Do Media Data Help to Predict German Inflation?

Konstantin A. Kholodilin* Dirk Ulbricht‡

June 16, 2015

e-mail:

Abstract

In an uncertain world, decisions by market participants are based on expectations. Therefore, sentiment indicators reflecting expectations have proven track record at predicting economic variables. However, survey respondents largely perceive the world through media reports. Here, we want to make use of that. We employ a rich data set provided by Media Tenor International, based on sentiment analysis of opinion-leading media in Germany from 2001 to 2014, transformed into several monthly indices. German industrial production is predicted in a real-time out-of-sample forecasting experiment and media indices are compared to a huge set of alternative indicators. Media data turn out to be valuable for 10 to 12 months horizon forecasts. This holds in the period during and after the financial crisis when many models fail.

Keywords: media data, German industrial production, forecast breakdown, real-time experiment, model confidence set.

JEL classification: C10; C52; C53; E32.

*Research associate, DIW Berlin, Mohrenstraße 58, 10117 Berlin, Germany, e-mail: kkholodilin@diw.de.
‡Research associate, DIW Berlin, Mohrenstraße 58, 10117 Berlin, Germany, e-mail: dulbricht@diw.de.

Contents

List of Tables

List of Figures

1 Introduction

Typically, the data on gross domestic product (GDP) are available on a quarterly basis. In addition, they are published half a quarter following the end of the reference quarter. Therefore, in order to gain quick insight into the current economic situation, a monthly series of industrial production is used. It is considered as a key monthly indicator for business activity. This is especially true in the case of Germany. Although the share of industrial production has been shrinking since the 1980s, it remains relatively high when compared to other OECD and, especially, other EU member countries.[1] Furthermore, the European Commission plans to raise the contribution of industry to GDP to as much as 20% by 2020 (**?**) in order to increase the competitiveness of the EU. Moreover, industrial production contributes substantially to the business cycle dynamics.

Consequently, there have been many attempts to improve the forecast accuracy of this variable.[2] Most of these studies employ hard economic indicators, such as interest rates, manufacturing orders, etc. There are also several studies using soft data, such as business surveys, like the ifo or ZEW indicator (see, for example, **?** or **?**). It is demonstrated that due to their forward-looking nature, the soft data are well-suited for forecasting industrial production. The underlying idea of this approach is to employ a measure of the intentions or the expectations of the managers or analysts, respectively. The main advantages of these indicators are their high frequency, timeliness, and the fact that they are never subject to revisions, unlike many other statistical indicators.

While in classical economics the *homo oeconomicus* is omniscient and decides independently, with his decisions leading to efficient outcomes at the market level, **?** underlines the role of uncertainty concerning decisions and behavior as well as the related (suboptimal) outcomes at the macro level, just as **?** points to the pretense of knowledge. Similarly, **?** as well as **?** show that actual human behavior clearly deviates from the behavior predicted by standard economic models. Due to their limited information processing capacity, individuals use subjective models for the perception of reality. If these models are shared because of common cultural background and experience, in accordance with **?**, one can speak of shared mental models. In media societies, media reporting forms relevant parts of those shared mental models not only because investors, consumers, politicians,

[1] According to the OECD Factbook 2011: Economic, Environmental and Social Statistics, in 2010, the percentage of total value added in industry (including energy) was 24% in Germany, 19% in the EU, and 21% in the OECD countries.

[2] See, for example, **?**, **?** or **?**.

and voters receive lots of information via the media, but because additional information perceived directly is interpreted on the basis of the frame determined by the media reporting. Therefore, what is on the agenda ("agenda setting") and what is not ("agenda cutting") becomes highly relevant, as well as the way in which these things are described in the media, such as with a positive, negative or neutral tone. At least in part, individuals decide and behave based on the information they receive from the media. This is also important in the context of business surveys, as respondents interpret their own economic situation and build their expectations within the frame set by the media.

A growing literature employs media data to explain economic sentiment. For instance, **?** as well as **?** show an impact of media reporting on consumer climate. For **?** and **?** the assessment of the state of the economy depends at least in parts on media reports. In their comprehensive contribution **?** analyze the role of media reporting for inflation forecasts of households and professional forecasters.

The literature can be split into two main streams. The first one counts the number of times a single word or a group of words, which can be associated with a certain event, occur in the media. The second strand of literature captures content expressed in the media.

Most economic analyses using media focus on the United States. Using word counts, *The Economist* newspaper introduced the R-word index, which is a proxy for the US business cycle. It counts how many articles in *The Washington Post* and *The New York Times* use the word "recession" in a quarter. This simple indicator was expanded by **?**, who count the number of articles in 30 American newspapers that contain 9 keywords or expressions in the title or the first paragraph of an article and use this statistic to forecast US private consumption.

Beyond simple word counts, content analysis focuses on the underlying sentiment expressed in media reports using both automated methods and human analysts to evaluate the news. **?** evaluates the sentiment of *Wall Street Journal* articles, while **??** uses sentiment data of newspaper and TV-news, provided by Media Tenor International, to forecast US private consumption.

? use the number of queries of listed companies in the US search engine Yahoo! as a predictor for stock market volumes. Using the number of queries in Google, **?** try to improve forecasts of US private consumption. **?** employ the OpinionFinder software to analyze Twitter tweeds automatically with the aim of forecasting stock prices.

For Germany, the R-word index was adopted HypoVereinsbank, which counted the word *Rezession* ("recession" in German) in articles published in the *Frankfurter Allgemeine Zeitung*, *Handelsblatt*, and *WirtschaftsWoche*; but publication of the index was quickly given up.[3] **?** revived the index for their study, but at that time the Great Recession period could not be considered. Their study uses media indices to predict German industrial production, contrasting the R-word index for Germany and a Media Tenor International index to predict growth rates of industrial production and of recession probabilities. For both indices the results are rather mixed. Other media studies include **?**, who use the R-word index to forecast the growth rates of real GDP in Germany and Switzerland. While media indicators are helpful for Switzerland, it is not the case for Germany. **?** compute the number of mentions of a lexicon of 236 words in the online archive of *Handelsblatt* with the aim of predicting yields of the German stock market DAX index. They show that newspaper content is a valuable predictor of future DAX returns.

