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Does negative news reporting on the economy get reflected in companies' business situation?

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KOF Swiss Economic Institute

Does Negative News Reporting on the Economy Get Reflected in Companies' Business Situation?

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Abstract

We examine the effects of negative economic news reporting on companies' self-assessment of their business situation. In order to measure this negativity effect, we introduce a new daily business indicator for the Swiss manufacturing sector and examine the influence of newspaper articles, which we scan for particular keywords, on a daily basis. We use OLS and VAR models to examine the mutual influence of negative news and the business situation of private companies. The results show a negative influence of news reporting on the self-assessment of the companies surveyed, also when controlling for the overall economic situation. However, the negative effect is not stable in all our set-ups.

Keywords: Media Data, News, Business Situation

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1 Introduction

We live in media societies and media economies. People as well as companies adapt to their news consumption, which is basically driven by negative news, especially about the economy. In this paper, we examine if companies get somewhat influenced by their supposed news consumption. Since negative shocks are more economically relevant and the media traditionally focuses more on the negative consequences of specific events, we define the news environment as negative economic coverage. In order to measure this negative news impact, we build a unique data set that consists of daily data on the assessment of the business situation and the influence of daily news coverage on the former. To the best of our knowledge, the use of a daily business situation indicator for Switzerland is new. In doing so, we distinguish ourselves from the existing literature on measuring the news effect on the economy, see e.g. [Lamla et al. \(2007\)](#) or [Buchen \(2014\)](#). These studies generally use monthly data to assess news influence.

The news shapes our information environment and hence our view of the economy. It does so by affecting the public sentiment about the current situation or the near-future. Accordingly, we adjust our expectations. We might consume more or less or invest more or less, depending on our news environment. [Pigou \(1927\)](#) noted the importance of news information and its influence on expectations. [Beaudry and Portier \(2007\)](#) show the economic impact of expectations that are driven by news coverage. They also find evidence that news generally drive business cycle fluctuations. Of particular influence are news in markets where financial information is crucial. Here, “media frenzies”, i.e. intense media coverage of a specific topic that is seen as of great interest to the public, increased in numbers in recent years ([Veldkamp, 2006](#)).

The news is different from other goods as [Romer \(1990\)](#) emphasizes. There is a fixed cost of discovery, but almost zero cost of replication. Once the information is there, anybody can use it. The non-rivalry in consumption and the low marginal cost of replication make aggregated news information attractive in adjusting the expectations on the economy. This not only holds for firms and agents in financial markets, but also for companies in, for example, the manufacturing sector. Managers in the manufacturing sector are more likely to inform themselves on the general economy through mass media as gathering sector specific economic information would be costly ([Lamla et al., 2007](#)). As [Veldkamp \(2006\)](#) states, the number of articles in mass media functions as a proxy for how easily information is accessible. The higher the news coverage about the business cycle, the less effort is needed to inform oneself or search for information.

The idea of adjusting views on the economy through news consumption is linked to the rational inattention hypothesis. Sims (2003) points out that individual people have limited capacity for processing information. Knowing this, it becomes rational for consumers to only partially pay attention to new information. This rational inattention hypothesis is in line with Keynes' idea of "sticky prices" as people do not act as continuously optimizing agents but merely jump from one position to the next. The erratic behavior might also apply to private companies. They do not have the time or resources to constantly adapt to their environment when new information is presented. Furthermore, as Brettschneider (2000) and Ju (2008) show, economic news coverage is mostly negative over time. In addition, public response to negative economic information is stronger than the response to positive information (Soroka, 2006). This is triggered by the asymmetric response of mass media to economic information and the additional asymmetric response by the public. This downward spiral is expected to ultimately influence the economy itself. The negative bias in news reporting has been related to the phenomenon of "negativism" (Kholodilin et al., 2015). News is almost naturally "negative" or put another way, "only bad news is good news". A proliferation of negative news can lead to a negative judgment albeit the real actual situation would suggest otherwise. Through a self-fulfilling prophecy, this can affect the entire economy, as individuals adapt their consumption and investment behavior, getting more cautious. Further, from a policy-maker's point of view, negative effects are more important as they might demand policy reactions, whereas positive shocks can, to some extent, be treated as windfall gains. Hence, the emphasis lies on negative rather than on positive news.¹

In this paper, we are interested in the following research question: *Can we detect an influence of negative macroeconomic news reporting on companies' assessments of their business situation?* This is similar to the approach taken by Buchen (2014) and Lamla et al. (2007), who investigated whether information complementarities can explain some of the sectoral co-movement.

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. We find indeed an impact of negative news on companies' self reported business situation in the manufacturing sector. The (negative) effect stays robust within an OLS framework, and stands a Granger-Causality test in a VAR environment. The study adds further

¹We are aware of the fact that there might be a bias towards the negative that affects our coefficients as we are ignoring positive news. However, there is no equivalent for the word "recession" on the positive spectrum. In further studies this should be taken into consideration.

evidence on the impact of news coverage.

The remainder of this paper is organized as follows. Section 2 explains our data. Section 3 introduces our methodology. Section 4 contains the empirical analysis and the results. Section 5 concludes.

2 Data

2.1 Survey data

The KOF Swiss Economic Institute at ETH Zurich conducts monthly surveys of companies in the Swiss manufacturing sector. Firms are asked, among other things, to assess their current business situation. To keep the procedure as simple as possible, there are only three possible answers: “good”, “satisfying”, or “bad”. The data is then aggregated to a sector-wide indicator representing the sectors’ respective business situation. As [Lui et al. \(2011\)](#) show, these qualitative, firm-level answers correspond accurately with quantitative outcomes and therefore are judged as good predictors of the business cycle (see also [Hansson et al., 2005](#), [Claveria et al., 2007](#), [Kholodilin and Siliverstovs, 2012](#) or [Kaufmann and Scheufele, 2015](#)). In our analysis, we use the so-called balance score (or statistic), measured as the difference between the answers shares of “good” and “bad”.

The basic idea of surveys is to gather information at a micro level and then aggregate it to a macro level to get an idea of the overall situation across different sectors. However, as the questions asked are not strictly quantitative it is possible that answers are, to some extent, prone to the influence of news reporting. Companies’ answers are likely to be based on a mix of hard-wired facts (e.g. the accounting side) and soft factors, often transmitted through media channels. On the other hand, the sentiment of firms might simply be reflected in the media.

The KOF survey data is usually bundled into a monthly indicator. However, due to the aggregation, we might lose interesting information from a more finely grained time structure. Since 2004, some companies can use an online tool to fill out the questionnaires of KOF’s monthly business tendency surveys. One special feature of the online survey is particularly interesting for deeper examination: Companies leave an exact time stamp when they answer the questionnaire. Hence, it is not only possible to assess the monthly situation of companies but also to extract a daily business situation indicator. We use the daily data in a —to our knowledge— pioneering attempt.

