Noise trading, firm characteristics and Institutional behavior

Denys Glushkov*

First draft: July 6, 2004
This version: Dec 21, 2004

Preliminary and incomplete

Abstract

This paper develops a new measure of noise trading at the individual stock level defined as sensitivity of stock returns to the sentiment index changes. The sentiment index is shown to predict aggregate market returns as well as contemporaneously explain small and retail stock returns spreads. Using this proxy I first test "hard-to-value, difficult-to-arbitrage" (HV-DA) hypothesis of noise trader behavior. During the period 1975-1999 I find some evidence in support of HV-DA: a) stocks with higher sentiment-induced noise trading tend to be smaller, younger and more liquid stocks with lower earnings, cash flows and dividend yields as well as greater volatility and short sales constraints. Given size and past volatility, glamour stocks appear to have higher exposure to sentiment changes than value stocks. In contrast to HV-DA, greater numbers of analysts, higher likelihood of being an S&P 500 member and higher institutional ownership are found in stocks with the higher sentiment sensitivity in the past, ceteris paribus. The patterns are particularly pronounced in the second half of the sample (from 1988 to 1999). Institutional analysis reveals that institutions changed their behavior with respect to their holdings of stocks with higher noise trader risk: institutions have been avoiding the latter stocks throughout the 80's, however, were seeking exposure towards these stocks in the 90's. This is consistent with the hypothesis of more sophisticated institutional (arbitrageur) behavior in the 90's: instead of simply counteracting the actions of sentiment traders in the short-run, institutions might have been exacerbating sentiment-driven mispricing

JEL classification: G1

Keywords: Noise trading, sentiment, firm characteristics, institutions

---

*Red McCombs School of Business, University of Texas at Austin, B6600, Austin, TX, 78712. Contact email is denys.glushkov@phd.mccombs.utexas.edu. I would like to thank Greg Brown, Meir Statman, Ivo Welch and Prachi Deuskar for providing the sentiment proxies. I am also indebted to Roberto Wessels, John Griffin, Andres Almazan and Sheridan Titman for valuable comments and suggestions. I am responsible for any errors.

Introduction

In recent years, there is a growing body of both theoretical and empirical literature investigating the behavior of noise traders and its implications for financial markets. This literature has improved our understanding of some unexplained phenomena in the real-world financial markets, such as the existence of predictability in returns and excess volatility. Recent research showed that the role of noise traders may be non-trivial and both the finance practitioners and academics came to realize the importance of understanding the drivers of these traders' behavior and their trading patterns.

Some theoretical models in financial economics[1] have come to describe the asset price dynamics through the interplay of the so-called "noise traders" who are unable to fully exploit available information or to correctly maximize their utility[2] and the sophisticated rational arbitrageurs that have correct beliefs and expectations. Underlying this noise trading literature is the premise that subsets of agents trade in response to extraneous variables that convey no information about fundamentals, such as sentiment. In the framework of these models, Friedman's (1953) "non-destabilizing speculation" argument relies on two assumptions: first, rational arbitrageurs push asset prices towards their fundamental value; second, that over time irrational "noise" traders will have bad results and, therefore, be driven out of the markets. Behavioral finance literature, on the other hand, questions the validity of these arguments and predicts that sentiment-induced noise trading can have a non-trivial impact on the asset prices. The debate is still going back and forth, both in theoretical and empirical literature, and there is no uniform consensus on the matter in the academic community.

Contributing to this debate, this paper is an attempt to look at both "sides of the coin": noise traders' behavior and arbitrageurs' behavior. Looking at one "side of the coin", I would like to test the "Hard-to-value, Difficult-to-Arbitrage" hypothesis of noise trader behavior. The basic message of this hypothesis is that some stocks are more prone to the shifts in the noise trader sentiment than the others because of the subjectivity of their valuations. It predicts that smaller, younger, unprofitable stocks with a short earnings history and the presence of virtually unlimited growth

[1] See De Long et al. (1990, 1991), Shleifer and Vishny (1997), Palomino (1996), Kogan et al. (2003), Slezak (2003) Kanatas and Wang (2004), Wang (2004).
[2] As early as 1986, Black described the possible effects of noise on financial markets. According to him, noise traders "trade on noise as if it were information" and in doing so make markets possible.

opportunities will be more subject to sentiment changes because such characteristics allow unsophisticated investors to defend, with equal plausibility, a wide spectrum of valuations, from much too low to much too high, as suits their sentiment. In the empirical parlor, testing whether this hypothesis is a good representation of the noise trader behavior is as same as asking whether we would observe any patterns in firm characteristics conditional on the levels of noise trading present in the stocks of these firms and, if yes, are these patters in line with "Hard-to-Value, Difficult-to-Arbitrage" assertion's predictions?

The other "side of the coin" is the nature of interaction between the noise traders and the arbitrageurs in the market, more precisely, the role the latter play in counteracting mispricing caused by the actions of noise traders. Even if there are no limits of arbitrage, are the arbitrageurs (institutions) always standing ready to eliminate the sentiment-induced mispricing or they might exhibit a more sophisticated behavior, which could, in fact, exacerbate it? In other words, the tested hypothesis of interest claims that the rational market players' primary objective is to counteract mispricing by pushing the prices back to fundamental values. This paper is an attempt to address these mentioned issues from an empirical standpoint.

The related literature could be classified into two groups. The papers in one group try to shed light on the behavior of noise traders by developing proxies for sentiment and non-fundamental factor using the data from trading accounts of individuals. The underlying premise of this work is that individuals are the noise traders in question and the evidence of this literature is rather mixed. For instance, Kumar and Lee (2003) argue that buy-sell imbalance in individual investors' trades (their proxy for investor sentiment) contains a systematic component that is uncorrelated with overall market movements and only weakly correlated with standard risk factors and macro variables. They also find that residual buy-sell imbalance (after accounting for fundamental factors) has incremental power for small stocks, value stocks, stocks with low institutional ownership and stocks with lower prices. In the related work, Hong and Kumar (2002) demonstrate that the price trend rather than the information content of an event is the primary determinant of individual investors' trading decisions around earnings announcements and analysts' stock recommendation changes. Barber, Odean and Zhu (2003) using a variety of empirical approaches, document that trading of individuals is more coordinated than one would expect by mere chance.

In the more recent study by Kaniel et al (2004) that uses a unique dataset of individual investors' trades, authors document that individual investor sentiment (proxied by buy-sell imbalance) has significant ability to predict future returns and that the information content of investor sentiment is distinct from that of past returns or past volume. However, contrary to the results of Kumar and Lee (2003) and Barber at al. (2003), they find very little cross-sectional correlation of individual investor sentiment across stocks in their sample, in other words, no evidence of non-fundamental factor in the trades of individuals. Jackson (2003 a,b) analyzes a comprehensive database from 47 Australian retail brokers and shows that institutional frictions such as common investment strategies, performance related mutual fund flows and career concerns are a much more plausible source of noise trader risk than is individual investor sentiment. Finally, Brown et al. (2003) provide suggestive evidence of a price sentiment factor in the US and Japan equity markets using daily mutual fund flows as a sentiment proxy.

The other set of papers seeks the answer to the question of how noise traders influence markets by using aggregate measures of investor sentiment rather than individual trading accounts. Lee et al. (1991) argue that closed-end fund discount is a measure of investor sentiment and find that discounts narrow when small stocks do well, as would be expected if closed-end funds were subject to the same sentiment as small stocks. Lee et al. (2003) find that sentiment, proxied by Investor Intelligence Index, is a systematic risk that is priced and the magnitude of bullish (bearish) changes in sentiment leads to downward (upward) revisions in volatility and higher (lower) future excess returns. Lemmon and Portniaguina (2004) report evidence that consumer confidence (measured by Univ. of Michigan Consumer Sentiment Index) regarding the economic conditions predicts the future quarterly premium of small stocks returns over large stock returns, after controlling for a number of other macroeconomic factors. A number of other empirical papers also find the support for the noise trading theory either on the basis of event-studies or at the aggregate market level[3]. On the other hand, Elton et al. (1998), Sias et al. (2001) and more recently Doukas and Milonas (2004) show that investor sentiment does not enter the return generating process and noise trader risk does not appear to be priced.

Probably, the closest in spirit to my paper is Baker and Wurgler (2004b) that looks at how sentiment affects the cross-section of stock returns and demonstrates that when sentiment is low, smaller, more volatile, unprofitable stocks earn higher subsequent returns, whereas the pattern

[3] See Neal and Wheatley (1998), Bodurtha et al. (1995), Cooper, Dimitrov and Rau (2001), Mitchell, Pulvino and Stafford (2002), Lamont and Thaler (2003), Barberis et al (2003), Barber, Odean and Zhu (2003) and Jackson (2003b).

reverses when the sentiment is high. Related to the behavior of arbitrageurs (institutions) is the work by Bennett et al. (2003), which finds that in the last decade institutions shifted their preferences towards smaller and riskier stocks.

The results can be deemed to have important policy and optimal investment decision-making implications. The presented evidence could be very relevant from the perspective of money managers (professional investors), whose purpose is to provide investors with the expected rate of return on their investments, heads of firms (CEOs) whose compensations could be tied to the firm's stock performance. Additionally from a welfare perspective, better understanding of the noise traders' and arbitrageurs' behavior may support regulation, taxation or education of these investors to ameliorate any adverse economic effects.

In this paper I use a theoretically motivated proxy for noise trading in each stock that does not rely explicitly on assumptions about who the relevant noise traders are (individual vs. institutional investors). *The noise trading in a stock is measured as a sensitivity of stock returns to the changes in sentiment index.* The latter is constructed as a principal component of several proxies shown to be good potential measures of investor sentiment (net of macro and business cycles factors). Using these sensitivities (which I call sentiment betas) I find that, in line with HV-DA hypothesis stocks having greater sentiment sensitivity tend to be smaller, younger, more volatile stocks with lower dividend yields and greater short sales constraints. Holding size fixed, more sentiment sensitive stocks are more liquid, volatile, lower book-to-market (glamour) stocks that subsequently earn *lower* raw and risk-adjusted returns. The zero-investment equal-weighted portfolio which is short in the stocks with highest sentiment beta and long in the stocks with the lowest sentiment beta earns 3.1% per quarter on a risk-adjusted basis. Most of the differences are both statistically significant and economically important. These results also support the intuition of Barberis and Shleifer (2003) that some classes of investors ("switchers" in their model) tend to consider a stock as "a bundle of salient characteristics", rather than its statistical properties such as mean and variance.

If such major characteristics as size and volatility are controlled for, there is very weak evidence that more-prone-to-speculation stocks have higher growth potential as measured by Tobin Q, R&D expenditures, sales/assets growth and external finance activity. Neither do results support the view that noise traders are more active in unprofitable stocks. In fact, during 1988-1999 period, stocks with higher sentiment sensitivities were *more* profitable (in terms of rate of return on assets) by around 0.5% on the annual basis. Strikingly, keeping size and prior stock volatility constant, greater number of analysts, higher likelihood of being an S&P 500 member and more institutional ownership (IO) are associated with stocks that have higher sentiment sensitivities in the past. In the entire sample, the difference between the group of stocks with the lowest noise trading and the group with the highest noise trading are highly statistically significant in terms of analysts, S&P 500 membership and IO (-0.91, -3% and -2.2% respectively) and these characteristics display a near-monotonic increasing pattern across the deciles conditioned on past sentiment sensitivities. These differences become more pronounced in the second half of the sample, covering the period from Jan 1988 till March 1999: -1.5 and -3.7% for analysts and IO respectively. The issue of economic importance will be discussed later, but it is worth mentioning that, for instance, the differences in analyst coverage between the stocks in the lowest and highest deciles of noise trading represent from 23% to 38% of the average analyst coverage during the sample period, which appears to be economically significant given that firm market capitalization is similar across the sentiment beta deciles.

Flexibility of our measure of noise trading allows us to explicitly relate it to the behavior of institutions, because it does not rely explicitly on the assumption about which group of investors is causing mispricing (noise). This allows us to link it directly to the institutional holdings in order to shed some light on the role institutions played during the sample period. Results of quarterly Fama-Macbeth regressions of institutional holdings on the noise trading measure and different sets of controls provide an interesting insight into the institutional behavior from 1980 to march 1999. Time-series pattern of FM coefficients on the noise trading measure suggests that institutions changed their behavior around late the 80's-early 90's. Namely, they have been staying away from stocks with high noise trader risk throughout 80's (as indicated by institutional ownership loading negatively on the sentiment betas), but appeared to have been holding relatively more of these stocks throughout the 90's. These findings question the conventional wisdom that institutions are always standing ready to eliminate any mispricing immediately (at least, during the 90's) and support the evidence from some recent literature (see Sias 1996, 2004; Griffin et al., 2003; Jones et al., 1999; Jackson, 2003b; Pirisnky and Wang, 2004) reporting that institutions engage in past returns chasing and introduce the non-fundamental factor in returns co-movement.

The paper is organized as follows. Section 1 contains a model that provides theoretical motivation for the empirical use of the noise trading proxy. Section 2 outlines the methodology of constructing the sentiment index and shows why it is a good measure. Section 3 provides the results on the relationship between noise trading and stock characteristics. Section 4 presents evidence on the dynamics of the institutional behavior with respect to stocks with different degrees of noise trader risk. The last section concludes.

Simple Model of Noise trading

We present a simple general equilibrium model which can be viewed as a stylized version of DSSW (1990) and has also been applied in Jackson (2003b). The purpose of this model is twofold. First, we would like to demonstrate the channel through which volatility in the market is affected by the levels of noise trading (the relative proportion of noise traders in the market). Second, the model also provides theoretical justification for the empirical measure of noise trading applied later in the paper.

At each time t, the market is assumed to be populated by the two types of traders: sentiment or noise traders who are subject to common sentiment shocks and present in proportion of μ, whereas second type are fully rational traders present in the proportion 1-μ.

Consistent with an extensive literature in finance, assume that the fundamental value evolves as a random walk over time:

$$F_t^j = F_{t-1}^j + \eta_t^j$$

where F_t^j is the fundamental value of the asset j (or the asset's rational equilibrium price) at time t and $\eta_t^j \sim 0, \sigma_\eta^2$ are iid (across time and assets) and mean zero innovations, which become public knowledge to the market at the end of each period t. The independence assumption assures that the shocks are idiosyncratic and can not induce the comovement among stocks.

Each type of traders is also subject to random liquidity shocks, which are also independent across time and traders. This assumption is made in order to generate some trading activity unrelated to trading resulting from sentiment shifts.

At time t, the demand functions per unit of each investor-type's mass (i.e. a typical rational trader i) in the market can be stated as follows (in the reduced form):

$$D_t^r = 1 + b_t(F_t^j - P_t^j) + z_t^{i,r}$$

For the typical sentiment trader, the demand function looks as follows:

$$D_t^s = 1 + b_t(F_t^j + \rho_t - P_t^j) + z_t^{i,s}$$

where

- P_t^j is the price of stock j at time t,

- ρ_t is the common sentiment (non-fundamental) factor affecting all sentiment traders at time t, across all stocks (changes in sentiment are assumed to be uncorrelated with changes in the fundamental value)[4].

- $z_t^{i,h}$ h={r,s} is the trader's normally distributed liquidity shock at time t, iid across time and traders.

- b_t is a positive parameter (to simplify the exposition, b is assumed to be constant across two types of traders) that captures the slope of the rational component of the demand function for the stock. We can think of b_t as being whatever solves for the optimal demand given a utility function, in other words, it could be a function of the investor's current and past information sets.[5]

The sentiment factor may enter into the optimal demand of the noise traders with either positive or negative sign depending on whether they positive or negative feedback trade on the sentiment. There is some empirical evidence[6] suggesting that individual investors tend to be contrarian investors (that is, sell stocks when the market sentiment is high), though there are reasons to believe that behavioral biases such as representativeness heuristic may cause noise traders to extrapolate past performance too far into the future and behave like momentum investors as well.

[4] Note that for simplicity of exposition, there is an implicit assumption that all sentiment traders are affected by the sentiment factor in the same direction, that is, ρ_t enters with the same sign (in this case, positive) in the demand of each sentiment trader. This caveat would be important later in the section discussing sentiment beta estimation.

[5] In terms of DSSW (1990), F_t is essentially $E(P_{t+1})$ and b_t can be thought of as $\frac{1}{2\gamma E(\sigma^2_{p_{t+1}})}$

[6] See Kaniel et al. (2004), Grinblatt and Keloharju (2000) and Jackson (2003a).

Assuming the asset is in fixed supply normalized to one unit and imposing the market clearing condition we obtain:

$$\mu\left[\lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}D_t^{j,i,s}\right]+(1-\mu)\left[\lim_{M\to\infty}\frac{1}{M}\sum_{i=1}^{M}D_t^{j,i,r}\right]=1$$

Solving the market clearing condition[7] yields the equilibrium price:

$$P_t^j = F_t^j + \mu\rho_t$$

This means that equilibrium price is equal to the fundamental value in case when the market is populated only by fully rational investors or if existent noise traders on average are neither bullish nor bearish. The price change is then given by

$$P_t^j - P_{t-1}^j = \eta_t^j + \mu_t^j(\rho_t - \rho_{t-1})$$

The model implies excess correlation of the stocks having higher proportion of sentiment traders with the sentiment factor. That is, increases in the proportion of noise traders in a stock should increase the correlation of the stock with the common sentiment factor.

$$\mathrm{cov}(P_t^j - P_{t-1}^j, \rho_t - \rho_{t-1}) = \mathrm{cov}(\eta_t^j, \rho_t - \rho_{t-1}) + \mu_t^j\ \mathrm{var}(\rho_t - \rho_{t-1}) = \mu_t^j\ \mathrm{var}(\rho_t - \rho_{t-1})$$

Direct implication of the expression above is that the proportion of sentiment traders in stock j is nothing else but a coefficient in the regression of the price changes on the changes in the sentiment factor:

$$\mu_t^j = \frac{\mathrm{cov}(P_t^j - P_{t-1}^j, \rho_t - \rho_{t-1})}{\mathrm{var}(\rho_t - \rho_{t-1})}$$

This provides the main rationale for the empirical proxy (the proportion of noise traders in a stock) used in the future tests. A priori, stocks that have the highest proportion of noise traders should have the highest correlation with the common sentiment factor. This proxy has a solid theoretical foundation whereas proxies used earlier were motivated mostly by the empirical observations ex-post.

