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Abstract

We examine the effects of negative news reporting on companies' self-assessment of their business situation. We compare survey data in the manufacturing sector in Switzerland with thousands of newspaper articles which we scan for particular keywords. Simple OLS regressions do not show a significant influence of news reporting on the self-assessment of the surveyed companies. However, the fact that our news data are available on a higher frequency permits us to examine if a MIDAS approach (regressing the daily news data on the monthly survey data) leads to any gain in information. Our results show influence of particular days which could give an early hint how companies see their business environment before the actual survey results are available.

Keywords: Media Data, News, Uncertainty, Business Situation, Mixed Frequency Data, MIDAS

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1 Introduction

"Media determine our situation [...]", is the often-quoted beginning of media scientist Friedrich Kittler's book *Gramophone, Film, Typewriter* (Kittler, 1986), which he published 30 years ago. Although Kittler was rather writing about a post-human era than the daily influence of our media consumption, his remark can be taken as media theory in a nutshell. Humans are influenced by their media surrounding, i.e. mainly media consumption. Consequently, it can be assumed that news reports also affect how individuals judge the current state of the economy. This holds in particular true in times of high uncertainty about the future. A proliferation of negative news can lead to a negative judgment albeit the real actual situation would suggest otherwise. This can eventually harm the entire economy trough a self-fulfilling prophecy effect, as individuals might adapt their consumption and investment behavior by getting more cautious. In this study, we are interested if those effects can also be seen in companies' judgment. The question would therefore be: Can we see an effect of negative reporting on the economy in companies' assessment of their business situation? This would give economists an early and accessible indication in what direction the economy is heading as the aggregated business situation is a good indicator for the short-term performance of an economy. In this study, we try to grasp the impact of news on companies' business situation by combining survey and news data. The survey data stem from the self-assessment of companies in the manufacturing sector in Switzerland and the news data are generated by scanning a vast amount of newspapers for particular keywords.

Business surveys are a useful qualitative tool for monitoring the state of the economy (Hansson, Jansson, and Löf (2005), Claveria, Pons, and Ramos (2007), Kholodilin and Siliverstovs (2012), and Kaufmann and Scheufele (2015)). The basic idea of surveys is to gather information on a micro level and then aggregate it to a macro level to get an idea of the overall situation of different sectors. However, as the questions asked are not strictly quantitative it can be assumed that answers are at least to some extent prone to be influenced by news reporting. Individuals and therefore companies answer survey questions at least partly depending on the news they receive through their media consumption. The answer is a mix of hard-wired facts (e.g. the accounting side) and soft factors, transmitted through media channels. In this study we try to focus on this transmitter function of news. We assume (as others do, e.g. Lamla and Sturm (2013)) that getting an idea of what the media (in our case: newspapers and news agencies) are reporting can be a good predictor of companies' assessment of their current business situation, in our case of the manufacturing sector in Switzerland.[1]

The remainder of this paper is organised as follows. Section 2 continues with a literature overview. Section 3 explains our data. Section 4 introduces our methodology. Section 5 contains the empirical analysis and the results. Section 6 concludes.

2 Literature

Measuring the economy by taking media data into account has become popular in recent years. According to Kholodilin, Thomas, and Ulbricht (2014) the growing literature about exploiting media data to explain economic sentiment can be divided into two main strands. One is a simple word count, where researchers scan media outlets for a single word or a group of words that can be associated with a certain economic event, such as a recession or depression. The second class captures the specific media content. Whereas Kholodilin, Thomas, and Ulbricht (2014) certainly have a point in distinguishing these two classes we would rather split the literature along two other strains: one is a focus on media content that gets edited (newspapers, professional blogs and the like) and hence somebody can be held responsible for the content. The second strain is the literature about the vast content produced by either web searches or users directly (such as over social media) where no particular gate-keeping has been applied. In this case, the sources are often unknown and nobody can be held responsible for the quality of the content.

