All three datasets reflect various aspects of the respective economy and contain information typically taken into consideration by central banks. The variables can be grouped into the following categories: real economy (such as industrial production, orders, labour market indicators, and housing market indicators), money and prices (such as monetary aggregates, wages, consumer prices, producer prices, and commodity prices), financial markets (such as exchange rates, interest rates, term spreads, and stock indices), and surveys. The datasets vary in size (both with respect to T and N), but all three cover the recent economic crisis.

For the United States, we use an updated version of the dataset employed by Giannone et al. (2004) containing 168 time series from January 1970 to December 2010.[8] The data are also used by Henzel and Rengel (2013). For Germany, we use the dataset by Drechsel and Scheufele (2012), which contains 217 time series from January

[8] For a full list of the series, see Giannone et al. (2004). Three series were not available (series 104, 126 and 132) and two series are quarterly (series 172 and 173), so they are excluded. We used the monthly analogues of the authors' stationarity transformations, i.e., transformation 2 is the monthly difference, transformation 3 is the monthly annualised growth rate and transformation 4 is the yearly growth rate in the respective month.

1992 to May 2011. In addition to the categories mentioned above, the German dataset also contains information on governmental indicators (such as tax revenue and customs duties) as well as a range of international indicators (such as survey indicators or share indices of export partners).[9] The smallest dataset is the one for the euro area. It contains 78 time series from February 1994 to October 2010, which are listed with the respective stationarity transformation in the Appendix.[10]

1.3.2 Forecasting Approach

The component-wise boosting procedure applied in this study uses OLS as learner[11] and a squared error loss function to estimate an autoregressive distributed lag (ADL) model:[12]

$$y_{t+h} = \alpha + \boldsymbol{\beta}'\boldsymbol{x}_t + \varepsilon_{t+h} = \alpha + \sum_{i=1}^{12} \gamma_i y_{t+1-i} + \sum_{j=1}^{N}\sum_{i=1}^{12} \delta_{ji} z_{j,t+1-i} + \varepsilon_{t+h}.$$

Those variables and lags that are not selected have a zero coefficient. To save computational time, the size of the shrinkage parameter ν is set to 0.1, the upper bound of the interval suggested by the literature (Bühlmann and Hothorn, 2007a; Hastie et al., 2009). The optimal number of iterations M^* is estimated with several stopping criteria: the corrected AIC and the gMDL criterion as information criteria—both with the trace of the boosting hat matrix and the size of the active set as measures for the

[9] For a list of the series and the stationarity transformations, see Drechsel and Scheufele (2012). To ensure that all series have the same length, we discarded the following variables. Real economic indicators: WTEXMOG, WHTCFWH, WHTCHEH, WHTCNMH, WHTSLGH, USLA01B, RVN, RETTOTG, EMPTOTO, EMPOWHH. Finance: SPR-NF2AE, SPR-NF3BE, SPR-P3BE, SPR-EUCU, VDAXNEW, VDAXIDX, MLNF2AE, MLNF3BE, MLNP3BE, MLHEUCU, TSD304B. Survey indicators: IFOMTLQ, IFOMTKQ, IFOMTAQ, IFOMCAQ, IFOMCLQ, IFOMCKQ, IFOBDOQ, IFOBDQQ, IFOBDPQ, IFOWHIQ, IFOWHAQ, IFORTIQ, IFORTHQ, CONSNT, EUSVCIQ, PMIBD, PMIBDS, PMIEUR. International indicators: POEUSESIG, CZEUSESIG, CHOL0955R.

[10] The datasets are available upon request from the authors.

[11] We have also tried P-splines as nonlinear learners allowing us to estimate more flexible models. However, the number of predictors used here seems to be too large to address both issues, nonlinearity and high dimensionality; the forecasting performance of boosting with nonlinear learner was considerably inferior to that of boosting with linear learner. Moreover, the computational burden for our study would have been immense.

[12] For estimation, we employed the R package mboost (Hothorn et al., 2009). For an introduction, see Hofner et al. (2014).

degrees of freedom—and 10-fold cross-validation as a resampling method.[13] All results are compared for the case when the maximal number of iterations is set to $M^{max} = 50$ and 100.

We produce forecasts for the horizons $h = 1, 3, 6$, and 12 months. All forecasts are computed directly and pseudo-out-of-sample using a rolling estimation window. The forecast period starts in January 1990 for the United States, and in January 2000 for the euro area and Germany. Since our aim is to obtain a broad picture of the predictive performance of boosting in a macroeconomic context, we forecast all the variables in the datasets. The specific form of the target variable depends on its stationarity transformation and can be either the (log) level in the respective month, the monthly first difference, the monthly first (second) log difference, or the yearly log difference. Due to computational considerations, all variables were centered for the respective estimation window.

We assess the forecasting accuracy of boosting relative to the standard autoregressive (AR) model, where the lag length p is determined by the Bayesian information criterion (BIC). To summarise the overall forecasting accuracy, we employ a multivariate version of the mean squared forecast error (MSFE) as proposed by Christoffersen and Diebold (1998). The multivariate MSFE is given by $\text{MSFE} = \text{E}(\boldsymbol{\varepsilon}'_{t+h}\boldsymbol{W}\boldsymbol{\varepsilon}_{t+h})$, where $\boldsymbol{\varepsilon}_{t+h}$ is the vector of the h-step-ahead forecast errors and $\boldsymbol{W}$ is an $N \times N$ weighting matrix with N being the number of target variables. In accordance with Carriero et al. (2011), we choose a diagonal matrix $\boldsymbol{W}$ with the elements of the diagonal being the inverse of the variances of the target series. Consequently, a series that has large variance—and is thus less predictable—is given less weight.

1.3.3 Results

To give a first impression of the forecasting performance of boosting, we plot the distribution of the mean squared forecast errors across all target variables. It is shown

[13] We have also experimented with subsampling and bootstrapping as alternative resampling methods. However, all these procedures are computationally quite intense, while producing similar results. So we restricted ourselves to K-fold cross-validation.

for all three datasets and for different forecast horizons in Figure 1.1, where we use $M^{max} = 50$ and K-fold cross-validation as stopping criterion. The largest spikes tend to be close to one. But in most cases, more than 50% of the MSFE ratios are below one, that is, boosting performs better than the AR(p) benchmark. For the United States and Germany, most of the ratios are concentrated between roughly 0.8 and 1.2, while for the euro area the spread is somewhat wider.[14]

The multivariate MSFE ratios in Table 1.1 summarise the forecasting accuracy of boosting across all variables in the datasets while taking into account their predictability. These aggregate results give us insights in how boosting generally performs when forecasting any kind of macroeconomic time series. First of all, it is confirmed that boosting beats the AR(p) benchmark on average. Many of the multivariate ratios are close to one, but boosting can lead to improvements relative to the benchmark of up to 47%. Second, its relative forecast accuracy tends to improve with increasing forecasting horizon, although for the U.S. data, boosting also performs very well at a forecast horizon of one month. Third, the number of boosting iterations leading to the smallest MSFEs seems to be quite low, at most, 50. The different stopping criteria are not completely robust to the choice of the maximum number of iterations. Instead, the estimated optimal number of iterations tends to rise with larger M^{max}. However, the differences vary across criteria and are largest when the degrees of freedom to be employed in the computation of the information criteria is approximated by the trace of the boosting hat matrix (cAIC Trace or gMDL Trace). Estimating the degrees of freedom by the size of the active set (cAIC Actset or gMDL Actset) delivers better and more robust results. But finally, using 10-fold cross-validation (CV) appears to be the dominant stopping criterion. Not only does it yield the smallest multivariate MSFE ratio for a given forecast horizon (entries in bold) in most of the cases, but it is also very robust to the choice of the candidate number of iterations.

Figure 1.2 gives more insights into the functioning of the different stopping criteria. It compares the multivariate MSFE ratios as well as the average across variables and

[14]Due to graphical reasons, outliers larger than 2 are excluded.

time of the estimated optimal number of iterations M^* and of the number of variables that enter the models. Basically, we use the same forecasting approach as described in Section 1.3.2, but we compare the results for a wider range of choices regarding the maximum number of iterations ($M^{max} = 10, 20, ..., 500$). Due to computational reasons, we only compute the forecasts for the last 120 months, which leads to a smaller evaluation sample especially for the U.S. dataset. Here, we display exemplarily the results for a forecast horizon of one month.

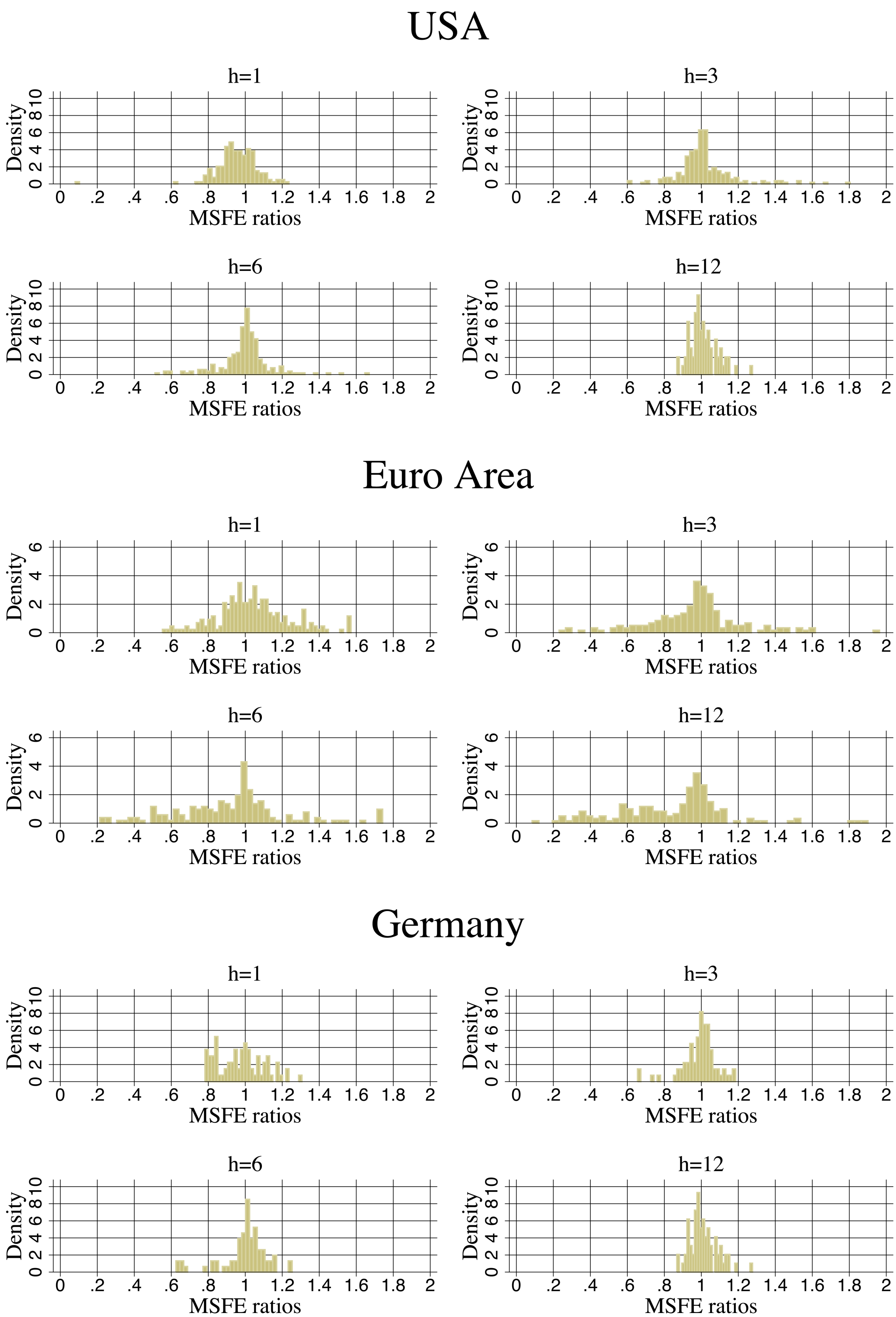
Figure 1.2 confirms what was already indicated by Table 1.1; on average, the MSFE ratios are smallest when the number of iterations is highly restricted. With rising M^{max}, the forecasting performance of boosting deteriorates. But this deterioration is most pronounced for the trace criteria, and much less important for K-fold cross-validation and for the gMDL criterion when using the size of the active set to estimate model complexity. Overall, K-fold cross-validation yields the best results. While the cAIC Actset stopping criterion often leads to smaller forecast errors at lower numbers of iterations allowed for, they rise strongly at larger values of M^{max} (see panels in first column).

The reason for this differing forecasting accuracy can be seen from the panels in the second column of Figure 1.2. They display the optimal number of iterations M^* that is estimated by the various stopping criteria as a function of M^{max}. When using the trace information criteria, the chosen number of iterations tends to go to the limit allowed for.[15] Hence, these criteria indeed seem to overfit and lead to very large models with many variables (see panels in third column).[16] Conversely, the gMDL Trace criterion and K-fold cross-validation are much less sensitive to the choice of M^{max}.

[15]In that case, M^{max} should actually be set higher.

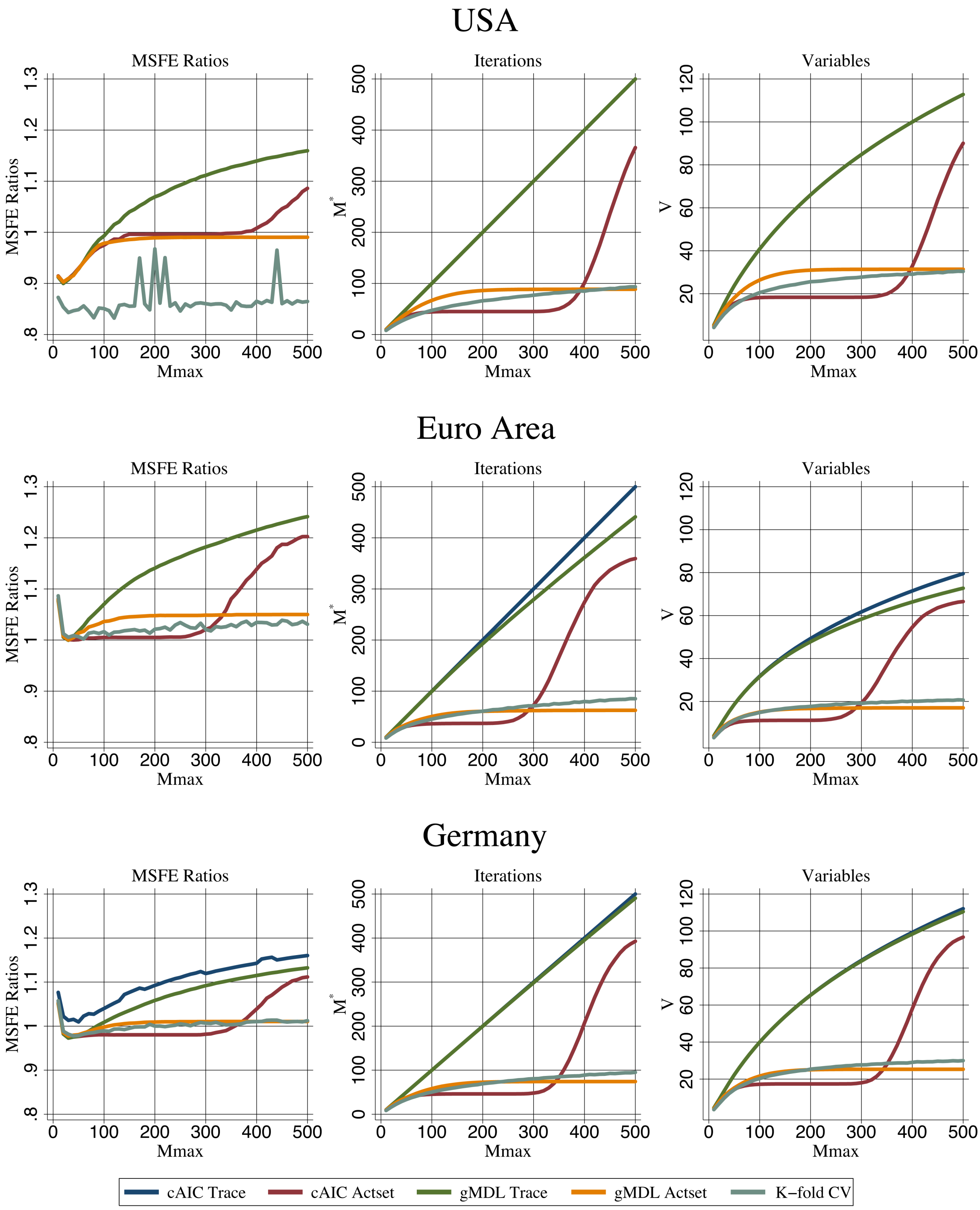
[16]Keep in mind that the contribution of each variable is shrunk and that each variable can be chosen several times. So while some of the variables are fitted completely (that is, with a shrinkage factor of $\nu = 0.1$, they are selected 10 times), some are only chosen once or twice.

Figure 1.1: Histograms of MSFE ratios



Notes: This figure displays the frequency distribution of the MSFE ratios of boosting using $M^{max} = 50$ and K-fold cross-validation as stopping criterion, relative to the AR(p) benchmark.

