Sentiment beta

Denys Glushkov*

Abstract

This paper develops a novel stock-by-stock measure of investor sentiment which I call sentiment beta. It is defined as a sensitivity of stock returns to sentiment changes. Using this measure I test two hypotheses. First hypothesis postulates that sentiment affects stocks of some firms more than others due to differences in firm characteristics. Second hypothesis predicts that stocks which are more sensitive to shifts in investor sentiment are more likely to be held by individual investors. Consistent with the first hypothesis, I find that more sentiment-sensitive stocks are smaller, younger, with greater short-sales constraints, higher idiosyncratic volatility and lower dividend yields. Accounting for size and volatility, high sentiment beta stocks have more of an analyst following, greater institutional ownership, a higher likelihood of S&P500 membership, higher turnover and lower book-to-market ratios. Stocks that are more exposed to sentiment changes deliver lower future returns inconsistent with the idea that noise trader risk is priced. Evidence in support of second hypothesis is mixed: analysis reveals that institutions stayed away from sentiment-sensitive stocks in the 1980's, but held more of these stocks since the early 1990's. This suggests that institutions may well have been exacerbating sentiment-driven mispricing instead of countering the actions of sentiment traders.

JEL classification: G1

Keywords: Investor sentiment, firm characteristics, institutions

---

*PhD Candidate in Finance, 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 Lorenzo Garlappi, Andrea Frazzini, John Griffin, Eric Hirst, Paul Tetlock, Sheridan Titman, Senyo Tse, Roberto Wessels and all UT Finance Research Seminar participants for valuable suggestions. I also thank Greg Brown, Prachi Deuskar, Meir Statman, Mark Trombley and Ivo Welch for providing data as well as Soeren Hvidkjaer, Evgenia Portniaguina and participants of the 2005 Eastern Finance Association, European FMA (Milan) and FMA (Chicago) meetings for insightful discussions and helpful comments. Any errors are my responsibility.

Introduction

There is a growing body of both theoretical and empirical literature that examines the role of investor sentiment and its implications for financial markets and institutions. This literature has improved our understanding of some financial anomalies documented in prior work, such as the predictability in stock returns, excessive trading and volatility and evidence of investors' underreaction to corporate announcements. There is now mounting evidence that suggests that the role played by sentiment traders should not be ignored. As a result, contemporary research explores the drivers of their behavior, their trading patterns and implications for market efficiency. However, most evidence remains controversial, at best, and the debate about sources of investor sentiment and the importance of sentiment for asset prices, is ongoing.

The motivation behind this paper is twofold. Recent work (e.g. Baker and Wurgler (2006), Frazzini and Lamont (2006), Lemmon and Portniaguina (2006)) provides evidence that investor (and consumer) sentiment has explanatory power for the cross-section of stock returns. First, motivated by this result, this paper posits that firm characteristics play a key role in how investor sentiment affects returns. I show this by testing what I call the "Hard-to-Value, Difficult-to-Arbitrage" hypothesis (HV-DA) which states that stocks of some firms are more affected by shifts in investor sentiment than others due to the differences in firm characteristics. Specifically, smaller, younger, unprofitable, non-dividend or low-dividend-paying stocks with greater short sales constraints, shorter earnings histories and a presence of relatively high growth opportunities are predicted to be more prone to sentiment shifts because such characteristics make these stocks hard to value and difficult to arbitrage[1]. Alternatively, classic finance theory postulates that investor sentiment has no systematic impact on the valuation process and asset prices regardless of firm characteristics.

The second goal of the paper is to test the prediction of the hypothesis that stocks that are more vulnerable to sentiment changes are more likely to be held by retail investors, because their personal judgment is more likely to be affected by behavioral biases than that of institutions. The efficient markets hypothesis is based on the presumption that rational speculators would find it optimal to exert a correcting force on asset prices. However, some recent theoretical and empirical papers (Jackson (2003b), Abreu et al. (2002, 2003), Brunnermeier et al. (2005)) indicate that rational investors might find it optimal to "ride" on bubbles for a while before attacking them, making the actions of rational investors destabilizing rather than stabilizing (Gabaix et al. (2005)). Moreover, there is also mixed evidence regarding whether individual or institutional sentiment is more

[1] For example, there is evidence that individuals tend to be more overconfident in settings where more subjective judgment is needed to evaluate information, see Einhorn (1980), Daniel and Titman (1999), Chan et al (1999), Klibanoff et al (1999)

important in explaining the cross-section of stock returns. Some researchers (e.g., Barber et al. (2003), Kaniel et al (2006), Kumar and Lee (2006) and Frazzini et al. (2006)) argue that it is individual investor sentiment that matters, whereas others (e.g., Brown and Cliff (2005)), Pirinsky and Wang (2003), Jackson (2003b)) empirically document the existence and importance of non-fundamental factor in returns, which is associated with institutional trading. This paper contributes to this debate by investigating the relationship between institutional ownership and sensitivity of stock returns to shifts in investor sentiment.

To explore the predictions of these two hypotheses, this study adopts the following empirical approach. First, it develops an aggregate measure of investor sentiment (sentiment factor) constructed as the first principal component of several investor sentiment measures[2]. To mitigate the possibility that the sentiment factor may also represent economic factors, all sentiment measures are orthogonalized with respect to several variables that may be correlated with fundamentals[3]. The composite sentiment index based on these orthogonalized proxies is shown to have predictive power for the aggregate market returns (positive changes in sentiment index tend to be followed by lower market returns) during 1965-2003, whereas alternative popular measures such as Baker and Wurgler's (2006) BW measure and UMich Consumer Confidence Index (UMCCI) do not. My sentiment factor also has contemporaneous explanatory power for small and retail stock return spreads even in the presence of BW and UMCCI measures, which are desirable features of sentiment measure[4]. I also demonstrate that this sentiment proxy adds a significant incremental explanatory power for time-series of individual stock returns (as much as Pastor and Stambaugh (2003) liquidity factor).

Second, using the constructed sentiment index, I develop and validate (both theoretically and empirically) a stock-by-stock measure of sentiment, which I call sentiment beta. It is defined as the sensitivity of returns to sentiment. Specifically, sentiment beta is the coefficient in the time-series

---

[2] Sentiment measures are the widely-followed Investors Intelligence Index (i.e. bull-bear spread), dividend premium, closed-end fund discount, percentage change in margin borrowing, ratio of specialist short sales to total short sales, new net cash flow into equity mutual funds, average first-day IPO returns and number of IPOs.

[3] These variables are the growth in industrial production, consumption of durables, non-durables and services, aggregate employment, NBER recession dummy, term/credit spreads and returns of the factor-mimicking portfolio that has the highest exposure to fluctuations in macroeconomic factors. I also control for the market returns in my subsequent time-series regressions.

[4] In fact, the composite sentiment index constructed in this paper *subsumes* the explanatory power of Baker and Wurgler measure for small and retail stock return spreads. 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 return spread". The retail stock return 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 institutional ownership" stocks

regression of individual stock returns on changes in sentiment (net of macro factors) after controlling for the risk factors associated with the market, size, book-to-market and liquidity.

Using this measure, I first test whether more sentiment sensitive stocks earn higher returns (whether the "noise trader" risk is priced). I find that stocks with greater exposure to investor sentiment tend to *underperform* stocks with low exposure. Investors will fare better in the future by holding the portfolio of stocks with close-to-zero loadings on the sentiment factor: a zero-net investment long-short (LS) equal-weighted portfolio that is long in low sentiment beta stocks and short in high sentiment beta stocks has higher raw (27 bp) and risk-adjusted (38 bp) excess returns per month[5]. The result is qualitatively similar in sub-periods and robust to the horizons over which returns are measured: over a year horizon low sentiment beta portfolio delivers cumulative risk-adjusted returns that are 250 basis points higher than those of high sentiment beta portfolio. This is inconsistent with the idea that noise trader risk is priced, but in line with the findings of Ang et al. (2005) who find that stocks with high idiosyncratic volatility relative to Fama and French (1993) model (as I show later, these stocks tend to have higher absolute loadings on sentiment factor) have abysmally low average returns. Evidence also shows that variation in sensitivity to sentiment factor is not related to the momentum effect, in other words, momentum profits do not appear to be a result of different sensitivities of stock returns to shifts in investor sentiment.

Second, I perform unconditional and conditional sorts on sentiment beta and several control characteristics,[6] and look for hypothesized patterns in firm characteristics predicted by the HV-DA story. I find that stocks with greater sentiment sensitivity are significantly smaller, younger growth stocks with higher idiosyncratic volatility. Accounting for return volatility, the size result remains strong: the average size of the bottom sentiment beta portfolio is almost twice as large as that of the top sentiment beta portfolio. This suggests that investor sentiment has a stronger impact on the subjectivity of valuations of small stocks. Accounting for size and volatility, more sentiment sensitive stocks tend to be younger growth stocks that have subsequently higher total and idiosyncratic volatility, higher turnover, lower dividend yields, greater short-sales constraints and lower book-to-market ratios[7]. Most of the differences are both statistically and economically

[5] The fact that risk-adjusted returns are higher than raw return payoffs suggests that the high sentiment beta stocks are riskier than their low sentiment beta counterparts, and hence, the described strategy does not have positive exposure to systematic risk factors.

[6] If sentiment beta were measured without sampling error, these sorts should produce relative rankings identical to those one would get if she could sort on the unobserved proportion of noise traders in a stock (see DSSW (1990)).

[7] The fact that growth ("glamor") stocks tend to be more sensitive to sentiment changes is consistent with Elsewarapu 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.

significant. For example, the difference between average dividend yields of low vs. high sentiment beta portfolios with similar market cap and return volatility constitutes around 82% of the average dividend yield during 1989-2003. The analogous numbers for turnover, short-sales constraints proxy, age and book-to-market are 40%, 59%, 11% and 9%. Overall, these results suggest that dividends, turnover, short-sales constraints, age and growth potential have size- and volatility-independent effects on the interaction between changes in investor sentiment and the process of equity valuation.

After netting out differences in size and volatility, high sentiment beta stocks have more of an analyst following, a higher likelihood of being in S&P 500 and higher institutional ownership (IO). In the entire sample these variables display a near-monotonic increasing pattern as sentiment sensitivity rises. These differences become more pronounced in the second part of the sample (1989-2003). For instance, the difference in the average analyst coverage (IO) between extreme sentiment beta groups represents 45% (20%) of the average number of analysts (average IO) during that period. Empirical evidence does not support the notion that broad waves of sentiment influence unprofitable stocks more than profitable stocks once effects of size are accounted for. In fact, during 1989-2003 stocks with higher sentiment sensitivities appeared to be more profitable relative to their low sentiment beta counterparts in terms of their return on assets (on average, by about 0.5% on the annual basis). These findings are robust to controlling for the lagged market returns.

One of the implications of HV-DA hypothesis is that we should observe greater disagreement among investors about stock's future earnings in stocks that are more prone to shifts in sentiment. Empirically, this implies that sentiment beta should be positively associated with the extent to which investors disagree on the stock's fair value and its earnings prospects. I use the analysts' forecast dispersion measure to proxy for the level of investors' disagreement (Diether et al, 2002). Consistent with the predictions of HV-DA hypothesis, I find that analyst forecast dispersion next month is significantly higher if stock's sentiment sensitivity was higher over 5 years preceeding this month. There is also evidence that the greater forecast dispersion this period predicts greater exposure to sentiment in the future. This result is robust to controlling for the number of analysts following the stock, its size and volatility. Overall, these findings are in line with HV-DA explanation of the reasons why some stocks may be more sensitive to sentiment changes than others.

