On Individual and Institutional Noise Trading

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Abstract

Previous research suggests that individual investor sentiment has incremental explanatory power for returns of small cap stocks, value stocks, stocks with low institutional ownership, and stocks with lower prices (Kumar and Lee (2003)) and that there is a strong link between institutional sentiment and the returns of large stocks (Brown and Cliff (2004)). With respect to return volatility, Jackson (2003a,b) found that larger trading share of individuals in certain stocks does not increase their subsequent volatility; however, the opposite is true for institutional participation, which increases conditional volatility. We propose an integrated framework that jointly tests for the effects of individual as well as institutional sentiment on return *and* volatility. Using implicit measures of sentiment for the German stock market over the period 02/2000 until 04/2005, our results suggest that institutional sentiment has only minor incremental explanatory power for returns and conditional volatility of large cap stocks, but we find strong evidence that individual sentiment is the important market-wide risk factor and does affect the return and conditional volatility of large as well as small cap stocks.

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1 Introduction

The rationality of investors lies at the core of the classical understanding of financial markets and security prices. Investors are assumed to be Bayesian in forming fully rational expectations about future returns and risks, given the relevant information available to them. Consequently, they correctly price securities at their fundamental value. However, even classical theory acknowledges that some investors might not be all that rational – they trade on noise rather than information. Nevertheless, as long as their misperceptions are uncorrelated, they are likely to cancel out or disappear from the market, as they tend to buy high and sell low, which has devastating wealth effects in the long run. Finally, even if misperceptions across irrational investors are correlated, the remaining rational investors would engage in arbitrage and bring prices back to fundamental value. This argument has been most forcefully made both by Friedman (1953) and Fama (1965). In the ideal case, arbitrage guarantees a riskless profit and as a result, arbitrageurs will crowd out irrational investors.

The most voluminous set of critique questions the classical view of investors' rationality. Black (1986) laid the foundation by emphasizing the role of noise on a wide range of economic activities, including financial markets. Black contrasts noise with information. In a financial context, information is relevant news about fundamentals of risk and return, whereas noise is irrelevant news. According to his predictions, trading on noise is a vital function that only makes financial markets possible. If there are only trades on information, "taking the other side's information into account, is it still worth trading?" (Black, p. 531). Thus noise trading, defined as trading on irrelevant information as if it were relevant, provides liquidity to informed traders, but it also makes stock prices noisy as they reflect the opinions of noise traders alongside the fundamentals of risk and return. Consequently, prices will be less efficient, which encourages informed traders to engage in the market, as they should be able to exploit their informational advantage. However, if their information is already priced, their trading would resemble noise trading, which makes the distinction between both groups blurry. If unsophisticated traders act on noise as if it was value-relevant information, it becomes possible for events such as index inclusions to influence prices and push prices away from the fundamental value. Volatility of prices will thus be greater than volatility of the fundamental value, and it will change over time. In sum, "noise creates the opportunity to trade profitably, but at the same time makes it difficult to trade profitably" (Black, p. 534).

De Long, Shleifer, Summers and Waldmann (1990, DSSW henceforth) formulate a theoretical model that demonstrates the effect the participation of noise traders in financial markets has and which implications their misperceptions have for expected returns and volatility. In their model, two classes of investors interact: rational investors and noise traders. Whereas the first hold fully rational expectations about future stock returns, the latter trade on an external, noisy signal that differs from information. This signal is sentiment, which is abstract for expectations that are formed subject to behavioural and cognitive biases and thus need not be completely rational. Misperceptions may induce noise traders to take irrational positions, thus driving prices away from fundamental value through their trading activity. If arbitrageurs have finite horizons and are risk averse (Shleifer & Vishny (1997)), stochastic noise trader sentiment creates a risk, as prices may deviate even more from value in the short run. Arbitrageurs concerned with liquidating their positions in the foreseeable future are likely to perceive this as an additional risk and limit their positions. Consequently, even in the absence of fundamental risk, noise trader sentiment, if systematic, creates a risk that limits arbitrage and thus allows prices to persistently differ from fundamental value. Furthermore, noise trader risk lowers asset prices as arbitrageurs pull out. If noise traders' opinions then entice themselves to invest in these assets, their expected return may be higher than the arbitrageurs'. Consequently, through their mere existence, "noise traders can earn higher relative expected returns solely by bearing more of the risk they themselves create" (DSSW, p. 706). It is important to realise that noise traders do not necessarily have to be pessimistic about a security in order to drive its price down – underpricing is simply an adjustment for the risk created by the variability of misperception or sentiment. These results have severe implications for the functioning of markets, but also bear consequences for asset price.

In this paper, we study the impact of the unpredictability of investor sentiment – of future noise trader demand for assets – on the return and conditional volatility of the German stock market. Using implicit measures of individual as well as institutional sentiment, we are able to empirically investigate the relationship between the opinions of different classes of investors and stock prices. While the empirical evidence regarding that issue is mixed, we are the first to use an integrated framework to jointly test the impact of individual and institutional sentiment on prices.

The remainder of the paper is organized as follows. In Section 2, we review empirical researches that study the influence of noise traders on stock prices. Section 3 explains the data and defines the quantitative model, Section 4 discusses the empirical analysis, and Section 5 concludes.