Figure 1.2: Comparison across stopping criteria



Notes: This figure compares across various stopping criteria the multivariate MSFE ratios as well as the average (across variables and time) estimated optimal number of iterations M^* and the average number of variables that enter the models for different choices of the maximum number of iterations M^{max}, where $M^{max} = 10, 20, ..., 500$. The stopping criteria are the following: the corrected Akaike information criterion (cAIC) and the Minimum Description Length criterion using a g-prior (gMDL), both when the trace of the boosting hat matrix (Trace) and the size of the active set (Actset) is used to approximate the degrees of freedom of the respective model, as well as K-fold cross-validation (CV). The forecasts are computed for the last 120 months of the respective dataset and we only display the results for a forecast horizon of one month.

Table 1.1: Multivariate MSFE ratios

		USA				Euro Area				Germany			
		$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
Criterion	M^{max}	Ratio Relative to the AR(p) Benchmark											
cAIC Trace	50	0.842	0.995	0.951	0.899	1.051	0.997	0.836	0.559	0.949	0.939	0.902	0.835
cAIC Actset	50	0.843	0.993	0.949	0.896	**1.025**	0.946	0.783	0.529	**0.943**	0.922	0.882	0.808
gMDL Trace	50	0.842	0.995	0.951	0.899	1.051	0.997	0.836	0.559	0.949	0.939	0.902	0.835
gMDL Actset	50	0.844	0.995	0.951	0.899	1.041	0.982	0.821	0.546	0.950	0.937	0.896	0.820
K-fold CV	50	**0.779**	0.981	**0.936**	**0.884**	**1.025**	**0.943**	**0.779**	**0.528**	0.946	**0.913**	**0.875**	**0.805**
cAIC Trace	100	0.883	0.985	1.020	0.969	1.112	1.074	0.902	0.591	0.981	0.977	0.942	0.879
cAIC Actset	100	0.879	0.973	1.004	0.954	1.031	0.953	0.789	0.530	0.946	0.925	0.886	0.811
gMDL Trace	100	0.883	0.985	1.020	0.969	1.112	1.074	0.901	0.591	0.981	0.977	0.942	0.879
gMDL Actset	100	0.881	0.982	1.016	0.965	1.073	1.021	0.854	0.556	0.967	0.959	0.918	0.839
K-fold CV	100	0.784	**0.956**	0.989	0.940	1.039	0.964	0.797	0.538	0.955	0.928	.886	0.820

Notes: This table reports multivariate MSFE ratios for various boosting methods relative to the AR(p) benchmark, where the boosting methods differ with respect to the stopping criterion: the corrected Akaike information criterion (cAIC) and the Minimum Description Length criterion using a g-prior (gMDL), both when the trace of the boosting hat matrix (Trace) and the size of the active set (Actset) is used to approximate the degrees of freedom of the respective model, and K-fold cross-validation (CV). A value smaller than 1 indicates that boosting delivers on average a smaller MSFE, taking into account the predictability of the series. Entries in bold indicate the best MSFE ratio for a given forecast horizon h.

1.4 Conclusion

Component-wise boosting is a variable selection method that can be used in a data-rich environment. It starts with a simple model that is iteratively updated by adding the predictor with the largest contribution to the fit. We assess whether the predictive qualities of boosting that have been reported in many other areas can be confirmed when forecasting a wide range of macroeconomic variables. To that aim, we use large-scale datasets for the United States, the euro area, and Germany. Moreover, we analyse to what extent the forecasting accuracy of the boosting algorithm depends on the method chosen to determine its key regularisation parameter, the number of iterations.

Indeed, we find that boosting performs well in macroeconomic forecasting; it outperforms the benchmark in most cases. Furthermore, the choice of the stopping criterion determining the number of iterations has an important influence on the forecasting performance of boosting. We compare information criteria based on the trace of the boosting hat matrix as a measure of model complexity, which were proposed by Bühlmann (2006) and are widely used, with information criteria based on the size of the active set as well as with K-fold cross-validation as an example of a resampling method. Our results confirm the critique by Hastie (2007) and suggest that the trace criteria indeed underestimate model complexity. So the boosting procedure is stopped too late and overfits, which is reflected in larger forecasting errors. Using the number of selected variables as a measure of model complexity, as proposed by Hastie (2007) abates the problem. But overall, K-fold cross-validation is the dominant stopping criterion.

To conclude, component-wise boosting is a powerful method that can be used to forecast a wide range of macroeconomic variables. However, to achieve the best possible results, it is important to choose the model selection criterion carefully and not to adopt it by mere convention.

Acknowledgements

I am indebted to Klaus Wohlrabe who is co-author of Chapter 1. We would like to thank Kai Carstensen and the anonymous referee for very valuable comments and suggestions. Many thanks also go to Katja Drechsel and Rolf Scheufele as well as to Steffen Henzel and Malte Rengel for making their datasets available. Last but not least, we would like to thank Nikolay Robinzonov for introducing us to the R package mboost.

Appendix 1.A Euro Area Data

Table 1.A.1: List of variables (euro area)

Series	Transformation
REAL ECONOMY	
Eurostat, manufacturing, production, total	3
Eurostat. manuf., prod., textiles	3
Eurostat, manuf., prod., food, beverages and tobacco products	3
Eurostat, manuf., prod., motor vehicles, trailers, semi-trailers and other transport	3
Eurostat, manuf., prod., machinery and equipment	3
Eurostat, manuf., prod., basic pharmaceutical products and pharmaceutical preparations	3
Eurostat, manuf., prod., coke and refined petroleum products	3
Eurostat, manuf., prod., chemicals and chemical products	3
Eurostat, manuf., prod., basic metals	3
Eurostat, manuf., prod., rubber and plastic products	3
Eurostat, manuf., prod., intermediate goods	3
Eurostat, manuf., prod., consumer goods	3
Eurostat, unemployment	3
Eurostat, unemployment rate	2
Eurostat, manufacturing, order books	2
OECD, manufacturing, export order books or demand	2
OECD, retail trade volume	3
MONEY AND PRICES	
ECB, M1	4
ECB, M2	4
ECB, M3	4
HWWI, total index, average	4
HWWI, agricultural raw materials index, average	4
HWWI, crude oil index, average	4
HWWI, industrial raw materials index, average	4
HWWI, energy raw materials index, average	4
ECB, consumer prices, index	4
ECB, consumer prices excluding energy and unprocessed food	4
Eurostat, domestic producer prices, manufacturing	4
Eurostat, dom. prod. prices, energy	4
Eurostat, dom. prod. prices, food products and beverages	4
Eurostat, dom. prod. prices, tobacco products	4
Eurostat, dom. prod. prices, chemicals and chemical products	4
Eurostat, dom. prod. prices, motor vehicles, trailers and semi-trailers	4
Eurostat, dom. prod. prices, intermediate goods	4
Eurostat, dom. prod. prices, capital goods	4
Eurostat, dom. prod. prices, durable consumer goods	4
Eurostat, dom. prod. prices, non-durable consumer goods	4
FINANCIAL MARKETS	
OECD, real effective exchange rate, EUR, average	3
OECD, EUR/US$ exchange rate, average	3
Eurostat, interbank rates, 3 month, yield, average	2
ECB, government benchmarks, bid, 2 year, yield, average	2

Series	**Transformation**
ECB, government benchmarks, bid, 3 year, yield, average	2
ECB, government benchmarks, bid, 5 year, yield, average	2
ECB, government benchmarks, bid, 7 year, yield, average	2
ECB, government benchmarks, bid, 10 year, yield, average	2
ECB, term spread, government benchmarks, 5-3 years	1
ECB, term spread, government benchmarks, 7-3 years	1
ECB, term spread, government benchmarks, 10-3 years	1
STOXX Limited, STOXX, broad index, end of month	3
STOXX Limited, STOXX 50, end of month	3
SURVEYS	
CEPR, EuroCOIN, industry sector	1
DG ECFIN, economic sentiment indicator	1
DG ECFIN, manufacturing, industrial confidence indicator	1
DG ECFIN, construction confidence indicator	1
DG ECFIN, retail trade confidence indicator	1
DG ECFIN, manufacturing, export order books	1
DG ECFIN, manufacturing, order books	1
DG ECFIN, construction, order books	1
DG ECFIN, retail trade, employment expectations	1
DG ECFIN, construction, employment expectations	1
DG ECFIN, manufacturing, employment expectations	1
DG ECFIN, services, expectation of demand over next 3 months	1
DG ECFIN, manufacturing, production expectations	1
DG ECFIN, manufacturing, selling-price expectations	1
DG ECFIN, consumer surveys, consumer confidence indicator	1
DG ECFIN, cons. surv., general economic situation over next 12 months	1
DG ECFIN, cons. surv., unemployment expectations over next 12 months	1
DG ECFIN, cons. surv., price trends over next 12 months	1
DG ECFIN, cons. surv., financial situation of households over next 12 months	1
DG ECFIN, cons. surv., major purchases at present	1
DG ECFIN, cons. surv., major purchases over next 12 months	1
DG ECFIN, cons. surv., savings at present	2
DG ECFIN, cons. surv., savings over next 12 months	1
OECD, total leading indicator, quantum, normalised	1
OECD, total leading indicator, trend restored	2
OECD, total leading indicator, amplitude adjusted	1

Transformation - 1: x_t, 2: $x_t - x_{t-1}$, 3: $\ln(x_t/x_{t-1})$, 4: $\ln(x_t/x_{t-1}) - \ln(x_{t-1}/x_{t-2})$.

Chapter 2

Forecasting with Many Predictors: Is Boosting a Viable Alternative?*

This paper evaluates the forecasting performance of boosting in comparison to the forecast combination schemes and dynamic factor models presented in Stock and Watson (2006). Using the same data set and comparison methodology, we find that boosting is a serious competitor for forecasting U.S. industrial production growth in the short and medium run, and that it performs best in the longer run.

*This chapter is based on Buchen and Wohlrabe (2011).

2.1 Introduction

Growing attention has recently been paid to the use of large datasets for macroeconomic forecasting. Since both the availability of data and the computational power to handle them have increased tremendously, researchers have been trying to enrich their forecasting models by taking advantage of a broader information base. Conventional econometric methods are not suitable for incorporating a large number of predictors, so new methods have been developed. Basically, there are two ways of exploiting high-dimensional data without overfitting the model, information condensation and variable selection.

The most common approaches, factor models and forecast combination schemes, perform information condensation.[1] Factor models summarise the information contained in all the data in a few common factors, which are then used as predictors. Combination methods generate a large number of forecasts based on small-scale models and average them according to some weighting scheme.

This paper compares the forecast performance of these standard methods with boosting, a prediction method for high-dimensional data stemming from the machine learning literature.[2] It is a stagewise additive modelling procedure, which iteratively estimates the model by sequentially adding new terms. Generally, boosting can accommodate all sorts of nonlinearities. But when estimating a (generalised) linear model, it becomes a variable selection device (called component-wise boosting) that in each iteration step adds the predictor with the largest contribution to the fit.[3]

Boosting has become popular in machine learning and statistics because it can handle large datasets in a computationally efficient manner and since it has proven an excellent prediction performance in a wide range of applications (Bühlmann and Hothorn, 2010). However, it has only recently been considered in macroeconometrics. While Ng (2014), Robinzonov et al. (2012), and Shafik and Tutz (2009) estimate

[1] For overviews of factor models and forecast combination, see Stock and Watson (2011) and Timmermann (2006), respectively.

[2] For the origins of boosting, see Freund and Schapire (1996), and Friedman et al. (2000).

[3] For an overview of boosting methods, see Bühlmann and Hothorn (2007a).

nonlinear additive models, the other studies evaluate the more common linear models. Carriero et al. (2011) consider multivariate boosting, which is an extension of the standard boosting approach developed by Lutz and Bühlmann (2006). It can be used in a VAR framework where the predictors are selected according to a multivariate measure of fit. But in comparison to several reduced-rank models, factor models and Bayesian VARs, multivariate boosting only performs best when forecasting CPI inflation, one of the three chosen key variables, one month ahead. Results for standard boosting are much more promising. Bai and Ng (2009) find that either direct boosting of the predictors or boosting of common factors which are first estimated from the predictors can improve upon the forecast of factor models and is far superior to the autoregressive benchmark. However, boosting of factors is only advantageous for two out of five target variables, while for the others it is better to boost the predictors directly. The results in Kim and Swanson (2014) confirm that pure boosting outperforms a conjunction with factor models.

The contribution of this paper is twofold. First, we do not only compare the forecast performance of (standard) boosting with factor models, but also with forecast combination as another common approach to incorporate many predictors. Second, we show that relevant improvements in terms of forecasting accuracy can be achieved when using a resampling method as stopping criterion for the boosting algorithm instead of an information criterion as carried out by Bai and Ng (2009), and Kim and Swanson (2014).[4] The number of iterations is the key parameter regularising the trade-off between bias and variance that determines the forecasting performance.

As a basis of comparison, we build on Stock and Watson (2006) who examine the performance of different forecast combination schemes, factor models, Bayesian model averaging and empirical Bayes methods. Thereby, they are one of the few that compare the forecast accuracy of pooling information versus pooling forecasts. We go one step further and include boosting into the horse race with these most prominent approaches to deal with large datasets. In our empirical application to U.S. industrial production

[4]The disadvantage of grid search, which is applied by Carriero et al. (2011) in order to determine the number of boosting iterations, is that it is computationally very demanding.

we use the same methods for forecast comparison and the same dataset consisting of 131 economic time series from 1959 to 2003.

The remainder of this paper is organised as follows. While Section 2.2 outlines the boosting procedure, Section 2.3 describes the empirical application. Finally, Section 2.4 concludes the paper.

2.2 Component-wise Boosting

Boosting is a greedy strategy that iteratively estimates an unknown function $f(\boldsymbol{X})$, which can be linear or nonlinear. However, for multi-dimensional datasets with N larger or of the order of T it is mostly necessary to do some sort of variable selection in order to reduce the complexity of the fitting procedure (Bühlmann and Yu, 2003). To do this, component-wise boosting estimates a (generalised) additive model. We specify a simple autoregressive distributed lag (ADL) model, which is well accepted in the forecasting literature:

$$\begin{aligned} \mathrm{E}(y_{t+h}|\boldsymbol{x}_t, \boldsymbol{\beta}) &=: f(\boldsymbol{x}_t) \\ &= \alpha + \boldsymbol{\beta}' \boldsymbol{x}_t \\ &= \alpha + \sum_{i=1}^{p} \gamma_i y_{t+1-i} + \sum_{j=1}^{N} \sum_{i=1}^{p} \delta_{ji} z_{j,t+1-i}, \end{aligned} \tag{2.1}$$

where h is the forecasting horizon. The vector $\boldsymbol{x}_t$ contains lags of the endogenous variable y_t as well as lags of the exogenous predictors $z_{j,t}$, and p and N denote the number of lags and of exogenous variables, respectively. Those variables that are not chosen, obtain a zero coefficient. The predictors are selected according to a loss function, which, in regression problems with $Y \in \mathbb{R}$, is usually squared error (L_2) loss:[5]

$$L(y_t, \hat{f}_m(\boldsymbol{x}_t)) = \frac{1}{2}(y_t - \hat{f}_m(\boldsymbol{x}_t))^2.$$

[5]The loss function is scaled by the factor $\frac{1}{2}$ in order to ensure a convenient representation of the first derivative.

Note that component-wise boosting treats the lags of each variable as separate predictors such that the algorithm simultaneously selects variables and lags. So from all potential predictors $x_{k,t}$, where $k = 1, ..., p(1+N)$, the algorithm chooses in every iteration m one variable $x_{k_m^*,t}$—and not necessarily a different one for each iteration—which yields the smallest sum of squared residuals (SSR). The previous model is then updated by adding the term $b(x_{k_m^*,t}; \hat{\beta}_{k_m^*})$, called learner, which is estimated by OLS for a linear model.

The algorithm can be summarised as follows.

1. Initialise $\hat{f}_0(\boldsymbol{x}_t) = \bar{y}$.

2. For $m = 1$ to M:

   (a) Compute the negative gradient $-\frac{\partial L(y_t, f)}{\partial f}$ and evaluate at $\hat{f}_{m-1}(\boldsymbol{x}_t)$:
   $u_t = y_t - \hat{f}_{m-1}(\boldsymbol{x}_t)$.

   (b) For $k = 1, ..., p(1+N)$, regress the negative gradient u_t on $x_{k,t}$ to obtain $\hat{\beta}_k$ and compute $\text{SSR}_k = \sum_{t=1}^{T}(u_t - x_{k,t}\hat{\beta}_k)^2$.

   (c) Choose $x_{k_m^*,t}$ such that $\text{SSR}_{k_m^*} = \min \text{SSR}_k$.

   (d) Update $\hat{f}_m(\boldsymbol{x}_t) = \hat{f}_{m-1}(\boldsymbol{x}_t) + \nu b(x_{k_m^*,t}; \hat{\beta}_{k_m^*})$, where $0 < \nu < 1$.

From steps 2(a) and (b), it can be seen that boosting with L_2-loss is simply repeated least squares fitting of residuals. The final function estimate results as the sum of the M learner estimates multiplied by the shrinkage parameter ν:

$$\hat{f}_M(\boldsymbol{x}_t) = \bar{y} + \sum_{m=1}^{M} \nu b(x_{k_m^*,t}; \hat{\beta}_{k_m^*}),$$

where the number of iterations M that minimises the expected forecast error is estimated by a resampling method or an information criterion. The shrinkage parameter ν was introduced into the boosting algorithm by Friedman (2001) as a second regularisation parameter in order to reduce the variance of the learner and thus to improve the prediction performance of boosting.