With respect to the second hypothesis which suggests negative relationship between sentiment sensitivity and institutional ownership, results of quarterly Fama-MacBeth (FM) regressions of institutional ownership (IO) on the sentiment beta and different sets of controls suggest that institutions changed their behavior around the late 80's/early 90's, consistent with the findings of

Bennett et al. (2003) who find that institutional preferences shifted towards smaller and riskier stocks since the 1990's. Specifically, the paper shows that institutions stayed away from stocks with high sentiment sensitivity throughout the 80's (as indicated by institutional ownership loading negatively on the sentiment betas), but held relatively more of these stocks in their portfolios throughout the 90's (as indicated by institutional ownership loading positively on the sentiment betas). Once the aggregate IO is decomposed into five groups (banks, insurance companies, mutual funds, independent investment advisors and others), analysis demonstrates that negative relationship between IO and sentiment sensitivity in the 80's is driven mainly by bank trust departments and independent investment advisors, whereas the positive relationship in the 90's is attributable for the most part to mutual funds and endowments. These results contribute to the recent literature which documents that some types of institutions may be the source of the non-fundamental factor in returns (see Sias (1996), Jones et al. (1999), Jackson (2003b), Pirinsky and Wang (2004), Hughen et al. (2004)).

This paper is not the first to analyze the role of sentiment in the financial market. However, only a few studies comprehensively addressed the questions of what types of stocks are more sensitive to sentiment changes and how sentiment is related institutional trading. The closest in spirit to this paper is Baker and Wurgler (BW, 2006), whose main finding is that when sentiment is low, smaller, more volatile, unprofitable, non-dividend-paying, extreme growth *and* distressed stocks earn higher subsequent returns, whereas the patterns largely reverse when sentiment is high. My paper contributes to and differs from their work in several important respects.

First, in addition to offering qualitative evidence on the validity of sentiment proxy, I provide tests to ensure that the sentiment measure is good at capturing fluctuations in investor optimism/pessimism that are orthogonal to fundamentals[8]. Second, in contrast to BW, sentiment in this paper is treated not as a conditioning variable in the characteristics-based model of returns, á la Daniel & Titman (1997), but rather as a factor in returns that is orthogonal to fundamentals. This time-series approach allows me to explore whether or not sentiment exposure is priced. Third, this paper extends the set of security characteristics to include analyst coverage, short-sales constraints, S&P 500 membership and others and also examines the relationship between institutional ownership and sentiment in more detail.

---

[8]The results of these tests show that even though BW measure visibly aligns itself with historical accounts of bubbles and crashes, it does not do as well when taken to quantitative tests. For example, Lemmon and Portniaguina (2004) document that the University of Michigan Consumer Sentiment index (UMCCI) has explanatory power for the cross-section of stock returns and report that BW measure is significantly negatively correlated with UMCCI prior to 1977.

One of my findings is consistent with Baker and Wurgler (2006), most prominently, with respect to size: smaller stocks tend to be more sensitive to changes in sentiment, ceteris paribus. However, there are important differences. First, since smaller stocks, on average, tend to be younger, unprofitable, non-dividend-paying and more volatile simply by virtue of being smaller, it is not entirely clear from BW work whether these characteristics have a size-independent or volatility-independent impact on the subjectivity of valuations[9]. This study reveals several new findings not documented in BW: a) empirical evidence suggests that age, the firm's dividend policy and growth potential have power in explaining relative sentiment sensitivities beyond what is explained by size, b) given size and volatility, growth stocks are more sensitive to sentiment than distressed stocks. In contrast to the BW result that unprofitable stocks are more affected by sentiment, I find that profitable and unprofitable stocks of similar size appear to have similar sentiment sensitivities (with profitable stocks being even more sensitive from 1989 to 2003).

This work also builds on and contributes to literature exploring the role of sentiment both at the aggregate and individual stock level. To proxy for aggregate sentiment, previous research (with the exception of BW (2005) and Brown and Cliff (2005)) predominantly used proxies based on one time series such as close-end fund discounts, equity share of new issues or survey measures, that captured different dimensions of variation in unobserved sentiment factor[10]. To proxy for sentiment at the individual stock level, literature used buy-and-sell imbalance (Kumar and Lee (2006), Barber et al. (2003), Kaniel et al., (2006)) and mutual fund flows (Brown et al. (2003), Frazzini and Lamont (2006)). This paper is among the first to provide an important link between these two strands of research: it uses a composite aggregate measure of sentiment to develop a meaningful stock-by-stock measure, the sentiment beta.

The rest of the paper is organized as follows. Section 1 discusses theoretical predictions, provides definition of sentiment and describes the possible channel(s) through which it may affect asset prices. Section 2 describes the data, the methodology of constructing the sentiment index and details of sentiment beta estimation. Section 3 contains empirical results and interpretation. Robustness checks and measure validation results are presented in Section 4. The last section concludes the paper.

[10]For aggregate sentiment measures see: CEF discounts - Elton et al (1998), Sias et al (2001), Lee et al (1991), Neal and Wheatley (1998); the University of Michigan Consumer Confidence Index – Lemmon and Portniaguina (2006), Qiu and Welch (2005); the Investors Intelligence Index – Lee et al. (2003), Soltman and Statman (1988), equity share of new issues – Baker and Wurgler (2000), the composite index – Brown and Cliff (2005), Baker and Wurgler (2006)

1. Hard-to-value, Difficult-to-Arbitrage Hypothesis (HV-DA)

HV-DA states that some stocks are more affected by irrational investor sentiment than others due to differences in their characteristics. The combination of certain characteristics creates difficulties in applying conventional equity valuation models, as a result, investors have to rely more heavily on personal judgment, which may be subject to behavioral biases. For instance, for younger growth stocks with short earnings history and no dividends it is more difficult to build DCF models and reliably estimate the present values of growth opportunities. This means that at this stage of equity valuation personal judgment plays a more important role. There is psychological and behavioral finance research that suggests that people tend to react differently to information that is difficult to interpret[11]. This may lead hard-to-value stocks to be more sensitive to fluctuations in sentiment that are unwarranted by changes in fundamentals.

Small stocks are likely to be more sensitive to sentiment because they are difficult to short (Jones and Lamont (2002), D'Avolio (2002)). Even if able to short sell, the arbitrageurs may find it difficult and costly to maintain a short position for a sustained period of time, with the result that the excessive buying pressure of non-fully rational sentiment traders on certain stocks may be hard to counter. When sentiment traders push the prices of some stocks below the fundamental values, on the other hand, it is risky for even the smartest arbitrageur to profit from contrarian investing in these particular stocks unless she is very patient or her pockets are very deep (Shleifer and Vishny, 1997).

Knowing that hard-to-value stocks are more sensitive to changes in the sentiment, sophisticated investors will be less willing to arbitrage mispricing away in these stocks. This "noise trader" risk (DSSW, 1990) makes stocks that are hard to value also difficult to arbitrage. In summary, given the constraints and risks faced by the arbitrageur, sentiment investors may have significant influence over the prices of smaller, younger and more volatile stocks, making them more vulnerable to sentiment swings. A clear alternative to HV-DA story is the classical finance view which predicts that sentiment plays has no systematic impact on either stock valuations or returns, regardless of firm characteristics.

I want to be specific about what I mean by "investor sentiment", "sentiment traders" and channels through which sentiment is likely to affect stock returns. Generally, sentiment can be viewed as the aggregate market-wide expectations of investors relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever the ''average'' may be (e.g. an

[11] There is evidence that individuals tend to be more overconfident in settings where more subjective judgment is needed to evaluate information, see Einhorn (1980), Daniel and Titman (1999), Chan et al (1999), Klibanoff et al (1999)

average which could be justified solely on the basis of stock fundamentals)[12]. In the context of this paper, I consider sentiment which reflects fluctuations in the opinions of investors regarding the future prospects for the stock market which are *orthogonal* to fundamentals. Sentiment traders are defined according to DSSW (1990) as investors whose demand for a risky asset is affected by the sentiment factor.

Sentiment is more likely to make an impact on asset prices through discount rates, because it cannot affect cash flows, at least, not directly. Price movements that are associated with changing rational forecasts of cash flows may ultimately be driven by investor sentiment, but the mechanism can be an only indirect one, for example, through the feedback from stock prices to fundamental cash flows (Subrahmanyam and Titman, 2001). One might expect that shocks to the market-wide discount rate (risk-premium) that induce negative autocorrelation in aggregate returns would be reflected in all groups of stocks. The distinguishing prediction of the HV-DA hypothesis is that it implies that given the shift in economic factors, the cross-section of required rates of return will be affected *disproportionately* due to trading of sentiment traders: discount rates for some groups of stocks will shift more than for the others.

This "sentiment effects through discount rates" view is supported by recent theoretical work. For example, Barberis and Huang (2001) use the idea of "loss aversion" in prospect theory and build a model which predicts that high returns of the stocks (driving up the relative demand of positive feedback traders) are followed by a decrease in investors' degree of risk aversion because investors feel they are "gambling with the house money" (Benartzi and Thaler, 1995). This causes the discount rates of these stocks to go down after a price run-up. The discount rate channel is consistent with the phenomenon called "individual stock accounting", where prior outcomes of individual stocks (in our case, those most prone to the sentiment movements) can affect the risk-aversion of the investors. Hence, changes in the degree of risk aversion caused by prior outcomes of sentiment sensitive stocks also affect the expected returns of the aggregate stock market.

2. Sentiment index

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

[12] For example, Frazzini and Lamont (2005) propose a fund flow-based measure of sentiment defined as the actual ownership by mutual funds minus the counterfactual ownership that would have occurred if every fund had received proportional inflows. Others (Kumar and Lee, 2006; Kaniel et al., 2006) define sentiment as the stock buy-sell imbalance in excess of the average buy-sell imbalance.

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[13].

2.1. Sentiment measures

Sentiment data are available from different sources at the monthly frequency and cover the period from March 1965 till December 2003. There are total of eight proxies used in the sentiment index construction. One of the sentiment proxies used in the paper is Investors Intelligence Index (SENT)[14], which was shown to have predictive power for market returns (Siegel, 1992). The Investors Intelligence Sentiment Index Survey reflects the outlook of over 100 independent financial market newsletter writers and has been compiled since 1964. Following Brown and Cliff (2005) I am using the difference between percent of bullish and bearish letters ("bull-bear spread") as a forward-looking sentiment indicator[15]. 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 and represents the direct sentiment measure.

The 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,

$$\mathrm{DIVPREM}_t = \log\left[\frac{1}{N_{DIV}}\sum_{j=1}^{N_{DIV}}\frac{ME_{j,t}}{BE_{j,t}}\right] - \log\left[\frac{1}{N_{N-DIV}}\sum_{j=1}^{N_{N-DIV}}\frac{ME_{j,t}}{BE_{j,t}}\right]$$

N_{DIV} – number of dividend paying companies, $N_{N\text{-}DIV}$ – number of non-dividend paying companies, $BE_{j,t}$ – book equity of the company j in the month t[16], $ME_{j,t}$ – market equity of the company j in the month t. The intuition of DivPrem measure is that when the sentiment is high, investors tend to value dividend non-paying companies such as young growth stocks highly compared to companies having a stable dividend paying policy. This translates into relative higher valuations of dividend non-

---

13 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 has an average cross-sectional correlation of 0.77 with the NumEst variable from I/B/E/S Summary Historical File.