2 Investor sentiment and stock returns

In a first attempt to test the influence of noise traders on stock returns, Kelly (1997) examines what consequences the extent of noise trader participation has on returns. He conjectures that higher participation of noise traders is a negative predictor of stock returns, as noise traders tend to buy high and sell low (DSSW's "Friedman" effect)[1]. He assumes that the likelihood of a person to be a noise trader diminishes with household income, while the opposite is true for the chance of being smart money. Investors from intermediate-income households are assumed to be passive investors who do not have a direct bearing on the variation of stock market prices. His empirical results, after analysing data on U.S. dividend income tax from 1947-1980, support the theoretical predictions. Higher market participation by noise traders is a negative predictor of stock returns, while the opposite holds for smart money participation. The share of intermediate-income investors had no predictive power. Kelly thus managed to first pinpoint the influence of noise traders on stock market prices. However, he did not venture into making predictions about the nature of investor sentiment's influence on the variation in stock market prices. Consequently, researchers after that started running tests of how some measure of sentiment is statistically related to the movement in stock prices. In this field, two general approaches are to be distinguished, regarding the nature of the sentiment variable. The first is to formulate proxies of investor sentiment that are somewhat justified by financial theory. This is done by taking observable, objective variables that implicitly indicate investor sentiment and use them for statistical analyses. The second approach is to rely on explicit, mostly survey-based measures that try to capture the mood of the market more directly. Both approaches have their advantages and drawbacks. Objectively observable variables are more reliable with respect to their generation process; however their theoretical link to investor sentiment may be debatable. On the other hand, while survey-based measures are more direct in that respect, they often lack the sample size and statistical representativeness. Empirical studies employing both approaches will be reviewed separately in the following.

[1] This proposition is not to be confused with DSSW's finding that noise traders on average earn higher expected returns than sophisticated investors. While DSSW are concerned with the *unconditional* expected returns to noise traders, Kelly (1997) refers to expected returns *conditional on the participation level of noise traders.*

2.1 Implicit measures of investor sentiment

Swaminathan (1996) examines the predictive power of individual investor sentiment for the excess expected returns on small firms. In accordance with Lee *et al.* (1991), he uses an index of closed-end fund discounts to proxy for sentiment. His empirical findings are quite unambiguous. Individual investor sentiment, as reflected in closed-end fund discounts, is able to forecast small firm returns. The information contained in the sentiment index is independent from other macro-economic variables such as the dividend yield on the market and term spread. Closed-end fund discounts only forecast the small firm factor, but in that they are exclusive. These results seem to support the hypothesis of Lee *et al.* that, as individual investors are the major shareholders in small firm and close-end fund shares, the fluctuating discounts should reflect their irrational sentiment and forecast small firm returns. However, as his closed-end fund discount index also seems to be correlated with expectations of future earnings growth and expected inflation, Swaminathan suggests that closed-end fund discounts reflect investors' *rational* expectations, rather than irrational sentiment. Nevertheless, in his study closed-end fund discounts were able to forecast returns. In contrast to that, Elton, Gruber and Busse (1998) present evidence against the theory of Lee *et al.* They show that an index of closed-end fund discounts enters the return-generating process of small firms not more often than expected by chance and even less than purely non-fundamental industry-indices consisting of large, institutionally-held firms. The incorporation of the closed-end fund index into an asset pricing model does not yield support for the hypothesis that sentiment is priced either. Doukas and Milonas (2004) come to the same conclusion upon extending the work of Elton *et al.* (1998) to an out-of-sample dataset of Greek closed-end funds and stock market returns. The latest paper on the subject by Wang (2004) however again supports the use of closed-end fund discounts to proxy for sentiment. He constructs portfolios dependent on the exposition to closed-end fund discounts and finds significant excess returns than can not be explained by traditional financial models such as the one by Fama and French (1993). The discussion seems to remain whether closed-end fund discounts are the appropriate indicator of investor sentiment.

Next to closed-end fund discounts, Neal and Wheatley (1998) test two more measures of investor sentiment: the odd-lot[2] balance and net mutual fund redemptions. The first measure describes the ratio of odd-lot stock sales to purchases. The theory is that only individual investors trade in these small quantities. So when they are selling more than they are buying,

[2] Odd-lot: a stock transaction with volume of less than 100 stocks bought or sold at a time.

they are bearish, which is when the odd-lot balance indicator rises to signal a potential buying opportunity for rational investors.[3] The same kind of logic applies to net mutual fund redemptions. If investors redeem more shares of mutual funds than others buy, their sentiment is assumed to be low. As small investors hold a high stake in mutual funds, this measure is also seen as a proxy for *individual* investor sentiment[4]. The findings of Neal and Wheatley (1998) suggest that both closed-end fund discounts and net mutual fund redemptions bear explanatory power for the small firm premium, while the odd-lot balance does not seem to have a meaning in this respect. However, once the so-called Keim-Stambaugh factor (the cross-sectional average share price of small firms) is included in the analysis, only net mutual fund redemptions remain a statistically significant factor in explaining small firm excess returns. Along the same lines of argumentation, Brown et al. (2002) confirm the applicability of mutual fund flows. They construct a new index from mutual fund flow data, and validate that it is priced, both for the U.S. and Japan.

The approach to draw inferences about investor sentiment from trading statistics such as the odd-lot balance has been taken to the next level by Kumar and Lee (2003), Jackson (2003a), and Kaniel, Saar and Titman (2005). Kumar and Lee (2003) examine a dataset from a major discount broker. They find that the broker's clients – individual investors – seem to trade systematically, in that their trading activity is correlated. This is the prerequisite for their activities to influence market prices. Their measure of investor sentiment – basically the ratio of share sales to purchases – is also highly correlated with recommendations from investment newsletters. Individual investors seem to adhere to this "expert" advice. Next, Kumar and Lee discover that their measure of retail investor sentiment "has incremental explanatory power for [returns of] small stocks, value stocks, stocks with low institutional ownership, and stocks with lower prices" (p. 4f). Their statistics show that when investors are bullish, these stocks earn higher excess returns. Finally, to further explore the significance of their sentiment measure, they relate it to observed seasonal patterns such as the January effect and the Day-of-the-Week effect. While they find strong evidence that retail investor sentiment partly explains the January effect, fluctuations in sentiment do not seem to have a special impact on particular weekdays.