Another strength of this measure is that it does not rely on the conventional assumption usually made in the previous literature that the individuals are the noise traders in question (traders trading on noise or non-fundamental information). Previous research on investor sentiment either implicitly or explicitly relies on the assumption about who the relevant noise traders are or uses

[7] See the appendix A.

limited data (e.g. just few proxies like closed-end fund discounts, or only the survey index or employ individual transactions data which is mostly restricted to the period of the 90s only). The above-mentioned assumption might not be justified in the view of the growing body of empirical papers suggesting that this might not be the case that retail investors are the noise traders in question[8]. For example, Brown and Cliff (2004) conclude that “our research does not suggest that sentiment is limited to individual investors. To the contrary, it appears that the strongest relations exist between our measures on institutional sentiment and large stocks. This has implications for existing research which typically assumes “noise" traders are individuals who affect small stocks”.

Finally, the composite sentiment index used in the analysis is constructed from one the most comprehensive dataset of sentiment proxies used so far, running all the way back to march 1965 and including nine proxies that were shown to be related to the investor sentiment. This creates a good opportunity to study the phenomenon of noise trading in greater detail.

Sentiment measures

One of the sentiment proxies used in the paper is Investors Intelligence Index (SENT)[9], which is widely recognized to reliably predict market movements (Siegel, 1992). Investors Intelligence (II) has compiled its sentiment data weekly by categorizing approximately 150 market newsletters since 1964[10]. Newsletters are read and marked staring on Friday each weekend reported on the following Wednesday. Letters are labeled “bullish” when the advisory services recommends stock for purchase or predicts that the market will rise. Letters are rated as “bearish” when the advisory service recommends closing long positions or opening short ones because the market is predicted to decline. Letters are classified as “correction” when the advisory service predicts a bull market but advises clients to hold off buying, or predicts a bear market but sees a short-term rally in the near future.

We are using the difference between percent of bullish and bearish letters (“bull-bear spread” as a sentiment indictor[11]. Technicians perceive a decrease in the proportion of advisory letters that are

[8] See Hugen and McDonald, 2004; Jackson, 2003b, Brown and Cliff, 2004; Kaniel et al., 2004 for the recent evidence
[9] An investment service is based in New Rochelle, NY. Index has been developed and published by Chartcraft.com.
[10] The consistency over time of the sentiment index rating is maintained because there have only been two editors of Investors’ Intelligence since its inception, namely, the late founder of the service, Abe Cohen, and the present editor, Michael Burke.
[11] For example, the bull-bear spread is published weekly in Barron’s and is often mentioned in financial press articles.

bearish below 20% as a signal of an approaching market peak and the onset of a bear market. An increase in the proportion of advisory letters that are bearish to 60% is an indication of pervasive pessimism and is interpreted by contrarians as a signal of an approaching market trough and the onset of a bull market (Reilly and Brown, 1997, p.779). Since many of the writers of these newsletters are current or past market professionals, this difference can be considered a proxy of institutional investors' sentiment[12] and represents the direct sentiment measure.

However, there is a problem in using only survey-based measures in gauging investor sentiment. We can ask traders or institutions whether they are bullish, bearish, or neutral on stocks, but this will not necessarily correlate well with their actual trading or investment behavior. Several factors may be at work in this discrepancy. First is the issue of time frame. When reporting their sentiment to be bearish, traders might (implicitly) be referring to one time frame, while they are trading a very different interval. Second is risk-aversion. We may see the market as bullish given its recent trend, but be unwilling to commit funds if we also perceive that volatility is high. Just because we think the market will make a move doesn't mean that we will commit funds to that move. We can have a sentiment, but also have uncertainty. For these reasons, a sentiment measure that is grounded in actual investor behavior makes the most sense. This reasoning motivates the use of some other sentiment proxies described below.

The value-weighted dividend premium (DIVPREM) is the log difference of the average market-to-book ratios of payers and non-payers measured every month and is supposed to capture the time-varying premium that investors demand for dividend paying stocks. That is,

$$Div\Pr em_t = \log\left[\frac{1}{N_{DIV}}\sum_{j=1}^{N_{DIV}}\frac{BE_{j,t}}{ME_{j,t}}\right] - \log\left[\frac{1}{N_{N-DIV}}\sum_{j=1}^{N_{N-DIV}}\frac{BE_{j,t}}{ME_{j,t}}\right]$$

N_{DIV} – number of dividend paying companies

N_{N-DIV} – number of non-dividend paying companies[13]

$BE_{j,t}$ – book equity of the company j in the month t[14]

$ME_{j,t}$ – market equity of the company j in the month t

[12] This point was made Solt and Statman (1988) and Brown and Cliff (2004)

[13] A company is defined as dividend paying if it pays any dividend in that year (Compustat data21>0)

[14] Since daily figures of book equity are not available, annual values from Compustat at the end of the year are used.

Baker and Wurgler (2004a) suggest that the dividend premium could serve as a proxy for relative investor demand for dividend payers. The intuition of DivPrem measure is that if when the sentiment is high, investors tend to value dividend non-paying companies such as young, growth, hi-tech stocks highly compared to companies having a stable dividend paying policy. This translates into relative higher valuations of dividend non-paying firms and, hence, DivPrem is low. Bulan et al (2004) provide the evidence on the relation of dividend premium to the future returns as they show that firms appear to time their dividend initiations to coincide with periods when investor sentiment favors dividends, even after controlling for life-cycle factors. They also find that the abnormal stock returns around an initiation are significantly higher when the dividend premium is higher, but is not related to the change in fundamentals across the initiation.

Prior work suggests that the closed end fund discount (CEFD) is inversely related to sentiment. The closed-end fund discount (CEFD) is the average difference between their market prices and the NAV of closed-end stock fund shares (measured as a premium to NAV). The average monthly closed-end fund discount (CEFD) is measured by taking the monthly equal-weighted average of all domestic equity fund discounts. Lee et al. (1991) find that the returns of stocks with lower institutional ownership and smaller size are positively related to changes in closed-end fund discounts. They argue that because closed-end funds are primarily held by individual investors, the fluctuations in the discount of these funds reflect the changing sentiment of these investors. Gemmil and Thomas (2002) use mutual fund flows as a more direct measure of individual investor sentiment and confirm that the fluctuations in closed-end fund discounts are indeed influenced by the trading activities of individual investors. More recent evidence comes from Flynn (2004) where he shows that arbitrageurs lack incentive to take advantage of the profits created by the existence of discount and argues that in the absence of arbitrage, observed fund pricing behavior is likely to reflect changing investor sentiment about fund prospects.

A next category of sentiment indicators are the variables that are related to the trading activity type. At the monthly aggregate market level, the available variables are the percent change in margin borrowing (Δ MARGIN), as reported by Federal Reserve and the ratio of specialists' short sales to total short sales (SPECIAL). The margin debt is often cited as bullish sign as it represents the changes in relative demand of investors for additional investment funds. Specialists tend to be considered as better informed and more sophisticated investors, so when their short-selling activity is relatively large, the market is said to be more likely to decline. Also available is the monthly data on the net purchases of mutual funds (FUNDFLOW). Neal and Wheatley (1998) find it is useful in predicting the premium of small stocks over large stocks.

IPO activity is often associated with market tops and is considered as a measure of sentiment because of information asymmetries between managers and investors. High first-day returns on IPOs may also be a measure of investor enthusiasm. Baker and Wurgler (2000) and Dorn (2003) provide empirical support of this claim[15].

Table 1 presents the summary statistics and the contemporaneous correlations between the sentiment measures and business cycle variables. Each time series is at the aggregate market level and available at the monthly frequency during different time sub-periods within Jan 1962 and Sep 2004 time span. II bull-bear spread has positive significant correlations with de-trended (log) NYSE turnover, specialist short-selling, changes in margin borrowing, industrial production index and University of Michigan Consumer Sentiment Index, and it negatively covaries both with recession dummy and term spreads. Smaller closed-end fund discounts (higher investor sentiment) are associated with more IPOs and greater mutual fund equity purchases. Some correlation signs suggest the contrarian relationships. Specialists' short selling and dividend premiums tend to be high in the periods of high sentiment, suggesting that the market is more likely to decline in the future[16].

Data and Methodology

Stock returns, market capitalization and turnover are from the CRSP Monthly Stocks Combined File, which includes NYSE, AMEX, and NASDAQ stocks. Throughout, ADRs, REITs, closed-end funds, and primes and scores are excluded– that is, stocks that do not have a CRSP share type code of 10 or 11. Volatility is computed using daily CRSP files. Firm characteristics are from CRPS/Compustat Merged Industrial Annual database. Institutional ownership data are at the quarterly frequency and come from the 13F filings of the different types of institutions as recorded electronically in the CDA/Spectrum database. The data on analyst coverage are from the I/B/E/S Detail History File and available on a monthly basis beginning in 1976[17]. Sentiment data is

[15] The data on the monthly number of IPOs (IPON) and average first-day IPO returns (IPORET) are obtained from the Jay Ritter's website.

[16] This underlines the importance of taking into account the lead-lag relationships in constructing the sentiment index.

[17] Analyst coverage in a given month is calculated as the total number of non-repeating occurrences of analyst codes ("analyst code" variable in I/B/E/S) associated with analysts who provide fiscal year 1 EPS estimates in that month. It

available from different sources at the monthly frequency and covers the period from march 1965 till December 1998 including.

Sentiment index construction

Unlike many other studies that use either only direct (survey data) or indirect sentiment proxies, in order to construct the sentiment factor proxy this paper utilizes both information contained in the measures reflecting the trading behavior of millions of investors (such closed-end fund discounts, dividend premium, IPO returns and fund flows), firm supply responses (number of IPOs) as well as opinions of the market professionals (II index)[18]. The sentiment does not have to be completely an irrational phenomenon. In fact, it could be the case that substantial proportion of its time variation is due to the changes in the macro conditions reflecting fundamentals of the economy.

Therefore, in order to reduce the likelihood that variation in the sentiment measures is related to the systematic macro risks, each individual proxy was orthogonalized with respect to several variables that were argued to reflect business cycle fluctuations and varying macroeconomic conditions. The following were used: the growth in the industrial production index, growth in consumer durables, non-durables and services, employment (Federal Reserve Statistical Release G.17 and BEA National Income Accounts Table 2.10), a dummy for NBER recessions as well as term and credit spreads.[19] Most macroeconomic variables are slowly moving over time and the simple adjustment with respect to the growth rates may not be sufficient to account for rational variation in sentiment. Therefore, the orthogonalization procedure is performed with respect to the innovations in the growth rates defined as deviations from the prior year moving average (except for term and credit spreads that were left as are). As a main proxy for the aggregate sentiment we use the first principal component (SENTINDEX) of the all mentioned sentiment-related proxies after netting out the variation related to change in macro conditions.

---

has an average cross-sectional correlation of 0.77 with the “number of estimates” variable from I/B/E/S Summary Historical File.

[18] Initially, the available range of sentiment proxies also included some technical indicators like NYSE Hi/Lo, Adv/Dec and ARMS ratios as well as aggregate percentage change in short interest and ratio of odd-lot sales to purchases. They were excluded from the analysis for the reasons of either having low loadings on the common factor (short interest, odd-lot ratio) or high correlations with Investor Intelligence index (Hi/Lo, Adv/Dec and ARMS), thus, not providing much of new information.

[19] Term spread is the difference between the yields of the 10-year and 3-month T-bills. Credit spread is computed as the difference between the yield on a market portfolio of Baa-rated corporate bonds and the yield on Aaa corporate bonds. Fama and French (1989) argue that movements in these variables seem to be related to long-term business episodes that span several measured business cycles.

Since the used sentiment measures may reflect the same sentiment factor at different times, the possibility of the lead-lag relationships needs to be taken into consideration when constructing the sentiment index. As Baker and Wurlger (2004b) note, proxies that involve firm supply responses are likely to lag proxies that are based on investor demand/behavior. To help us identify the best relative timing of the proxies, the following procedure was performed. First, in each estimation period, we run the factor analysis with all proxies and their lags. In the second stage we construct the sentiment index as a first principal component of the correlation of matrix of sentiment proxies – each measure's lead or lag, whichever has a higher factor loading according to the factor analysis carried in the first stage. The procedure yields the following sentiment index (in changes):

$$\Delta SENTINDEX(t)=0.41\Delta SENT(t-1)+0.27\Delta CEFD(t-1)+0.43\Delta MARGIN(t)-0.16\Delta DIVPREM(t)+0.48\Delta FUNDFLOW(t-1)+0.24\Delta IPON(t)+0.41\Delta IPORETS(t-1)+0.31\Delta SPECIAL(t-1).$$

Why is this a good measure of sentiment?

Figure 1 presents the resulting sentiment index (level estimated for the entire period from March 1965 till December 1998) plotted against the bull-bear spread of Investor Intelligence Survey and the University of Michigan Consumer Confidence Index. The latter was shown to be a good measure of sentiment (Qiu and Welch, 2004) and have the ability to explain the cross-section of the stock returns (Lemmon and Portniaguina, 2004). The correlation between UMich index and SENTINDEX (levels) is 0.26*** and about the same between the sentiment index and lagged II bull-bear spread[20]. Closer look at the figure reveals that peaks and troughs line up well with the anecdotal evidence on the market sentiment: the bubble of 1967 and 1968, low sentiment during the period of oil crisis of 1973-74, decline in the sentiment in the mid 80's and the high-tech dotcom bubble of the late 90's. This suggests that the composite index is able to capture the common variation in the noise trader sentiment not accounted for by changes in the macro conditions.

Besides this qualitative eye-ball evidence, I provide more convincing quantitative evidence on the quality of this proxy. If we are to have a good sentiment factor which would allow us to distinguish between risk and behavioral stories, we should expect the sentiment index a) to be truly

[20] For comparison, Baker and Wurgler (2004b) measure has no or very weak relation to the University of Michigan index levels: year-based correlation is 0.03, monthly-based correlation is 0.09*.

orthogonal to the factors reflecting fluctuations in business cycles, b) to have a reliably positive relationship with the direct survey measures (e.g. II Index and UMich index); c) to be influenced by recent positive stock returns – and especially recent high overall stock market returns, and to have (mild) persistent effects on return spreads, such as small and retail stock return spreads (stocks where proportion of potential noise traders could be assumed to be relatively higher).

First two points were already addressed. In order to address the third point, I first look at the persistence patterns of my measure versus the Baker and Wurgler (2004b) measure[21]:

Table 2. Persistence patterns of sentiment index vs. BW sentiment index

Lag of Small Stock Return Spread											
	-5	-4	-3	-2	-1	0	1	2	3	4	5
ΔSENTINDEX	-0.01	-0.0	-0.07	-0.04	0.02	0.26***	0.25***	0.07	-0.03	-0.04	0.06
Δ BW measure	0.03	-0.04	-0.02	0.07	-0.05	-0.02	0.20***	0.17***	-0.02	-0.01	0.05
Lag of Market-Adjusted Retail Stock Return Spread											
	-5	-4	-3	-2	-1	0	1	2	3	4	5
Δ SENTINDEX	-0.12*	-0.01	0	-0.01	0.12*	0.15**	0.13**	0.03	-0.06	-0.01	0.06
Δ BW measure	-0.01	0.03	0.01	0.1	-0.07	0.03	0.29***	0.06	-0.01	0.02	0.01
Lag of Value-weighted CRSP Market Index											
	-5	-4	-3	-2	-1	0	1	2	3	4	5
Δ SENTINDEX	-0.03	0.08*	-0.02	-0.7	-0.14***	0.08*	0.61***	0.12***	0.001	-0.04	-0.05
Δ BW measure	-0.0	-0.05	-0.06	0.03	-0.01	-0.04	0.10**	0.09*	0.06	0.02	0.03

Significant numbers on the left indicate that the sentiment index is related to the future return, numbers on the right show how much the sentiment index is influenced by the return. The market adjustment in the middle panel is done by netting out the in-sample value-weighted CRPS return via regression. The changes in SENTINDEX appear to be both affected by both the lagged retail stock return spread and influence future retail stock return spread as well as seem to be related contemporaneously to the small stock spread. This pattern is even more pronounced for the market-wide returns. Arguably, these correlations are desirable feature for an investor sentiment index.

[21] It is worth noting that Baker and Wurgler (2004b) do not orthogonalize with respect to terms/credit spreads. This adjustment turns out to be important as back-of-the-envelope calculations suggest that BW measure is significantly positively related to term spreads both at the annual and monthly frequencies. Therefore, BW measure still appears to reflect the business cycle fluctuations.

As a further check, the regression analysis is conducted to see if the changes in the sentiment index have explanatory power for small stock and retail stock returns spreads[22] and whether they reliably predict the aggregate market returns. The results are presented in the tables 3 and 4. It is worth noting that changes in SENTINDEX help explain (contemporaneously) the variation in the small and retail stock return spreads (which, theoretically, are more likely to be affected by the actions of sentiment traders), whereas BW measure does not. Coefficients on ΔSENTINDEX are significant in all model specifications[23] and whether equal-weighted or value-weighted returns used on the left hand-side. This is comforting as it suggests that the sentiment measure is able to capture the effects of sentiment-induced noise trading, which, in theory, is supposed to affect the time-series variation in small and retail stock return spreads. Table 4 confirms this intuition: ΔSENTINDEX reliably predicts lower future market-wide returns. The negative relationship is present in the sub-periods and robust to the inclusion of lagged market returns, term and credit spreads, BW sentiment measure and lagged market turnover. Remarkably, the inclusion of ΔSENTINDEX increases adjusted R-square by 1.22%, which is economically significant given that the overall R-squared is around 4%. Overall, the analysis suggests that our measure serves as a reasonably good proxy for the investor sentiment as it satisfies the criteria mentioned earlier.

