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Published stock recommendations as investor sentiment in the near-term stock market

by

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Published stock recommendations as investor sentiment in the near-term stock market

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Abstract

This paper investigates the role of published stock recommendations in print and online media as investor sentiment in the near-term German stock market. In line with extant literature on other sentiment measures, vector autoregressions reveal that past stock returns drive today's sentiment, but not the other way around, and that sentiment is a powerful predictor of itself. In particular, sentiment based on printed analyst recommendations follows reversals, that is, when analysts face a stock market downturn, they see a buying opportunity and become optimistic.
Keywords: analyst forecasts, investor sentiment, media content, VAR analysis

1. Introduction

National and international measures of sentiment play an important role in investment decisions for many market participants. Several empirical studies test whether measures of sentiment impact stock returns, or vice versa. Most authors divide sentiment into two groups: Brown and Cliff (2004), for example, distinguish between direct and indirect measures, whereas others use terms like non-financial or survey-based measures and financial measures, for example Wang et al. (2006). The first group of direct measures is derived from survey data, while indirect measures are based on financial variables, such as closed-end fund discounts, put to call ratio, and bank-issued warrants. Moreover, the definition of investor sentiment is consistent in neither theoretical nor empirical studies. We follow the definition of Brown and Cliff (2005), which states that "sentiment represents the expectations of market participants relative to a norm."

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In this paper, we construct a sentiment index based on stock recommendations by professional analysts, which are published in print and online media, using two different datasets: Dataset 1 provides selected analyst forecasts published in a high-profile German newspaper. Dataset 2 uses stock recommendations from a leading financial news agency in the German-speaking region. We refer the first source to print and the second to online media. Both sources categorize recommendations in buy, sell, and neutral. This allows us to apply the traditional bull-bear spread, which is defined as the difference between the percentages of bullish (buy) and bearish (sell) recommendations. Since stock recommendations are made by professional financial analysts, we interpret this measure as professional investor sentiment. We assume that financial analysts are informed market participants who evaluate and interpret relevant market information. Using vector autoregressions (VARs) we test the predictive power of print and online media sentiment for the near-term German stock market. In line with previous studies, such as Solt and Statman (1988); Clarke and Statman (1998); Brown and Cliff (2004); Kling and Gao (2008), we find that sentiment has no forecasting power, but that past stock returns impact future sentiment and that sentiment is a powerful predictor of itself. In contrast to these studies, we find that market sentiment turns optimistic after a decline in stock returns, that is, sentiment follows trend reversal instead of trend following. This result favors the "bargain shopper hypothesis", that is, when analysts see stocks becoming a bargain (proxied as a negative return), they see a buying opportunity and become bullish (Brown and Cliff, 2004).

This paper contributes to the existing literature by developing a new sentiment measure for the German stock market and narrowing the gap between the role of media in financial markets and the forecasting ability of professional sentiment. Solt and Statman (1988); Clarke and Statman (1998); Fisher and Statman (2000); Tetlock (2007) also study the interactions between sentiment derived from media content and the stock market. Solt and Statman (1988), and Clarke and Statman (1998) analyze sentiment based on a survey of investment advisory newsletters and find that sentiment does not predict future stock movement, but that newsletter writers are trend followers, that is, they become bearish after a market decline. Fisher and Statman (2000) study different groups of investors and their market sentiment, differentiating among Wall Street strategists, investment newsletter writers, and individual investors. They find that sentiment of Wall Street strategists and individual investors are contrary indicators for future stock returns, while sentiment of newsletter writers provide no evidence of predictability of future returns. However, all groups of investors are trend followers. Recently, Tetlock (2007) studied a popular *Wall Street Journal* column and finds that media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals.

There are a number of studies for the German financial market, which, however, pay no attention to published analyst recommendation as a proxy for sentiment. Glaser et al. (2009) create a daily measure based on bank-issued warrants for individual investor sentiment, but cast doubt on whether sentiment is beneficial in forecasting stock returns.[1] Finter et al. (2012) use different sentiment proxies to extract one sentiment indicator for

[1] A European study in the context of bank-issued warrants is also published by Burghardt et al. (2008).

the German stock market. They find that investors respond more strongly to negative than to positive news and that sentiment has only weak predictive power on future price movements. Schmeling (2007) uses *Sentix*, a weekly survey-based proxy for investor sentiment, which distinguishes between institutional and individual investors. He finds that institutional investors, but not individual investors, have correct expectations in the medium run. Hengelbrock et al. (2010) test the predictive power of sentiment for stock returns in the medium and long runs using U.S. survey data from the American Association of Individual Investors and German data from *Sentix*. Their findings replicate the results for the U.S. (Brown and Cliff, 2005) and for Germany (Schmeling, 2007) that sentiment proxies have medium-term forecasting power. In contrast, Lux (2010) uses *animusX Investor Sentiment* survey data over short and medium time horizons and finds evidence that this proxy has also near-term forecasting power.

The rest of the paper is organized as follows: Section 2 describes the two data sources and provides descriptive statistics of our sentiment measure and the return series. Section 3 documents the results from VARs followed by a discussion in Section 4. This paper offers a separate appendix with supplementary material of the econometric analysis, which is attached to this document.

2. Data

In this section we construct a stock market sentiment measure that is based on analyst recommendations published in Germany. We obtain stock recommendations from two different sources, one from print and one from online media. For each source we provide one sentiment measure together with the corresponding stock return series. The subsequent empirical analysis is performed at a weekly frequency.

