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The Impact of Investor Sentiment on the German Stock Market

P. Finter • A. Niessen-Ruenzi • S. Ruenzi

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Philipp Finter[†]

Alexandra Niessen-Ruenzi

Stefan Ruenzi

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Abstract

This paper develops a broad-based sentiment indicator for Germany and investigates whether investor sentiment can explain stock returns on the German stock market. Based on a principal component analysis, we construct a sentiment indicator that condenses information of several well-known sentiment proxies. We show that this indicator explains the return spread between sentiment sensitive stocks and stocks that are not sensitive to sentiment fluctuations. Specifically, stocks that are difficult to arbitrage and hard to value are sensitive to the indicator. However, we do not find much predictive power of sentiment for future stock returns.

JEL-Classification Codes: G12, G14

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[*] Finter is at Sal. Oppenheim jr. & Cie. AG & Co. KGaA, Asset Allocation, Unter Sachsenhausen 4, 50667 Köln, Tel. ++49-221-145-2532, Fax ++49-221-145-92532, e-mail: Philipp.Finter@oppenheim.de. Niessen-Ruenzi and Ruenzi are at the University of Mannheim, L9, 1-2, 68131 Mannheim, Germany. Niessen-Ruenzi: Tel. ++49-621-181-1595, Fax ++49-621-181-1664, e-mail: niessen@bwl.uni-mannheim.de. Ruenzi: Tel. ++49-621-181-1640, Fax ++49-621-181-1664, e-mail: ruenzi@bwl.uni-mannheim.de. Finter acknowledges financial support from the Centre for Financial Research (CFR) Cologne. We thank Laurens Swinkels, Gabriele M. Lepori, and participants of the SGF annual meetings, the FMA European meetings, CFR Intern Seminar, and the European Retail Investment Conference for their helpful comments and suggestions. All errors are our own.

[†] Corresponding Author

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Abstract

This paper develops a broad-based sentiment indicator for Germany and investigates whether investor sentiment can explain stock returns on the German stock market. Based on a principal component analysis, we construct a sentiment indicator that condenses information of several well-known sentiment proxies. We show that this indicator explains the return spread between sentiment sensitive stocks and stocks that are not sensitive to sentiment fluctuations. Specifically, stocks that are difficult to arbitrage and hard to value are sensitive to the indicator. However, we do not find much predictive power of sentiment for future stock returns.

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1. Introduction

This paper develops a new investor sentiment indicator for Germany and investigates the impact of sentiment on the German stock market. The question whether irrational sentiment or mood of investors has an impact on asset prices is extensively discussed in the finance literature. Several theoretical and empirical papers have shown that investor sentiment has a strong impact on stock prices with important implications for portfolio selection and asset management (see, e.g., Barberis, Shleifer, and Vishny (1998), Kumar and Lee (2006), and Baker and Wurgler (2006)).

The question whether investor sentiment has an impact on stock prices is of foremost importance because investor sentiment can lead to market bubbles followed by massive devaluations (see, e.g., Brown and Cliff (2004)). Two large stock market crashes during the last decade, i.e. the tech bubble crash in 2000 and the real estate bubble crash in 2008, underline the severe consequences of investor sentiment on asset prices. In addition, several papers have shown that there are profitable trading strategies that take advantage of stock price movements caused by investor sentiment (see, e.g., Baker and Wurgler (2006), Fisher and Statman (2000)). However, most of the papers on sentiment focus on the U.S. stock market and rely on the notion that it is mainly retail investors who are affected by sentiment waves and who cause stock prices to drift away from their fundamental values (Kumar and Lee (2006)). These papers implicitly assume that institutional investors are more rational in their trading behavior whereas retail investors are responsible for the impact of sentiment on markets. Therefore, it is important to test the robustness of findings from the U.S. market for other markets that are characterized, for example, by a different composition of the investor population. We address this issue by developing a broad based sentiment indicator for Germany and using this new indicator to provide out-of sample evidence on the impact of investor sentiment for the German stock market.

Specifically, the German stock market has some characteristics that might lead to a different reaction of stock returns to investor sentiment. Most importantly, the free float of German stocks is very small while it is about 80% in the U.S. (see, e.g., Faccio and Lang (2002)). In a study based on all non-financial companies listed on the 'official' trading segment of the Frankfurt Stock Exchange, Andres (2008) finds that 84.5% of all constituents have one large shareholder with a stake of more than 25%. More importantly, the share of retail investors is much lower in Germany than on the U.S. stock market and most other developed markets: Only 5.2% of the German population are shareholders (DAI-Factbook, 2009). This is a very low proportion relative to all other major capital markets including the U.S. (25.4%), Japan (27.7%), or U.K. (23.0%) and gives rise to the question whether investor sentiment plays any role on the German stock market.

To investigate the impact of investor sentiment on the German stock market we first compute a condensed measure of investor sentiment. The measurement of investor sentiment is difficult and the literature has proposed numerous sentiment proxies (see, e.g., Qiu and Welch (2006)). While all of these proxies are likely to capture some aspect of sentiment, they also contain an idiosyncratic, non-sentiment related, component. Thus, it is difficult to choose a specific 'best' proxy out of the individual proxies suggested in the literature. To circumvent this problem, we follow the approach suggested in Brown and Cliff (2004), Baker and Wurgler (2006), and Glushkov (2009): based on a principal component analysis (PCA) of various empirical sentiment proxies, we condense the information that is provided by these proxies. The individual sentiment proxies we consider are consumer confidence, aggregate net flows into equity mutual funds, put-call ratio, aggregate trading volume, IPO returns and number of IPOs, as well as the equity to debt ratio of new issuances. After several robustness checks, we identify the best combination of these proxies and construct an overall German sentiment indicator (GSI). Showing in detail how the GSI can be constructed (and providing it for the use of other researchers) is one of the main contributions of this paper.

To test whether our new indicator is valid, we correlate it with the returns of stocks that have been identified to be sensitive to sentiment fluctuations. The literature identifies these "sentiment sensitive stocks" based on proxies for limits of arbitrage, difficulty of objective valuation, and the investor clientele of a firm. The rationale behind this is that arbitrageurs cannot arbitrage away sentiment-driven misvaluations caused by unsophisticated investors if limits of arbitrage are severe. We find that the returns of sentiment sensitive stocks correlate much stronger with our sentiment proxy than the returns of other stocks. In addition our sentiment proxy peaks at the tech bubble and sharply decreases afterwards. Both results support the validity of our sentiment indicator.

The sentiment effects we document have important implications for the portfolio selection of asset managers. For example, mutual funds typically face inflows in periods of positive sentiment and outflows in periods of negative sentiment (see, e.g., Indro (2004)). They have to react to flows by buying or selling assets. Thus, if they would only hold very sentiment sensitive stocks, they would have to sell (buy) these stocks due to flows at exactly the time when they trade at prices which are too low (high). Therefore, asset managers whose money inflows and outflows depend on investor sentiment might want to avoid putting too much weight on sentiment sensitive stocks in their portfolios.

Additionally, we investigate the predictive power of investor sentiment for future stock returns. We find only weak explanatory power of our sentiment indicator for future stock return spreads between sentiment sensitive and sentiment insensitive stocks. The latter effect is mainly driven by periods following negative sentiment.

Overall, our results suggest that investor sentiment plays an important role for contemporaneous returns in Germany. However, unlike suggested by evidence for the US, sentiment in Germany does not seem to generally cause mispricing over extended periods of time that would allow for highly profitable trading strategies. These findings are consistent with the idea that the lower fraction of retail investors in Germany leads to a lower level and a shorter horizon of sentiment driven mispricing of stocks. Because the market is dominated by institutional investors, they will quickly observe the relative mispricing of sentiment sensitive stocks that we document and correct it. However, at the same time, the group of sentiment investors is important enough even in Germany to give rise to the documented impact of sentiment on contemporaneous returns. Given that the group of retail investors (the main suspect of investors that are subject to sentiment) is relatively small in Germany, this result would be consistent with them being important enough even in Germany or with at least a fraction of institutional investors being subject to sentiment as well.

Our paper contributes to the large literature on the impact of investor sentiment on stock returns (see, e.g., Shleifer and Vishny (1997), Neal and Wheatley (1998), Qiu and Welch (2006), Baker and Wurgler (2006), Kumar and Lee (2006)). We show that although the German stock market differs in several aspects from the U.S. stock market, investor sentiment has a significant impact on contemporaneous German stock market returns, too. However, closely following the established methodology of Baker and Wurgler (2006), we are not able to find strong predictive power of sentiment in Germany. The papers most closely related to ours are some studies on the German stock market: Schmeling (2009) uses consumer confidence as a proxy for sentiment and finds a negative impact on future aggregated returns over forecast horizons up to 24 months. Hengelbrock, Theissen, and Westheide (2010) also use a poll-based measure, the Sentix index, and document a positive relation to future DAX30 returns for intermediate horizons. Burghardt, Czink, and Riordan (2008) find that investor sentiment measured based on transactions in bank-issued warrants is negatively correlated with current DAX30 returns, while Schmitz, Glaser, and Weber (2009) find that DAX30 returns have a negative impact on sentiment and sentiment has a positive impact on DAX30 returns for the next trading day only. Finally, in an international study of six stock markets including Germany, Baker, Wurgler, and Yuan (2011) find some evidence for a negative relationship between sentiment and future aggregate stock market returns. However, their study does not report results for Germany individually and their sentiment index is based on a small set of only three market-based proxies. Besides looking at a much broader sample of virtually all German stocks rather than only blue chip index returns, our results differ from these papers in several important aspects: (i) We not only focus on one specific sentiment proxy. Rather we show how the information from several important sentiment proxies for Germany can be used to extract their common component based on a PCA. In doing so, we get a cleaner measure of investor sentiment and are not subject to any data-mining concerns. (ii) Additionally, none of the existing papers on sentiment in Germany takes into account the potential impact of systematic risk exposures by controlling for the Fama and French (1993) and Carhart (1997) risk factors, while our paper does so. (iii) Our paper is also the first to develop a comprehensive German sentiment indicator based on market data. (iv) Furthermore, we contribute to the literature by examining for the first time how sentiment explains contemporaneous cross-sectional return differences between sentiment sensitive stocks and sentiment insensitive stocks in Germany. (v) Finally, our paper is also the first analysis of sentiment in Germany that conducts an adjustment for the impact of changing macro-economic conditions.

The paper proceeds as follows. Section 2 contains a description of the individual sentiment proxies and the stock market data used in our analysis. Section 3 develops a German sentiment indicator based on a PCA. In Section 4 we test whether the proposed sentiment indicator is able to explain and predict the return spread between sentiment sensitive stocks and non-sentiment sensitive stocks. Section 5 concludes.

2. Data

2.1 Stock Market Data and Sentiment Proxies

Our sample consists of 955 German stocks that are listed at the Frankfurt Stock Exchange between 1993 and 2006. Stock prices, adjusted for dividends, splits and equity offerings, are obtained from Karlsruher Kapitalmarktdatenbank (KKMDB) in Germany and are used to calculate monthly returns. Our sample covers virtually the complete market capitalization. Particularly, it also contains many small, risky and hard to arbitrage stocks that are arguably most sensitive to sentiment fluctuations (see, e.g., Baker and Wurgler (2006)).

