Market Response to Investor Sentiment

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Abstract

Recent empirical research suggests that measures of investor sentiment have predictive power for future stock returns at intermediate and long horizons. Given that sentiment indicators are widely published, smart investors should exploit the information conveyed by the indicator and thus trigger an immediate market response to the publication of the sentiment indicator. The present paper is the first to empirically analyze whether this immediate response can be identified in the data. We use survey-based sentiment indicators from two countries (Germany and the US). Consistent with previous research we find predictability at intermediate horizons. However, the predictability in the US largely disappears after 1994. Using event study methodology we find that the publication of sentiment indicators affects market returns. The sign of this immediate response is the same as the sign of the intermediate horizon predictability. This is consistent with sentiment being related to mispricing but is inconsistent with the sentiment indicator providing information about future expected returns.

Keywords: Investor Sentiment, Event Study, Return Predictability

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1 Introduction

Recent empirical research suggests that survey measures of investor sentiment have predictive power for future stock returns at intermediate and long horizons. The usual econometric approach is to regress future stock index returns on a sentiment indicator and appropriate control variables. The controls are intended to capture variables (such as the term and yield spread) which are known to predict future returns. A significant coefficient on the sentiment indicator is interpreted as evidence that sentiment predicts future returns.

There are at least two potential explanations for the predicitve ability of sentiment indicators. First, sentiment indices may contain information about future expected returns which is not already captured by the control variables. In this case the predictive ability of sentiment indicators does not violate market efficiency. Second, sentiment indicators may be related to mispricing (as also proposed by Brown and Cliff (2005)). Positive sentiment, for example, may go hand in hand with over-optimistic investors driving share prices above fundamentals. The resulting pricing errors are corrected in the future. Consequently, current sentiment indicators will be negatively related to future returns. In this case the predictive power of sentiment measures does violate market efficiency.

The two explanations have very different implications. It is thus very important to discriminate between the expected return news scenario and the mispricing scenario. The present paper makes a step in this direction. Our approach is to simultaneously consider intermediate and long-horizon predictability on the one hand and the immediate market reaction to the publication of sentiment indicators on the other hand. The approach has a simple intuition. Current prices and future expected returns are negatively related. If sentiment indicators contain information about future expected returns the sign of the immediate market reaction should be the opposite of the sign obtained in the long term predicitive regressions. If, on the other hand, sentiment indicators are related to mispricing we should find that the immediate market reaction has the same sign as that found in the predicitve regressions. The reason is that smart investors exploit the information contained in the sentiment indicator. If the sentiment indicator indicates overvaluation (and thus negative future returns) smart money investors will sell and thus cause a negative market reaction.

Our paper is, to the best of our knowledge, the first paper which empirically analyzes the immediate response of stock returns to the publication of survey-based sentiment measures. We use data from two countries (Germany and the US). In the first part of our analysis we rely on the methodology proposed by Brown and Cliff (2005). We replicate their tests for medium and long-term predictability. Consistent with previous results in the literature, we find a significant negative relation between the sentiment indicator and subsequent medium term (up to three months) index returns in the US for the first part of our sample period (1987-1994 and, to a much lesser extent, 1994-2001). This relation disappears towards the end of our sample period. The sentiment indicator for the German market is *positively* related to future returns.

In the second step of our analysis, we use event study methodology to test whether daily index returns respond to the publication of the sentiment indicator. We do find a significant positive announcement day effect in Germany. However, not all of the predictive power of the indicator is captured on the announcement day. This pattern is consistent with the mispricing scenario and limited arbitrage. Smart investors are aware of the predictive power of the sentiment indicator and trade accordingly. However, they do not fully arbitrage the predictability away, possibly because of increased noise trader risk (as in the model of De Long et al. (1990)).

For the US market there is evidence of a negative publication day effect in the 1987-1994 subperiod. As in the case of Germany this result is consistent with the mispricing scenario and limited arbitrage. In later subperiods there is no significant publication day effect. This comes as no surprise because the intermediate to long-horizon predictability also largely disappears towards the end of the sample period.

The results for Germany and the US are consistent in so far as they both support the mispricing scenario. However, they are inconsistent in that sentiment is negatively related to future returns in the US (at least prior to 1994) but positively related to future returns in Germany. A tentative explanation for these different findings is that the US sentiment index indicates current mispricing while the German index indicates future mispricing. The coefficient patterns which we find for different forecasting horizons are consistent with this explanation.