2.3 Application to U.S. Data

2.3.1 Data

The dataset is the same used in Stock and Watson (2006). Covering the period from 1959 to 2003 it contains U.S. industrial production as target series and 130 monthly time series from three broad categories: real economy, money and prices, and financial markets. The series were standardised, transformed to stationarity and corrected for outliers according to Stock and Watson (2004).

2.3.2 Methods

Following Stock and Watson (2006) we forecast the h-month growth of industrial production at an annual rate $y^h_{t+h} = (1200/h)\ln(\mathrm{IP}_{t+h}/\mathrm{IP}_t)$, where $h = 1, 3, 6$ and 12. The forecasts are computed directly and pseudo-out-of-sample using a recursive scheme with a forecast period from 1974:7 to 2003:12-h. When evaluating the forecast accuracy, we use the relative mean squared forecast errors (MSFEs), where the benchmark is an AR(AIC) model:

$$\mathrm{E}(y^h_{t+h}|\boldsymbol{y}_t) = \alpha + \sum_{i=1}^{p} \beta_i y_{t+1-i}.$$

For the boosting procedure, we estimate the ADL model in Equation (2.1) using OLS as learner and an L_2-loss function. Since the boosting algorithm is relatively insensitive to the value of the shrinkage parameter ν—as long as it is sufficiently small—we set it to the commonly used value of 0.1 (Lutz and Bühlmann, 2006). The number of iterations M, which is the main regularisation parameter, is determined both by the corrected Akaike criterion (cAIC) and bootstrapping[6], where we set a large upper bound of iterations ($M^{max} = 1000$).

[6]Bootstrapping draws datasets with replacement from the observed dataset, each of the same size as the original dataset. Those observations that are not drawn are used as test sample. The model is then refit to each of the bootstrap datasets and the mean squared error over the test samples is calculated. This is done for $m = 1, 2, ..., M^{max}$ and the M^* yielding the minimum MSE is chosen.

2.3.3 Results

Table 2.3.1: Forecasting accuracy comparison

Method	$h=1$	$h=3$	$h=6$	$h=12$
Stock and Watson (2006)				
Univariate benchmark				
AR(AIC)	1.00	1.00	1.00	1.00
AR(4)	0.99	1.00	0.99	0.99
Multivariate Forecasts				
(1) OLS	1.78	1.45	2.27	2.39
(2) Combination forecasts				
Mean	0.95	0.93	0.87	0.87
SSR-weighted average	0.85	0.95	0.96	1.16
(3) DFM				
PCA(3,4)	0.83	**0.70**	0.74	0.87
Diagonal weighted PC(3,4)	0.83	0.73	0.83	0.96
Weighted PC(3,4)	**0.82**	**0.70**	**0.66**	0.76
(4) BMA				
X's, $g=1/T$	0.83	0.79	1.18	1.50
Principal components, $g=1$	0.85	0.75	0.83	0.92
Principal components, $g=1/T$	0.85	0.78	1.04	1.50
(5) Empirical Bayes				
Parametric/g-prior	1.00	1.04	1.56	1.92
Parametric/mixed normal prior	0.93	0.75	0.81	0.89
(6) Component-wise boosting				
OLS learner (cAIC)	1.02	0.91	0.86	0.82
OLS learner (bootstrap)	0.86	0.81	0.79	**0.63**

Notes: Entries are MSFEs relative to the AR(AIC) benchmark. The smallest MSFE ratio is in bold. All forecasts are recursive, and the MSFEs were computed over the period 1974:7-(2003:12-h). For details on (1) to (5) see Stock and Watson (2006).

The results are summarised in Table 2.3.1. As the entries are relative MSFEs, numbers less than 1 indicate an improvement over the AR benchmark forecast. It can be seen that the relative forecasting performance of boosting improves with increasing forecast horizon. However, it matters which criterion is used in order to estimate the optimal number of iterations. The information criterion seems to be much more prone to overfitting than resampling, resulting in larger models and consequently in sizeable forecast errors. So while (apart from the one-month forecast based on the cAIC) boosting is always able to beat the benchmark, bootstrapping leads to larger improvements than the cAIC. In comparison to the results obtained in Stock and Watson (2006), boosting is very competitive to all alternative methods. It almost always outperforms the combination forecasts, although the Bayesian counterpart (BMA) is somewhat more difficult to improve upon. The toughest adversaries are the dynamic factor models (DFM), which perform best in the short and medium run. However, for a 12-month forecast horizon, they are beaten by boosting based on bootstrapping.

2.4 Conclusion

This paper introduces component-wise boosting as a variable selection method into a horse race between factor models and forecast combination, two prominent approaches to deal with large numbers of predictors in forecasting. In an application to U.S. industrial production, we show that boosting is a serious competitor, especially when a resampling method is used to determine the number of iterations. Based on a single dataset and target variable, it is not possible to draw any general conclusions about the forecasting performance of boosting. However, it has been shown that boosting is a viable alternative to other methods using many predictors.

Acknowledgements

I am indebted to Klaus Wohlrabe who is co-author of Chapter 2. We thank Mark W. Watson for making his dataset available and thus enabling a direct comparison of the results. We also thank Kai Carstensen and Nikolay Robinzonov, as well as our anonymous referee for helpful comments.

Chapter 3

News Media and Expectation Formation of Firms

Forming expectations about the future path of the economy and about the own business prospects is not costless for a firm. Instead, acquiring and processing the relevant macroeconomic information requires valuable resources. Thus many firms rely on the coding services provided by the mass media. We investigate empirically whether news media have an independent influence on the expectation formation process of firms that goes beyond actual economic developments. Using Ifo survey data that explicitly measure business expectations, as well as data that cover the intensity and the tone of media coverage, we come to four conclusions. First, a firm is more likely to update its business expectations when the volume of macroeconomic news increases. Second, news media act as an amplifier of fundamental developments. Third, firms are more susceptible to business cycle news when the macroeconomic situation is below average. Finally, the tone of news reports does not play a role for the expectation updating decision of firms.

3.1 Introduction

The working horse of economics has long been the hypothesis of rational expectations originally proposed by Muth (1961) and promoted by Lucas (1972, 1976). According to the rational expectations hypothesis individuals are not only forward-looking and have knowledge of the true model for the future path of the economy, but they also update their expectations continuously by constantly feeding all relevant data into the forecasting model. In reality, however, economic agents face information costs in their process of expectation formation; they have to spend money and time to obtain and evaluate all the relevant information. Costs of information acquisition and processing lie at the heart of the sticky information model by Mankiw and Reis (2002, 2006), arguably the most prominent deviation from the rational expectations hypothesis. The authors suggest that individuals only sporadically update their information sets and otherwise stick to outdated information when building their expectations. Accordingly, new information disseminates slowly through the economy and macroeconomic aggregates react only gradually to shocks.

In his rational inattention model, which provides a microfoundation of the sticky information model, Sims (2003) also sheds light on the role that mass media play in the economic agents' expectation formation. The latter may rationally choose not to pay attention to some information because they have limited processing capacities. They receive an erratic signal of a macroeconomic shock, and the idiosyncratic coding errors do not average out, but have an aggregate effect because individuals rely largely on the coding services provided by news media. Carroll (2003) models the impact of the mass media on macroeconomic expectations more explicitly. He develops a simple epidemiologic model of expectations according to which macroeconomic information spreads across an economy like an epidemic with mass media being the common source of infection. He shows that the rate of infection, that is, the share of households that learn about experts' current macroeconomic expectations, depends on the intensity of news coverage. Since greater news coverage lowers information costs, the probability that a household updates its inflation expectations, for instance, rises when there are more reports about inflation.

This paper is the first to analyse on a microlevel whether coverage of macroeconomic news also affects the probability of a firm revising its own business expectations. Carroll (2003) has initiated a considerable amount of research, but most papers deal with the impact of news reports on macroeconomic expectations of households and professional forecasters (Badarinza and Buchmann, 2009; Curtin, 2003; Doepke et al., 2008; Dräger, 2011; Easaw and Ghoshray, 2010; Lamla and Lein, 2008; Lamla and Maag, 2012; Lamla and Sarferaz, 2012). Only Lamla et al. (2007) look at the effect of news media on business expectations, but as most of the above-mentioned studies, their analysis is confined to the aggregate level.[1] In contrast, we employ panel data at the firm level that allow for a more direct study of the expectation formation process.

But our analysis goes beyond models of sticky information and rational inattention. We take the animal-spirits view put forward by Keynes (1936) and revived by Akerlof and Shiller (2010), according to which noneconomic motives and irrational behaviour are the main driving force of economic fluctuations. Akerlof and Shiller (2010) explicitly mention stories as one of the five psychological factors that are of particular importance.[2] They argue that the news media have a tendency to overinterpret economic facts. By creating stories about the nature of the economy they influence the confidence of people, which, in turn, can lead to feedback effects on the real economy. These real effects are due to the fact that changes in confidence go hand in hand with changes in the expectations for personal success in business, for entrepreneurial activity and for payoffs to investments. So in contrast to Carroll (2003), mass media do not necessarily bring expectations closer to rationality, but can lead to overoptimism or overpessimism.

Consequently, we do not only investigate along the lines of Carroll (2003) whether a firm is more likely to update its business expectations when media coverage of economic news is more intense. More importantly, we also analyse whether the effect of news

[1] Exceptions among studies of macroeconomic expectations are Dräger and Lamla (2012), and Santoro and Pfajfar (2013), who use household data on inflation expectations.

[2] The other factors they name are confidence, fairness, corruption and bad faith, and money illusion.

coverage merely mirrors the economic situation or whether it acts as an amplifier of actual developments. Additionally, we examine the impact of the content of media coverage, a channel that is highlighted by Doms and Morin (2004). In fact, positive and negative stories could differ in their infectiousness, leading to asymmetric effects on the propensity to revise business expectations. Finally, media coverage could also affect the expectation formation process of firms asymmetrically depending on whether the economy is in an expansion or in a downturn. The remainder of this paper is laid out as follows. Section 3.2 discusses the econometric models, Section 3.3 describes the data, Section 3.4 reports the results, and Section 3.5 concludes.

3.2 Econometric Models and Identification

3.2.1 Does the News Volume Matter?

The first questions we analyse are whether the intensity of media coverage has an independent influence on the expectation formation of firms and whether it reinforces the impact of economic developments on their updating behaviour. Agenda-setting theories, which play a major role in media research, attach great importance to the amount of media attention (often referred to as media salience) devoted to a certain issue. It is argued that reporting intensity increases accessibility of information and thus raises public concern for the respective issue (Dearing and Rogers, 1996; McCombs, 2013; McCombs and Shaw, 1972). When analysing the impact of media coverage on expectations, the macroeconomic literature also discusses the role of news volume. Carroll (2003) finds that the probability of a household updating its macroeconomic expectations depends on the intensity of news coverage. This result can be explained by the fact that greater news coverage makes macroeconomic information more easily accessible, that is, it lowers costs of information acquisition. The rational inattention literature rather emphasises the relevance of information-processing costs, and Sims (2003) argues that news media fulfill a vital information-processing service. In this sense, an increase in coverage of economy-wide news could signal to firms that macroeconomic conditions have become more important and should be taken into consideration when forming expectations. Based on these arguments, our first hypothesis is that *an increase in the volume of macroeconomic reports raises the probability that a firm updates its business expectations.*

Moreover, we analyse whether the effect of news volume on the updating behaviour of firms reinforces the impact of the economy. Akerlof and Shiller (2010) suggest that stories drive the ups and downs of an economy, creating cycles of overoptimism and overpessimism and, consequently, excessive booms and busts. In our context, this means that the influence of reporting intensity is stronger in booms or recessions compared to more moderate economic conditions. So our second hypothesis is that *the reaction of business expectation updating to news volume is disproportionately high in relation to economic developments.*

To test these hypotheses, we estimate a simple linear probability model with firm fixed effects and robust standard errors that account for heteroskedasticity. The model is given by:

$$
\begin{aligned}
y_{it} = \alpha &+ \beta_1 \mathrm{NEWSVOL}_t + \sum_{i=0}^{p} \beta_{2,i} \mathrm{ECON}_{t-i} + \beta_3 (\mathrm{NEWSVOL}_t \times \mathrm{ECON}_t) \\
&+ \boldsymbol{\beta}_4' \mathbf{FIRM}_{it} + c_i + u_{it}, \qquad (3.1)
\end{aligned}
$$

where

$$
y_{it} = \begin{cases} 1, & \text{if expectations updated} \\ 0, & \text{if expectations unchanged.} \end{cases}
$$

Identification is mainly ensured by control variables. Most importantly, we control for the macroeconomic situation and outlook, measured by the variable ECON[3], to check whether the media effect goes beyond the pure economic data that are reported. Since positive as well as negative and neutral news enter the news volume measure (NEWSVOL), we capture the extent to which the macroeconomic situation changes

[3]Details are given in Section 3.3.3.

either in a good or in a bad way by computing the absolute deviation (a.d.) of ECON from its mean. We also consider p lagged values of ECON to take into account that firms rely on outdated information as suggested by the sticky information literature. The frequency with which firms update their information sets varies across countries. Fabiani et al. (2006) find for Germany that the median firm reviews its prices three times a year (30% at least 12 times, 17% 4-11 times, and 53% a maximum of three times a year). Assuming that firms update the information on which they base their general business expectations at least as often as the information on the basis of which they review their prices, six lags (corresponding to two updates) should cover the relevant information used by firms. Moreover, we use a vector of firm controls, **FIRM**,[4] to take into account that firms could experience changes in the macroeconomic situation in their own books. This reduces the need for information from news media.

The interaction term between news volume and the macroeconomic situation (named INTECON in the following) is the reason why we estimate a linear probability model instead of a logit or probit model; in nonlinear models, interaction terms are difficult to interpret (Ai and Norton, 2003).[5] Moreover, marginal effects cannot be identified in nonlinear panel models. So another advantage of the linear model is that we can exploit the panel structure of the data and estimate firm-specific fixed effects, c_i. Although they are of minor importance as they are time-invariant and thus cannot be correlated with the variables of interest, which only vary over time, there could be an indirect relationship through the correlation with the firm-specific variables. After all, although many textbooks argue that linear regression models are inappropriate when the dependent variable is binary, from the point of view of Angrist and Pischke (2009), model choice is less important because the interpretation of the average causal effect is not heavily model dependent.

Finally, there could still be reverse causality between business expectations and media coverage. However, three elements of the identification strategy help to circumvent

[4] The firm data is described in Section 3.3.1.

[5] All models without interaction terms are also estimated as pooled logit models with cluster-robust standard errors, and the results are very similar.

this problem. Firstly, NEWSVOL (as well as all other measures of media coverage) contains only macroeconomic news, not news about single firms. If the latter were included, the effect of news coverage would not be exogenous because a firm's economic situation and plans are reflected in its business expectations. One could argue that the macroeconomic situation depends on the condition of all firms. However, every single firm is too small to influence the economy on an aggregate level. Secondly, we skip all news of the category "business sentiment" from the news measures because they mainly consist of reports about the Ifo cyclical indicators, which are computed from the survey data. Thirdly, as described in Section 3.3.2 the time structure of the media measures is such that they only capture news that are disseminated between the first and the 20th of the month, thus before the Ifo cyclical indicators are published and reported in the media.

3.2.2 Does the News Tone Matter?

When people do not treat all kinds of information the same, but selectively process news, the tone of media coverage could also influence the expectation formation process of firms. In fact, mass media convey signals about the state of the economy not only by the intensity of reporting, but also by the evaluative tone of news reports (Doms and Morin, 2004). Is there evidence for an asymmetric updating process where a certain kind of information is avoided? Do firms respond more to predominantly positive or negative reporting?

Theories of overoptimism suggest that agents have a tendency to avoid or deny bad news when forming expectations (Bénabou, 2013). There is a long-standing body of work giving evidence for such information avoidance with respect to people's own traits or future prospects. Eil and Rao (2011), and Möbius et al. (2011), for instance, show that individuals systematically underrespond to negative information about their IQ or beauty score. According to Karlsson et al. (2009) individual investors also seem to suffer from fear to learn bad outcomes; the authors find that far more go online to look up the value of their portfolios on days when the market is up than when it is down.

However, there is also evidence that people are more prone to bad than to good news. Lau (1985) finds that greater weight is given to negative information than comparable positive information in the perception of political persons. One of the explanation he gives is that people are more strongly motivated to avoid costs than to approach gains, so negative information is perceived to be more important. Schoenbach and Semetko (1992) analyse the effects of news coverage on perceived salience of political issues. Extending the original agenda-setting hypothesis, they argue that not only the intensity of media coverage is relevant, but also the tone. They find that a more positive evaluation actually diminishes the perceived importance of an issue. Sheafer (2007) confirms this result for the perception of economic issues. The latter are deemed to be more important when the media present the economy in a more negative way. Finally, Dräger (2011) finds that only bad news influence inflation perceptions. With our third hypothesis we test whether *the probability to revise business expectations is higher when the news tone of macroeconomic reports becomes more negative.*

The model is given by:

$$y_{it} = \alpha + \beta_1 \mathrm{NEWSTONE}_t + \sum_{i=0}^{p} \beta_{2,i} \mathrm{ECON}_{t-i} + \boldsymbol{\beta}_3' \mathbf{FIRM}_{it} + c_i + u_{it}, \tag{3.2}$$

where

$$y_{it} = \begin{cases} 1, & \text{if expectations updated} \\ 0, & \text{if expectations unchanged.} \end{cases}$$

Details on how the tone of media coverage (NEWSTONE) is measured can be found in Section 3.3.2. Most remarks concerning estimation and identification of Model (3.1) also apply here. A difference though is that the variable ECON enters untransformed since we want to capture positive and negative movements in the macroeconomic situation and outlook.