Investor Sentiment can be measured based on two different approaches. First, investor sentiment can be elicited by surveys that directly ask individuals how they feel about current or future economic and stock market conditions. We refer to these survey based measures as *explicit sentiment proxies*. Second, investor sentiment can be measured based on market variables. These indirect measures of sentiment use trading patterns, price movements, or other market statistics to derive the overall degree of investor sentiment. We refer to these measures as *implicit sentiment proxies*. In the following, we describe the specific implicit and explicit sentiment proxies that we will use in our analysis. A detailed description of these proxies is also included in Panel A of the Appendix of this paper.

E*xplicit sentiment proxies* that are mostly used in the sentiment literature are consumer confidence surveys (see, e.g., Bram and Ludvigson (1998)). Therefore, we include the monthly series of GFK consumer confidence index, GFK_m, in our analysis. This index is published by the Gesellschaft für Konsumforschung (GFK) and obtained via Bloomberg. The index measures the level of confidence households have in current and future economic performance. Consumer confidence indices are one of the most important investor sentiment indicators (see, e.g., Otoo (1999), and Qiu and Welch (2006)) and are thus indispensable in our PCA.

There are two other survey based sentiment indicators that have been developed for the German stock market. The G-Mind (German Market Indicator) is published monthly by the Centre for European Economic Research, ZEW. In this survey, analysts and institutional investors are asked about their stock and bond market expectations on a monthly basis. Based on their answers, the ZEW computes the G-Mind index. The Sentix indicator is published weekly by the sentix GmbH. It is based on an internet survey in which individuals can participate on a voluntary basis. Among other questions, participants are asked about their stock market expectations for different horizons.[1] Based on their answers, sentix GmbH calculates a sentiment index, labelled as 'Sentix'. If we include the Sentix or the G-Mind in our principal component analysis (results not reported), the first does not load on the first principal component at all, while the G-Mind exhibits a large and negative loading on the first principal component. This is opposite of what we would expect if it would capture sentiment. Since these results cast some doubt on the usefulness of historical Sentix and G-Mind data to capture sentiment, we do not include these survey-based measures as additional sentiment proxies in our PCA.[2]

Although several papers rely on surveys to measure investor sentiment (see, e.g., Brown and Cliff (2004), Brown and Cliff (2005), Otoo (1999)), the use of surveys can also be problematic because of inaccurate responses (see, e.g., Campbell (2003)), misunderstood questions (see, e.g., Betrand and Mullainathan (2001)), and non-response biases (Groves (2006)). Therefore, papers such as Lee, Thaler, and Shleifer (1991) and Dorn (2009) suggest to use market variables as *implicit sentiment proxies* instead.

Baker and Stein (2004) argue that *aggregate trading volume* is a good proxy for investor sentiment. In a market with short-sale constraints, investors only participate when they are optimistic. Especially individual investors tend to overreact to new information and have a tendency to trade in concert (see, e.g., Kumar and Lee (2006), Lee and Swaminathan (2000)). Thus, trading volume increases when investor sentiment is high. In support of this view, Jones (2002) finds that high turnover forecasts low aggregate market returns. Therefore, we use trading volume, $TradVol_m$, defined as trading volume in million EUR in a given month divided by the total number of listed firms in this month as an implicit sentiment proxy in our PCA.[3]

Net fund flows are proposed as a sentiment indicator by Frazzini and Lamont (2008) and Indro (2004). In times of high investor sentiment, individual investors cumulatively buy mutual funds (see, e.g., Brown and Cliff (2004)). We obtain monthly data on net fund flows, $Flows_m$, by Deutsche Bundesbank and include them in our analysis. They are computed as the aggregate difference between inflows and outflows of German open end equity mutual funds.[4]

We also use *IPO Returns* and *IPO Activity* as sentiment proxies as proposed by Baker and Wurgler (2006), Cornelli, Goldreich, and Ljungqvist (2006), and Glushkov (2009). IPO activity is strongly correlated with market conditions. For example, Loughran and Ritter (1995) state that corporate executives time their IPOs to take advantage of fluctuations in investor sentiment. Similar evidence for Germany is provided in Oehler, Rummer, and Smith (2005). As a measure for IPO activity we simply compute the number of IPOs in a given month, $IPO\text{-}Num_m$. IPO returns are calculated as the difference between the IPO offer price and the initial price of the stock at the beginning of the first trading day. We use equal-weighted IPO returns in a given month, $IPO\text{-}Ret_m$, in our analysis.[5] We compute the number of IPOs per month and IPO returns based on data collected from Deutsche Börse AG, DAI Factbooks, and Hoppenstedt Aktienführer.[6]

Based on a similar logic, we also use a firm's *equity debt ratio* to measure investor sentiment. According to Baker and Wurgler (2000), investor sentiment causes equity to be overvalued. Thus, managers who try to time the market prefer to issue equity rather than debt when sentiment is high, and vice versa. We calculate the ratio of aggregate equity issuance to aggregated debt issuance, $E/D\text{-}Ratio_m$, based on data from Deutsche Bundesbank. Issuances from government or state agencies are excluded.

Finally, we use the put-call ratio, which is also a prominent proxy for investor sentiment (see, e.g., Dennis and Mayhew (2002), Brown and Cliff (2004)). The put-call ratio measures how bullish or bearish the market is. In times when most stocks perform strongly, the number of calls bought typically far outweighs the number of puts bought, resulting in a relatively low put-call ratio. The opposite holds in times when most stocks perform poorly. We compute the ratio of the volume of call and put options in month *m* based on all German stock options as the number of calls traded divided by the number of puts traded. The data are acquired from Deutsche Börse AG. Note, that this ratio is the *inverted* put-call ratio, which we thus label $IPCR_m$. We use the inverted version as this unifies the interpretation of the impact of all variables because it increases when sentiment is positive. Thus, all sentiment proxies in our analysis should now be positively related to sentiment.

While some of our sentiment proxies are available for a longer time period, all of these proxies are available starting in 1993 at the very latest. Thus, our study covers the years 1993 to 2006. Summary statistics of the individual sentiment proxies are presented in Table 1. As is evident from these figures, the various sentiment proxies are measured on different scales. While trading volume is measured in absolute Euro values divided by the number of firms in a given month and net fund flows is measured in absolute Euro values, inverted put-call ratio and IPO returns are measured in relative terms, and consumer confidence is published as an index with a midpoint of zero. Correlations between all sentiment proxies are presented in Table 2. They show that our sentiment proxies are strongly correlated. All of the correlations are in the expected direction: all proxies are positively correlated. For example, the correlation between GFK consumer confidence and net fund flows (IPO returns) is 0.53 (0.52). Most correlations are also highly statistically significant. This strongly suggests that there is some common underlying component that is shared by these indicators. Therefore, we are confident that the indicators used in our analysis are useful to measure investor sentiment. Nevertheless, the correlation between the indicators is not perfect which underlines the potential gain in measurement accuracy by extracting the common component all indicators share by conducting a PCA.

2.2 Orthogonalization of Sentiment Proxies

It is very likely that some of the sentiment proxies described above are related to the current economic situation. Thus, to make sure that our results are not driven by fluctuations in macroeconomic conditions rather than fluctuations in sentiment, we adjust our sentiment proxies for the influence of business cycle fluctuations. Following Baker and Wurgler (2006), we use macroeconomic data on growth rates in industrial production, inventory orders, factory orders, retail sales, and employment levels for this adjustment. The macroeconomic variables and data sources are described in Panel B in the Appendix. To get rid of seasonal trends, we compute the monthly growth rate of the 12 month moving averages of the indicators and use this transformation in our further analysis. For example, as industrial production growth rate for January 2000 we use the percentage growth between the average monthly industrial production over the period February 1999 to January 2000 and the average monthly industrial production of the period January 1999 to December 1999.

To orthogonalize our sentiment indicators, we run the following regression for each sentiment indicator *i*:

$$Sent_{i,m} = \alpha_i + \beta_{1,i} \cdot IndProd_{m+x1} + \beta_{2,i} \cdot InvOrd_{m+x2} + \beta_{3,i} \cdot FacOrd_{m+x3} + \beta_{4,i} \cdot RetSal_{m+x4} + \beta_{5,i} \cdot Empl_{m+x5} + \varepsilon_{i,m} \quad (1)$$

In this regression, $Sent_{i,m}$ is one of the sentiment variables described in Section 2.1. The explanatory variables are industrial production in month $m + x1$, $IndProd_{m+x1}$, inventory orders in month $m + x2$, $InvOrd_{m+x2}$, factory orders in month $m + x3$, $FacOrd_{m+x3}$, retail sales in month $m + x4$, $RetSal_{m+x4}$, and employment levels in month $m + x5$, $Empl_{m+x5}$, as described above. As published macroeconomic indicators can sometimes reflect relevant economic content with a lead or a lag, we follow Baker and Wurgler (2006) and include explanatory variables in (1) as contemporaneous variables or as lead or lag variables, respectively. To determine the appropriate lag structures $x1$ to $x5$ we first calculate the correlation between the respective proxy and various lags and leads of the macroeconomic variables from months -6 to +6 for the adjustment of each sentiment proxy individually and include the one with the highest correlation in our actual adjustment model. The resulting lead/lag structure that is used for each sentiment proxy in our macro-adjustments is presented in Table 3. It can be seen that the contemporaneous realization of the macroeconomic variable is typically chosen, i.e. it typically has the strongest correlation with the sentiment proxies. For example, in the macro-adjustment of the sentiment proxy mutual fund flows, $Sent_{i,m} = Flows_m$, we include the first lead of the employment growth variable, $Empl_{m+1}$, and the contemporaneous realization of all other macro-variables, $IndProd_m$, $InvOrd_m$, $FacOrd_m$, and $RetSal_m$.

In our following analysis, we will use the lead/lag structure presented in Table 3 and extract residuals $\varepsilon_{i,m}$ from the corresponding modification of regression (1). We normalize these residuals so they have a mean of zero and a standard deviation of one and label the resulting orthogonalized (macro adjusted) sentiment indicators as $Sent^A_{i,m}$.

3. Construction of a German Sentiment Indicator (GSI)

The various sentiment proxies described above are all plausible candidates to measure some aspect of sentiment - but even after macro-adjusting they still also have an idiosyncratic, non-sentiment related component. To circumvent the problem that all proxies partially capture other aspects of investor behavior, we now extract the principal components of our sentiment proxies and use the first principal component as our main measure of sentiment. This procedure follows Baker and Wurgler (2006) as close as possible to allow comparability of results. We conduct the PCA based on normalized sentiment proxies that are adjusted for fluctuations in macroeconomic conditions, $Sent_{i,m}^{A}$, as described in Section 2. We label this PCA as PCA(a). As a robustness check, we conduct PCA(a) based on normalized but unadjusted sentiment proxies, $Sent_{i,m}$. All sentiment proxies are included contemporaneously in our analysis. Results on the coefficient matrix for the first two principal components I and II are presented in the first two columns in Table 4.

Results in the first column of Panel A (Panel B) show that the first principal component derived from all sentiment proxies (PCA(a)) explains about 32% (37%) of the total variation in the macro-adjusted (unadjusted) sentiment proxies. The smaller explanatory power of the principal component based on macro-adjusted sentiment proxies is due to the fact that the joint impact of macroeconomic conditions is only influencing the unadjusted component. Furthermore, all sentiment proxies have the expected sign regarding their correlation with the principal component. As expected, we find positive correlations for all proxies.