Our paper is related to previous papers investigating the predictive power of sentiment indicators. Brown and Cliff (2004, 2005), Clarke and Statman (1998), Fisher and Statman (2000), Kaniel et al. (2004), Otoo (1999), Shiller (2000), Solt and Statman (1988) and Verma et al. (2008) all analyze survey-based sentiment measures for the US market.[1]

[1] A large number of papers uses market-based sentiment measures. These sentiment proxies include, but are not limited to, mutual fund flows (Brown et al. (2003)), the closed-end fund discount (Elton et al. (1998), Lee et al. (1991), Neal and Wheatley (1998)), put-call ratios (Dennis and Mayhew (2002)) and various measures of trading activity (Barber and Odean (2008), Kumar and Lee (2002, 2006). Baker and Wurgler (2006) construct a composite sentiment measure based on six underlying proxies. Brown and

Although the results are mixed (most likely due to differences in sample periods, methodology and the forecasting horizons), the most recent and econometrically advanced paper by Brown and Cliff (2005) finds evidence of long-horizon predictability. Schmeling (2007) applies a similar methodology to data from the German stock market and also reports evidence of predictability. Although some papers have tested for short-term predictability (e.g. at the weekly and monthly level as in Brown and Cliff (2004)), to our knowledge, the present paper is the first one testing for announcement day effects.

On a more general level our paper is related to previous research testing for return predictability (see Ang and Bekaert (2007) for a recent contribution). In particular, certain methodological concerns (the problem of using persistent regressors, first addressed by Stambaugh (1999), and the problem of using overlapping return data) are also present in our study. We account for these problems by adopting the bootstrap-based bias correction proposed by Brown and Cliff (2005).

This paper is structured as follows. Section 2 describes our data set. In section 3 we present methodology and results of our predictability tests. Section 4 describes our tests for the existence of announcement day effects. Section 5 concludes.

2 Data

2.1 German Data

The analysis of intermediate and long-horizon predictability is based on weekly data. We use survey data from Sentix as our investor sentiment proxy. Sentix conducts weekly surveys among institutional and private investors, currently covering over 2700 registered participants, about 800 of which participate each week. Individual investors constitute on average about 76% of respondents, the fraction typically varying between 70% and 80%. Voting is possible from Thursday afternoon through Sunday. The participants are asked whether they are bullish, bearish, neutral, or whether they do not have any opinion with regard to the development of the DAX30 stock index for horizons of one and six months, respectively.[2] In our analysis we use data for the six months horizon only because the AAII survey which we use in our US sample is also based on a six months forecasting horizon.

Cliff (2004) analyze market-based and survey-based sentiment measures and conclude that many of these measures are correlated.

[2]Additionally, Sentix publishes an index named neutrality index measuring the fraction of neutral respondents among all respondents.

From the individual opinions Sentix computes the so-called value index, also known as the bull-bear spread. It is defined as

$$S_t = \frac{\#bullish - \#bearish}{\#total}$$

The Sentix index is published every Sunday evening or Monday morning prior to the stock market's opening and is available to all participants, and additionally, since January 2004, via Thomson DataStream and Bloomberg. Furthermore, sub-indices only covering individual and institutional investors, respectively, are made available to participants only. The Sentix data starts on February 26, 2001 and ends on June 30, 2008. In our predictive regressions we use forecasting horizons of 1, 4, 8, 13 and 26 weeks. To this end we combine the Sentix data with data on the DAX index for the period February 26, 2001 to December 31, 2008. In the predicitve regressions we want to test whether the sentiment indicator contains information about future returns beyond the information inferrable from other publicly observable variables. We therefore control for variables that are known to predict future market returns. We include the past week's DAX30 returns, the exchange rate EUR/USD, the interest rate term spread between 10 year German government bonds and the Euribor 3 month rate, the credit spread (defined as the spread between yields on A rated corporate bonds of maturities between three and five years and the mean of 3 and 5 year German government bond yields), the liquidity spread (defined as the spread between the Euribor 3 month and 1 month rates), and the Euribor 1 month rate.

For the short-term analysis, i.e. the analysis whether the publication of the sentiment indicator has an immediate price effect, we use daily data. As the Sentix index is published on the weekend, we look at the return of the DAX30 from the closing price on Friday to prices on Monday.[3] To this end we regress daily DAX returns on a variable which is equal to the sentiment indicator on Mondays and zero on all other days. The regression includes lagged DAX returns, lagged S&P 500 returns (to control for spillover effects from the US market) and a Monday dummy (to control for a weekend effect) as control variables.

Table 1 provides summary statistics of all variables.

[3] The results shown in the paper are based on Monday closing prices. As a robustness check we also consider index values recorded on Monday morning at 9.30 a.m.. We do not use the opening value of the DAX because the opening value is partly based on previous day's closing prices.