14 An investment service is based in New Rochelle, NY. Index has been developed and published by Chartcraft.com. Newsletters are read and marked starting 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. I would like to thank Meir Statman for generously providing this data.

15 For example, the bull-bear spread is published weekly in Barron's and is often mentioned in financial press articles.

16 A company is defined as dividend paying if it pays any dividend in that year (Compustat data21>0). Since daily figures of book equity are not available, annual values from Compustat at the end of the year are used.

paying firms and, hence, DivPrem is low. Baker and Wurgler (2004) and Bulan et al. (2004) suggest that the dividend premium could serve as a proxy for relative investor demand for dividend payers.

The closed-end fund discount (CEFD) is the difference between the market price and the NAV of closed-end stock fund shares and measured by taking the monthly average of all domestic equity fund discounts[17]. Prior work suggests that CEFD is inversely related to sentiment (Bodurtha et al., 1995). Lee et al. (1991) 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.

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 level of (MARGIN) and the percent change (Δ MARGIN) in margin borrowing as well as the ratio of specialists' short sales to total short sales (SPECIAL)[18]. The de-trended level of 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. I also collect the monthly data on the net new cash flows of US equity mutual funds (FUNDFLOW) from Investment Company Institute (I exclude the flows in and out of international funds). Mutual fund investors are generally considered to be the least informed investors in the market because they delegate their investment management to fund managers. As Warther (1995) points out, "mutual fund flows are a logical place to look for indicators of unsophisticated investor sentiment"[19]. IPO activity (IPON) 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 (IPORETS) may also be a measure of investor enthusiasm. Baker and Wurgler (2000) and Dorn (2003) provide empirical support of this claim[20.]

Table 1 presents the summary statistics and the contemporaneous correlations between the monthly levels of sentiment measures and business cycle variables between April 1965 and Dec

---

[17] I would like to thank Ivo Welch for providing data on CEFDs from 1965 till 2001. The last two years of data were hand collected from the end of the month issues of Barron's.

[18] Margin debt and Specialist short-selling are from Pinnacle Data Corp http://www.pinnacledata.com/

[19] Neal and Wheatley (1998) find fund flows useful in predicting the premium of small stocks over large stocks and Indro (2004) provides evidence that the behavior of mutual fund investors is influenced not only by economic fundamentals, but also by investor sentiment.

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

2003. Figures 1a plots all eight proxies at the annual frequency over the same time period. For comparison I also collect data on the rest of sentiment measures used in Baker and Wurgler (2006): de-trended level of NYSE turnover and equity share of new issues (the latter available till June 2003). II bull-bear spread has positive significant correlations with de-trended (log) NYSE turnover, specialist short-selling, dividend premium, net equity fund flows, University of Michigan Consumer Sentiment Index and term/credit spreads and negative correlation with the recession dummy. Smaller closed-end fund discounts (potentially indicating higher investor sentiment) are associated with more IPOs and greater net flows into equity funds. Some correlation signs suggest the contrarian relationships. Specialists' short selling tends to be higher in the periods of high sentiment, suggesting that the specialists expect the market to decline in the near future; this fact underlines the importance of taking into account the lead-lag relationships in constructing the sentiment index.

As expected, dividend premium is negatively correlated with equity shares of new issues and number of IPOs, reflecting the fact that during the periods of low sentiment investors are considering payment of dividends as a salient feature of "safe" stocks, causing the dividend premium to be higher. De-trended level of margin borrowing tends to move together with IPO market variables and net equity flows suggesting that optimistic sentiment leads, on average, to higher levels of margin debt, higher IPO returns, more IPOs and more money flowing into equity mutual funds.

2.2. 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 (Investor Intelligence Index) by constructing a composite measure of sentiment which is the first principal component of these measures[21].

Obviously, the procedure for constructing the sentiment index is not perfect, however, overall properties of the resulting index align well with what we would expect of a good sentiment measure. The advantage of constructing a composite index for sentiment versus examining the component series separately is that the composite index allows the relative strength of the components to change over time. Since there is no good theory which would describe which component (e.g., either fund

[21] 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.

flows or IPO returns or closed-end fund discount) should be more important at a certain point of time and would explain why these changes in relative importance of different sentiment measures occur to begin with, I attempt to address this theoretical gap by using statistical technique. Furthermore, the sentiment does not have to be completely an irrational phenomenon. In fact, the substantial proportion of time variation in investor sentiment may be due to the changes in the macro conditions reflecting fundamentals of the economy. Table 1 confirms this view: most of the sentiment proxies exhibit though not high, but statistically significant correlations with macroeconomic variables. This paper focuses on the irrational part of sentiment, that is, variation in sentiment measures which is unrelated to the underlying economic fundamentals.

In order to reduce the likelihood that variation in the sentiment measures is related to the systematic macro factor risks, each individual proxy is orthogonalized with respect to several variables that are argued to reflect business cycle fluctuations and varying macroeconomic conditions such the growth in the industrial production index (IP), growth in consumption of durables (DUR), non-durables (NONDUR) and services (SERV), employment (SERV, from the Federal Reserve Statistical Release G.17 and BEA National Income Accounts Table 2.10) and a dummy for NBER recessions (RECESS). Most macroeconomic variables are moving slowly over time and the simple adjustment with respect to growth rates may not be sufficient to account for the rational variation in sentiment. Therefore, in addition to orthogonalizing with respect to the abovementioned variables, I net out variation attributable to term (TS) and credit spreads (CS) as well as returns of the long-short factor-mimicking portfolio which is constructed to have the highest exposure to the fluctuations in aggregate consumption growth[22]. FUNDFLOW is additionally regressed on January dummy to take out the seasonality in fund flows as many employees invest their year-end bonuses at the beginning of the next year (Cassidy, 2002).

Finally, since sentiment measures may reflect the same sentiment, but at different times, the possibility of the lead-lag relationships are taken into consideration when constructing the composite sentiment proxy (SENTINDEX). As Baker and Wurlger (2006) note, proxies that involve firm supply responses are likely to lag proxies that are based on investor demand/behavior. To identify the best relative timing of the proxies, the following procedure was performed. First, in each

[22]Term spread is the difference between the yields of the 10-year T-notes 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. The factor-mimicking portfolio represents a zero-net investment portfolio long in the stock quintile with the highest positive loadings to a given macroeconomic factor (e.g., aggregate consumption growth) and short in stock quintile with the most negative loadings on the factor (i.e., short stocks that provide the hedge against negative shocks in consumption growth). By construction, this portfolio has the highest exposure to changes in macroeconomic conditions. I would like to thank Paul Tetlock for this valuable suggestion.

estimation period, the factor analysis with all proxies *and* their lags is run. In the second stage the sentiment index is constructed as a first principal component based on the correlation matrix of sentiment proxies – each measure's lead or lag, whichever has a higher loading on the main factor, identified in the first (factor analysis) stage. Without orthogonalizing, the sentiment index in changes looks as follows (explains 27.5% of variation in changes of sentiment proxies and 35% in levels)[23]:

ΔSENTINDEX(t)=0.45ΔSENT(t-1)-0.17ΔDIVPREM(t)+0.19ΔCEFD(t-1)+0.54ΔMARGIN(t)-
+0.25ΔSPECIAL(t-1)-0.34ΔFUNDFLOW(t) +0.41ΔIPORETS(t-1)+0.32ΔIPON(t) .

The procedure which includes orthogonalization with respect to variables that may be correlated with fundamentals yields the following sentiment index (the first principal component explains 29% of the total variation in changes and 37% of variation in levels):

ΔSENTINDEX(t)=0.45ΔSENT(t-1)-0.16ΔDIVPREM(t)+0.17ΔCEFD(t-1)+0.55ΔMARGIN(t)+
+0.26ΔSPECIAL(t-1)-0.32ΔFUNDFLOW(t) +0.42ΔIPORETS(t-1)+0.30ΔIPON(t).

Both specifications use sentiment proxies over the whole period from April 1965 to December 2003[24]. The correlation between raw and cleaned (net of macro factors) measures constructed from changes in sentiment proxies is 0.95 from March 1965 till December 2003, whereas the correlation between raw and cleaned SENTINDEX estimated in levels is 0.88 (see figure 1b). This suggests that macroeconomic risk factors are of secondary importance in influencing time variation in sentiment measures. The negative sign on the fund flow variable indicates that fund flow data appears to be useful as a counter indicator – that is, buy when mutual fund investors are selling and vice-versa. History confirms this pattern: inflows for US funds peaked at $259.5bn – 37% higher than in any other year – in 2000, as investors bought at the top of the dotcom boom, just in time to catch the ensuing bear market.

I also build ΔSENTINDEX which allows for the time-variation in the covariance structure of inputs (sentiment index components) by using five-year rolling time window. For example, the first principal component is extracted using 60 months of orthogonalized sentiment measures, say, from March 1965 till March 1970, the next estimation period is from June 1965 till June 1970 and so on, rolling the estimation window forward every 3 months. This procedure also mitigates the possibility of a look-ahead bias. The principal component analysis is repeated to yield the 136 sentiment indices

[23] Baker and Wurgler (BW, 2006) report that their first principal component explains around 50% of the total variance of six proxies. The reasons why 27.5% (the number I get) is not necessarily a low number are a) BW use levels, I use changes (it is harder to explain changes), b) BW use annual data, I use monthly, the latter being more noisy

[24] To mitigate the concern that there could be more than one important principal component, I check the correlations between the 1st, 2nd and 3rd principal components of my sentiment measure with UMCCI. The first principal component has the highest correlation with UMCCI – 25%, the second and third has 12% and 9% respectively.

each five-year long. The loadings on II Index, closed-end fund discount, IPO and fund flow variables are relatively stable over time, whereas the loadings on the specialist short-selling and dividend premium vary over time[25]. The time-series loadings (averaged across 136 estimation periods) of the first principal component on inputs is below:

ΔSENT(t-1)	ΔDIVPREM (t)	ΔCEFD(t-1)	Δ MARGIN (t)	ΔSPECIAL(t-1)	ΔFUNDFLOW(t)	ΔIPORET(t-1)	ΔIPON (t)
0.35	-0.11	0.18	0.43	0.06	-0.33	0.36	0.27

These loadings do not differ substantially from the loadings obtained when the sentiment index is estimated only once over the entire estimation period of 1965-2003, except for the specialist-shortselling. 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.