2.1. Dataset 1

We collected analyst recommendations published in the *Frankfurter Allgemeine Zeitung* (henceforth called print media), a high-profile German newspaper published daily except Sundays. The *Frankfurter Allgemeine Zeitung* has a circulation of more than 360,000 and is released in 120 countries around the globe.[2] Analyst recommendations are normally published one day after a trading day–from Tuesday to Saturday–on page two or three in the financial section. A recommendation commonly contains the name of the recommended asset, the recommending institute, the type of recommendation (i.e., buy, sell, or neutral), the current and predicted price, and the predicted time frame before the predicted price is reached. The dataset comprises 2,818 primarily stock recommendations published in the period from September 26, 2008, to January 22, 2011. Only ten of the recommendations are for bonds, currencies, or commodities, so they are omitted from the sample. As our primary focus is the German stock market, we also omit 521 recommendations for stocks not listed on the Frankfurt stock exchange. Of the remaining 2,287 recommendations, 52 percent are positive (buy), 16 percent are

[2] This information was obtained on March 11, 2012 from www.faz.net.

negative (sell), and 32 percent are neutral.[3] Around 40 percent of the remaining recommendations are for DAX (German large caps) constituents; nine percent are for SDAX (German small caps) constituents.[4] Figure 1(a) shows the percentages of buy, sell, and neutral recommendations over time. Buy recommendations dominate neutral and sell recommendations, and neutral recommendations dominate sell recommendations, except for the second quarter in 2009, when stock markets were under high pressure because of the subprime crisis.

2.2. Dataset 2

The second dataset, provided by *dpa-AFX Wirtschaftsnachrichten GmbH*[5] (henceforth called online media), one of the leading news agencies for German-language real-time financial news, is comprised of 50,789 stock recommendations from June 16, 2008, to September 13, 2010. After dropping recommendations that are for stocks not listed at the Frankfurt stock exchange, the remaining sample contains 27,106 recommendations, of which 37 and seven percent are for DAX and SDAX constituents, respectively. Unlike print media data, online media recommendations also contain the names of the analysts and the type of the previous recommendation the analyst gave a particular stock. The proportions of buy, sell, and neutral recommendations are 54, 18, and 28 percent, respectively, which are similar to those published in print media and in line with previous studies[6]. Figure 1(b) shows the percentages of buy, sell, and neutral recommendations over time. Here again, buy recommendations dominate neutral and sell recommendations, and neutral recommendations dominate sell recommendations. Figure 1(b) also shows a clear downward slope for buy recommendations in the second half of 2008, when the subprime crises peaked, and a clear upward slope from the 2nd quarter of 2009 to the 3rd quarter of 2010, when the German stock market rallied.

2.3. Sentiment and Stock Returns: Descriptive Statistics

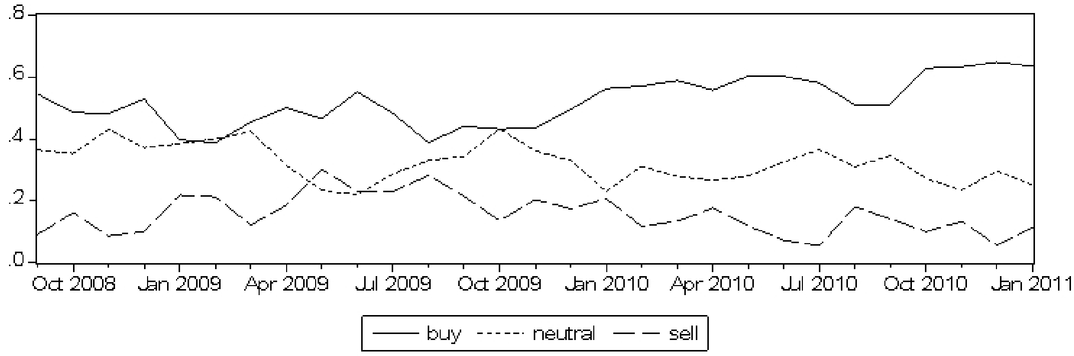
We aggregate published stock recommendations on a weekly basis and calculate the traditional bull-bear spread for each calender week. The weekly median number of printed recommendations is 19 (standard deviation is 6.23), and the median number of online recommendations is 220 (standard deviation is 83.67). Sentiment is, thus, a weekly measure covering a period of 122 and 118 calender weeks, respectively. Figure 2 shows the two measures and the weekly returns of the German stock price index DAX over time. Returns are defined as the log differences between Mondays' opening prices of the DAX.

[3]Notably, if we include all 2,818 recommendations, the percentages remain the same.

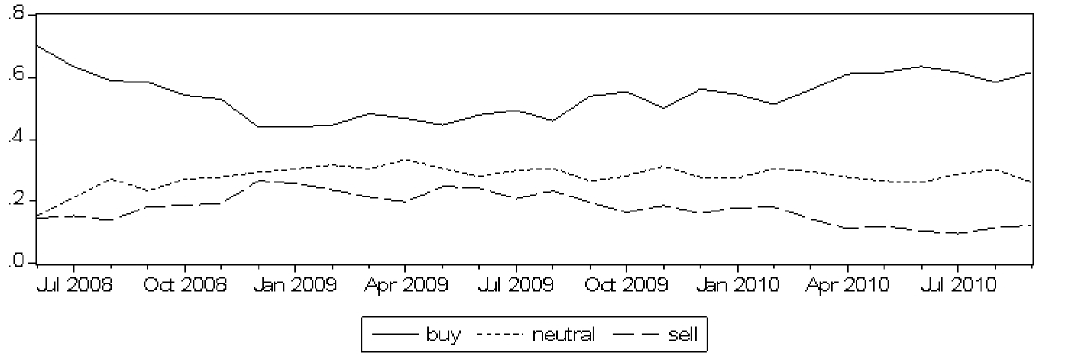
[4]We approximate these percentages by taking the DAX composition of January 2009 and the SDAX composition of December 2009 as a basis.