2.1 Newspapers

Since the publication of the so called R-word index by the magazine Economist[2] there have been many attempts to exploit media based content for forecasting or nowcasting the state of the economy (see Iselin and Siliverstovs (2013b) for an overview). Hisano, Sornette, Mizuno, Ohnishi, and Watanabe (2013) use more than 24 million news records provided by Thompson Reuters which show news related to 206 major firms included in the S&P 500 index. They show that whole landscapes of news that affect stock price movements can be automatically summarized by conducting a simple regularized regression between trade related activity and news. They decompose these news in their —as the authors call it— 'thematic' features by applying simple topic modeling techniques. They

[1] A good example of the before mentioned fact was the decision of the Swiss National Bank to abandon the lower ceiling of the exchange rate of the Swiss franc against the Euro on January 15, 2015. Companies got the news of the National Bank's action through media outlets.

[2] In the early 1990s the weekly Magazine Economist (2011) invented the so called R-word index.

are able to synchronize this pieces of information well with the trading activity of those firms' titles.

Alexopoulos and Cohen (2009) and Baker, Bloom, and Davis (2013) use newspapers archives to get an idea of the uncertainty of particular times. Alexopoulos and Cohen (2009) show that uncertainty shocks, based on keyword searches in newspaper based, are an important source of business cycle fluctuations. Baker, Bloom, and Davis (2013) partly base their uncertainty measure by linking to the frequency of newspaper references to economic policy uncertainty. In a similar direction goes a paper by Chadefaux (2014). He shows that news reports about conflicts dramatically increase prior to the onset of a conflict. He scans historical newspaper articles by a set of keywords and countries and then bundles them to predict conflict outbreaks with relatively high accuracy.

As Hisano, Sornette, Mizuno, Ohnishi, and Watanabe (2013) write, traditional newspapers might have lost quite an amount of their interpretation sovereignty, but they still differ from direct publishing by a quality oriented fact-checking procedure, where they can be hold accounted for their published opinion.

2.2 Online Searches and Social Media

This is not the case for the proliferation of data in online searches and social media. Regardless of this fact, the use of internet searches, mainly through the gatekeeper Google, for assessing or predicting economic activities has soared in recent years, starting with the 2009 Google research paper by Hyunyoung Choi & Hal Varian(Choi and Varian (2009) which led to the 2012 paper (Choi and Varian (2012)) we refer to. They show that Google searches have predictive power for consumption in the US. [3]

On the shoulders of Choi and Varian (2012), McLaren and Shanbhogue (2011) examine the use of online searches as indicators for economic activity in the UK. The data on the volume provide additional information relative to other existing surveys.[4] Carrière-Swallow and Labbé (2010)

[3]The paper of Chadefaux (2014) could be cited here as he uses Google searches as well. However his data is by Google definition limited to media sites. The line in my separation between traditional media content and content from web searches and social media online searches is a little blurry as a vast amount of 'traditional' media content finds its way to online searches over Google. I would still stick to this differentiation setting as the sources are at least clear cut if we crawl through media databases.

[4]McLaren and Shanbhogue (2011) also list the potential benefits and problems of internet search data as economic indicators. The benefits are: timeliness and coverage. As these data is collected as by-product problems usually associated with surveys such as non-response or inaccurate responses can be avoided. Information is collected continually, that means no special surveys are needed in the event of issues that arise unexpectedly. The difficulties with using search data are the following: representation and purpose of search. Although online activity has become widespread specific searches are highly correlated with factors such as age and income. Regarding the purpose of a search activity: there exists a lot of noise in the search data.

examine whether Google search results provide relevant information about sales of cars in Chile. They show that an index based on these searches as a regressor in a simple nowcasting model helps to outperform competing benchmark specifications in both in- and out-of-sample nowcasting exercises. Kholodilin, Podstawski, and Siliverstovs (2010) investigate if Google search results can help in nowcasting the year-on-year growth rates of monthly US private consumption using a real-time data set. As they can show the Google search improves the nowcasts of the private consumption in US.

Exploiting the prediction performance of media and social media generated content in particular has only recently become possible as most of the social media networks hardly existed more than 10 years ago.[5] One of the favorite social media platforms among academics is Twitter that was launched in 2006. Twitter has a history of systematic opening up its data to academics.[6] Bollen, Mao, and Zeng (2011) investigate whether Twitter feeds (labelled 'public mood') are correlated to the value of the Dow Jones Industrial Average (DJIA) over time. Their results indicate that changes in the public mood can be tracked from the content of large-scale Twitter feeds by means of rather simple text processing techniques. However, not all of the mood dimensions are Granger causative of the DJIA.