3.2.3 Does the Economic Regime Play a Role?

The final part of our analysis compares the effects of media coverage in expansions and downturns. Hypothesis 2 from Section 3.2.1 implies that the impact of media coverage on the expectation formation of firms is stronger in unusual than in moderate economic times. However, this effect could be asymmetric depending on the macroeconomic regime. This question is rather neglected in the literature. But Dräger (2011), who uses Swedish data, finds that households' inflation perceptions react more to news reports when inflation is high and volatile. Our fourth hypothesis is that *a below-average macroeconomic situation reinforces the effect of media coverage on the updating of business expectations, whereas an above-average environment dampens it.*

We estimate two separate models for the effects of positive and negative news reports on the probability of an expectations update upwards or downwards, respectively. The first models is given by:

$$\begin{aligned} y_{it} = \alpha + \beta_1 \text{NEWSPOS}_t + \sum_{i=0}^{p} \beta_{2,i} \text{ECONPOS}_{t-i} + \beta_3 (\text{NEWSPOS}_t \times \text{ECONPOS}_t) \\ + \boldsymbol{\beta}_4' \mathbf{FIRM}_{it} + c_i + u_{it}, \end{aligned} \tag{3.3}$$

where

$$y_{it} = \begin{cases} 1, & \text{if expectations updated upwards} \\ 0, & \text{otherwise.} \end{cases}$$

Analogously, the second model is given by:

$$\begin{aligned} y_{it} = \alpha + \beta_1 \text{NEWSNEG}_t + \sum_{i=0}^{p} \beta_{2,i} \text{ECONNEG}_{t-i} + \beta_3 (\text{NEWSNEG}_t \times \text{ECONNEG}_t) \\ + \boldsymbol{\beta}_4' \mathbf{FIRM}_{it} + c_i + u_{it}, \end{aligned} \tag{3.4}$$

where

$$y_{it} = \begin{cases} 1, & \text{if expectations updated downwards} \\ 0, & \text{otherwise.} \end{cases}$$

NEWSPOS and NEWSNEG are volume measures, which contain the number of positive and negative news, respectively. ECONPOS and ECONNEG are dummy variables that are constructed from the variable ECON, which take value 1 when ECON has a larger (smaller) value than its mean, indicating a positive (negative) macroeconomic environment. Again, we control for lagged values of the macroeconomic regime, as well as for firm-specific variables and fixed effects. Positive coefficients of the interaction terms (named INTECONPOS and INTECONNEG in the following) indicate a reinforcing media effect of the respective regime; an above-average (below-average) environment would strengthen the effect of positive (negative) news coverage.

3.3 Data

The dataset consists of monthly data from January 1998 to May 2011, which we have retrieved from various sources: the business survey compiled by the Ifo Institute, data from the media research institute Media Tenor, and macroeconomic data from Datastream as well as the German Bundesbank.

3.3.1 Ifo Business Survey

The Ifo Business Survey is well-known for the Ifo Business Climate Index, which is a widely observed early indicator for cyclical developments in Germany based on around 7,000 monthly survey responses of firms in manufacturing, construction, wholesaling and retailing. The Ifo Business Climate Index is computed from the two main questions in the survey, the firms' assessments of their current business situation and their business expectations for the following six months.[6] While the cyclical indicator is published

[6]For details on how the Ifo Business Climate Index is calculated, see http://www.cesifo-group.de/ifoHome/facts/Survey-Results/Business-Climate/Calculating-the-Ifo-Business-Climate.html

Table 3.3.1: Transition probabilities

Business expectations	Business expectations better	same	worse	Total
better	60.01	36.03	3.97	100
same	10.36	79.37	10.27	100
worse	4.97	34.06	60.98	100
Total	18.64	62.96	18.40	100

every month, the micro survey data are only available for research purposes.[7] The panel used here comprises 7,390 product groups within the manufacturing sector. For the sake of convenience, the product groups will be referred to as firms in the following, although they correspond to only 6,910 firms because each enterprise can answer several questionnaires for its various product groups. The sample is unbalanced as new firms can enter, firms can exit the survey or cease to exist, or simply not answer from time to time. Based on the assumption that observations are missing at random we drop these to obtain an equal number of data points across all models, which amounts to 444,898 observations.

One of the main advantages of the Ifo Business Survey is that it asks directly for business expectations: *"With respect to the business cycle, our situation for product group XY is expected to be somewhat better, more or less the same, or somewhat worse in the next six months."* We use this question for the dependent variable and recode the three possible answers into 1 when the firm expects a changed business situation as compared to the current situation ("better" or "worse"), and 0 if it does not ("same"). This is interpreted as an update of business expectations (B.EXP UPDATE), not over time, but between two states—with and without the incorporation of new information.

It would be desirable to examine the expectation updating behaviour of firms over time. A straightforward approach would be to compute the difference between the responses of month t and month $t+1$, and to assume a change in expectations whenever the difference is unequal zero. However, there are limitations to the data. Firstly, we only have qualitative, not quantitative data on expectations. So whether an answer

[7]For more information about the Ifo Business Survey and about data access, see Becker and Wohlrabe (2008).

series can be interpreted as a change or no change of expectations depends on how the business situation evolved in the meantime. For instance, if a firm reports better business expectations several months in a line, this does not necessarily mean that its expectations have remained unchanged. Instead, if the economy is in a cyclical upturn, the company could report even better expectations month by month. Secondly, the consecutive questionnaires refer to overlapping periods because firms are asked for their expectations *in the next six months*. This furthermore complicates the interpretation of expectations over time. So if, for instance, in time t a firm reports worse business expectations for the period until $t+6$ and unchanged business expectations in $t+1$ for the period until $t+7$, this does not necessarily mean a change in expectations as the business situation could already have deteriorated to the expected extent in month $t+1$. Thirdly, the response behaviour is very persistent. Table 3.3.1 shows the transition probabilities for a change in business expectations over time. More than 60% of the firms that report better or worse business expectations in one month give the same answer in the following month, and even almost 80% of those who report unchanged expectations. Due to these reasons, we choose the alternative approach and interpret this as an update of expectations whenever firms indicate the answers "better" or "worse". The underlying assumption we take is that, *ceteribus paribus*, without the incorporation of macroeconomic news firms expect their business situation to remain unchanged.[8] From Table 3.D.1, which reports all summary statistics, it can be seen that the probability that a firms updates its expectations (B.EXP UPDATE) is 37%, and that it is approximately as likely that the firm changes its expectations upwards (B.EXP UP) as downwards (B.EXP DOWN).

The Ifo Business Survey panel also contains detailed firm-specific information that is used by control variables because the macroeconomic situation can be reflected in the situation of the firm. Thus the enterprise could be less dependent on information

[8]Still, the overlapping time periods could be a problem because we could measure a change in expectations although the firm had already incorporated the information concerning the respective time period in the previous month. To take this into account, we estimate all models using six different datasets, where we only use the data for January and July, February and August, and so on. In the majority of cases, the results are robust.

from mass media. The firm controls are the following: state of business (STATE), domestic production versus previous month (PROD), demand versus previous month (DEMAND), orders on hand (ORD), orders versus previous month (ORDVPM), domestic selling prices versus previous month (PRICES), as well as the number of employees (EMPL).[9] From all categorial firm variables we construct two distinct dummy variables indicating improvements and deteriorations (indicated by + and -) to capture potential asymmetric effects. The vector of firm-specific variables is then given by $\mathbf{FIRM}'_{it} = (\mathrm{STATE}_{it}^{+,-}, \mathrm{PROD}_{it}^{+,-}, \mathrm{DEMAND}_{it}^{+,-}, \mathrm{ORD}_{it}^{+,-}, \mathrm{ORDVPM}_{it}^{+,-}, \mathrm{PRICES}_{it}^{+,-}, \mathrm{EMPL}_{it})$.

3.3.2 Media Data

The second data source is the research institute Media Tenor, which analyses all economic news in a range of print and TV sources of at least five lines or five seconds, respectively. To increase accuracy, the content analysis is performed by humans instead of a computer algorithm. Altogether, we use 26 different media sources, which belong to the most popular newspapers (DIE WELT, Frankfurter Allgemeine Zeitung, Süddeutsche Zeitung, Frankfurter Rundschau, BILD, BILD am Sonntag), magazines (Focus, DER SPIEGEL, manager magazin, Wirtschaftswoche) and 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) in Germany. For numbers on the scope of these media, see Table 3.B.1.

Our sample covers news about current and future cyclical developments in Germany and its most important export countries.[10] The news reports fall into the following macroeconomic categories: Economic climate, gross domestic product and its components, Euro exchange rate, competitiveness, productivity, (un-)employment, labour costs, consumer confidence, insolvencies, start-ups, capital resources and bank lending,

[9] For the wording of the survey questions, see Table 3.A.1.

[10] 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.

and future prospects.[11] To make sure that we capture news that could potentially influence the 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 the firms fill out the questionnaires.[12]

From the media data, we construct four news indexes. The first one, news volume (NEWSVOL), captures media intensity by counting all news per month. The second one is a news tone index (NEWSTONE), which captures how the journalists evaluate the current economic developments. The news tone index is a balance index of the proportion of positive and negative news per month, where news reports are coded as positive or negative if they contain either an explicit judgement or an implicit valuation from the context. Finally, we measure positive and negative news (NEWSPOS and NEWSNEG) coverage separately by counting the number of positive and negative news, respectively.

The average number of news reports per month is around 60, and varies between 9 and 165 (see Table 3.D.1). These numbers might appear rather low, but this is due to the fact that only some of the sources are available for the whole time span.[13] The news tone index, which by construction can vary between -100 and 100 balance points, has a negative value of roughly -18 on average.[14]

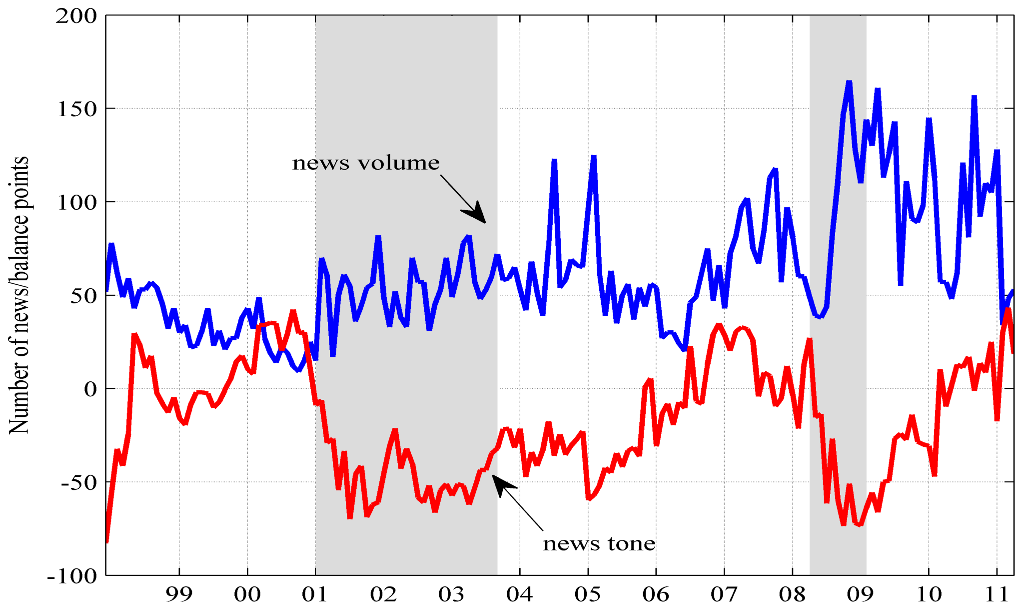
[11] In fact, fiscal and monetary policy also influence business expectations. However, it is unclear according to which criteria media reports evaluate economic policy and which role business cycle considerations play hereby. Hence, reports on economic policy in general, on its instruments such as taxes, subsidies and the interest rate, and on its consequences like inflation and public debt are excluded in the baseline specification. However, robustness checks including them are performed and the results hold.

[12] However, there is a tendency to respond early, so that news that are disseminated later in the month do not play a role in the expectation formation of the majority of firms; 75% of those who responded online (a means chosen by around 52% of the respondents) send back the questionnaire until the 14th day of the month. Thus, as a robustness check, we calculated all media indices using only those media reports published between the first and the 14th day of each month, and the results remain nearly unchanged.

[13] This is only the case for the following magazines and television broadcasts. Tagesthemen, Tagesschau, heute journal, heute, RTL aktuell, SAT.1 18:30, Focus, and DER SPIEGEL.

[14] The fact that the mean NEWSTONE value is almost identical for a shorter sample excluding the recent financial and economic crisis points to a negative bias in reporting about the macroeconomic situation.

Figure 3.3.1: News volume and news tone



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

Figure 3.3.1 displays the news volume and the news tone index from 1998 to mid 2011. The news tone index quite nicely captures the beginning of the recessions in 2001 and in 2008. Furthermore, there is a negative relationship between news tone and news volume; a higher number of reports tends to be driven by a larger number of negative news. Figure 3.B.1, which plots the volume indexes of positive and negative news, shows that the number of unfavourable news reports is much more variable than the number of favourable reports.

3.3.3 Macroeconomic Data and Principal Components

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 macroeconomic time series. One could imagine even a bigger dataset, however, not all indicators are available in real time, that is, taking into account publication lags and data revisions.[15] It is important though for our analysis to mimic the information set that is available to media as well as to firms when forming expectations. The first group of indicators covers the real economy and includes production, orders received, and employment. It is retrieved from the real-time database of the German Bundesbank.[16] From that same source, we obtained real-time information on prices. Another big bloc of time series are business survey indicators (most notably the Ifo indicators), consumer survey indicators, and composite indicators. These time series are lagged one month, since they are usually not revised, but are not available before the end of the month, that is, after the period during which firms fill out the Ifo Business Survey questionnaires. 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 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 3.C.1.

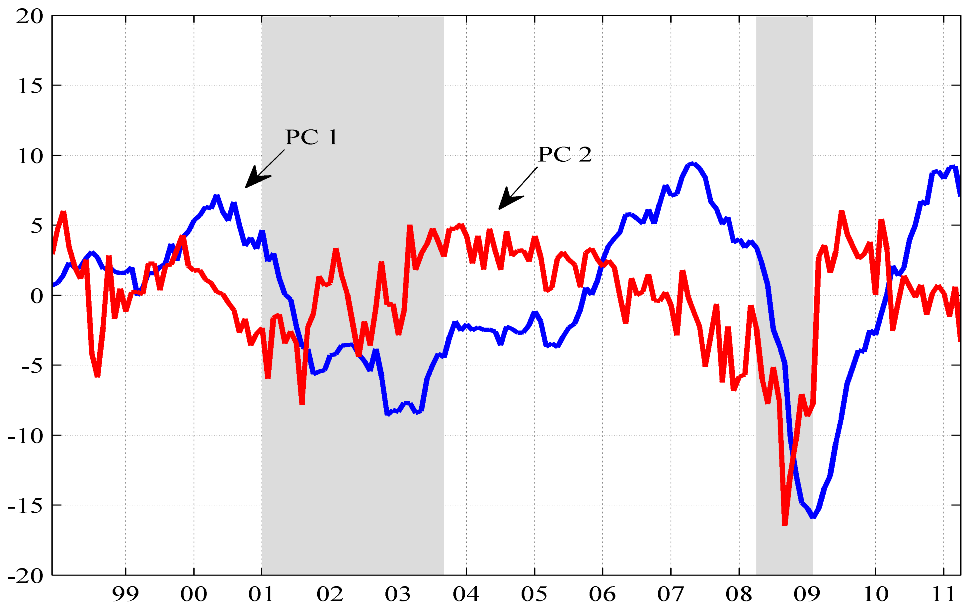
Of course, we cannot include all these variables into our models without running into dimensionality problems. So we have to employ some kind of data reduction method to condense the information into one or few variables that proxy the macroeconomic situation and outlook. In the macroeconomic literature, factor analysis is a popular method to cope with high-dimensional data. The idea is that a small number of latent factors, F_t, drive the comovements of an N-dimensional vector of time-series variables X_t:

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

[15] We have also run a robustness check with a dataset that consists of 259 time series but does not take into account real-time information, taken from Drechsel and Scheufele (2012). The results are very similar.