Table 1: Summary Statistics of German data

	Mean	Std. Dev.	ρ_i	$\rho_{s,i}$
Sentix_t	0.121	0.113	0.773	1.000
ΔSentix_t	-0.000	0.067	-0.301	0.334
InnoSentix_t	0.002	0.058	0.067	0.724
$\text{Sentix}_t^{Institutional}$	0.138	0.129	0.674	0.539
$\Delta\text{Sentix}_t^{Institutional}$	-0.000	0.103	-0.447	0.171
$\text{InnoSentix}_t^{Institutional}$	0.015	0.090	-0.079	0.366
$\text{Sentix}_t^{Individual}$	0.119	0.115	0.781	0.941
$\Delta\text{Sentix}_t^{Individual}$	-0.001	0.075	-0.295	0.314
$\text{InnoSentix}_t^{Individual}$	-0.002	0.063	0.043	0.689
$r_{t-1,t}^{DAX}$	0.000	0.032	0.031	0.123
$r_{t-2,t-1}^{DAX}$	0.000	0.033	0.027	0.050
$r_{t-2,t-1}^{S\&P500}$	0.000	0.032	-0.056	0.007
EUR/USD_{t-1}	1.185	0.187	0.988	0.029
Term Spread_{t-1}	0.011	0.008	0.986	-0.107
$\text{Credit Spread}_{t-1}$	0.011	0.003	0.946	-0.243
$\text{Liquidity Spread}_{t-1}$	0.001	0.001	0.951	0.112
Euribor 1m_{t-1}	0.031	0.009	0.990	-0.024

t denotes the week that is concerned. All returns are from Friday close to the next Friday close. Other control variables are from Friday. The Sentix variables are from Monday. Sentix denotes the 6 month value aggregate Sentix survey for the DAX 30 stock index. ΔSentix_t denotes its weekly change, InnoSentix its innovation when controlling for past week's returns and past sentiment level. Statistics of the Sentix sub-indices including responses of institutional and individual investors are depicted as $\text{Sentix}^{Institutional}$ and $\text{Sentix}^{Individual}$, respectively. ρ_i depicts autocorrelation of variable i, $\rho_{s,i}$ denotes correlation between Sentix and variable i.

2.2 US Data

We use data from the American Association of Individual Investors (AAII). The AAII conducts weekly surveys among its members, which are published each Thursday[4] morning before the stock market opens. The participants are asked whether they expect the direction of the stock market over the next six months to be "up", "no change", or "down" and can participate once in every weekly period ranging from Thursday to Wednesday. We use a value index (bull-bear spread) calculated from this data for the period July 24, 1987 to June 26, 2008. As Table 2 shows, mean, standard deviation and first order autocorrelation of the AAII indicator are comparable to those of the German Sentix 6 months survey.

As the AAII survey does not specify which stock index it refers to, we use the Dow Jones Industrial Average, the Standard & Poors 500, the NASDAQ 100, and the Russell 3000 indices. We estimate predictive regressions for forecasting horizons of 1, 4, 8, 13 and 26 weeks. Again, we include other variables known to have predicitve power for market returns as control variables. We include the same variables as in the German sample but replace the Euribor rates with Treasury bill rates. Thus, we control for the past week's return of the stock index considered, the exchange rate EUR/USD, the interest rate term spread between 10 year US Treasury bonds and the Treasury bill 3 month rate, the credit spread (defined as the yield spread between Baa and Aaa rated corporate bonds), the liquidity spread (defined as the spread between the US Treasury bill 3 month and 1 month rates) and the US Treasury bill 1 month rate. Additionally we include the past week's Fama-French size and book-to-market factor returns.

In the short-term analysis we again use daily data. We regress daily index returns on a variable which is equal to the sentiment indicator on Thursdays and zero on all other days. The regression includes lagged index returns and a Monday dummy (to control for a weekend effect) as control variables.

Table 2 provides summary statistics for the period July 24, 1987 to June 30, 2008.

[4]This applies to the period from November 1993 onwards. Before, the day of publication had been Friday. In case of public holidays, the index is published on the last trading day before that holiday. In our analysis, we take account of the exact publication days.

Table 2: Summary Statistics of US data

	Mean	Std. Dev.	ρ_i	$\rho_{s,i}$
AAII_t	0.099	0.188	0.675	1.000
ΔAAII_t	-0.001	0.152	-0.341	0.405
InnoAAII_t	0.008	0.135	-0.141	0.737
$r^{S\&P500}_{t-1,t}$	0.001	0.022	-0.059	-0.029
$r^{S\&P500}_{t-2,t-1}$	0.001	0.021	-0.059	0.131
USD/EUR_{t-1}	1.167	0.149	0.991	-0.194
Term Spread_{t-1}	0.017	0.012	0.992	0.026
Credit Spread_{t-1}	0.009	0.002	0.980	-0.198
Liquidity Spread_{t-1}	0.027	0.013	0.988	-0.135
Treasury bill 1m_{t-1}	0.017	0.009	0.988	-0.143
$\text{SMB}_{t-2,t-1}$	0.000	0.006	0.173	0.149
$\text{HML}_{t-2,t-1}$	0.000	0.005	0.206	0.088

t denotes the week that is concerned. All returns are from the day's close prior to publication of the AAII sentiment indicator to the following week's. Other control variables are from Wednesday. The AAII variables are from the day of publication. AAII denotes the denotes the AAII sentiment level. ΔAAII_t denotes its weekly change, InnoAAII its innovation when controlling for past week's returns and past sentiment level. ρ_i depicts autocorrelation of variable i, $\rho_{s,i}$ denotes correlation between AAII and variable i.