For our data set, we start by only taking those days into account when at least *three* companies answered the questionnaire. We then calculate a daily balance score. Figure 1 shows a summary of our daily data. The surveys are not conducted continuously, but instead start at the beginning of the month and conclude around the 23rd day of a month. Most studies therefore generally truncate their data to conclude around this date and assume that all firms that were willing to participate have participated by that time.² However, in fact, we observe survey results over the entire month, therefore we do not have to truncate our sample, as opposed to other studies (Lamla et al., 2007 or Buchen, 2014). We know exactly when a company answered a question. As a robustness check, we increase the minimum answers per day to over 20 answering companies a day in order to avoid that the selection of companies on a particular day is biased as, for instance, only pharmaceutical or companies in the metal industry answered. This should prevent us from generating data driven by events that affect only a particular segment of the manufacturing sector.

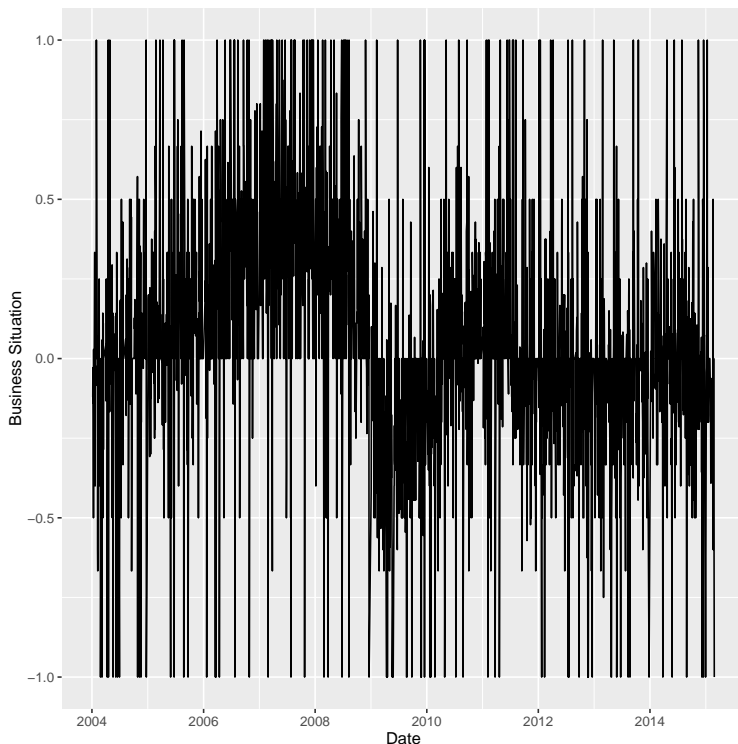


Figure 1: KOF balance score business situation

Figure 1 generally mirrors, concentrating on the “thick” areas, the overall development of the Swiss economy during the last 10 years. We notice the beginning of the financial crisis at the end of 2008 and the rather fast recovery afterwards. We also see that the peak levels of 2006/2007 have not been reached again in subsequent years.

²This is necessary because the aggregation and preparation of the results requires some time before publications.

In addition, we include a daily assessment of industrial production, also stemming from the KOF surveys, controlling for companies’ general state. The companies are asked if their production this month was “higher”, “the same” or “lower” than in the previous month. We assume that industrial production is less influenced by the current information inflow and more by the “books” than the business situation assessment. Figure 2 depicts the daily “industrial production”, for days that we have more than two answers for the business situation.

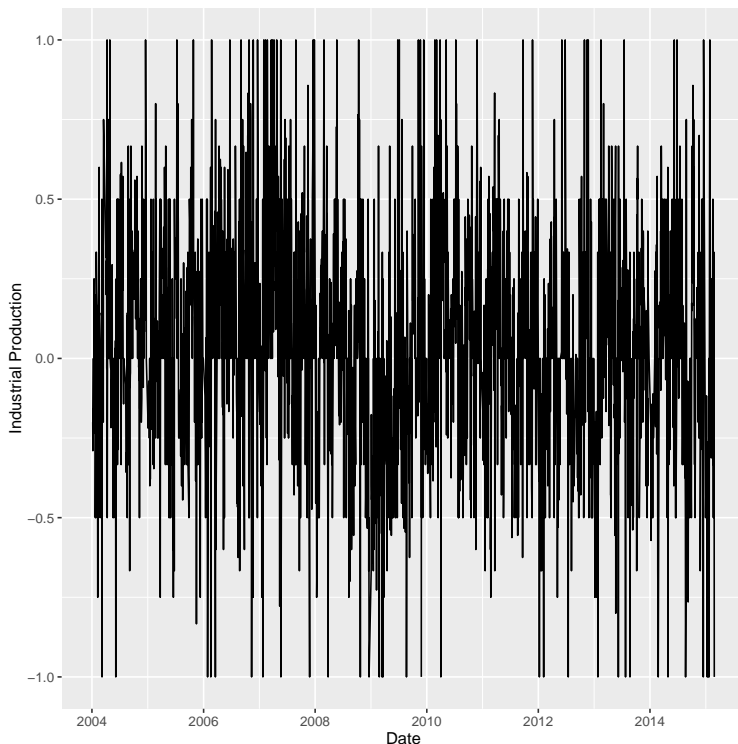


Figure 2: KOF balance score industrial production

2.2 News-based indicator

To track news reporting over time we use newspapers and news agencies reports through [Genios](#), a general database on German-speaking media. We construct a web crawler that enables us to export articles, which feature specific search terms, and count the number of these articles per day. Genios is —to our knowledge— the most abundant and broad source on the German-speaking media sector, a web archive that stores all relevant German-speaking news outlets. We scan Genios for the keywords “recession+Switzerland” (Rezession+Schweiz). This keyword combination has already proved fruitful in a forecasting context (see ?). We assume that the regional development in the French- and the Italian-speaking parts of Switzerland is strongly intertwined with the German-speaking part and we refrain from regionally differentiating across companies’ locations.

Following a suggestion by [Baker et al. \(2013\)](#), we deal with changes in the volume of articles over time by dividing the raw count of “recession” articles by the total number of the articles with the keyword “economy”. In the data, we see that the general volume of news coverage has increased over time. By dividing the number of articles referencing the “economy”, we are canceling out this volume effect. Further, we standardize our news series to unit standard deviation from 2004 to 2015 as [Baker et al. \(2013\)](#) do for their economic uncertainty index. Finally, we correct the entry number of January 1 by taking the average of the whole month of December into account instead of the registered number, as there seems to be a systematic error with the January 1 data. [Figure 3](#) shows our news indicator. What would seem to be outliers on particular days are in fact data mirroring special events or decisions, such as the abandoning of the lower ceiling for the Swiss franc by the Swiss National Bank in January 2015 or the days around the introduction of the same ceiling in the beginning of September 2011. Hence, we refrain from deleting these data points.