2.3. Estimation of sentiment betas

One of the empirical implications of the theory (see appendix A for a simple model of investor sentiment) is that the relative proportion of sentiment traders can be proxied by the regression coefficient of individual stock returns on the sentiment changes. Therefore, the estimation methodology is based on the following model:

$$R_{i,t} = \alpha_i + \beta_{MRKT,i} R_t^{MRKT} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{LIQ,i} LIQ_t + \beta_{SENT,i} \Delta SENTINDEX_t + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \sim \mathrm{N}(0, \sigma_\varepsilon^2) \tag{1}$$

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, LIQ_t is the Pastor and Stambaugh (2003) liquidity factor and $\Delta SENTINDEX_t$ is the standardized sentiment factor proxy[26]. I use ΔSENTINDEX constructed over the *same* five years in which returns are measured. Following Fama and French (1993), the model is estimated using a five-year window rolled forward every 3 month to obtain sentiment beta $\beta_{SENT,i}$ for individual stocks.

The correlations between the factors for the entire time period (march 1965-dec 2003) and the average correlations among factors computed across different overlapping estimation periods are

[25] Before loadings are computed, all sentiment measures are standardized to mean 0, standard deviation 1.

[26] Fama-French factors were obtained from the Kenneth French website. I would like to thank Satyajit Chandrashekar and Christian Tiu for providing the liquidity factor of Pastor and Stambaugh (2003). 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, there are theories (e.g., Baker and Stein, 2003) and empirical research (Deuskar, 2004) suggesting that market liquidity can serve as a sentiment indicator, where the periods of unusually high liquidity signal that the sentiment is positive. I include the liquidity factor to mitigate the concern that sentiment beta captures the effects of liquidity instead of measuring the covariance of the residual part of stock returns unexplained by macro systematic factors with the sentiment factor as I intend.

below. The correlation patterns generally suggest multi-collinearity is not a serious issue in sentiment beta estimation:

Factor correlations with SENTINDEX (level) and ΔSENTINDEX (changes)

	Δ SENTINDEX	SMB	HML	MARKET	LIQUIDITY
Correlations over the entire time period (464 months)					
SENTINDEX	0.21	-0.11	-0.04	0.02	0.11
Δ SENTINDEX	1.00	0.20	-0.03	0.09	0.24
Average correlations across 136 estimation periods					
Δ SENTINDEX	1.00	0.18	-0.02	0.03	0.17

The theoretical idea of sentiment betas is similar 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 irrational traders affect security prices. For example, the preference of these traders for growth stocks may raise the prices of growth stocks relative to those of value stocks, thus making BAPM mean variance efficient portfolio tilted towards growth stocks. However, $\beta_{SENT,i}$ should not be interpreted in the same manner as in Shefrin and Statman, because $\Delta SENTINDEX_t$ are not portfolio returns.

It is documented that betas obtained from the model (1) could be statistically imprecise and may contain a fair amount of statistical noise due to a relatively low number of degrees of freedom and other statistical problems associated with the use of individual stock returns[27]. Researchers developed several approaches to mitigate this problem. One of them is based on 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, as it is subject to data-mining concerns. For example, Daniel and Titman (2005) point out that forming portfolios on the basis of common variables such as size and book-to-market (BM) is likely to wash out any variation in factor loadings that are independent of size and BM leading to the low test power to reject the null. Also, 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.

[27] Kan and Zhang (1999) caution that t-stats from Fama-MacBeth (1973) regressions of returns on factor loadings can be mis-specified when a factor is not useful in time series.

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. The “shrinkage” estimate of beta is the weighted average of the usual OLS estimate and of the shrinkage target. Shrunk betas can be justified as so-called “Bayesian” estimators, in that they reflect not only current 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), Jorion (1986)). For instance, Chan et al.’s (1992) results indicate that such robust “Bayesian” estimators (including ones that are using the information contained in the prior cross-section) are superior in terms of precision than usual OLS estimates. The latter approach is adopted in this paper[28].

Specifically, in the first stage, sentiments betas are estimated separately for each stock using the traditional rolling OLS regression approach. The five-year period monthly regressions are run for each stock that has no fewer than 60 months of successive returns history and Bayesian updating is performed each quarter. Prior is formed using empirical Bayesian approach, that is, the 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 non-overlapping five-year estimation period and the prior variance is the cross-sectional variance of the last available cross-section of absolute values of sentiment betas. The posterior sentiment 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 “sentiment betas”, $\sigma^2_{\beta,t+1}$ is the sampling variance of the OLS estimator computed in the period t+1 and $\beta_{i,t+1}$ is the standard OLS regression coefficient $\beta_{SENT,i}$ from the model (1), henceforth referred to as “original sentiment betas”. 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

[28] I would like to thank Roberto Wessels for this suggestion

of the shrinkage approach (vs. portfolio approach) is that the standard error of each sentiment beta is directly taken into account. This procedure yields the "shrunk" estimates of sentiment beta for individual stocks starting from March 1975 till Dec 2003.[29]

The negative original sentiment betas indicate that contrarian sentiment traders, who sell when sentiment goes up and vice versa, are influences stock prices relatively more than momentum sentiment traders, who buy when sentiment changes are positive. Suppose, we have three stocks, A, B and C, with sentiment betas of -1, 0 and 1 respectively. If beta is 0, this means that stock B does not covary with sentiment changes after accounting for its covariance with the conventional risk factors, and, hence, the relative proportion of sentiment traders is either zero *or* the actions of contrarian and momentum sentiment traders offset each other, and, as a result, the equilibrium price reflects the fundamental value[30]. Stock A, on the other hand, has a beta of -1, which implies that stock A's price is affected more by investors with the demand function of this form $D_t^s = 1 + b(F_t^j - \rho_t - P_t^j) + z_t^{i,s}$, whereas stock C's price 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 different signs on the sentiment factor ρ_t, see Appendix A for details). Since the absolute value of sentiment betas for stock A and C are the same, the net effect of sentiment traders on the stocks A&C's price is the same[31] , with the only difference being that the stock A's price is too low and stock C's price is too high relative to what is explained by fundamentals. However, to address the concerns that there may be a loss of information from using absolute values, I also perform tests *without* resorting to the concept of absolute sentiment betas.

Tables/figures 2a and 2b present summary statistics/empirical distributions of original and Bayes-Stein sentiment beta estimates. We can see that the distribution of the original sentiment betas is relatively symmetric around zero, though the null hypothesis that the mean of the distribution is zero is rejected at 1% level using standard t-test. This indicates that the average impact of sentiment investors in the market is non-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.

[29] First 60 months of data are used to obtain the parameters of the prior distribution and subsequent 60 months (rolled every quarter) are used for estimation

[30] Because sentiment traders do not all commit the same cognitive errors, cognitive biases cause some to be positive feedback traders (buy when sentiment changes are positive), and others to be negative feedback traders (sell when sentiment changes are negative). As a result, both momentum and contrarian traders may simultaneously participate in financial markets (see Shefrin and Statman (1994))

[31] By "net effect" I mean absolute value of the difference between momentum sentiment traders and contrarian sentiment traders

3. Empirical Results

3.1. Sentiment beta and future returns

If DSSW (1990) noise trader risk is priced, we should observe that portfolios with higher exposure to sentiment factor should earn higher average returns in the future. To test this prediction, each month I match excess returns to the last available sentiment betas stock-by-stock, form equal-weighted quintile portfolios on the basis of sentiment beta and hold them for different periods of time. The tables 3a,b show the cumulative excess returns of these portfolios and returns of zero-net investment portfolio which is long stocks in portfolio 1 (lowest sentiment sensitivity) and short stocks in portfolio 5 (highest sentiment sensitivity).

The key result is that the high sentiment beta portfolio, on average, *underperforms* low sentiment beta portfolio, suggesting that not only do investors not get compensated for bearing "noise trader risk", but they will be losing money by holding more sentiment-sensitive stocks. Excess returns exhibit a near-monotonic decreasing trend as we move from low to high sentiment sensitivity. For example, from the table 3a where sentiment beta portfolios are rebalanced monthly, we can see that in the full sample returns go down from 0.98% to 0.70% (0.20% to -0.19%) on a raw (risk-adjusted) basis. The risk-adjusted difference is significant 0.38% per month with t-stat of 4.14. Even though the difference in raw returns between 1 and 5 is higher during second half of the sample (0.23% during 1975-1989 vs. 0.32% during 1989-2003), the risk-adjusted difference is higher in the first half of the sample (0.49% during 1975-1989 vs. 0.38% during 1989-2003), indicating that even though the strategy of buying low sentiment beta and shorting high sentiment beta stocks earned higher raw returns during 1989-2003 relative to 1975-1989, this outperformance was a result of greater exposure to systematic factors in the second half of the sample. The difference between portfolio 1 and 5 is larger than raw return payoffs and more statistically reliable after the four-factor Carhart (1997) risk-adjustment. The reason for this is that the zero-cost portfolio 1-5 has negative exposure to the risk factors associated with the market and size, the average monthly premia on which were positive during 1975-2003 (0.67% and 0.32% respectively)[32].

Further analysis shows that underperformance of stocks with high sentiment factor exposure is mainly driven by low future returns of stocks that tend to covary *positively* with sentiment changes. "Stocks with positive sent.betas" section of table 3a shows that zero-cost portfolio delivers 38 bp per month (t=2.04) and 40 bp per month (t=2.94) on a raw and risk-adjusted basis respectively. Stocks that tend to covary negatively with sentiment changes also underperform relatively to their near-zero

[32] This portfolio has a significant positive exposure to the value factor. This provides evidence that growth (glamour) stocks tend to be more sensitive to changes in irrational investor sentiment than value stocks.

sentiment beta counterparts, but significantly so only after risk adjustment. This suggests that stocks that tend to positively comove with sentiment changes are more likely to experience greater sentiment-induced mispricing and, hence, larger price revisions in the future.

This poor performance of high sentiment beta stocks versus their low sentiment beta counterparts is robust in sub-periods and whether size-adjusted or market-adjusted returns are used[33]. For additional robustness, I excluded small stocks below 20% NYSE/AMEX breakpoints and looked at longer time horizons - results are qualitatively similar. Results in table 3b demonstrate that as the holding period increases, the return difference between portfolio 1 and 5 diminishes from about 23 to 16 bp (34 to 19 bp) per month on a raw (risk-adjusted) basis. The overall conclusion of this "sentiment sensitivity – future returns" analysis is that, first, the noise trader risk in the sense of DSSW (1990) is not priced and, second, investors would do better by holding stocks with, ideally, zero exposure to the sentiment factor and avoiding (getting rid of) stocks that load highly on the sentiment factor.

3.2. Sentiment beta and firm characteristics: unconditional sorts

The direct empirical implication of Hard-to-Value, Difficult-to-Arbitrage hypothesis is that stocks with higher sentiment sensitivities (i.e., higher sentiment betas) are more likely to be smaller younger non-dividend paying stocks with relatively greater volatility and short-sales constraints, higher growth indicators (i.e., lower dividend yields and book-to-market ratios, higher assets growth etc). To test this implication, I start out with unconditional sorts. The relative advantage of sorts vis-à-vis the regression analysis is that it does not require that a particular parametric structure is imposed on the relationship between firm characteristics. Another reason why performing sorts makes more sense is because there are not many confounding factors that might drive cross-sectional variation in sentiment betas[34].

I match average firm characteristics to the last available Bayes-Stein estimates of sentiment beta stock-by-stock and form deciles on the basis of sentiment sensitivities. First important piece of evidence in support of the HV-DA hypothesis is the "size" result: small stocks tend to have greater sensitivity to sentiment changes. Average (median) size falls almost by a factor of 6 (8) and the idiosyncratic volatility increases more than twofold as the average sentiment factor exposure rises from the lowest to the highest. The decreasing trend is observed for earnings, cash flows, dividend yields and age, and an increasing trend for short-sales constraints, asset growth and share turnover.