[5]*dpa-AFX Wirtschaftsnachrichten GmbH* is a business-to-business news supplier to financial institutions and media companies which then distribute dpa-AFX news over their intranets, web pages or terminals. On German language finance and media portals on the internet dpa-AFX is the market leader among financial news services suppliers.

[6]Barber et al. (2001) analyze 378,326 analyst recommendations for the period 1985 to 1996 and find 54.1 percent buys, 6.5 sell, and 39.4 percent neutrals.



(a) Print media recommendations



(b) Online media recommendations

Figure 1: Percentages of buy, sell and neutral recommendations over time

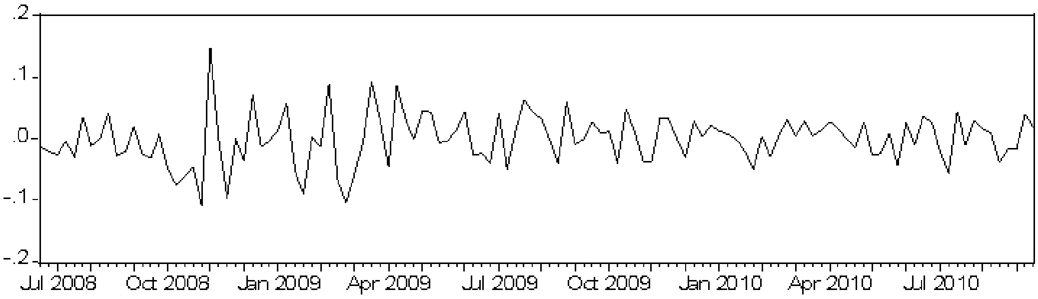
Figure 2(c) shows extreme online media sentiment at the year ends, which is caused by a very small number of recommendations during these periods. Specifically, for these periods, the number of recommendations is smaller than two standard deviations below average. To address this outlier problem, we locally smooth online media sentiment by taking all recommendations of the previous and the next week into account. Thus, we calculate the bull-bear spread for these periods using a "local moving average" of the number of recommendations. Figure 2(c) shows both the original and the smoothed series. The econometric analysis uses the smoothed series. Comparing the figures 2(b) and 2(c), it appears that print media sentiment is more volatile than its online media counterpart. Table 1 provides some sample statistics of the data that confirm this impression. The other statistical moments of both sentiment measures are similar, but whereas online media sentiment is highly autocorrelated at lag one ($\rho_1 = 0.728$), which has also been observed for other sentiment measures (Brown and Cliff, 2004; Lux, 2010), its print media counterpart is not ($\rho_1 = 0.111$). The ADF statistics confirm the expected stationarity of the return series, but reveal mixed results for the sentiment series. There is little reason to doubt the stationarity of print media sentiment, however, for online media sentiment the non-stationarity cannot be rejected. Since both sentiment series are bounded between -1 and 1 by construction, strict non-stationarity seems practically impossible. Therefore, we analyze level sentiment together with stock returns in the main body of the paper, but provide the same analysis with first differences in sentiment in a separate appendix to check for robustness.[7] The directions and statistical significance of levels and first differences are the same. The correlation between print and online media sentiment for the overlapping period from the 39th calender week of 2008 and the 37th calender week of 2010 is only 0.35, so we perform econometric analyses for both sentiment measures separately and jointly.

Table 1: Summary statistics for sentiment and stock returns

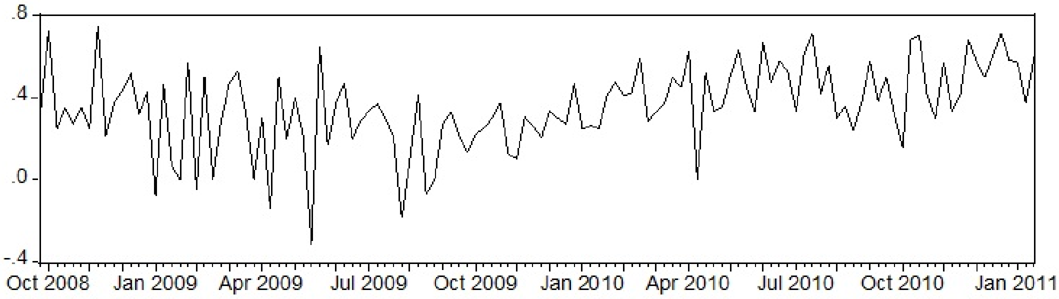
	Mean	SD	Skewness	Kurtosis	ρ_1	ADF	n
Print media sentiment	0.356	0.205	-0.540	3.474	0.111	-3.128 (0.027)	122
Online media sentiment	0.356	0.128	-0.124	2.141	0.728	-1.991 (0.291)	118
DAX returns	-0.001	0.041	0.137	4.108	0.006	-5.675 (0.000)	118

Note: The ADF test statistics have been computed with lag three and intercept for the sentiment series and no intercept for the return series. The one-sided p-values in parentheses indicate doubts of the stationarity of online media sentiment, but not of the returns and print media sentiment.