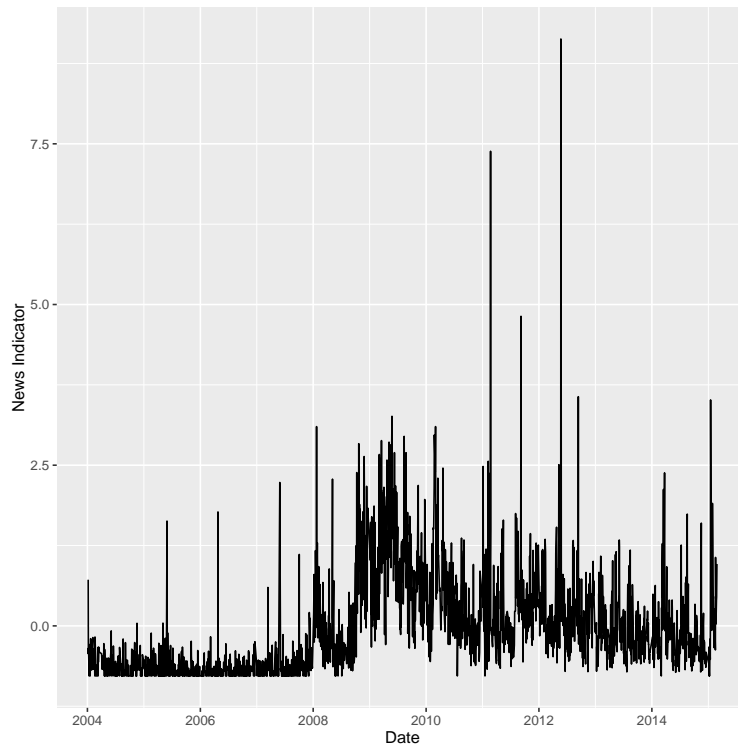


Figure 3: News indicator

In this context, timing might play a crucial role. Companies usually answer the questionnaires on weekdays. We therefore only take days when companies in fact fill out their questionnaires into account, eliminating a possible weekend bias. To be on the safe side, we use weekday dummies in our regression analysis. Further questions hover around the exact answering time. What time a day do companies answer the questionnaire? When do they get their news? It can be assumed that

the majority of the people responsible for completing the KOF questionnaires get their first news in the morning. We know from the time stamp on the survey that the average firm answered the questionnaire around noon. Only a few survey participants gave their answers before 7 a.m., but even then they could have already seen the news that morning via online consumption. Nevertheless, as we cannot assure that the responsible person consumes the current day’s news reporting, we take lags of our news indicator (between 2 and 6 days) before the registered answer. If, for instance, three companies answered the question about their business situation on February 14, we analyse the impact of news published between the 9th and the 14th of February.

One advantage of our approach, compared to the aforementioned studies by [Lamla et al. \(2007\)](#) and [Buchen \(2014\)](#), is the fact that we are not restricted to answers before the 20th of the month. [Buchen \(2014\)](#), for instance, is restricted to use reports published in the first two thirds of a month to limit interference with the business situation indicator itself. Moreover, our keyword generation process has some advantages. Our data is easily reproducible and not provided by specialized institutes such as Media Tenor. Although those data have certainly many advantages, such as the possibility to define the tone of news or to look at the precise direction of an article, they require then much more effort and resources to be collected.

In another step, we add data available daily that control for the business cycle, such as the exchange rate of the Swiss franc against the Euro and a stock market index, the SPI. [Table 1](#) summarizes our data set. Our final data set consists of 2125 observations (for at least *three* answering companies per day), spanning over 11 years (January 2004 to February 2015).

Table 1: Basic statistics

	Mean	SD	N
KOF business situation (BS)	0.057	0.284	2,125
News indicator (NI)*	0	1	2,125
KOF industrial production (IP)	0.021	0.306	2,125
Exchange rate CHF/EUR (EXR)	1.417	0.172	2,125
SPI	6,028	1,283	2125

* We normalize our news indicator by using unit standard deviation and zero mean.

3 Methodology

To analyze a possible influence of our news-based data, we start with an Ordinary Least Squares (OLS) approach, where we regress our dependent variable Y_t , the Business Situation (BS), on an autoregressive term Y_{t-i} and our news indicator (NI) along with a set of control variables, all included in X_{t-1} :

$$Y_t = \alpha_0 + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{j=1}^q \gamma_j X_{t-i} + \epsilon_t, \quad (1)$$

where α_0 stands for the weekday dummy variables, and γ_i s are the slope coefficients on the components of X . We control for the business cycle movement by incorporating the exchange rate of the Swiss franc against the Euro (EXR) and the Swiss Performance Index (SPI), one of the leading stock exchange indicators in Switzerland. We add an indicator of industrial production (IP) from the KOF survey results in the manufacturing sector.

We continue with a Granger-causality in a Vector Auto Regression (VAR) model following [Lamla et al. \(2007\)](#). In the VAR model set-up, several endogenous variables are considered jointly. Each variable is explained by the lagged values of the variable itself and the lagged values of the other endogenous variables. Constants or trend variables can be included if necessary. Following [Lamla et al. \(2007\)](#) in their set-up, we have our five variables of interest and this gives us the following VAR(p) model:

$$\begin{pmatrix} NI_t \\ BS_t \\ IP_t \\ EXR_t \\ SPI_t \end{pmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) & A_{14}(L) & A_{15}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) & A_{24}(L) & A_{25}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) & A_{34}(L) & A_{35}(L) \\ A_{41}(L) & A_{42}(L) & A_{43}(L) & A_{44}(L) & A_{45}(L) \\ A_{51}(L) & A_{52}(L) & A_{53}(L) & A_{54}(L) & A_{55}(L) \end{bmatrix} \begin{pmatrix} NI_{t-1} \\ BS_{t-1} \\ IP_{t-1} \\ EXR_{t-1} \\ SPI_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \\ \epsilon_{5t} \end{pmatrix}, \quad (2)$$

where A_{jk} , with $j, k = 1, \dots, 5$, are polynomials of order p in the lag operator L , and ϵ_{jts} are independent and identically distributed disturbance terms. We estimate the equations in the system by OLS. OLS is consistent and asymptotically efficient if it has the same lag structure ([Lamla et al., 2007](#)). In case the lagged values of the independent variables have a statistically significant effect, then we can claim a Granger-causality impact of a strong form (see [Lamla et al., 2007](#) and [Kawai, 1980](#)).

If the error terms in our estimation are contemporaneously correlated, shocks that hit the economy might affect all variables in the current period. As a consequence, the effect of a separate shock cannot be singled out. One solution is to impose some form of restrictions. We use a Cholesky decomposition which requires ordering the variables by intensity. Hence, we order the variables from the most pervasive (i.e. a shock to this variable affects all others) to the least pervasive (i.e. a shock does not affect any other variable in the current period). In our set-up, it is not self-evident which variables are more pervasive than the others. Our initial ordering is: $NI \Rightarrow BS \Rightarrow IP \Rightarrow EXR \Rightarrow SPI$. As non-sample information can be used to decide on the proper set for a particular given model (Lütkepohl, 2005) we impose a time structure on our model. It seems reasonable to suggest that there is a timely hierarchy in our variables of the following order: $EXR \Rightarrow SPI \Rightarrow NI \Rightarrow BS \Rightarrow IP$. The exchange rate is expected to react the fastest, followed by the SPI and then our news indicator. The business situation and the industrial production from the KOF surveys are available later. It has to be added that the importance of the ordering depends on the extent of the correlation coefficient between the error terms (Lamla et al., 2007). The ordering is negligible if the estimated correlations are close to zero. This holds true in our example, with the exception of the correlations between the error terms of BS and IP, and EXR and SPI respectively.