The analysis by Jackson (2003a) is similar, but comes to different conclusions. He uses an extensive dataset of some 40 million trades with Australian retail brokers. Analogous to Kumar and Lee, he finds that trading is significantly correlated on the market and cross-

[3] This line of argumentation goes back to Hardy (1939).
[4] Malkiel (1977) first suggested that net mutual fund redemptions reflect "general investor sentiment" (p. 856).

sectional level, and both within and across broker firms. Investors exhibit patterns of negative feedback trading, i.e. they buy after losses and sell after gains, a behaviour normally not associated with individual investors. Consequently, trading patterns by individual investors positively forecast short-term subsequent returns, which is at odds with the general assumption of small investor irrationality.

Kaniel *et al.* (2005) analyse another dataset on individual investor trades, this time from the New York Stock Exchange. Their analysis shows two things. First, individual investors seem to be quite good at predicting short-term returns. Stocks that experience a surge in individual buying for one week show an average excess return of 1.4% for the following 20 days. However, the contrary is not evident: stocks that individual investors sell do not perform worse than average in the following 20 days. Secondly, and quite surprisingly, Kaniel *et al.* discover that individual investors seem to follow contrarian investment strategies: "The mean market-adjusted returns in the 20 days prior to a week of intense individual selling is 3.97%, while prior to a week of intense individual buying it is −2.54%" (p. 3). These results mirror those of Jackson (2003a). In contrast to Kumar and Lee (2003) and Jackson, however, they can not confirm that the trading activity of individual investors is correlated across stocks, so that sentiment does not pose a systematic factor that should be priced in equilibrium.

Summarizing, closed-end fund discounts do not seem to be able to explain subsequent stock returns, while net mutual fund flows could be more a promising statistic. Detailed data on the trading behaviour of individual investors yields surprising implications. While the trading of individual investors can explain part of the subsequent variation in stock prices, this relationship seems to be positive. When sentiment is high, subsequent returns tend to be more positive. Surprisingly, investors seem to follow contrarian strategies themselves – they buy after low returns, and sell after gains. Individual trading seems to be highly correlated.

After closed-end fund discounts and other implicit measures of investor sentiment had been studied extensively, researchers turned to explicit, i.e. survey-based, measures in order to confirm their conclusions with data presumed to reflect sentiment more directly. These studies will be treated in the following section.

2.2 Explicit measures of investor sentiment

Fisher and Statman (2000) were among the first to include survey-based measures of investor sentiment into their research on opinions of different classes of investors. They identified three groups: small (individual) investors, medium investors (newsletter writers), and large, institutional investors (Wall Street strategists). First, to measure the sentiment of small investors, they drew on the weekly surveys the American Association of Individual Investors (AAII), which has collected weekly data since 1987. Members of AAII simply classify themselves as bullish, bearish or neutral. Fisher and Statman (2000) use the percentage of bearish investors as their sentiment indicator. Second, in order to capture the appraisement of newsletter writers, the service of Investors Intelligence (II) has been employed. Also on a weekly basis, since 1964 II classifies opinions published in newsletters as bullish, bearish or waiting for a correction. Again, Fisher and Statman take the percentage of bearish newsletter writers as their measure of sentiment. Finally, data compiled by Merrill Lynch quantifies institutional sentiment. The investment bank determines the share of stock in portfolios recommended by up to 20 investment strategists on a monthly basis since 1985. Drawing on these time-series, Fisher and Statman arrive at several findings. First, while sentiment of individuals and newsletter writers is significantly (though not perfectly) correlated, the investment bankers did not seem to follow any of the two. Fisher and Statman then turn to the predictive power of the sentiment measures for next-month stock returns, both for the S&P 500 and an index of small stocks. While all regressions yield negative coefficients for the sentiment variables, suggesting their potential use as a contrary indicator, the only significant relationship is between small investor sentiment and next-month S&P 500 returns. Subsequently, the issue of the influence of returns on sentiment is examined, so that the variables in the regressions are basically flipped. The results are quite clear. Both small investors and newsletter writers are strongly influenced by past returns. After periods of positive market developments, their sentiment rises significantly. Surprisingly, and in contrast to the assumptions of e.g. Lee, Shleifer and Thaler (1991), individual investors seem follow the development of the S&P 500 more closely than small-cap stocks. The same is true for newsletter writers. In contrast, Wall Street strategists' opinions are not that easily influenced by past returns, which again is in line with the general assumption of their relative rationality. Finally, individual investors' allocation of funds to stocks is examined through AAII fund allocation survey data. Luckily for them, small investors do not seem to act on their sentiment. While surges in their sentiment tend to be followed by negative S&P 500 returns, returns tend to be higher after small investors invest more of their funds in stocks, so they do not seem that irrational after all.

In another study, Solt and Statman (2001) investigated whether investment strategies based on sentiment indicators can be profitable. They concentrate on the Investors Intelligence index and relate it to Dow Jones Industrial Average (DJIA) returns. They conclude that "there is no statistically significant relation between the index and changes in the DJIA in the subsequent four-week periods", so that the "sentiment index is not useful as a contrary indicator" (Solt & Statman, 2001, p. 47).