In a more recent study, Antenucci, Cafarella, Levenstein, Ré, and Shapiro (2014) construct a social media index to measure labor market flows, based on 19.3 billion tweets in the time range of July 2011 until November 2013. They show that the signal to noise ratio is better than is initial claims. There is no other data available at an as high frequency and in pseudo real-time for assessing job flows. Furthermore, the authors emphasize —as many others do— the benefits of variables derived from social media: measurements at relatively low cost, with high frequency.

Asur and Huberman (2010) use the chatter from Twitter to forecast box-office revenues for movies. Similar to the objective of the study by Asur and Huberman (2010), but by other means, Goel, Hofman, Lahaie, Pennock, and Watts (2010) analyze the predictive power of web search activity for activities such as attending movies and purchasing music or video games.

In our approach, we go along the more traditional way. Hisano, Sornette, Mizuno, Ohnishi, and Watanabe (2013) mention the high quality of the news sources scanned, which results in high signal-over-noise ratio. This is one reason why we rather stick to official news sources such as

[5] Using media or social media-based time series is not without criticism (see Lazer, Kennedy, King, and Vespignani (2014)). Lazer, Kennedy, King, and Vespignani (2014) critic the lack of transparency of the statistical procedures, the lack of replicability because of the use of property data and the instability of time series.

[6] It facilitates scanning its content by the Twitter API, read more about it in this article in the magazine WIRED.

newspapers rather than blogs or Google Trend searches to get an idea of the influence of news on the companies' self-assessment of their business situation.

3 Data

The KOF Swiss Economic Institute of ETH Zurich has been asking manufacturing companies since 1955 how they judge their current business situation. To keep the procedure as simple as possible, there are just three possible answer categories: 'good', 'satisfying' or 'bad'.[7] The data is then usually aggregated to a sector indicator representing the respective business situation.

To track the news reporting over time we use newspapers and news agencies reports coming from Genios, a general database for German-speaking media. We construct a web crawler which enables us to export on a daily basis articles which feature our search terms and count the number of articles per day.

3.1 Survey Data

Each month companies in the manufacturing sector are surveyed by the KOF Swiss Economic Institute of ETH Zurich. They are requested among other questions to assess their current business situation. They may class their situation as 'good', 'satisfying' or 'bad'. The balance of the current business situation is the difference difference between the answers shares 'good' and 'bad'. You find the respective time series in Figure 1.

[7] Lui, Mitchell, and Weale (2011) show that qualitative answers at the firm-level are corresponding nicely with quantitative outcomes.

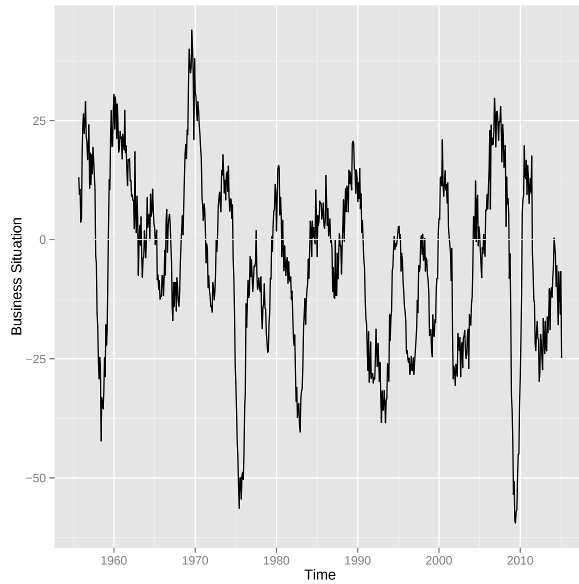

Figure 1: Assessment of Business Situation in Swiss Manufacturing Sector 1955:M9–2015:M2

As we can see from Figure 1 all major economic events in the last 60 years can be detected in the business situation of Swiss manufacturing companies. The oil shock in the 70s, the economic turmoils after the burst of the housing bubble in Switzerland in the early 90s, the Lehman Brothers bankruptcy in 2008, and lately the strong appreciation of the Swiss franc, first in September 2011, and then again in January 2015.