4 Results

In order to test the influence of our news indices, we start with an OLS regression approach. As mentioned earlier, we control for the business cycle by taking the exchange rate between the Swiss franc and the Euro, the SPI, a stock market index for Swiss companies, and the index of industrial production in the manufacturing sector as reported in the monthly KOF survey (qualitative data) into account.³ For the EXR and the SPI we use logged levels. Finally, we add dummies for the days of the week to see if particular days have an influence. For the manufacturing industry, the exchange rate of the Swiss franc is one of the major drivers of the business situation, as many companies are active in the export sector. The SPI gives us an idea about the general situation in the economy, with a focus on financial markets. The industrial production is particularly useful as we have time stamps on the answers if industrial production has “gone up”, “down” or “remained equal”.⁴ Table 2 reports the results.

³Values for the exchange rate are taken from the Swiss National Bank’s data base and for the SPI from the website finanzen.ch.

⁴All computations were made using the program *R*.

Table 2: OLS regression results

	Model 1	Model 2
BS (t-1)	0.164 (0.022)***	0.171 (0.036)***
BS (t-2)	0.118 (0.022)***	0.160 (0.037)***
BS (t-3)	0.070 (0.023)**	0.102 (0.036)**
BS (t-4)	0.094 (0.023)***	0.164 (0.037)***
BS (t-5)	0.088 (0.023)***	0.126 (0.036)***
BS (t-6)	0.089 (0.022)***	0.115 (0.036)**
NI (t-1)	-0.003 (0.007)	-0.008 (0.007)
NI (t-2)	-0.009 (0.007)	-0.002 (0.007)
NI (t-3)	-0.007 (0.007)	-0.005 (0.007)
NI (t-4)	-0.001 (0.007)	0.011 (0.007)
NI (t-5)	-0.001 (0.007)	0.001 (0.007)
NI (t-6)	-0.010 (0.007)	-0.012 (0.007)
Monday	-1.233 (0.258)***	-0.468 (0.236)*
Tuesday	-1.224 (0.258)***	-0.472 (0.236)*
Wednesday	-1.230 (0.258)***	-0.493 (0.236)*
Thursday	-1.233 (0.258)***	-0.482 (0.236)*
Friday	-1.240 (0.257)***	-0.476 (0.236)*
Saturday	-1.248 (0.258)***	-0.486 (0.236)*
Sunday	-1.222 (0.258)***	-0.467 (0.237)*
log EXR (t-1)	0.083 (0.799)	0.413 (0.522)
log EXR (t-2)	0.352 (1.100)	0.181 (0.703)
log EXR (t-3)	-0.168 (1.109)	-0.744 (0.706)
log EXR (t-4)	-1.344 (1.108)	0.555 (0.758)
log EXR (t-5)	1.210 (1.108)	0.614 (0.800)
log EXR (t-6)	0.214 (0.809)	-0.905 (0.591)
log SPI (t-1)	0.362 (0.438)	0.213 (0.259)
log SPI (t-2)	-0.633 (0.616)	-0.306 (0.367)
log SPI (t-3)	0.083 (0.616)	0.282 (0.367)
log SPI (t-4)	0.684 (0.615)	-0.531 (0.366)
log SPI (t-5)	-1.465 (0.609)*	0.166 (0.366)
log SPI (t-6)	1.099 (0.429)*	0.228 (0.260)
IP (t-1)	-0.023 (0.018)	-0.002 (0.025)
IP (t-2)	0.020 (0.019)	-0.023 (0.027)
IP (t-3)	0.012 (0.019)	0.033 (0.028)
IP (t-4)	0.005 (0.019)	0.041 (0.028)
IP (t-5)	0.024 (0.019)	-0.060 (0.027)*
IP (t-6)	-0.035 (0.018)	0.068 (0.025)**
R ²	0.409	0.739
Adj. R ²	0.399	0.726
Num. obs.	2119	806
RMSE	0.225	0.121

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$

Note: The number of observations decreases from Regression 1 to 2. We only count the balance score on a particular day as single observation, not all answering companies.

Model 1 shows the results when we have more than 2 answering companies per day. Model 2 includes our results when more than 20 companies answered on a given days and serves as a robustness test for Model 1. Overall, we find a negative effect of negative news, also when additionally controlling for the economic environment. As the first column in Table 2 shows, all lagged news indicators, in the case with more than two companies, show the expected negative albeit not significant influence.

In the second column (> 20 companies) lag 6 becomes statistically significant, yet only on a 10% level. Furthermore, we have a significant, yet positive value for lag 4, contrary to our ex ante expectations. Model 2 indicates that neither the exchange rate (EXR) nor the SPI have a significant influence on the business situation. Contrary to our ex-ante expectations, the weekday dummies are significant. However, we have to put these dummies into perspective. As we perform a regression 'through the origin' with dummies, they represent an intercept term broken up into several parts. A regression with intercept shows, as expected, no significant influence of the dummy variables. Hence, we refrain from taking the weekday dummies into account in our further analyses. What clearly does have an impact are the lagged balance scores of the business situations, and, for lags 5 and 6, the reported industrial production. However, the negative sign for IP (t-5) does not match our ex ante expectations of the direction of influence.

In order to check if our variable of interest, the news indicator, has any influence, we conduct an F-test (see 3) between our model in Table 2 and a reduced model that excludes the news indicators. We use an analysis of variance (ANOVA) test and find a significant difference between the models in the case of at least 3 companies (p-value = 0.002). This indicates that the inclusion of our news indicators is indeed necessary. In the case of more than 20 companies, the difference becomes insignificant (p-value = 0.120). The lags of the business situation alone seem to have enough explanatory power for the current business situation. A studentized Breusch-Pagan test does not indicate heteroskedasticity (p-values = 0.265 for Model 1, and 0.169 for Model 2, respectively), hence we refrain from computing robust errors.