3 Predictive Regressions

3.1 Results for Germany

In this section we analyze whether investor sentiment, measured by the Sentix survey, is able to predict asset returns for horizons from one to 26 weeks. As proposed by Brown and Cliff (2005) we use a bootstrap simulation to account for problems caused by overlapping observations and persistent regressors.[5] We estimate

$$(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)}, \qquad (1)$$

where r_{t+k} denotes the k period future log DAX return. $\alpha(k)$ is the constant for a forecasting horizon of k weeks, z_t is a vector of the control variables listed in section 2.1. SX_t is the value of the long-term Sentix survey. From the bootstrap procedure we obtain coefficient estimates and associated p-values based on the distribution of the estimated coefficients. Details of the procedure are explained in the appendix.

Results for the aggregate sentiment index are depicted in Table 3. They show that the aggregate Sentix index, which, on average, consists of roughly three quarters individual and one quarter institutional respondents, has predictive power for future DAX 30 returns for periods from one to 8 weeks. The bootstrap coefficient estimates are always larger than the OLS estimates, although the differences are small. In spite of their larger numerical values, the bootstrap coefficients have higher p-values. Our interpretation of the results will be based on the more conservative bootstrap procedure.

The sign of the relation between the sentiment indicator and future DAX returns is positive. This may indicate that the sentiment index foreshadows future misvaluation. Interestingly, the coefficient in the 26-week predictive regression is the smallest of all five predictive regressions. This pattern is consistent with the sentiment index indicating a future misvaluation which is subsequently corrected in the second half of the 26-week horizon.Alternatively the sentiment indicator may contain information on future expected returns. The analysis of the announcement day effects in section 4.1 will allow to discriminate among these interpretations.

As it is generally found in the literature that institutional investors gain at individual investors' costs, we are interested in whether the Sentix's ability to predict stock index returns stems from the institutional or individual investors' responses. Therefore, we conduct the same analysis separately for the institutional and the individual investors'

[5] Compare also Brown and Cliff (2005), p. 418.

Table 3:

Sentiment Coefficient in k-Week Regressions for Aggregate 6 Month DAX Sentiment

Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0395**	0.011	0.0404**	0.038
4 weeks	0.1101***	0.000	0.1140*	0.068
8 weeks	0.1783***	0.000	0.1876*	0.058
13 weeks	0.1337***	0.000	0.1498	0.248
26 weeks	-0.0455	0.712	-0.0220	0.913

The table presents β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)}$ from OLS estimations and bootstrap simulations as explained in the appendix. Results are for horizons of k weeks. Controls are the variables listed in section 2.1. Sig. level denotes the p-values obtained from the distributions of coefficients obtained from the bootstrap, rather than assuming a normal distribution. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

Sentix subindices, respectively. The results we obtain subtly disagree with the common belief that individual investors are noise traders while institutional investors "get it right". Table 5shows that the coefficients for individual investors are actually positive and significant in the near term and only reverse at longer horizons. In contrast, Table 4 indicates that institutional investor sentiment has more predictive power for longer horizons.

3.2 Results for the US

We conduct the same analysis as for the Sentix data for the American Association of Individual Investors sentiment index. We use the Standard & Poors 500 index as the index the return of which is to be predicted. However, results are qualitatively identical for the Dow Jones Industrial Average, the NASDAQ 100, and the Russell 3000 indices[6]. First, we apply our procedure for the whole period from 1987 to 2008. The results we find are at odds with those for the Sentix. Table 6 shows that American individual investor sentiment is negatively related to future S&P 500 returns. Based on the bootstrap results this relation is significant for the 26 week ahead forecast. These findings are fully consistent with the results of Fisher and Statman (2000) and Brown and Cliff (2005). These authors also find a negative relation between sentiment and future returns for samples covering

[6] Results are available upon request.