Regarding the second principal component (Column 2), we find that some of the input factors are correlated with the second component in the opposite direction. Thus, it is unlikely that the second component also captures investor sentiment. Therefore, only the first principal component should be used as a proxy for sentiment.

Besides the PCA using all input variables (PCA(a)), we also look at a reduced set of input proxies, in order to avoid double counting of individual proxies that capture very similar aspects of sentiment. We label this reduced PCA as PCA(b). Specifically, equity debt ratio, number of IPOs, and the average IPO return all capture equity issuance activity, which we do not want to overweight in our analysis (see, e.g., Derrien and Kecskes (2009)). When looking at the macro-adjusted sentiment proxies (Panel A), however, only the average IPO return shows a high correlation of 57% with the first principal component. Therefore, in the reduced PCA(b), we only use the latter variable, because in contrast to the number of IPOs, IPO returns additionally include information on underpricing. The explanatory power of the PCA increases for our reduced set of input factors (PCA(b)), i.e. the first principal component explains about 43% (42%) of the total variation in the macro-adjusted (unadjusted) sentiment proxies in Column 3. This is due to the fact that fewer proxies are included in the construction of PCA(b) which mechanically increases the explained variance. The impact of the individual proxies on the first principal component in column 3 are very similar to those in PCA(a). Again, all correlations are in the expected direction. Thus, the first principal component seems to be a useful candidate for a German Sentiment Indicator. Furthermore, the second principal component again does not seem to capture sentiment.

One could argue that lagged stock market returns also serve as a sentiment proxy (see, e.g., Brown and Cliff (2004)). In addition, a high price level at the stock market might influence some of our sentiment proxies such as net fund flows. Therefore, we alternatively conduct a PCA which includes the previous month stock market return as an additional sentiment indicator (results not reported in tables). Specifically, we include either macro-adjusted or unadjusted, normalized, previous month CDAX returns in our PCA analysis. As expected, both variables load positively on the first principal component but their weight is lower than that of the other proxies. More importantly for our further analysis, the correlation between the first principal component of PCA(b) (macro-adjusted or unadjusted) and the first principal component of this analysis is 0.99. Thus, our further results do not differ if we include lagged stock market returns. To keep our sentiment index as simple as possible, we therefore do not include lagged CDAX returns in our further analysis.

The correlations between the first principal components are presented in Panel C of Table 4. The pair-wise correlations between the macro-adjusted and unadjusted first principal component are 68% and 81%, suggesting that macroeconomic factors are of importance in influencing time series fluctuations in sentiment proxies. Furthermore, the pair-wise correlations between the first principal component from PCA(a) and PCA(b) are between 93% and 98% for unadjusted as well as macro-adjusted data. Thus, little to no information is lost in dropping some of the variables capturing very similar aspects of sentiment. In the following analysis, we will use the first principal component from PCA(b) using macro-adjusted data and refer to this variable as the macro-adjusted German Sentiment Index (GSI_m^A). Our sentiment index looks as follows:

$$GSI_m^A = 0.320 \cdot GFK_m^A + 0.366 \cdot IPCR_m^A + 0.260 \cdot TradVol_m^{A,ta} + 0.294 \cdot Flows_m^A \\ +0.275 \cdot IPO\text{-}Ret_m^A, \qquad (2)$$

where all variables are defined as described above and in the Appendix. The relative importance of the impact of the individual proxies on the GSI can be directly assessed, because all proxies are normalized as described above before they are used in the PCA.[7] It can be seen that all individual sentiment proxies have a similar impact (around 0.3) in the equation for the GSI. Thus, all individual sentiment proxies contribute to our overall measure of sentiment, which supports the case for developing a sentiment indicator using PCA. This result generally remains stable if we look at sub-periods (1993-1999 and 2000-2006) and if we exclude the Tech-Bubble period (July 1999-June 2001).[8] Nevertheless, when updating the GSI, the PCA should be repeated in order to obtain updated weights which reflect a possible change in the relative importance of the individual sentiment proxies.
The development of the macro-adjusted sentiment index (GSI_m^A) and the unadjusted sentiment index (GSI_m) over time is plotted in Figure 1. It shows strong time-series variation. Confirming the validity of the sentiment indicator, we observe that sentiment is particularly high during the tech bubble and sharply declines afterwards.[9]

4. Properties of the German Sentiment Index (GSI)

4.1 Sentiment and Contemporaneous Returns

The coefficients of the individual sentiment proxies in Table 4 suggest that the first principal component reflects some joint information that all individual sentiment proxies contain. To validate that the information reflects investor sentiment, we now examine how the first principal component from PCA(b) relates to the differences between contemporaneous returns of stocks that are sensitive to sentiment fluctuations (sentiment sensitive stocks) and those that are not.

To test whether contemporaneous returns are affected by fluctuations in sentiment, we first sort firms into equal-weighted quintile portfolios depending on their sentiment sensitivity.[10] Strictly speaking, in doing so, we test the joint hypothesis that the sorting criterion used does capture the sentiment-sensitivity of a stock and that the GSI does actually capture sentiment, i.e. explains the returns of sentiment sensitive stocks.[11] To alleviate this potential concern, we use different sorting criteria to capture the sentiment sensitivity of a stock that are suggested in the literature.[12] These sorting criteria are generally based on proxies for limits of arbitrage, difficulty of objective valuation, and the investor clientele of a firm. For instance, Baker and Wurgler (2006) argue that in particular stocks of smaller, younger, unprofitable, high volatility, non-dividend paying stocks are strongly sensitive to investor sentiment because they are harder to arbitrage and more difficult to value. The same rationale holds for stocks with high idiosyncratic risk (see, e.g., Glushkov (2009)). Additionally, retail investors who are particularly prone to sentiment fluctuations typically carry out small trades. Thus, stocks with many small trades should also be more prone to sentiment fluctuations (see, e.g., Hvidkjaer (2008)).[13]

Except for profitability and dividends, portfolios are rebalanced every month. Portfolios formed on profitability and dividends are formed in June of each year based on previous year information. The conservative six month lag is imposed to ensure that the required accounting data is known before ranking. The returns of sentiment sensitive stocks are expected to be higher than returns of non-sensitive stocks in periods when sentiment is high, vice versa. The reason for this is that sentiment investors strongly buy stocks in concert during these periods which leads to inflated prices of sentiment sensitive stocks. Thus, if returns of sentiment sensitive stocks co-move more with our first principal component than non-sentiment sensitive stocks, this provides evidence that the first principal component is indeed a measure of investor sentiment.

After sorting firms into quintiles based on their sentiment sensitivity, we compute equal weighted returns for each of the five sentiment portfolios in month m. We also construct a difference portfolio, $Q(1)$-$Q(5)$, where we subtract the equal weighted return of the low sentiment portfolio $Q(5)$ from the equal weighted return of the high sentiment portfolio $Q(1)$. Finally, we validate our sentiment proxy by testing how sensitive the respective portfolio returns are to fluctuations of the sentiment proxy by relating the excess portfolio returns over the risk-free rate $Q(s)_m - r_m$ with $s = 1,...,5$, to the first principal component, GSI_m^A, using the following time-series regression:

$$Q(s)_m - r_m = \alpha + \beta^Q(s) \cdot GSI_m^A + \varepsilon_m \quad (3)$$

We expect $Q(1)$ to co-move much stronger with sentiment, GSI_m^A, than $Q(5)$, i.e. we expect $\beta^Q(1) > \beta^Q(5)$. Consequently, we also expect the return of the difference portfolio, $Q(1)$-$Q(5)$, to be positively related to GSI_m^A.

To control for the impact of the market return on returns of the sentiment portfolios, we alternatively also estimate a one-factor model where we include contemporaneous market returns as explanatory variable:

$$Q(s)_m - r_m = \alpha + \beta^Q(s) \cdot GSI_m^A + \beta_1 \cdot RMRF_m + \varepsilon_m \quad (4)$$

In this regression, $RMRF_m$ is the excess market return over the risk free rate in month m. As a proxy for the market portfolio we use the Deutscher Aktienforschungsindex (DAFOX), a value-weighted performance index calculated by Karlsruher Kapitalmarktdatenbank (KKMDB) for research purposes. The DAFOX is available until December 2004, afterwards we use the value-weighted CDAX performance index of Deutsche Börse AG as our market portfolio.[14] As a proxy for the monthly risk free rate we take the one-month money market rate as reported by Deutsche Bundesbank.

Furthermore, to control for a potential impact of size-, value-, and momentum-effects on the returns of our sentiment portfolios, we also estimate the Carhart (1997) four-factor model:

$$Q(s)_m - r_m = \alpha + \beta^Q(s) \cdot GSI_m^A + \beta_1 \cdot RMRF_m + \beta_2 \cdot SMB_m + \beta_3 \cdot HML_m + \beta_4 \cdot WML_m + \varepsilon_m \quad (5)$$

In this regression, SMB_m and HML_m denote the Fama and French (1993) size and value factors for Germany. SMB_m represents the return difference between a small firm and a large firm portfolio in month m. HML_m is the difference between the returns to portfolios of high and low book-to-market equity stocks in month m. WML_m represents the Jegadeesh and Titman (1993) momentum anomaly and is the return of a hedge-portfolio which is long in high past return stocks (winners) and short in low past return stocks (losers) in month m.[15]

The first sorting criterion that we use to identify sentiment sensitive stocks is volatility. Volatile stocks are more difficult to value and more difficult to arbitrage than less volatile stocks (see, e.g., Baker and Wurgler (2007)), i.e. limits to arbitrage that prevent sentiment-based price deviations from fundamental values to quickly disappear are eventually more severe for these stocks. Thus, volatile stocks should be more sentiment sensitive than less volatile stocks. We present results for this sorting criterion in some detail, before we summarize the results using alternative sorting criteria. Return volatility is measured as the standard deviation of monthly returns over the previous year. Consequently, *Q*(1) (*Q*(5)) now contains the stocks with the highest (lowest) volatility.

Descriptive statistics on our *Q(1) – Q(5)* volatility portfolios for each sample year are presented in Table 5. As expected, firms within the sentiment sensitive portfolio *Q(1)* are generally smaller in terms of market capitalization than sentiment insensitive firms in portfolio *Q(5)*. Average trade size is also smaller for sentiment sensitive firms. The overall number of firms in our sample increases substantially over time, with a particularly strong increase from 1999 to 2001.

To get a first impression on how the portfolio returns are related to sentiment, we visualize the loadings on our macro-adjusted (GSI_m^A) and unadjusted sentiment index (GSI_m), from model (5) for the quintile portfolios *Q*(1) to *Q*(5) in Panel A of Figure 2. The graphical pattern is consistent with our expectation. The loading on our sentiment index is clearly highest for sentiment-sensitive stocks (high volatility stocks) in the first quintile Q(1). It is much smaller or even negative for quintiles *Q(2)* to *Q(5)* with low to medium sensitive stocks. This result holds for both the macro-adjusted and the macro-unadjusted sentiment index. However, it is more pronounced for the macro-adjusted version of *GSI*. Overall, these results are consistent with our *GSI* actually capturing sentiment.