To control for outliers and in order to make our data more stable we perform a log transformation which in our case means that we first have to get rid of the negative sign. We do this by adding 100 points to any data point before the logaritmization. In addition, we cut our data series and focus on a more recent time period, i.e. January 1990 to February 2015 (see Figure 2). This is necessary to perform our regressions later as our news data are not very yielding in the periods before.

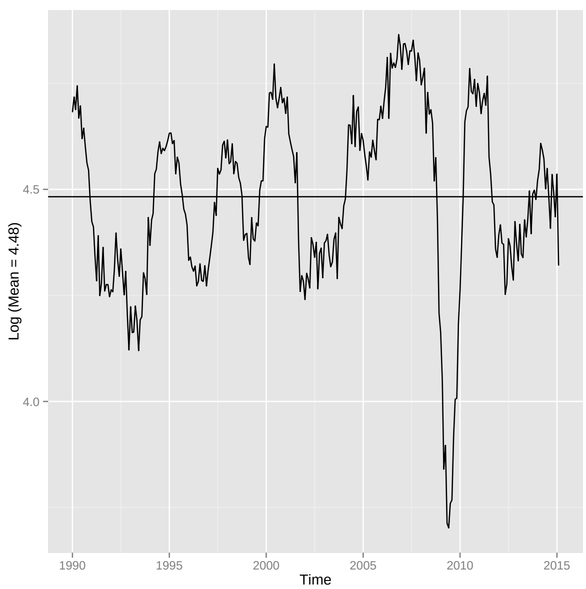

Figure 2: Log Assessment of Business Situation 1990:M1–2015:M2

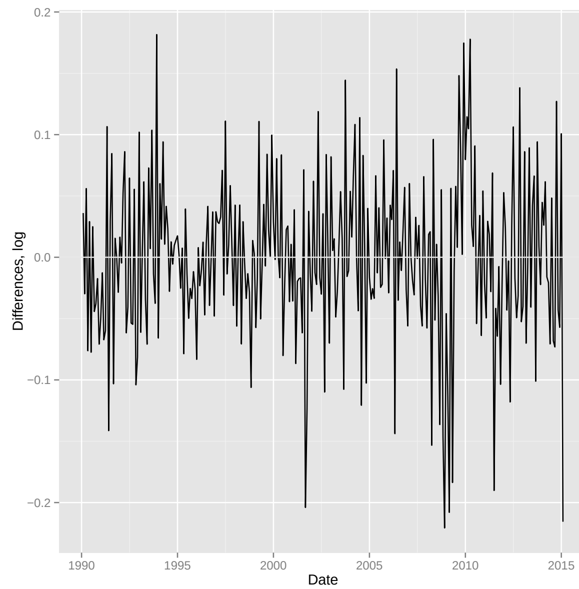

Figure 3: First Differences Log Assessment of Business Situation 1990:M1–2015:M2

In order to get an idea about companies' judgment of the future, which might be even more influenced by news coverage, we also include the companies expected incoming orders in the next 3 months into our analysis.

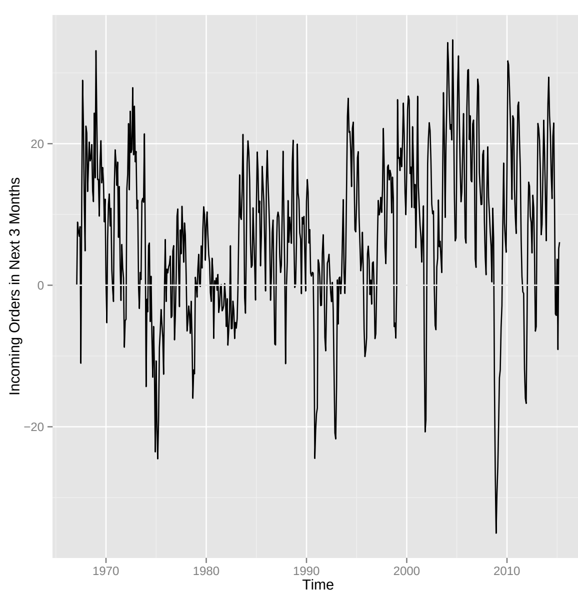

Figure 4: Incoming Orders in Next 3 Months 1967:M2–2015:M4

3.2 News-based Indicator

For our news-based indicator, We use a newspaper crawler we built that enables us to scan online newspaper archives on a daily basis for particular keywords (also combination of keywords). The most abundant and broad source in the German-speaking world to our knowledge in this context is Genios, the web archive for all German-speaking news outlets. We scan Genios for the keywords 'recession+Switzerland' (Rezession+Schweiz) and later on 'uncertainty' (Unsicherheit).[8] The first keyword combination has already proofed fruitful in a forecast context (see Iselin and Siliverstovs (2013a), and Iselin and Siliverstovs (2013b)). And the second has gained popularity in particular thanks to the work about the concept of uncertainty by Baker, Bloom, and Davis (2013).