Here, we test the predictive content of media indicators performing a pseudo-out-of-sample forecast experiment. Since we want to compare the performance of the media indicators to that of an as complete as possible set of rival indicators, we collect and update the database of **?**, which set a standard in this respect.

This paper makes five contributions: First, unlike **?** who use a single aggregate Media Tenor International business conditions index, we employ 16 more indicators that differ in their time perspective (present, future, and climate), their underlying topic (government budget, monetary policy, labor market, and business cycle, taxation), and the region it is reported about (Germany and the rest of the world, ROW). Second, in contrast to **?**, we use monthly instead of quarterly data. Third, in contrast to **?** and **?** we take advantage of real-time data provided by the Deutsche Bundesbank for the industrial production as well as for other crucial variables such as inflation. This is particularly important in this context as one of the great benefits of media data is that they do not need to be revised *ex post*. Fourth, we test media-based models against *data snooping* using Model Confidence Set approach (**?**). Fifth, we separately test the media indicators' relative performance over a period when forecasting becomes particularly difficult. To the best of our knowledge we are the first to identify such a period using the concept of forecast breakdowns introduced by **?**. Finally, we employ the same concept

[3] The German R-word index was reported in the mass media several times in the early 2000s but no instances were were identified after July 5 2001.

to compare the reliability of different indicators.

Summing up, we find that media indicators based on news that are related to future events are very useful for predicting 10 to 12 months ahead. This is also true during periods when forecasting becomes harder.

This paper is structured as follows. The second section presents the empirical approach and the third section describes the forecast accuracy tests employed. In section four the data used in the analysis are presented, in section five the results are discussed and the last section concludes.

2 Empirical approach

We follow the approach of existing studies that concentrate on the comparison of single models that include one different alternative indicator at a time in a horse race with respect to forecast accuracy.

Due to the different release lags of indicators such as macroeconomic or survey indicators, data unbalancedness often emerges at the end of multivariate samples. This phenomenon is sometimes referred to as the ragged-edge of the data. In order to account for this we adapt the basic empirical setup for individual models from **?** that explicitly addresses this issue. The estimation equation for the individual models is given as:

$$y^h_{t+h} = \alpha + \sum_{p=\underline{p}}^{P} \beta_p y_{t-p} + \sum_{q=\underline{q}}^{Q} \gamma_q x_{t-q} + \epsilon^h_{t+h} \tag{1}$$

where y^h_{t+h} is the annualized growth rate of industrial production at time t over the next h months, $y_{t+h} = 1200/h \times \ln(\mathrm{IP}_t/\mathrm{IP}_{t-h})$. The growth rate of industrial production in levels, IP_t, is defined as $y_t = \Delta \ln \mathrm{IP}_t$; x_t is a candidate predictor; ϵ^h_{t+h} is an error term; and α, β, and γ are regression coefficients. The timely availability of indicator variable can be taken account of by $\underline{p}$ and $\underline{q}$. German industrial production is available only with a time lag of $\underline{p} = 3$ months. The publication lags of the candidate regressors vary from $\underline{q} = 0$, mostly for financial and media data, up to $\underline{q} = 2$ months. The lag length is optimized using the Akaike information criterion. First, P is estimated. Then, holding P fixed, Q is estimated.

Forecasts for 1 to 12 months horizons are computed in a pseudo-out-of-sample real-time setup:

- The first forecast is made based on the information set as it has been available in 2005:12.

- Each iteration, the information set is extended by one month, that is, in the second iteration, data are used as they have been available in 2006:01, in the third iteration data available in 2006:02 are used, and so on.

- For each horizon, individual models are estimated and forecasts are made.
- Each iteration, the lag-length are optimized and the model is updated.
- All real indicators are deflated using consumer price index as it has been available at the point in time the forecast is made.
- The estimations are based on a rolling window of 60 months. Employing rolling windows is a method of dealing with slowly moving non-stationarities, see, e.g., **?**. Furthermore, it is required for the Model Confidence Set (MCS) test, see **?**.
- The last one is based on the information set available in 2014:11 for $h = 1$, respectively 2013:11 for $h = 12$.

After having completed the estimation and forecasting exercise, the forecasts are used to compute the forecast errors based on the data as they have been available 2015:02 (current vintage data).

3 Forecast accuracy tests

To compare the usefulness of media indicators relative to rival indicators for predicting German industrial production we need to evaluate the forecast performance of competing models. Thereby, we recur to simple forecast accuracy measures, pairwise and multiple statistical tests, and a test for forecast breakdowns.

3.1 Simple measures

In the following, we concentrate on one of the standard loss functions adopted in the forecasting literature: the squared forecast error, $L_{it} = e_{it}^2$. Let $e_{it} = y_t - \hat{y}_{it}$ be the forecast error of model i in period t, where y_t is the realization of the target variable and $\hat{y}_{it}$ is the value forecast by model i. Usually, the forecast performance of alternative models is compared using the mean squared forecast error (MSFE) defined as

$$MSFE_i = \frac{\sum_{t=T_E+1}^{T_E+T_F} e_{it}^2}{T_F}, \tag{2}$$

where T_E is the length of estimation period, and T_F is the number of forecasts. However, by making use of squared forecast errors the $MSFE_i$ tends to overly emphasize differences between models. Thus, we will concentrate on the root mean squared forecast error, $RMSFE_i$. Moreover, for pairwise comparisons we employ the Theil's U defined as

$$TU_i = \frac{RMSFE_i}{RMSFE_0} \tag{3}$$

measuring the relative performance of model i, $RMSFE_i$, with respect to that of a benchmark model, $RMSFE_0$. A value exceeding one implies that the alternative model i is less accurate than the benchmark, whereas a value lower than one implies that it is more accurate.