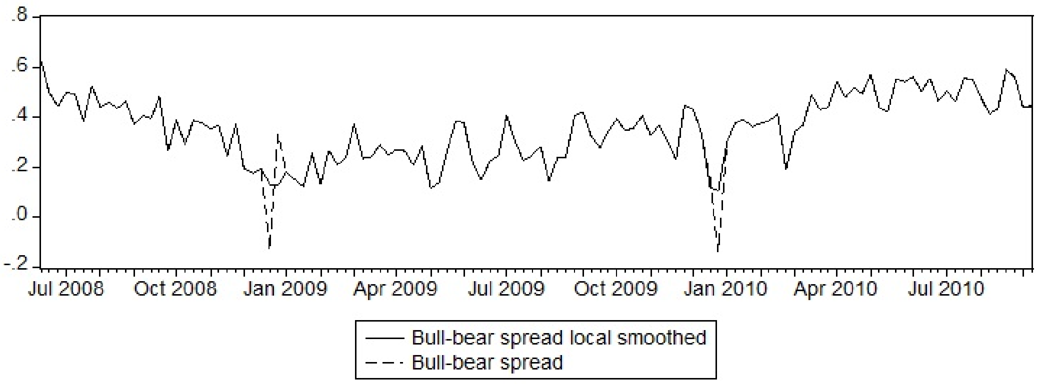
[7] Both changes and levels might have an impact on stock returns and it is not clear which specification better reveals the effects of sentiment. If sentiment changes from very bearish to bearish the positive change may lead to an increase in the return, anyhow, the level of sentiment is still low (Brown and Cliff, 2004).



(a) Weekly stock (DAX) returns



(b) Print media sentiment



(c) Online media sentiment

Note: Weekly stock returns are plotted for the same period as online media sentiment, which differs from the time horizon of print media sentiment.

Figure 2: Sentiment and stock returns over time

3. Sentiment and stock returns: VAR Analysis

Following Brown and Cliff (2004), and Lux (2010), we assume that sentiment and stock returns act as a system, so we estimate a set of bivariate and trivariate VAR models. The goal is to investigate the interaction and the statistical causality between sentiment and stock returns. The VAR(p) model is

$$Y_t = \mu + \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + \varepsilon_t \,, \tag{1}$$

where $Y_t = [\text{DAX, Sentiment}]^T$, μ is a vector of intercepts, the Φ_i's are coefficient matrices, ε_t is a vector of innovations, and p is the lag number. In the following three subsections, we focus on the essential results, but provide additional material and robustness checks in the appendix.

3.1. Bivariate VAR: Print media sentiment and stock returns

In this subsection, we analyze the interaction between print media sentiment and stock returns, that is, VARs with $Y_t = [\text{DAX, Print media sentiment}]^T$. Model selection criteria suggest different lag orders: Akaike information (AIC), final prediction error (FPE), and Hannan-Quinn (HQ) criteria suggest three lags, whereas the Schwarz (SC) criterion suggests no lag be included in the model. Lag exclusion test statistics indicate that it is reasonable to include lags up to order six in the VAR analysis. We run regressions from lag three to six, but find no substantial differences in the results.[8]

Table 2 shows the estimation output of our baseline specification, that is a VAR(3). Each column of the table corresponds to one equation of the VAR. The blocks of rows show the contribution of the independent variables up to lag three. The p-values in parentheses document statistical significance. The first column reveals that neither lagged DAX returns nor lagged print media sentiment predict DAX returns. The second column is our main concern, as it indicates that recent stock returns drive print media sentiment. We find a negative and significant (p-value 0.021) relationship at lag three. Furthermore, the second block in the second column of Table 2 documents that print media sentiment is a powerful predictor of itself. Both the 2- and 3-week lags are positive and significant at the one percent level.

To check the robustness of the VAR(3) results we run several specification tests. First, Figure 3 shows accumulated impulse response functions on a one standard deviation shock of the DAX (left panel) and sentiment (right panel) residuals. The left panel indicates that an impulse of the DAX residuals vanishes over time since the accumulated response quickly converges. The right panel indicates that an impulse to the sentiment residuals may have a permanent effect, which is more pronounced for sentiment. Second, multivariate normality tests (see appendix) show that residuals are significantly skewed, but do not suffer from excess kurtosis. To address these specification problems, we run several robustness checks: First, lag exclusion tests suggest to include up to six lags.

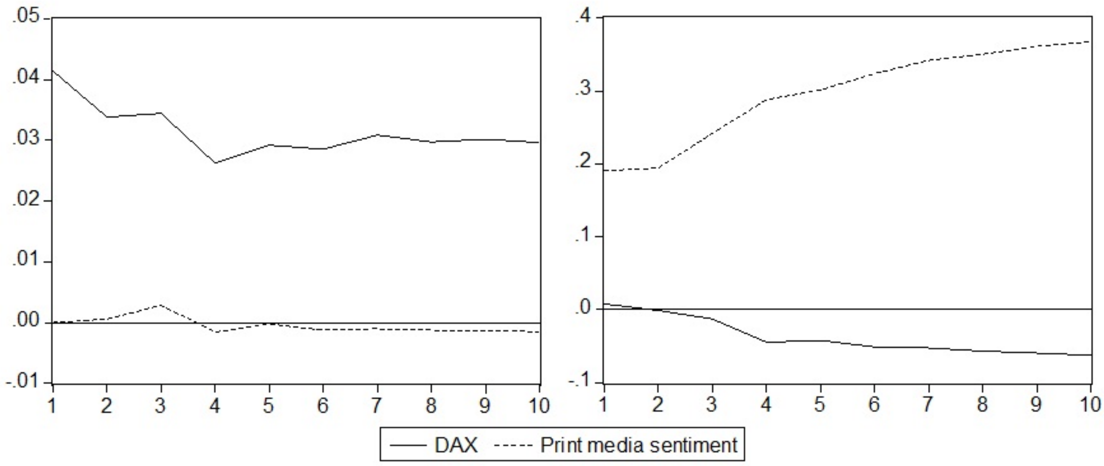
[8]All selection criteria are discussed in Lütkepohl (1991, pp. 118-138). The results of the lag selection criteria and lag exclusion tests are provided in the appendix.