Fisher and Statman (2004) investigated the expectations by individual investors and Wall Street strategists again, this time on the background of the millennium stock market bubble. They use postings on Yahoo message boards and results form both the Gallup/UBS and BusinessWeek surveys to gauge the opinion of investors during times of high gains and losses around the 2000 stock market bubble. Again, sentiment seems to follow returns, as reflected in a higher percentage of optimistic investors at the climax of the market compared to the trough in the middle of 2002. Wall Street investors however, according to BusinessWeek surveys, were less bullish after strong gains, but became more so after the crash of the market, in contrast to the bearish individual investors at the time. This is in line with their previous findings. They conclude that "stock price of the late 1990s were likely driven higher by the exuberance of investors about their favourite individual stocks, as captured on the Yahoo message boards, or by the combined drive of many investors, each with modest expectations" (Fisher & Statman, 2002, p. 20).

Brown and Cliff perform two extensive studies on the relationship of measures of investor sentiment and stock returns. While in Brown and Cliff (2002) they examine the long-run effects of investor sentiment on stock returns, they concentrate on the near-term stock market in their later study (G. W. Brown & Cliff, 2004). In their analysis, Brown and Cliff (2002) test two basic hypotheses:

1. "Excessive optimism leads to periods of market overvaluation", and
2. "High current sentiment is followed by low cumulative long-run returns"

They focus on the long-run reversal of returns to fundamental value, as arbitrage that could force prices back to value might be effective in the short run, but limited in the long. The first hypothesis is tested by relating sentiment as reflected in the aforementioned Investors Intelligence (II) surveys to S&P 500 pricing errors. The second hypothesis is investigated by finding significant relationships between high levels of sentiment and subsequent returns on the Fama and French (1993) and other portfolios over differing horizons. In all their analyses Brown and Cliff use ten control variables to distinguish the rational part of sentiment from the irrational. After all, changes in sentiment may not be completely irrational, but also simply reflect changes in fundamental factors. Their results are coherent. First, investor sentiment is significant in explaining parts of stock market misvaluations, even in presence of control variables. Second, positive shocks (over one standard deviation) to investor sentiment are nearly always followed by reduced returns over horizons of six, twelve, 24 and 36 months.

Summarizing, survey-based measures help to better understand the formation of investor sentiment and its impact on the behaviour of stock markets. Sentiment seems to follow recent stock market developments. Especially individual investors seem to become more bullish after gains on the stock market. Wall Street strategists in contrast seem to be less enthusiastic in bull markets, however they do believe in faster recovery when in bear markets. Optimistic investors are possibly able to influence market valuations and make them less efficient, especially over longer horizons. Finally, surges in survey-based sentiment indicators seem to be followed by negative returns, which would render them candidates for contrarian indicators.

2.3 Combined im- and explicit measures of investor sentiment

Both implicit and explicit measures of investor sentiment have been employed which were partly able to add to the discussion on whether investor sentiment is an important determinant of stock returns. However, it has remained unclear which measures are actually most appropriate, and to which extent they represent the same informational content. To further clarify this issue, two studies have gone further and attempted to integrate several measures.

The aforementioned research by Brown and Cliff (2004) complements their study of long-term return patterns and sentiment in that they focus on short-term effects this time. They come to their conclusions in two steps. First, they explore the interrelationships of a wide range of implicit and explicit measures of sentiment. Second, the explanatory power of investor sentiment for stock returns is inspected. As others before, Brown and Cliff (2004) rely on the AAII and II survey data. For the implicit measures, they use a wide range from indicators of recent market performance (e.g. the ARMS index), type of trading activity (e.g. the odd-lot balance, short sales activity), derivatives variables (e.g. put/call ratio, implied volatility) to IPO data (number of offerings, first day returns) and others such as the known closed-end funds discounts and mutual fund flows[5]. Their first main result is that all these measures contain similar information, which is why they use integration techniques such as the Kalman filter and principal components analysis in order to arrive at new, unobserved measures of sentiment. These measures correlate significantly with contemporaneous returns. Further, causal analysis reveals that while returns strongly affect subsequent swings in sentiment, "very little evidence suggests sentiment causes subsequent market returns" (G. W. Brown &

[5] See Brown and Cliff (2004) for a complete and detailed overview of the used indicators as well as their common classification as bullish or bearish

Cliff, p. 3). Finally, and surprisingly, the strongest link between sentiment and returns appears to be between institutional sentiment and large stocks. Although statistically not significant, this relationship would counter the usual assumptions that individual investors are the ones to add noise to stock prices.