The underlying estimation results from model (5) as well as the detailed estimation results for models (3) and (4) are presented in Table 6. Consistent with the graphical impression, the results in Panels A to C clearly show that the return of the high volatility portfolio ($Q(1)$) strongly co-moves with sentiment, i.e. the higher investor sentiment, the higher the return of this portfolio. This result holds for all estimated models (3), (4) and (5).[16] In contrast, the return of the low volatility portfolio ($Q(5)$) is not significantly related to GSI_m^A in models (3) and (4) and significantly negatively related to GSI_m^A in model (5).[17] Most importantly, the difference portfolio between high and low sentiment sensitive stocks always yields a significantly positive coefficient on the sentiment indicator, i.e. the return spread between high and low volatility stocks can be explained by our sentiment indicator. This is a strong indication that the first principal component indeed reflects investor sentiment.

To provide further evidence that the first principal component is a useful measure of investor sentiment, we now use other sorting criteria that have been shown to reflect sentiment sensitivity of stocks. Results using these other sorting criteria are presented in the following section.

4.2 Other Sorting Criteria

According to the literature on investor sentiment, there are various other characteristics of stocks that allow differentiating between sentiment sensitive and non-sensitive stocks. We now use these sorting criteria to construct portfolios of (non-) sentiment sensitive stocks and then run the same regressions as in the previous section. The rationale for the different sorting criteria (idiosyncratic volatility, trade size, firm age, dividend payments, firm size, and profitability) as well as the detailed results will be described in the following.

Gao, Yu, and Yuan (2010) and Glushkov (2009) show that stocks with high *idiosyncratic risk* are more sensitive to investor sentiment than stocks with low idiosyncratic risk. The reason for this is that high idiosyncratic risk makes relative value-arbitrage risky (see, e.g., Wurgler and Zhuravskaya (2002)). Furthermore, stocks with high idiosyncratic risk are more costly to trade. We sort firms into quintiles based on their prior 12 month idiosyncratic volatility relative to a Carhart (1997) four-factor model and compute the equal weighted returns of each quintile portfolio.[18] We then calculate the return of the Q_1-Q_5 difference portfolio to estimate equations (3), (4), and (5). Consistent with results from the volatility sorts, results in Panel B of Figure 2 show that sentiment sensitive stocks in Quintile *Q(1)* are strongly positively related to GSI_m^A, while non-sentiment sensitive stocks in Quintile *Q(5)* are not. Regression results are presented in Table 7. For the sake of brevity, we only report the coefficients of the impact of the sentiment indicator on the return spread in Table 7. The results show that the difference portfolio (high idiosyncratic volatility portfolio minus low idiosyncratic volatility portfolio) is significantly positive related to GSI_m^A. This result holds regardless of whether we look at raw returns (Column 1), a one-factor model (Column 2), or a four-factor model (Column 3).

We also use *average trade size* of a firm's stock to differentiate between sentiment sensitive and sentiment insensitive stocks. According to Hvidkjaer (2008), predominantly small trades in a stock indicate that the fraction of retail investors holding the stock is relatively large.[19] Retail investors are often considered to be the main driver of investor sentiment (Kumar and Lee (2006)). Although the overall fraction of retail investors is relatively small on the German stock market, we still expect some cross-sectional variation and thus use the average trade size in a given month as an additional proxy for the sentiment sensitivity of a stock. It is important to mention that this proxy might be less useful in future studies focusing on more recent time periods where trading algorithms allow institutional investors to split large orders over time to minimize market impact and implementation costs. According to Hendershott and Riordan (2011), Deutsche Börse introduced its Automated Trading Program (ATP) that facilitated gradual trading in December 2007. As our data end in 2006, gradual trading of institutional investors should thus not bias our results.[20]

We sort firms into quintiles based on the average daily trade size in the last month. The daily trading volume and the number of daily trades are obtained from KKMDB. Results in Panel C of Figure 2 and the results presented in the second row of Table 7 show that the high vs. low sentiment portfolio (small average trade size minus large average trade size) is significantly positive related to GSI_m^A for all three models (Columns 1-3).

Baker and Wurgler (2006) argue that *firm age* can also be used to measure the sentiment sensitivity of a stock. Specifically, stocks of young firms are more sensitive to sentiment than stocks of old firms as young firms are more difficult to value because they have no long earnings history and a highly uncertain future. Thus, sentiment driven misvaluations are not corrected by arbitrageurs. Panel D of Figure 2 and the third row of Table 7 contain results where we sort firms into quintiles based on their age measured as the number of months since the date of firm foundation.[21] We find that there is again a significantly positive loading of GSI_m^A on the difference portfolio between sentiment sensitive (young) and sentiment insensitive (old) stocks, $Q(1)$ - $Q(5)$ for all specifications.

Baker and Wurgler (2006) expect that sentiment has a greater effect on stocks that do not *pay dividends* since such stocks' cash flows tend to occur far in the future. Thus, they are subject to speculation and typically hard to value. We follow Baker and Wurgler (2006) and sort firms into two portfolios depending on whether their stocks pay dividends or not. Data on whether firms pay dividends are from Hoppenstedt Aktienführer. We expect that the portfolio return of sentiment sensitive stocks (stocks that do not pay dividends) co-moves stronger with GSI_m^A than the portfolio return of sentiment insensitive stocks. The results in Panel E of Figure 2 are in line with this expectation. Furthermore, for all three specifications (Columns 1-3) in Table 7, we find a significantly positive coefficient for the impact of GSI_m^A on the difference portfolio.

Using *firm size* as a proxy to differentiate between sentiment sensitive and sentiment insensitive stocks is again based on the hard to value/difficult to arbitrage rationale. We measure size as the market value of equity in the previous month.[22] Results for sorts based on size are presented in Panel F of Figure 2 and in Panel E of Table 7. As expected, sentiment sensitive stocks (small stocks) co-move stronger with our sentiment indicator than sentiment insensitive (large) stocks as indicated by the positive impact of GSI_m^A on the return difference, which is significant in models (4) and (5). In the size sorts we do not include the size factor when estimating model (5).

According to Baker and Wurgler (2006), *profitable firms* are generally easier to value and thus easier to arbitrage. Therefore, stocks of firms with positive earnings should be less sensitive to investor sentiment than stocks of firms with negative earnings. In Panel G of Figure 2 and in Panel F of Table 7, we then sort firms into two portfolios, depending on whether they report positive or negative earnings for the previous year.[23] We classify the portfolio consisting of firms with positive earnings as sentiment insensitive, and the portfolio of firms with zero or negative earnings as sentiment sensitive, respectively. Earnings data are hand-collected from Hoppenstedt Aktienführer. The results show that the return of the difference portfolio is again significantly positive related to GSI_m^A across all model specifications (Columns 1-3).

Overall, the results on the relation between GSI_m^A and the return spread between sentiment sensitive and sentiment insensitive stocks show that sentiment is an important factor explaining stock returns in Germany. Furthermore, the uniform results we get based on the various different proxies to define sentiment sensitive stocks clearly show that the first principal component can safely be used as a proxy for investor sentiment in our case.

4.3 Sentiment and Future Stock Return Spreads

Baker and Wurgler (2006) show that when sentiment is high (low), sentiment sensitive stocks earn relatively lower (higher) returns in the subsequent year in the US. We now investigate whether sentiment has any predictive power for future stock returns in Germany. Thus, we relate the future return spread between high and low sentiment sensitive stocks, $Ret_{m1 \to m2}^{Q(1)-Q(5)}$, to the contemporaneous sentiment index in month m, GSI_m^A, where *m1* (*m2*) refers to the number of months after the sentiment measurement month (i.e. month m) that the return measurement starts (ends):[24]

$$Ret_{m1 \to m2}^{Q(1)-Q(5)} = \alpha + \beta_s \cdot GSI_m^A + \varepsilon_{m1 \to m2} \quad (6)$$

For example, for *m=August 2000*, *m1=1* and *m2=3*, we regress the three-month cumulative return of the difference portfolio from the beginning of September 2000 to the end of November 2000, $Ret_{1 \to 3}^{Q(1)-Q(5)}$, on the sentiment index obtained for August 2000, $GSI_{08/00}^A$.

As a second specification, we additionally include the market factor to control for the impact of the systematic market risk of the difference portfolio:

$$Ret_{m1 \to m2}^{Q(1)-Q(5)} = \alpha + \beta_s \cdot GSI_m^A + \beta_1 \cdot RMRF_{m1 \to m2} + \varepsilon_{m1 \to m2} \quad (7)$$

Finally, we also include the further systematic risk factors identified in Fama and French (1993) as well as the momentum factor of Carhart (1997) as described in the previous chapter:

$$Ret_{m1 \to m2}^{Q(1)-Q(5)} = \alpha + \beta_s \cdot GSI_m^A + \beta_1 \cdot RMRF_{m1 \to m2} + \beta_2 \cdot SMB_{m1 \to m2} + \beta_3 \cdot HML_{m1 \to m2} + \beta_4 \cdot WML_{m1 \to m2} + \varepsilon_{m1 \to m2} \quad (8)$$

It is particularly important to control for the momentum factor, because sentiment sensitive stocks are likely to be winners (losers) in periods of high (low) sentiment (see Section 4.1 and 4.2) and the momentum effect predicts an outperformance of past winners. The momentum effect for Germany is documented in Schiereck, DeBondt, and Weber (1999).

As in the previous section, we first look at detailed results where we classify high and low sentiment sensitive stocks based on stock volatility, before we shortly summarize the results using the other sorting criteria.

We investigate the future return of a difference portfolio between stocks with the highest ($Q1$) and the lowest ($Q5$) sentiment sensitivity and analyze different time horizons, i.e. we investigate future stock returns over the next 3 months, $Ret_{1 \to 3}^{Q(1)-Q(5)}$ the next four to six months, $Ret_{4 \to 6}^{Q(1)-Q(5)}$, the next seven to nine months, $Ret_{7 \to 9}^{Q(1)-Q(5)}$, and finally the next ten to twelve months, $Ret_{10\to12}^{Q(1)-Q(5)}$.[25] We look at different time periods to examine how the return of the difference portfolio develops over time. While there might be some persistence in sentiment (and thus return differentials), it is expected to eventually mean-revert, i.e. we expect the portfolio with sentiment sensitive stocks to outperform non-sentiment sensitive stocks in the short run and to eventually underperform non-sentiment sensitive stocks in the long run.

In addition to this analysis, we also differentiate between subsequent return differentials after positive and after negative sentiment. Therefore, we replace GSI_m^A in models (6) to (8) by two dummy variables, $GSIDUM(Hi)_m^A$ and $GSIDUM(Lo)_m^A$. $GSIDUM(Hi)_m^A$ ($GSIDUM(Lo)_m^A$) takes on the value one, if sentiment is larger than 1 (lower than -1), and zero otherwise.[26] Results are presented in Table 8.

Panel A of Table 8 presents results from Model (6).We observe a positive relation between the return spread and our sentiment indicator over the first 3 months. The relation then reverses and turns negative over the next 4 to 12 months. This is consistent with sentiment sensitive stocks outperforming for up to a quarter after a high sentiment month, but then starting to underperform as compared to non-sentiment sensitive stocks. We find similar evidence after controlling for the market factor (Panel B) and the Carhart (1997) four-factor model (Panel C). However, the effects are generally not statistically significant, which is likely to be due to the fact that sentiment is often at relatively moderate levels (see Figure 1) and thus might not have a strong impact. Therefore, we now look at the results for future return spreads if sentiment is very high or very low.