Table 2: OLS estimation results for a VAR(3)

Independent Variable	Lag	Dependent Variable: DAX	Dependent Variable: Print media sentiment
DAX	1	-0.185	-0.227
		(0.127)	(0.527)
	2	-0.020	-0.364
		(0.900)	(0.450)
	3	-0.190	-0.816
		(0.247)	(0.021)
Print media sentiment	1	0.003	0.020
		(0.893)	(0.841)
	2	0.013	0.250
		(0.488)	(0.001)
	3	-0.022	0.237
		(0.310)	(0.005)
Constant		0.006	0.177
		(0.490)	(0.000)
R-squared		0.108	0.178

Note: This table documents OLS estimation results for a VAR(3) with Y_t = [DAX, Print media sentiment]^T using weekly data from September 26, 2008 to January 22, 2011. White (1980) standard errors correct for heteroskedasticity. p-values are in parentheses.

For instance, in the VAR(6), the 3-week lags impact of returns on sentiment remains negative and significant, and specification problems reduce. Second, following Brown and Cliff (2004) we run VARs with changes in sentiment rather than levels. The appendix documents the estimation output of the VAR(3) and justifies the results from Table 2. Third, as our sentiment measure also includes recommendations for stocks that are not constituents of the DAX, we additionally consider the SDAX index (German small caps). Specifically, we follow Brown and Cliff (2004) and run VARs with Y_t = [DAX, ODAX, Print media sentiment]^T, in which ODAX is the part of SDAX returns orthogonal to the DAX returns. The appendix contains the estimation output for the VAR(3) and justifies the result of our baseline specification. For instance, the predictive power of DAX returns at lag three on sentiment remains negative and now significant at the one percent level. Moreover, we document predictive power of one lag sentiment on ODAX returns (p-value 0.053), which has also been documented by Brown and Cliff (2004). However, Granger causality tests do not confirm this direction, but do confirm the impression we get from the baseline VAR(3) (Table 2) that DAX returns are Granger causal for print media



Note: Accumulated impulse response functions of a one SD shock to the DAX (left panel) and print media sentiment (right panel) innovations for 10 lags, respectively. Orthogonal innovations are calculated using the Cholesky factorization of the innovations covariance matrix (see Lütkepohl and Krätzig, 2004, pp. 165).

Figure 3: Accumulated impulse response functions of DAX returns and print media sentiment

sentiment[9]. Taken as a whole, we do not find predictive power of print media sentiment on stock returns, but vice versa, which is in line with previous studies, such as Solt and Statman (1988); Clarke and Statman (1998); Brown and Cliff (2004); Kling and Gao (2008).

3.2. Bivariate VAR: Online media sentiment and stock returns

In this subsection we analyze the interaction between online media sentiment and stock returns, that is, VAR models with Y_t = [DAX, Online media sentiment]^T. Model selection criteria suggest different lag orders: AIC and FPE criteria suggest five lags, whereas HQ and SC criteria suggest one lag be included in the model. Lag exclusion test statistics indicate that it is reasonable to include lags up to order five in the VAR analysis.[10] We run regressions up to lag five and analyze their causality structure.

Table 3 shows the estimation output of our baseline specification, that is a VAR(3). The second block in the first column reveals that online media sentiment has no predictive power on stock returns. Again, the second column is our main concern, as it indicates that recent stock returns drive online media sentiment. We find a positive and significant relationship at lag three (p-value 0.045), which is in contrast to the negative relationship we found for print media sentiment. The second block in the second column of Table 3 documents that online media sentiment is a predictor of itself. The 1-week lag is positive

[9]The null hypothesis states that DAX returns do not Granger cause sentiment. The corresponding p-value is 0.004. Thus, the null can be rejected.

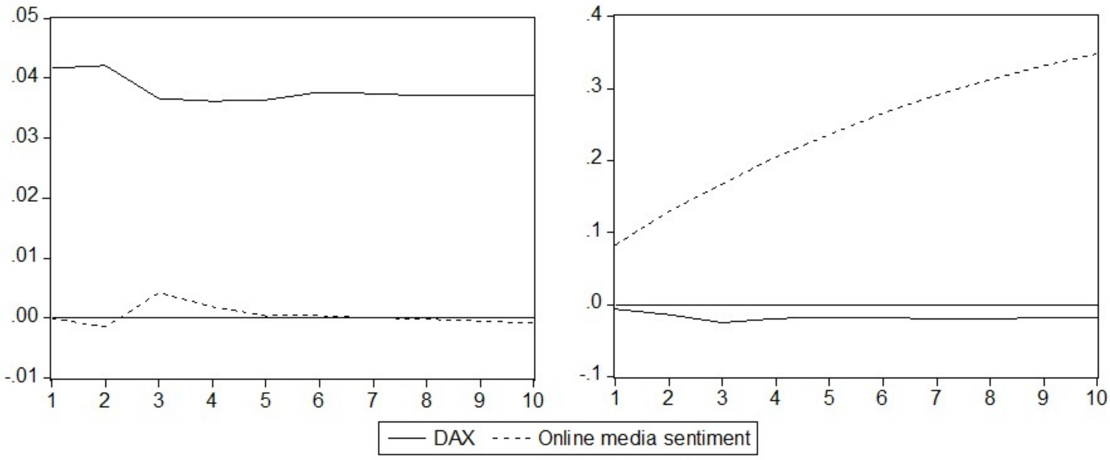
[10]The results of the lag selection criteria and lag exclusion tests are provided in the appendix.