The second, extensive study that integrates several measures of investor sentiment has been presented by Baker and Wurgler (2004). While Brown and Cliff use marketwide return data, Baker and Wurgler (2004) discuss cross-sectional differences in the time-series of stock returns. They propose two distinct mechanisms through which the cross-sectional return differences might become evident. First, sentiment, which they define as "propensity to speculate" (p. 5) might differ across stocks. The value of stocks with certain characteristics might be more subjective than for others, which allows inexperienced investors to justify a range of valuations. Then, e.g. in a bull market when people want to invest, they buy these stocks because they expect prices to rise to the upper end of their pricing range. Second, arbitrage possibilities might vary across stocks. As the values of stocks with certain characteristics are more subjective, arbitrageurs cannot objectively determine value either, which limits arbitrage for these stocks. In effect, both mechanisms lead to the same result: some stocks are more susceptible to misvaluations. If that was true, they would display distinct return pattern when prices and values converge eventually. In particular, Baker and Wurgler suppose that if changing sentiment caused mispricings, it would have a comparatively higher impact on young, small, highly volatile, unprofitable, non-dividend paying, high-growth or distressed stocks. Their methodology is simple: After splitting their records into high and low levels of marketwide beginning-of-period sentiment, they sort corresponding stock returns by every aforementioned characteristic, respectively. Just as Brown and Cliff, they employ a wide range of implicit sentiment measures, although they do not make use of survey data. Unlike Brown and Cliff, they orthogonalize these indicators with respect to several macroeconomic variables[6]. By that technique, Baker and Wurgler filter some rational content reflected in sentiment from their indicators in order to achieve cleaner measures for the irrational mood swings of investors. Their results are clear: when initial sentiment is low, smaller, younger, higher-return volatility, more unprofitable, non-dividend paying, high-growth and distressed stocks earn higher returns in the following month than their counterparts. When sentiment is high, the effects reverse. The empirical evidence thus supports the theoretical predictions that firms with these characteristics are more affected by swings in sentiment, so that when inves-

[6] See Baker and Wurgler (2004) for an overview of used indicators and variables

tors are bearish, they are undervalued and thus show above-average subsequent returns, and vice-versa.

Summarizing, the integration of several measures of sentiment has proven a fruitful approach to exploring the relationship of investor sentiment and stock returns. On a marketwide basis, integrated measures of sentiment are not yet able to forecast returns. For the cross-section of stocks, the opposite is true. Stocks with subjective valuations are influenced by swings in sentiment and show distinguishable return patterns.

2.4. Investor sentiment, volatility and stock returns

Only few researchers have ventured into the field of relating investor sentiment to volatility. Nevertheless, this seems appropriate, as "the most fundamental prediction of the noise trader-model is that irrational investors acting in concert on a noisy signal […] cause a risk" (G. W. Brown, 1999, p. 84) which can reasonably assumed to be volatility. Brown (1999) investigates this issue by relating AAII sentiment survey data to closed-end fund discount volatility. Through his parsimonious regression analysis, he reveals several things. First, deviations from mean levels of sentiment lead to statistically significant higher discount volatility, which supports noise trader theory as it suggests that sentiment poses a systematic risk. Second, Brown shows that extreme levels of investor sentiment affect discounts only during trading hours, which is a prerequisite for the theory that noise traders influence prices through their trading activity. The fact that the number of trades in closed-end funds is significantly higher in periods of extreme sentiment corroborates this finding. Finally, when sentiment is extreme, total trading volume does not increase, meaning that the average trade size decreases, so that "the larger traders actually give way, to some degree, to noise traders" (p. 88). With his study, Brown laid the foundation for studying the impact of sentiment on volatility.

Extending the focus to a broader equity market context, Jackson (2003b) uses the same database as in his companion paper (Jackson, 2003a). He comes to surprising results. Larger trading share of individuals in certain stocks does not increase their subsequent volatility. Additionally, individual participation does not lead stock returns to be correlated with a small stock portfolio. However, the opposite is true for *institutional* participation, which increases conditional volatility and leads to a higher correlation with other, mostly institutionally held stocks. Finally, Jackson finds a significant noise trader risk factor that is priced in equilibrium. In line with his previous results, and in contrast to the common interpretation of noise trader theory, the source of this risk seems to be *institutional* traders. According to Jackson, "institutional frictions are a much more plausible source of non-fundamental demand shocks than is an individual sentiment effect" (p. 6).

The next step was to integrate all former work and conduct an empirical study that incorporates the elements of sentiment, returns, and risk (volatility). This is exactly what W.Y. Lee, Jiang and Indro (2002) have done. They start off by arguing that empirical models that analyse only the impact of sentiment on either expected returns or volatility are "mispecified and at best incomplete" (p. 2280). This holds as the DSSW theory, to which they closely adhere, states four effects that affect returns, both directly and through the effects of changing misperceptions on return volatility. Consequently, an empirical model should include both channels, and not focus merely on returns. They propose a generalized autoregressive conditional heteroskedasticity (GARCH) in-mean model. As returns, Lee *et al.* (2002) employ data from the Dow Jones Industrial Average, NASDAQ, and S&P 500 indices. To model investor sentiment, survey data from Investors Intelligence is used, just as in several studies before. The empirical results are consistent with the noise trader model. Lee *et al.* find that "investor sentiment is an important factor in explaining equity excess returns and changes in conditional volatility" (p. 2291). Specifically, changes in sentiment are significantly and positively related to excess returns. This means that the "hold more" effect dominates the adverse "price pressure" effect. Investors earn higher expected returns when they are bullish, because their optimism leads them to hold more of the risky asset, for which they are compensated. While the increased demand for the risky asset increases its price (and thus lowers its expected return), this does not offset the positive effect completely. In contrast, when investors turn bearish, their trading pushes prices down. They pull out of the risky asset so that they can not reap compensation for bearing noise trader risk. Returns are also found to be significantly influenced by volatility, which in turn is subject to changes in sentiment. Bullish shifts in sentiment lead to subsequent downward adjustment of future volatility, whereas bearish shifts lead to increased volatility. When investors are optimistic, the "create space" effect dominates the "Friedman" effect, and thus raises expected returns. However, this relationship turns with sentiment when it becomes bearish. Then the space noise traders create is not sufficient any more so that their poor market timing hurts them. Their results are robust to the selection of sub-periods and different measures of sentiment (absolute vs. % change).