For the purposes of estimating stock returns sensitivity to the sentiment factor (which in theory is supposed to proxy for the proportion of noise traders in a particular stock), the principal component analysis is performed on the 60 months window rolled ahead every 3 months. That is, the first principal component is extracted using 60 months of orthogonalized sentiment measures, say, from March 1965 till March 1970, then the next estimation period is from June 1965 till June 1970 and so on, rolling the estimation window each quarter. This procedure allows one to avoid look-ahead bias and take into account possibility of changing covariance structure of inputs over time as well as helps incorporate changes in the relative timing of sentiment proxies (lead-lag relationships) as they reflect common sentiment factor. Principal component analysis is repeated to yield the 116 sentiment index five-year time series. The loadings on SENT, IPORETS, IPON and SPECIAL are quite stable over time, whereas the loadings on the rest of measures vary over

[22] I refer to the average return of the smallest capitalization CRPS decile of stocks minus the average return of the largest capitalization CRSP decile stocks as the "small stock returns spread". The retail stock spread is defined as the return on stocks with zero institutional holdings (taken from 13f filings) minus the return on stocks in the top decile of institutional holdings of the remaining non-zero IO stocks

[23] Note that in the regression with the retail stock return spread on the left hand-side, ΔSENTINDEX retains its significance even after controlling for small stock return spread.

time[24], so the rolling window procedure appears to be justified as it allows us to take into account the time-varying covariance structure. The average time-series loadings of the first principal component on the different proxies look as follows (across 116 estimation periods):

SENT	CEFD	Δ MARGIN	DIVPREM	FUNDFLOW	IPON	IPORET	SPECIAL
0.33	0.29	0.31	-0.21	0.41	0.23	0.29	0.44

All the inputs have the expected correlation with the sentiment index (CEFD is measured as the premium to NAV). Positive changes in sentiment are associated with positive changes in specialist short-selling, more active IPO market and an increase in the margin borrowing. The mutual fund data suggest that during times of high sentiment mutual funds are increasing their investments in equities.

Sentiment beta estimation

The theory presented earlier provides guidance with respect to how one can measure for the degree of noise sentiment-induced trading in a stock (e.g. relative proportion of noise traders holding the stock). It is nothing else but the regression coefficient measuring the sensitivity of the price changes (returns) to the changes in the sentiment factor. Therefore, the estimation methodology is based on the following model:

$$R_{i,t} = \alpha_i + \beta_{MRKT,i} R_t^{MRKT} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{LIQ,i} LIQ_t + \beta_{SENT,i} \Delta SENT_t + \varepsilon_{i.t}\,,$$
$$\varepsilon_{i,t} \sim \mathrm{N}(0, \sigma_\varepsilon^2) \qquad (1)$$

Where R_t^i - excess returns of the stock i at time t, R_t^{MRKT}, SMB_t and HML_t are the Fama-French factors[25], LIQ_t are the innovations in aggregate liquidity[26] and $SENT_t$ is the sentiment factor[27] proxy standardized to have mean zero and standard deviation one in each estimation period. Reasons for including liquidity are twofold. Firstly, there is evidence that liquidity risk is a priced factor in the market (see Pastor and Stambaugh, 2003). Secondly, as Baker and Stein (2003) build a model that market liquidity can serve as a sentiment indicator, where the periods of unusually

[24] Before loadings are computed, all sentiment measures are standardized to mean 0, standard deviation 1.
[25] Fama-French factors were obtained from the website of Kenneth French at Darmouth College.
[26] I would like to thank Lubos Pastor for providing the liquidity data.
[27] In each estimation period, the sentiment factor was standardized to mean 0 and std 1 to allow the comparison of betas across time.

high liquidity signal that the sentiment of irrational investors is positive. The inclusion of the liquidity factor is an attempt to ensure that β_{SENT} does not merely capture the effects of liquidity, but rather measures the covariance of the residual part of stock returns not explained by rational systematic factors with the irrational part of the investor sentiment (net of macro factors). Thus, future tests are robust to the potential criticism of it being liquidity driving the results.

The theoretical idea of sentiment betas is somewhat similar (at least in terms of methodology) to that of Shefrin and Statman (1994) where they develop a behavioral asset-pricing theory as an analog to the standard CAPM. In their BAPM model the expected returns of securities are determined by their "behavioral betas", betas relative to the tangent mean-variance efficient portfolio, which is not the market portfolio because noise traders affect security prices. For example, the preference of noise traders for growth stocks may raise the prices of growth stocks relative to those of value stocks, thus making BAPM MV efficient portfolio tilted towards value stocks. However, β_{SENT} , probably, should not be interpreted in the same manner as in Shefrin et al., because SENT is not portfolio returns, though it is designed to capture the noise trader exposure. In our case it is more convenient to think of sentiment betas as a proxy for the relative proportion of noise traders in a stock.

The correlations between the factors estimate for the entire time period (march 1965-dec 1998) and the average factors' correlations computed across different overlapping estimation periods are in the following table.

Factor correlations with SENT and ΔSENT

Correlation over the entire time period (406 months)					
	Δ sent	SMB	HML	MARKET	LIQUIDITY
SENT	0.16***	-0.02	-0.07	0.10**	0.15***
Δ SENT	1.00	0.16***	0.09*	-0.08*	0.14***
Average correlation across 116 estimation periods					
Δ SENT	1.00	0.12*	0.09***	-0.10*	0.11

The correlation patterns generally suggest that the variation in the sentiment index (net of systematic macro factors) captures something beyond just variation in the FF factors and the liquidity factor of Pastor-Stambaugh, and multi-collinearity is not an issue.

It is well-known that betas obtained from the model (1) could be statistically imprecise and may contain a fair amount of statistical noise due to the relatively low number of degrees of freedom and other statistical problems. Researchers developed two approaches to tackle this problem. The first is related to the portfolio formation because if the errors in the individual security betas are substantially less then perfectly positively correlated, the betas of portfolios can be much more precise estimates of true betas. However, there is always a dilemma about what the appropriate portfolio formation procedure is. Besides, assigning portfolio betas to the securities in this portfolio discards the fact that true betas are not the same for all stocks in a portfolio.

The other common and useful way of reducing noise in the beta estimates is to "shrink" the usual estimates to a reasonable value, the procedure often referred to as the Bayes-Stein adjustment. Essentially, the "shrinkage" estimate of beta is the weighted average of the usual OLS estimate and of the shrinkage target. Shrinkage betas can be justified as so-called "Bayesian" estimators, in that they reflect not only data but also prior knowledge or judgment. Bayesian estimators have solid axiomatic foundations in statistics and decision theory, unlike many other estimators commonly used by statisticians (see Vasicek, 1973; Blume 1971, 1973; Scholes&Willams, 1977 and Jorion, 1986). Chan et al (1992) results indicate that such robust estimators (including ones that are using the information contained in the prior cross-section) are superior in terms of precision than usual OLS estimates.

Therefore, as a first stage, sentiments betas are estimated separately for each stock using the traditional OLS rolling regression approach. The five-year period monthly regressions are run for each stock that has no fewer than 60 months of returns history and updating is performed each quarter. Prior is formed using empirical Bayesian approach, that is, prior density of sentiment betas is assumed to be normal with the mean β_t^{prior} and variance $\sigma^2_{prior,t}$; $\beta_{i,t} \sim N(\beta_t^{prior}, \sigma^2_{prior,t})$, where the prior mean is an average of the absolute values of cross-sectional betas from the previous estimation period (60 months prior) and the prior variance is the cross-sectional variance of the prior cross-section of betas (their absolute values) The posterior betas are obtained as follows:

$$\beta_{i,t+1}^{posterior} = \frac{\sigma^2_{prior,t}}{\sigma^2_{prior,t} + \sigma^2_{\beta,t+1}} \times \left|\beta_{i,t+1}\right| + \frac{\sigma^2_{\beta,t+1}}{\sigma^2_{\beta,t+1} + \sigma^2_{prior,t}} \times \beta_t^{prior} \qquad (2)$$

$$\beta_t^{prior} = \frac{1}{N_t}\sum_i \left|\beta_{i,t}\right|, \quad \sigma^2_{prior,t} = \frac{1}{N_t}\sum_i (\left|\beta_{i,t}\right| - \beta_t^{prior})^2$$

Where

N_t is the number of stocks used in estimation at time t.

$\beta_{i,t+1}^{posterior}$ is the shrinkage estimate of sentiment beta (henceforth referred to as "shrunk" betas")

$\sigma^2_{\beta,t+1}$ is the sampling variance of the OLS estimator computed in the period t+1 (corrected for autocorrelation using Newey-West estimator) and $\beta_{i,t+1}$ is the standard OLS regression coefficient ($\beta_{SENT,i}$ from the model (1), henceforth referred to as original betas). The negative sentiment betas merely indicate that contrarian noise traders (who sell when sentiment goes up and buy when the sentiment goes down) are trading in this stock relatively more often than momentum noise traders (who buy when sentiment changes are positive and sell when changes in sentiment are negative). Therefore, the absolute values of betas are used in the shrinkage procedure, because in theory two stocks with the sentiment beta estimates of different signs and the same absolute value have equal relative proportions of noise traders in them, simply the stock with the negative beta is traded relatively more often by the contrarian noise traders.

The intuition for the use of absolute betas in the Bayes-Stein adjustment can be illustrated by the following example. Suppose, we have three stocks, A, B and C with sentiment betas of -1, 0 and 1 respectively. Theoretically, if beta is 0, then this means that stock B does not covary with sentiment changes (after accounting for its covariance with conventional risk factors), and, therefore, has $\mu = 0$ (the relative proportion of noise traders is zero or *the actions of contrarian and momentum sentiment traders offset each other and the equilibrium price reflects the fundamental value*). Stock A, on the other hand, has a beta of -1, that is, negative covariance with sentiment changes, which, in the framework of our theoretical model, implies that stock is traded more often by investors with the demand function $D_t^s = 1 + b(F_t^j - \rho_t - P_t^j) + z_t^{i,s}$ (note negative sign on the sentiment factor), whereas stock C's return is influenced more by investors with the demand function of the form $D_t^s = 1 + b(F_t^j + \rho_t - P_t^j) + z_t^{i,s}$ (note positive sign on the sentiment factor). Since the absolute value of sentiment betas for stock A and C are the same, the noise in the stock (which could be thought of as the deviation of price from the fundamental value) caused by the action of noise traders) is the same, with the only difference being that the stock A's price is too low and stock C's price is too high.

The intuition of the formula (2) is straightforward: less precise betas get shrunk towards the prior with the weight reflecting the estimate's precision relative to the precision of the prior. The comparative advantage of the shrinkage approach (vs. portfolio approach) is that the standard error of each and every sentiment beta is directly taken into account. This procedure yields the "shrunk" improved precision estimates of sentiment beta for individual stocks starting from march 1975 (first 60 months of data are used to obtain the parameters of the prior distribution and subsequent (non-overlapping) 60 months are used for estimation).

Summary statistics and the empirical distributions of the original and "shrunk" sentiment beta estimates are presented in Tables 5, 6 and Figures 2, 3 respectively. As can be seen both from the graph and the table, the distribution of the original sentiment betas is skewed to the right suggesting that, on average, there are relatively more stocks having higher returns when changes in sentiment are positive. Even though the majority of betas are centered around 0, the t-test for the null hypothesis that the mean of distribution is zero is rejected at 1% level. This indicates that the average sentiment-induced noise in the market is not zero and actions of sentiment-driven momentum and contrarian traders do not seem to cancel each other when the market is considered as a whole.

How precise are the sentiment betas?

Besides performing shrinkage procedure (which directly takes into account the standard error of each estimate in order to improve the overall precision and reduce the noisiness), I assess the meaningfulness of sentiment betas in two ways[28]. First, a la Griffin (2002), I look at the incremental explanatory power of the sentiment factor (beyond and above market, size and book-to-market factor). For instance, sentiment factor contributes three times more to the average adjusted R-squared than the liquidity factor of Pastor-Stambaugh and its incremental explanatory power is around 1/5 of that of HML factor. This is heartening, as it suggests that sentiment factor is able to capture the stock return variation which is due to the sentiment changes. Second, it is also informative to gauge the persistence of sentiment betas relative to the persistence of betas on

[28] Simple assessment of the statistical significance of sentiment betas could be misleading because significance levels might be misspecified in the short samples.

market, size and book-to-market factors over non-overlapping time intervals[29]. The average cross-sectional correlation of sentiment betas over time is 0.18***, compared to 0.23*** for market betas, 0.34*** for SMB betas and 0.14*** for HML betas. When stocks in each cross-section are ranked into quintiles based on the value of "shrunk" sentiment beta estimates and the percentage of stocks that remain in the same quintile 5 years later is computed, I find that, on average, around 20% belong to the same quintile in terms of their sensitivity to the sentiment changes. For comparison, the respective numbers for market, SMB and HML betas are 28%, 31% and 26%[30].

Finally, it could be possible that sentiment betas (mechanically, due to the method of estimation) are simply capturing stock volatility: stocks with higher volatility tend to have higher betas on any factor, not just sentiment factor. The back-of-the-envelope calculations suggest that even though (log of) contemporaneous total/idiosyncratic volatility[31] does help explain some cross-sectional variation of (log of) "shrunk" sentiment betas, its explanatory power is not too high: R^2s range between 9.6% and 28% with the average value of 18%. The correlation between the "shrunk" betas and residual betas net of stock volatility[32] is significant 0.86, confirming the previous intuition that cross-section of stock volatility is not the main factor driving the cross-sectional variation of sentiment betas. The analyses above provide evidence that a) potential imprecision caused by the used statistical procedure is not a major issue to seriously affect the results; b) relation to the contemporaneous stock volatility is not a likely driver of the cross-sectional variation in sentiment betas.

Empirical Results

Noise trading and stock characteristics

The first research question is asking "what characteristics do securities tend to have conditional on their sentiment sensitivity? Are characteristics' patterns in line with HV-DA hypothesis of noise

[29] E.g., the cross-sectional persistence is computed between betas estimated over two non-overlapping time periods, e.g. Apr 70-March 75 and Apr 75-March 80.

[30] The results are qualitatively similar when "ranks-on-ranks" regressions are performed. Average R^2s in the regression of ranks based on sentiment betas estimated in [t-5,t] on the ranks based on sentiment betas estimated in [t,t+5] is 4.38%. For comparison, the average R^2s of the "ranks-on-ranks" regressions for market, SMB and HML betas are 7.88%, 18.66% and 3.71% respectively.

[31] Contemporaneous total volatility is measured as a standard deviation of monthly excess returns over the same period in which sentiment betas are estimated. Idiosyncratic volatility is the standard deviation of the residuals from Fama-French model.

[32] To control for the relationship between stock volatility and its "shrunk" sentiment beta, I construct residual sentiment betas, defined as the difference between the sentiment beta for a stock and the average sentiment beta for stocks in the same volatility decile.

trader behavior?" In other words, the question can be stated as follows: if a stock A had the relative proportion of noise traders μ_A and a stock B had the proportion μ_B, and, say, $\mu_A < \mu_B$ (empirically, stock B has greater absolute sensitivity to the sentiment changes than stock A, i.e. stock's B sentiment beta>stock's A sentiment beta), which are characteristics, on average, do these stocks tend to have? To address this question, I adopt a simple, non-parametric approach, which allows one to avoid imposing a linear dependence structure among different characteristics and the measure of noise trading. In each quarter of the year t stock characteristics are conditioned on the values of sentiment betas that were estimated using 60 months prior to the beginning of the quarter of interest.[33] Then stocks are placed in 10 deciles depending on the relative values of sentiment betas, and time-series averages of cross-sectional means are calculated.

The table below presents the equal-weighted cumulative quarterly returns, both raw and risk-adjusted using four-factor model of Carhart (1997), for sentiment beta sorted portfolios, with 1 and 10 being portfolios consisting of stock with the lowest and the highest sentiment sensitivity respectively.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1-10**
Raw	0.018	0.017	0.013	0.008	0.000	-0.004	-0.006	-0.008	-0.004	-0.009	0.026
Risk-adjusted	-0.002 (-0.75)	-0.005 (-2.41)	-0.01 (-5.30)	-0.016 (-5.11)	-0.023 (-6.78)	-0.03 (-7.61)	-0.032 (-8.71)	-0.034 (-7.92)	-0.029 (-7.87)	-0.033 (-9.79)	0.031 (5.99)
Market beta	0.89	0.95	1.01	0.99	1.01	0.98	0.99	1.00	1.01	0.98	
SMB beta	0.25	0.51	0.73	0.96	1.06	1.23	1.25	1.28	1.27	1.31	
HML beta	0.31	0.35	0.32	0.32	0.30	0.30	0.28	0.36	0.33	0.34	
Momentum beta	-0.05	-0.05	-0.05	-0.03	-0.07	0.01	0.05	-0.02	-0.04	-0.03	
Market cap (000)	2,321,177	1,476,178	1,078,926	824,049	666,665	553,798	471,731	387,171	341,974	270,418	

It is evident from the table that noise trader risk in the sense of DSSW (1990) does not appear to be priced, that is, not only does not the highest sentiment beta portfolio deliver higher average returns, but it, in fact, has negative both raw and risk-adjusted returns. The zero-investment portfolio long in the stocks with the lowest exposure to sentiment changes and short in the stocks with the highest exposure to the sentiment shifts over the last 5 years delivers 2.6% raw quarterly returns and 3.1%

[33] Note that these 60 months were used to perform the principal component analysis to obtain the corresponding sentiment factor, so there is no look-ahead bias in the sentiment beta estimation. Henceforth, I refer to "sentiment betas" as the "shrunk" estimates obtained using Bayes-Stein adjustment described in the section "Sentiment beta estimation"

on a risk-adjusted basis. When value-weighted quarterly returns are used instead of equal-weighted, the differences in raw and risk-adjusted returns are 0.8% and 0.91% (the t-stat for the latter being 1.95) respectively. The reason that the difference in risk-adjusted value-weighted returns is greater than that of raw value-weighted returns is that the lowest sentiment sensitivity portfolio has a higher (though insignificant) sensitivity to momentum factor than the highest sentiment sensitivity portfolio and the average quarterly momentum factor premium over 1975-1998 period was +2.5%.