Table 3: OLS estimation results for a VAR(3)

Independent Variable	Lag	Dependent Variable: DAX	Dependent Variable: Online media sentiment
DAX	1	0.008	-0.101
		(0.948)	(0.507)
	2	-0.124	-0.143
		(0.283)	(0.429)
	3	-0.008	0.321
		(0.949)	(0.045)
Online media sentiment	1	-0.018	0.562
		(0.678)	(0.000)
	2	0.079	0.143
		(0.183)	(0.149)
	3	-0.067	0.118
		(0.143)	(0.218)
Constant		0.002	0.062
		(0.892)	(0.010)
R-squared		0.041	0.588

Note: This table documents OLS estimation results for a VAR(3) with $Y_t = [\text{DAX, Online media sentiment}]^T$ using weekly data from June 26, 2008 to September 13, 2010. White (1980) standard errors correct for heteroskedasticity. p-values are in parentheses.

and significant at the one percent level. To check the robustness of our benchmark VAR(3) results we run several tests and analyze extended specifications. First, Figure 4 shows accumulated impulse response functions on a one standard deviation shock of the DAX (left panel) and sentiment (right panel) residuals. The left panel indicates that an impulse of the DAX residuals vanishes over time since the accumulated response quickly converges. The right panel indicates that an impulse to the sentiment residuals has a permanent effect on sentiment. This permanent effect appears even more pronounced than in the print media analysis of the the previous subsection. Second, multivariate normality tests (see appendix) show that residuals do not suffer from skewness and excess kurtosis. Third, as suggested by HQ and SC, and lag exclusion tests, we also estimate VARs at lag four and five and confirm the impression of the baseline VAR(3). Fourth, running VARs with changes in sentiment rather than levels (see appendix), also confirm the results from Table 3. Fifth, including the ODAX, which is the part of SDAX (German small caps) returns orthogonal to the DAX returns, the effect of past DAX returns on sentiment disappears. Most importantly, Granger causality tests for all specifications indicate that stock returns do not Granger cause online media sentiment. For instance, for the baseline VAR(3), the null hypothesis that DAX returns do not Granger cause



Note: Accumulated impulse response functions of a one SD shock to the DAX (left panel) and online media sentiment (right panel) innovations for 10 lags, respectively. Orthogonal innovations are calculated using the Cholesky factorization of the innovations covariance matrix (see Lütkepohl and Krätzig, 2004, pp. 165).

Figure 4: Accumulated impulse response functions of DAX returns and online media sentiment

sentiment cannot be rejected (p-value 0.270).

In line with the analysis for print media sentiment and previous studies, we do not find predictive power of online media sentiment on stock returns, but weak evidence for the reverse direction. In contrast to print media sentiment, the effect of past returns on future online media sentiment is positive, but, most importantly, not Granger causal.

3.3. Trivariate VAR: Print and online media sentiment and stock returns

Although both sentiment measures are obtained from two similar datasets of stock recommendations, the correlation between both measures for the overlapping period is only 0.35. One reason could be the time lag between print and online media. To clarify this issue, we run VARs with $Y_t = [\text{DAX, Print media sentiment, Online media sentiment}]^T$. This analysis serves also as a robustness check for the results of the last two subsections. The estimation output (see appendix) confirms the negative and significant effect of past DAX returns on print media sentiment and the weak, positive, but non-causal effect of past DAX returns on online media sentiment. It also confirms the expected time lag between print and online media since the effect of the 1-week online media sentiment on print media sentiment is positive and significant (p-value $< 1\%$). Both DAX returns and online media sentiment are Granger causal for print media sentiment. As expected, there is no effect on further lags and in the other direction.

4. Discussion

This paper systematically examines the relationship between stock returns and professional analysts' sentiment derived from their published stock recommendations. Calculating the traditional bull-bear spread for aggregated stock recommendations in print an online media and taking return indices for large and small caps, we examine the near-term relationship between sentiment and the stock market using VAR analysis. In line with previous studies, such as Solt and Statman (1988); Clarke and Statman (1998); Brown and Cliff (2004); Kling and Gao (2008); Glaser et al. (2009); Finter et al. (2012), we confirm that weekly sentiment has no near-term forecasting power on stock returns, but that sentiment is a powerful predictor of itself. Also in line with existing literature, we find that past stock movements drive sentiment. Unlike Solt and Statman (1988); Clarke and Statman (1998); Brown and Cliff (2004); Kling and Gao (2008), who find that sentiment follows a positive feedback process, we find the opposite. Hence, professional analysts express optimism in their printed stock recommendations when previous market returns were negative. For online media sentiment we find weak evidence for a positive feedback process, but this evidence does not survive all robustness checks and is not causal. However, the result for print media sentiment that professional analysts follow reversals is robust and causal. Thus, we argue for the "bargain shopper hypothesis", that is, when analysts see stocks becoming a bargain (proxied as a negative return), they see a buying opportunity and become optimistic (Brown and Cliff, 2004).

This analysis suffers from the relative short time period of around 120 calender weeks. Moreover, the analysis covers a very erratic market period as it starts with the crash of the housing bubble in 2008 and ends during the sovereign debt crises in 2011. Thus, extending the sample period would capture this drawback; it would allow for analyzing mid- and long-term behavior and less erratic market periods. As sentiment derived from media content has only played a minor role so far, at least for the German stock market, we encourage further investigations in this field.