3. Data and Econometric Framework

In this paper, we use survey-based sentiment indicators, as it is the most direct measure of investor sentiment. Unlike in the U.S., survey-based sentiment indicators have only recently become available for the German stock market. They range from monthly surveys of investors (“G-Mind”) over monthly summaries of newsletter opinions (“Notes”, similar to the Investor’s Intelligence index) to weekly surveys. As only weekly data seems appropriate for this analysis, both the G-Mind and the Notes will not be used here. One weekly index, the AnimusX-sentiment, had to be excluded as well, due to a very small sample size as a result of data loss on the side of the issuer. This leaves two sentiment indices: the Sentix and the Bull/Bear index. The Sentix sentiment index is a weekly, survey-based index issued and provided by Sentix Behavioral Indices GbR[7]. It has been published every Friday since February 2001. The survey method is Internet-based. Registered investors (individual as well as institutional investors seperately) are asked to give their appraisal of the respective market for the following month. In total, approximately 1,800 investors are now registered with Sentix. The respondents have three options: either they are bullish, bearish or neutral regarding the respective market (DAX as well as TecDAX). Given the raw data, we construct a sentiment index according to the following formula:

$$S_t = \frac{N_{bullish}}{N_{total} - N_{neural}},$$

where $N_{bullish}$ and $N_{neutral}$ refers to the number of respondents that classify themself as being bullish or neutral, respectively. N_{total} refers to the total number of respondents. Values of the sentiment index range from 0% to 100%, with larger values implying increased bullishness of market participants. In particular, we construct sentiment indices for individual, institutional and total investor sentiment. For the individual (institutional) sentiment index, only the opinions of private (institutional) investors are taken into consideration. For the total sentiment index, the opinions of all respondents are considered. In addition, we derive individual, institutional and total sentiment indices for the DAX as well as for TecDAX market. The DAX is a performance index of the 30 largest German ‘blue-chip’ stocks and the TecDAX is the market index that reflects the return of smaller companies from the technology sector.

[7] www.sentix.de.

Corresponding to the sentiment index used, the weekly closing prices on the sampling weekday (Friday) will be used to calculate a time series of continuously compounded returns.

Not surprisingly, sentiment of institutional and individual investors are not perfectly correlated (~70% correlations in both cases), which reflects a tendency of differing opinions between the two groups. This suggests that analysing both individual and institutional sentiment separately might be useful in further analysis.

In a first step, we determine an optimal base model for the returns and volatilities of both DAX and TecDAX. A general symmetric EGARCH in-mean specification is implemented, which is sufficiently flexible for the purpose at hand (see e.g. Lehnert (2003)). The model reads:

$$r_t - \mu = \lambda h_t^2 + h_t \varepsilon_t \quad \text{with } \varepsilon_t \sim N(0,1) \qquad \text{and}$$
$$\ln(h_t^2) = \beta_0 + \beta_1 \ln(h_{t-1}^2) + \beta_2 abs(\varepsilon_{t-1})$$

where r_t: Return for period t

μ: Unconditional Mean

λ: Asset Risk Premium

h^2: Conditional Variances

In a next step, we include investor sentiment in the return and conditional variance specification. The new model reads[8]:

$$r_t - \mu = \lambda h_t^2 + \gamma \Delta S_t + h_t \varepsilon_t \text{ with } \varepsilon_t \sim N(0,1) \text{ and}$$
$$\ln(h_t^2) = \beta_0 + \beta_1 \ln(h_{t-1}^2) + \beta_2 abs(\varepsilon_{t-1}) + \beta_3 abs(\Delta S_{t-1})$$

where ΔS_t: Log-Change in investor sentiment in period t

In a final step, we extend the model by incorporating individual *and* institutional investor sentiment separately. The final specification reads:

[8] We also worked with the asymmetric version of the model. (Results are not reported, but in line with Lee et al. (2002)). However, given the relatively small sample of weekly observations, it is not wise to further increase the number of parameters that have to be estimated. The symmetric version of the model is sufficient for the purpose at hand.

$$r_t - \mu = \lambda h_t^2 + \gamma_1 \Delta S^{ind}{}_t + \gamma_2 \Delta S^{inst}{}_t + h_t \varepsilon_t \text{ with } \varepsilon_t \sim N(0,1) \text{ and}$$
$$\ln(h_t^2) = \beta_0 + \beta_1 \ln(h_{t-1}^2) + \beta_2 abs(\varepsilon_{t-1}) + \beta_3 abs(\Delta S^{ind}{}_{t-1}) + \beta_4 abs(\Delta S^{inst}{}_{t-1})$$

where $\Delta S^{ind}{}_t$: Log-Change in individual sentiment in period t

$\Delta S^{inst}{}_t$: Log-Change in institutional sentiment in period t

In order to stabilize the estimation process, we numerically control for the fact that the unconditional volatility is equal to the sample standard deviation. In order to avoid over-parameterization, objective model selection criteria have to be employed. The two most commonly used model selection criteria are the Akaike and Schwartz information criteria (AIC and SIC, respectively). The purpose of model selection criteria is to formalize the trade-off between goodness of fit and model complexity. However, the standard criteria have to be modified in order to account for the particular features of GARCH models (Brooks & Burke, 2003). The proposed adjusted measures[9] are:

$$AIC = \sum_{t=1}^{n} \ln\left(h_t^2\right) + 2p \qquad \text{and} \qquad SIC = \sum_{t=1}^{n} \ln\left(h_t^2\right) + \ln(n)\, p$$

where n: Number of observations

h^2: Conditional Variances

p: Number of model parameters

Although the resulting absolute values for the criteria are considerably different, the use is similar: a lower value for the criterion indicates a better model. Again, the Schwartz criterion is more restrictive concerning the use of parameters.