[33] Size-adjusted returns are computed as a difference between individual stock return and the mean return of the corresponding size group (out of 20) to which the stock belongs.
[34] These confounding factors are measurement error (estimation imprecision) and stock volatility.

Sub-sample analysis reveals that this result is more pronounced in the second half of the sample (from 1989 to 2003) and among stocks that covary positively with sentiment changes[35]. For instance, for positive sentiment beta stocks the average (median) size of portfolio 10 is around 11 (13) times smaller than that of portfolio 1. The same ratio for stocks with the lowest negative loadings (portfolio 10) vs stocks with near-zero loadings on sentiment factor (portfolio 1) is just 3.5:1 for the mean size and 4.5:1 for the median. This is consistent with the idea that prices of smaller stocks that are hard to short sell are significantly more likely to be bid up, not pushed down, by sentiment traders when sentiment improves. The main takeaway from this unconditional analysis is that small stocks are more sensitive to changes in investor sentiment than large stocks. The patterns in other characteristics, e.g., profitability (return on assets), turnover, analyst coverage, institutional ownership, dividend yield and age should be treated with caution, however, because they may be driven by the size result.

3.3. Sentiment beta and firm characteristics: conditional sorts

Fama (1998) acknowledges that all common asset pricing models including the Fama and French (1993) three-factor model have difficulty explaining the average returns of small stocks. If their model has difficulty explaining small stocks returns, higher idiosyncratic volatility of these stocks will tend to be higher, too. Thus, higher absolute loadings of small stocks' returns on sentiment factor could be an artifact of their higher idiosyncratic volatility. It is important to ensure that the size result documented earlier is not due to the differences in either total or idiosyncratic volatility, that is, sentiment beta sort is not just a refined idiosyncratic volatility sort. Table 5 reports the results of conditional sorts on volatility-adjusted sentiment betas excluding extreme portfolios 1 and 10 to mitigate the possibility that outliers affect the means[36]. First, we can see that volatility is not driving the results. Controlling for past volatility reduces the dispersion in sentiment betas between extreme deciles only by around 10%. The size result is still strong and significant: for two portfolios with similar past volatility during 1989-2003, the one with highest sentiment factor exposure is twice as small as the one with the lowest sentiment exposure. SMB loadings confirm this finding: they go up monotonically from essentially zero to 0.21 as sentiment exposure increases. The size result is consistent with Baker and Wurgler (2006) who find that small stocks experience periods of over and under-pricing depending on whether sentiment level is high or low.

---

[35] Results of this sub-sample analysis are partially omitted and available upon request.

[36] To control for the relationship between stock's volatility and sentiment beta, I construct volatility-adjusted sentiment betas, defined as the difference between the sentiment beta for a stock i and the average sentiment beta for stocks in the volatility decile to which stock i belongs.

However, dividend and investment-related characteristics of small and large stocks could be fundamentally different: it can be that stocks are younger, more volatile and have lower dividend yields, profitability because they are small stocks, not necessarily because they are more sensitive to sentiment changes. Hard-to-value, difficult-to-arbitrage hypothesis postulates that in valuing two stocks of *similar* size and volatility *more* personal judgment (which is more likely to be biased by the overall market sentiment) will be required for younger unprofitable stocks with lack of earnings history, lower or non-existent dividends and higher growth potential

To control for size and volatility, I perform conditional sorts. Table 6 contains the results providing further evidence in support of HV-DA. Accounting for variation in size *and* volatility reduces the dispersion in sentiment beta between extreme deciles by about 15%, suggesting that sentiment exposure reflects more than just size and volatility. The key findings of these conditional sorts are that 1) more-sentiment-sensitive portfolios include relatively younger stocks with lower dividend yields and greater short-sales constraints[37], 2) they also are more likely to be more volatile and have higher turnover.

Comparison of book-to-market ratios across the deciles suggests that sentiment is relatively more pronounced in low B/M stocks. The difference in B/M ratio between lowest and highest sentiment beta portfolios is statistically significant at 1%, but the pattern is U-shaped rather than a monotonic decrease, implying that effects of investor sentiment are more pronounced not in extreme growth stocks but rather in moderate growth stocks. Further evidence on growth vs. value comes from the portfolios' HML loadings: decile 1 (lowest sensitivity) has an HML beta of 0.127, whereas the decile 10 (highest sensitivity) has an HML beta of only -0.076. The result that sensitivity to sentiment changes is higher among glamor stocks is consistent with findings by Frazzini and Lamont (2006) who report that high sentiment stocks tend to be stocks with low book-to-market ratios. It also supports evidence presented in Elsewarapu and Reinganum (2004), where authors 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. The result is in contrast to Baker and Wurgler (2006) who do not find any significant difference in future returns of growth and distressed (value) stocks following periods of particularly high or low investor sentiment.

As predicted by HV-DA, more sentiment-sensitive stocks have lower dividend yields. They monotonically fall from 3.1% to 2 as we move from decile 1 to decile 10. The difference of about

[37] 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. It is available at the monthly frequency from Feb 1984 till Jan 2001. For more detail on variable construction, see Ali and Trombley (2004).

1% is economically significant by any conventional standards as it constitutes around 45% of the 1975-2003 average dividend yield of 2.3% and around 80% of the average dividend yield of 1.4% during 1989-2003. Sales growth and Tobin Q exhibits an upward trend as we move from decile 1 to decile 10, with sales growth being reliably higher among high sentiment beta stocks. In contrast to Baker and Wurgler (2006), I find no evidence that less profitable stocks are more subject to shifts in investor sentiment once you control for size. If anything, during the period 1989-2003 the higher sentiment sensitive stocks were, on average, *more* profitable (by around 0.5% per annum) as measured by ROA. Given size and volatility, there is no significant difference in book leverage, past six month returns, external finance activity and PIN (probability of informed trading from Easley et al. (2002)) across deciles sorted on past sentiment sensitivity.

Further supporting evidence for HV-DA hypothesis comes from analyzing the relationship between investors' disagreement and sentiment beta. There are several reasons to believe that these are related. Higher sensitivity to shifts in investor sentiment potentially arises due to certain stock characteristics making it difficult for investors to value a stock, resulting in greater differences of opinion among investors regarding the fair value of the stock. If this interpretation is valid, we should expect that stocks with greater disagreement will, on average, have higher sensitivity to investor sentiment. Building on the existing "differences-of-opinion/heterogeneity of beliefs" literature (Diether et al., 2002) I use analysts' earnings forecast dispersion as a proxy for investors' disagreement about the stock value (Appendix C provides details on its construction). Table 7 reports time-series average of Fama-MacBeth coefficients in predictive regressions of next period forecast dispersion on current sentiment beta (Panel A) and next period sentiment beta on the current forecast dispersion (Panel B). As HV-DA story predicts, more sentiment-sensitive stocks appear to have greater dispersion of analysts' forecasts with causality running both ways. This positive relationship is robust to controlling for such fundamental stock characteristics such as size and volatility.

Several findings are in contrast to the predictions of HV-DA and deserve closer attention. Unconditional sorts (table 4) analyst coverage, S&P membership and institutional ownership (IO) display a decreasing trend as sentiment beta increases, but this is driven mainly by diminishing size[38]. Conditional sorts (table 6) that control for size and past volatility reveal a new result: for two stocks belonging to the same "size-volatility" group a stock with higher sentiment beta tends to have greater analyst coverage than the one with the lower sentiment beta. The difference in analyst

[38] In the full sample the average cross-sectional correlation of analyst coverage, S&P 500 membership and IO with market capitalization is 0.37, 0.42 and 0.15, respectively.

coverage between extreme deciles is -1.16 (t-stat -3.65) in the full sample: -0.47 (t-stat=-1.58) during 1975-1989 and -1.79 (t-stat=-9.39) during 1989-2003. The drastic increase in the difference in the 90's has two potential interpretations depending on the direction of causality: first, analysts exhibited increasing preference to cover high sentiment stocks throughout the 90s or it is also possible that stocks attracted attention of sentiment traders exactly because there were widely covered by analysts.

Institutional ownership shows a statistically significant increase from 22.0% to 25.6% in the full sample and from 25.8% to 31.2% during the second half of the sample, both differences being statistically significant at 1%[39]. The positive relationship between institutional ownership and sentiment beta in the 90's does not align well with the idea that trading activities of *individual* investors in stocks with "hard-to-value, difficult-to-arbitrage" characteristics are causing these stocks to be more sensitive to investor sentiment, but is consistent with recent literature on institutional behavior which shows that institutions may be a source of a non-fundamental factor in returns[40]. I will return to this question in greater detail when multivariate analyses are performed.

I also perform separate conditional sorts for groups of stocks with positive and negative loadings on sentiment factor in order to analyze the differences in characteristics of these stocks. Unreported evidence suggests that stocks with positive sentiment beta stocks (in comparison to their negative sentiment beta counterparts) are about twice as small, more volatile, younger, have lower turnover and book leverage, higher systematic risk and retail ownership, greater probability of informed trading (as measured by PIN) and significantly lower analyst coverage. Potential interpretation of this difference is that retail investors tend to be momentum sentiment traders – they tend to buy when overall sentiment improves, whereas institutions are contrarian – they tend to hold more of hard-to-value, difficult-to-arbitrage stocks when sentiment deteriorates.

3.4. Institutional analysis

Prior literature suggests that individual investors' personal judgment appears to be relatively more prone to behavioral biases (e.g. Barber et al, 2003). Therefore, it logically leads us to the second hypothesis tested in this paper. Namely, I hypothesize that stocks that are more sensitive to sentiment changes will be predominantly held by individual, not institutional, investors. Another important reason for why it is economically important to study "institutional vs. individual investor" issue is the fact that institutional investors represent now a large fraction of equity ownership and an

---

[39] As an indicator of univariate relationship, average cross-sectional correlation between institutional ownership and sentiment beta for the period of 1980-2003 is -.14, with the cross-sectional correlations ranging from -.21 to 0.01. When zero values of IO are excluded, the correlation is -.16, the values ranging from -.23 to 0.026.

[40] See, for example, Jones et al (1999), Brown and Cliff (2005), Jackson (2003b), Pirinsky and Wang (2004)

even larger proportion of trading volume. This implies that, for most firms, an institution is likely to be the price-setting marginal investor.

Since sentiment beta is an empirical proxy for the relative proportion of sentiment traders in a stock, I can test the hypothesis by directly relating institutional ownership (IO) to sentiment beta in a multivariate regression framework[41]. Specifically, I run quarterly cross-sectional regressions with the following full specification (where t stands for the month-year, all variable definitions are in table 8).

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

The analysis is performed for each of two sub-periods: from the first quarter of 1980 till the last quarter of 1989 and from the first quarter of 1990 till the last quarter of 2003. I exclude all non-common shares (share code not 10 or 11) and penny stocks with prices below \$5, and winsorize all variables at 1% and 99%. The sub-period analysis is motivated by the recent paper of Bennett et al. (2003) who document that institutional investors' preferences changed around late 80's-early 90's, i.e., institutional investors shifted their holdings towards smaller, riskier stocks that are hypothesized to offer "greener pastures". Given their findings, I choose the similar time breakpoint in my analysis.