3.2 Tests

3.2.1 Pairwise tests

Our aim is to test if media data contain any valuable information for forecasting purposes. A minimum requirement is that media data improve upon the forecasts obtained using a simple autoregressive (AR) model. This involves pairwise comparisons of the AR model and alternative models consisting of the AR model augmented with one additional explanatory variable at a time. Let the loss difference be $d_{it} = L_{0t} - L_{it}$. The starting point for pairwise forecast comparisons of a benchmark model, 0, and an alternative model i is the **?** test statistic defined as:

$$DM = \frac{\overline{d}_i}{\hat{V}(\overline{d}_i)} \tag{4}$$

where $\overline{d}_i$ and $\hat{V}(\overline{d}_i)$ are the estimated mean and long-run variance of d_{it}, respectively. The null hypothesis of the test is

$$H_0 : \quad E(d_{it}) = 0, \tag{5}$$

that is, that the two models perform equally well.

By construction, the AR is nested in the augmented model. Under the null hypothesis, the additional variables are useless and their regression coefficients are zero. However, estimating additional variables introduces noise into the forecasts of the alternative model. Consequently, under the null, the forecast accuracy of the smaller benchmark is higher than that of the larger alternative model. Thus, in the context of nested models, the DM statistic has lower power and size. Therefore, we apply the modified test statistic of **?**, which involves an adjustment term to improve upon the DM statistic when nested models are compared:

$$CW = \frac{\overline{d}_i - \overline{a}_i}{\hat{V}(\overline{d}_i - \overline{a}_i)}, \tag{6}$$

where $\overline{a}_i = \frac{1}{T_F} \sum_{t=T_E+1}^{T_E+T_F} (\hat{y}_{0t} - \hat{y}_{it})^2$.

3.2.2 Multiple tests

? points out that, even when no exploitable forecasting relation exists, looking hard enough at a given set of data will often reveal one or more forecasting models that appear to be good, but are, in fact, useless. In particular, sequential testing a number of models by comparing two of them at a time invalidates standard critical values and might result in *data snooping*. In much of economic time series analysis this is aggravated by the fact that typically there is only a limited number of observations available. To overcome this problem **?**, proposes a reality check test (RC-test) for data snooping. It compares the whole set of m rival models at a time to the benchmark. The null hypothesis is that none of the rival models is inferior to the benchmark:

$$H_0: \quad E(d_{it}) \leq 0 \quad \forall i = 1, \ldots, m. \tag{7}$$

It is rejected when at least one of the rivals yields significantly better forecasts. The expected loss differential can be consistently estimated using the sample mean, $\overline{d}_i$. White proposes the sample mean statistic

$$RC = \max_{k=1,\ldots,m} T_F^{1/2} \overline{d}_k. \tag{8}$$

This approach has subsequently been refined by **?**. He shows that the test statistic proposed by White is very conservative, if the set of rival models contains very poorly performing models, and proposes a refinement consisting of a studentized version of the RC-test that is known as the test for superior predictive ability (SPA).

However, selecting the benchmark independently of the data introduces the problem of *multiple comparisons with control*. To overcome this **?** propose the model confidence set (MCS) approach. This approach consists in looking for a set of best models, $\mathcal{M}^*$, such that, given the set of all forecasting models, $\mathcal{M}_0$, the MCS identifies the set of forecasting models that cannot be rejected as statistically inferior at a certain level of confidence:

$$\mathcal{M}^* = \{i \in \mathcal{M}_0 : \mu_{ij} \leq 0 \text{ for all } j \in \mathcal{M}_0\} \tag{9}$$

where $\mu_{ij} = E(d_{ij})$ is the expected loss differential $d_{ij} = L_{it} - L_{jt}$ based on one-by-one comparisons of all models.[4] The MCS is implemented using the following steps, where initially $\mathcal{M}$ is set $\mathcal{M} = \mathcal{M}_0$:

1. The null of equal predictive accuracy (EPA), $H_{0,\mathcal{M}} : \mu_{ij} \leq 0 \, \forall i, j$ is tested at significance level α.
2. If the null is rejected, the worst performing model is eliminated from $\mathcal{M}$.
3. The procedure is repeated until the null cannot be rejected. The set $\widehat{\mathcal{M}}^*_{1-\alpha}$ with the remaining models is defined as the MCS.

In order to test the null hypothesis in step **??** we apply the $T_{max,\mathcal{M}}$ statistic.[5] Let $\bar{d}_{ij} \equiv T_F^{-1} \sum_{t=T_E+1}^{T_E+T_F} d_{ij}$ be the relative sample loss between the ith and the jth models. Then let $\bar{d}_{i\cdot}$ be the loss of the ith model relative to the average across models in $\mathcal{M}$, $\bar{d}_{i\cdot} \equiv m^{-1} \sum_{j \in \mathcal{M}} \bar{d}_{ij}$, where the models in $\mathcal{M}$ are again indexed by $i = 1, \ldots, m$. Then, the t-statistic is defined as:

$$t_{i\cdot} = \frac{\bar{d}_{i\cdot}}{\sqrt{\widehat{V}(\bar{d}_{i\cdot})}} \tag{10}$$

where $\widehat{V}(\bar{d}_{i\cdot})$ is an estimate of $V(\bar{d}_{i\cdot})$. The t-statistic can be associated with the null $H_{i\cdot} : \mu_{i\cdot} = 0$, where $\mu_{i\cdot} = \mathrm{E}(\bar{d}_{i\cdot})$. **?** show that the hypothesis $H_{0,\mathcal{M}}$ is equivalent to $\{H_{i\cdot}$ for all $i \in \mathcal{M}\}$ such that $\{\mu_{i\cdot} \leq 0$ for all $i \in \mathcal{M}\}$. Thus, the null hypothesis $H_{0,\mathcal{M}}$ can be tested using the statistic:

$$T_{\max,\mathcal{M}} = \max_{i \in \mathcal{M}} t_{i\cdot} \tag{11}$$

[4] Here again, we choose the squared forecast error as loss.