If we consider periods after high sentiment by looking at the impact of $GSIDUM(Hi)_m^A$, we find a similar pattern: the return difference is still positive in the first one or two quarters and then tends to reverse in the third quarter. However, the effects are generally not significant in this case. Results are somewhat stronger after periods of low sentiment. Consistent with our expectations, we find that the return difference is negative in the first quarter after a very negative sentiment month. In the following quarters, the return difference then reverses and becomes significantly positive. This shows that sentiment sensitive stocks underperform relative to non-sentiment sensitive stocks for a short while after very negative sentiment, but then outperform in the following quarters. This result holds for raw returns (Panel A) as well as after controlling for the market factor (Panel B) and the Carhart (1997) four-factor model (Panel C). These findings are broadly consistent with evidence provided in Baker, Wurgler, and Yuan (2011) for a group of six major stock markets including Germany.[27]

In the following, we investigate the stability of our result by again using different sorting criteria other than volatility to define the sentiment sensitivity of a stock. As in the previous section, we classify stocks as sentiment sensitive stocks if they are characterized by high idiosyncratic risk, if their average trading size is small, if they are young, small, unprofitable, and do not pay dividends. For the sake of brevity, we only report results for the most conservative approach and use the Carhart (1997) four-factor model (8) as our main specification. For the size sorts, we again do not include the size factor when estimating model (5). Results are presented in Table 9 and show a similar pattern as we observe in Table 8. The results for model (8) are generally insignificant. Furthermore, there is a generally positive but also insignificant relation between the future return spread over the next three months and GSI_m^A if sentiment is strongly positive. We then observe that the relationship reverses over the course of the following months. This is consistent with findings reported in Baker and Wurgler (2006) for a similar set of sorting criteria. As before, our results are somewhat stronger after periods of low sentiment. Here, returns are typically first negative and then turn significantly positive.[28]

Overall, the predictive power of sentiment for future return spreads is weak. Although contemporaneous return spreads are strongly affected by sentiment fluctuations (see Section 4.1), generally this does not seem to lead to severe relative mispricing over time. We only find significant effects after periods of very low sentiment. This suggests that the observed effect is mainly driven by relative undervaluation of stocks after periods of very low sentiment rather than by relative overvaluation after periods of very high sentiment. This pattern is consistent with the general tendency of investors to react more strongly in response to bad news as compared to good news (Conrad, Cornell, and Landsman (2002)).

5. Conclusion

This paper develops a broad based sentiment indicator for Germany and investigates whether investor sentiment is still prevalent in a stock market where retail investors only play a minor role. We develop a sentiment indicator for the German stock market based on the first principal component of five well-established proxies for investor sentiment: consumer confidence, (inverted) put-call ratio, trend adjusted trading volume, net fund flows and IPO returns. Out of the different variations of input variables we analyse, we consider this indicator to be best suited to measure sentiment on the German stock market as it balances data input requirements and a broad representation of the main sentiment proxy categories. We show that this indicator has explanatory power for the return spread between sentiment sensitive and sentiment insensitive stocks based on several sorting criteria that have been shown to be characteristic for sentiment sensitive stocks. Furthermore, we show that our sentiment indicator has only weak power in predicting future return spreads between sentiment-sensitive and sentiment-insensitive stocks. The effect is mainly driven by periods after very low sentiment, while there is no strong impact of sentiment on future return spreads after periods of high sentiment. This result is consistent with evidence from the earnings announcements literature that investors react stronger to bad news than to good news (Conrad, Cornell, and Landsman (2002)).

While evidence for the U.S. shows severe relative mispricing and strong predictive power of sentiment, we find that sentiment does not generally predict future return spreads in Germany. The weak cross-sectional predictive power of sentiment is probably due to the fact that the German market is mainly populated by sophisticated (institutional) investors who are less prone to sentiment fluctuations. Interestingly, our results suggest that sentiment does still play a role in explaining contemporaneous stock returns. This raises the question whether institutional investors are at least to some extent subject to sentiment as well. While we are not aware of any papers that explicitly analyze whether institutional investors are subject to irrational sentiment fluctuations, there is now a growing body of literature that shows that not only retail investors but also professional investors are often – at least to a certain extent - subject to various behavioural biases.[29] However, our results show that even such a potential effect is not strong enough to give rise to a long-lasting strong mispricing of stocks that would allow creating a profitable trading strategy. The role of the fraction of retail investors and institutional investors for the importance of sentiment would be an interesting avenue for a future cross-country study involving data from more markets.

[1] We use six-months expectations instead of one-month expectations because Sentix one-month horizon answers are very noisy (Schmeling (2007)).

[2] As an alternative test of the usability of the Sentix and the G-Mind as sentiment indicators, we also conducted the same analysis as we did to validate our sentiment indicator GSI: We relate both alternative sentiment indicators, G-Mind and Sentix, to the differences between contemporaneous returns of stocks that are sensitive to sentiment fluctuations and those that are not. Our results (not reported) show that G-Mind (Stocks) as well as Sentix generally have no significant impact on the contemporaneous return spread between sentiment sensitive and sentiment insensitive stocks.

[3] Data on trading volume is provided by Deutsche Bundesbank, the total number of listed firms are collected from Deutsches Aktieninstitut's (DAI) Factbooks. The DAI Factbook is updated once a year and contains a comprehensive collection of statistics on the German stock market. We trend adjust trading volume as in Andersen (1996) and compute,

$$\mathrm{TradVol}_{\mathrm{m}}^{\mathrm{ta}} = \mathrm{LN}\left(\frac{\mathrm{TradVol}_{\mathrm{m}}}{\mathrm{TotalFirms}_{\mathrm{m}}}\right) - \frac{1}{24}\sum_{\mathrm{m}=-24}^{\mathrm{m}=-1} \mathrm{LN}\left(\frac{\mathrm{TradVol}_{\mathrm{m}}}{\mathrm{TotalFirms}_{\mathrm{m}}}\right)$$

where $TradVol_m$ is trading volume in million EUR in month m, and $TotalFirms_m$ is the total number of listed firms in month m.

[4] Another proxy regularly used in U.S. studies is the closed end fund discount (see, e.g., Lee, Thaler, and Shleifer (1991) and Neal and Wheatley (1998)). Since listed closed end equity funds do not exist in Germany, we cannot use this proxy in our study. However, net flows are the mutual fund equivalent of the closed end fund discount. Thus, we think that we do not miss an important aspect of sentiment by not being able to include the closed end fund discount.

[5] Using value-weighted IPO returns instead does not affect our results (not reported).

[6] The Hoppenstedt Aktienführer is updated annually and contains information about all listed German firms including balance sheet and profit and loss items.

[7] The resulting first principal component is also normalized and has a mean of zero and a standard deviation of one.

[8] The only exception is the impact of trading volume, which does not play a large role in the sub-period 2000 to 2006 anymore. However, this does not affect our results: The correlation between our GSI and the first component of a PCA estimated based on the same proxies as above but excluding trading volume is 99.98% in the 2000 to 2006 period.

[9] The time series data for the GSI is provided for the use of other researchers under http://sites.google.com/site/ruenzi/data.

[10] We follow Baker and Wurgler (2006) and use equal weighted portfolios, because large firms will probably be less affected by sentiment. Thus, using value weighting will "tend to obscure the relevant patterns".

[11] For the sake of brevity, we use GSI as an abbreviation for the German Sentiment indicator in the main text. It comprises both, the macro adjusted indicator (GSI_m^A) and the unadjusted indicator (GSI_m).

[12] The list of sorting criteria to define sentiment sensitive stocks is long. We mainly follow the article by Baker and Wurgler (2006) as a benchmark for the choice of sorting criteria. However, they also include additional proxies like expenditures for R&D or sales growth for which we could not get data for all of the firms in our sample.

[13] Another proxy for limits of arbitrage is stock illiquidity (Kumar and Lee (2006)). Thus, illiquid stocks might be particularly prone to sentiment fluctuations, too. However, at the same time Baker and Stein (2004) argue that high liquidity is a proxy for investor sentiment because it signals that the market is currently dominated by irrational investors. Thus, overall it is not clear how liquidity is related to sentiment. In unreported tests using the Amihud (2002) illiquidity ratio as a liquidity proxy we find no clear relationship between liquidity levels and sentiment fluctuations.

[14] DAFOX and CDAX have very similar return characteristics. In the overlapping period from January 1993 to December 2004 the monthly returns of DAFOX and CDAX are almost perfectly correlated (correlation coefficient of 0.978). The correlation coefficient between the monthly returns of the combined DAFOX/CDAX and a value-weighted index based on all stocks considered in our study is 0.979. Thus, the DAFOX/CDAX serves as an appropriate market proxy for our stock universe.

[15] SMB_m and HML_m are constructed for the German stock market as described in Fama and French (1993), while the design of WML_m generally follows Carhart (1997). We use the factor time series also used in Artmann et al. (2011).

[16] Interestingly, the non-sentiment sensitive stock portfolio Q(5) delivers a positive abnormal return, as indicated by the significantly positive intercept presented in the second to last column of Table 6, while the sentiment sensitive stock portfolio does not. This suggests that sentiment sensitivity is not a positively priced risk factor on the German stock market. This result is also consistent with recent findings in Koch (2010), who finds that German stocks with high idiosyncratic risk earn negative abnormal returns.

[17] Results for a not macro-adjusted sentiment indicator (not reported) are very similar.

[18] Alternatively, we compute idiosyncratic volatility relative to a one-factor model. Results (not reported) are virtually unchanged.

[19] For supportive evidence, see also Lee and Radhakrishna (2000). However, note that Hvidkjaer (2006) also shows that institutional investors make smaller trades in small stocks. Thus, trade size might also partially proxy for firm size. We examine the role of firm size explicitly in Section 4.2.

[20] Alternatively, we conduct this analysis for the first ten years of our sample period (1993-2003) only to make sure that our results are not biased by gradual trading of institutional investors that might have already slowly started in the last years of our sample. Results (not reported) are stable.

[21] Data on firm foundation dates are hand-collected from Hoppenstedt Aktienführer. The results do not change, if we measure firm age in number of month since the firm's first appearance in our sample.

[22] Market value of equity is computed as stock price times shares outstanding. Data on shares outstanding are from Hoppenstedt Aktienführer.

[23] Alternatively, we sort firms into profitability quintiles. Our results (not reported) remain stable.

[24] In unreported tests, we find no strong effects if we relate contemporaneous sentiment to future aggregate returns.

[25] In unreported tests, we also examine longer periods like months 13 to 24. We generally find no significant results for these longer horizons.

[26] As sentiment is standardized, this means that $GSIDUM(Hi)_m^A$ $(GSIDUM(Lo)_m^A)$ is one if sentiment in month m is more than one standard deviation above (below) its mean.

[27] Unfortunately, Baker, Wurgler, and Yuan (2009) do not provide country-level results.

[28] Note, that the sentiment indicator analyzed so far is calculated ex post. In unreported analysis, we also examine an alternative indicator which is again based on PCA. However, in contrast to the proxy used above, it is calculated at each point in time only using a rolling window of past data. This indicator is highly correlated with the aggregate sentiment measure used before and we find very similar results: Again, there is no strong predictive power of sentiment for future aggregate returns or return spreads.