The table 8 reports the times-series averages of cross-sectional coefficients for various model specifications run within the sub-samples. The model 6 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 (higher turnover) stocks with higher book-to-market ratios, higher prices, lower past volatility and lower dividend yields. They also tend to hold older stocks with lower prior returns, ceteris paribus.

Sentiment beta is the coefficient of interest. Empirical results show that throughout the 80's (upper panel of table 8) institutions avoided exposure to more-sentiment sensitive, higher sentiment beta stocks, ceteris paribus. According to the fully-specified model 5 the average coefficient during the period March 1980-Dec 1989 is -1.23 with t-stat of -2.52. The sub-period analysis performed separately for stocks with positive and negative loadings on sentiment factor (models 8 and 9) demonstrates that a negative coefficient on sentiment beta in the first time period is driven mainly by institutions holding less of stocks with the positive exposure to sentiment changes: the coefficient is

[41] Note, that this test has both empirical and theoretical motivations. Empirically, given the results of the literature on investor behavior, it is reasonable to hypothesize that individual ownership will be greater in stocks with higher sentiment sensitivities. Theoretically, even if we did not have an empirically based prior as to what the "IO-sentiment beta" relationship should look like, it is theoretically justified to explore this relationship because sentiment beta is a proxy for the proportion of sentiment traders.

-1.53 (t-stat -5.63)[42]. This result is borne out in model 7 by a negative sign of the coefficient on the term which is an interaction of sent.beta with the dummy which is equal one if sent.beta is positive and zero otherwise. Overall, results of the analysis of the aggregate institutional ownership throughout 1980-1989 period is consistent with the tested hypothesis, i.e., individual ownership was higher in stocks with greater sensitivities to shifts in investor sentiment. Specifically, evidence suggests that institutions held fewer sentiment-sensitive stocks, particularly those, that had positive exposure to sentiment.

The lower panel of table 8 reports the time-series averages of cross-sectional coefficients on nine firm characteristics and two terms related to sentiment exposure. The results refine the findings of the earlier dependent sorts: institutions changed their behavior around early 90's by shifting their preferences towards more sentiment-sensitive stocks. The coefficient on sentiment sensitivity is significant and *positive* in all model specifications. This does not align well with the idea that individual ownership is greater in more sentiment-sensitive stocks, at least, during 1990-2003 period. The sign on the interaction term Ind*Sent.Beta is still negative and highly significant, indicating that an increase in institutional holdings of stocks with greater exposure to sentiment changes observed during 1990-2003 is mainly attributable to institutions holding more of equities with *negative* exposure to sentiment factor – models 8 and 9 confirm this finding. Figure 3 plots quarterly time-series of cross-sectional coefficients on sentiment beta. There is a distinct pattern: graph generally stays below zero till the end of 1989 and fluctuates above zero for the most part since 1990. To summarize, in the 90's institutional investors appear to have changed their behavior by shifting their preferences towards stocks with higher sentiment risk as indicated by the positive coefficient on sentiment beta, and they did so in a particular manner by tilting their equity portfolios towards stocks that have negative sentiment betas.

To further understand what types of institutions drive this result, I disaggregate IO according to Thomson Financial classification that identifies five groups of institutional owners: bank trust departments, insurance companies, mutual funds (investment companies), independent investment advisors, and other institutional investors (e.g. endowments)[43]. For any particular firm, the fraction of outstanding shares held by institutions in aggregate is simply the sum of fractional ownership over the five classes[44]. The average coefficients to each group are presented in the table 9.

[42] Recall from our previous discussion that stocks with high positive sentiment sensitivities appeared to exhibit greater underperformance in the future relative to stocks with large negative sentiment sensitivities

[43] I would like to thank Soeren Hvidkjaer for this useful suggestion.

[44] The 13f data have some serious classification errors during 1998-1999 period. Many banks and independent investment advisors are improperly classified in the Others group. Besides this problem, classifications are potentially inexact – for instance, independent money managers who also manage mutual funds are classified as mutual funds if

Left part of the table covers the period from 1980 to 1989. A quick look at the coefficient on sentiment risk variable (sent.beta) reveals that the sign is negative for all types of institutions during 1980-1989, but it is statistically significant for independent investment advisors (at 1%) and bank trust departments (at 10%). Unreported results of standardized regressions (where both dependent and independent variables were standardized to mean 0 and std 1) suggest that the coefficient on sentiment beta for banks and investment advisors is more negative than for other types of institutions. As for the aggregate IO, coefficient on the interacted term Ind*Sent.Beta is either negative significant or positive insignificant. This suggests that these types of institutions were more conservative during the 80's.

Consistent with the results of Bennett et al. (2003), I find that all types of institutions shifted their preferences in the early 90's, but in different degrees. In particular, the right part of table 9 focuses on one aspect of this preference shift: all institutions regardless of their type tended to seek exposure to stocks with high sentiment risk (high absolute value of sentiment beta), ceteris paribus. However, only for two classes the coefficient on sentiment exposure is significant: for less conservative investment companies (mutual funds) and other (unclassified) institutional investors such as endowments. Furthermore, the sign on the interaction term for mutual funds indicates that throughout the 90's they have been tilting their portfolio holdings towards stocks with negative covariation with sentiment[45]. Note that result provides a new perspective on the finding of Bennett et al. (2003) who uncover a much stronger institutional preference for return volatility in the 90's, ceteris paribus. Tables 7-8 provide empirical evidence that since the 90's institutional investors (especially, mutual funds) were seeking exposure to particular type of return volatility: volatility associated with fluctuations in sentiment.

4. Robustness checks and measure validation

Due to the nature of sentiment beta estimation, there are only a few confounding factors that can affect documented results. This fact (small number of confounding factors) allows me to draw relatively reliable inferences using non-parametric rather than parametric regression-based analysis and avoid making assumptions on the nature of the relationship between various firm characteristics (for instance, whether it is linear or non-linear). However, it is still possible that variation in stock volatility, size of the stock and the estimation error across sentiment beta portfolios are responsible

more than 50% of managed assets are in mutual funds. To mitigate this problem, the fractional ownership for banks and investment advisors were set to the corresponding average ownership over the previous 2 quarters for Dec 1998, March 1999 and June 1999 (time frames which according to Thomson contain considerable classification errors)

[45] Results are qualitatively similar if absolute values of original sentiment betas ($\beta_{SENT\ ,i}$ estimated in model (1)) are used instead of "shrunk" Bayes-Stein estimates of sentiment sensitivities, obtained from formula (2).

for the results. First two concerns were addressed by performing dependent sorts aiming to control for differences in firm characteristics between sentiment beta deciles that may stem from differences in size and volatility. To further address these issues, independent and dependent sorts on a number of other characteristics were conducted to ensure that the sort on sentiment betas is not a hidden sort on any given firm characteristic. The latter would be true if the cross-sectional dispersion of average sentiment betas across decile portfolios becomes indistinguishable from zero after sorts on either size, volatility, dividend yield, turnover or book-to-market are performed. The results of these sorts[46] show that regardless of which characteristics the sort is conditioned upon (turnover, B/M, etc), the dispersion of average sentiment beta (between deciles 1 and 10) remains high, with the maximum decline of 15% in dispersion taking place when size and past volatility are controlled for.

Another reasonable concern is that it is possible that averages may not be good estimates of the true means due the influence of outliers. In order to address this issue, first, all firm characteristics were winsorized at 1% and 99% and, second, sorts were also performed where medians were used instead of means to mitigate the influence of potential outliers. Neither the use of medians nor the exclusion of NASDAQ stocks and bottom 20% of stocks in terms of market capitalization changes the qualitative nature of the results: turnover, book-to-market, age, dividend yields, analyst coverage, institutional ownership, sales growth exhibit similar trends from the lowest to the highest sentiment beta decile portfolio. In addition, these robustness checks confirm that given size and volatility, profitable stocks are just as likely to be affected by swings in investor sentiment as unprofitable ones.

To address the concern that statistical noise in sentiment beta estimation might affect the results, the following test is performed. A random factor is generated with realizations drawn from the normal distribution with the mean and variance equal to those of ΔSENTINDEX used in model (1). The latter is then used to estimate the "betas" on this random factor. The obtained "random factor betas" are matched to firm characteristics and sorts similar to those described above are performed. Results of these sorts do *not* reveal any consistent trends in the firm characteristics suggesting that the found patterns in firm characteristics are due to the differences in stock returns sensitivities to *sentiment* changes, not to changes in a randomly generated factor.

4.1. Validating Sentiment Index

Figure 4 presents SETNINDEX plotted along with the annual version of Baker and Wurgler (2006) measure[47] and the University of Michigan Consumer Confidence Index (UMCCI). The latter

---

[46] Available upon request

[47] Baker and Wurgler (2006) annual measure is from the Wurgler's website http://pages.stern.nyu.edu/~jwurgler/

was shown to be a good measure of sentiment in terms of its explanatory power for the time-series of returns (Qiu and Welch, 2005) and have the ability to explain the cross-section of the stock returns (Lemmon and Portniaguina, 2006). The correlation between SENTINDEX and UMCCI is 0.25 (0.19) and 0.75 (0.62) between SENTINDEX and BW measure, at the monthly (annual) frequency[48]. 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 and the bubble burst in 2000-2002.

In addition to this qualitative evidence based on anecdotal accounts, I provide quantitative evidence on the quality of SENTINDEX as a measure of sentiment. If we are to have a good sentiment factor which would allow us to distinguish between risk and behavioral explanations, we expect the sentiment index a) to be truly orthogonal to the factors reflecting fluctuations in business cycles, b) to have a reliably positive relationship with the direct survey measures (e.g. UMich index); c) to be influenced by lagged stock market returns and d) have mild but persistent effects on return spreads, such as small and retail stock return spreads (stocks, where proportion of sentiment traders is arguably higher).

First, I analyze the persistence patterns of ΔSENTINDEX measure versus the Baker and Wurgler BW (2006) measure[49]:

Persistence patterns of sentiment index vs. BW sentiment index during 03/65-12/03

Leads/Lag of Value-weightedSmall Stock Return Spread											
	Leads					Lags					
	5	4	3	2	1	0	-1	-2	-3	-4	-5
ΔSENTINDEX	-0.02	-0.05	-0.01	-0.06	0.03	0.24***	0.36***	0.02	-0.09*	-0.15***	0.06
Δ BW measure	-0.01	0.02	0.07	0.01	-0.03	0.18***	0.25***	-0.04	-0.12***	-0.15***	0.06
Leads/Lags of Market-Adjusted Value-weighted Retail Stock Return Spread											
	Leads					Lags					
	5	4	3	2	1	0	-1	-2	-3	-4	-5
Δ SENTINDEX	0.00	-0.07	0.06	-0.09	0.04	0.14**	0.24**	-0.04	-0.02	0	0.12**
Δ BW measure	0.00	-0.02	0.13**	-0.05	-0.01	0.14**	0.14***	-0.09*	-0.05	-0.05	0.08
Leads/Lags of Value-weighted CRSP Market Index											
	Leads (Sentiment anticipates return)					Lags (Return anticipates sentiment)					
	5	4	3	2	1	0	-1	-2	-3	-4	-5
Δ SENTINDEX	0.03	0.05	-0.02	-0.06	-0.08*	0.09*	0.59***	0.10***	-0.06	-0.02	-0.03
Δ BW measure	-0.02	0.00	0.03	0.02	-0.05	0.04	0.27**	0.02	-0.05	-0.09*	0.05

48 For comparison, Baker and Wurgler (2006) measure has no or weak relation to the University of Michigan index: yearly correlation is 0.15, monthly correlation is 0.06. Both are statistically insignificant

49 It is worth noting that Baker and Wurgler (2006) 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 credit spreads both at the annual and monthly frequencies with correlations 0.36 and 0.25 respectively. Therefore, BW measure still appears to reflect the business cycle fluctuations as documented in Fama and French (1989), unless one believes that credit spreads are either influenced by irrational investor sentiment or credit spreads do not reflect business cycles.