Table 4:

Sentiment Coefficient in k-Week Regressions for Institutional 6 Month DAX Sentiment

Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0163	0.244	0.0163	0.278
4 weeks	0.0386	0.115	0.0366	0.375
8 weeks	0.1364***	0.000	0.1340**	0.030
13 weeks	0.1497***	0.000	0.1459*	0.062
26 weeks	0.1492***	0.003	0.1458	0.175

The table presents β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)}$ from OLS estimations and bootstrap simulations as explained in the appendix. Results are for horizons of k weeks. Controls are the variables listed in section 2.1. Sig. level denotes the p-values obtained from the distributions of coefficients obtained from the bootstrap, rather than assuming a normal distribution. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

1987-1998 and 1963-2000, respectively. The negative coefficient is consistent with the sentiment index indicating current misvaluation which is corrected over the forecasting horizon.

The AAII sentiment index spans a much longer period of time than the Sentix index. In order to check whether the results are stable over time we split the AAII data into three subperiods of about equal length and apply our bootstrap procedure to these subsamples. The third subsample spans exactly the same period as our German sample. Table 7 shows that the negative relation between the AAII index and subsequent returns disappears over time.It is very pronounced and highly significant in the 1987-1994 sample. In the 1994-2001 sample the coefficients retain their sign but are smaller in magnitude and (at least when considering the bootstrap results) except for that for the four-week horizon insignificant. In the last subperiod most coefficient estimates are positive, and the coefficients for the one- and four-week horizons significant at the 10 percent level. In this subperiod then, the results for the US are qualitatively similar to those for Germany documented in Table 3. There, we also found coefficients that were unanimously positive and significant for short forecasting horizons.

The differences that are apparent from a comparison of Table 3 and Table 6 are thus not primarily due to differences between Germany and the US but are rather caused by changes in the predictive power of our US sentiment indicator over time. We can only

Table 5:

Sentiment Coefficient in k-Week Regressions for Individual 6 Month DAX Sentiment

Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0327**	0.013	0.0342**	0.046
4 weeks	0.0896***	0.000	0.0970*	0.067
8 weeks	0.1109***	0.000	0.1270	0.138
13 weeks	0.0771***	0.004	0.1010	0.372
26 weeks	-0.0767	0.887	-0.0399	0.792

The table presents β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)}$ from OLS estimations and bootstrap simulations as explained in the appendix. Results are for horizons of k weeks. Controls are the variables listed in section 2.1. Sig. level denotes the p-values obtained from the distributions of coefficients obtained from the bootstrap, rather than assuming a normal distribution. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

speculate about the reasons for this change. One possible explanation could be the change in the way the AAII survey is conducted. Traditionally, votes were collected by mail which resulted in a lag of some days. This lag was removed when AAII started to collect the votes via the internet in 2000. Besides that, the change in the procedure may have affected the composition of the subgroup of AAII members responding to the survey. Finally, it is conceivable that the characteristics of the AAII members in general have changed over time.

4 Announcement Day Effects

4.1 Results for Germany

Having established that the German investor sentiment survey Sentix is indeed able to predict the future market movement of the DAX index, we now test whether the market reacts to the publication of the sentiment indicator. To this end we regress daily DAX log returns $r_{t-1,t}^{DAX}$ on their first lag and on the variable $Sentiment_t$ which captures the information content of the sentiment indicator. Because the Sentix index is published on Sunday evenings or on Monday mornings prior to the start of trading the variable $Sentiment_t$ is non-zero on Mondays and zero from Tuesdays to Fridays. We furthermore

Table 6:

Sentiment Coefficient in k-Week Regressions for AAII Sentiment and S&P 500

Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0024	0.810	0.0028	0.445
4 weeks	-0.0159***	0.002	-0.0010	0.356
8 weeks	-0.0252***	0.000	-0.0171	0.306
13 weeks	-0.0433***	0.000	-0.0320	0.255
26 weeks	-0.0729***	0.000	-0.0607**	0.045

The table presents β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)}$ from OLS estimations and bootstrap simulations as explained in the appendix. Results are for horizons of k weeks. Controls are the variables listed in section 2.1. Sig. level denotes the p-values obtained from the distributions of coefficients obtained from the bootstrap, rather than assuming a normal distribution. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

include lagged log returns of the S&P 500 index, $r_{t-2,t-1}^{S\&P500}$, which are known to investors as additional information and are published on Friday evenings and hence, before the time window of the Sentix survey participation closes.[7] Finally, we include a Monday dummy $\mathbf{1}_{Monday_t}$ to capture possible day-of-the-week effects. For daily returns, problems induced by serial correlation are not an issue. However, the pattern of OLS residuals indicates strong ARCH effects, which we account for by specifying a GARCH(1,1) model. We estimate the following equation:

$$
\begin{aligned}
r_{t-1,t}^{DAX} &= a_0 + a_1 Sentiment_t + a_2 r_{t-2,t-1}^{DAX} + a_3 r_{t-2,t-1}^{S\&P500} + a_4 \mathbf{1}_{Monday_t} + e_t \qquad (2) \\
\sigma_t^2 &= b_0 + b_1 e_{t-1}^2 + b_2 \sigma_{t-1}^2.
\end{aligned}
$$

We estimate three specifications.[8] In the first, sentiment is measured by the level of the Sentix value index. The second specification uses the change in the value index rather than its level. The third specification includes unexpected changes in the value index. We obtain the unexpected changes by first regressiing the sentiment index on its lagged

[7] If we omitted the lagged S&P500 returns, the sentiment indicator could be significant merely due to the possibility that it served as a proxy for the US stock returns after the close of trading in Germany.