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A. Additional material for bivariate VAR: Print media sentiment and stock returns

Table 4: Lag exclusion test for bivariate VAR with print media sentiment and DAX returns

Lag	Print media sentiment	DAX returns	Joint
1	0.015	2.330	2.345
	(0.992)	(0.312)	(0.673)
2	1.149	11.542	12.221
	(0.563)	(0.003)	(0.016)
3	4.311	9.931	14.105
	(0.116)	(0.007)	(0.007)
4	0.177	1.300	1.444
	(0.915)	(0.522)	(0.837)
5	0.053	9.244	9.245
	(0.974)	(0.010)	(0.055)
6	0.013	12.335	12.364
	(0.994)	(0.002)	(0.015)
7	0.836	2.592	3.620
	(0.658)	(0.274)	(0.460)
8	1.397	2.620	4.262
	(0.497)	(0.270)	(0.372)

Note: For each lag, the Wald statistic for the joint significance of all endogenous variables at that lag is calculated for each equation separately and jointly. Numbers in parentheses are p-values.

Table 5: Residual Normality Tests for bivariate VAR with print media sentiment and DAX returns

Variable	Jarque-Bera	df	p-value
Print media sentiment	5.597	2	0.061
DAX returns	2.378	2	0.000
Joint	2.938	4	0.000

Note: Multivariate Jarque-Bera normality test using Cholesky factorization of the residuals covariance matrix (see Lütkepohl, 1991, pp. 152-158). H_0: Residuals are multivariate normal.

Table 6: Lag selection for bivariate VAR with print media sentiment and DAX returns

Lag	FPE	AIC	SC	HQ
0	5.32e-05	-4.166	-4.118*	-4.147
1	5.59e-05	-4.117	-3.973	-4.059
2	5.16e-05	-4.197	-3.957	-4.100
3	4.72e-05*	-4.285*	-3.949	-4.148*
4	4.97e-05	-4.234	-3.802	-4.058
5	4.90e-05	-4.249	-3.720	-4.034
6	4.78e-05	-4.275	-3.651	-4.022
7	4.89e-05	-4.252	-3.532	-3.960
8	5.04e-05	-4.225	-3.409	-3.894

Note: * indicates lag order selected by the criterion.

Table 7: OLS estimation results for a VAR(3) with changes in print media sentiment and stock returns

Independent Variable	Lag	Dependent Variable: DAX	Dependent Variable: ΔPrint media sentiment
DAX	1	-0.173	-0.383
		(0.219)	(0.380)
	2	-0.022	-0.483
		(0.900)	(0.371)
	3	-0.187	-0.777
		(0.249)	(0.053)
ΔPrint media sentiment	1	-0.001	-0.901
		(0.952)	(0.000)
	2	0.006	-0.534
		(0.792)	(0.000)
	3	-0.016	-0.180
		(0.373)	(0.043)
Constant		0.004	0.006
		(0.319)	(0.734)
R-squared		0.103	0.492

Note: This table documents OLS estimation results for a VAR(3) with $Y_t = [\text{DAX}, \Delta\text{Print media sentiment}]^T$ using weekly data from September 26, 2008 to January 22, 2011. FPE and AIC opt for 7 lags, whereas SC and HQ opt for 2 lags to be included in the system. To increase comparability with the baseline VAR in the main part of the paper we also present estimates for a VAR(3). White (1980) standard errors correct for heteroskedasticity. p-values are in parentheses.

Table 8: OLS estimation results for a VAR(3)

Independent Variable	Lag	Dependent Variable: DAX	ODAX	Print media sentiment
DAX	1	-0.181	0.096	-0.269
		(0.117)	(0.003)	(0.441)
	2	0.003	0.054	-0.263
		(0.983)	(0.045)	(0.621)
	3	-0.241	0.158	-1.070
		(0.115)	(0.000)	(0.002)
ODAX	1	-0.199	-0.044	-1.040
		(0.401)	(0.607)	(0.404)
	2	0.488	-0.126	2.449
		(0.095)	(0.114)	(0.056)
	3	-0.082	0.029	0.350
		(0.816)	(0.752)	(0.698)
Print media sentiment	1	0.007	-0.013	0.031
		(0.764)	(0.053)	(0.726)
	2	0.007	0.008	0.229
		(0.746)	(0.219)	(0.007)
	3	-0.014	0.007	0.278
		(0.452)	(0.316)	(0.001)
Constant		0.004	0.000	0.165
		(0.654)	(0.938)	(0.001)
R-squared		0.151	0.272	0.229

Note: This table documents OLS estimation results for a VAR(3) with Y_t = [DAX, ODAX, Print media sentiment]^T using weekly data from September 26, 2008 to January 22, 2011. FPE and AIC opt for 6 lags, whereas SC and HQ opt for no lag to be included in the system. To increase comparability with the baseline VAR in the main part of the paper we also present estimates for a VAR(3). White (1980) standard errors correct for heteroskedasticity. p-values are in parentheses. The ODAX is the part of the SDAX (German small caps) returns orthogonal to the DAX (German large caps).

B. Additional material for bivariate VAR: Online media sentiment and stock returns

Table 9: Lag exclusion test for bivariate VAR with online media sentiment and DAX returns

Lag	DAX	Online media sentiment	Joint
1	0.111	23.792	23.827
	(0.946)	(0.000)	(0.000)
2	3.023	1.070	4.339
	(0.221)	(0.586)	(0.362)
3	0.715	2.916	3.774
	(0.699)	(0.233)	(0.437)
4	0.120	2.906	3.113
	(0.942)	(0.234)	(0.539)
5	1.628	6.277	7.944
	(0.443)	(0.043)	(0.093)
6	0.609	0.706	1.337
	(0.737)	(0.703)	(0.855)
7	0.543	0.431	0.921
	(0.762)	(0.806)	(0.921)
8	0.528	1.433	1.920
	(0.768)	(0.488)	(0.750)

Note: For each lag, the Wald statistic for the joint significance of all endogenous variables at that lag is calculated for each equation separately and jointly. Numbers in parentheses are p-values.