[9] For derivation and discussion of the criteria see the appendix in Brooks and Burke (2003)

4. Empirical Results

Table 1 reports the parameter estimates of the various models and for both market indices. The volatility parameter in the mean equation has a positive sign. This is in line with classical capital asset pricing theory, which suggests that taking higher risks should be rewarded with higher expected returns (French et al. (1987)). However, more recently researchers have encountered the opposite phenomenon (Glosten, Jagannathan and Runkle (1993) and De Santis and Gerard (1997)) and argue that a negative relation can occur in times of high savings rates and limited alternative investment opportunities, or in times of high inflation and downward sloping term structures (Boudoukh, Richardson, & Smith, 1993). A more econometric explanation has been provided by Backus and Gregory (1993), who state that the relationship of returns and conditional volatility of asset returns can be positive, negative or flat, depending on the preferences of the representative agent and other statistical features.

The first and most important result is that including contemporaneous shifts in sentiment in the mean equation improves the model fit significantly (based on the AIC and SIC criteria). Most other parameters remain comparable to those of the base model and are in line with previous financial research on GARCH modeling. In general, in line with Lee et al. (2002), changes in sentiment are positively related to changes in the excess return. Additionally, increased variations in sentiment also increase conditional variance and thus expected returns due to the asserted positive λ. In the words of DSSW, the "hold more" effect dominates the "price pressure" effect. When investors becomes more bullish, they invest in assets they themselves make riskier than warranted by fundamentals, and thus reap extra returns. Additionally, the "create space" effect dominates the "Friedman" effect: increased sentiment volatility scares away rational investors, which overly compensates noise traders for their bad market timing.

The next question is which kind of sentiment better explains excess returns and conditional volatility: individual or institutional sentiment. Previous empirical research has mostly at least implicitly equalled noise traders with individual investors. They are supposedly "less sophisticated" and thus more prone to irrational behaviour. As noise traders have to trade in order to benefit from eventual excess returns, it is assumed that their sentiment should affect rather small capitalization stocks, which are traded more by individuals. As the DAX is Germany's blue chip index of stocks that are mainly traded by professionals, individual sentiment should accordingly minor incremental explanatory power. The opposite is true. When the sentiment measures are split into individual and institutional, a surprising result can be observed. While the other model parameters remain comparable, it becomes obvious that individual investor sentiment is much more important in comparison to institutional sentiment. Apparently, while the impact of noise traders on markets seems significant, previous research has not yet clearly revealed their identity.

For the TecDAX market and using TexDAX Investor Sentiment, the results are comparable. Adding sentiment parameters definitely improves the model when contemporaneous changes in sentiment are included in the mean equation. Again, individual investor sentiment performs better in comparison to institutional sentiment. Apparently, the shifting opinions of private investors as reflected in their sentiment has a stronger impact on markets, regardless of the type of stocks traded. The impact of changes in investor sentiment is largely similar to the DAX models. Bullish shifts in sentiment still raise expected returns, so the "hold more" effect still prevails.

Overall, adding sentiment always increases model fit significantly. Private investor sentiment seems to better explain the interplay of risk and return than institutional sentiment. Overall, noise traders seem to benefit from their alleged irrationality and are rewarded with higher expected returns, which is exactly in line with the theoretical predictions of DSSW.

5 Conclusion

In this paper, we propose an integrated framework that jointly tests for the effects of individual as well as institutional sentiment on return and volatility. When contemporaneous changes in sentiment are used to explain excess return and conditional volatility, we observe a significant improvement in model performance. In contrast to previous US studies, we find evidence that in the German stock market, individual sentiment is a market wide risk factor and does not only affect small cap stocks. Institutional sentiment has only minor incremental explanatory power for returns and conditional volatility of small and large cap stocks. Apparently, while the identity of noise traders is widely acknowledged, their impact on the cross section of stock prices was frequently underestimated. However, the results can be interpreted as being a characteristic of smaller markets, where also large cap stocks are widely held by private investors.

BIBLIOGRAPHY

Backus, D. K., & Gregory, A. (1993). Theoretical relations between risk premiums and conditional variances. *Journal of Business and Economic Statistics, 11*(2), 177-185.

Baker, M., & Wurgler, J. (2004). *Investor sentiment and the cross-section of stock returns* (Vol. 10449). Cambridge: National Bureau of Economic Research, Inc.

Black, F. (1986). Noise. *Journal of Finance, 16*(3), 529-543.

Boudoukh, J., Richardson, M., & Smith, T. (1993). Is the ex ante risk premium always positive? A new approach to testing conditional asset pricing models. *Journal of Financial Economics, 34*(3), 387-408.

Brooks, C., & Burke, S. (2003). Information criteria for GARCH model selection. *European Journal of Finance, 9*(6), 557-581.

Brown, G. W. (1999). Volatility, Sentiment, and Noise Traders. *Financial Analysts Journal, 55*(2), 82-91.

Brown, G. W., & Cliff, M. T. (2002). *Investor Sentiment and Asset Valuation*. Retrieved December 5, 2004, from http://ssrn.com/abstract=292139

Brown, G. W., & Cliff, M. T. (2004). Investor Sentiment and the Near-Term Stock Market. *Journal of Empirical Finance, 11*(1), 1-27.