[29] Studies that find signs of irrational behavior among professional investors include Haigh and List (2005), Coval and Shumway (2005), Glaser, Langer, and Weber (2010), and Puetz and Ruenzi (2011).

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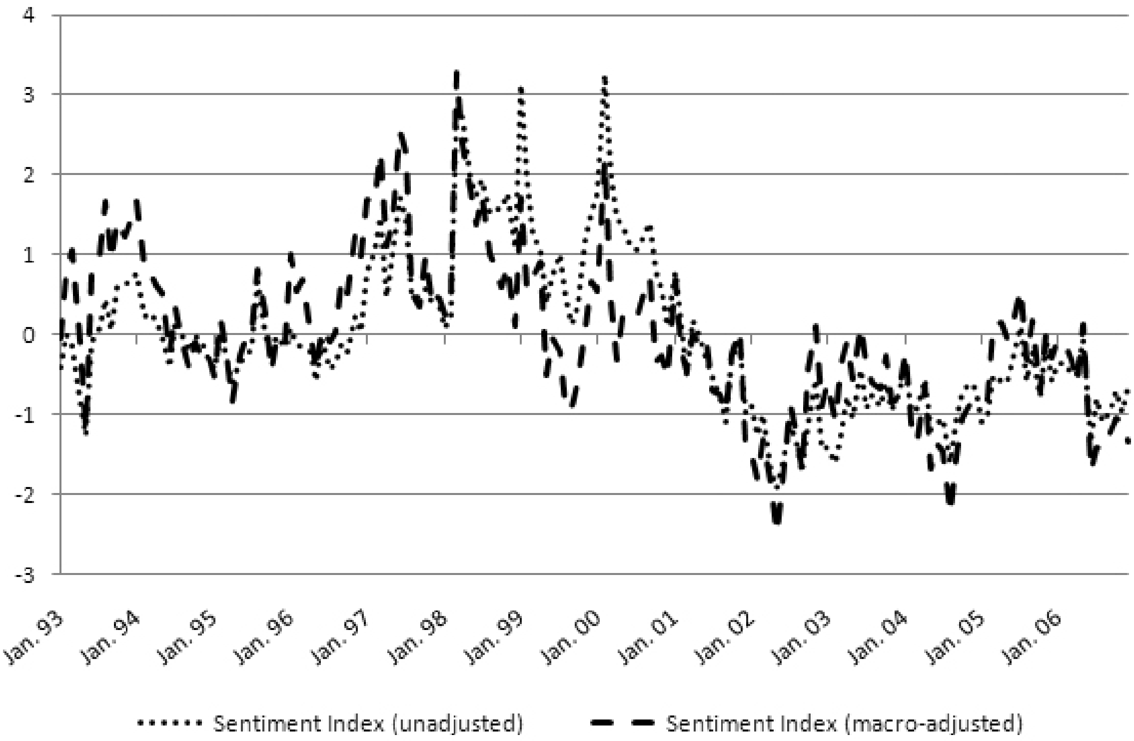
Appendix: List of Variables

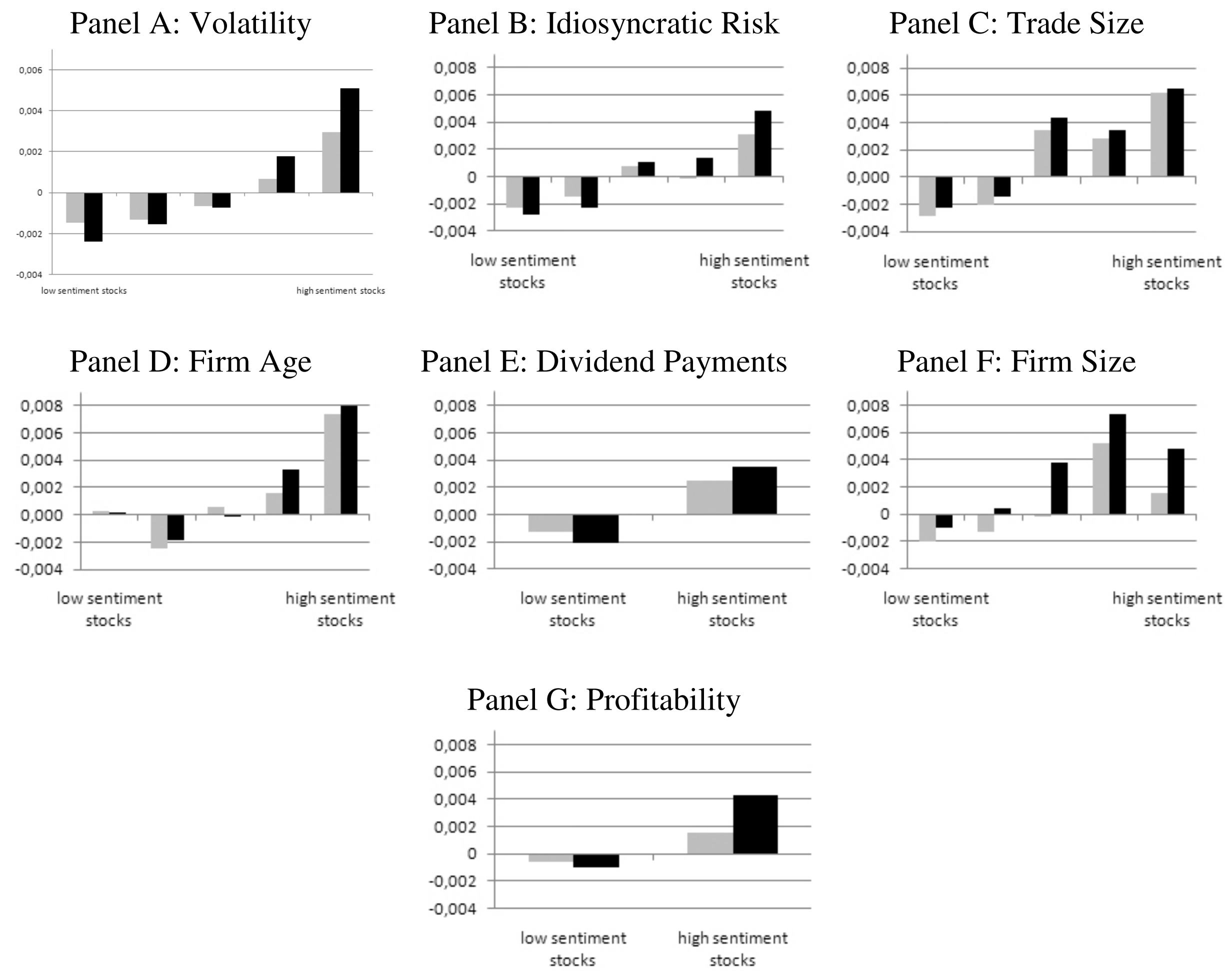
Panel A: Sentiment Proxies				
Abbreviation	Variable	Source	Frequency	Measurement
GFK_m	GFK Consumer Confidence Survey	Bloomberg	monthly	Index
$IPCR_m$	Inverted Put-Call Ratio	Deutsche Börse AG	monthly	Percent, number of calls traded divided by number of puts traded.
$TradVol^{ta}_m$	Trading Volume	Deutsche Bundesbank	monthly	Million EUR divided by number of firms; trend adjusted as in Andersen (1996).
$Flows_m$	Net Fund Flows	Deutsche Bundesbank	monthly	Level
$IPO\text{-}Num_m$	Number of IPOs	Deutsche Börse AG, DAI Factbooks, Hoppenstedt Aktienführer	monthly	Level
$IPO\text{-}Ret_m$	IPO Returns	Deutsche Börse AG, DAI Factbooks, Hoppenstedt Aktienführer	monthly	Percent
$E/D\text{-}Ratio_m$	Equity/Debt Ratio	Deutsche Bundesbank	monthly	Level
Panel B: Macroeconomic Variables				
Abbreviation	Variable	Source	Frequency	Measurement
$IndProd_{m+x1}$	Industrial Production	Deutsche Bundesbank	monthly	All macroeconomic variables are computed as month-over-month changes based on 12-month-moving-averages of the underlying index variables.
$InvOrd_{m+x2}$	Inventory Orders	Deutsche Bundesbank	monthly	
$FacOrd_{m+x3}$	Factory Orders	Deutsche Bundesbank	monthly	
$RetSal_{m+x4}$	Retail Sales	Deutsche Bundesbank	monthly	
$Empl_{m+x5}$	Employment	Deutsche Bundesbank	monthly	
Panel C: Risk Factors				
Abbreviation	Variable	Source	Frequency	Measurement
$RMRF_m$	Excess Market Return	Karlsruher Kapitalmarktdatenbank, Hoppenstedt Aktienführer	monthly	Excess market return over risk free rate.
SMB_m	Small Minus Big	Karlsruher Kapitalmarktdatenbank, Hoppenstedt Aktienführer	monthly	Return difference between portfolios of small and large firms.
HML_m	High Minus Low	Karlsruher Kapitalmarktdatenbank, Hoppenstedt Aktienführer	monthly	Return difference between portfolios of high and low book-to-market equity firms.
WML_m	Winner Minus Loser	Karlsruher Kapitalmarktdatenbank, Hoppenstedt Aktienführer	monthly	Return difference between portfolios of high and low return momentum firms.

Figure 1: German Sentiment Index, January 1993 to December 2006



Notes: This figure shows the development of the unadjusted and macro-adjusted sentiment index over time. The unadjusted sentiment index is the first principal component of five sentiment proxies: consumer confidence, aggregated trading volume, net fund flows, IPO returns, and the inverted put-call-ratio. The macro-adjusted sentiment index is based on sentiment proxies adjusted for growth in industrial production, inventory orders, factory orders, retail sales, and employment. The sentiment proxies are standardized to have a mean of zero and a standard deviation of one and the first principal component is also standardized in the same way.

Figure 2: Loadings of High and Low Sentiment Sensitive Stocks on the Unadjusted (grey) and Macro-Adjusted (black) Sentiment Index: Alternative Sorts



Notes: Panels A to G show loadings of equal-weighted quintile portfolios on the unadjusted sentiment index and the macro-adjusted sentiment index, respectively. In addition to the sentiment index, time-series regressions include the market, size, value, and momentum factor as explanatory variables. Quintile portfolios are formed on criteria that capture the sentiment sensitivity of a stock: volatility, idiosyncratic risk, trade size, firm age, and firm size. Quintile portfolios are rebalanced every month. In addition, following Baker and Wurgler (2006), firms are categorized based on whether they paid (did not pay) dividends and based on whether they did report positive (negative) earnings. In this case, firms are only sorted into one of two groups, respectively. Portfolios formed on profitability and dividend payments are formed in June of each year.

Table 1: Summary Statistics: Sentiment Indicators

Sentiment Indicators	Mean	STDV	Min.	Max.	Median	Obs.
GFK Consumer Conf. (GFK_m)	9.81	7.17	-3.50	26.20	8.75	168
Trading Volume ($TradVol_m^{ta}$)	250.10	96.52	115.16	638.67	227.73	168
Net Fund Flows ($Flows_m$)	736.95	1,226.62	-1,675.00	5,003.00	354.00	168
IPO Returns ($IPO\text{-}Ret_m$)	0.15	0.32	-0.42	2.31	0.01	168
Number of IPOs ($IPO\text{-}Num_m$)	4.06	5.47	0	22	2	168
Equity/Debt Ratio ($E/D\text{-}Ratio_m$)	0.04	0.05	0.00	0.43	0.03	168
Inverted P/C – Ratio ($IPCR_m$)	-0.73	0.17	-1.51	-0.44	-0.73	168

Notes: The table shows summary statistics of all (non-normalized) sentiment indicators used in our analysis. Trading volume is measured in Mio Euro per firm, net fund flows are measured in Mio Euro, and IPO returns are measured in percent. The sample period is from 1993 to 2006.