Table 3: F-Test between full and reduced models

	Model 1	Model 2
BS	$2.2e - 16^{***}$	$2.2e - 16^{***}$
NI	0.002386**	0.1195
IP	0.2919	0.01544*
EXR	$2.16e - 07^{***}$	0.08195
SPI	$6.793e - 05^{***}$	0.2857

Table 4: Stepwise AIC regression

	AIC model 1	AIC model 2
BS (t-1)	0.171 (0.022)***	0.187 (0.035)***
BS (t-2)	0.136 (0.022)***	0.164 (0.035)***
BS (t-3)	0.084 (0.022)***	0.103 (0.036)**
BS (t-4)	0.109 (0.022)***	0.172 (0.035)***
BS (t-5)	0.099 (0.022)***	0.129 (0.036)***
BS (t-6)	0.098 (0.022)***	0.128 (0.035)***
NI (t-2)	-0.016 (0.006)**	
NI (t-6)	-0.015 (0.006)*	-0.011 (0.005)*
log EXR (t-5)	0.187 (0.044)***	0.955 (0.536)
log EXR (t-6)		-0.932 (0.536)
log SPI (t-5)	-0.937 (0.393)*	
log SPI (t-6)	0.932 (0.393)*	
IP (t-3)		0.046 (0.022)*
IP (t-5)	0.028 (0.017)	-0.050 (0.025)
IP (t-6)	-0.030 (0.017)	0.074 (0.024)**
R ²	0.399	0.731
Adj. R ²	0.396	0.727
Num. obs.	2119	806
RMSE	0.226	0.121

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$

So far, the empirical results do not show a robust influence of our news indicator. This changes, once we apply an automated step-wise AIC model selection criterion (see Figure 4). With the AIC procedure, the influence of our news indicator (lag 6) becomes significant in both estimates. Furthermore, the EXR and the SPI variables become significant, but not in all cases in the expected positive direction. AIC model 2 is more in line with our ex ante expectations, yet the negative influence of IP (t-5) is somewhat difficult to explain. Together with the positive effects of IP (t-3) and IP (t-6) the effect would be neutralized at least.

We continue our analysis with a Vector Auto Regression VAR(p) model. The ordering of the components of our model is the following: $BS \Rightarrow NI \Rightarrow IP \Rightarrow EXR \Rightarrow SPI$. We choose the Schwarz Criterion (SC) criterion to determine the number of lags. As Lütkepohl (2005) shows, FPE, AIC, HQ, and SC all lead to similar forecast errors. This gives us a model with 2 and one with 6 lags.⁵ Accordingly, we chose 2 lags and then 6 and estimate VAR(2) and VAR(6) models respectively. We then apply an F-test to check if our joint coefficients are to be included into the

⁵The VAR for two lags is depicted in Table 7 in the Appendix 5.

model or not.⁶ In Table 5 and Table 6 respectively the p-values of the differences between a reduced and the full model are depicted. In the reduced model the coefficients of the independent variables are jointly set to 0 to test if they exert any influence.

Table 5: VAR regressions results: P-values

More than 2 companies						
Dep. variable:	Business situation		News indicator		Industrial production	
Lags	(2)	(6)	(2)	(6)	(2)	(6)
Expl. variable:						
BS	2.2e-16***	2.2e-16***	0.02022*	0.31	0.6931	0.7726
NI	2.52e-07***	0.002731 **	2.2e-16***	2.2e-16***	0.001284**	0.0564
IP	0.3329	0.2962	0.46	0.5239	2.2e-16***	2.2e-16***
EXR	2.2e-16***	2.409e-07***	0.0001371***	0.04098*	0.06398	0.4222
SPI	5.278e-12***	6.475e-05 ***	0.01167*	0.4299	0.3143	0.5395

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$

Note: EXR and SPI are deliberately left out in this context as they are not our variables of interest.

Table 6: VAR regression results: P-values

More than 20 companies						
Dep. variable:	Business situation		News indicator		Industrial production	
Lags	(2)	(6)	(2)	(6)	(2)	(6)
Expl. variable:						
BS	2.2e-16***	2.2e-16***	0.02039*	0.09383	0.3856	0.7385
NI	0.002352**	0.1294	2.2e-16***	2.2e-16***	0.1072	0.4746
IP	0.9432	0.01557*	0.1393	0.2099	2.2e-16***	2.2e-16***
EXR	1.849e-05***	0.06052	0.2508	0.1585	0.6484	0.6147
SPI	0.000171***	0.2438	0.1421	0.01971*	0.7906	0.9505

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.1$

Note: EXR and SPI are deliberately left out in this context as they are not our variables of interest.

The VAR models partly confirm our ex ante expectations. Our news indicator has an influence on the business situation: p-value = 2.52e-07*** in the case of more than 2 answering companies and p-value = 0.002** in the case of over 20 companies. Taking our news indicator as dependent

⁶The VAR were computed using the package 'vars' in R (Pfaff, 2008).

variable; however, shows an influence of the business situation as well in the case of 2 lags. This could be an indication that information flowing from companies could be mirrored in news coverage. In addition, in this set-up both the EXR and the SPI should be included in our model, whereas the industrial production does not seem to be necessary in the case of 2 lags and neither in the one of 6 lags. This changes in the model where we take more than 20 answering companies into account (see Table 6) for the case of 6 lags. Taken together, the results from Table 5 and 6 present mixed evidence, which coefficients exert influence.

To get an idea of the direction of influence and answers with respect to the time paths of impacts, we add impulse response functions (IRF). Figure 4 shows these functions for our variables in the initial ordering. We compute bootstrapped error bands for the impulse response coefficients with 100 runs. Figure 4, with 2 lags, indicates that in a impulse-response analysis, the impact of our news indicator on the business situation is negative as expected. This is in line with the statistics reported in Table 5. The maximum impact of news on the business situation is after about 4 days. On the other hand, the business situation does impact the news indicator in a negative direction as well. This seems reasonable, as a negative impulse suggests that less negative news is reported. The influence of news on the exchange rate and the SPI is, as expected, non existent. What we can see is a one time negative effect on the assessment of the industrial production. In the case of 6 lags (Figure 5 can be found in Appendix 5), our news indicator still exerts a negative impact on the business situation, albeit it only becomes significant after 6 days. To check if the ordering changes the results, we add the IRFs for the following timely ordering: $EXR \Rightarrow SPI \Rightarrow NI \Rightarrow BS \Rightarrow IP$. The results for lags 2 and 6 do not change substantially compared to the initial ordering and are relegated to the Appendix 5 to this paper (see Figures 6 and 7, respectively).