[16] http://www.bundesbank.de/statistik/statistik_realtime.php

Figure 3.3.2: Principal components



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

where e_t is an $N \times 1$ vector of idiosyncratic disturbances and Λ represents the factor loadings that determine the contribution of each variable to the factor. Stock and Watson (2002a) show that when the number of time series N and the time dimension T are large, the factors can be estimated consistently by 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 (ECON and ECON2 in the following) that represent those linear combinations explaining the largest and second largest part of variance in the data. As explained in Section 3.2.1 we include six lags of ECON to take into account that firms only occasionally update their information set. But instead of modelling the factor dynamics, we estimate static factors for each of the six lags of the variables because we have real-time data. Certainly, the number of factors that replaces the information in the large number of time series needs to be discussed. There is a number of criteria that can be used to determine the number of factors, such as scree plots or information criteria. In forecasting applications, the choice is often based on the accuracy of the forecasting models, and one or two factors are mostly found to perform well (Stock and Watson, 2002b). We primarily look at the fraction of variance that the factors explain. In Table 3.C.2, we list the estimation results for the first ten principal components. It can be seen that the first two principal components represent 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 3.3.2 gives a graphical representation of the first two principal components.[17]

3.4 Results

3.4.1 News Volume Matters—in Exceptional Times

Table 3.4.1: Effects of news volume on business expectations

Dependent variable: Business expectations update					
	(1)	(2)	(3)	(4)	(5)
NEWSVOL	0.09***	0.07***	0.05***	0.02***	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
ECON (a.d.)		0.97***	0.93***	0.86***	0.48***
		(0.08)	(0.08)	(0.07)	(0.09)
ECON2 (a.d.)			0.62***	0.48***	0.41***
			(0.04)	(0.04)	(0.04)
INTECON					0.01***
					(0.00)
CONSTANT	31.39***	30.80***	30.11***	18.60***	20.91***
	(0.14)	(0.17)	(0.17)	(0.36)	(0.48)
ECON LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	444,898	444,898	444,898	444,898	444,898
Adj. R^2	0.004	0.005	0.006	0.080	0.080

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5), a.d. - absolute deviation from the mean.

Table 3.4.1 reports the results (in percentage points) of the first model, which captures the effect of news intensity on business expectations. When the volume of business cycle

[17] As a robustness check, we also include the third and fourth principal component in the regressions, and the results are robust.

news rises, there is a highly significant positive effect on the probability that a firm updates its business expectations. The effect is moderate; overall, the probability of an expectations update rises by 0.02 percentage points, when there is one more news report per month (Equation (4)). Equation (5) shows why the volume effect of media coverage might be rather small. While it is insignificant at the 99%-level at the average value of ECON, it becomes more relevant in unusual economic circumstances.[18] The more important the changes in the macroeconomic situation, the stronger is the influence of media coverage on the expectation formation process of firms; the interaction term INTECON has a positive sign and is also highly significant. In March 2009, when the recession was at its worst, the effect of media intensity amounted to 11 percentage points; without any media reporting the model predicts an updating probability of 45.5%, whereas taking into account the 144 news reports means an updating propensity of 56.5%.

3.4.2 Irrelevance of News Tone

Table 3.4.2 reports the results of the second model, which we estimate to find out whether the tone of media coverage plays a role when firms are forming expectations. They are more likely to update their business expectations in a more negative macroeconomic environment, but there is no independent effect of the news tone; when controlling for the macroeconomic situation and firm-specific information businesses do not react differently to a more favourable or more unfavourable evaluation of economic developments (see Equation (4)). As a robustness check, we include NEWSPOS and NEWSNEG instead of NEWSTONE. Equation (5) shows that the effects of the number of positive and negative news are equal, a hypothesis that cannot be rejected by the Wald test.

[18]With such a large number of observations, it makes sense to choose a high significance level.

Table 3.4.2: Effects of news tone on business expectations

Dependent variable: Business expectations update	(1)	(2)	(3)	(4)	(5)
NEWSTONE	-0.12***	0.01***	0.00	-0.00	
	(0.00)	(0.00)	(0.00)	(0.00)	
NEWSPOS					0.03***
					(0.01)
NEWSNEG					0.03***
					(0.01)
ECON		-0.97***	-0.42***	-0.44***	-0.44***
		(0.07)	(0.07)	(0.08)	(0.08)
ECON2			-0.49***	-0.25***	-0.21***
			(0.03)	(0.04)	(0.04)
CONSTANT	34.94***	37.37***	37.23***	22.15***	21.06***
	(0.08)	(0.11)	(0.10)	(0.24)	(0.32)
ECON LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	444,898	444,898	444,898	444,898	444,898
Adj. R^2	0.006	0.009	0.010	0.080	0.080

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5).

3.4.3 Reinforcing Negative Environment

Although it does not play a role for the updating decisions of firms whether media report in a predominantly positive or negative way, there could be a differential media effect depending on the macroeconomic environment. To investigate this question, we estimate two separate models for the effects of positive and negative news reports (NEWSPOS and NEWSNEG) on the probability of an expectations update upwards or downwards, respectively. At the same time, these models serve as consistency checks of the response behaviour. In both Tables 3.4.3 and 3.4.4 the coefficients of the news measures are positive. Thus the reactions of the firms are consistent; they tend to adapt more favourable (unfavourable) business expectations when the number of positive (negative) news increases. The coefficients of NEWSPOS and NEWSNEG have about the same size, confirming the results from Section 3.4.2. However, Equations (5) reveal a crucial difference: The interaction term between the macroeconomic situation and the number of favourable news (INTECONPOS) has a negative sign (and is insignificant), while the corresponding interaction term with the volume of unfavourable news (INTECONNEG) has a positive coefficient. So in contrast to a positive macroeconomic situation, a negative environment reinforces the effects of media coverage. These results complement those obtained in Table 3.4.1; firms are more susceptible to business cycle news in unusual times, and especially when times are unusually bad.

Table 3.4.3: Effects of positive news on business expectations

Dependent variable: Business expectations up	(1)	(2)	(3)	(4)	(5)
NEWSPOS	0.21***	0.18***	0.18***	0.10***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
ECONPOS		4.78***	4.93***	3.25***	3.36***
		(0.30)	(0.29)	(0.31)	(0.34)
ECON2POS			2.02***	1.67***	1.65***
			(0.13)	(0.16)	(0.16)
INTECONPOS					-0.01
					(0.02)
CONSTANT	16.09***	17.40***	15.83***	10.91***	10.83***
	(0.11)	(0.11)	(0.15)	(0.26)	(0.28)
ECONPOS LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	444,898	444,898	444,898	444,898	444,898
Adj. R^2	0.004	0.010	0.010	0.069	0.069

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5).

3.4.4 Media Effects on Production Expectations

As a robustness check, we also estimate all models with production expectations as dependent variable to see whether the influence of media coverage on business expectations of firms translates into a modification of their behaviour. An advantage of this specification is that the variable production expectations can be more easily interpreted as an expectation update over time than the business expectation variable. Production expectations can be seen as production plans, so the answers "better" or "worse" production expectations compared to current production—which supposedly

Table 3.4.4: Effects of negative news on business expectations

Dependent variable: Business expectations down	(1)	(2)	(3)	(4)	(5)
NEWSNEG	0.26***	0.19***	0.19***	0.13***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
ECONNEG		6.90***	7.15***	3.96***	3.25***
		(0032)	(0.32)	(0.30)	(0.35)
ECON2NEG			2.15***	1.95***	1.97***
			(0.11)	(0.14)	(0.14)
INTECONNEG					0.04***
					(0.01)
CONSTANT	11.36***	12.13***	11.01***	5.15***	5.55***
	(0.10)	(0.09)	(0.10)	(0.22)	(0.25)
ECONNEG LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	444898	444898	444898	444898	444898
Adj. R^2	0.023	0.034	0.035	0.157	0.157

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5).

also followed a plan—then corresponds to a planning or expectations update.[19] The results in Appendix 3.E show that the effects with respect to news volume and news tone are robust. However, in contrast to business expectations, a production expectations revision is not more likely in a negative than in a positive macroeconomic environment. Consequently, firms adjust their production plans when the intensity of media coverage increases, similarly to business expectations. But for production expectations, we find no asymmetric updating behaviour, neither with respect to bad news nor to bad economic circumstances.

3.5 Conclusion

As it takes time and money to acquire and interpret macroeconomic information that is relevant for a firm's business prospects, many enterprises make use of news media to cut these information costs. Hence, media can impact the expectation formation process

[19] For an analog interpretation with respect to pricing plans, see Schenkelberg (2013).

of firms. We investigate empirically whether this influence goes beyond fundamental economic developments the media report about. Thereby, we analyse two potential channels, the intensity of media coverage and its tone. For our microeconometric study, we make use of two exceptional datasets. Firstly, we employ a large panel of business surveys for the German manufacturing sector conducted by the Ifo Institute, which explicitly measures business expectations. Secondly, we use a dataset obtained from the media research institute Media Tenor, which contains detailed information about news reports concerning current and future cyclical developments.

While the tone of media coverage does not play a role for the decision to update business expectations, we find evidence that a more intense media coverage increases the updating propensity. This effect is the stronger the larger the changes in the macroeconomic situation. Thus mass media reinforce the impact of actual economic developments on business expectations. Furthermore, an unfavourable macroeconomic regime reinforces the effect of business cycle news on the expectation formation of firms, while an above-average macroeconomic regime dampens the effects news reports.

Our results indicate that mass media are not an objective source of information that rational firms use to keep themselves fully informed about macroeconomic developments. Instead, firms seem to be susceptive to the stories that news media create and that often exaggerate the facts. But it depends on the economic environment how impressible businesses are by macroeconomic news. While in normal times, the influence of mass media on the willingness of firms to update expectations is insignificant, it becomes important in unusual times—and especially when times are unusually bad.

Appendix 3.A Ifo Business Survey Questions

Table 3.A.1: Ifo Business Survey

Variable	**Question**
Business expectations (B.EXP)	"With respect to the business cycle, our situation for product group XY is expected to be somewhat better, more or less the same, or somewhat worse in the next six months."
Production expectations (P.EXP)	"With respect to the business cycle, our domestic production activities concerning product group XY are expected to increase, stay the same, decrease in the next three months."
State of business (STATE)	"We evaluate our current business situation with respect to product group XY as good, satisfactory, unsatisfactory."
Production vs. previous month (PROD)	"With respect to the business cycle, our domestic production activities concerning product group XY increased, roughly stayed the same, decreased in the last month."
Demand vs. previous month (DEMAND)	"With respect to the business cycle, our demand situation for product XY improved, stayed the same, deteriorated in the last month."
Orders on hand (ORD)	"With respect to the business cycle, we evaluate our orders on hand for product group XY as superior, sufficient, inferior."
Orders vs. previous month (ORDVPM)	"With respect to the business cycle, our orders for product group XY increased, roughly stayed the same, decreased in the last month."
Selling prices vs. previous month (PRICES)	"Taking into account changed terms and conditions, our domestic selling prices for product group XY increased, stayed the same, decreased in the last month."

Notes: The questions are translated from German.

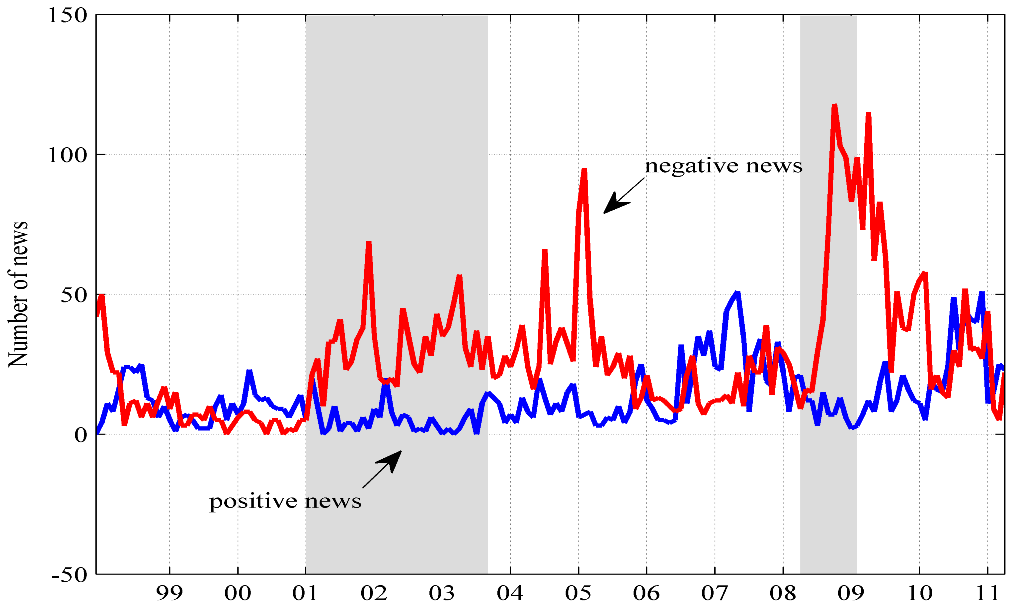
Appendix 3.B Media Coverage and Scope

Table 3.B.1: Media scope

Newspapers	BILD	2,438,684
(sold issues as of 4/2013)	BILD am Sonntag	1,259,622
	Süddeutsche Zeitung	400,647
	Frankfurter Allgemeine Zeitung	329,705
	DIE WELT	222,722
	Frankfurter Rundschau	no data
Magazines	DER SPIEGEL	842,322
(sold issues as of 4/2013)	Focus	509,983
	Wirtschaftswoche	154,261
	manager magazin	107,950
TV broadcasts	Tagesschau	8.79
(mio. viewers as of 2012)	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_von_Informationssendungen/409102/index.html, and http://daten.ivw.eu

Figure 3.B.1: Positive and negative news coverage



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

Appendix 3.C Macroeconomic Data and Principal Components

Table 3.C.1: List of macroeconomic variables

Series	Transformation
REAL ECONOMY	
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
PRICES	
Consumer price index, all categories, sadj	1
FINANCIAL MARKETS	
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
Spread BBF - gov, monthly avg.	0
DAX share price index, monthly avg.	1
Nominal effective exhange 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
SURVEYS AND COMPOSITE INDICATORS	
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

Series	Transformation
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
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
INTERNATIONAL INDICATORS	
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

Series	**Transformation**
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
EURO STOXX 50, monthly avg.	1

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

Table 3.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

Appendix 3.D Descriptive Statistics

Table 3.D.1: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.
Dependent variables				
B.EXP UPDATE	0.371	0.483	0	1
B.EXP UP	0.188	0.391	0	1
B.EXP DOWN	0.183	0.387	0	1
News indexes				
NEWSVOL	60.382	32.751	9	165
NEWSTONE	-17.836	30.736	-82.759	43.284
NEWSPOS	12.569	10.879	0	51
NEWSNEG	26.81	22.74	0	118
Macroeconomic data				
ECON	0.031	5.48	-15.942	9.429
ECON2	0.08	3.604	-16.485	6.060
Firm data				
STATE	-0.032	0.677	-1	1
PROD	-0.053	0.595	-1	1
DEMAND	-0.013	0.645	-1	1
ORD	-0.262	0.641	-1	1
ORDVPM	-0.068	0.642	-1	1
PRICES	0.005	0.429	-1	1
EMPL	476.939	3,421.354	0	900,079

Notes: Std. Dev. denotes the standard deviation, and Min. and Max. represent the minimum and maximum values.

Appendix 3.E Production Expectations as Dependent Variable

Table 3.E.1: Effects of news volume on production expectations

Dependent variable: Production expectations update					
	(1)	(2)	(3)	(4)	(5)
NEWSVOL	0.09***	0.07***	0.06***	0.03***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
ECON (a.d.)		0.84***	0.81***	0.68***	0.52***
		(0.08)	(0.07)	(0.06)	(0.08)
ECON2 (a.d.)			0.38***	0.25***	0.22***
			(0.03)	(0.04)	(0.04)
INTECON					0.00***
					(0.00)
CONSTANT	25.57***	24.82***	24.39***	11.29***	12.32***
	(0.16)	(0.16)	(0.17)	(0.32)	(0.43)
ECON LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	445,600	445,600	445,600	445,600	445,600
Adj. R^2	0.004	0.006	0.006	0.097	0.097

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5), a.d. - absolute deviation from the mean.

Table 3.E.2: Effects of news tone on production expectations

Dependent variable: Production expectations update					
	(1)	(2)	(3)	(4)	(5)
NEWSTONE	-0.07***	0.02***	0.01*	-0.00	
	(0.00)	(0.00)	(0.00)	(0.00)	
NEWSPOS					0.06***
					(0.01)
NEWSNEG					0.06***
					(0.01)
ECON		-0.57***	-0.05	-0.15**	-0.13*
		(0.08)	(0.07)	(0.07)	(0.07)
ECON2			-0.47***	-0.20***	-0.11***
			(0.03)	(0.03)	(0.03)
CONSTANT	29.90***	31.52***	31.39***	14.82***	12.54***
	(0.08)	(0.10)	(0.10)	(0.23)	(0.28)
ECON LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	445,600	445,600	445,600	445,600	445,600
Adj. R^2	0.002	0.004	0.005	0.096	0.096

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5).

Table 3.E.3: Effects of positive news on production expectations

Dependent variable: Production expectations up					
	(1)	(2)	(3)	(4)	(5)
NEWSPOS	0.24***	0.18***	0.18***	0.06***	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
ECONPOS		3.29***	3.30***	1.34***	0.69**
		(0.28)	(0.29)	(0.29)	(0.32)
ECON2POS			0.09	0.05	0.18
			(0.10)	(0.14)	(0.14)
INTECONPOS					0.08***
					(0.02)
CONSTANT	12.50***	12.38***	12.31***	7.61***	8.04***
	(0.09)	(0.10)	(0.12)	(0.22)	(0.24)
ECONPOS LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFCTS	No	No	No	Yes	Yes
Observations	445,600	445,600	445,600	445,600	445,600
Adj. R^2	0.005	0.008	0.008	0.083	0.083

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5).