[5] **?** propose an alternative test statisitics, $T_{R,\mathcal{M}}$. Here, we only report the results for $T_{\max,\mathcal{M}}$ statistic as it yielded the most conservative results, that is, the smallest confidence sets.

The asymptotic distribution of $T_{\max,\mathcal{M}}$ is nonstandard as it depends on nuisance parameters. However, it can be estimated using bootstrap methods.

In the best of all cases, the MCS contains only one model. However, if the data are uninformative, the MCS contains several models or even all models in $\mathcal{M}_0$. As a useful feature, the MCS procedure yields a p-values for all models under consideration where a small p-value indicates that the corresponding model is unlikely to enter the set of superior models, $\mathcal{M}^*$(for details, see **?**).

3.3 Forecast breakdowns

Reliability of models is crucial for forecasters. However, models may become unstable over time due to instabilities in the economy. Thus, forecasting performance depends on the success of the model at adapting to changes. **?** introduce an approach to test whether the model's future performance is consistent with what is expected on the basis of its past performance. They define a forecast breakdown as a situation, in which the out-of-sample performance of a forecast model, judged by some loss function, is significantly worse than its in-sample performance. Their test is based on the intuition that, in the absence of a forecast breakdown, the difference between expected out-of-sample and in-sample performances should be close to zero.

The approach has two major advantages: First, in contrast to the literature concentrating on structural breaks, such as, **?**, the forecast breakdown test allows for model misspecification. Second, the test is applicable in cases of instabilities in the data generating process of unknown form.

Let y_{t+h} be a sequence of $h-$step-ahead forecasts from an out-of-sample forecast experiment, which involves dividing the sample of size T into an in-sample window of size T_E and an out-of-sample window of size $T_F^h = T - T_E - h + 1$. A surprise loss at time $t+h$ is defined as the difference between the out-of-sample loss at time $t+h$ and the average in-sample loss:

$$SL_{t+h} = L_{t+h} - \overline{L}_t, \quad \text{for} \quad t = T_E, \ldots, T{-}h \tag{12}$$

where $\overline{L}_t$ is the average in-sample loss computed over the in-sample window. If a forecast is reliable, this mean should be close to zero. Thus, the null is defined as

$$H_0: \quad E\left(T_F^{-1} \sum_{t=T_E}^{T-h} SL_{t+h}\right) = 0, \tag{13}$$

where $T_F^{-1} \sum_{t=T_E}^{T-h} SL_{t+h}$ is the out-of-sample mean of the surprise losses. The test statistic is then defined as

$$t_{T_E,T_F,h} = T_F^{1/2} \overline{SL}_{T_E,T_F} / \hat{\sigma}_{T_E,T_F}, \tag{14}$$

where $\hat{\sigma}^2_{T_E,T_F}$ is an asymptotic variance estimator.

4 The data

Our contribution is based on the assessment by Media Tenor International (MTI), the Swiss-based media analysis institute, of the content of opinion-leading media in Germany, including five TV news programs, two weekly magazines, and one daily tabloid newspaper. News items only referring to the state of the economy in the media set were analyzed over the period from January 1, 2000 through March 31, 2014. Hence, the analyzed data set can be seen as a subset of a much bigger data set including news items on all possible protagonists, such as persons (politicians, entrepreneurs, managers, celebrities, etc.) and institutions (political parties, companies, football clubs, etc.). Each of these news items was analyzed with regard to the topic mentioned (unemployment, inflation, etc.), the region of reference (for example, Germany, EU, USA, UK, BRIC, worldwide), the time reference (past, present, and future), the source of information (journalist, politician, expert, etc.), as well as with regard to the tone of the information (negative, positive or neutral).[6] Overall 80,675 news items about the state of the economy are included in the analysis. For a description of the analyzed media set see Table **??**. Of all the topics only government budget, monetary policy, labor market, business cycle, and taxation contain enough observations to compute subindices with a complete set of monthly observations. Table **??** is a contingency table of these topics. It reports the number of observations of the topics in temporal (present,

[6] Media Tenor International employs professional coders to carry out media-analysis. Only coders that achieved a minimum reliability of 0.85 are cleared for coding. That means that the coding of these coders deviate at most by 0.15 from the trainers' master-versions. The reliability of the coding is checked on an ongoing basis, both with quarterly standard tests and random spot checks. For each month and coder, three analyzed reports are selected randomly and checked. Coders scoring lower than 0.80 are removed from the coding process. In none of the months the mean deviation among all coders was above 0.15.

past, and future) and spatial dimensions (Germany vs. the rest of the world).

Table [**??**] about here

We computed 17 MTI indices using different (sub)samples of the news data. We distinguish between two types of indices depending on the way they are constructed.

The first type is the difference between the percentage share of the positive ratings and that of the negative ratings:

$$B_{i,j,t} = 100 \times \frac{A^{+}_{i,j,t} - A^{-}_{i,j,t}}{A^{+}_{i,j,t} + A^{-}_{i,j,t} + A^{0}_{i,j,t}} \tag{15}$$

where $A^{+}_{i,j,t}$ is the number of positive ratings of media reports about events happening in time i in the country j, published in the period t, $A^{-}_{i,j,t}$ is the number of negative ratings, and $A^{0}_{i,j,t}$ is the number of neutral ratings. The index varies between -100 (all reports are negatively rated) and 100 (all reports are positively rated).

The second type uses the indices of the present and the future sentiment to construct a so-called **media climate index** analogous to the ifo business climate index:

$$MCI = \sqrt{(B^{P}_{j,t} + 100)(B^{F}_{j,t} + 100)} \tag{16}$$

where $B^{P}_{j,t}$ is the present sentiment index and $B^{F}_{j,t}$ is the future sentiment index. By construction, the MCI can take values between 0 indicating extremely bad media climate and 200 pointing to an excellent media climate.

Based on these two types, we distinguish between four groups of MTI indicators:

1. The first set of indicators differ only in the time reference of the respective databases. MT.all uses all the data with all time references (past, present, and future). MT.present and MT.future are based on the data with the time references present and future, correspondingly. Finally, MT.climate, is computed based on the items with present and future reference as in equation (**??**).