Significant numbers on the left indicate that the sentiment index predicts returns, numbers on the right show how much the sentiment index is affected by returns. The market adjustment in the The middle panel is done by netting out the in-sample value-weighted CRPS return via regression. The changes in SENTINDEX appear to both be affected by the lagged retail and small stock return spread and also contemporaneously related to these spreads[50]. This pattern is even more pronounced for the influence of past market returns. Arguably, the magnitude and persistence of these correlations make ΔSENTINDEX look more favorable compared to ΔBW.

As a further robustness check, the regression analysis is conducted to see if ΔSENTINDEX has explanatory power for small stock and retail stock returns spreads and whether they predict market returns[51]. Table 10 shows that ΔSENTINDEX helps contemporaneously explain the variation in the small and retail stock return spreads, whereas ΔBW does not, once both measures are included simultaneously. Coefficients on ΔSENTINDEX are significant at 5% in all model specifications except one where significance is retained at 10%. Results are robust to the inclusion of UMCCI which is significant (consistent with Qiu and Welch, 2005). Adjusted R-squared in the regression where small stock return spread is a dependent variable doubles from 6% to 12% as ΔSENTINDEX is added to the model and increases by 5% (from 18% to 23%) in the regression where retail stock return spread is a dependent variable, indicating that variation in sentiment is important in explaining time-series variation of these return spreads.

Table 11 presents evidence that ΔSENTINDEX has predictive power for the 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, UMCCI, lagged market turnover and lagged aggregate dividend yield[52]. The inclusion of ΔSENTINDEX increases adjusted R-square by 0.8%, which is economically significant given that the overall R-squared is around 1.8%.

Another potential concern is associated with the effect that the inclusion of average first-day IPO returns in ΔSENTINDEX may have on the results. Note, IPO return is the only return-based

[50] 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 follows. Within each institutional holdings decile portfolio and within the zero-institutional holdings decile portfolio, stocks are sorted by dollar trading volume. The retail stock return spread is the return of the portfolio long in the low-trading volume zero-institutional holding stocks and short in the high-trading volume high-institutional holding stock portfolio.

[51] The fact that my measure helps explain the time-series variation in small and retail stock return spreads is a favorable feature of the sentiment index because many financial anomalies were found to be more pronounced in smaller stocks with higher individual ownership.

[52] The negative relationship between sentiment changes and future market returns is consistent with the practitioners' interpretation of sentiment indicators: e.g., a decrease in the proportion of advisory letters in II index below 20% is perceived as a bearish 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).

sentiment proxy in the index. To address the possibility that results are sensitive to whether this measure is included/excluded from the final index I construct two sentiment indices (with and without IPO returns), analyze their properties and properties of sentiment betas estimated using these two constructs of sentiment index.

Exclusion of IPORETS changes neither signs nor timing of the rest of sentiment index inputs. The loadings do not change significantly either, indicating their relative stability whether return-based measure IPORETS is included or not. Correlation between both constructs of ΔSENTINDEX (one including and one excluding IPORETS) is 0.94. The correlation between $\Delta SENTINDEX_{noiporets}$ and IPORETS is statistically significant 0.19 indicating that these different measures are potentially correlated with the unobserved sentiment factor[53]. I further check the relationship (ordinal ranking) between sent.betas estimated separately using the index including and excluding IPO returns. The average cross-sectional correlation between sentiment betas estimated using two different sentiment indices is 0.94, ranging from 0.85 to 0.99 depending on the sample period. Overall, these results suggest that the presence of the return-based factor in sentiment index estimation does not drive the main results documented in the paper.

Finally, I also check whether there is more than one important principal component of sentiment measures. The quick look at correlations of correlations (the table below) of 1st (ΔSENTINDEX), 2nd (PC2) and 3rd (PC3) principal components with other factors suggests that only the first component has expected signs (greater innovations in aggregate liquidity – larger changes in sentiment, lag market returns has positive influence on next period sentiment, small stocks outperform large stocks in times when sentiment change is positive):

	Market (t)	SMB (t)	HML (t)	Liquidity (t)	Market (t-1)
ΔSENTINDEX (t)	0.10**	0.21***	-0.035	0.24***	0.59***
PC2	-0.10**	-0.17***	0.09**	-0.05	-0.05
PC3	0.05	0.03	-0.09**	0.00	-0.16***

4.2. Validating sentiment beta measure

Sentiment beta measure has several advantages over previously used measures. First, it is theoretically motivated. As the model in Appendix A shows, sensitivity of stock returns to sentiment changes proxies for the relative proportion of uninformed sentiment traders in a stock. Second, in arguing that sentiment beta is a stock-by-stock measure of sentiment I do not have to explicitly rely on the assumption about which traders are more influenced by sentiment, institutions or individuals. These advantages are important because prior research tended to use proxies that are either

[53] All measures are orthogonalized with respect to a set of macroeconomic variables before correlations are computed and principal component is extracted.

empirically motivated/based on datasets that cover only short period of time or make explicit assumptions about individuals being the sentiment traders in question.

In addition to the shrinkage procedure, which is used to address the problem of estimation error and statistical imprecision, I assess the meaningfulness of sentiment betas in two ways[54]. First, following Griffin (2002), I look at the incremental explanatory power of the sentiment factor (beyond and above FF factors and relative to the liquidity factor of Pastor and Stambaugh(2003)). The sentiment factor contributes as much as the liquidity factor of Pastor-Stambaugh to the average adjusted R-squared and its incremental explanatory power is around 1/5 of that of HML factor (when measured above and beyond the explanatory power of market and size factors). This suggests that the sentiment factor is relevant in explaining time-series variation of stock returns as a whole beyond what is explained by the conventional risk factors (consistent with the work by Kothari and Shanken (1997) and Baker and Wurgler (2000) documenting that sentiment helps explain the time-series of returns).

Second, it is also informative to gauge the persistence of sentiment betas over time relative to the persistence of betas on market, size and book-to-market factors over non-overlapping time intervals. The average cross-sectional correlation of sentiment betas over time is 0.19, compared to 0.22 for market betas, 0.32 for SMB betas and 0.14 for HML betas. When every quarter stocks are ranked into quintiles based on the value of sentiment beta estimates, the average percentage of stocks that remain in the same sentiment beta quintile 5 years (using *non*-overlaping periods) later is around 23%, 25% and 20% for $\beta_{SENT,i}$ (original sentiment beta), $\beta_{SENT,i}^{posterior}$ (Bayes-Stein estimate of sentiment beta) and volatility-adjusted sentiment betas, respectively. For comparison, the respective numbers for market, SMB and HML betas are 28%, 31% and 26%. The results are qualitatively similar when "ranks-on-ranks" regressions are performed. Average R-squared in the regression of ranks based on sentiment betas estimated in [t,t+5] on the ranks based on sentiment betas estimated in [t,t-5] is 4.43%. For comparison, the average R^2s of the "ranks-on-ranks" regressions for market, SMB and HML betas are 6.67%, 14.92% and 3.34% respectively.

Since ΔSENTINDEX has a positive and significant correlation with the lagged market returns, there is a possibility that sentiment betas may reflect the influence of the latter on individual stock returns55. To check whether sentiment sensitivities are picking up the covariance of stock returns

[54] Standard t-stat based assessment of the statistical significance of sentiment betas could be misleading because significance levels might be misspecified in the short samples.
[55] The lagged market return is not the whole story in explaining the time-series variation in sentiment changes: R-square in the regression of the latter on the former is only 35%. Besides, microstructure concerns (such as non-synchronous trading and reaction to the information with a lag) are less likely to be an issue in the monthly data.

with the lagged market returns, I separately estimate the model (1) including the lagged market returns simultaneously along with the other factors. If lagged market returns are driving the results, we should expect that a) betas on the lagged market return explain a large part of cross-sectional variation of sentiment betas; b) average cross-sectional correlation between sentiment betas estimated with and without lagged market should be low, since inclusion of lagged market as a control should wash out any meaningful variation in sentiment betas. I first find that lagged market betas explain only 32% of cross-sectional variation in sentiment betas, not a very high number, given the correlation between sentiment index and lagged market returns. Furthermore, the average correlation between sent.betas estimated with and without the lagged market return in the model is high 0.78, confirming that the correlation of ΔSENTINDEX with lagged market return does not wash out meaningful variation of sentiment beta in the cross-section. Sorts on sentiment betas estimated with the inclusion of lagged market returns in the model yield qualitatively similar results.

I repeat the analysis with signed sentiment betas, not their absolute values. Namely, after matching sentiment betas to firm characteristics, i dont lump negative and positive sentiment betas together as before, but treat them separately and group stocks in deciles with decile 1 containing stocks with the smallest values of sentiment beta (most negative) and decile 10 containing stocks with the largest sentiment betas (most positive) and calculate value-weighted values of different firm characteristics across deciles. From Decile 1 to Decile 10, average loadings on market factor and SMB exhibit a clear U-shaped pattern, indicating that stocks with greater exposure to investor sentiment changes tend to smaller stocks with have higher systematic risk. A number of other firm characteristics such as turnover, volatility, market-to-book, investment growth and changes in R&D display a clear U-shaped pattern. On other hand, the *inverse* U-shaped pattern across sentiment beta deciles is found for such characteristics as market cap, ROA and ROE, various measures of profit margins, dividend yields and the probability of being an S&P 500 index member.

These patterns suggest that *regardless* of the sign of sentiment beta, stocks with greater exposure (in terms of magnitude) to sentiment tend to be smaller, more volatile, growth stocks that have higher market-to-book ratios, greater turnover, more intensive investment and R&D growth, lower profitability and dividend yields. This is consistent with the predictions of „Hard-to-Value Difficult-to-Arbitrage“ hypothesis.

Furthermore, results (not presented here) show that there is a negative monotonic relationship between sentiment betas and liquidity betas after controlling for FF and momentum factors, i.e., positive sentiment beta stocks tend to have relatively lower liquidity risk compared to negative sentiment beta stocks. One potential interpretation of this finding is that stocks with positive sentiment betas tend to be primarily traded by risk-averse individial investors that provide liquidity to meet institutional demand for immediacy (Kaniel et al. 2006). Consistent with this interpretation, positive beta stocks tend to have lower sales and assetsg growth (relative to negative SB stocks) and higher levels of advertising, whereas stocks with negative sentiment betas tend to have higher residual analyst coverage and greater institutional ownership.