Table 7a presents a simple uniform sort on the sentiment betas, *net of volatility effects*, over the entire time period from March 1975 till Jan 1999. The table conservatively reports results for deciles from 2 to 9 to ensure that the patterns are not just concentrated in extreme deciles that are more likely to have outliers[34]. First important piece of evidence is that small stocks tend to have greater sensitivity to the changes in sentiment index. Fama (1998) acknowledges that all common asset pricing models including the Fama and French (1993) 3-factor model have difficulty explaining the average returns of small stocks, therefore, it is important to make sure that size pattern is not driven by the differences in volatility, in particular, idiosyncratic volatility, because if FF-model performs relatively worse for smaller stocks, one could suspect that higher absolute loadings of small stocks' returns on sentiment factor are a mere artifact of higher idiosyncratic volatility of these stocks. Besides, we already know that there is a weak, but reliably positive cross-sectional relationship between sentiment beta and stock volatility.

Quick look at the table suggests that the monotonic decreasing pattern in size as the sentiment sensitivity increases is not driven by the relationship between sentiment beta and stock volatility: the volatility in the portfolios is roughly the same and the its differences between top and bottom portfolios are statistically significant neither for the total volatility nor for idiosyncratic volatility. Additional sorts reveal that this pattern is particularly strong among stocks that covary positively with sentiment changes: for this subset the average size of highest sentiment beta portfolio is almost 3 times smaller than for the lowest sentiment beta portfolio, whereas the same proportion for stocks with negative loadings on sentiment changes is 2:1.

[34] For further robustness, all COMPUSTAT firm characteristics were winsorized at 0.5% and 99.5% in each quarter.

Profitability characteristics seem to point into one direction: earnings and cash flows (absolute measures of profitability) display an almost monotonically decreasing pattern across the deciles of sentiment sensitivity. Stocks with higher noise trading tend to be stocks of low-dividend-paying firms as measured by dividend to equity ratio. Higher sentiment sensitivity stocks tend to be relatively more liquid as measured by turnover despite the fact that those stocks are almost twice as small as those in the 2nd decile. This result, though, is statistically significant only in the second half of the sample (1988 – 1999). These patterns are robust in the sub-periods as demonstrated by tables 7b and 7c, though during 1987-1998 time period they seem to be much more pronounced.

However, some of these patterns could be simply due to the variation in size. Indeed, tables 7 a/b/c do not provide any evidence that the sort on the sentiment exposure is not just a refined size sort. In other words, it could be that is not the sentiment sensitivity what drives the results, but, rather, stocks tend to have low dividends, low earnings and cash flows and high volatility simply because they are smaller stocks. Keeping in mind that the profitability, dividend and investment-related characteristics of small and large stocks might be fundamentally different, it is important to check if patterns are robust once size is controlled for.

To do that, each quarter all the stocks are placed into 25 size groups based on NYSE/AMEX breakpoints and then sorted on sentiment betas within each size group, so that the lowest and highest noise trading deciles contain both similar number of large and small stocks and not tilted towards either of them. Table 8a contains the results of the two-dimensional dependent size-sentiment beta sort. I also include a greater variety of firm characteristics to shed more light on the issue in question.

After controlling for size, variation in sentiment beta between decile 2 and decile 9 is reduced by 28% suggesting that size is responsible for little less than 1/3 of the cross-sectional variation in sentiment sensitivity. Between two portfolios with similar size, more sentiment-sensitive portfolios tend to contain relatively younger stocks with lower earnings, lower cash flows and smaller dividend yields. The stocks with higher sentiment betas also are more likely to be more volatile and liquid (measured by turnover), *holding prior volatility fixed*. "Higher sentiment - higher liquidity" link is consistent with both theoretical and empirical literature on investor sentiment[35].

[35] For instance, Baker and Stein (2004) build a model in which sentiment traders underestimate the information content in the trades of privately informed agents. In the presence of short sales constraints, this implies that higher

Comparison of book-to-market ratios across the deciles suggests that sentiment traders are relatively more active in the growth stocks (low B/M ratios), however, the difference between 0.97 (B/M of the portfolio with the lowest noise trading) and 0.94 (B/M of the portfolio with the highest noise trading) is just marginally significant, and the pattern across deciles looks more like U-shape rather than a monotonic decrease. Stronger evidence that more noise trading is concentrated among growth stocks comes from the average HML loadings of the portfolios: decile 1 (lowest sensitivity) has an HML beta of 0.36, whereas the decile 10 (highest sensitivity) has an HML beta of only 0.21, the difference of 0.14 being statistically significant at 1%. The fact that mispricing (at least, one stemming from effects of broad shits in sentiment) is more likely to be associated with glamor stocks is in line with the evidence provided by Eleswarapu and Reinganum (2004) who find that annual excess returns on the stock market index are negatively related to the returns of glamour stocks in the previous 36-month period, whereas neither returns of value stocks nor aggregate stock market returns, net of glamor stock effects, have any predictive power.

Noise traders seem to prefer stocks of the firms paying lower dividends: both dividend yield and dividend-to-equity ratio exhibit a nearly monotonic decrease (from 3.34% to 2.32% for dividend yield; from 5.4% to 4.25% for dividend-to-equity). Besides, the difference between dividend yields in the top and bottom deciles is around 1%, which is economically significant by any conventional standards as it constitutes around 40% of the 1975-1998 average dividend yield of 2.5% (3.3% during 1975-1987 and 1.5% during 1988-1998). Stocks with higher sentiment sensitivity also tend to be stocks with relatively lower earnings and cash flows in absolute terms, holding the market capitalization of the firm roughly the same. The differences are $13.9M, $24M respectively and highly statistically significant. In terms of economic significance, these differences constitute 21% and 27% of the average values for absolute earnings and cash flows during the sample period[36].

"Hard-to-value, Difficulty-to-arbitrage" hypothesis also makes a prediction that stocks with higher growth potential would be more prone to swings in investor sentiment (holding size and prior stock volatility fixed). I find only weak evidence of that and most of it is concentrated in the second half of the sample, see the table 8c. Though variables proxying for growth potential

sentiment leads to higher liquidity. Deuskar (2004) finds empirical support for this theory: higher liquidity does seem to be associated with higher investor sentiment. Greene and Smart (1999) that noise trading generated by Wall Street Journal's "Investment Dartboard" leads to higher liquidity and decrease in in the adverse selection component of bid-ask spread.

[36] These findings are not due to the drastic differences in the precision of cross-sectional means across different sentiment beta deciles, as in each quarter deciles 1 and 10 contain, on average, 305 and 327 firms respectively.

generally exhibit increasing trends as we move from decile 1 to decile 10, the only piece of evidence supporting this prediction comes from sales growth (both in the full sample and in the second half, but not in the first half), whereas there are no significant differences between Tobin Q and assets growth either in the entire sample or in any sub-samples[37]. Also, once size and past volatility are controlled for, *there is no evidence that less profitable stocks are more subject to shifts in investor sentiment*. If anything, during the period 1988-1998 the higher sentiment sensitive stocks were more likely to be *more* profitable (by around 0.5% per annum) as measured by ROA. Consistent with HV-DA argument stocks which are harder to short sell tend to be more prone to shifts in sentiment investor.[38] Book leverage and PIN (Probability of informed trading from Easley et al. (2002)) do not display any particular pattern across deciles sorted on past sentiment sensitivity. Economic significance of the differences is presented in the table 9. If we focus our attention on the sub-period where the results are particularly strong (1988-1999) several variables stand out: dividend yield, dividend to equity ratio, sales growth, analyst coverage, S&P 500 membership, turnover and short-sales constraints proxy. For these variables the differences seem to be important both statistically and economically.

Several findings are of particular interest. First, analyst coverage of the stock is increasing as its sentiment beta increases. In simple unconditional sorts on sentiment betas only, analyst coverage displays slowly decreasing trend from Decile 1 to Decile 10. However, this is mainly due the fact that the size is decreasing too, as the literature on the analysts documented strong positive relationship between the number of analysts covering the stock and its market value[39]. However, conditional sorts reveal an interesting phenomenon: between two average stocks belonging to the same “size-past volatility” group a stock with higher return sensitivity to sentiment changes in the past tends to have a greater number of analysts following. The difference in analyst coverage between 1st and 10th decile (that have similar market capitalization and past stock return volatility) is -0.91 (t-stat -2.89) in the full sample, -0.4 (t-stat -1.59) in 1975-1987 period and -1.50 (t-stat -5.53) in 1987-1998 period. Interestingly, this difference is of large economic magnitude given that the average *quarterly* analyst coverage is 2.74 in the entire sample, 1.65 between 1975 and 1987,

[37] When one allows for prior volatility (past sigma in the table) to vary across deciles, I do find monotonically increasing patters in R&D expenditures, both sales and assets growth as well as Tobin Q as sentiment sensitivity increases. This suggests that R&D expenditures and stock return volatility are closely positively related.

[38] I would like to thank Mark Trombley for generously providing short-sales proxy. Short sales variable represents the probability that the loan fee for a stock is relatively high and available at the monthly frequency from Feb 1984 till Jan 2001. For more detail on variable construction, see Ali and Trombley (2004).

[39] In the sample the average cross-sectional correlation between analyst coverage and size is around 0.4

and 3.98 between 1988 and 1998[40]. In other words, the differences in analyst coverage represent between 24% and 38% of the average quarterly analyst coverage.

On the surface of it, analyst coverage result seems at odds with the finding of Hong, Lim and Stein (2000) who document stronger momentum (and, therefore, potential mispricing) in stocks with lower residual analyst coverage. To address this seeming puzzle I explore whether exposure of stock returns to changes in sentiment has anything to do with momentum effect. Unreported results demonstrate that the loadings of sentiment beta portfolios on the momentum factor do not appear to significantly differ from each other and do not display any clear pattern as we go from decile 1 to decile 10. This finding is borne out by comparing past six months (equal-weighted) returns across various deciles: there is no evident trend. This suggests that noise trading induced by trading on sentiment does not seem to be related to mispricing associated with the existence of momentum in stock returns.

A growing literature has shown that analysts do not pick the firms they follow randomly, nor are they unbiased in their forecasts. O'Brien and Bhushan (1990) find that analysts following increases with institutional ownership and industry growth. Pearson (1992) documents a positive relation between analyst following and beta, firm value, and the number of firms operating in an industry, and a negative relation between analyst following and the market model idiosyncratic volatility. One possible explanation for this pattern (especially given that it is pronounced in the 90's) is that analysts have the ability to identify stocks with the potential mispricing caused by sentiment traders and prefer to provide the coverage for these securities more, ceteris paribus.

Second interesting finding is that institutional ownership is also increasing as sentiment exposure grows[41]. Based on the entire sample (table 8a) it shows a steady statistically significant increase from 19.4% to 21.6% from decile 1 to decile 10, and this trend is not driven by institutional preferences for larger stocks. Sub-sample analysis (Tables 8 b,c) demonstrates that result is mainly attributable to the second half of the sample, 1988-1998 – now the difference between institutional ownership in two extreme deciles is around 3.7% (t-stat 6.45), whereas there is no significant

[40] These are computed as time-series averages of cross-sectional means. The latter, in turn, are calculated each quarter for the cross-section of firms that have a full five year returns history prior to the beginning of the quarter.
[41] Even though the simple average quarterly cross-sectional correlation between institutional ownership and sentiment beta (at the individual stock level) for the period of 1980-1999 is -.17, with the cross-sectional correlations ranging from -.21 to -.11. When zero values of IO are excluded, the correlation is -.196, the values ranging from -.24 to -.13.

difference in the first half of the sample. What is evident from this analysis is that there appears to be change in the behavior of institutions with respect to stocks with high degrees of sentiment-induced noise trading in them. This is supportive of the literature providing different reasons to suspect that institutional sentiment can be important[42]. " Sorts were also performed replacing mean with the median instead to make sure that too large or too small values of characteristics are not biasing either time-series or cross-sectional aggregation and results are qualitatively similar. Presented evidence is also robust to the exclusion of NASDAQ stocks

As additional robustness checks, I perform sorts on a number of other characteristics to see if a sort of sentiment betas is just an artifact of their indirect link to them. That would be true if the dispersion of sentiment betas becomes considerably reduced. The results of dependent sorts (not reported here and available upon request) show that regardless of which characteristics the sort is conditioned upon (turnover, B/M, etc), the dispersion of sentiment beta (from the decile 1 to the decile 10) remains high, with the max decline of 35% in dispersion taking place size and past volatility are controlled for. Furthermore, as mentioned before, sentiment beta sort is not a simple artifact of past volatility sort, since even performing the two-way dependent sorts on past 5 year volatility and sentiment betas reduces dispersion (decile 1 – decile 10) in sentiment betas by around 16% telling us that we are not simply picking up characteristics typical for only highly volatile stocks. Overall this is heartening because it demonstrates that sentiment sensitivity sort is not a mere refined sort on other characteristics.

Discussion of the sorts results

Most of these results are consistent with the HV-DA assertion of noise trader behavior. It predicts that some stocks are more vulnerable to shift in the propensity to speculate because of the subjectivity of the valuations for these stocks. Ambiguity in valuations of young, small, less profitable and low-dividend-paying stocks across the investors might fuel their desire to speculate in them. By contrast, the value of a firm with a long earnings history and stable dividends is much less subjective, so its stock is likely to be less affected by fluctuations in the propensity to speculate". The evidence provided so far in this paper supports this assertion with respect to several predictions. However, IO, S&P 500 membership and analyst coverage findings do not see to align well with "HV-DA" hypothesis. Note that we do not want to argue about the causality of

[42] See, for example, Grinblatt, Titman and Wermers (1995), Wermers (1999), Griffin et al (2003), Jones et al (1999), Brown and Cliff (2004)

the relationship (between sentiment-induced trading and analyst coverage) as simple sorts are not suited for this purpose, but the more noise-more analysts association seems to be there. It could be that analysts prefer to cover “hot”, extreme-growth potential stocks as the demand from speculators for this kind of analysis is high.

Noise trading and institutional investors

Previous literature on noise trading usually made an assumption that individual investors are the relevant noise traders who tend to be subject to the fads, whims and rumors in making their investment decisions. In the theoretical literature there is, however, a debate about the role of arbitrageurs (usually assumed to be institutional investors) in correcting mispricing caused by noise traders. The nature of this debate was well articulated by Barberis and Shleifer (2003):

“… it is not clear that they (arbitrageurs) would counteract the mispricing to any greater degree; on the contrary, they might exacerbate it. This is the finding of De Long et. al. (1991), who consider an economy with positive feedback traders (similar in some ways to our switchers as well as arbitrageurs). When an asset's price rises above fundamental value, the arbitrageurs do not sell or short the asset. Rather, they buy it, knowing that the extra upward jolt to the price that this causes will attract more feedback traders, leading to still higher prices, at which point the arbitrageurs can exit at a profit. This suggests that sophisticated arbitrageurs may amplify, rather than counteract the effect of switchers[43]…”

Our measure gives us a good chance to relate the proxy for the proportion of noise traders in the stock to the proportion of institutions holding it both in cross-sectional and time-series frameworks. To shed some light on this arbitrageurs-noise traders interaction, we decide to investigate the behavior of institutions with respect to the stocks with different sentiment sensitivities in the past. In order to do it I run the following quarterly Fama-MacBeth regressions from the first quarter 1980 till March 1999 with the following full specification:

$$\begin{aligned} IO^{j}_{t,t+3} = \alpha_t + \theta_{1,t}\beta^{SENT}_{j,t} + \theta_{2,t}(B/M)^{j}_{t} + \theta_{3,t}Size^{j}_{t-3,t} + \theta_{4,t}\sigma^{j}_{t-60,t} \\ + \theta_{5,t}Turn^{j}_{t-3,t} + \theta_{6,t}\,\mathrm{Pr}ice^{j}_{t-3,t} + \theta_{7,t}SP500^{j}_{t} + \\ + \theta_{8,t}\,\mathrm{Re}t^{j}_{t-3,t} + \theta_{9,t}Age^{j}_{t} + \theta_{10,t}DivYield^{j}_{t} + \upsilon^{j}_{t} \end{aligned} \quad (4)$$

[43] Noise traders trading on sentiment in our context.

The table 10 reports the results for various model specifications. The first model is analogous to that of Gompers and Metrick (2001). Generally, the results are consistent with their previous findings: institutions tend to hold more of larger, more liquid and higher priced stocks with lower past volatility and dividend yields as well as higher book-to-market ratios. They also prefer older stocks with lower prior returns, ceteris paribus. When this model is estimated during the entire 1980-1999 period, the coefficient on sentiment beta is positive, but insignificant. However, it is documented that institutions tend to change their preferences for stock characteristics. For example, Bennett, Sias and Starks (2003) report increased institutional preference for smaller firms with high risk. Therefore, it makes sense to conduct the analysis in the different sub-periods.

The findings of this analysis are intriguing and confirm the earlier results of dependent sorts. In the 80's institutions seem to have been avoiding exposure to the stocks with higher noise trader risk (greater sentiment sensitivities in the past). According to model 3 (full specification): the average FM coefficient during the period March 1980-Jun 1989 is -0.234 with t-stat -2.57 and 37% FM coefficients being significant in the cross-sectional regressions. Interestingly, the subsample analysis in which the regressions are run separately for the stocks having positive and negative loadings on sentiment factor suggests that a negative sign in the first time period is driven mainly by stocks with the negative sentiment betas: the coefficient is -0.356 (tstat -3.35), whereas for the subsample of stocks with positive loadings on sentiment factor it is -0.125 and insignificant. The difference between these two coefficients is statistically significant at 1%. In other words, in the 80's institutions preferred to stay away from the stocks that covaried negatively with sentiment changes.