2. The second group is the same as the first. However, it exclusively uses data with a reference to Germany. The indices are labeled with "de".

3. The second group of indicators only uses data related to specific topics: The government budget (MT.budget),

monetary issues (MT.monetary), the labor market (MT.labor), the business cycle (MT.cycle), and taxation (MT.taxation). The selection of subsets is restricted by data availability. The more specialized the topic, the fewer observations available.

4. The fourth group is the same as the third, however, it exclusively uses data with a reference to Germany. The indices are again labeled with "de".[7]

Table **??** shows the mean and the median of the media indices. Except for MT.climate and MT.de.climate all indices have a negative mean. This is in line with the literature (see, for example, **?**) that finds that negative news dominates the media. Moreover, the standard deviations of of some subindices, particulary MT.cycle and MT.de.cycle are very high when compared to MT.all, which is based on the whole data set. Figure **??** shows the indices with a regional reference to all countries (groups 1 and 3) and Figure **??** show the indices with a reference to only Germany (groups 2 and 4).

In addition to the media indicators, we collected variables from the database used in **?**. This is a large data set comprising financial indicators, survey indices, prices and wages, indicators of the real economy, and composite indicators. For details see Table **??** and **?**.[8] The different transformations of the raw data are: level (L), differences (D), differences of natural logarithms (Dln), or second differences of natural logarithms (D2ln). For the reference month the data are available with a publication lag $\underline{q}$ that varies from 0 to 2.

However, unlike **?**, we employ real-time data. Revisions of measures of real economic activity, such as employment, sales, and, in particular, industrial production, are sometimes large, and may occur years after official figures are first released. The information set that has been available at different points in time —the different vintages of the data— frequently convey a different picture of the same period of time. Thus, the use of current-vintage data, that is, the data as they are available when the experiment is conducted can lead an analyst to include variables in his forecasting model that, in real time, have little marginal predictive power (see, for example, **?** or **?**). Furthermore, if we assume that revisions lead to an improvement of the indicators, this puts indicators that are unrevised, such as financial data or the media data that are analyzed here, in a

[7] As the number of observations for MT.de.monetary would have been too small, it was not constructed.

[8] Some of their variables are missing in our data set. We could not construct five spread series involving corporate rates computed by Merryl Lynch and the early bird indicator of the Commerzbank as we did not obtain the data. Furthermore, we only obtained very short series for the purchasing manager index of Markit. Finally, we did not include monetary aggregates as, since the introduction of the euro, no country-specific monetary aggregate can be identified. Since the introduction of the euro in Germany, there is only an indicator for money supply of the entire Euro Area available.

disadvantageous position.

5 Results

We analyze the whole set of out-of-sample predictions for each horizon. Furthermore, we are interested in the models' reliability during challenging times from a forecaster's perspective. **?** implement this by comparing the forecast performance before and during the Great Recession as identified by the Euro Area Business Cycle Dating Committee at the Centre for Economic Policy Research (CEPR). However, we find that applying this chronology to the German case is inappropriate. CEPR analyzes recession dates for the whole Euro Area but individual countries reacted differently to the crisis. In particular, in Germany the recession was much milder and shorter than in other EA countries, especially Greece and Spain. Thus, it would be more appropriate to consider instead Germany-specific recession dates, such as the dates provided by the Economic Cycle Research Institute (ECRI). While according to CEPR the recession covered the period from 2008:01 to 2009:06, according to ECRI, the it started 2008:02 and lasted until 2009:02. We use ECRI chronology as a reference. However, we are aware of the fact that the official recession dating and the times, when the forecast performance of many models substantially deteriorates, need not coincide. We focus on those periods when considerably more models than usually suffer a forecast breakdown, as defined by **?**. We define an unstable period as a time when more than 20% of all models across different forecast horizons suffer a breakdown. The period of model instability starts in 2008:12 and ends in 2010:06. Thus, most of the forecast breakdowns of single models happen when values of periods at the end and long after the recession are predicted.

Figure [**??**] about here

This is reflected in the reaction of industrial production to the recession. Figure **??** shows German industrial production over the forecast subsample. On top of the figure, the recession period as defined by ECRI (empty circles) and periods of the model instability (filled circles) are shown. Large changes of the dependent variable happen at the end of the official recession dates and many months thereafter. At the beginning of the official start of the recession in 2008:05, industrial production dropped only by less than 5%. It took 6 more months until the end of the ECRI recession in 2009:01 that it went down to about 80% of its pre-crisis level. However, the trough was not reached until 2009:04. Only in mid-2011 did industrial production return to its pre-crisis level.

Figure [**??**] about here

Figure **??** reports the percentage of models included in the MCS and how many of the models included are media models.[9] The upper panel of Figure **??** displays the results over the whole range of forecasts, where each forecast horizon is depicted individually. The differences of forecasts are relatively informative for all horizons, except for the 8 and the 9 months horizons. For all the other periods, more than 50% of the models are dropped from the MCS. For short horizon up to 5 months, media models are not included in the MCS. The lower panel presents the results for the unstable period only. Here, the data are very informative, which leads to a considerable exclusion of models from the MCS. Media models only enter for horizons greater than 8 months.

Table [**??**] about here

Table **??** reports the RMSE, the Theil's U, the rank according to Theil's U, and the MCS p-value of the best media models for each horizon over all periods. In line with the literature, our benchmark model is the autoregressive model. It is defined as in equation (**??**) under restriction that $\gamma_q = 0$, $\forall q$, which means that only own lags of the dependent variable are included. Two models, MT.de.future and MT.de.climate stand out as particularly useful for horizons from 10 to 12 months. The former has the lowest Theil's U for 10 and 12 months horizons with values of 0.83 and 0.77, respectively. Furthermore, for both horizons it forms part of the $\mathcal{M}^*_{75\%}$ as the best model[10] having an MCS p-value of 1. Moreover, it significantly outperforms the AR model at the 1% level for both horizons. For the 11 months horizon MT.de.climate is the best model both with respect to the Theil's U as well as the MCS p-value. It also significantly outperforms the AR at the 1% level.