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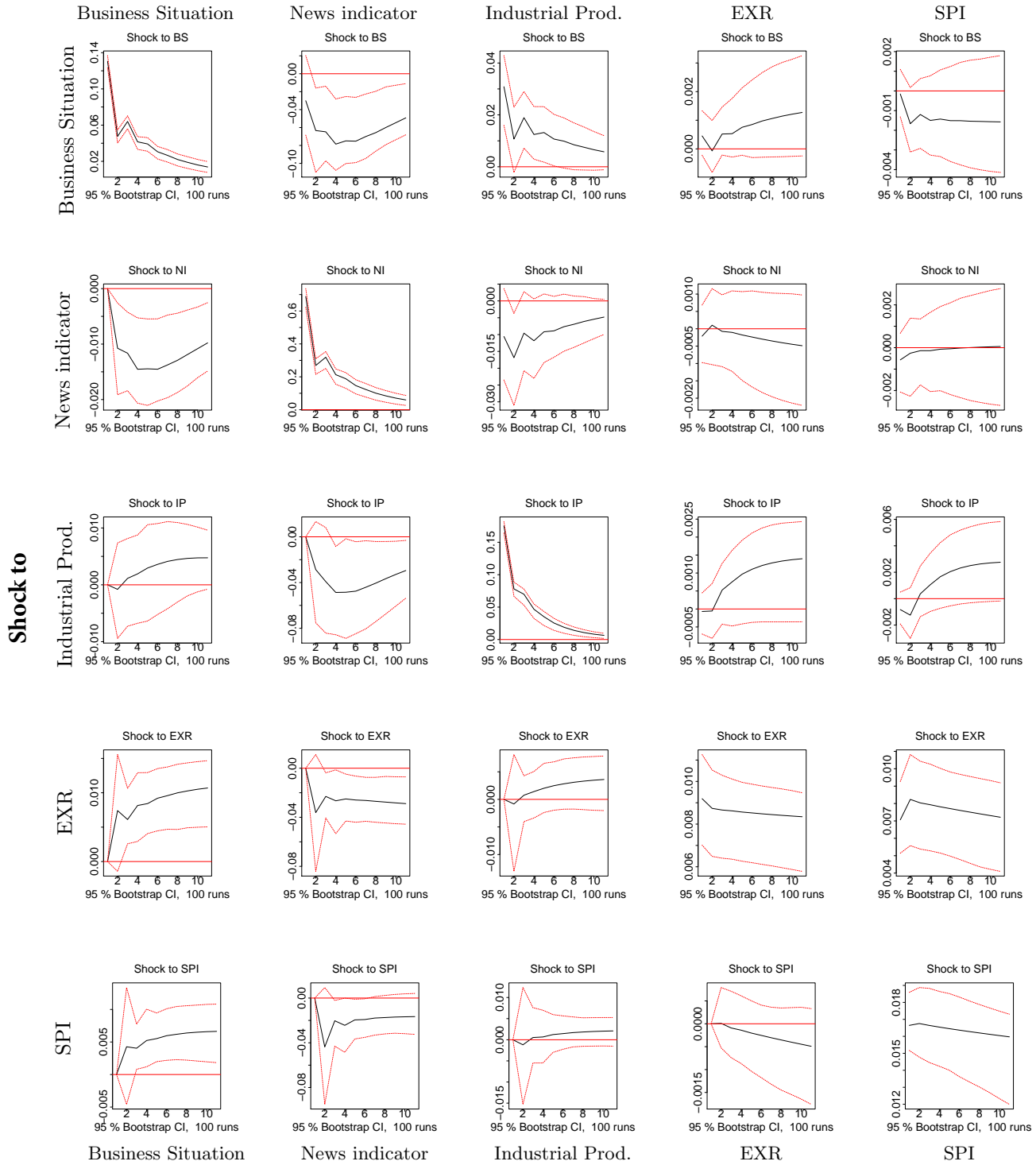


Figure 4: IRF I, ordering: BS \Rightarrow NI \Rightarrow IP \Rightarrow EXR \Rightarrow SPI, $p = 2$

5 Conclusion

The news, particularly negative news, influences our view on the world. A fact that might be trivial, but at the same time, hard to measure. In this paper, we tried to distill the impact of negative news on the business situation of private companies in the manufacturing sector as reported in the KOF business tendency surveys. Our null hypothesis states that news should not influence the business situation; however, we can reject this hypothesis based on our OLS and VAR model approaches. This indicates a possible impact of negative economic news. With our estimation results, we add evidence to other studies that show that news influences companies (see [Beaudry and Portier, 2007](#) among others). In our case, we find some evidence that the manufacturing sector is not immune to negative daily economic news shocks in the form of negative reporting on the economy. Our news indicator, which consists of keywords coming from an online archive for all German-speaking newspapers, partly seems to drive companies' assessment of the current economic situation. This confirms the findings of [Lamla et al. \(2007\)](#) and [Buchen \(2014\)](#) and highlights the role of news as an active ingredient in business cycle movements. Since the business situation, particularly in the manufacturing sector, is considered a good indicator for the real movements of the entire economy (see [Kaufmann and Scheufele, 2015](#) or [Nierhaus and Sturm, 2007](#)), the information transmission via news coverage could indeed have an impact on not only one sector—in our case the manufacturing sector—but the whole economy.

The daily assessment of the business situation of companies in the manufacturing sector and the simultaneous assessment of news influence is a new and promising approach to measure the current state of the economy on the fast track. In our step-wise AIC regression (see [Table 4](#)), we find an effect of -0.011 points for the balance score of the assessment of the business situation when negative news increases by one recession-related article per day (with a lag of 6 days). The magnitude of the effect seems small, but must be seen in context. If, for instance, a day with negative news coverage occurs, this could easily negate a positive balance score for the business situation. A shock to the news indicator decreases the business situation for up to four days and then starts to fade out slowly as can be seen from the impulse response function of our VAR model in [Figure 4](#).

However, our results are not as straightforward as we might wish. The business situation itself seems to be reflected in the news indicator, as we reject the hypothesis of no influence along this line, and the impulse response function of our VAR model depicts an impact of the business situation. This is not totally surprising, as the news will reflect the information coming from companies. Furthermore, our news indicator is not significant in all set-ups and there might be an endogeneity

problem at work. Which variable is influencing which and to what extent are they independent from each other? Is there an uncontrolled confounder causing both variables in our model? We cannot entirely escape the endogeneity issue, but we control for the latter by incorporating additional variables such as the exchange rate of the Swiss franc and the stock market index SPI. Another critique can be associated with the low-dimensional VAR model we are using. In economic systems almost everything depends on everything else, but with the low-dimensional VAR systems all the effects of omitted variables are assumed to be in innovations ([Lütkepohl, 2005](#)), which could lead to distortions in the impulse response functions.

What implications can we then draw from the results? First, there might be implications for surveying companies. Should their news consumption somehow be controlled for? Alternatively, should the daily news context be given more attention when the economic surveys take place? Second, in a more interdependent economy, the influence of the news might rise. “Media frenzies”, as reported by [Veldkamp \(2006\)](#), could lead to shocks that destabilizes economic agent’s real situation. Our study that analyses these kinds of negative shocks via VAR is a step towards better measurement of the media influence, but possible extensions are many. For instance, companies could directly be asked about their media consumption to cross-check our hypothesis of news consumption and its influence. In addition, the definition of negative news could be approached differently by giving more weight to the tone of the news coverage instead of merely counting the number of articles. But we leave this for further research.