As a sideline exercise we also scan the archive of the Neue Zürcher Zeitung which goes back to the year 1780 (!).[9] It is noteworthy that the word 'recession' appears for the first time in the Neue Zürcher Zeitung archive in the 1920's.[10] Words are subject to trends. Although we surely entered many recessions before 1920, obviously nobody was using the word itself in Switzerland in the time before the 1920's.[11]

Figure 5 shows our news-based indicator together with the survey results. From a purely graphical analysis we get some indication that our news index leads the assessment of the business situation most of the time. To check if this lead can be exploited somehow we continue with our empirical analysis.

[8] We also used 'appreciation+franc' (Aufwertung+Franken), to take the strong dependence of the Swiss manufacturing sector on the national currency's development, but that did not change our results significantly.

[9] In addition, we scan through the archives of the Financial Times (FT). Although it is very interesting to see how the economic situation in Switzerland is reported on from the outside, the small number of articles in the FT is not very informative. The same holds true for the Swiss Radio and Television e.g.

[10] According to the historical database started by collaborators of Angus Maddison Switzerland had 1852 and 1920 27 years with a negative GDP growth (see Bolt and van Zanden (2014) for more information on the underlying data).

[11] What becomes clear from our media data is the fact that we have a week day bias. There used no be no Sunday papers for a long time. However, as the web cut the connection between news and the need to print it, the particular day of the week lost some of its significance. Hence, we assume that —at least— since about 2000 there is not really a significant restriction on news depending on the day (except maybe for Christmas and Easter).To get an idea how the news are distributed over the week see Figure 6 in the appendix section.

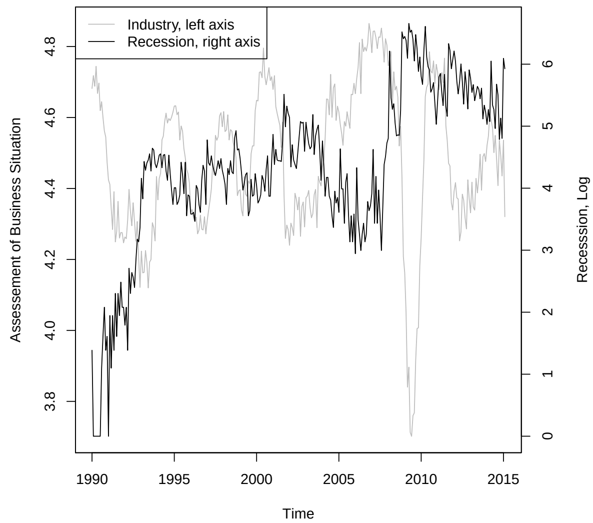

Figure 5: Assessment of Business Situation and News-based Indicator

4 Methodology

To analyse a possible influence of our news based data we start with a simple time averaging OLS approach, where we aggregate our daily news index to a monthly time series:

$$\hat{X}_t = \sum_{k=1}^{m} L_{HF}^{k} X_t.$$

With the two variables Y_t and X_t in the same time domain, our regression approach is simply:

$$Y_t = \sum_{i=1}^{p} \beta_i L^i Y_t + \sum_{j=1}^{n} \gamma_j L^j X_t + \epsilon_t, \tag{1}$$

where the γ_js are the slope coefficient on the time-averaged Xs. Notice that the third term in equation (1) employs the higher-frequency lag operator, indicating that we are using, for example, the prior jth month's average of daily X_ts. In our analysis, we will use a lag of 0, meaning that we take data of the same month and then will proceed with a lag of 1.