Table [**??**] about here

Table **??** shows the results for the unstable period. They remain robust. MT.de.future has a Theil's U of 0.82 and 0.77 for the 10 and 12 months horizons forecasts and significantly outperforms the AR model. However, it is slightly worse, according to the model ratings, since it attains only the third and second rank for the 10

[9] As suggested by **?** we used one size for the block bootstrapping, 6 months, and checked that the results were insensitive to different specifications of the block size.

[10] **?** employ $\mathcal{M}^*_{75\%}$ and $\mathcal{M}^*_{90\%}$. We use the former, as it is more restrictive in the sense that it selects less models into the MCS.

and 11 months horizons. While still forming part of $\mathcal{M}^*_{75\%}$ with high MCS p-values of 0.80 and 0.89 for the 10 and 12 months horizons, it is not the best model in the MCS. MT.de.climate significantly outperforms the AR ranking second for the 11 months forecast horizon. As with MT.de.future, it is not the best model in the $\mathcal{M}^*_{75\%}$ having a MCS p-value of 0.76.

Table [**??**] about here

In the first two rows of Table **??**, the percentage of times MT.de.future and MT.de.climate have failed over all periods and the unstable period for horizons 10 to 12 months is reported. The third row shows the respective averages over all models. A value of 0 implies that the model has never failed, whereas a value of 1 means that the model has always failed. For all periods, the average of all models rises slightly from $h = 10$ to $h = 12$ from 19% to 21%. Both media models' percentages are roughly at the same level. However, for the unstable periods, they are markedly less reliable than the average. On average all models fail 56%, 51%, and 51% of times for horizons 10, 11, and 12 respectively. MT.de.future fails in 74%, 58%, and 63% of times, whereas MT.de.climate fails in 58%, 58%, and 68% of times for horizons 10, 11, and 12, respectively.

6 Conclusion

In this paper, we examine the usefulness of media indicators for predicting the monthly series of German industrial production. We use Media Tenor International indices that are based on human analysis of reports in German opinion-leading media. The forecast performance is evaluated through a real-time forecast experiment covering the period from December 2005 through April 2014. In addition, we identify a period when many models fail with respect to their previous performance. This period begins at the end of the recession as dated by ECRI and ends more than a year afterwards. By doing this we evaluate the stability of models based on the media indices and see whether they are useful during large economic fluctuations. The performance of media indices is compared to that of a large set of alternative indicators.

The forecast performance was evaluated using several criteria. First, we use two measures of forecast accuracy, namely the Root Mean Squared Forecast Error and the Theil's U with respect to the simple autoregressive process. The performance of individual models is tested against that of the autoregressive model using the test proposed by **?**. Moreover, the best performing models are identified using the model confidence set procedure of **?**. Finally, as a measure of reliability, we employ the test for forecast breakdowns proposed by **?**.

Surprisingly, none of the media indices was particularly useful for short-term horizon forecasts (up to 6 months). Concentrating on specific issues such as the labor market, monetary policy related issues, and notably, the business cycle, does not improve the results, nor is the use of international economic news helpful.

Nevertheless, the results clearly show that models using media data outperform models without media data for relatively large forecast horizons, ranging from 10 to 12 months. Media data that contain economic information on all issues for only Germany and are constructed along the lines of the ifo climate and expectation indices rank first, according to RMSE, Theil's U, and the p-value of the model confidence set, and outperform the benchmark autoregressive model individually. Nonetheless, they are unreliable in the sense that they fail more frequently during the unstable period at the end of and almost one year after the German Great Recession.

Still, the use of the media sentiment indicators can be recommended for longer forecast horizons , since it significantly improves the performance of the forecast models.

Appendix

Table 1: Analyzed media set

TV-Program / Newspaper	Name	Number of news items
TV-newscasts:	ARD Tagesschau	11,472
	ARD Tagesthemen	14,933
	ZDF heute	10,158
	ZDF heute journal	15,415
	RTL Aktuell	6,167
Weekly magazines:	Spiegel	4,833
	Focus	7,111
Daily newspaper:	Bild	10,586
Total		**80,675**

Table 2: Media data, contingency table

Time reference	Present		Past		Future		All times		Total
Region	Germany	ROW	Germany	ROW	Germany	ROW	Germany	ROW	Total
Government budget	4,286	6,470	232	441	2,864	3,778	7,382	10,689	18,071
Monetary policy	1,145	1,115	115	136	382	449	1,642	1,700	3,342
Labor market	8,865	2,140	519	126	4,296	361	13,680	2,627	16,307
Business cycle	4,227	6,257	253	510	2,719	1,649	7,199	8,416	15,615
Taxation	3,167	694	123	21	3,420	295	6,710	1,010	7,720
Others	6,905	4,343	549	591	4,235	2,997	11,689	7,931	19,620
Total	28,595	21,019	1,791	1,825	17,916	9,529	48,302	32,373	80,675

Note: ROW stands for the rest of the world.

Table 3: Descriptive statistics of media indices

	mean	standard deviation
MT.all	-29.89	16.04
MT.de	-20.85	19.07
MT.present	-35.14	16.96
MT.future	-20.13	18.91
MT.climate	71.58	16.26
MT.monetary	-26.77	34.24
MT.taxation	-26.33	15.17
MT.cycle	-22.37	35.43
MT.labor	-28.06	19.74
MT.budget	-42.83	26.92
MT.de.present	-24.92	22.27
MT.de.future	-14.41	18.94
MT.de.climate	79.57	18.62
MT.de.taxation	-26.67	15.61
MT.de.cycle	-1.57	47.91
MT.de.labor	-23.35	22.00
MT.de.budget	-29.07	33.48