Brown, S. J., Goetzmann, W. N., Hiraki, T., Shiraishi, N., & Watanabe, M. (2002). *Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows*. Retrieved March 21, 2005, from http://ssrn.com/abstract=302829

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy, 98*(4), 703-739.

De Santis, G., & Gerard, B. (1997). International asset pricing and portfolio diversification with time-varying risk. *Journal of Finance, 52*(5), 1881-1912.

Doukas, J. A., & Milonas, N. T. (2004). Investor Sentiment and the Closed-end Fund Puzzle: Out-of-sample Evidence. *European Financial Management, 10*(2), 235-267.

Elton, E. J., Gruber, M. J., & Busse, J. A. (1998). Do Investors Care about Sentiment? *Journal of Business, 71*(4), 477-500.

Fama, E. F. (1965). The Behavior of Stock Market Prices. *Journal of Business, 38*(1), 34-106.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics, 33*(1), 3-57.

Fisher, K. L., & Statman, M. (2000). Investor Sentiment and Stock Returns. *Financial Analysts Journal, 56*(2), 16-24.

Fisher, K. L., & Statman, M. (2002). Bubble expectations. *Journal of Wealth Management, 5*(2), 17-23.

Fisher, K. L., & Statman, M. (2004). Sentiment, Value, and Market Timing. *Journal of Investing, 13*(3), 10-21.

French, K. R., & Roll, R. (1986). Stock Return variances: The Arrival of Information and the Reaction of Traders. *Journal of Financial Economics, 17*(1), 5-27.

Friedman, M. (1953). The Case for Flexible Exchange Rates. In *Essays in Positive Economics*. Chicago: University of Chicago Press.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance, 48*(5), 1779-1801.

Jackson, A. (2003a). *The aggregate behaviour of individual investors*. Retrieved April 3, 2005, from http://phd.london.edu/arjackson/smallinvestorpaper15.pdf

Jackson, A. (2003b). *Noise trader risk exists...but the noise traders are not who you think they are*. Retrieved February 21, 2005, from http://phd.london.edu/arjackson/noisetraderrisk.pdf

Kaniel, R., Saar, G., & Titman, S. (2005, September 2004). *Individual Investor Sentiment and Stock Returns.* Paper presented at the AFA Meeting, Philadelphia.

Kelly, M. (1997). Do noise traders influence stock prices? *Journal of Money, Credit & Banking, 29*(3), 351-364.

Kumar, L., & Lee, C. M. (2003). *Individual investor sentiment and comovement in small stock returns*. Retrieved March 21, 2005, from http://wpweb2k.gsia.cmu.edu/wfa/wfapdf/KumarLee03_InvSenti.pdf

Lee, C. M. C., Shleifer, A., & Thaler, R. H. (1991). Investor Sentiment and the Closed-End Fund Puzzle. *Journal of Finance, 64*(1), 75-110.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking & Finance, 26*(12), 2277-2299.

Lehnert, T. (2003). Explaining Smiles: GARCH Option Pricing with Conditional Leptokurtosis and Skewness. *Journal of Derivatives*, 10, 3, 27-39.

Neal, R., & Wheatley, S. R. (1998). Do measures of investor sentiment predict returns? *Journal of Financial & Quantitative Analysis, 33*(4), 523-548.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance, 52*(1), 35-56.

Solt, M. E., & Statman, M. (2001). How useful is the sentiment index? In H. Shefrin (Ed.), *Behavioral Finance* (Vol. 2, pp. 3-13). Cheltenham, U.K.: Elgar Reference Collection.

Swaminathan, B. (1996). Time-Varying Expected Small Firm Returns and Closed-End Fund Discounts. *Review of Financial Studies, 9*(3), 845-887.

Wang, X. (2004). *Sentiment Strategies*.Unpublished manuscript.

Table 1: Parameter Estimates

Panel A: DAX 30				
	Excluding Sentiment	Including Total DAX Sentiment	Including Individual ***and*** Institutional DAX Sentiment	
		Total	Individual	Institutional
$h_{i,t}$	2.431*	1.431*	1.559*	
$\Delta S_{i,t}$		0.041***	0.035***	0.006
β_0	-1.200*	-2.022*	-1.891*	
$\ln(h_{i,t-1})$	0.860***	0.790***	0.806***	
$abs(\varepsilon_{i,t-1})$	0.344**	0.459*	0.437*	
$abs(\Delta S_{i,t})$		0.880**	0.848**	-0.021
MLE	63.6	98.2	98.5	
AIC	-1387.3	-1413.7	-1410.4	
SBC	-1374.0	-1393.7	-1383.7	

Panel B: TecDAX				
	Excluding Sentiment	Including Total TecDAX Sentiment	Including Individual ***and*** Institutional TecDAX Sentiment	
		Total	Individual	Institutional
$h_{i,t}$	0.833*	0.839*	0.895*	
$\Delta S_{i,t}$		0.050***	0.033**	0.016
β_0	-0.537*	-0.504*	-0.567*	
$\ln(h_{i,t-1})$	0.941***	0.952***	0.945***	
$abs(\varepsilon_{i,t-1})$	0.235**	0.194*	0.206**	
$abs(\Delta S_{i,t})$		0.229*	0.166*	0.081
MLE	25.4	49.7	49.4	
AIC	-1229.6	-1240.1	-1236.5	
SBC	-1216.2	-1220.0	-1209.8	

Notes. *** significant at the 1% level, ** significant at the 5% level, *significant at the 10% level