In the 90's, however, institutional behavior changed: loading on sentiment sensitivity is significant and *positive* in all model specifications using different set of controls and subsamples. Figure 4 shows the one year moving average of the time-series of quarterly Fama-MacBeth coefficients. Including stock exchange dummies does not alter the results. The potential interpretation of this result is that institutions were "riding" on the market sentiment, so to speak, and were loading upon stocks with higher noise trader risk in order to exploit the predictable patterns in the noise trader demand.

(the conclusions section is to be completed)

References

1. Abraham, A. and Ikenberry, D.L., 1994. The individual investor and the weekend effect. Journal of Financial and Quantitative analysis 29, pp. 263-277.
2. Ali, A. and Trombley, M., 2004. Short sales constraints and momentum in stock returns. University of Arizona working paper.
3. Baker, M. and Stein, J. 2004. Market liquidity as a Sentiment Indicator, Journal of Financial Markets, forthcoming.
4. Baker, M. and Wurgler, J., 2000. The Equity Share in New issues and Aggregate Stock Returns. Journal of Finance, October.
5. Baker, M. and Wurgler, J., 2004a. A catering theory of dividends, The Journal of Finance Volume 59, Issue 3, pp. 1125.
6. Baker, M. and Wurgler J., 2004b. Investor Sentiment and the Cross-Section of Stock Returns, Working Paper, New York University.
7. Barber B., Odean T., and Zhu, N. 2003. Systematic Noise, Working paper, University of California at Berkeley.
8. Barberis, N. and Shleifer, A. 2003. Style investing. Journal of Financial Economics, 68, pp.161-199
9. Barberis, N., Shleifer, A., and Wurgler, J., 2003. Comovement, *Journal of Financial Economics*, forthcoming.
10. Bennett, J., Sias, R., and Starks, L. 2003, Greener pastures and the impact of dynamic institutional preferences, Review of Financial Studies 16, 1199 1234.
11. Black, F., 1986. Noise, *Journal of Finance* 41, pp. 529-543
12. Blume, M.E., 1971. On the Assessment of Risk, Journal of Finance, 26, pp. 1-10.
13. Blume, M.E., 1973. Beta's and Their Regression Tendencies, Journal of Finance, 28, pp. 785-795.
14. Bodurtha Jr., J.N., Kim, D.S., Lee, C.M.C., 1995. Closed-end country funds and U.S. market sentiment. Review of Financial Studies 8(3), pp. 879-918.
15. Brown,G.W. and Cliff, M.T., 2004. Investor sentiment and the near-term stock market. Journal of Empirical Finance, issue 1, volume 11, pp. 1-27.
16. Brown G.W. and Cliff, M.T. 2003. Investor Sentiment and Asset Valuation. Journal of Business, forthcoming.
17. Brown, S., Goetzmann, W., Hiraki, T., Shiraishi, N., and Watanabe, M., 2003. Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows, Working Paper, Yale University.
18. Bulan, L.T., Subramanian, N., and Tanlu, L.D., 2004. On the timing of dividend initiations. Working paper, Brandies University, International Business School.
19. Chan, L.K.C. and Lakonishok, J., 1992. Robust Measurement of Beta Risk, Journal of Financial and Quantitative Analysis, 27, pp. 265-282.
20. Cooper, Dimitrov and Rau, 2001. A Rose.com by Any Other Name, *Journal of Finance* 56, pp. 2371-2388.
21. De Long J.B., Shleifer, A., Summers, L.H., and Waldmann, R.J., 1990. Noise trader risk in financial markets, *Journal of Political Economy* 98, pp. 703-738.
22. De Long J.B., Shleifer, A., Summers, L.H., and Waldmann, R.J., 1991. Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance* 45, pp. 379-395.
23. Deuskar, P., 2004. Aggregate liquidity and Investor Sentiment: Empirical Connection, working paper, Stern School of Business, New York University.
24. Dorn, D., 2003. Does sentiment drive the retail demand for IPOs? Working Paper, Drexel University.

25. Doukas, J. and Milonas, N., 2004. Investor sentiment and the Closed-end Fund Puzzle: Out-of-Sample Evidence, European Financial Management, vol. 10, No. 2, pp. 235-266.
26. Easley, D., Hvidkjaer, S., and O'Hara, M. 2002. Is information risk a determinant of asset returns? Journal of Finance, 57.
27. Elsewarapu, V.R., and Reinganum M.R., 2004. The Predictability of Aggregate Stock Market Returns: Evidence based on Glamour Stocks, Journal of Business, vol. 77, No. 2.
28. Elton E.J., Gruber, M.J., and Busse J.A., 1998. Do investors care about sentiment?, Journal of Business, Vol. 71 (4), 1998, pp. 477-500.
29. Fama, E.F., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49, 283-306.
30. Fama, E.F., and French, K.R., 1989. Business conditions and Expected returns on Stocks and Bonds, Journal of Financial Economics 25, pp. 23-49.
31. Fama, E.F., and French, K.R., 1993. Common risk factors in returns on stocks and bonds, Journal of Financial Economics 33, pp. 3-56..
32. Flynn, S.M., 2004. Arbitrage in Closed-end Funds: New Evidence, working paper, Vassar College.
33. Friedman, M., 1953. The case for flexible exchange rates. In "Essays in Positive Economics", University of Chicago Press, Chicago, pp. 157-203.
34. Hughen C.J, and McDonald C., 2004. Who are the noise traders? Forthcoming in the Journal of Financial Research.
35. Jackson, A., 2003a. The Aggregate Behavior of Individual Investors. Working paper, London Business School.
36. Jackson, A., 2003b. The noise trader risk exists…but the noise traders are not who you think they are. Working paper, London Business School.
37. Jones, S.L., Lee, D., and Weis, E., 1999. Herding and feedback trading by different types of Institutions and the effects on stock prices, working paper, Indiana University.
38. Jorion, P., 1986. Bayes-Stein Estimation for Portfolio Analysis. Journal of Financial and Quantitative Analysis, Vol. 21, No. 3, Columbia University, pp. 279-292..
39. Gemmill, G. and Thomas, D.C., 2002. Noise Trading, Costly Arbitrage and Asset Prices: Evidence from Closed-End Fund Discounts, Journal of Finance, Vol. LVII (6)
40. Greene, J. and Smart, S., 1999. Liquidity Provision and Noise Trading: Evidence from the Investment Dartboard" Column, Journal of Finance, Vol. 54, No.5, pp.1885-1899.
41. Griffin, J.M., 2002. Are the Fama and French Factors Global or Country-Specific? Review of Financial Studies, 15, pp. 783-803.
42. Griffin, J.M., Harris, J.H., and Topaloglu, S. 2003. The Dynamics of Institutional and Individual Trading, Journal of Finance 6, December.
43. Grinblatt, M. and Keloharju, M., 2000. The investment behavior and performance of various investor types: A study of Finland's unique data set. Journal of Financial Economics 55, pp.43-67.
44. Grinblatt, M., Titman, S., and Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, American Economic Review 85, pp. 1088-1105.
45. Kanatas, G., and Wang., A. 2004. Predictable price patterns and excess volatility: A noise trader approach, Working Paper, Rice University.
46. Kaniel, R., Saar, G., and Titman S., 2004. Individual Investor Sentiment and Stock Returns, working paper, Fuqua School of Business, Duke University.
47. Kogan, Ross, Wang, and Westerfield, 2003. The Price Impact and Survival of Irrational Traders, Working Paper, MIT Sloan School of Management.

48. Kumar, A. and Lee, C., 2003. Individual investor sentiment and comovement in small stock returns, Working paper, Cornell University.
49. Lamont, O. and Thaler, R., 2003. Can the Market Add and Subtract? Mispricing in Tech Stock Carveouts, *Journal of Political Economy* 111, 227-26.
50. Lee, Jiang and Indro., 2002. Stock market volatility, excess returns and the role of investor sentiment. Journal of Banking and Finance, 26.
51. Lee, C., Shleifer, A. and Thaler, R., 1991. Investor Sentiment and the closed-end fund puzzle, Journal of Finance 46, 75-109.
52. Lemmon, M. and Portniaguina, E., 2004. Consumer Confidence and Asset Prices: Some Empirical Evidence, University of Utah, Working paper.
53. MacKinnon, J.G. and H. White. 1985. Some heteroskedasticity consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics, 29, 53-57.
54. Mitchell, Pulvino, T. and Stafford, 2002. Limited Arbitrage in Equity Markets, *Journal of Finance* 57, pp. 551-584.
55. Neal, R. and Wheatley, S.M., 1998. Do measures of investor sentiment predict returns?, Journal of Financial and Quantitative Analysis 33, pp. 523-547.
56. O'Brien, Patricia C. and Ravi Bhushan, 1990, Analyst following and institutional ownership, Journal of Accounting Research 28 Supplement, 55-76.
57. Palomino F., 1996. Noise trading in Small Markets, *Journal of Finance*, Vol. 51, No. 4.
58. Pastor, L, and Stambaugh, R., 2003. Liquidity risk and Expected Stock Returns. Journal of Political Economy, 111, pp.642-685.
59. Pearson, Neil D, 1992, Determinants of the production of information, Mimeo, University of Rochester.
60. Pirinsky and Wang, 2004. Institutional Investors and the Comovement of Equity Prices, working paper, Texas A&M University.
61. Reilly, F.K., Brown, K.C., 1997. Investment Analysis and Portfolio Management, fifth ed. The Dryden Press, USA.
62. Qiu, L., and Welch, I., 2004. Investor Sentiment Measures, Brown University, Working paper.
63. Scholes, M. and Williams, J., 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics, vol. 5, No 3.
64. Shleifer, A. and Vishny R., 1997. The limits of arbitrage. *Journal of Finance*, 52, pp. 35-55.
65. Sias, R.W., 1996. Volatility and the Institutional Investor, Financial Analysts Journal, Mar/Apr
66. Sias, R.W., 2004. Institutional herding, Review of Financial Studies, Vol. 17, No.1.
67. Sias R.W., Starks, L., and Tinic, S.M, 2001. Is noise trader risk priced? The Journal of Financial Research, Vol. XXIV, No. 3, pp.311-329.
68. Siegel, J.J., 1992. Equity risk premia, corporate profit forecasts, and investor sentimenty around the stock crash of October 1987. Journal of Business 65 (4), 557-570.
69. Shefrin, H., and Statman, M., 1994. Behavioral Capital Asset Pricing Theory. Journal of Financial and Quantitative Analysis 29, No. 3 pp. 323-349.
70. Slezak, 2003. On the impossibility of weak-form efficient markets, *Journal of Financial and Quantitative Analysis,* Vol 38, No. 3, pp. 523-554.
71. Swaminathan, B., 1996, Time-varying expected small firm returns and closed-end fund discounts, Review of Financial Studies 9, pp.845-887.
72. Vasicek, O., 1973. A Note on using Cross-sectional Information in Bayesian Estimation on Security Beta's, Journal of Finance, 28(5), pp. 1233-1239.
73. Wang, A., 2004. Strategic trading with naïve noise traders. Working Paper, Rice University.
74. Wermers, R. 1999. Mutual fund herding and the impact on stock prices, Journal of Finance 54, pp. 581-622.

Appendix A. Equilibrium price

Market clearing condition states that in equilibrium aggregate demand must be equal to aggregate supply:

$$\mu[\lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N} D_t^{j,i,s}] + (1-\mu)[\lim_{M\to\infty}\frac{1}{M}\sum_{i=1}^{M} D_t^{j,i,r}] = 1$$

Plugging in the expressions for the demand of rational and noise traders we obtain:

$$\mu(1+bF_t^{\,j}+b\rho_t-bP_t^{\,j})+\mu\left[\lim_{N\to\infty}\frac{1}{N}\sum_i z_t^{i,s}\right]+(1-\mu)(1+bF_t^{\,j}-bP_t^{\,j})+(1-\mu)\left[\lim_{M\to\infty}\frac{1}{M}\sum_i z_t^{i,r}\right]=1$$

By the assumptions imposed on the liquidity trading, we can apply law of large numbers:

$$\lim_{N\to\infty}\frac{1}{N}\sum_i z_t^{i,s} = 0 \qquad\qquad \lim_{M\to\infty}\frac{1}{M}\sum_i z_t^{i,r} = 0$$

Therefore, after the simplifications from the market clearing condition it follows that

$$P_t^{\,j} = F_t^{\,j} + \mu\rho_t$$

Hence, the price change is given by

$$P_t^{\,j} - P_{t-1}^{\,j} = \eta_t^{\,j} + \mu_t^{\,j}(\rho_t - \rho_{t-1})$$

Appendix B. Definitions of stock characteristics

We subdivide the characteristics into several categories. First, basic characteristics such as size and age. Size (market equity) is measured as price time shares outstanding from CRSP and taken as average value over the quarter; age is the number of months since the firm's first appearance on the CRSP tapes.

We use two dividend characteristics, dividend yield (DivYield) and dividends to equity (DivToEq). First one is defined as cash dividends for the fiscal year ended anytime in year t, divided by the market equity as of December 31 during that fiscal year. Dividends to equity is dividends per share at the ex date times shares outstanding divided by book equity.

Some characteristics reflect the firm's growth potential, investment opportunities and distress. Book to market ratio is computed as the ratio of book value reported anytime during the fiscal year t divided by size as of December 31 in that fiscal year. Tobin Q is defined as the ratio of market value net of common equity plus firm's assets to the total assets. R&D expenditures are also measured relative to the total assets. Sales growth (assets growth) is the change in net sales (total assets) divided by prior-net sales (total assets). External finance activity is the change in assets net of the change in retained earnings measured relative to the firm's total assets. Book leverage is the ratio of long-term debt to assets.

Profitability characteristics include earnings defined as income before extraordinary items plus deferred taxes minus preferred dividends, if earnings are positive and zero, if negative. Cash flow measure is income before extraordinary items minus the share of depreciation that can be allocated to (after-interest) income, plus any deferred taxes. Return on equity ROE (return on assets) is then earnings divided by book equity (total assets).

One more group consists of characteristics related to the stock returns. Excess returns are compounded quarterly returns in excess of the risk-free rate. Price is the average quarterly price computed over the three months from monthly CRSP files. Sigma is the standard deviation of daily returns over the quarter. It is set to missing if there are less than 55 observations. Turnover is the average of the monthly turnover calculated over the quarter, where the monthly turnover is the volume divided by shares outstanding, measured over the prior month.

Final characteristics group contains institutional ownership (IO) and analyst coverage. To compute IO for a specific stock in a given quarter, the holdings of all reporting institutions are summed up and divided by the total shares outstanding for the firm. If a stock in CRSP is not held by any institution, then IO is set to 0. For each stock on CRSP, we set the analyst coverage in any given month equal to the number of I/B/E/S analysts who provide fiscal year 1 earnings estimates that month. If no I/B/E/S value is available (the CRSP cusip is not matched in the I/B/E/S database), the coverage is set to zero.

Every quarter book-to-market, sales and assets growth as well as external finance activity and dividend yield variables are winsorized at 1% and 99% levels to eliminate outliers that could affect the means.

Figure 1. Investor Sentiment. The thick line depicts the standardized first principal component index of the eight orthogonalized proxies (levels) estimated from March 1965 till Dec 1998. Thin dashed line is the standardized bull-bear spread of Investor's Intelligence Survey net of the business cycles variation. Thick dashed line is the standardized University of Michigan Consumer Confidence Index. The measures entering principal component analysis are the corresponding monthly lead-lags (see section "Sentiment Index Construction") of Investor Intelligence Index (bull-bear spread), aggregate equal-weighted closed-end funds discount, changes in the margin borrowing, dividend premium, aggregate equity fund flows, number of IPOs, average first-day returns on IPOs and the ratio of specialists' short sales to total short sales. Each measure is orthogonilized with respect to macro variables (innovations in the growth of industrial production, durable, nondurable and services consumption, the growth in employment, NBER recession dummy as well as monthly term and credit spreads).