Table 4: Data: definitions, transformations, and sources

Block	Name	Label	L	D	Dln	D2ln	Lag	Source
Dependent variable								
	Industrial production	IP	-	-	1	-	3	Buba RTDB
Financial								
	Money market rate (monthly average)	IS-M	1	1	-	-	0	Buba
	Discount rate/short term repo rate (monthly average)	IS-D	1	1	-	-	0	Buba
	3m-money market rate (monthly average)	IS-3M	1	1	-	-	0	Buba
	Yields on debt securities outstanding (maturity 3-5 years)	IL-3	1	1	-	-	0	Buba
	Yields on debt securities outstanding (maturity 5-8 years)	IL-5	1	1	-	-	0	Buba
	Long term government bond yield-9-10 years	IL-10	1	1	-	-	0	Buba
	Term spread (10 years - money market rate)	SPR-10Y-M	1	-	-	-	0	Buba
	Term spread (10 years - discount rate)	SPR-10Y-D	1	-	-	-	0	Buba
	Term spread (10 years - 3 months-money market rate)	SPR-10Y-3M	1	-	-	-	0	Buba
	Term spread (discount rate - money market rate)	SPR-1D-M	1	-	-	-	0	Buba
	Corporate bond-government bonds	SPR-C-G	1	-	-	-	0	Buba
	Nominal effective exchange rate	EX	-	-	1	-	1	Buba
	Real effective exchange rate	EXR	-	-	1	-	1	Buba
	DAX	DAX	-	-	1	-	0	Buba
	DAX volatility new	VOLA1	1	1	-	-	0	Buba
	DAX volatility old	VOLA2	1	1	-	-	0	Buba
	Hwwa index of world market prices of raw materials	HWWA	-	-	1	1	1	datastream
	HWWA index, real	HWWAR	-	-	1	1	-	datastream
	HWWA index ,energy	HWWA-E	-	-	1	1	1	Buba
	HWWA index, energy real	HWWA-ER	-	-	1	1	-	Buba
	HWWA index ,excl. energy	HWWA-EX	-	-	1	1	1	Buba
	HWWA index, excl. energy real	HWWA-EXR	-	-	1	1	-	Buba
	Oil prices (euros per barrel)	OIL	-	-	1	1	0	ECB
	Oil prices (euros per barrel), real	OILR	-	-	1	1	-	ECB
Surveys								
	Ifo index climate	IFO-C	1	1	-	-	0	ifo
	Ifo expectations climate	IFO-EXP	1	1	-	-	0	ifo
	Ifo index manufacturing	IFOM-C	1	1	-	-	0	ifo
	Ifo expectations manufacturing	IFOM-EXP	1	1	-	-	0	ifo
	Ifo index capital goods	IFOMI-C	1	1	-	-	0	ifo
	Ifo expecations capital goods	IFOMI-EXP	1	1	-	-	0	ifo
	Ifo index intermediate goods	IFOMV-C	1	1	-	-	0	ifo
	Ifo expectations intermediate goods	IFOMV-EXP	1	1	-	-	0	ifo
	Ifo index wholesale	IFOWH-C	1	1	-	-	0	ifo
	Ifo expectations wholesale	IFOWH-EXP	1	1	-	-	0	ifo
	GFK consumer climate survey - business cycle expectations	GFK-EXP	1	1	-	-	0	datastream
	ZEW economic sentiment	ZEW	1	1	-	-	0	datastream
	Assessment of order-book levels	ECBS2	1	1	-	-	0	EC
	Assessment of export order-book levels	ECBS3	1	1	-	-	0	EC
	Assessment of stocks of finished products	ECBS4	1	1	-	-	0	EC
	Production expectations for the months ahead	ECBS5	1	1	-	-	0	EC
	Selling price expectations for the months ahead	ECBS6	1	1	-	-	0	EC
	Employment expectations for the months ahead	ECBS7	1	1	-	-	0	EC
	Industrial confidence indicator (40%)	ESI-INDU	1	1	-	-	0	EC
	Services confidence indicator (30%)	ESI-SERV	1	1	-	-	0	EC
	Consumer confidence indicator (20%)	ESI-C	1	1	-	-	0	EC
	Retail trade confidence indicator (5%)	ESI-TRADE	1	1	-	-	0	EC
	Construction confidence indicator (5%)	ESI-CTR	1	1	-	-	0	EC
	Economic sentiment indicator (average)	ESI	1	1	-	-	0	EC
	Confidence Indicator (Q2 + Q4 - Q7 + Q11) / 4	ECCS99	1	1	-	-	0	EC
	Financial situation over last 12 months	ECCS1	1	1	-	-	0	EC
	Financial situation over next 12 months	ECCS2	1	1	-	-	0	EC
	General economic situation over last 12 months	ECCS3	1	1	-	-	0	EC
	General economic situation over next 12 months	ECCS4	1	1	-	-	0	EC
	Price trends over last 12 months	ECCS5	1	1	-	-	0	EC
	Price trends over next 12 months	ECCS6	1	1	-	-	0	EC
	Unemployment expectations over next 12 months	ECCS7	1	1	-	-	0	EC
	Major purchases at present	ECCS8	1	1	-	-	0	EC
	Major purchases over next 12 months	ECCS9	1	1	-	-	0	EC
	Savings at present	ECCS10	1	1	-	-	0	EC
	Savings over next 12 months	ECCS11	1	1	-	-	0	EC
	Statement on financial situation of household	ECCS12	1	1	-	-	0	EC

Table 4: Data: definitions, transformations, and sources (continued)