Table 2: Cross Correlations

	GFK_m	$Trad\ Vol_m^{ta}$	$Flows_m$	$IPO\text{-}Num_m$	$IPO\text{-}Ret_m$	$E/D\text{-}Ratio_m$	$IPCR_m$
GFK_m	1.000						
$TradVol_m^{ta}$	0.399 (0.000)	1.000					
$Flows_m$	0.528 (0.000)	0.429 (0.000)	1.000				
$IPO\text{-}Num_m$	0.553 (0.000)	0.392 (0.000)	0.406 (0.000)	1.000			
$IPO\text{-}Ret_m$	0.516 (0.000)	0.470 (0.000)	0.390 (0.000)	0.337 (0.000)	1.000		
$E/D\text{-}Ratio_m$	0.284 (0.000)	0.116 (0.134)	0.173 (0.025)	0.268 (0.000)	0.125 (0.106)	1.000	
$IPCR_m$	0.218 (0.000)	0.305 (0.000)	0.274 (0.000)	0.003 (0.968)	0.198 (0.010)	0.092 (0.235)	1.000

Notes: The table shows cross-correlations for the sentiment indicators used in our analysis. The sample period is from 1993 to 2006. p-values are presented in parentheses.

Table 3: Lead Lag Structure for Macroeconomic Adjustment

	$IndProd_{m+x1}$	$InvOrd_{m+x2}$	$FacOrd_{m+x3}$	$RetSal_{m+x4}$	$Empl_{m+x5}$
GFK_m	x1=0	x2=0	x3=0	x4=+1	x5=+1
$TradVol^{ta}_m$	x1=0	x2=0	x3=0	x4=0	x5=-3
$Flows_m$	x1=0	x2=0	x3=0	x4=0	x5=+1
$IPO\text{-}Num_m$	x1=0	x2=0	x3=0	x4=0	x5=0
$IPO\text{-}Ret_m$	x1=0	x2=0	x3=0	x4=0	x5=+2
$E/D\text{-}Ratio_m$	x1=0	x2=0	x3=0	x4=0	x5=0
$IPCR_m$	x1=0	x2=0	x3=0	x4=0	x5=0

Notes: The table shows the lead/lag structure that is used for each sentiment proxy in our macro-adjustment model (1) from the main text.

Table 4: Principal Component Analysis

Panel A: Macro-Adjusted Sentiment Proxies

PCA Version	PCA(a)		PCA(b)	
Principal Component	I	II	I	II
Factor Loadings				
GFK_m^A	0.703	0.061	0.686	-0.529
$IPCR_m^A$	0.759	-0.222	0.786	-0.007
$TradVol_m^{A,ta}$	0.524	-0.368	0.557	0.771
$Flows_m^A$	0.628	0.051	0.631	-0.117
$IPO - Ret_m^A$	0.569	-0.151	0.590	0.022
$IPO - Num_m^A$	0.176	0.763	-	-
$E/D - Ratio_m^A$	0.363	0.658	-	-
Variance Explained	31.79%	17.58%	42.90%	17.79%
Eigenvalue	2.225	1.230	2.145	0.890

Panel B: Unadjusted Sentiment Proxies

PCA Version	PCA(a)		PCA(b)	
Principal Component	I	II	I	II
Factor Loadings				
GFK_m	0.846	0.187	0.787	0.394
$IPCR_m$	0.373	-0.743	0.550	-0.613
$TradVol_m^{ta}$	0.057	-0.842	0.216	-0.862
$Flows_m$	0.749	-0.118	0.780	0.087
IPO-Ret_m	0.693	-0.045	0.740	0.196
IPO-Num_m	0.705	0.341	-	-
E/D-Ratio_m	0.430	0.110	-	-
Variance Explained	36.90%	20.57%	42.49%	26.41%
Eigenvalue	2.583	1.440	2.124	1.321

Panel C: Correlations Between First Principal Components

	PCA(a)	PCA(b)	$PCA(a)^A$	$PCA(b)^A$
PCA(a)	1.000			
PCA(b)	0.933	1.000		
$PCA(a)^A$	0.683	0.798	1.000	
$PCA(b)^A$	0.638	0.811	0.980	1.000

Notes: The table reports results of two Principal Component Analyses. In Panel A, PCA(a) denotes a principal component analysis of seven normalized and macro-adjusted sentiment proxies: GFK consumer confidence (GFK_m^A), inverted put-call-ratio ($IPCR_m^A$), aggregated trading volume ($TradVol_m^{A,ta}$), net fund flows ($Flows_m^A$), IPO returns (IPO-Ret_m^A), number of IPOs (IPO-Num_m^A), and equity debt ratio in new issues (E/D-Ratio_m^A). PCA(b) denotes a principal component analysis of a reduced set of sentiment proxies where the number of IPOs and the equity debt ratio in new issues are excluded. In Panel B, all sentiment proxies are normalized but not macro adjusted. Panel C shows cross-correlations for first principal components of PCA(a) and PCA(b), respectively. All variables are measured on a monthly basis from 1993-2006.

Table 5: Descriptive Statistics: Portfolios Sorted on Volatility

		1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Q5 (Low Sentiment)	Mean Mcap (Mio €)	1,395	762	601	1,608	1,532	673	725	803	1,630	2,249	1,138	2,763	4,819	8,550
	Mean Trade Size (€)	18,055	12,126	10,921	12,774	12,702	11,334	10,620	7,573	8,188	19,348	14,488	7,895	10,183	12,153
	Mean Number of Firms	70	69	71	73	73	75	81	99	116	126	115	121	118	110
	Min Number of Firms	69	68	70	71	72	73	75	89	106	119	111	117	114	106
	Max Number of Firms	70	70	72	74	74	76	88	108	125	131	118	125	123	115
Q4	Mean Mcap (Mio €)	1,647	1,590	1,627	2,141	2,827	991	2,037	2,531	2,986	1,656	1,909	2,859	2,808	2,534
	Mean Trade Size (€)	24,786	21,506	19,141	19,506	20,228	11,103	10,837	11,113	9,319	6,349	5,739	7,521	8,386	7,546
	Mean Number of Firms	70	69	70	72	73	74	81	99	115	126	115	121	118	110
	Min Number of Firms	69	68	69	71	72	73	75	88	106	119	110	117	114	106
	Max Number of Firms	70	69	71	73	74	76	87	107	124	130	118	125	123	115
Q3	Mean Mcap (Mio €)	897	1,664	1,660	1,405	2,148	3,490	2,933	3,106	3,118	2,282	1,352	861	493	721
	Mean Trade Size (€)	16,995	25,896	47,913	17,084	17,740	16,407	11,708	9,473	19,823	6,610	4,716	4,196	4,793	4,897
	Mean Number of Firms	69	69	70	72	73	74	81	99	115	126	114	121	118	110
	Min Number of Firms	68	68	69	70	72	73	75	88	106	119	110	117	114	106
	Max Number of Firms	70	69	72	74	74	76	88	107	125	131	118	124	123	115
Q2	Mean Mcap (Mio €)	878	1,423	1,363	1,088	1,946	4,548	3,156	1,995	1,333	1,148	1,064	288	141	488
	Mean Trade Size (€)	16,542	21,295	17,850	13,505	15,106	17,774	11,798	7,716	6,458	3,424	3,066	2,980	2,386	3,395
	Mean Number of Firms	70	69	70	72	73	74	81	99	115	126	115	121	118	110
	Min Number of Firms	69	68	69	71	72	73	75	88	106	119	110	117	114	106
	Max Number of Firms	70	69	71	73	74	76	87	107	124	130	118	125	123	115
Q1 (High Sentiment)	Mean Mcap (Mio €)	212	352	526	333	893	2,589	3,076	1,537	694	390	926	332	71	262
	Mean Trade Size (€)	8,288	8,997	10,075	7,660	8,039	13,553	8,185	6,066	3,336	1,780	2,728	1,689	1,598	2,643
	Mean Number of Firms	69	68	70	72	73	74	80	98	115	125	114	120	117	109
	Min Number of Firms	68	68	69	70	71	73	74	88	105	118	110	116	114	105
	Max Number of Firms	70	69	71	73	73	75	87	107	124	130	118	124	123	115

Notes: The table shows descriptive statistics of firms sorted into portfolios depending on their stock volatility. For each year and each portfolio, we compute mean market capitalization, mean trade size, the mean number of firms as well as the minimum and maximum number of firms contained in a portfolio, respectively.

Table 6: Contemporaneous Returns: Portfolios Sorted on Volatility

Panel A Raw Returns	GSI_m^A	$RMRF_m$	SMB_m	HML_m	WML_m	Intercept	adj. R^2
Q(5) (Low Sent)	0.0029					0.0061	1.82%
(t-stat)	(1.56)					(3.03)	
Q(1) (High Sent)	0.0240					-0.0044	11.60%
(t-stat)	(4.73)					(-0.70)	
Q(1)-Q(5) (High-Low)	0.0211					-0.0105	11.70%
(t-stat)	(4.66)					(-2.00)	
Panel B 1-Factor Model							
Q(5) (Low Sent)	-0.0013	0.2287				0.0042	38.37%
(t-stat)	(-0.95)	(7.74)				(2.84)	
Q(1) (High Sent)	0.0088	0.8412				-0.0113	47.71%
(t-stat)	(2.23)	(9.16)				(-2.52)	
Q(1)-Q(5) (High-Low)	0.0100	0.6124				-0.0156	36.50%
(t-stat)	(2.43)	(6.98)				(-3.61)	
Panel C 4-Factor Model							
Q(5) (Low Sent)	-0.0024	0.3550	0.3001	0.1012	0.0331	0.0046	66.16%
(t-stat)	(-2.90)	(14.16)	(13.79)	(4.20)	(3.35)	(4.57)	
Q(1) (High Sent)	0.0051	1.0455	0.7334	-0.3900	-0.1831	-0.0034	71.55%
(t-stat)	(1.81)	(12.84)	(5.67)	(-3.05)	(-3.36)	(-1.16)	
Q(1)-Q(5) (High-Low)	0.0075	0.6905	0.4333	-0.4912	-0.2162	-0.0080	60.41%
(t-stat)	(2.48)	(8.68)	(3.28)	(-3.59)	(-3.76)	(-2.59)	

Notes: This table presents coefficient estimates of time-series regressions of monthly contemporaneous portfolio excess returns (portfolio return minus the risk-free rate) on GSI_m^A (Panel A), on GSI_m^A and $RMRF_m$ (Panel B), and on GSI_m^A, $RMRF_m$, SMB_m, HML_m, and WML_m (Panel C). Quintile Portfolios are sorted on volatility. GSI_m^A denotes the macro adjusted sentiment index. $RMRF_m$ is the excess market return over the risk-free rate. SMB_m and HML_m are the Fama and French (1993) factors, hedge-portfolios long in small (high BE/ME) stocks and short in big (low BE/ME) stocks. WML_m captures the Jegadeesh and Titman (1993) momentum anomaly and is long in short-term winner stocks and short in short-term loser stocks (see, e.g., Carhart (1997)). t-statistics based on Newey and West (1987) standard errors are presented in parentheses.