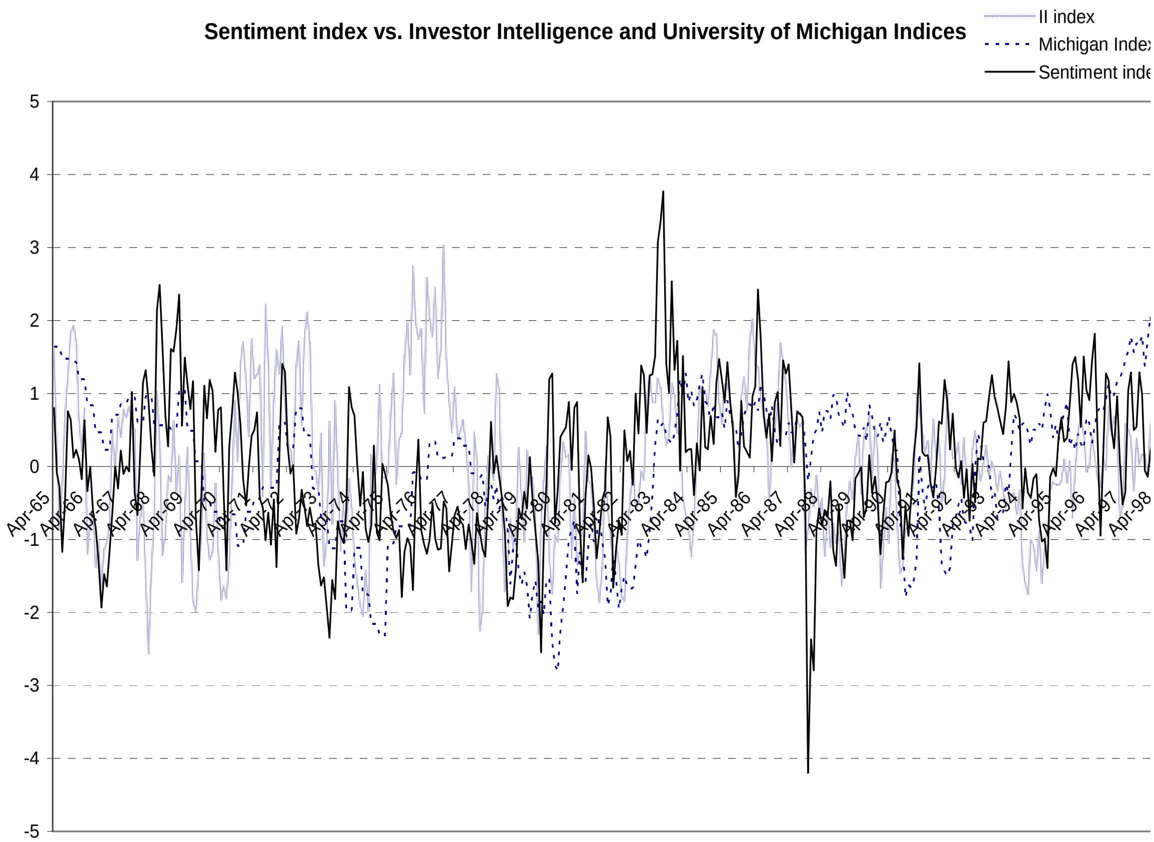

Figure 2. The empirical distribution of sentiment betas

Regression (1) is run every 3 months using 60 months rolling window from March 1970 till Dec 1998. Sentiment betas for each stock are averaged over 96 overlapping time intervals. The figure represents the empirical cross-sectional (total of 9797 stocks) distribution of the time-series averages

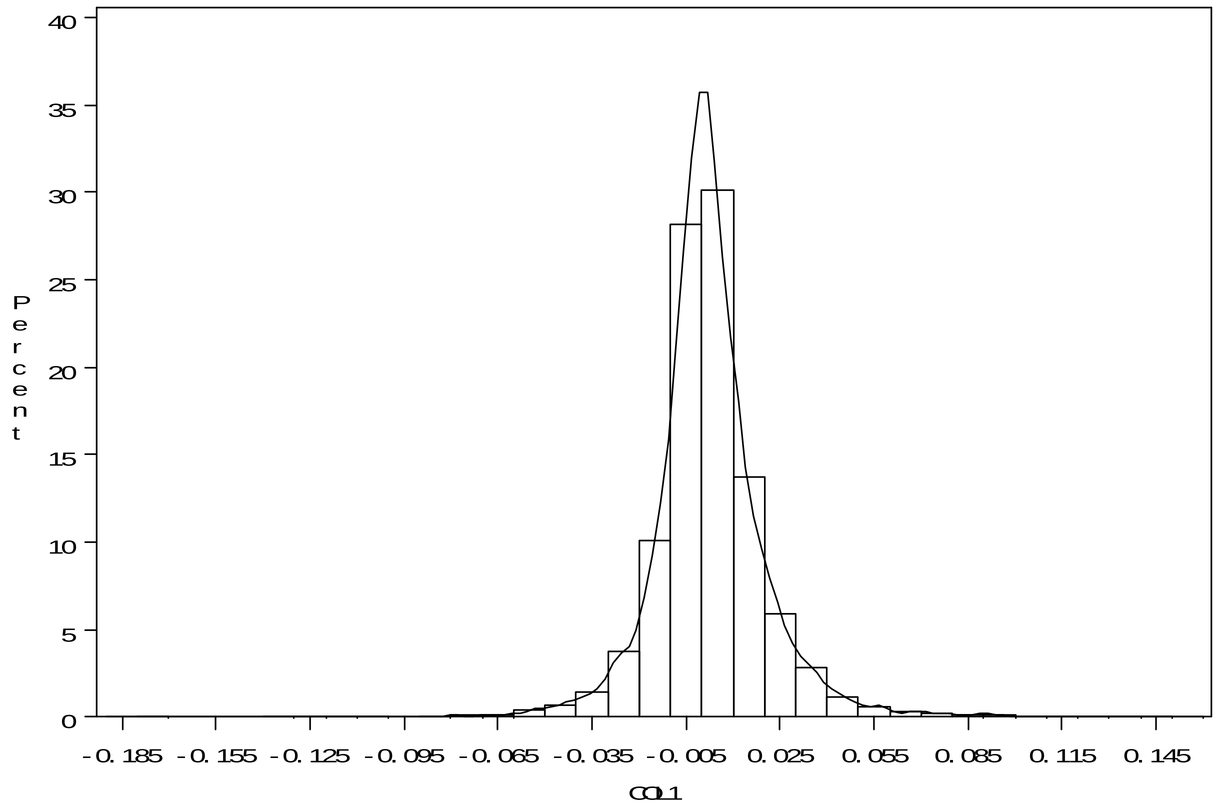

Figure 3. Empirical distribution of "shrunk" sentiment betas

Regression (1) is run every 3 months using 60 months rolling window from March 1970 till Dec 1998. Obtained sentiment betas are "shrunk" using the procedure described in the section "Sentiment beta estimation". For each stock the "shrunk" estimates are averaged out over 96 over-lapping estimation periods. The figure represents the empirical cross-sectional (total of 9797 stocks) distribution of the time-series averages

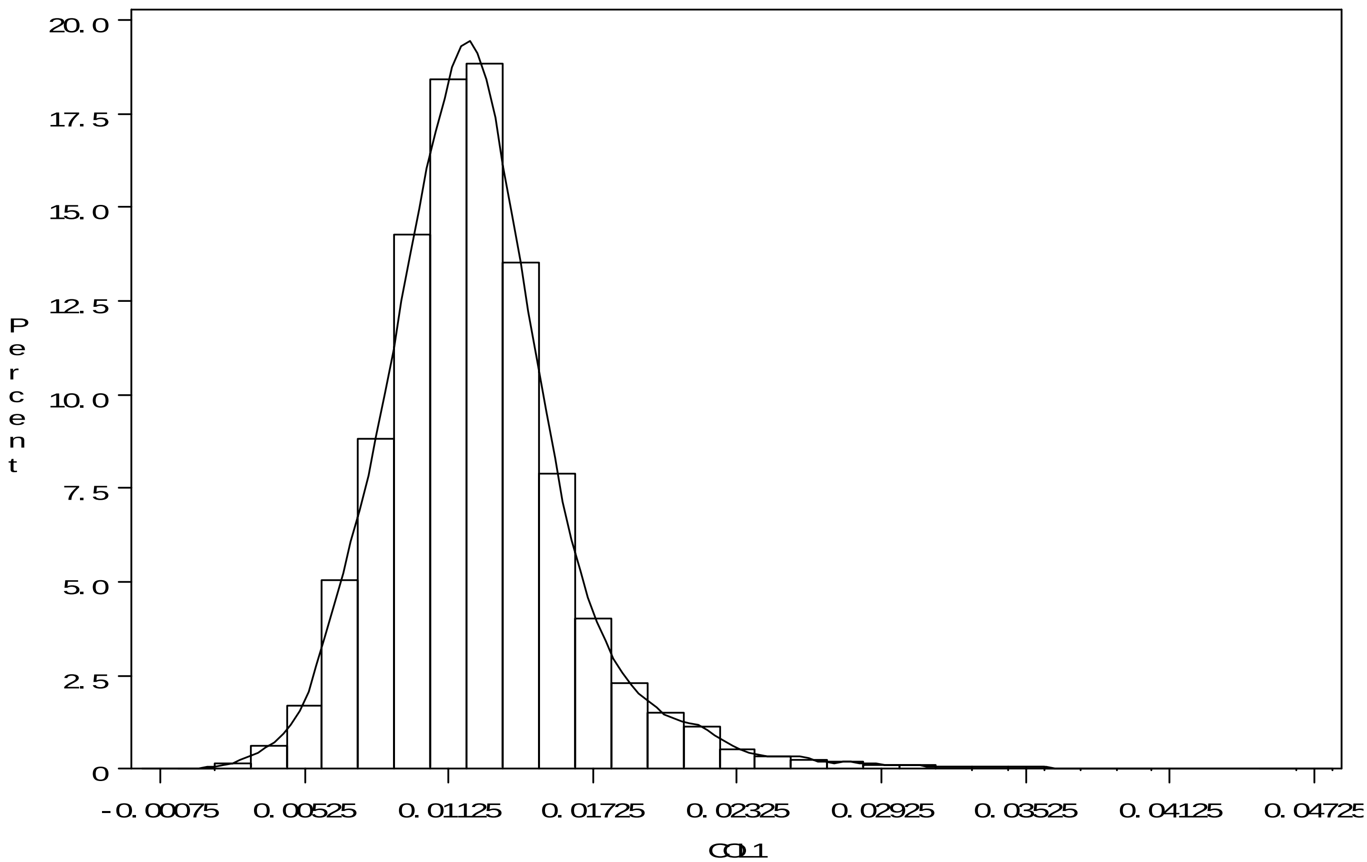

Figure 4. Noise trading and Institutional Behavior

The table presents the three-quarter moving average of the time-series of Fama-MacBeth coefficients in the cross-sectional regressions of institutional ownership on the sentiment betas and controls (see model 4)

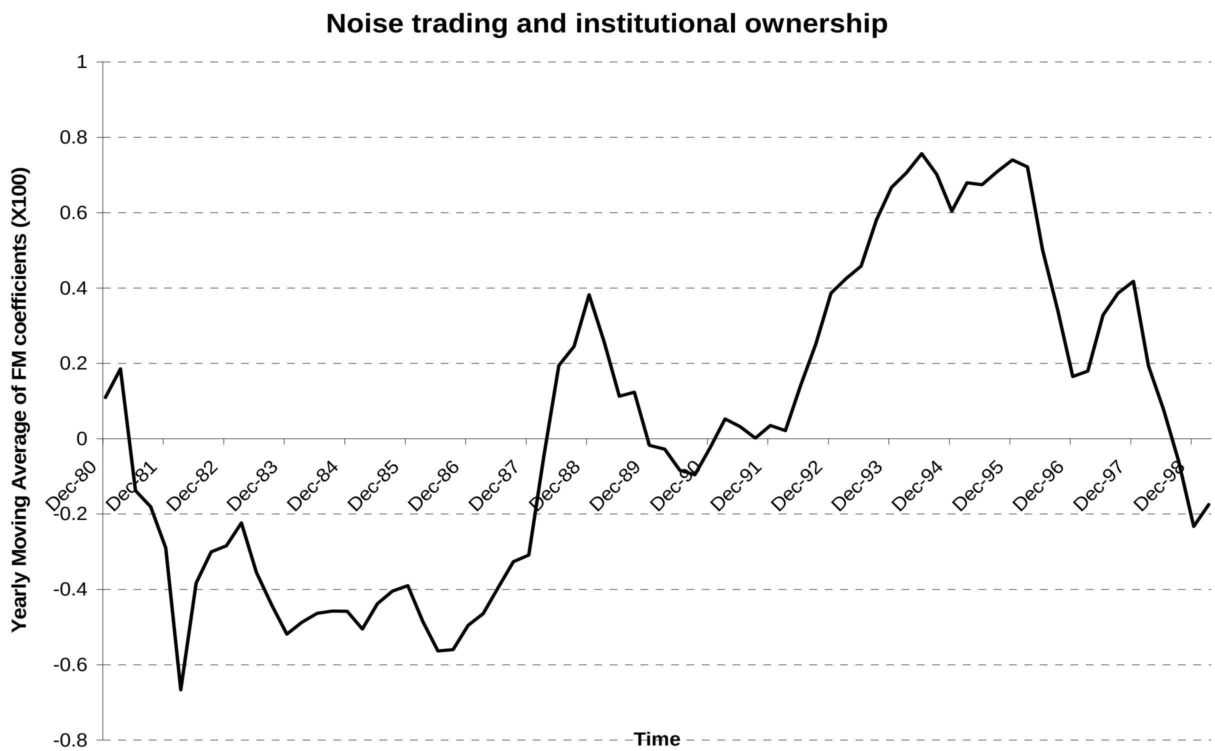

Table 1. Correlations among sentiment proxies and macro economic variables (overall period 1963-2003)

Table presents contemporaneous correlations between sentiment proxies and macroeconomic variables computed within 1963-2003 time span.
CEFD Vw/Ew is the aggregate value-weighted/equal-weighte closed-end fund discount, II index is the Investor Intelligence Index, Turn is the detrended NYSE turnover (current turnover minus past six month moving average), ES is the aggregate equity share in the total issues (debt+equity), Spec is the ratio of specialist short-sales to total short sales, Iporet is the average first-day return on IPO, NIPO is the number of IPOs, DP is the Dividend Premium ΔIP is the growth in the industrial production index, ΔDur is the growth in durables, ΔNonDur is the growth in non-durables, ΔServ is the growth in services Δ Emp is the growth in employment, Recess is the NBER recession dummy, FundF is the net equity purchases of mutual funds, ΔMargin is the change in margin borrowing, TS is the term spread, CS is the credit (default) spread, UMI is the University of Michigan Consumer Confidence Index

	Premium to NAV																			
	Cefd Vw	Cefd Ew	II index	Turn	ES	Spec	Iporet	NIPO	DP	ΔIP	Δ Dur	Δ Nondur	Δ Serv	Δ Emp	Recess	FundF	Δ Margin	TS	CS	UMI
Mean	-9.06	-8.65	11.43	0.02	0.21	0.46	16.66	28.76	-0.55	0.26	0.65	0.53	0.69	0.17	0.13	0.29	0.92	6.84	1.01	87.70
Std	7.22	7.42	20.96	0.16	0.11	0.09	21.10	25.07	0.46	0.72	2.84	0.74	0.38	0.22	0.34	0.94	3.23	2.31	0.44	12.16
N	430	430	501	480	486	432	505	492	485	503	503	503	503	500	501	407	431	499	499	505
Cefd Vw	1																			
Cefd Ew	0.93	1																		
II index	-0.05	-0.06	1																	
Turn	-0.01	-0.02	**0.26**	1																
ES	0.05	0.05	-0.05	-0.09	1															
Spec	0.03	0.15	**0.22**	0.12	-0.03	1														
Iporet	-0.01	0.05	0.04	0.16	0.01	**0.15**	1													
NIPO	0.38	**0.42**	0.07	-0.08	0.34	-0.27	0.09	1												
DP	0.1	0.05	0.17	0.01	-0.22	**0.41**	-0.09	-0.25	1											
ΔIP	-0.02	0.03	0.21	-0.03	0.12	0.12	0.07	0.16	0.08	1										
Δ Dur	0.02	0.01	0.1	-0.02	0.02	0.01	-0.01	0.02	0.03	0.2	1									
Δ Nondur	-0.11	-0.11	-0.07	0	0.08	0.11	0.06	-0.09	0.03	0.12	0.19	1								
Δ Serv	-0.09	-0.12	-0.01	-0.11	0.18	0.05	0.02	-0.11	-0.04	0.03	0.05	0.09	1							
Δ Emp	-0.07	-0.02	0.11	-0.03	0.09	0.17	0.11	0.13	0.09	0.38	0.04	0.09	0.01	1						
Recess	0.04	-0.02	**-0.29**	0.03	0	-0.1	-0.13	**-0.23**	-0.01	-0.46	-0.08	-0.04	0.09	-0.56	1					
FundF	0.44	**0.51**	0.16	0.05	-0.06	-0.19	0.01	0.51	-0.07	0.08	0.1	-0.17	-0.22	-0.03	-0.15	1				
Δ Margin	0.01	0.02	**0.34**	**0.21**	0.12	0.06	**0.27**	**0.26**	-0.02	0.29	0.08	0.04	-0.05	0.12	-0.3	0.1	1			
TS	-0.14	-0.18	**-0.23**	-0.02	**0.51**	**-0.51**	0.02	0.15	-0.53	-0.16	-0.02	0.02	0.26	-0.13	0.27	-0.15	-0.06	1		
CS	-0.1	-0.15	0.02	0.12	**0.4**	**-0.23**	-0.02	0.01	-0.39	-0.24	0.05	-0.02	0.24	-0.37	0.35	-0.14	0.03	0.71		
UMI	0.12	**0.24**	**0.29**	-0.04	-0.25	0.11	0.17	**0.26**	0.07	0.34	0.01	-0.06	-0.25	0.41	-0.55	0.3	0.19	**-0.46**	**-0.55**	

Table 3. Small and retail stock return spread and sentiment index

The dependent variables are in the top row (EW and VW stand for "equal-weighted" and "value-weighted" returns). The regressions are estimated from May 1965 till Dec 1998 for in the first 4 columns and from Apr 1980 till Dec 1998 in the last 2 columns. Small stock return spread is the average return of the smallest capitalization CRPS decile of stocks minus the average return of the largest capitalization CRSP decile stocks. The retail stock spread is defined as the return on stocks with zero institutional holdings (taken from 13f filings) minus the return on stocks in the top decile of institutional holdings of the remaining stocks. ΔSENTINDEX is the principal component of the changes in eight sentiment proxies (II Index, IPORET, IPON, SPECIAL, CEFD, FUNDFLOW, MARGIN, DIVPREM) net of macro effects. Δ BW measure is the principal component of the changes in six sentiment proxies from Baker and Wurgler (2004b). "Market" is the value-weighted CRSP market return. All coefficients are multiplied by 100. T-statistics are in the parentheses.