[8] In additional regressions (not shown) we test whether the market reaction is already incorporated in the Monday morning level of the DAX. The results are insignificant, indicating that the announcement day effect is gradually incorporated in the course of the trading day.

values and lagged DAX and S&P 500 returns and then using the residuals from this regression This procedure is implemented using rolling windows. Thus, the first-pass regression used to identify the unexpected component of the sentiment index only uses information available at time (t-1). Results are depicted in table 8.

We find a significant announcement day effect irrespective of the specification used. Thus, all three sentiment variables are significantly positively related to daily closing log returns. Hence, the market seems to react to the publication of the investor sentiment index. Market participants buy after a rise and sell after a decrease in the sentiment indicator. Lagged index returns are highly significant, while we find no evidence for a Monday effect on the German stock market.

The announcement day effect is positive and thus has the same sign as the intermediate-horizon predictabilit documented in section 3.1. This pattern is inconsistent with the sentiment indicator providing information about future expected returns. In this case we would expect the announcement day effect to have the opposite sign as that in the intermediate-horizon predictive regressions. Thus, our results support a misvaluation interpretation of the predicitve power of sentiment indicators.

In a final step we investigate whether it is one of the sub-indices (i.e., the institutional or individual investor subindex) that induces the announcement day effect. We do this by testing for the significance of the institutional and individual sentiment separately. Table 9 shows that the reactions to the institutional and individual sentiment indicators are similar with reactions to changes in sentiment being more pronounced for the individual investors. Hence, it appears that the market reacts to the aggregate index (which is distributed more broadly than the subindices).

4.2 Results for the US

We conduct an equivalent analysis as above for the AAII sentiment survey. Judging from the long term regression results, we would expect there might be a negative reaction to the publication of the sentiment indicators at least in the first part of the sample period. Indeed, as can be seen from the first panel of table 10, for the whole period there is no significant announcement day reaction to the AAII sentiment survey publication. Considering the same subsamples as before, we find that the publication of the sentiment index triggers a negative announcement day effect in the first subsample. The respective coefficient is significant (at the 10% level or better) in two out of three specifications. For the later subsamples we do not find a significant announcement day effect. This is not surprising because the predictive regressions presented earlier led to the conclusion that the AAII index is largely unrelated to future returns in these subperiods.

The announcement day effect has the same sign as that of the coefficients in the predictive regressions presented earlier. Thus, the results for the US, like those for Germany, are inconsistent with the expected return news scenario. Rather, they support the interpretation that investor sentiment is related to misvaluation.

5 Conclusion

If sentiment indicators predict future stock returns at intermediate and long horizons (as is suggested by previous empirical research) smart traders can be expected to exploit the information conveyed by the indicator and thus trigger an immediate market response to the publication of the sentiment indicator. The sign of the immediate price reaction will be the same as the sign of the intermediate and long-horizon predictability. If, on the other hand, sentiment indicators provide new information on future expected returns, the sign of the immediate price reaction will be the opposite of the sign of the intermediate and long-horizon predictability.

The present paper is the first to empirically analyze whether an immediate market reaction can be identified in the data and whether the sign of the immediate reaction corresponds to the sign of the intermeidtae and long-horizon predictive ability. We use survey-based sentiment indicators from the US (the AAII sentiment index) and for Germany (the Sentix index). In a first step we replicate earlier results showing that the sentiment indicators indeed have predictive power for future stock market returns at intermediate horizons. We further document that the predicitve power of the AAII index has largely disappeared in recent years.

Surprisingly, the sentiment indicator is negatively related to future index returns in the US but is positively related to future returns in Germany. A tentative explanation for these different findings is that the US sentiment index indicates current mispricing while the German index indicates future mispricing. The coefficient patterns which we find for different forecasting horizons are consistent with this explanation. The slope coefficients in the predictive regressions for Germany are largest for the 8 and 13 week forecasting horizons but fall back to almost zero for the 26 week horizon.