Table 7: Contemporaneous Returns: Other Sorting Criteria

	Raw Returns	1-Factor Model	4-Factor Model
Panel A: Idiosyncratic Risk			
Q(1)-Q(5) (High-Low)	0.0179	0.0104	0.0076
(t-stat)	(4.48)	(2.86)	(2.83)
Panel B: Trade Size			
Q(1)-Q(5) (High-Low)	0.0064	0.0113	0.0087
(t-stat)	(1.83)	(3.76)	(3.17)
Panel C: Age			
Q(1)-Q(5) (High-Low)	0.0185	0.0109	0.0056
(t-stat)	(3.92)	(2.56)	(2.69)
Panel D: Dividends			
No Div-Div (High-Low)	0.0112	0.0079	0.006
(t-stat)	(4.33)	(2.97)	(2.69)
Panel E: Size			
Q(1)-Q(5) (High-Low)	0.0014	0.0056	0.0058
(t-stat)	(0.51)	(2.12)	(2.65)
Panel F: Profitability			
Neg.-Pos. Earnings (High-Low)	0.0084	0.0069	0.0053
(t-stat)	(3.47)	(2.81)	(2.62)

Notes: This table presents coefficient estimates for GSI_m^A of time-series regressions of monthly contemporaneous spread portfolio returns on GSI_m^A (Column 2), on GSI_m^A and $RMRF_m$ (Column 3), and on GSI_m^A, $RMRF_m$, SMB_m, HML_m, and WML_m (Column 4). Quintile portfolios are formed on criteria that capture the sentiment sensitivity of a stock: idiosyncratic risk (Panel A), trade size (Panel B), firm age (Panel C), and firm size (Panel E). We use two portfolios when we form on dividend payments (Panel D: dividend payer vs. non dividend payer) and profitability (Panel F: positive vs. negative earnings). When we use size as a sorting criterion, results in Column 4 are from a model that does not include the size factor SMB_m. GSI_m^A denotes the macro adjusted sentiment index. $RMRF_m$ is the excess market return over the risk-free rate. SMB_m and HML_m are the Fama and French (1993) factors, hedge-portfolios long in small (high BE/ME) stocks and short in big (low BE/ME) stocks. WML_m captures the Jegadeesh and Titman (1993) momentum anomaly and is long in short-term winner stocks and short in short-term loser stocks (see, e.g., Carhart (1997)). t-statistics based on Newey and West (1987) standard errors are presented in parentheses.

Table 8: Return Prediction: Portfolios Sorted on Volatility

Panel A: Raw Returns	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	0.0160	-0.0004	-0.0133	-0.0184
(t-stat)	(1.29)	(-0.03)	(-1.14)	(-1.50)
$GSIDUM(Hi)_m^A$	0.0285	0.0150	-0.0167	0.0124
(t-stat)	(1.10)	(0.64)	(-0.80)	(0.66)
$GSIDUM(Lo)_m^A$	-0.0625	-0.0157	0.0708	0.1046
(t-stat)	(-1.49)	(-0.32)	(2.05)	(3.06)
Panel B: 1-Factor Model	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	0.0079	-0.0053	-0.0237	-0.0208
(t-stat)	(0.92)	(-0.54)	(-2.64)	(-2.35)
$GSIDUM(Hi)_m^A$	0.0326	0.0241	-0.0284	-0.0167
(t-stat)	(1.77)	(1.14)	(-1.43)	(-0.85)
$GSIDUM(Lo)_m^A$	-0.0372	0.0405	0.0930	0.0937
(t-stat)	(-1.33)	(1.36)	(4.65)	(3.98)
Panel C: 4-Factor Model	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	0.0066	-0.0074	-0.0149	-0.0033
(t-stat)	(1.04)	(-0.94)	(-2.07)	(-0.45)
$GSIDUM(Hi)_m^A$	0.0203	-0.0049	-0.0300	0.0026
(t-stat)	(1.06)	(-0.23)	(-1.47)	(0.14)
$GSIDUM(Lo)_m^A$	-0.0303	0.0324	0.0562	0.0483
(t-stat)	(-1.75)	(1.54)	(3.10)	(2.77)

Notes: This table presents coefficient estimates for GSI_m^A of time-series regressions of future difference-portfolio return on GSI_m^A (Panel A), on GSI_m^A and RMRF (Panel B), and on GSI_m^A, RMRF, SMB, HML, and WML (Panel C). The hedge-portfolio return is the return difference between the High and the Low quintile volatility portfolio. GSI_m^A denotes the macro adjusted sentiment index. RMRF is the excess market return over the risk-free rate. SMB and HML are the Fama and French (1993) factors, hedge-portfolios long in small (high BE/ME) stocks and short in big (low BE/ME) stocks. WML captures Jegadeesh and Titman`s (1993) momentum anomaly and is long in short-term winner stocks and short in short-term loser stocks (see, e.g., Carhart (1997)). The second and third row of each panel present results where the future return of the difference portfolio is regressed on a dummy variable, $GSIDUM(Hi)_m^A$ ($GSIDUM(Lo)_m^A$), instead of GSI_m^A directly. $GSIDUM(Hi)_m^A$ ($GSIDUM(Lo)_m^A$) takes on the value one, if sentiment in month *m* is more than one standard deviation above (below) its mean. t-statistics based on Newey and West (1987) standard errors are presented in parentheses.

Table 9: Return Prediction: Other Sorting Criteria

Panel A: Idiosync. Risk	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	0.0056	-0.0070	-0.0115	-0.0007
(t-stat)	(0.92)	(-1.04)	(-1.86)	(-0.11)
$GSIDUM(Hi)_m^A$	0.0205	-0.0009	-0.0267	0.0109
(t-stat)	(1.23)	(-0.05)	(-1.51)	(0.66)
$GSIDUM(Lo)_m^A$	-0.0235	0.0330	0.0404	0.0487
(t-stat)	(-1.44)	(1.71)	(2.64)	(2.96)
Panel B: Trade Size	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	0.0113	0.0079	0.0037	-0.0004
(t-stat)	(1.62)	(1.18)	(0.61)	(-0.06)
$GSIDUM(Hi)_m^A$	0.0213	0.0246	0.0083	0.0039
(t-stat)	(1.38)	(1.95)	(0.48)	(0.20)
$GSIDUM(Lo)_m^A$	-0.0530	-0.0055	0.0271	0.0536
(t-stat)	(-4.35)	(-0.22)	(1.37)	(2.22)
Panel C: Firm Age	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	0.0021	-0.0122	-0.0098	-0.0098
(t-stat)	(0.31)	(-1.54)	(-1.60)	(-1.58)
$GSIDUM(Hi)_m^A$	0.0014	-0.0118	-0.0149	0.0000
(t-stat)	(0.07)	(-0.68)	(-0.78)	(0.00)
$GSIDUM(Lo)_m^A$	-0.0230	0.0396	0.0475	0.0564
(t-stat)	(-1.29)	(2.23)	(2.84)	(4.03)
Panel D: Dividends	$Ret_{1\to3}^{Q(No\ Div)-Q(Div)}$	$Ret_{4\to6}^{Q(No\ Div)-Q(Div)}$	$Ret_{7\to9}^{Q(No\ Div)-Q(Div)}$	$Ret_{10\to12}^{Q(No\ Div)-Q(Div)}$
GSI_m^A	0.0026	-0.0042	-0.0013	-0.0032
(t-stat)	(0.55)	(-0.79)	(-0.27)	(-0.62)
$GSIDUM(Hi)_m^A$	0.0193	0.0019	-0.0040	0.0051
(t-stat)	(1.20)	(0.14)	(-0.26)	(0.37)
$GSIDUM(Lo)_m^A$	-0.0138	0.0228	0.0265	0.0349
(t-stat)	(-1.33)	(1.85)	(2.64)	(3.16)
Panel E: Firm Size	$Ret_{1\to3}^{Q(1)-Q(5)}$	$Ret_{4\to6}^{Q(1)-Q(5)}$	$Ret_{7\to9}^{Q(1)-Q(5)}$	$Ret_{10\to12}^{Q(1)-Q(5)}$
GSI_m^A	-0.0016	-0.0104	-0.0144	-0.0181
(t-stat)	(-0.30)	(-1.44)	(-2.28)	(-2.54)
$GSIDUM(Hi)_m^A$	-0.0190	-0.0047	-0.0267	-0.0163
(t-stat)	(-1.67)	(-0.32)	(-1.97)	(-1.12)
$GSIDUM(Lo)_m^A$	-0.0128	0.0379	0.0495	0.0827
(t-stat)	(-1.05)	(2.01)	(2.90)	(3.46)
Panel F: Profitability	$Ret_{1\to3}^{Q(neg.\ E.)-Q(pos.\ E.)}$	$Ret_{4\to6}^{Q(neg.\ E.)-Q(pos.\ E.)}$	$Ret_{7\to9}^{Q(neg.\ E.)-Q(pos.\ E.)}$	$Ret_{10\to12}^{Q(neg.\ E.)-Q(pos.\ E.)}$
GSI_m^A	0.0034	0.0002	-0.0024	-0.0073
(t-stat)	(0.69)	(0.04)	(-0.52)	(-1.52)
$GSIDUM(Hi)_m^A$	0.0213	0.0216	-0.0137	-0.0030
(t-stat)	(1.50)	(1.57)	(-1.13)	(-0.26)
$GSIDUM(Lo)_m^A$	-0.0129	0.0179	0.0148	0.0389
(t-stat)	(-1.10)	(1.44)	(1.78)	(3.92)

Notes (for Table 9): This table presents coefficient estimates for GSI_m^A of time-series regressions of future difference-portfolio returns on GSI_m^A (Column 2), on GSI_m^A and RMRF (Column 3), and on GSI_m^A, RMRF, SMB, HML, and WML (Column 4) in the first row of each panel. The difference-portfolio return is the return difference between the High and the Low quintile sentiment portfolio. Quintile portfolios are formed on criteria that capture the sentiment sensitivity of a stock: volatility, idiosyncratic risk, trade size, firm age, dividend payments, firm size, and profitability. When we use size as a sorting criterion (Panel E), results are from a model that does not include the size factor SMB. GSI_m^A denotes the macro adjusted sentiment index. RMRF is the excess market return over the risk-free rate. SMB and HML are the Fama and French (1993) factors, hedge-portfolios long in small (high BE/ME) stocks and short in big (low BE/ME) stocks. WML_m captures Jegadeesh and Titman`s (1993) momentum anomaly and is long in short-term winner stocks and short in short-term loser stocks (see, e.g., Carhart (1997)). The second and third row of each panel present results where the future return of the difference portfolio is regressed on a dummy variable, $GSIDUM(Hi)_m^A$ ($GSIDUM(Lo)_m^A$), instead of GSI directly. $GSIDUM(Hi)_m^A$ ($GSIDUM(Lo)_m^A$) takes on the value one, if sentiment in month *m* is more than one standard deviation above (below) its mean. t-statistics based on Newey and West (1987) standard errors are presented in parentheses.

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cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
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kempf@cfr-cologne.de
www.cfr-cologne.de