Table 3.E.4: Effects of negative news on production expectations

Dependent variable: Production expectations down					
	(1)	(2)	(3)	(4)	(5)
NEWSNEG	0.21***	0.14***	0.14***	0.09***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
ECONNEG		3.76***	3.86***	0.51*	0.06
		(0.26)	(0.31)	(0.27)	(0.32)
ECON2NEG			0.89***	0.78***	0.79***
			(0.12)	(0.13)	(0.13)
INTECONNEG					0.02***
					(0.01)
CONSTANT	10.08***	10.37***	9.91***	2.91***	3.16***
	(0.09)	(0.09)	(0.09)	(0.20)	(0.22)
ECONNEG LAGS	No	Yes	Yes	Yes	Yes
FIRM CONTROLS	No	No	No	Yes	Yes
FIXED EFFECTS	No	No	No	Yes	Yes
Observations	445,600	445,600	445,600	445,600	445,600
Adj. R^2	0.017	0.025	0.025	0.170	0.170

Notes: Results in percentage points, * p<0.10, ** p<0.05, *** p<0.01, values in parentheses are bootstrapped standard errors for pooled models (1) to (3), and robust standard errors for panel models (4) and (5).

Chapter 4

News Media, Common Information, and Sectoral Comovement

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.

4.1 Introduction

It is one of the defining characteristics of business cycles that output and inputs move up and down together across most industries.[1] 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 et al. (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 et al. (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 costs of replication. Hence, the average costs of information

[1] 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 et al. (2007).

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 et al. (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 4.2 develops the model and the estimation approach. Sections 4.3 and 4.4 present how we measure sectoral comovement, media coverage of business cycle news as well as the macroeconomic environment the media report about. Section 4.5 discusses the estimation results and Section 4.6 concludes.

4.2 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.[2] 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.*

[2]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:

$$\mathrm{NEWS}_{k,t} = \alpha_k + \sum_{i=1}^{p} \beta_{k,i} \mathrm{NEWS}_{k,t-i} + \boldsymbol{\gamma}_k' \mathbf{ECON}_t + \varepsilon_{k,t}, \text{ with } k = 1, 2, \tag{4.1}$$

where NEWS_k is a measure of news volume ($k = 1$) or a measure of the news tone ($k = 2$), respectively.[3] **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.[4] 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, ε_k, reflect structural media shocks that are not backed by actual economic developments

[3]For details on the media data and the two measures of media coverage, please refer to Section 4.4.1.
[4]Details are given in Section 4.4.2.

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.[5]

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):

$$\begin{aligned} \text{COMBE} &= \alpha_k + \sum_{h=0}^{p} \phi_{k,h} \hat{\varepsilon}_{k,t-h} + u_{k,t}, \;\; k = 1, 2 \\ \text{COMIP} &= \beta_k + \sum_{h=0}^{p} \psi_{k,h} \hat{\varepsilon}_{k,t-h} + \nu_{k,t}, \;\; k = 1, 2, \end{aligned} \tag{4.2}$$

where $\hat{\varepsilon}_k$ are the residuals from Equation (4.1). The impulse response coefficients at horizon h correspond to ϕ_h and ψ_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 ν_t are potentially serially correlated, we use block-bootstrap confidence intervals to conduct inference on the response estimates.[6]

---

[5] For a quantification, see Section 4.5.

[6] 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.

4.3 Measuring Sectoral Comovement

4.3.1 Connectedness Framework

When measuring sectoral comovement, most studies simply use pairwise sectoral correlations or correlations of the sectoral quantity with the aggregate quantity.[7] However, the correlation coefficients are conditional on market volatility and biased upward during volatile periods (Boyer et al., 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 forecast 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

[7] 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.

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 et al. (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 4.3.2, 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 4.A.

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

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

Each element $w_{ij}^{g}(H)$ expresses the proportion of the H-step forecast error variance of some variable i, MSE$[y_{i,t}(H)]$, which is accounted for by a standard deviation shock in variable j at time t. σ_{jj} is the variance of the shock to the jth equation, Φ_h represent the $K \times K$ MA-coefficient matrices for step h, Σ_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 ith or jth 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,

$$C^g(H) = \frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{K} \tilde{w}^g_{ij}(H)}{\sum_{i,j=1}^{K} \tilde{w}^g_{ij}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{K} \tilde{w}^g_{ij}(H)}{K} \cdot 100. \tag{4.3}$$

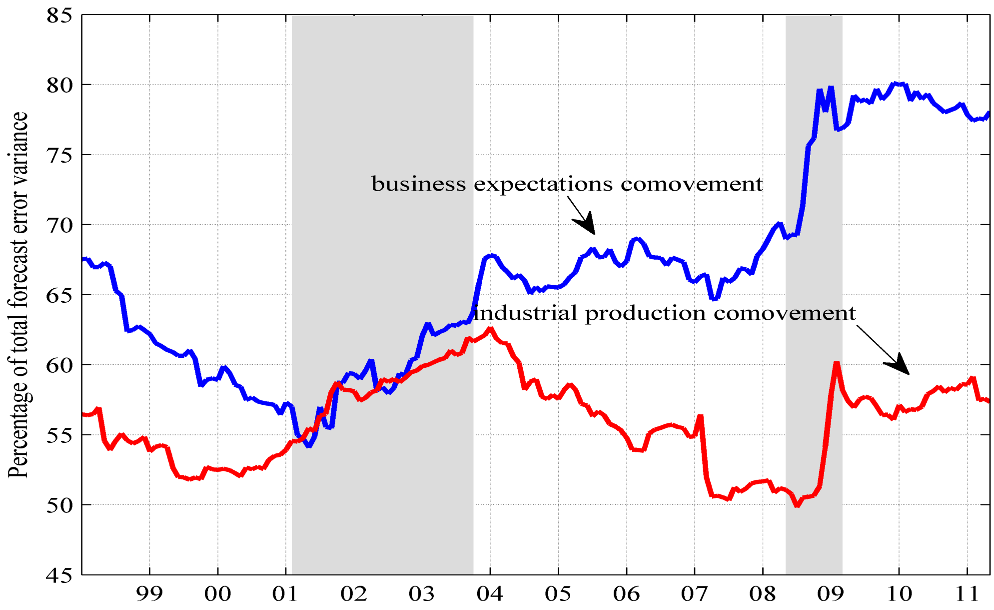
Diebold and Yilmaz (2009, 2012) obtain a time-varying version, $C^g_t(H)$, by calculating the variance decomposition over a rolling window, which at each period only uses the most recent N periods. However, when using the connectedness measure as a dependent variable in a time series model, one needs 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, $C^g_t(H)$ 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 (4.2), 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, $\triangle C^g_t(H)$.

4.3.2 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 subdivisions.[8]

[8]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.

Figure 4.3.1: Connectedness of sectoral business expectations and output (rolling window)



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

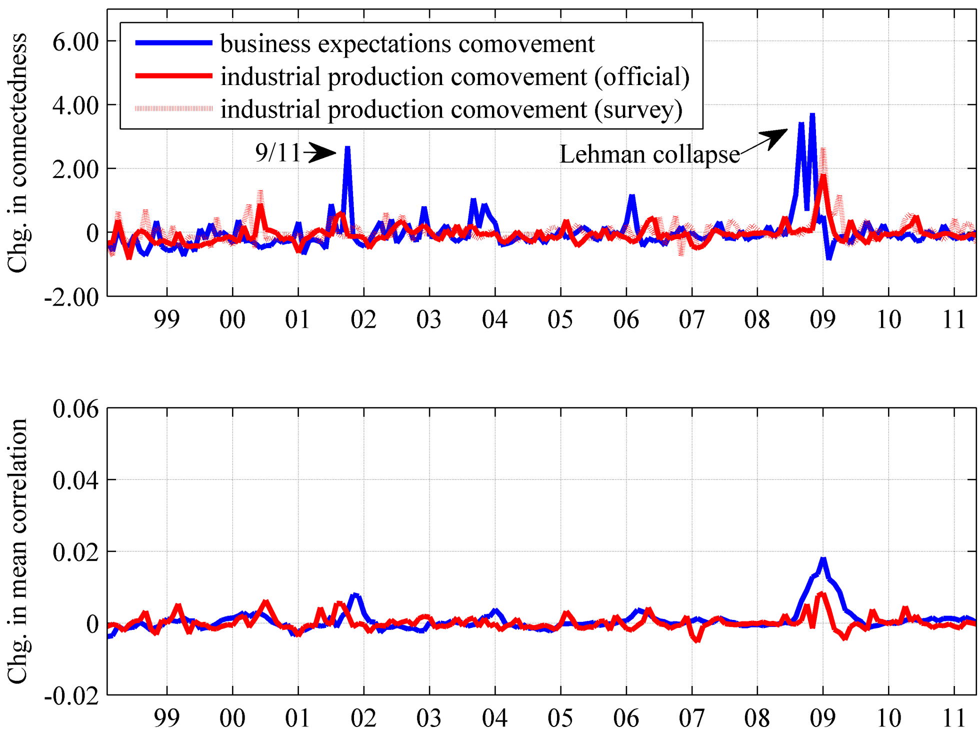
The connectedness measures are computed according to Equation (4.3) from two VAR models, one containing the monthly growth rates of the sectoral industrial production indexes and the other consisting of the sectoral Ifo business expectations indexes within the manufacturing industries.[9] For illustrative 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.[10] Figure 4.3.1 reveals that both sectoral output and business

[9]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 next six months."

[10]We also tried forecast horizons of 1, 3 and 12 months, but the results merely change.

expectations exhibit strong comovement. On average, the sum of the covariances shares amounts 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.

Figure 4.3.2: Change in comovement (recursive window)



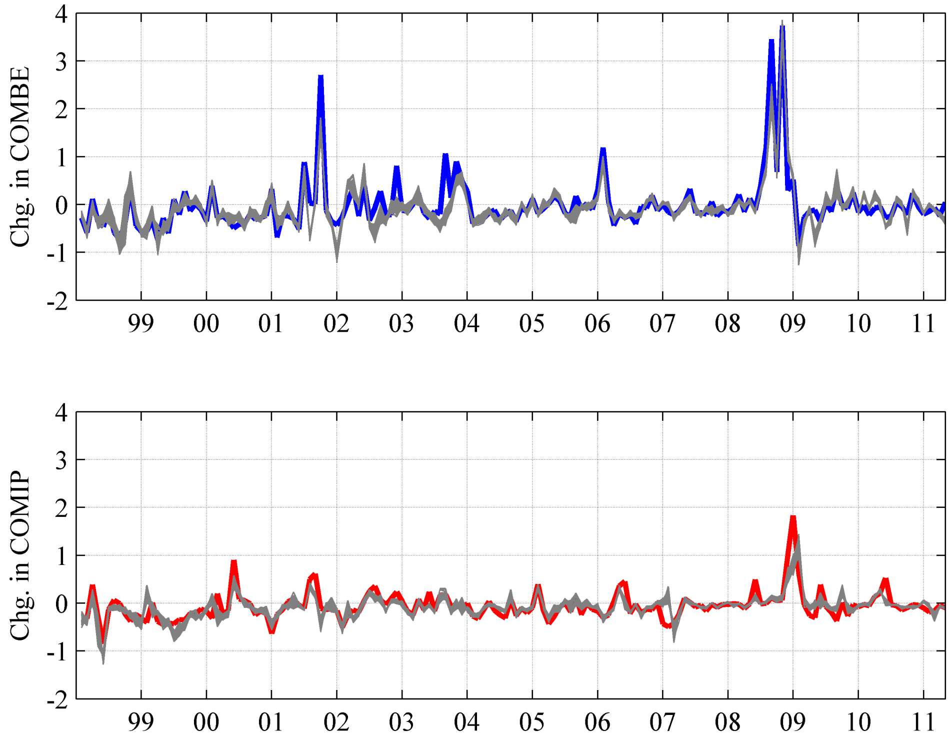
Notes: This figure displays the change in comovement measured by two alternative methods. The upper panel plots the percentage point change in the connectedness indexes, computed over a recursive window. The lower panel shows the difference of the average correlation of the sectoral quantities with the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

While the level of connectedness depends on the forecast horizon, the pattern over time is merely affected. The upper panel of Figure 4.3.2 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.[11] The biggest spikes of expectations connectedness are associated with the September 11 attacks[12] 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 4.3.2). 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 4.3.3 compares the change in the generalised connectedness 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.[13]

[11] 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.”
[12] In fact, the spike occurs one month later, in October 2001.
[13] In fact, the residuals are only weakly correlated, thus close to orthogonal. Tables 4.A.1 and 4.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.

Figure 4.3.3: 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.

4.4 Measuring Aggregate Information

4.4.1 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).[14] 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[15] 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, 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.

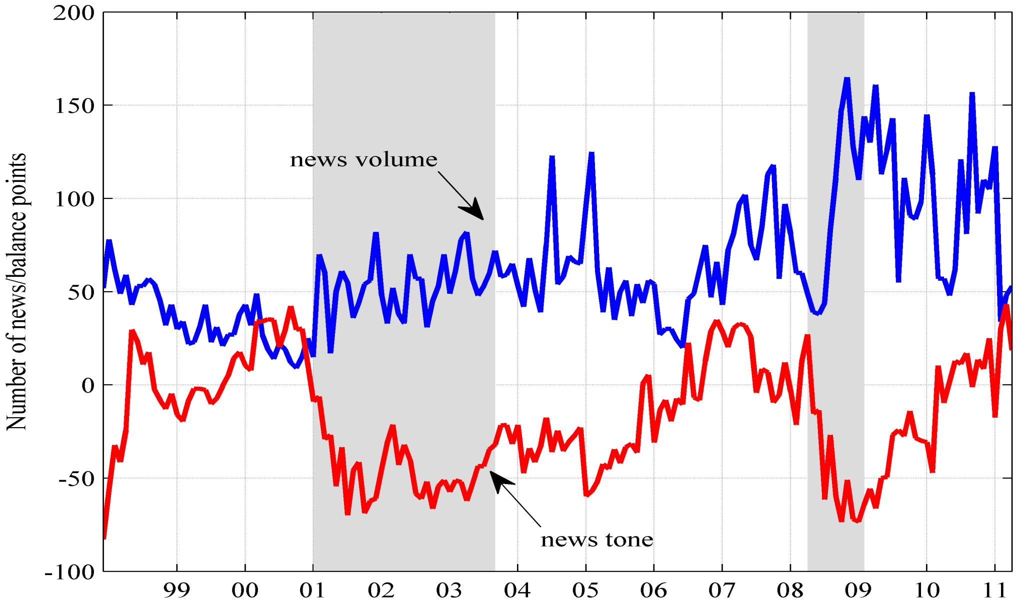
From the media data we construct two measures of news coverage. Firstly, we capture the extent to which aggregate information is available by "news volume", that is, the number of macroeconomic news reports per month.[16] The higher the number of news, the cheaper is any piece of macroeconomic information. 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 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

[14]For numbers on the scope of these media, see Table 4.B.1.

[15]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.

[16]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.

Figure 4.4.1: News indexes



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

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 4.4.1 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.

4.4.2 Macroeconomic Environment

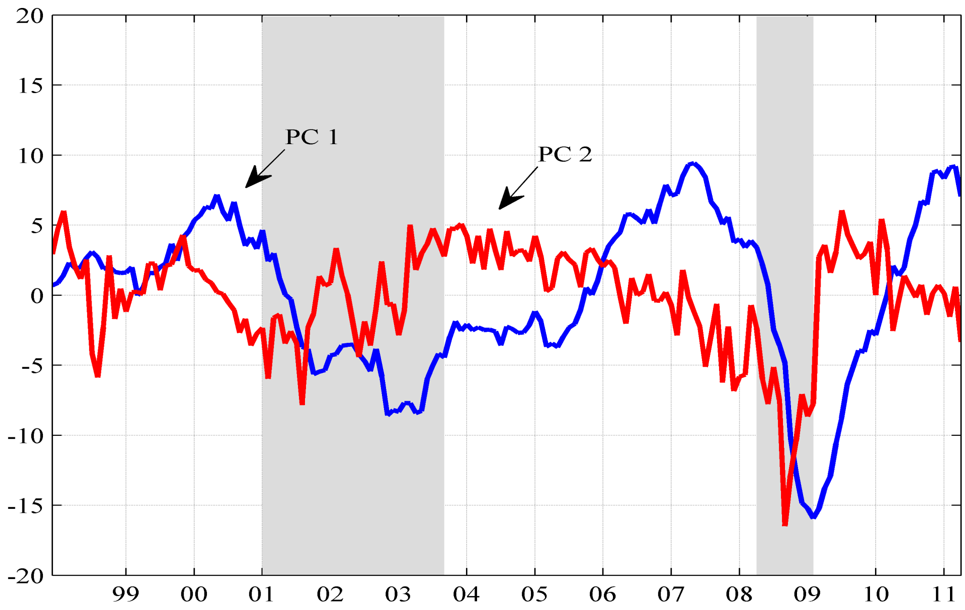
Macroeconomic events that are reported by news media stem from a variety of fields. Our media dataset already contains 13 broad categories, and each of them can be represented by numerous variables. To obtain a comprehensive picture of the present state of the economy as well as expectations regarding 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.[17] Another big bloc of time series are business surveys (most notably the Ifo Business Survey), consumer surveys, and composite indicators. These 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 4.C.1.

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:

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

[17] http://www.bundesbank.de/statistik/statistik_realtime.php

Figure 4.4.2: Principal components



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

where e_t is an $N \times 1$ vector of idiosyncratic disturbances and Λ 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 (2002a) 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 4.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 4.4.2 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.