Block	Name	Label	L	D	Dln	D2ln	Lag	Source
Prices and wages								
	Consumer price index	CPI	-	-	1	1	0	Buba RTDB
	Core consumer price index	CPI-EX	-	-	1	1	0	Buba RTDB
	Negotiated wage and salary level	TARIF	-	-	1	1	0	Buba RTDB
Real economy								
	Intermediate goods production	IP-VORL	-	-	1	-	0	Buba RTDB
	Manufacturing orders - consumer goods	ORD-C	-	-	1	-	0	Buba RTDB
	Manufacturing orders - capital goods	ORD-I	-	-	1	-	0	Buba RTDB
	Employed persons (work-place concept)	EW	-	-	1	-	0	Buba RTDB
	1+unemployment (% civilian labour)	ALQ	-	1	-	-	1	datastream
	Vacancies	VAC	-	-	1	-	1	datastream
	Capacity utilisation	CAPA	1	1	-	-	0	datastream
	Hours worked	WHOUR	1	1	-	-	0	Buba RTDB
Composite indicators								
	FAZ indicator	FAZ	-	-	1	-	1	datastream
	Composite leading indicator (amplitude restored)	OECDL1	1	1	-	-	2	OECD
	Composite leading indicator (trend restored)	OECDL2	-	1	-	-	2	OECD
	Composite leading indicator (normalized)	OECDL3	1	1	-	-	2	OECD
Media indicators								
	All observations	MT.all	1	1	-	-	0	MTI
	All observations related to the future	MT.future	1	1	-	-	0	MTI
	All observations related to the present	MT.present	1	1	-	-	0	MTI
	all observations related to the future and present	MT.climate	1	1	-	-	0	MTI
	All observations related to Germany	MT.de	1	1	-	-	0	MTI
	All observations related to Germany and the future	MT.de.future	1	1	-	-	0	MTI
	All observations related to Germany and present	MT.de.present	1	1	-	-	0	MTI
	All observations related to Germany, and future and present	MT.de.climate	1	1	-	-	0	MTI
	All observations related to government budget	MT.budget	1	1	-	-	0	MTI
	All observations related to monetary issues	MT.monetary	1	1	-	-	0	MTI
	All observations related to the labor market	MT.labor	1	1	-	-	0	MTI
	All observations related to the business cycle	MT.cycle	1	1	-	-	0	MTI
	All observations related to taxation	MT.taxation	1	1	-	-	0	MTI
	All observations related to the German government budget	MT.de.budget	1	1	-	-	0	MTI
	All observations related to the German labor market	MT.de.labor	1	1	-	-	0	MTI
	All observations related to the German business cycle	MT.de.cycle	1	1	-	-	0	MTI
	All observations related to German taxation	MT.de.taxation	1	1	-	-	0	MTI

Note: The different transformations of the raw data are either level (L), differences (D), differences of natural logarithms (Dln) or second differences of natural logarithms (D2ln). The publication lag (Lag) ranges from 0 to 3 months. The sources are Datastream, Deutsche Bundesbank (Buba), Deutsche Bundesbank Realtime Database (Buba RTDB), European Commission (EC), European Central Bank (ECB), Ifo institute for economic research (ifo), Organization for Economic Co-operation and Development (OECD), and Media Tenor International (MTI).

Table 5: Best media models, all periods (2005:12-2014:04)

h	Model	RMSE	Theil's U	Rank Theil's U	MCS p-value
1	MT.de.present	28.37	0.91	93	0.00
2	MT.de.present	32.73	0.89	94	0.00
3	MT.present	33.78	0.87	90	0.00
4	MT.present	31.08	0.84	71	0.00
5	MT.de.present	23.27	0.74	44	0.13
6	MT.de.present	17.50	0.66	33	0.25*
7	MT.present	13.33	0.68	27	0.24
8	MT.present	10.53	0.83*	13	0.40*
9	MT.de.future	9.17	0.85**	5	0.43*
10	MT.de.future	8.43	0.83**	1	1.00*
11	MT.de.climate	8.69	0.77**	1	1.00*
12	MT.de.future	8.46	0.77**	1	1.00*

Note: * (**) for Theil's U denotes significant outperformance of the AR model to the 5 (1) percent level, whereas * for MCS p-values indicates, that the respective model is in the $\mathcal{M}^*_{75\%}$.

Table 6: Best media models, unstable period (2008:12-2010:06)

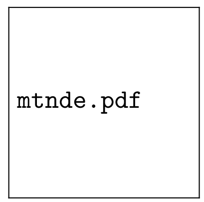
h	Model	RMSE	Theil's U	Rank Theil's U	MCS p-value
1	MT.de.present	63.73	0.88	92	0.00
2	MT.de.present	74.88	0.88	94	0.00
3	MT.present	77.27	0.85	89	0.00
4	MT.present	70.76	0.82	71	0.00
5	MT.de.present	51.98	0.72	46	0.00
6	MT.de.present	37.96	0.63	35	0.02
7	MT.de.present	26.60	0.62	26	0.00
8	MT.present	19.94	0.77	12	0.00
9	MT.de.future	18.09	0.86**	14	0.00
10	MT.de.future	15.90	0.82**	3	0.80*
11	MT.de.climate	14.08	0.77**	2	0.76*
12	MT.de.future	13.98	0.77**	2	0.89*

Note: * (**) for Theil's U denotes significant outperformance of the AR model to the 5% (1%) level, whereas * for MCS p-values indicates, that the respective model is in the $\mathcal{M}^*_{75\%}$.

Table 7: Percentage of forecast breakdowns

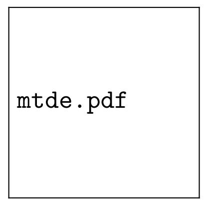
Models	$h = 10$		$h = 11$		$h = 12$	
	all periods	unstable	all periods	unstable	all periods	unstable
MT.de.future	0.19	0.74	0.21	0.58	0.20	0.63
MT.de.climate	0.18	0.58	0.20	0.58	0.23	0.68
mean all models	0.19	0.56	0.20	0.51	0.21	0.51

Figure 1: Media indices (Reference: all regions)



Note: Media Tenor International indices are represented with a solid line (left scale). As a reference industrial production is plotted as well represented by a dashed line (right scale).

Figure 2: Media indices (Reference: Germany)



Note: Media Tenor International indices are represented with a solid line (left scale). As a reference industrial production is plotted as well represented by a dashed line (right scale).

Figure 3: Industrial production, recession, and forecast breakdowns

Figure 4: Percentage of models included in MCS

(a) All periods, 2005:12-2014:04

(b) Unstable (forecast breakdown) period, 2008:12-2010:06