As we have our news-based data also in a higher frequency, we can consider a MIxed DAta Sampling

(MIDAS) based regression approach as well, taking the high frequency data of our news indicator to regress on the low-frequency data of the self-assessment. This would prevent us from losing information from our daily observations (see e.g. Andreou, Ghysels, and Kourtellos (2010) or Armesto, Engemann, and Owyang (2010)). The MIDAS approach has some nice features (see e.g. Foroni, Marcellino, and Schumacher (2011)): It allows to explain a low-frequency variable like GDP by high-frequency indicators and their lags without resorting to time aggregation. In addition, MIDAS regressions are a 'simple, parsimonious, and flexible class of time series models' (Breitung, Roling, and Elengikal (2013), p. 16). In our case we use the simple unrestricted MIDAS which can be estimated by OLS as suggested in Marcellino and Schumacher (2008). The following specification is taken from Kvedaras and Zemlys (2015):

$$Y_t = \sum_{j=1}^{p} \alpha_j Y_{t-j} + \sum_{i=0}^{k} \sum_{j=0}^{l_i} \beta_j^{(i)} X_{tm_i-j}^{(i)} + \epsilon_t, \tag{2}$$

where $X_t^{(i)}, i = 0, ...k$ are regressors of higher (or similar) frequency than Y_t. Given certain assumptions the coefficients can be estimated using usual OLS and they have the familiar properties associated with simple linear regression, as Kvedaras and Zemlys (2015) note.

5 Results

A simple OLS regression (see Table 1) where we take the same month for our dependent variable and our explanatory variables shows a high auto-correlation of the dependent variable and a negative albeit non-significant effect of our news-based indicator. The high R^2 can be explained by the strong auto-correlation of our dependent variable which is not surprising as the aggregated business situation of companies does not change very quickly from month to month.

Table 1: Regression Results

	Dependent variable:	
	Assessment of Business Situation	
	(1)	(2)
1st Lag of Business Situation	0.947*** (0.917, 0.978)	0.946*** (0.916, 0.977)
News Index	−0.001 (−0.006, 0.004)	
1st Lag of News Index		−0.002 (−0.007, 0.003)
Constant	0.239*** (0.095, 0.383)	0.247*** (0.104, 0.391)
Observations	301	301
R^2	0.901	0.901
Adjusted R^2	0.900	0.900
Note:		*p<0.1; **p<0.05; ***p<0.01

The same holds true for our future oriented indicator of incoming orders in the next 3 months (see Table 2). We still have a negative albeit non-significant effect of our news-based index.

Table 2: Regression Results

	Dependent variable:	
	Expected Incoming Orders	
	(1)	(2)
1st Lag of Incoming Orders	1.000*** (1.000, 1.000)	1.000*** (1.000, 1.000)
News Index	−0.000 (−0.000, 0.000)	
1st Lag of News Index		−0.000 (−0.000, 0.000)
Constant	0.000 (−0.000, 0.000)	0.000 (−0.000, 0.000)
Observations	302	302
R^2	1.000	1.000
Adjusted R^2	1.000	1.000
Note:		*p<0.1; **p<0.05; ***p<0.01

Until now we have focused on time series with equal frequencies. We aggregated the daily data of our media based index to a monthly indicator and we checked how the daily indicators are moving. The results seem to support the hypothesis of not much additional information in our news based indicator. In a next step we take the fact that we have our news-based indicator on a daily basis. This allows us to check if the higher-frequency data are a stronger indicator than the aggregated data. Hence, in a next section we focus on the MIDAS approach to exploit the characteristics of higher frequency.

The MIDAS approach demands that low-frequency and the high-frequency data must be dividable by an integer. Hence, we first have to transform our data. We add up all months to 31 days by copying the last day's value in.[12]

As we can see from Table 3, there are single days (e.g. day 13) that significantly influence the business situation of the Swiss manufacturing as reported in the KOF surveys, independent of the inclusion of a lag for our dependent variable. This corresponds perfectly with the usual procedure of sending out the surveys in the beginning of the month with the written indication to fill in the questionnaire until the 12th, and then again sending out a reminder after the 12th. We also check for spurious correlations by taking recursively one day out of the regression, starting with day 31 going down to day 13. Day 13 remains negative, and significant so, in all different set-ups. What remains to be investigated is the fact that we also get significant positive effects from particular days. We would expect a negative influence as the higher the news-based indicator is, the worse the public mood should be.