4.5 Empirical Results

After having described how the variables are measured, we can now present our results when estimating models (4.1) and (4.2). Table 4.5.1 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 4.5.1 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.[18] 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 4.5.2 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 at the 10%-level, but both variables have the expected sign; the more positive the macroeconomic environment becomes, the

[18]Apparently, the residuals are heteroskedastic, so we use robust standard errors when estimating the first stage for news volume.

Table 4.5.1: First-stage regression for news volume

Dependent variable: news volume			
Variable	Coefficient	t-statistic	t-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
σ^2	504.96	Nvars	4

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

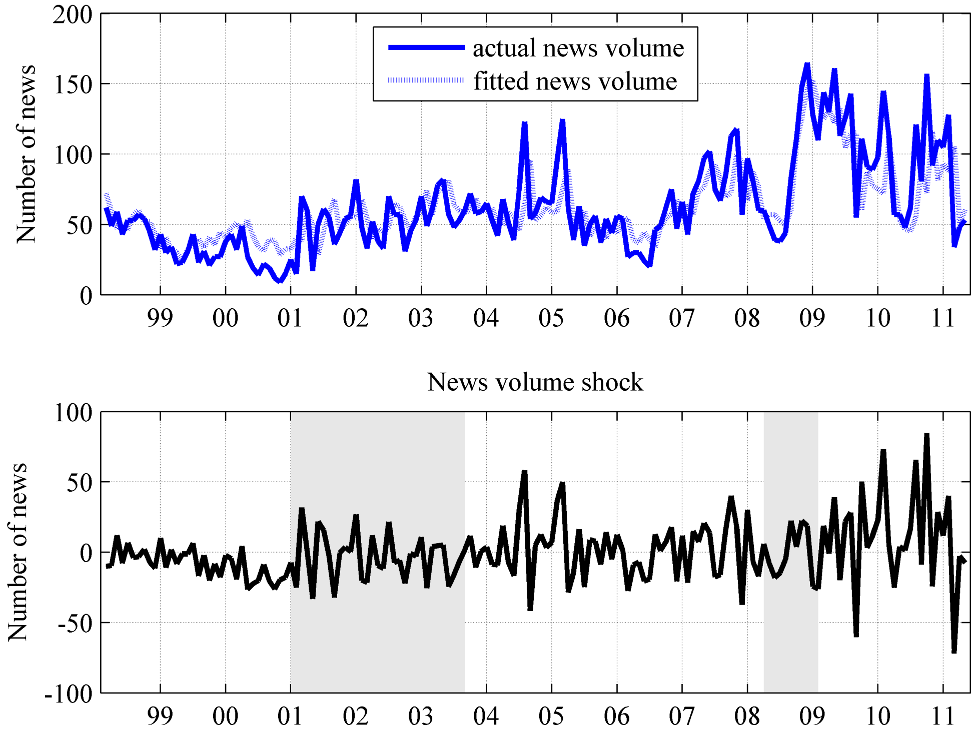
Table 4.5.2: First-stage regression for news tone

Dependent variable: news tone			
Variable	Coefficient	t-statistic	t-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
σ^2	216.60	Nvars	4

more positive is the tone of media reports. But as can be seen in Figure 4.5.2 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 4.5.3 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 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

Figure 4.5.1: First-stage regression for news volume



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

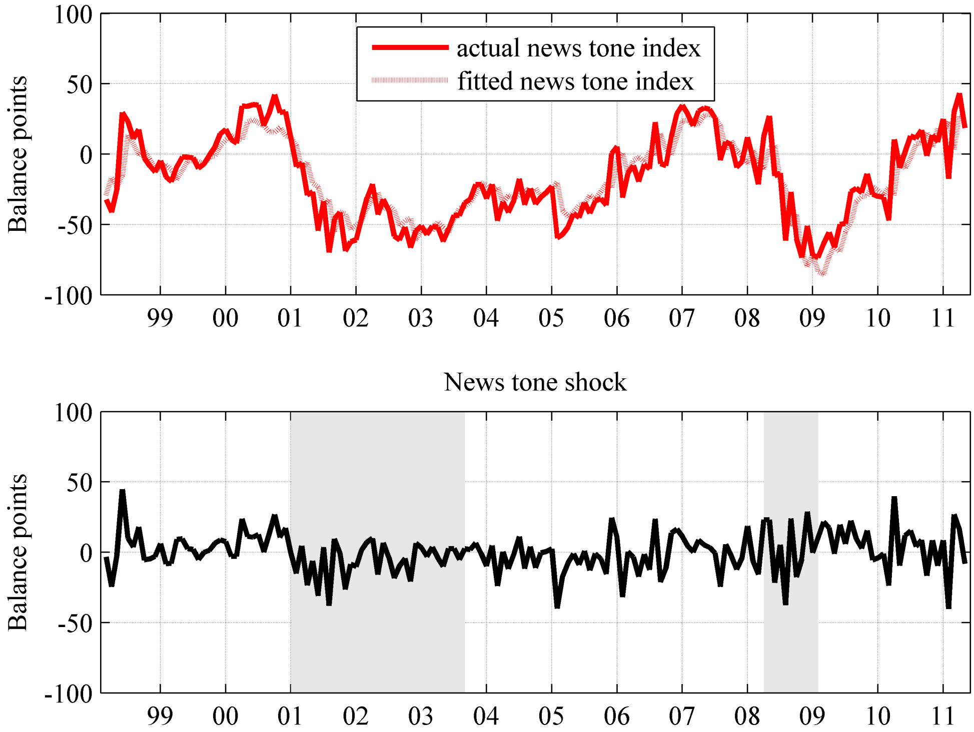
delayed positive response of production comovement, which becomes significant after five months. However, the effect fades quickly and its size is much smaller with a cumulative increase of 0.08 percentage points after seven months.[19]

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 4.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

[19]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 should lie somewhere in between.

Figure 4.5.2: First-stage regression for news tone

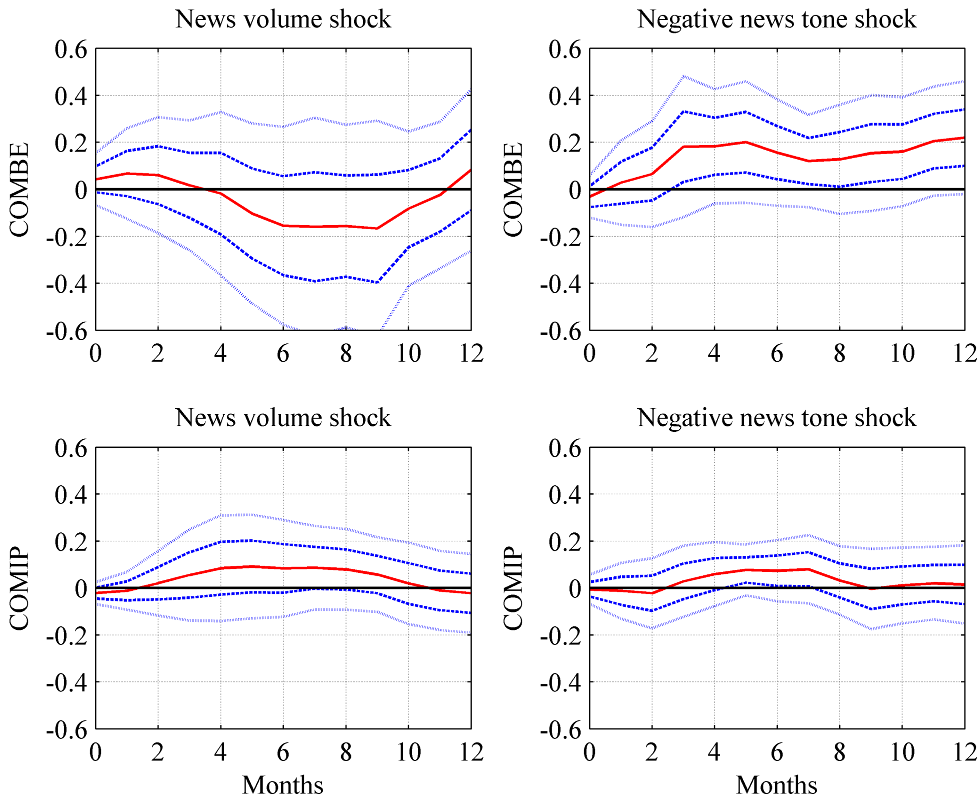


Notes: The shaded grey areas represent recessions as dated by the Economic Cycle Research Institute.

implement a counterfactual analysis, where we set all news tone shocks equal to zero and compare the counterfactual time series with the actual change in comovement. Figure 4.5.4 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%.[20]

[20]Figure 4.E.1 displays the counterfactual analysis for the whole sample and both media shocks.

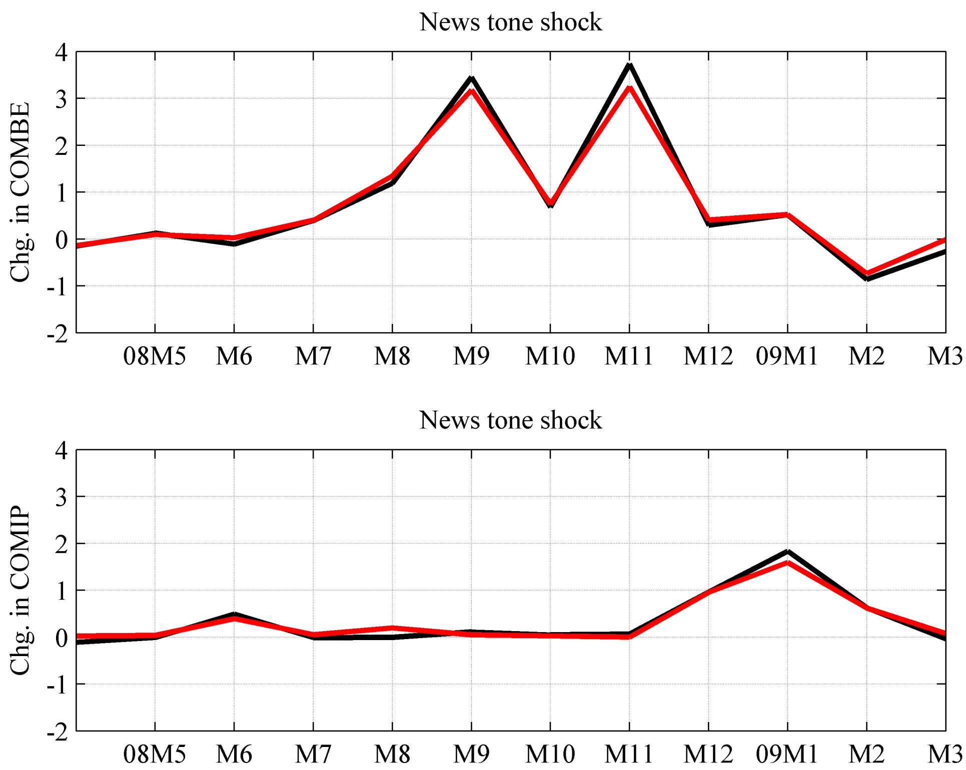
Figure 4.5.3: Responses of sectoral comovement to media shocks



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.

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.

Figure 4.5.4: 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.

4.6 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 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 4.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

$$y_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i}. \tag{4.4}$$

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 δ ($u_t = \delta$), whereas the other is not. Furthermore, it is assumed that no other shocks occur between time t and $t+h$. It is given by

$$\begin{aligned} I_y(h, \delta, \Omega_{t-1}) = &\operatorname{E}[y_{t+h} | u_t = \delta, u_{t+1} = ... = u_{t+h} = 0, \Omega_{t-1}] \\ &- \operatorname{E}[y_{t+h} | u_t = 0, u_{t+1} = ... = u_{t+h} = 0, \Omega_{t-1}]. \end{aligned} \tag{4.5}$$

The traditional impulse response function is independent of Ω_{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 δ, 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 Σ_u, $PP' = \Sigma_u$, where P is a $K \times K$ lower triangular matrix. Equation (4.4) can now be written as

$$y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i}, \tag{4.6}$$

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 (4.5) and (4.6), the orthogonalised impulse response function of a unit shock to the jth equation on y_{t+h} is given by

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

where e_j is a $K \times 1$ selection vector with unity as its jth 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 Σ_u as observed in the history Ω_{t-1},

$$I_j^g(h, \delta_j, \Omega_{t-1}) = \mathrm{E}[y_{t+h}|u_{jt} = \delta_j, \Omega_{t-1}] - \mathrm{E}[y_{t+h}|\Omega_{t-1}]. \tag{4.7}$$

Koop et al. (1996) show that under the assumption that u_t has a multivariate normal distribution, its conditional expectation is given by

$$\mathrm{E}[u_t|u_{jt} = \delta_j] = \Sigma_u e_j \sigma_{jj}^{-1} \delta_j. \tag{4.8}$$

Using Equations (4.4), (4.7) and (4.8), the unscaled h-step generalised impulse response to a shock in the jth 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 jth equation in time t,

$$I_j^g(h) = \sigma_{jj}^{-1/2} \Phi_h \Sigma_u e_j, \text{ with } h = 1, 2, ... \tag{4.9}$$

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

Pesaran and Shin (1998) show how the generalised impulse reponses from Equation (4.9) 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[21]

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

Analogously, the entries of the generalised forecast error variance decomposition are given by[22]

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

[21] See Lütkepohl (2005) for the derivation.

[22] Pesaran and Shin (1998) scale the numerator with the variance of the variable to be decomposed, σ_{ii}. However, since the numerator should contain the sum of the squared impulse responses, σ_{ii} should in fact be replaced by σ_{jj}, the variance of the shock to the jth equation as in Diebold and Yilmaz (2011).

Table 4.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 4.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.

Appendix 4.B Scope of Media Coverage

Table 4.B.1: Media scope

Newspapers	BILD	2,438,684
(sold issues as of 4/2013)	BILD am Sonntag	1,259,622
	Süddeutsche Zeitung	400,647
	Frankfurter Allgemeine Zeitung	329,705
	DIE WELT	222,722
	Frankfurter Rundschau	no data
Magazines	DER SPIEGEL	842,322
(sold issues as of 4/2013)	Focus	509,983
	Wirtschaftswoche	154,261
	manager magazin	107,950
TV broadcasts	Tagesschau	8.79
(mio. viewers as of 2012)	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__von__Informationssendungen/409102/index.html, and http://daten.ivw.eu

Appendix 4.C Macroeconomic Data and Principal Components

Table 4.C.1: List of macroeconomic variables

Series	Transformation
REAL ECONOMY	
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
PRICES	
Consumer price index, all categories, sadj	1
FINANCIAL MARKETS	
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
Spread BBF - gov, monthly avg.	0
DAX share price index, monthly avg.	1
Nominal effective exhange 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
SURVEYS AND COMPOSITE INDICATORS	
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

Series	**Transformation**
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
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
INTERNATIONAL INDICATORS	
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

Series	**Transformation**
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
EURO STOXX 50, monthly avg.	1

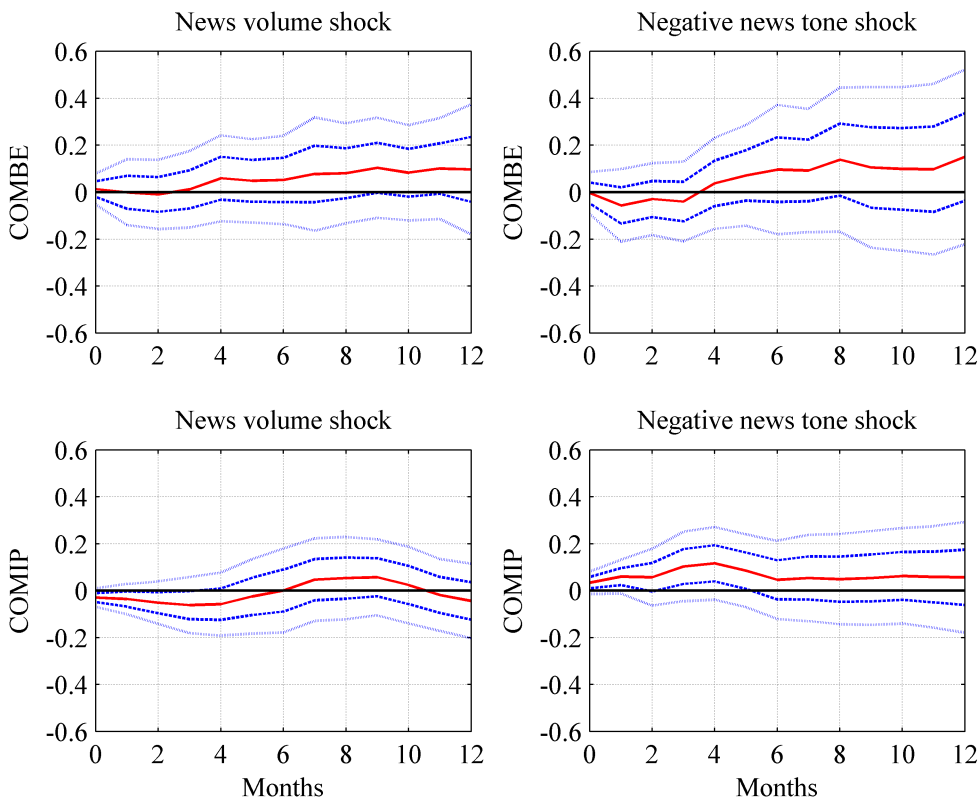
Transformation - 0: x_t, 1: $\ln(x_t/x_{t-1})$, 2: 2: $x_t - x_{t-1}$.