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Appendix

Table 7: VAR regression results

	Dependent variable:		
	Business situation	News indicator	Industrial production
BS (t-1)	0.360*** (0.305, 0.416)	-0.347* (-0.641, -0.053)	-0.026 (-0.102, 0.050)
BS (t-2)	0.354*** (0.299, 0.410)	-0.105 (-0.398, 0.188)	0.063 (-0.013, 0.139)
NI (t-1)	-0.015** (-0.025, -0.004)	0.389*** (0.333, 0.444)	-0.018** (-0.032, -0.004)
NI (t-2)	-0.006 (-0.016, 0.005)	0.303*** (0.248, 0.359)	0.007 (-0.008, 0.021)
IP (t-1)	-0.002 (-0.045, 0.040)	-0.172 (-0.396, 0.052)	0.444*** (0.386, 0.502)
IP (t-2)	0.008 (-0.034, 0.051)	-0.082 (-0.306, 0.143)	0.198*** (0.140, 0.256)
EXR (t-1)	0.616 (-0.278, 1.509)	-1.872 (-6.596, 2.852)	-0.038 (-1.259, 1.184)
EXR (t-2)	-0.388 (-1.282, 0.506)	1.465 (-3.264, 6.194)	0.100 (-1.122, 1.323)
SPI (t-1)	0.254 (-0.196, 0.704)	-2.694* (-5.074, -0.314)	-0.077 (-0.693, 0.539)
SPI (t-2)	-0.144 (-0.597, 0.308)	2.601* (0.207, 4.994)	0.101 (-0.518, 0.720)
Intercept	-1.011*** (-1.409, -0.614)	0.987 (-1.116, 3.090)	-0.228 (-0.772, 0.316)
Observations	810	810	810
R ²	0.652	0.533	0.390
Adjusted R ²	0.648	0.527	0.383
Res. Std. Error (df = 799)	0.130	0.688	0.178
F Statistic (df = 10; 799)	149.953***	91.066***	51.119***

Note:

*p<0.1; **p<0.05; ***p<0.01

Note: EXR and SPI are deliberately left out in this context as they are not our variables of interest.

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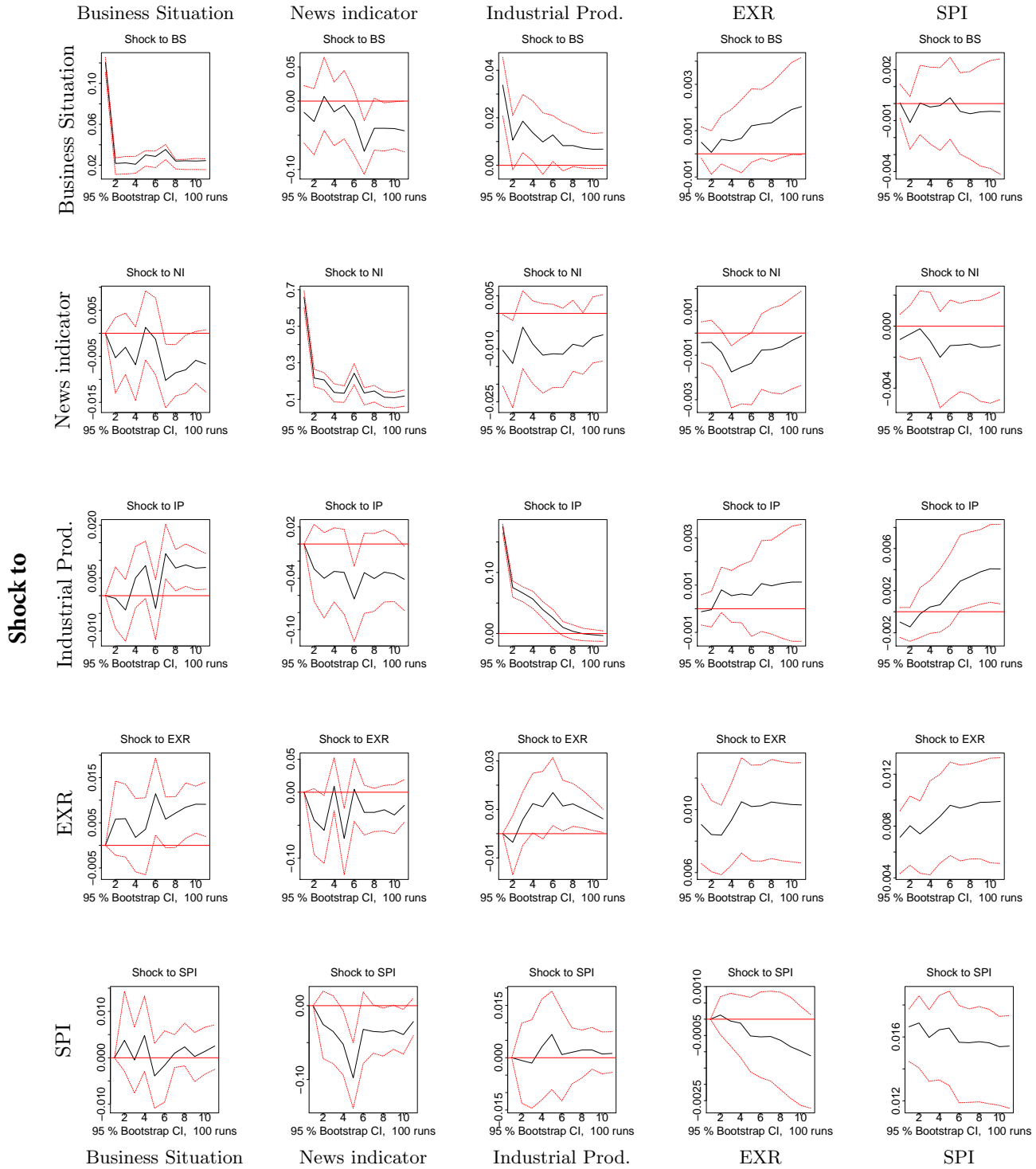


Figure 5: IRF II, ordering: BS \Rightarrow NI \Rightarrow IP \Rightarrow EXR \Rightarrow SPI, $p = 6$