[12] We also examined the alternative with cutting all months down to 28 days. This did not change the results we are reporting here.

Table 3: MIDAS Regression Results

	Dependent variable:
	Assessment of Business Situation (log)
1st Lag of Business Situation	0.011*** (0.010, 0.011)
Day 31	0.0001 (−0.002, 0.002)
Day 30	0.0001 (−0.001, 0.001)
Day 29	0.003** (0.001, 0.005)
Day 28	−0.004*** (−0.005, −0.002)
Day 27	0.001 (−0.001, 0.003)
Day 26	0.001 (−0.001, 0.003)
Day 25	0.001 (−0.001, 0.003)
Day 24	−0.001 (−0.002, 0.001)
Day 23	−0.002* (−0.005, −0.0001)
Day 22	−0.001 (−0.003, 0.001)
Day 21	0.002 (−0.0001, 0.003)
Day 20	−0.001 (−0.003, 0.001)
Day 19	−0.001 (−0.002, 0.001)
Day 18	−0.003*** (−0.005, −0.001)
Day 17	0.001 (−0.001, 0.003)
Day 16	−0.00004 (−0.002, 0.002)
Day 15	0.001 (−0.0003, 0.003)
Day 14	0.001 (−0.001, 0.003)
Day 13	−0.003*** (−0.005, −0.001)
Day 12	−0.0004 (−0.003, 0.002)
Day 11	0.001 (−0.001, 0.003)
Day 10	0.002** (0.0004, 0.004)
Day 9	0.002 (−0.0005, 0.004)
Day 8	0.0005 (−0.001, 0.002)
Day 7	0.001 (−0.001, 0.003)
Day 6	−0.001 (−0.003, 0.001)
Day 5	−0.0002 (−0.002, 0.002)
Day 4	−0.001 (−0.003, 0.002)
Day 3	−0.002 (−0.004, 0.0003)
Day 2	0.0002 (−0.002, 0.002)
Day 1	−0.0002 (−0.002, 0.002)
Constant	4.599*** (4.590, 4.608)
Observations	301
R^2	0.915
Adjusted R^2	0.905
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: MIDAS Regression Results without Lag

	Dependent variable:
	Assessment of Business Situation (log)
Day 31	0.024 (−0.012, 0.060)
Day 30	−0.012 (−0.047, 0.023)
Day 29	0.014 (−0.022, 0.050)
Day 28	−0.016 (−0.053, 0.020)
Day 27	0.008 (−0.024, 0.040)
Day 26	0.002 (−0.032, 0.036)
Day 25	−0.022 (−0.057, 0.013)
Day 24	−0.032 (−0.069, 0.006)
Day 23	−0.018 (−0.055, 0.020)
Day 22	0.013 (−0.022, 0.047)
Day 21	0.020 (−0.014, 0.054)
Day 20	−0.010 (−0.044, 0.024)
Day 19	−0.016 (−0.052, 0.020)
Day 18	−0.008 (−0.043, 0.027)
Day 17	0.015 (−0.020, 0.051)
Day 16	0.010 (−0.025, 0.045)
Day 15	0.019 (−0.019, 0.058)
Day 14	−0.018 (−0.054, 0.017)
Day 13	0.008 (−0.026, 0.042)
Day 12	−0.044** (−0.080, −0.007)
Day 11	0.018 (−0.018, 0.053)
Day 10	−0.021 (−0.057, 0.014)
Day 9	0.026 (−0.011, 0.063)
Day 8	0.005 (−0.031, 0.041)
Day 7	−0.024 (−0.060, 0.013)
Day 6	−0.009 (−0.042, 0.025)
Day 5	0.009 (−0.025, 0.042)
Day 4	0.003 (−0.031, 0.036)
Day 3	0.008 (−0.029, 0.045)
Day 2	−0.011 (−0.036, 0.015)
Day 1	−0.022 (−0.055, 0.011)
Constant	4.564*** (4.528, 4.601)
Observations	301
R^2	0.165
Adjusted R^2	0.069
Note:	*p<0.1; **p<0.05; ***p<0.01

For our future oriented time series, the expected incoming orders in 3 months, we do not find, as it was already the case with the simple time averaging approach, any influence of our indicator (you find the results in the appendix, see 5). Here, we use the time series not in log transformation.