	EW small stock return spread	EW small stock return spread	VW small stock return spread	VW small stock return spread	EW retail stock spread	VW retail stock spread
	X 100	X 100	X 100	X 100	X 100	X 100
Constant	0.29 *(1.05)*	0.27 *(1.02)*	-0.09 *(-0.38)*	-0.08 *(-0.30)*	0.19 *(1.40)*	0.15 *(1.26)*
Δ SENTINDEX		**1.03** ***(2.92)***	**0.93** ***(2.83)***		**0.25** ***(2.14)***	**0.25** ***(1.96)***
Δ BW measure	**0.97** ***(3.13)***	**0.44** ***(1.15)***	**0.26** ***(0.79)***	**0.74** ***(2.83)***	**0.02** ***(0.13)***	**-0.19** ***(-1.32)***
Market	7.31 *(0.94)*	9.16 *(1.20)*	20.03 *(2.85)*	18.36 *(2.58)*	-15.7 *(-4.39)*	-19.99 *(-6.92)*
Small stock return spread					57.52 *(20.36)*	-4.47 *(-1.62)*
R-square	0.04	0.07	0.08	0.056	0.69	0.25
Nobs	404	404	404	404	225	225

Table 4. Sentiment measure and aggregate market returns

The dependent variable is the lead CRSP value-weight return (market_{t+1}). Term spread is the difference between the yields of the 10-year and 3-month T-bills. Credit spread is computed as the difference between the yield on a market portfolio of Baa-rated corporate bonds and the yield on Aaa corporate bonds. ΔSENTINDEX is the standardized (mean 0, std 1) principal component of the changes in eight sentiment proxies (II Index, IPORET, IPON, SPECIAL, CEFD, FUNDFLOW, MARGIN, DIVPREM) net of macro effects. ΔBW measure is the standardized principal component of the changes in six sentiment proxies from Baker and Wurgler (2004b).

	Lead CRSP value-weighted return			
Constant	0.01	0.01	0.01	0.01
	(1.72)	*(1.7)*	*(1.53)*	*(1.52)*
Market t	0.016	0.016	0.005	0.002
	(0.27)	*(0.29)*	*(0.10)*	*(0.04)*
Market t-1	-0.08	-0.08	0.008	0.012
	(-1.72)	*(-1.51)*	*(0.13)*	*(0.20)*
Market t-2	-0.03	-0.03	-0.02	-0.017
	(-0.53)	*(-0.51)*	*(-0.32)*	*(-0.32)*
Market t-3	-0.04	-0.04	-0.04	-0.04
	(-0.90)	*(-0.90)*	*(-0.90)*	*(-0.88)*
Term spreads	-0.46	-0.46	-0.42	-0.42
	(-2.99)	*(-2.97)*	*(-2.68)*	*(-2.67)*
Credit spreads	2.96	2.95	2.72	2.71
	(3.83)	*(3.80)*	*(3.48)*	*(3.47)*
Δ BW measure		-0.001		**0.002**
		(-0.53)		***(0.73)***
Δ SENTINDEX			-0.006	**-0.0075**
			(-2.51)	***(-2.61)***
Adjusted R-squared	0.0295	0.0276	0.0398	0.0384
Nobs	402	402	402	402

Table 5. Summary statistics for the time-series averages of sentiment betas

Descriptive statistics		Extreme observations			
		Lowest		Highest	
		Value	Nobs	Value	NObs
N	9797				
Mean	0.0024				
Median	0.0013				
Std	0.0179	-0.1751	1160	0.1120	8028
Skewness	0.3628	-0.1325	5576	0.1206	9522
Kurtosis	7.0835	-0.1279	1154	0.1353	9416
Interquartile Range	0.0160	-0.1215	9138	0.1366	764
t-stat for mean=0	13.33	-0.1194	9215	0.1436	1825

Quantiles	
100% Max	0.1436
99%	0.0570
95%	0.0312
90%	0.0218
75% Q3	0.0101
50% Median	0.0013
25% Q1	-0.0060
10%	-0.0151
5%	-0.0237
1%	-0.0449
0% Min	-0.1751

Table 6. Summary statistics for the time-series averages of the "shrunk" sentiment betas

Descriptive statistics		Extreme observations			
		Lowest		Highest	
		Value	LowObs	Value	HighObs
N	9797				
Mean	0.0124				
Median	0.0121				
Std	0.0039	0.0008	9147	0.0374	8984
Skewness	1.2157	0.0013	3462	0.0379	9143
Kurtosis	4.5341	0.0017	8950	0.0387	9217
Interquartile Range	0.0043	0.0018	9171	0.0402	9080
t-stat for mean=0	317.1	0.0018	9150	0.0460	9144

Quantiles	
100% Max	0.0460
99%	0.0251
95%	0.0190
90%	0.0167
75% Q3	0.0142
50% Median	0.0121
25% Q1	0.0100
10%	0.0080
5%	0.0069
1%	0.0048
0% Min	0.0008

Table 7a. Sentiment-induced noise trading and firm characteristics: one-dimensional sort, March 1975-Jan 1999

Each quarter characteristics for each firm are matched to its sentiment beta estimated in the 60 months prior to the quarter. Then stocks are sorted into 10 portfolios conditional on their sentiment factor sensitivities. Columns are the time-series averages of cross-sectional means within each of the deciles. Only deciles 2-9 are shown for the purpose of eliminating possible outliers. In a given quarter: size is the average market capitalization, past sigma is standard deviation of returns over 60 months prior to the quarter, past idiosyncratic volatility is the standard deviation of regression residuals in the Fama-French model over the 60 months prior to the quarter, excess return is the raw cumulative quarter stock return minus risk-free rate, Sigma is the stock return standard deviation in that quarter, Turnover is the average of monthly turnover in that quarter, past six month return is the raw cumulative return 6 months prior to the quarter. Detailed description of the rest of variables is provided in the Appendix B. “2-9” raw reports the difference in the means between deciles 2 and 9. T-statistics are corrected for the autocorrelation induced by the overlapping periods in sentiment beta estimation.

	Sent. beta	Size (000's)	Past sigma	Past idiosyn. sigma	Earnings (mil. $)	Div/ Equity	External Finance Activity	Cash flow (mil. $)	Sigma	Turnover	Past six month return
2	0.0086	913,191	0.1304	0.1101	69.97	0.0445	0.0576	93.46	0.0299	0.041	0.0461
3	0.0096	756,052	0.1349	0.1150	56.48	0.0426	0.0610	73.79	0.0312	0.043	0.0398
4	0.0105	740,980	0.1361	0.1163	57.17	0.0419	0.0569	74.10	0.0319	0.042	0.0378
5	0.0114	700,751	0.1344	0.1147	54.80	0.0415	0.0579	71.55	0.0316	0.042	0.0389
6	0.0125	694,507	0.1328	0.1134	54.99	0.0404	0.0574	71.27	0.0314	0.043	0.0387
7	0.0138	610,850	0.1316	0.1124	48.37	0.0400	0.0573	60.89	0.0312	0.042	0.0404
8	0.0155	551,309	0.1299	0.1111	46.59	0.0437	0.0555	58.74	0.0312	0.042	0.0381
9	0.0196	403,108	0.1283	0.1096	34.73	0.0360	0.0516	42.76	0.0312	0.041	0.0339
2-9	-0.011	510,082	0.0022	0.0004	35.25	0.0085	0.0060	50.70	-0.0014	-0.00	0.0122
t-stat	-12.53	2.10	0.55	0.11	2.89	3.68	2.89	3.08	-1.08	-0.03	2.76

Table 7b. Sentiment-induced noise trading and firm characteristics: one-dimensional sort, 1975-1987

	Sent. beta	Size (000's)	Past sigma	Past idiosy. sigma	Earnings (mil. $)	Div/ Equity	External Finance Activity	Cash flow (mil. $)	Sigma	Turnover	Past six month return
1	0.0088	423,524	0.1288	0.1040	50.73	0.0452	0.0522	66.02	0.0256	0.036	0.0815
2	0.0095	374,991	0.1286	0.1050	44.24	0.0445	0.0547	56.33	0.0254	0.037	0.0796
3	0.0103	371,564	0.1293	0.1058	46.06	0.0448	0.0521	58.56	0.0258	0.037	0.0781
4	0.0111	379,576	0.1282	0.1050	45.60	0.0458	0.0526	58.36	0.0256	0.037	0.0785
5	0.0120	381,943	0.1265	0.1036	47.38	0.0448	0.0505	59.76	0.0254	0.037	0.0762
6	0.0131	364,806	0.1240	0.1016	44.61	0.0466	0.0508	56.09	0.0250	0.036	0.0805
7	0.0146	389,560	0.1212	0.0992	48.46	0.0452	0.0494	60.77	0.0247	0.036	0.0829
8	0.0180	332,323	0.1194	0.0976	39.17	0.0413	0.0455	47.43	0.0244	0.034	0.0771
1-8	-0.0092	91,201	0.0094	0.0065	11.56	0.0039	0.0067	18.58	0.0012	0.002	0.0044
t-stat	-26.85	2.28	12.29	9.12	1.84	1.76	4.08	2.35	5.76	1.71	1.19

Table 7c. **Sentiment-induced noise trading and firm characteristics: one-dimensional sort, 1988-1998**

	Sent. beta	Size (000's)	Past sigma	Past idiosyn. sigma	Earnings (mil. $)	Div/ Equity	External Finance Activity	Cash flow (mil. $)	Sigma	Turnover	Past six month return
2	0.0085	1,468,146	0.1323	0.1169	91.78	0.0437	0.0638	124.57	0.0347	0.047	0.0060
3	0.0097	1,187,921	0.1423	0.1265	70.35	0.0404	0.0681	93.58	0.0378	0.049	-0.0053
4	0.0108	1,159,651	0.1440	0.1281	69.76	0.0387	0.0625	91.72	0.0389	0.049	-0.0079
5	0.0118	1,064,749	0.1415	0.1256	65.24	0.0366	0.0639	86.50	0.0383	0.049	-0.0061
6	0.0130	1,048,747	0.1400	0.1244	63.61	0.0355	0.0652	84.31	0.0381	0.050	-0.0038
7	0.0145	889,700	0.1403	0.1246	52.64	0.0325	0.0647	66.33	0.0382	0.049	-0.0052
8	0.0165	734,624	0.1400	0.1245	44.47	0.0421	0.0625	56.44	0.0386	0.049	-0.0126
9	0.0213	483,332	0.1385	0.1233	29.68	0.0300	0.0585	37.47	0.0389	0.049	-0.0150
2-9	-0.0128	984,814	-0.0062	-0.0064	62.10	0.0137	0.0053	87.10	-0.0042	-0.0020	0.0210
tstat	-19.80	3.72	-1.65	-1.49	5.04	7.32	1.24	5.39	-5.28	-1.25	3.03

Table 8a. Sentiment sensitivities and stocks characteristics: controlling for past volatility and size (75-99)

Each quarter (from march 1975 till March 1999) firm characteristics are matched to its stock sentiment beta estimated over the prior 60 months. Then stocks are placed into 25 size groups conditional on the average market capitalization in agiven quarter. Within each size group stocks are ranked into deciles conditional on their residual sentiment betas (net of volatility effects). After portfolio formation, the times series averages of the cross-sectional means are computed. B/M is the Book-To-Market ratio, DivYield is the dividend yield, DivToEq is the ratio of total dividend payments to the book equity, ROA is the return on the assets, PIN is the probability of informed trading, SP500 is the probability of being in the S&P500 index in a given quarter, IO is the institutional ownership, Short Sales is from Ali&Trombley (2003) and represents the probability that the loan fee for a stock is relatively high, Sigma is the daily returns standard deviation in a given quarter. B/M, DivYield, External Finance Activity, Sales and Assets Growth are Winsorized at 0.5% and 99.5%. "1-10" raw reports the difference between decile 1 (with the lowest sentiment sensitivity) and decile 10 (with the highest sentiment sensitivity). T-statistics are corrected for autocorrelation induced by the overlapping periods in sentiment beta estimation

	Sent.Beta	Size (in '000s)	Past sigma	Idiosyn. sima	B/M	Market beta	SMB	HML	DivYield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Tobin Q	Past 6 months return
1	0.006	862,788	0.127	0.107	0.98	0.90	0.86	0.36	0.033	78.82	0.054	0.056	0.052	1.44	0.046
2	0.008	840,018	0.126	0.106	0.94	0.98	0.88	0.26	0.027	67.53	0.048	0.057	0.053	1.42	0.042
3	0.009	852,850	0.131	0.110	0.92	1.00	0.93	0.26	0.025	67.85	0.045	0.058	0.054	1.47	0.044
4	0.009	809,274	0.132	0.112	0.91	1.00	0.93	0.24	0.023	62.49	0.046	0.059	0.054	1.48	0.042
5	0.010	866,124	0.131	0.111	0.92	0.99	0.93	0.22	0.023	67.68	0.044	0.059	0.054	1.51	0.044
6	0.011	843,631	0.131	0.111	0.92	1.00	0.93	0.22	0.023	65.85	0.043	0.059	0.054	1.50	0.044
7	0.012	829,445	0.129	0.109	0.93	0.99	0.91	0.23	0.023	64.93	0.043	0.056	0.055	1.49	0.043
8	0.014	836,839	0.128	0.109	0.92	0.99	0.92	0.23	0.024	66.80	0.042	0.060	0.054	1.49	0.044
9	0.015	824,733	0.127	0.108	0.93	0.98	0.92	0.23	0.024	65.48	0.042	0.056	0.055	1.54	0.044
10	0.019	848,062	0.125	0.106	0.94	0.97	0.90	0.21	0.023	64.89	0.043	0.054	0.055	1.57	0.040
1-10	**-0.013**	**14,726**	**0.002**	**0.002**	**0.04**	**-0.07**	**-0.05**	**0.15**	**0.010**	**13.92**	**0.012**	**0.002**	**-0.002**	**-0.13**	**0.006**
t-stat	**-14.27**	**0.32**	**1.24**	**1.10**	**1.89**	**-1.46**	**-1.06**	**2.97**	**9.30**	**5.08**	**5.13**	**0.52**	**-1.12**	**-1.68**	**1.65**

	Sent.Beta	Book Leverage	Cash flow ($Mil)	R&D	Sales growth	Assets Growth	Sigma	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	Average number of firms
1	0.006	0.181	107.90	0.048	0.095	0.116	0.027	2.21	0.207	0.138	0.194	0.032	182.7	0.013	305
2	0.008	0.187	89.74	0.051	0.105	0.122	0.029	2.55	0.207	0.151	0.203	0.038	178.7	0.021	317
3	0.009	0.190	90.45	0.051	0.112	0.120	0.030	2.65	0.207	0.152	0.205	0.040	176.9	0.026	315
4	0.009	0.187	82.67	0.053	0.113	0.126	0.031	2.75	0.207	0.157	0.205	0.043	174.9	0.032	318
5	0.010	0.188	89.84	0.054	0.110	0.152	0.030	2.82	0.208	0.158	0.208	0.043	175.6	0.032	320
6	0.011	0.187	86.96	0.054	0.110	0.122	0.030	2.75	0.208	0.155	0.208	0.043	174.9	0.034	312
7	0.012	0.186	83.38	0.053	0.114	0.126	0.030	2.80	0.207	0.159	0.208	0.043	175.1	0.033	315
8	0.014	0.188	88.18	0.053	0.113	0.124	0.030	2.83	0.209	0.159	0.211	0.043	174.6	0.032	318
9	0.015	0.183	84.34	0.051	0.108	0.124	0.030	2.91	0.209	0.159	0.210	0.043	174.9	0.036	315
10	0.019	0.187	83.86	0.048	0.111	0.119	0.030	3.13	0.210	0.169	0.216	0.044	176.7	0.034	327
1-10	**-0.013**	**-0.006**	**24.04**	**0.000**	**-0.016**	**-0.003**	**-0.003**	**-0.91**	**-0.003**	**-0.031**	**-0.022**	**-0.012**	**6.0**	**-0.021**	
t-stat	**-14.27**	**-0.72**	**5.86**	**0.04**	**-1.88**	**-0.47**	**-4.46**	**-2.89**	**-1.29**	**-3.71**	**-2.26**	**-3.31**	**1.25**	**-2.69**	

Table 8b. Sentiment sensitivities and stocks characteristics: controlling for past volatility and size:1975-1987

Each quarter (from march 1975 till Dec 1987) firm characteristics are matched to its stock sentiment beta estimated over the prior 60 months. Then stocks are placed into 25 sizegroups conditional on the average market capitalization in agiven quarter. Within each size group stocks are ranked into deciles conditional on their residual sentiment betas (net of volatility effects). After portfolio formation, the times series averages of the cross-sectional means are computed. B/M is the Book-To-Market ratio, DivYield is the dividend yield, DivToEq is the ratio of total dividend payments to the book equity, ROA is the return on the assets, PIN is the probability of informed trading, SP500 is the probability of being in the S&P500 index in a given quarter, IO is the institutional ownership, Short Sales is from Ali&Trombley (2003) and represents the probability that the loan fee for a stock is relatively high, Sigma is the daily returns standard deviation in a given quarter. B/M, DivYield, External Finance Activity, Sales and Assets Growth are Winsorized at 0.5% and 99.5%. "1-10" raw reports the difference between decile 1 (with the lowest sentiment sensitivity) and decile 10 (with the highest sentiment sensitivity). T-statistics are corrected for autocorrelation induced by the overlapping periods in sentiment beta estimation