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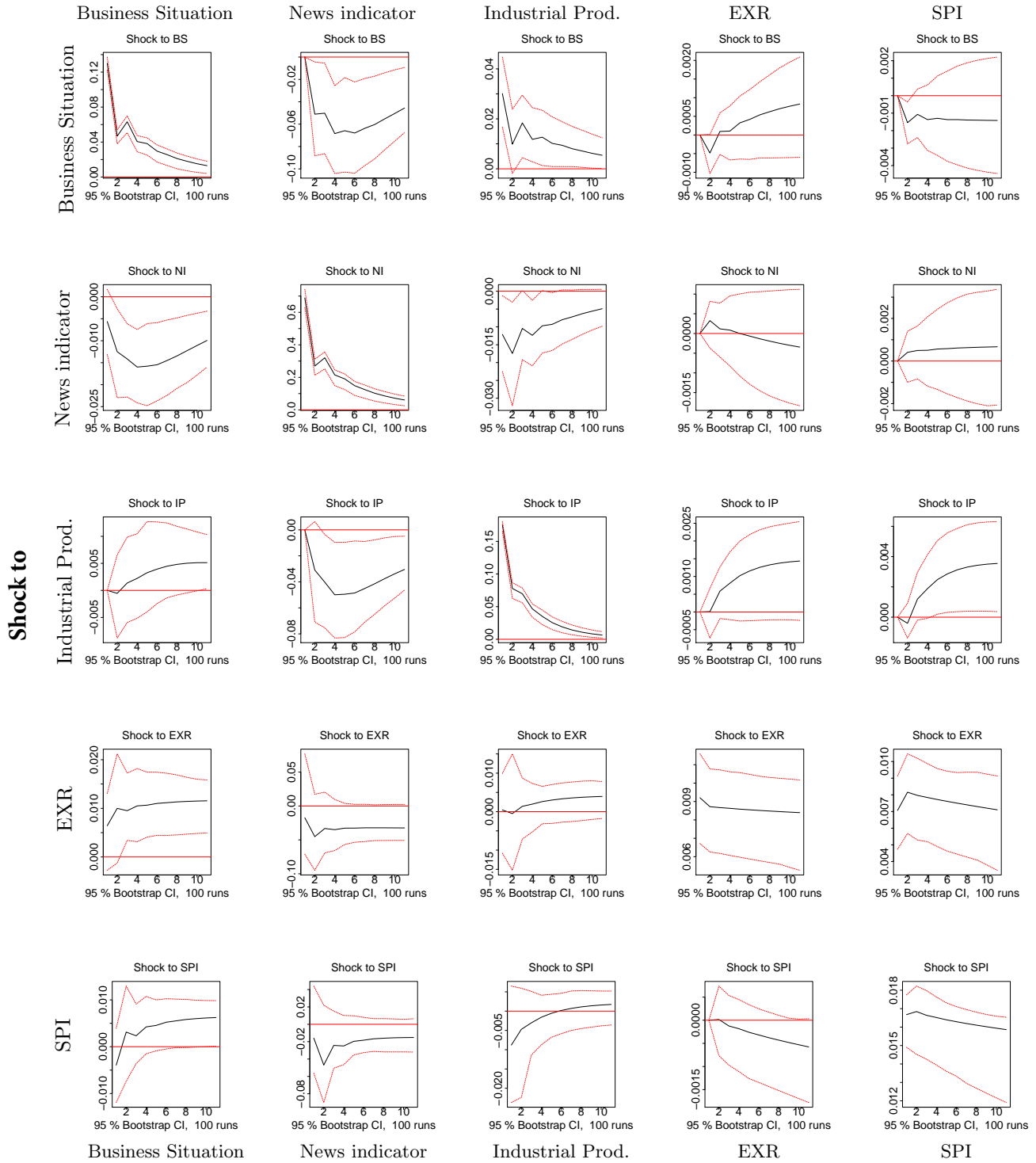


Figure 6: IRF III, ordering: EXR \Rightarrow SPI \Rightarrow NI \Rightarrow BS \Rightarrow IP, $p = 2$

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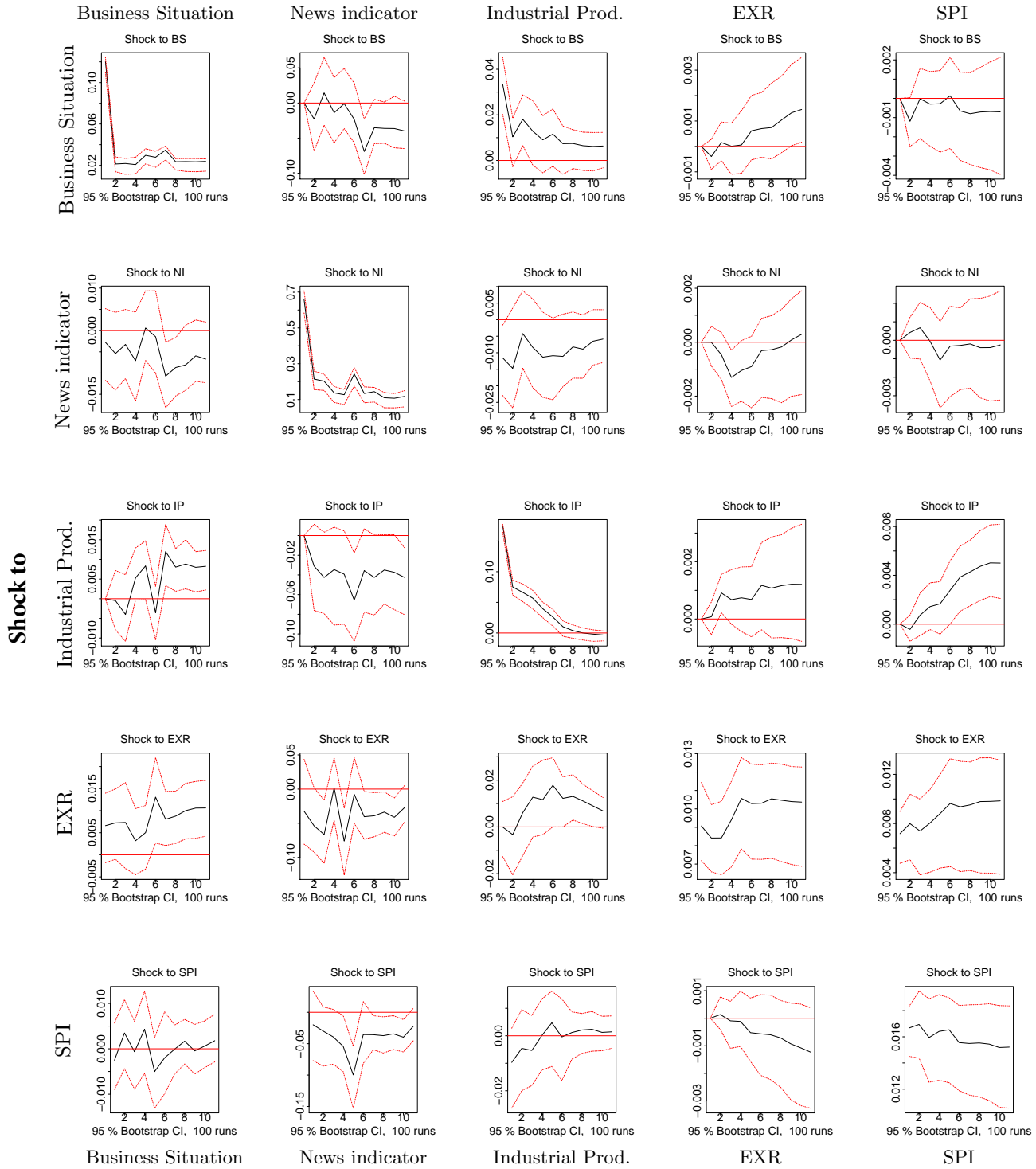


Figure 7: IRF IV, ordering: EXR \Rightarrow SPI \Rightarrow NI \Rightarrow BS \Rightarrow IP, $p = 6$