6 Discussion

The introductory question was: Is there a measurable and significant influence of negative news reporting about the economy on companies' self-assessment of their business situation? The answer is a mixed one. We do not find an impact of the media coverage on the judgment of Swiss manufacturing companies on a month to month comparison level. However, taking the high-frequency quality of our data into account gives us more insights, whether there are special days which influence companies' assessment. We find some influence of our news based data, which, given the survey schedule, seems reasonable. A limitation of our results lies in the possibility of spurious correlations which are hard to address. Hence, it would be important to dig deeper into the relationship between the daily news and companies' behavior. Therefore, in a next step we step go onto the micro level and take the daily answers of companies into account. The fact that companies fill in their surveys online and leave an exact time stamp that indicates exactly when they have answered the questionnaire, we have access to an even more direct measuring possibility. This gives us a quasi real-time assessment of the business situation of companies in the manufacturing sector.

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Appendix

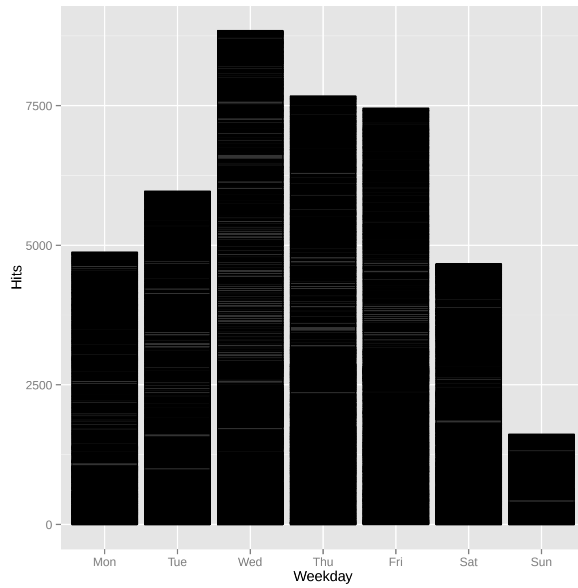

Figure 6: Distribution of Total Number of Articles over Week Days 1990 M1–2015 M2

Table 5: MIDAS Regression Results

	Dependent variable:
	Incoming Orders
1st Lag of Incoming Orders	0.810*** (0.696, 0.923)
Day 31	−0.434* (−0.821, −0.046)
Day 30	0.180* (0.017, 0.343)
Day 29	−0.401 (−0.882, 0.080)
Day 28	0.380 (−0.029, 0.788)
Day 27	0.308 (−0.129, 0.745)
Day 26	−0.142 (−0.563, 0.278)
Day 25	−0.103 (−0.508, 0.301)
Day 24	0.206 (−0.106, 0.518)
Day 23	0.149 (−0.344, 0.643)
Day 22	0.048 (−0.327, 0.423)
Day 21	−0.195 (−0.587, 0.198)
Day 20	−0.506* (−0.977, −0.034)
Day 19	0.064 (−0.307, 0.436)
Day 18	−0.148 (−0.583, 0.286)
Day 17	0.234 (−0.208, 0.677)
Day 16	−0.132 (−0.576, 0.312)
Day 15	0.178 (−0.210, 0.566)
Day 14	−0.041 (−0.449, 0.366)
Day 13	−0.232 (−0.677, 0.214)
Day 12	−0.076 (−0.538, 0.386)
Day 11	0.471* (0.009, 0.933)
Day 10	0.105 (−0.314, 0.525)
Day 9	−0.086 (−0.524, 0.351)
Day 8	0.123 (−0.253, 0.499)
Day 7	−0.177 (−0.577, 0.222)
Day 6	0.148 (−0.322, 0.618)
Day 5	−0.134 (−0.528, 0.260)
Day 4	−0.548* (−1.076, −0.020)
Day 3	0.055 (−0.390, 0.500)
Day 2	0.097 (−0.317, 0.510)
Day 1	−0.277 (−0.681, 0.126)
Constant	82.496*** (79.909, 85.083)
Observations	300
R^2	0.456
Adjusted R^2	0.391
Note:	*p<0.1; **p<0.05; ***p<0.01