In the second step of our analysis we use event study methodology to test whether daily index returns respond to the publication of the sentiment indicator. We do find a significant positive announcement day effect in Germany. This pattern is consistent with mispricing and limited arbitrage. Smart investors are aware of the predictive power of the sentiment indicator and trade accordingly. However, they do not fully arbitrage the predictability away, possibly because of increased noise trader risk (as in the model of de Long et al. (1990)). For the US market there is evidence of a negative publication day effect in the 1987-1994 subperiod. As in the case of Germany this result is consistent with the mispricing scenario and limited arbitrage. In later subperiods there is no significant publication day effect. This comes as no surprise because the intermediate to long-horizon predictability also disappears towards the end of the sample period.

Notwithstanding the differences between the results for Germany and the US , the results for both countries share one characteristic. They are both consistent with a mispricing interpretation of the predicitve power of sentiment and inconsistent with the hypothesis that the sentiment indicator contains information about future expected returns.

Appendix

Similar to Brown and Cliff (2005), we regress future k-week returns on current sentiment and control variables

$$(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)},$$

where variables are defined as in section xy. The fact that we use overlapping observations for the regressand induces an $MA(k-1)$ structure in the error terms under the null hypothesis that $\epsilon^{(1)}$ is serially uncorrelated. Since robust standard errors, suggested by Hansen and Hodrick (1980), are known to perform poorly in small samples and the existence of persistent regressors leads to a bias in the coefficient estimates, we opt for a simulation approach to account for the bias and to obtain appropriate critical values for inference.

We replicate the bootstrap simulation of Brown and Cliff (2005), pp. 437, and start by estimating a VAR(1) model for $y_t = [r_t SX_t z_t']$. After the estimation, we impose the null hypothesis that the sentiment Sentix survey does not predict 1-week returns by setting the appropriate element in the coefficient vector of the return equation equal to zero. We then adjust the constant in the constrained model by adding the contribution of average sentiment to returns obtained by multiplying the original slope value of sentiment by the average sentiment level to the constant of the return equation. We bootstrap the residuals from the calibration estimations to account for heteroscedasticity, and generate and discard 100 additional observations to delete possible starting effects. In each of the replications, a number equal to our original sample of simulated observations is used to estimate our equation of interest for horizons from one to 26 weeks. Analogous to Brown and Cliff, we repeat the procedure 10,000 times in order to obtain a distribution of the values of $\hat{\beta}(k)$.

In order to gauge the statistical significance of the coefficient estimates we compare the sentiment coefficient of the original model with the simulated probability distribution to obtain p-values. Because these p-values are based on the actual distribution of the residuals they are robust to deviations from the normal distribution.

Table 7:

Sentiment Coefficient in k-Week Regressions for AAII Sentiment and S&P 500

07/1987 to 06/1994				
Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	-0.0054*	0.090	-0.0045	0.518
4 weeks	-0.0526***	0.000	-0.0403**	0.046
8 weeks	-0.0699***	0.000	-0.0625**	0.047
13 weeks	-0.1158***	0.000	-0.0920**	0.024
26 weeks	-0.1746***	0.000	-0.1400**	0.012
07/1994 to 01/2001				
Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	Sig. level	$\tilde{\beta}^{SIM}$	Sig. level
1 week	-0.0015	0.827	-0.0005	0.958
4 weeks	-0.0520***	0.000	-0.0439**	0.042
8 weeks	-0.0550***	0.009	-0.0426	0.183
13 weeks	-0.0618**	0.022	-0.0447	0.268
26 weeks	-0.1118***	0.000	-0.0859	0.115
02/2001 to 06/2008				
Reg. Horizon	OLS		Bootstrap	
	$\hat{\beta}^{OLS}$	(t-stat.)	$\tilde{\beta}^{SIM}$	Sig. level
1 week	0.0100	0.338	0.0108*	0.086
4 weeks	0.0219	0.458	0.0287*	0.073
8 weeks	0.0200	0.897	0.0299	0.191
13 weeks	0.0168	0.308	0.0282	0.316
26 weeks	-0.0182***	0.000	-0.0061	0.842

The table presents β coefficients of equation $(r_{t+1} + ... + r_{t+k}) = \alpha(k) + \Theta'(k)z_t + \beta(k)SX_t + \epsilon_t^{(k)}$ from OLS estimations and bootstrap simulations as explained in the appendix. Results are for horizons of k weeks. Controls are the variables listed in section 2.1. Sig. level denotes the p-values obtained from the distributions of coefficients obtained from the bootstrap, rather than assuming a normal distribution. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8: Estimation Results for Daily DAX Log Returns of Closing Prices