	Sent.Beta	Size (in '000s)	Past sigma	Idiosyn. sima	B/M	Market beta	SMB	HML	DivYield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Tobin Q	Past 6 months return
1	0.006	498,722	0.121	0.096	1.09	0.96	0.87	0.35	0.042	69.78	0.054	0.050	0.060	1.25	0.046
2	0.008	461,424	0.124	0.099	1.07	1.02	0.94	0.25	0.035	55.73	0.049	0.051	0.059	1.24	0.042
3	0.009	453,801	0.127	0.102	1.04	1.02	0.96	0.23	0.032	56.09	0.046	0.054	0.060	1.27	0.044
4	0.009	433,098	0.127	0.103	1.03	1.02	0.93	0.21	0.031	51.29	0.046	0.054	0.061	1.27	0.042
5	0.010	444,787	0.126	0.103	1.03	1.01	0.93	0.20	0.031	54.20	0.046	0.055	0.060	1.26	0.044
6	0.011	451,093	0.126	0.102	1.05	1.01	0.92	0.21	0.031	53.78	0.047	0.053	0.061	1.26	0.044
7	0.012	428,626	0.124	0.101	1.06	0.99	0.90	0.21	0.032	52.43	0.047	0.051	0.062	1.25	0.043
8	0.013	446,804	0.123	0.100	1.06	0.99	0.91	0.23	0.033	56.71	0.046	0.054	0.060	1.23	0.044
9	0.015	423,388	0.120	0.098	1.06	0.96	0.88	0.22	0.033	52.70	0.046	0.051	0.061	1.25	0.044
10	0.018	421,855	0.118	0.096	1.09	0.96	0.87	0.22	0.032	52.70	0.042	0.047	0.059	1.40	0.040
1-10	**-0.012**	**76,867**	**0.003**	**0.000**	**0.00**	**0.01**	**0.01**	**0.13**	**0.010**	**17.08**	**0.012**	**0.002**	**0.001**	**-0.15**	**0.006**
t-stat	**-24.46**	**2.75**	**1.74**	**0.37**	**0.22**	**0.17**	**0.11**	**1.98**	**5.24**	**3.86**	**3.24**	**1.09**	**0.26**	**-1.00**	**1.65**

	Sent.Beta	Book Leverage	Cash flow ($Mil)	R&D	Sales growth	Assets Growth	Sigma	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	average number of firms
1	0.006	0.190	93.74	0.034	0.101	0.121	0.023	1.39	0.215	0.16	0.158	0.029	157.3	0.010	267
2	0.008	0.197	73.92	0.035	0.103	0.121	0.024	1.57	0.216	0.17	0.161	0.035	156.9	0.015	280
3	0.009	0.198	73.57	0.034	0.111	0.116	0.025	1.62	0.217	0.17	0.163	0.036	156.8	0.017	278
4	0.009	0.196	66.08	0.034	0.109	0.120	0.025	1.68	0.218	0.18	0.161	0.037	156.4	0.019	280
5	0.010	0.194	70.04	0.035	0.110	0.125	0.025	1.65	0.216	0.18	0.163	0.037	157.7	0.019	282
6	0.011	0.194	69.47	0.034	0.108	0.115	0.025	1.64	0.218	0.18	0.160	0.037	157.5	0.017	274
7	0.012	0.196	66.56	0.032	0.106	0.116	0.025	1.71	0.214	0.18	0.157	0.037	158.2	0.017	277
8	0.013	0.201	71.86	0.032	0.107	0.115	0.025	1.73	0.215	0.18	0.162	0.036	157.6	0.017	281
9	0.015	0.194	67.91	0.031	0.104	0.114	0.025	1.74	0.217	0.18	0.161	0.036	159.2	0.016	277
10	0.018	0.197	65.00	0.030	0.101	0.115	0.024	1.79	0.218	0.20	0.159	0.035	159.8	0.016	290
1-10	**-0.012**	**-0.007**	**28.74**	**0.004**	**0.000**	**0.006**	**-0.002**	**-0.40**	**-0.0036**	**-0.04**	**-0.0012**	**-0.006**	**-2.5**	**-0.005**	
t-stat	**-24.46**	**-0.47**	**5.12**	**3.37**	**0.03**	**0.47**	**-3.32**	**-1.59**	**-0.74**	**-3.82**	**-0.12**	**-4.05**	**-1.95**	**-2.51**	

Table 8c. Sentiment sensitivities and stocks characteristics: controlling for past volatility and size: 1988-1999

Each quarter (from march 1988 till March 1999) firm characteristics are matched to its stock sentiment beta estimated over the prior 60 months. Then stocks are placed into 25 sizegroups conditional on the average market capitalization in agiven quarter. Within each size group stocks are ranked into deciles conditional on their residual sentiment betas (net of volatility effects). After portfolio formation, the times series averages of the cross-sectional means are computed. B/M is the Book-To-Market ratio, DivYield is the dividend yield, DivToEq is the ratio of total dividend payments to the book equity, ROA is the return on the assets, PIN is the probability of informed trading, SP500 is the probability of being in the S&P500 index in a given quarter, IO is the institutional ownership, Short Sales is from Ali&Trombley (2003) and represents the probability that the loan fee for a stock is relatively high, Sigma is the daily returns standard deviation in a given quarter. B/M, DivYield, External Finance Activity, Sales and Assets Growth are Winsorized at 0.5% and 99.5%. "1-10" raw reports the difference between decile 1 (with the lowest sentiment sensitivity) and decile 10 (with the highest sentiment sensitivity). T-statistics are corrected for autocorrelation induced by the overlapping periods in sentiment beta estimation

	Sent.Beta	Size (in '000s)	Past sigma	Idiosyn. sigma	B/M	Market beta	SMB	HML	DivYield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Tobin Q	Past 6 months return
1	0.006	1,275,395	0.135	0.120	0.85	0.84	0.84	0.37	0.024	89.05	0.055	0.064	0.044	1.66	0.007
2	0.007	1,269,091	0.129	0.113	0.80	0.93	0.81	0.28	0.019	80.90	0.046	0.064	0.045	1.62	-0.003
3	0.009	1,305,106	0.135	0.119	0.78	0.97	0.89	0.29	0.016	81.19	0.044	0.063	0.047	1.71	0.000
4	0.010	1,235,607	0.138	0.121	0.77	0.98	0.93	0.28	0.015	75.19	0.046	0.065	0.046	1.72	0.000
5	0.011	1,343,639	0.137	0.120	0.78	0.98	0.93	0.25	0.014	82.95	0.042	0.064	0.046	1.80	0.002
6	0.012	1,288,507	0.137	0.120	0.77	0.98	0.93	0.24	0.014	79.53	0.038	0.066	0.047	1.76	0.000
7	0.013	1,283,707	0.135	0.119	0.77	0.99	0.92	0.24	0.014	79.09	0.039	0.062	0.047	1.76	0.005
8	0.014	1,278,878	0.135	0.118	0.76	0.99	0.94	0.23	0.013	78.23	0.037	0.067	0.048	1.78	0.003
9	0.016	1,279,591	0.134	0.118	0.78	1.00	0.96	0.23	0.013	79.95	0.039	0.062	0.048	1.87	0.001
10	0.021	1,331,096	0.133	0.117	0.77	0.99	0.94	0.21	0.013	78.71	0.043	0.062	0.050	1.76	-0.002
1-10	**-0.015**	**-55,701**	**0.002**	**0.003**	**0.08**	**-0.16**	**-0.11**	**0.16**	**0.011**	**10.34**	**0.012**	**0.001**	**-0.005**	**-0.09**	**0.010**
t-stat	**-30.65**	**-0.62**	**0.58**	**1.06**	**2.91**	**-3.23**	**-3.09**	**3.43**	**6.41**	**3.45**	**4.01**	**0.21**	**-5.97**	**-0.96**	**1.59**

	Sent.Beta	Book Leverage	Cash flow ($Mil)	R&D	Sales growth	Assets Growth	Sigma	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	average number of firms
1	0.006	0.171	123.94	0.065	0.088	0.110	0.032	3.14	0.203	0.114	0.220	0.035	211.5	0.014	347
2	0.007	0.176	107.68	0.069	0.107	0.124	0.035	3.66	0.203	0.129	0.234	0.041	203.4	0.023	360
3	0.009	0.182	109.57	0.071	0.114	0.124	0.036	3.82	0.202	0.127	0.236	0.046	199.6	0.029	357
4	0.010	0.177	101.46	0.074	0.116	0.133	0.037	3.96	0.203	0.132	0.238	0.048	195.9	0.036	360
5	0.011	0.180	112.27	0.076	0.110	0.183	0.036	4.14	0.204	0.135	0.240	0.049	195.8	0.036	362
6	0.012	0.178	106.78	0.076	0.113	0.130	0.036	4.02	0.204	0.131	0.243	0.050	194.7	0.040	355
7	0.013	0.175	102.44	0.076	0.123	0.137	0.036	4.05	0.204	0.132	0.246	0.050	194.2	0.039	357
8	0.014	0.173	106.68	0.077	0.120	0.135	0.036	4.07	0.206	0.137	0.248	0.051	193.9	0.038	360
9	0.016	0.172	102.95	0.073	0.113	0.135	0.036	4.22	0.205	0.137	0.246	0.052	192.7	0.043	357
10	0.021	0.176	105.24	0.069	0.121	0.124	0.036	4.64	0.206	0.138	0.257	0.054	195.9	0.041	370
1-10	**-0.015**	**-0.005**	**18.70**	**-0.004**	**-0.034**	**-0.014**	**-0.004**	**-1.50**	**-0.003**	**-0.025**	**-0.0372**	**-0.019**	**15.6**	**-0.027**	
t-stat	**-30.65**	**-1.56**	**3.37**	**-0.72**	**-5.71**	**-1.37**	**-10.79**	**-5.53**	**-1.31**	**-2.28**	**-6.45**	**-5.10**	**2.10**	**-3.05**	

Table 9. Economic significance

"Diff" row is the difference between average quarterly characteristics in decile 1 (lowest sentiment sensitivity) and decile 10 (highest sentiment sensitivity). "Average" row represents the average value of a given characteristic across all quarters for the cross-section of firms that have a full five year returns history prior to a given quarter. "Diff/Average" row is the absolute value of the ratio of "Diff" row to "Average" row expressed in percentage.

1975-1999

	MRKT beta	SMB beta	HML beta	B/M	DivYield	Earnings ($Mil)	ROE	DivToEq	ROA	Tobin Q	Book Leverage	R&D	Cash flow ($Mil)
diff	-0.070	-0.046	0.146	0.037	0.010	13.92	-0.011	0.012	-0.002	-0.13	-0.006	0.000	24.04
average	0.980	0.913	0.248	0.931	0.025	66.72	0.129	0.045	0.054	1.50	0.187	0.052	87.95
diff/average	**7.09%**	**5.09%**	**58.74%**	**4.01%**	**41.12%**	**20.87%**	**8.32%**	**26.47%**	**4.08%**	**8.35%**	**3.26%**	**0.24%**	**27.33%**

	Sales growth	Assets Growth	Sigma	Analysts	PIN	SP500	Size (in 000's of $)	IO	Turnover	Age	Past sigma	Idiosyn. sigma	Short sales
diff	-0.016	-0.003	-0.003	-0.91	-0.003	-0.03	14,726	-0.022	-0.012	5.97	0.002	0.002	-0.021
average	0.108	0.124	0.030	2.74	0.208	0.16	841,275	0.207	0.041	176.49	0.129	0.109	0.030
diff/average	**14.53%**	**2.65%**	**9.47%**	**33.32%**	**1.42%**	**19.84%**	**1.75%**	**10.63%**	**29.27%**	**3.38%**	**1.88%**	**1.68%**	**72.33%**

1975-1987

	MRKT beta	SMB beta	HML beta	B/M	DivYield	Earnings ($Mil)	ROE	DivToEq	ROA	Tobin Q	Book Leverage	R&D	Cash flow ($Mil)
diff	0.007	0.006	0.129	0.002	0.010	17.08	0.000	0.012	0.001	-0.15	-0.007	0.004	28.74
average	0.993	0.912	0.233	1.058	0.033	55.10	0.132	0.047	0.060	1.27	0.196	0.033	71.14
diff/average	**0.72%**	**0.66%**	**55.33%**	**0.15%**	**29.30%**	**31.00%**	**0.27%**	**24.89%**	**1.08%**	**12.13%**	**3.51%**	**11.94%**	**40.40%**

	Sales growth	Assets Growth	Sigma	Analysts	PIN	SP500	Size (in 000's of $)	IO	Turnover	Age	Past sigma	Idiosyn. sigma	Short sales
diff	0.000	0.006	-0.002	-0.40	-0.004	-0.04	76,867	-0.001	-0.006	-2.51	0.003	0.000	-0.005
average	0.105	0.117	0.025	1.65	0.217	0.18	446,010	0.161	0.036	157.75	0.124	0.100	0.016
diff/average	**0.11%**	**5.22%**	**6.25%**	**23.90%**	**1.65%**	**20.61%**	**17.23%**	**0.73%**	**17.80%**	**1.59%**	**2.39%**	**0.46%**	**33.11%**

1988-1999

	MRKT beta	SMB beta	HML beta	B/M	DivYield	Earnings ($Mil)	ROE	DivToEq	ROA	Tobin Q	Book Leverage	R&D	Cash flow ($Mil)
diff	-0.157	-0.106	0.165	0.078	0.011	10.34	-0.023	0.012	-0.005	-0.09	-0.005	-0.004	18.70
average	0.966	0.914	0.265	0.786	0.015	79.90	0.125	0.043	0.047	1.77	0.177	0.073	107.00
diff/average	**16.21%**	**11.59%**	**62.14%**	**9.90%**	**69.86%**	**12.94%**	**18.54%**	**28.41%**	**11.64%**	**5.28%**	**2.95%**	**5.75%**	**17.48%**

	Sales growth	Assets Growth	Sigma	Analysts	PIN	SP500	Size (in 000's of $)	IO	Turnover	Age	Past sigma	Idiosyn. sigma	Short sales
diff	-0.034	-0.014	-0.004	-1.50	-0.003	-0.02	-55,701	-0.037	-0.019	15.58	0.002	0.003	-0.027
average	0.112	0.132	0.036	3.98	0.205	0.13	1,289,242	0.241	0.048	197.73	0.135	0.119	0.034
diff/average	**30.16%**	**10.56%**	**11.99%**	**37.76%**	**1.31%**	**18.66%**	**4.32%**	**15.43%**	**39.82%**	**7.88%**	**1.35%**	**2.86%**	**78.98%**

Table 10. Noise trading and institutional behavior

The dependent variable is the percentage quarterly aggregate holdings of institutions. Sent beta is the sensitivity of stock returns to the sentiment index changes in the 5 years prior to the beginning of that quarter. BM is the lagged book-to-market ratio, Size is the lagged average market capitalization over the previous quarter, Volatility is the standard deviation of monthly returns over the 5 years preceeding the beginnibg of the quarter, Turnover is the average lagged share turnover over the previous quarter, Price is the lagged average price over the previous quarter SP500 is a dummy taking 1 if the stock was a member of S&P 500 Index in the month prior to the beginning of the quarter, Return is the lagged compouned quartely stock return over the previous quarter, Age is the number of months since the month the stock appeared on CRPS tapes to beginning-of-the-quarter month, DivYield is the lagged dividend yield. Sent beta is standardized in each cross-section to have mean 0 std 1. All variables are log transformations

	80-99		**80-89**					**90-99**				
	Entire sample		Model 1	Model 2	Model 3	with sent. betas >0	with sent. betas<0	Model 1	Model 2	Model 3	with sent. betas>0	with sent. betas<0
Sent beta (X100)		**0.026**	**0.100**	**0.105**	**-0.234**	**-0.125**	**-0.356**	**0.543**	**0.567**	**0.280**	**0.322**	**0.276**
		0.19	*1.09*	*1.14*	*-2.57*	*-3.24*	*-3.35*	*4.2396*	*3.92*	*2.50*	*3.09*	*2.04*
BM	0.045	0.027			0.012	0.011	0.010			0.042	0.044	0.040
	3.69	*3.40*			*2.03*	*1.69*	*1.41*			*11.05*	*7.66*	*12.67*
SIZE	0.027	0.023	0.027	0.022	0.021	0.023	0.020	0.026	0.026	0.024	0.025	0.023
	16.71	*13.29*	*29.19*	*25.26*	*10.95*	*16.25*	*8.39*	*20.21*	*11.21*	*10.48*	*7.47*	*14.71*
VOLATILITY	-0.286	-0.313	0.047	0.043	-0.388	-0.395	-0.354	-0.177	-0.169	-0.240	-0.229	-0.272
	-3.26	*-3.84*	*1.76*	*1.44*	*-3.26*	*-3.36*	*-3.16*	*-3.43*	*-3.18*	*-3.17*	*-2.60*	*-4.09*
TURNOVER	0.175	0.279	0.325	0.244	0.245	0.213	0.283	0.354	0.355	0.311	0.291	0.340
	3.06	*6.29*	*2.82*	*2.69*	*2.97*	*2.06*	*4.53*	*14.44*	*11.98*	*7.51*	*5.71*	*10.06*
PRICE	0.039	0.040	0.033	0.038	0.035	0.030	0.039	0.032	0.033	0.045	0.045	0.044
	6.09	*14.69*	*10.26*	*10.30*	*14.90*	*16.95*	*10.13*	*20.57*	*32.87*	*26.34*	*19.26*	*13.81*
SP500	0.015	0.019		0.040	0.032	0.032	0.030		0.015	0.007	0.000	0.010
	1.55	*2.81*		*27.41*	*6.07*	*6.55*	*6.20*		*2.09*	*1.60*	*0.04*	*3.74*
RETURN	-0.013	-0.016		-0.019	-0.019	-0.015	-0.022		-0.011	-0.014	-0.015	-0.013
	-4.73	*-5.30*		*-3.41*	*-3.47*	*-2.66*	*-3.54*		*-3.96*	*-4.50*	*-4.00*	*-3.70*
AGE	0.011	0.007			0.001	0.002	0.002			0.013	0.014	0.013
	5.09	*1.80*			*0.34*	*0.42*	*0.32*			*2.96*	*3.20*	*2.83*
DIVYIELD	-1.002	-1.263			-1.063	-0.848	-1.111			-1.458	-1.420	-1.423
	-7.27	*-7.97*			*-25.77*	*-12.12*	*-20.50*			*-6.34*	*-9.76*	*-4.89*
Avr Nobs	2477	2472	2700	2700	2147	1069	1078	3658	3658	2824	1438	1385
Adj.R-squared	0.326	0.328	0.286	0.294	0.308	0.312	0.311	0.324	0.326	0.349	0.362	0.342