Table 4.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

Appendix 4.D Results for Restricted Sample (01/1998-08/2008)

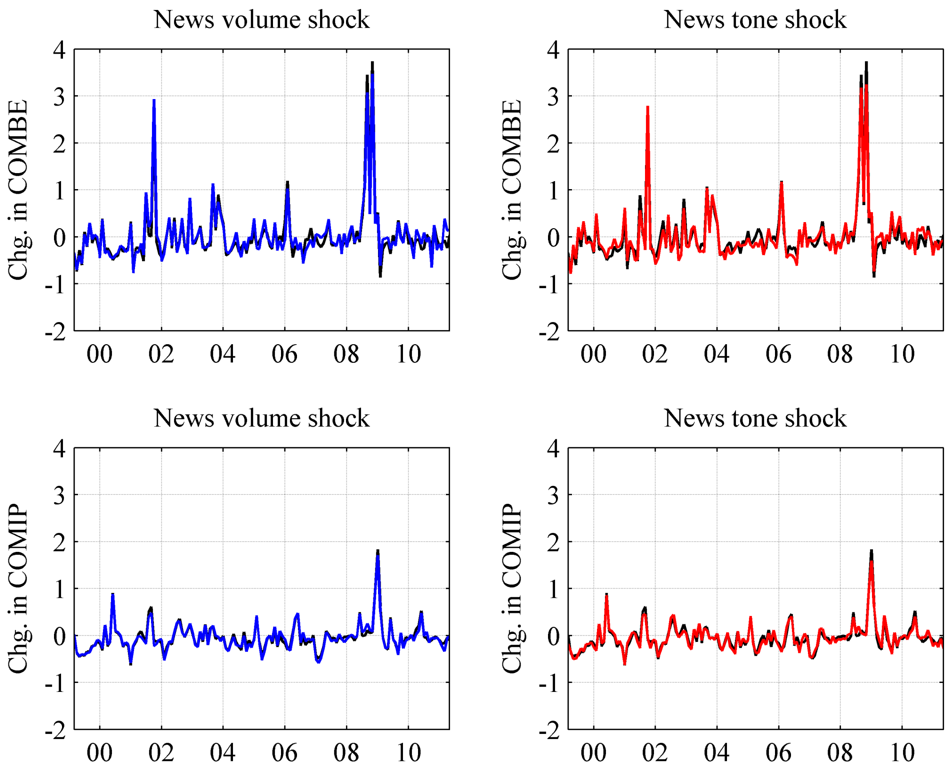
Figure 4.D.1: Responses of sectoral comovement to media shocks (restricted sample)



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.

Appendix 4.E Counterfactual Analysis

Figure 4.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.

References

Acemoglu, D., Carvalho, V., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80:1977–2016.

Ai, C. and Norton, E. (2003). Interaction terms in logit and probit models. *Economics Letters*, 80:123–129.

Akerlof, G. and Shiller, R. (2010). *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism.* Princeton and Oxford: Princeton University Press.

Andrada-Félix, J. and Fernández-Rodríguez, F. (2008). Improving moving average trading rules with boosting and statistical learning methods. *Journal of Forecasting*, 27:433–449.

Angrist, J. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion.* Princeton and Oxford: Princeton University Press.

Audrino, F. and Barone-Adesi, G. (2005). Functional gradient descent for financial time series with an application to the measurement of market risk. *Journal of Banking & Finance*, 29:959–977.

Audrino, F. and Trojani, F. (2007). Accurate short-term yield curve forecasting using functional gradient descent. *Journal of Financial Econometrics*, 5:591–623.

Badarinza, C. and Buchmann, M. (2009). Inflation perceptions and expectations in the euro area: The role of news. European Central Bank Working Paper 1088.

Bai, J. and Ng, S. (2009). Boosting diffusion indices. *Journal of Applied Econometrics*, 24:607–629.

Becker, S. and Wohlrabe, K. (2008). Micro data at the Ifo Institute for Economic Research: The "Ifo Business Survey", usage and access. *Journal of Applied Social Science Studies*, 128:307–319.

Bénabou, R. (2013). Groupthink: Collective delusions in organizations and markets. *Review of Economic Studies*, 80:429–462.

Boyer, B., Gibson, M., and Loretan, M. (1997). Pitfalls in tests for changes in correlations. Board of Governors of the Federal Reserve System International Finance Working Paper 597.

Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science*, 16:199–231.

Buchen, T. and Wohlrabe, K. (2011). Forecasting with many predictors: Is boosting a viable alternative? *Economics Letters*, 113:16–18.

Bühlmann, P. (2006). Boosting for high-dimensional linear models. *Annals of Statistics*, 34:559–583.

Bühlmann, P. and Hothorn, T. (2007a). Boosting algorithms: Regularization, prediction and model fitting. *Statistical Science*, 22:477–505.

Bühlmann, P. and Hothorn, T. (2007b). Rejoinder: Boosting algorithms: Regularization, prediction, and model fitting. *Statistical Science*, 22:516–522.

Bühlmann, P. and Hothorn, T. (2010). Twin boosting: Improved feature selection and prediction. *Statistics and Computing*, 20:119–138.

Bühlmann, P. and Yu, B. (2003). Boosting with the L2 loss: Regression and classification. *Journal of the American Statistical Association*, 98:324–339.

Burns, A. and Mitchell, W. (1946). *Measuring business cycles*. New York: NBER.

Carriero, A., Kapetanios, G., and Marcellino, M. (2011). Forecasting large datasets with Bayesian reduced rank multivariate models. *Journal of Applied Econometrics*, 26:715–734.

Carroll, C. (2003). Macroeconomic expectations of households and professional forecasters. *Quarterly Journal of Economics*, 118:269–298.

Christiano, L. and Fitzgerald, T. (1998). The business cycle: It's still a puzzle. *Economic Pespectives—Federal Reserve Bank of Chicago*, 22:56–83.

Christoffersen, P. and Diebold, F. (1998). Cointegration and long-run forecasting. *Journal of Business and Economic Statistics*, 16:450–458.

Cooper, R. and Haltiwanger, J. (1990). Inventories and the propagation of sectoral shocks. *American Economic Review*, 80:170–190.

Curtin, R. (2003). Unemployment expectations: The impact of private information on income uncertainty. *Review of Income and Wealth*, 49:539–554.

Dearing, J. and Rogers, E. (1996). *Agenda Setting*. Thousand Oaks, CA: Sage Publications.

Diebold, F. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119:158–171.

Diebold, F. and Yilmaz, K. (2011). On the network topology of variance decompositions: Measuring the connectedness of financial firms. NBER Working Paper 17490.

Diebold, F. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28:57–66.

Doepke, J., Dovern, J., Fritsche, U., and Slacalek, J. (2008). The dynamics of European inflation expectations. *B.E. Journal of Macroeconomics*, 8:1–21.

Doms, M. and Morin, N. (2004). Consumer sentiment, the economy, and the news media. FRB of San Francisco Working Paper 2004-09.

Dräger, L. (2011). Inflation perceptions and expectations in Sweden: Are media reports the "missing link"? KOF Working Paper 273.

Dräger, L. and Lamla, M. (2012). Updating inflation expectations: Evidence from micro-data. *Economics Letters*, 117:807–810.

Drechsel, K. and Scheufele, R. (2012). Bottom-up or direct? Forecasting German GDP in a data-rich environment. Swiss National Bank Working Papers 2012-16.

Easaw, J. and Ghoshray, A. (2010). News and households' subjective macroeconomic expectations. *Journal of Macroeconomics*, 32:469–475.

Efron, B. and Tibshirani, R. (1986). Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy. *Statistical Science*, 1:54–75.

Eil, D. and Rao, J. (2011). The good news-bad news effect: Asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics*, 3:114–138.

Eklund, J. and Kapetanios, G. (2008). A review of forecasting techniques for large data sets. *National Institute Economic Review*, 203:109–115.

Fabiani, S., Druant, M., Hernando, I., Kwapil, C., Landau, B., Loupias, C., Martins, F., Mathä, T., Sabbatini, R., and Stahl, H. S. A. (2006). What firms' surveys tell us about price-setting behavior in the euro area. *International Journal of Central Banking*, 2:3–47.

Foerster, A., Sartre, P.-D., and Watson, M. (2011). Sectoral versus aggregate shocks: A structural factor analysis of industrial production. *Journal of Political Economy*, 119:1–38.

Forbes, K. and Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, 57:2223–2261.

Freund, Y. and Schapire, R. (1995). A decision-theoretic generalization of on-line learning and an application to boosting. In *Computational Learning Theory*, pages 23–37. Berlin and New York: Springer.

Freund, Y. and Schapire, R. (1996). Experiments with a new boosting algorithm. In *Proceedings of the Thirteenth International Conference on Machine Learning*, pages 148–156.

Friedman, J. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29:1189–1232.

Friedman, J., Hastie, T., and Tibshirani, R. (2000). Additive logistic regression: A statistical view of boosting. *Annals of Statistics*, 28:337–407.

Gavrishchaka, V. (2006). Boosting-based frameworks in financial modeling: Application to symbolic volatility forecasting. *Advances in Econometrics*, 20:122–151.

Giannone, D., Reichlin, L., and Sala, L. (2004). Monetary policy in real time. *NBER Macroeconomics Annual*, 19:161–200.

Hand, D. (2009). Mining the past to determine the future: Problems and possibilities. *International Journal of Forecasting*, 25:441–451.

Hand, D., Mannila, H., and Smyth, P. (2001). *Principles of data mining*. MIT Press.

Hansen, M. and Yu, B. (2001). Model selection and the principle of minimum description length. *Journal of the American Statistical Association*, 96:746–774.

Harri, A. and Brorsen, B. (2009). The overlapping data problem. *Quantitative and Qualitative Analysis in Social Sciences*, 3:78–115.

Hastie, T. (2007). Comment: Boosting algorithms: Regularization, prediction, and model fitting. *Statistical Science*, 22:513–515.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction*. Berlin: Springer.

Henzel, S. and Rengel, M. (2013). Dimensions of macroeconomic uncertainty: A common factor analysis. Ifo Working Paper 167.

Hofner, B., Mayr, A., Robinzonov, N., and Schmid, M. (2014). Model-based boosting in R: A hands-on tutorial using the R package mboost. *Computational Statistics*, 29:3–35.

Hornstein, A. (2000). The business cycle and industry comovement. *Economic Quarterly—Federal Reserve Bank of Richmond*, 86:27–48.

Hornstein, A. and Praschnik, J. (1997). Intermediate inputs and sectoral comovement in the business cycle. *Journal of Monetary Economics*, 40:573–595.

Horvath, M. (2000). Sectoral shocks and aggregate fluctuations. *Journal of Monetary Economics*, 45:69–106.

Hothorn, T., Bühlmann, P., Kneib, T., Schmid, M., and Hofner, B. (2009). mboost: Model-based boosting, R package, version 1.0-7. http://CRAN.R-project.org/package=mboost.

Kahneman, D. and Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, 80:237–251.

Karlsson, N., Loewenstein, G., and Seppi, D. (2009). The "Ostrich effect": Selective avoidance of information. *Journal of Risk and Uncertainty*, 38:95–115.

Keynes, J. (1936). *The general theory of employment, interest, and money*. London: Macmillan.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99:1053–1069.

Kim, H. and Swanson, N. (2014). Forecasting financial and macroeconomic variables using data reduction methods: New empirical evidence. *Journal of Econometrics*, 178:352–367.

Koop, G., Pesaran, M., and Potter, S. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74:119–147.

Lamla, M. and Lein, S. (2008). The role of media for consumers' inflation expectation formation. KOF Working Paper 201.

Lamla, M., Lein, S., and Sturm, J. (2007). News and sectoral comovement. KOF Working Paper 183.

Lamla, M. and Maag, T. (2012). The role of media for inflation forecast disagreement of households and professional forecasters. *Journal of Money, Credit and Banking*, 44:1325–1350.

Lamla, M. and Sarferaz, S. (2012). Updating inflation expectations. KOF Working Paper 301.

Lau, R. (1985). Two explanations for negativity effects in political behavior. *American Journal of Political Science*, 29:119–138.

Long, J. and Plosser, C. (1983). Real business cycles. *Journal of Political Economy*, 91:39–69.

Long, J. and Plosser, C. (1987). Sectoral vs. aggregate shocks in the business cycle. *American Economic Review*, 77:333–336.

Loretan, M. and English, W. (2000). Evaluating 'correlation breakdown' during periods of market volatility. Board of Governors of the Federal Reserve System International Finance Working Paper 658.

Lucas, R. (1972). Expectations and the neutrality of money. *Journal of Economic Theory*, 4:103–124.

Lucas, R. (1976). Econometric policy evaluations: A critique. In Brunner, K. and Meltzer, A., editors, *The Phillips curve and labor markets*, pages 19–46. Amsterdam: North Holland.

Lucas, R. (1977). Understanding business cycles. In *Carnegie-Rochester Conference Series on Public Policy*, volume 5, pages 7–29.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Berlin and Heidelberg: Springer.

Lutz, R. and Bühlmann, P. (2006). Boosting for high-multivariate responses in high-dimensional linear regression. *Statistica Sinica*, 16:471.

Mankiw, N. and Reis, R. (2002). Sticky information versus sticky prices: A proposal to replace the New Keynesian Phillips curve. *Quarterly Journal of Economics*, 117:1295–1328.

Mankiw, N. and Reis, R. (2006). Pervasive stickiness. *American Economic Review*, 96:164–169.

McCombs, M. (2013). *Setting the agenda: The mass media and public opinion*. Cambridge: Polity Press.

McCombs, M. and Shaw, D. (1972). The agenda-setting function of mass media. *Public Opinion Quarterly*, 36:176–187.

Möbius, M., Niederle, M., Niehaus, P., and Rosenblat, T. (2011). Managing self-confidence: Theory and experimental evidence. NBER Working Paper 17014.

Muth, J. (1961). Rational expectations and the theory of price movements. *Econometrica*, 29:315–335.

Ng, S. (2014). Viewpoint: Boosting recessions. *Canadian Journal of Economics*, 47:1–34.

Pesaran, H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58:17–29.

Powell, W. and Snellman, K. (2004). The knowledge economy. *Annual Review of Sociology*, 30:199–220.

Rebelo, S. (2005). Real business cycle models: Past, present and future. *Scandinavian Journal of Economics*, 107:217–238.

Robinzonov, N., Tutz, G., and Hothorn, T. (2012). Boosting techniques for nonlinear time series models. *AStA Advances in Statistical Analysis*, 96:99–122.

Romer, R. (1990). Endogenous technological change. *Journal of Political Economy*, 98:71–102.

Santoro, E. and Pfajfar, D. (2013). News on inflation and the epidemiology of inflation expectations. *Journal of Money, Credit and Banking*, 45:1045–1067.

Schenkelberg, H. (2013). The determinants of sticky prices and sticky plans: Evidence from German business survey data. *German Economic Review*, forthcoming.

Schoenbach, K. and Semetko, H. (1992). Agenda-setting, agenda-reinforcing or agenda-deflating: A study of the 1990 German national election. *Journalism Quarterly*, 69:837–846.

Shafik, N. and Tutz, G. (2009). Boosting nonlinear additive autoregressive time series. *Computational Statistics and Data Analysis*, 53:2453–2464.

Shea, J. (2002). Complementarities and comovements. *Journal of Money, Credit, and Banking*, 34:412–433.

Sheafer, T. (2007). How to evaluate it: The role of story-evaluative tone in agenda setting and priming. *Journal of Communication*, 57:21–39.

Sims, C. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50:665–690.

Starr, M. (2012). Consumption, sentiment, and economic news. *Economic Inquiry*, 50:1097–1111.

Stock, J. and Watson, M. (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97:1167–1179.

Stock, J. and Watson, M. (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20:147–162.

Stock, J. and Watson, M. (2004). An empirical comparison of methods for forecasting using many predictors. Princeton University manuscript.

Stock, J. and Watson, M. (2006). Forecasting with many predictors. In Graham, E., Granger, C., and Timmermann, A., editors, *Handbook of Economic Forecasting*, volume 1, pages 516–550. Amsterdam: North Holland.

Stock, J. and Watson, M. (2011). Dynamic factor models. In Clements, M. and Hendry, D., editors, *Oxford Handbook of Economic Forecasting*, pages 35–59. Oxford: Oxford University Press.

Timmermann, A. (2006). Forecast combinations. In Granger, C., Elliot, G., and Timmermann, A., editors, *Handbook of Economic Forecasting*, pages 135–196. Amsterdam: North Holland.

Veldkamp, L. (2006). Media frenzies in markets for financial information. *American Economic Review*, 96:577–601.

Veldkamp, L. (2011). *Information choice in macroeconomics and finance*. Princeton and Oxford: Princeton University Press.

Veldkamp, L. and Wolfers, J. (2007). Aggregate shocks or aggregate information? Costly information and business cycle comovement. *Journal of Monetary Economics*, 54:37–55.

Wohlrabe, K. and Buchen, T. (2014). Assessing the macroeconomic forecasting performance of boosting: Evidence for the United States, the euro area and Germany. *Journal of Forecasting*, forthcoming.

Yilmaz, K. (2010). International business cycle spillovers. CEPR Discussion Paper 7966.

Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebene Anregungen sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Sofern ein Teil der Arbeit aus bereits veröffentlichten Papers besteht, habe ich dies ausdrücklich angegeben.

München, den 23. Juni 2014

Teresa Buchen