Table 10: Lag selection for bivariate VAR with online media sentiment and DAX returns

Lag	FPE	AIC	SC	HQ
0	3.35e-05	-4.628	-4.578	-4.608
1	2.14e-05	-5.077	-4.929*	-5.017*
2	2.11e-05	-5.091	-4.846	-4.992
3	2.17e-05	-5.065	-4.721	-4.926
4	2.21e-05	-5.045	-4.603	-4.866
5	2.08e-05*	-5.1072*	-4.567	-4.888
6	2.20e-05	-5.051	-4.412	-4.792
7	2.31e-05	-5.003	-4.267	-4.704
8	2.22e-05	-5.045	-4.210	-4.706

Note: * indicates lag order selected by the criterion.

Table 11: Residual Normality Tests for bivariate VAR with online media sentiment and DAX returns

Variable	Jarque-Bera	df	p-value
DAX	0.126	2	0.939
Online media sentiment	1.861	2	0.394
Joint	1.987	4	0.738

Note: Multivariate Jarque-Bera normality test using Cholesky factorization of the residuals covariance matrix (see Lütkepohl, 1991, pp. 152-158). H_0: Residuals are multivariate normal.

Table 12: OLS estimation results for a VAR(3) with changes in online media sentiment and stock returns

Independent Variable	Lag	Dependent Variable: DAX	Dependent Variable: ΔOnline media sentiment
DAX	1	0.007	-0.006
		(0.955)	(0.971)
	2	-0.121	-0.167
		(0.293)	(0.368)
	3	-0.006	0.338
		(0.964)	(0.051)
ΔOnline media sentiment	1	-0.014	-0.422
		(0.737)	(0.000)
	2	0.068	-0.296
		(0.114)	(0.002)
	3	0.006	-0.319
		(0.879)	(0.000)
Constant		0.000	0.000
		(0.928)	(0.973)
R-squared		0.041	0.246

Note: This table documents OLS estimation results for a VAR(3) with Y_t = [DAX, ΔOnline media sentiment]^T using weekly data from September 26, 2008 to January 22, 2011. FPE and AIC opt for 3 lags, whereas SC and HQ opt for no lag to be included in the system. Lag exclusion tests indicate that it is reasonable to include lags up to order 5. White (1980) standard errors correct for heteroskedasticity. p-values are in parentheses.

Table 13: OLS estimation results for a VAR(3)

Independent Variable	Lag	Dependent Variable DAX	ODAX	Online media sentiment
DAX	1	-0.001	0.012	-0.109
		(0.993)	(0.125)	(0.475)
	2	-0.135	0.023	-0.166
		(0.165)	(0.001)	(0.342)
	3	-0.017	0.019	0.273
		(0.880)	(0.069)	(0.128)
ODAX	1	0.337	-0.029	2.493
		(0.886)	(0.742)	(0.248)
	2	-0.045	0.004	-1.332
		(0.971)	(0.965)	(0.569)
	3	3.043	-0.068	0.740
		(0.019)	(0.513)	(0.716)
Online media sentiment	1	-0.015	0.006	0.555
		(0.706)	(0.045)	(0.000)
	2	0.067	-0.007	0.134
		(0.222)	(0.087)	(0.169)
	3	-0.057	-0.004	0.139
		(0.295)	(0.271)	(0.144)
Constant		0.001	0.001	0.060
		(0.935)	(0.095)	(0.011)
R-squared		0.097	0.223	0.592

Note: This table documents OLS estimation results for a VAR(3) with Y_t = [DAX, ODAX, Online media sentiment]^T using weekly data from September 26, 2008 to January 22, 2011. FPE and AIC opt for 4 lags, whereas SC and HQ opt for one and two lags to be included in the system, respectively. Lag exclusion tests indicate that it is reasonable to include lags up to order 3, only. We present estimation results of a VAR(3), however, in a VAR(4) the overall impression remains the same. White (1980) standard errors correct for heteroskedasticity. *p*-values are in parentheses. The ODAX is the part of the SDAX (German small caps) returns orthogonal to the DAX (German large caps).

C. Additional material for trivariate VAR: Online and print media sentiment, and stock returns

Table 14: OLS estimation results for a VAR(2)

Independent Variable	Lag	Dependent Variable: DAX	Print media sentiment	Online media sentiment
DAX	1	0.022	-0.491	-0.116
		(0.863)	(0.314)	(0.446)
	2	-0.156	-0.959	-0.172
		(0.178)	(0.017)	(0.357)
Print media sentiment	1	-0.032	-0.219	-0.066
		(0.125)	(0.039)	(0.161)
	2	0.009	0.129	0.022
		(0.691)	(0.129)	(0.658)
Online media sentiment	1	-0.014	0.645	0.641
		(0.766)	(0.001)	(0.000)
	2	0.046	0.134	0.185
		(0.353)	(0.459)	(0.089)
Constant		-0.003	0.091	0.075
		(0.829)	(0.138)	(0.003)
R-squared		0.046	0.300	0.585

Note: This table documents OLS estimation results for a VAR(2) with $Y_t = [\text{DAX, Print media sentiment, Online media sentiment}]^T$ using weekly data from the 39th calender week of 2008 and the 37th calender week of 2010. FPE and AIC opt for two lags, while SC and HQ opt for only one lag to be included in the system. White (1980) standard errors correct for heteroskedasticity. p-values are in parentheses.