Specification	(1)	(2)	(3)
	Coef.	Coef.	Coef.
Variable	$(\|t-stat.\|)$	$(\|t-stat.\|)$	$(\|t-stat.\|)$
$Sentix_t$	0.013**		
	(2.47)		
$\Delta Sentix_t$		0.025***	
		(2.73)	
$InnoSentix_t$			0.026***
			(2.58)
$r^{DAX}_{t-2,t-1}$	-0.185***	-0.188***	-0.202***
	(7.19)	(7.03)	(7.20)
$r^{S\&P500}_{t-2,t-1}$	0.368***	0.374***	0.385***
	(12.41)	(11.88)	(11.63)
$\mathbf{1}_{Monday_t}$	-0.002*	4e-04	6e-05
	(1.71)	(0.72)	(0.11)
$Const.$	7e-04***	7e-04***	7e-04***
	(2.70)	(2.69)	(2.85)
$Obs.$	1,916	1,911	1,695
$Adj.R^2$	0.045	0.046	0.049

Remark: ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively. We estimate the models by OLS and fit a GARCH(1,1) model to account for time-varying volatility.

Table 9: Estimation Results for Daily DAX Log Returns of Closing Prices (Institutional and Individual Investor Sentiment)

	Institutional Investors			Individual Investors		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Variable	$(\lvert t-stat.\rvert)$	$(\lvert t-stat.\rvert)$	$(\lvert t-stat.\rvert)$	$(\lvert t-stat.\rvert)$	$(\lvert t-stat.\rvert)$	$(\lvert t-stat.\rvert)$
$Sentix_t$	0.013***			0.009**		
	(3.20)			(1.99)		
$\Delta Sentix_t$		0.008			0.025***	
		(1.32)			(3.08)	
$InnoSentix_t$			0.013**			0.024**
			(2.05)			(2.45)
$r^{DAX}_{t-2,t-1}$	-0.185***	-0.187***	-0.202***	-0.185***	-0.187***	-0.202***
	(7.22)	(7.02)	(7.18)	(7.16)	(7.00)	(7.17)
$r^{S\&P500}_{t-2,t-1}$	0.366***	0.373***	0.385***	0.369***	0.374***	0.386***
	(12.16)	(11.93)	(11.57)	(12.51)	(11.86)	(11.68)
$\mathbf{1}_{Monday_t}$	-0.002**	4e-04	1e-04	-0.001	4e-04	1e-04
	(2.01)	(0.66)	(0.22)	(0.25)	(0.72)	(0.22)
$Const.$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(2.63)	(2.70)	(2.85)	(2.71)	(2.69)	(2.86)
$Obs.$	1,916	1,911	1,695	1,916	1,911	1,695
$Adj.R^2$	0.044	0.045	0.049	0.044	0.045	0.049

Remark: ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively. We estimate the models by OLS and fit a GARCH(1,1) model to account for time-varying volatility.

Table 10: Estimation Results for Daily S&P 500 Log Returns of Closing Prices

	07/1987 to 06/2008			07/1987 to 06/1994		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
Variable	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)
$AAII_t$	0.000			-0.005**		
	(0.17)			(2.43)		
$\Delta AAII_t$		-0.001			-0.003	
		(0.77)			(1.23)	
$InnoAAII_t$			-0.000			-0.004*
			(0.06)			(1.71)
$r_{t-2,t-1}^{S\&P500}$	-0.007	-0.007	-0.007	0.006	0.003	0.011
	(0.43)	(0.48)	(0.47)	(0.20)	(0.10)	(0.46)
$\mathbf{1}_{Monday_t}$	0.000	0.000	0.000	0.001	0.001	0.001**
	(1.15)	(1.17)	(1.40)	(1.22)	(1.33)	(2.18)
$Const.$	0.000***	0.000***	0.000***	0.000	0.000	0.000
	(3.50)	(3.63)	(3.06)	(1.58)	(1.28)	(0.42)

	07/1994 to 01/2001			02/2001 to 06/2008		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
Variable	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)	Coef. ($\|t-stat.\|$)
$AAII_t$	-0.001			0.002		
	(0.31)			(0.86)		
$\Delta AAII_t$		0.002			-0.001	
		(0.54)			(0.49)	
$InnoAAII_t$			0.001			0.001
			(0.24)			(0.30)
$r_{t-2,t-1}^{S\&P500}$	0.041	0.041	0.041	-0.061**	-0.061**	-0.061**
	(1.53)	(1.54)	(1.54)	(2.40)	(2.40)	(2.39)
$\mathbf{1}_{Monday_t}$	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.62)	(0.60)	(0.58)	(0.58)	(0.44)	(0.44)
$Const.$	0.001***	0.001***	0.001***	0.000	0.000	0.000
	(4.04)	(4.32)	(4.23)	(0.98)	(1.28)	(1.28)

Remark: ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively. We estimate the models by OLS and fit a GARCH(1,1) model to account for time-varying volatility.

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