Finally, it is also possible that sentiment betas are just picking up stock volatility mechanically, due to the method of estimation, i.e., stocks with higher volatility tend to have higher betas on any factor, not just the sentiment factor. The back-of-the-envelope calculations show that even though (log of) contemporaneous total and idiosyncratic volatility[56] helps explain the cross-sectional variation of (log of) "shrunk" sentiment betas, its explanatory power is not high: R-squares range between 9.3% and 26% with the average value of 17%. The correlation between the Bayes-Stein betas and volatility-adjusted betas is significant 0.88, indicating that the cross-section of stock return volatility is not the main factor driving the cross-sectional variation in sentiment betas. Overall, robustness analysis provides evidence that a) potential statistical imprecision is not a serious issue to affect the results; b) the relation to the contemporaneous stock volatility is unlikely to be a driver of the cross-sectional variation in sentiment betas.

Economic significance and discussion

Economic significance of the differences in average firm characteristics between bottom and top sentiment beta portfolios is reported in the table 12. Economic significance is assessed as a fraction that the difference in average characteristics between bottom and top sentiment beta portfolios constitutes in the average value of the characteristic throughout the sample period *after* controlling for the differences in size and volatility. If we focus our attention on the sub-period where the results are particularly strong (1989-2003), it can be seen that differences for dividend yield, sales growth, HML loading, earnings, cash flows, analyst coverage, share turnover and short-sales constraints proxy are quite significant. For example, the difference in analyst coverage between top and bottom deciles is -1.79 and is of large economic magnitude as it represents around 46% of the average quarterly analyst coverage of 3.93 during 1989-2003. Also note that the magnitude of these differences as a fraction of the corresponding averages (i.e., "diff/average" ratio) increased for analyst coverage, institutional ownership, turnover and dividend yield as we move from 1975-1989 to 1989-2003 sub-period, suggesting that differences in these characteristics between high and low

[56] 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 the Fama-French model.

sentiment-sensitive stocks became more attenuated during the recent decade. Level of economic significance for dividend yield is quite large (around 82%) and seems to indicate that biases in personal judgment are particularly strong when investors value stocks with low or non-existent dividends.

Overall, most of the findings are consistent with the HV-DA argument. As it predicts, equities with higher growth potential, lack of earnings history, smaller size and greater volatility and turnover tend to be more sensitive to fluctuation in investor sentiment. The turnover result is consistent with the existing theoretical and empirical literature on investor sentiment: for example, Fisher Black (1986) noted that the presence of noise traders increases market's liquidity by providing newly informed traders with a method of revealing their information while still profiting from it[57].

However, results with respect to IO (institutional ownership), S&P 500 membership and analyst coverage do not seem to align well with "HV-DA" hypothesis, at least, at the first glance. Given the results of the recent research on analyst coverage[58], which showed that analysts do not pick the firms they follow randomly, nor are they unbiased in their forecasts, there can be several potential explanations for the observed pattern. One possible explanation 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, because they expect greater rewards. On the other hand, it is also possible that analysts' recommendations themselves fuel speculative demand of sentiment traders, making stocks they cover more prone to the swings in investor sentiment.

Furthermore, 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 across portfolios with different sentiment factor sensitivities. This finding is borne out further by comparing past six months equal-weighted returns across various deciles: there is no evident trend (see tables 7-8,

[57] 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 sentiment leads to higher liquidity. Greene and Smart (1999) that noise trading generated by Wall Street Journal's "Investment Dartboard" leads to higher liquidity and decrease in the adverse selection component of bid-ask spread.

[58] For example, 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.

column "past six month return"). This suggests that sensitivity to irrational sentiment changes does not seem to be related to momentum in stock returns.

Both univariate and multivariate analyses point to the positive association between institutional ownership and sentiment sensitivity (beta) in the 90's. More specifically, given conventional risks (like return volatility), institutional investment constraints, liquidity and past equity returns, institutions appear to have been tilting their equity portfolios more aggressively towards stocks with higher exposure to sentiment changes since the beginning of the 90's. One potential interpretation of this result is that institutions were "riding" on the market sentiment, aiming to exploit the predictable patterns in the demand of sentiment traders. This view is consistent with the idea expressed by Barberis and Shleifer (2003) who point out that sophisticated arbitrageurs (e.g., institutions) may amplify rather than counteract the effect of sentiment traders (e.g., individuals) if the former understand the form of demand function of the latter. This interpretation also seems appealing in the view of the theoretical result in this paper which shows that in a market populated by fully rational arbitrageurs (e.g., institutions) and non-fully rational sentiment traders (individual investors), sentiment beta proxies for the proportion of the latter (see appendix A). Thus, empirically, greater institutional presence in stocks with higher absolute values of sentiment sensitivity potentially suggests that institutions may have behaved as if they were sentiment traders (i.e. adjusting their investment strategies depending on how sentiment changes, and in doing so, influencing security prices)[59]. Some of the recent research (e.g., Abreu and Brunnermeir, 2003; Brunnermeir and Nagel, 2005; Jackson, 2005) supports the idea that institutions might have exacerbated sentiment-driven mispricing rather than countering it. However, it still remains unclear why institutions preferred to hold stocks that exhibited negative covariance with sentiment factor – do they like to hold stocks that provide a hedge against unpredictable sentiment fluctuations or does their trading cause particular subset of stocks to have negative loadings on sentiment factor?

Conclusions

In this paper I test two related hypotheses. The first hypothesis which I call "Hard-toValue, Difficult-to-Arbitrage" (HV-DA) postulates that investor sentiment affects stocks of some firms more than others due to the differences in firm characteristics. The second hypothesis posits that stocks with higher sentiment sensitivities are predominantly held by individual, not institutional, investors. Evidence on the validity of these hypotheses is important for investors' portfolio allocation because it helps them understand in what types of stocks sentiment effects are most

[59] In an efficient market, trading based on changes in sentiment which are orthogonal to fundamentals should not systematically affect asset prices.

pronounced (if any), which firm characteristics play a determining role in how large the effects may be as well as what the potential implications are.

To test these hypotheses, I first construct a sentiment index as the first principal component of several sentiment proxies. To mitigate the possibility that sentiment index may reflect an active economic factor I orthogonalize all eight sentiment proxies (investor intelligence index, dividend premium, CEFDs, percent change in margin borrowing, specialist short selling, net flows into equity mutual funds, the number of IPOs and average first-day IPO returns) with respect to variables that may be correlated with fundamentals. The paper provides evidence that this sentiment proxy compares favorably with the alternative measures used in earlier literature (Baker and Wurgler (2006) measure and the University of Michigan Consumer Sentiment Index) and also shows that this sentiment factor proxy has predictive power for aggregate market returns and contemporaneous explanatory power the small stock and retail stock return spreads.

Second, the paper develops and validates a novel measure of investor sentiment at the individual stock level, defined as a sensitivity of stock returns to changes in the sentiment factor (the sentiment beta). More specifically, it is the coefficient in the time-series regression of individual stock returns on sentiment factor, constructed in the first step, after accounting for the risks associated with the market, size, book-to-market and liquidity. The paper demonstrates that that the sentiment beta measure has a solid theoretical foundation (proxies for the relative proportion of uninformed sentiment traders) and possesses good statistical properties.

I find that the sentiment factor has incremental explanatory power for time-series of returns (adds as much as Pastor and Stambaugh (2003) liquidity factor), however, "noise trader risk" in the sense of DSSW (1990) is not priced in the cross-section. Portfolio consisting of stocks with high exposure to sentiment underperforms the portfolio of stocks with low sentiment exposure by around 25 (38) basis points per month on a raw (risk-adjusted) basis. Further evidence suggests that, unconditionally, more sentiment-sensitive stocks are smaller, younger and more volatile stocks with low dividend yields and greater short-sales constraints. Conditional on size and volatility, high sentiment beta stocks tend to be younger, have high subsequent turnover, volatility and sales growth, lower dividend yields and book-to-market ratios consistent with the prediction of HV-DA. However, high sentiment beta stocks tend to have more of analyst following, higher chance of being an S&P 500 member and greater institutional ownership. There is no reliable evidence that irrational sentiment affects unprofitable stocks more. If anything, during the 1989-2003, stocks with higher sentiment sensitivities seemed more profitable. Most of the differences in firm characteristics between high and low sentiment beta portfolios are both statistically significant and economically important. Overall, this evidence suggests that firm characteristics play a key role in how sentiment affects stock returns.

Institutional analysis confirms the results of conditional sorts and shows that institutions changed their behavior with respect to stocks that are more prone to shifts in investor sentiment. Institutions stayed away from stocks with higher sentiment betas throughout the 1980's, but held relatively more of these stocks since the late 1980's and early 1990's. These findings question the presumption of the efficient markets hypothesis that rational speculators would find it optimal to exert a correcting force on prices and support recent evidence suggesting that institutions may be the source of the non-fundamental factor in returns.

The presented evidence is relevant from the perspective of professional investors, whose purpose is to provide investors with an expected rate of return on their investments, and heads of firms (CEOs) whose compensations could be tied to the firm's stock performance. Additionally, from a welfare perspective, a better understanding of the sentiment traders' and arbitrageurs' behavior may support regulation, taxation or education of these investors to ameliorate adverse economic effects.

References

1. Abreu, D., and Brunnermeier, M., 2002. Synchronization risk and Delayed Arbitrage, *Journal of Financial Economics* 66, 341-360
2. Abreu, D. and Brunnermeier, 2003. Bubbles and Crashes, *Econometrica* 71, 173-204
3. Ali, A. and Trombley, M., 2004. Short sales constraints and momentum in stock returns, Working paper, University of Arizona.
4. Ang, A., Hodrick, R., Xing, X., and Zhang, X. 2005. The cross-section of volatility and expected returns, *Journal of Finance*, forthcoming
5. Baker, M. and Stein, J. 2004. Market liquidity as a Sentiment Indicator, *Journal of Financial Markets*, forthcoming.
6. Baker, M. and Wurgler, J., 2000. The Equity Share in New issues and Aggregate Stock Returns, *Journal of Finance*, October.
7. Baker, M. and Wurgler, J., 2004. A catering theory of dividends, *Journal of Finance,* Volume 59, Issue 3, pp. 1125.
8. Baker, M. and Wurgler J., 2006. Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance*, forthcoming
9. Barber B., Odean T., and Zhu, N. 2003. Systematic Noise, Working paper, University of California at Berkeley.
10. Barberis, N. and Huang, 2001. Mental Accounting, Loss Aversion and Individual Stock Returns, *Journal of Finance*, August 2001
11. Barberis, N. and Shleifer, A. 2003. Style investing, *Journal of Financial Economics*, 68, pp.161-199
12. Barberis, N., Shleifer, A., and Wurgler, J., 2003. Comovement, *Journal of Financial Economics*, forthcoming.
13. Bennett, J., Sias, R., and Starks, L. 2003, Greener pastures and the impact of dynamic institutional preferences, *Review of Financial Studies* 16, 1199–1234.

14. Black, F., 1986. Noise, *Journal of Finance* 41, pp. 529-543
15. Blume, M.E., 1971. On the Assessment of Risk, *Journal of Finance*, 26, pp. 1-10.
16. Blume, M.E., 1973. Beta's and Their Regression Tendencies, *Journal of Finance*, 28, pp. 785-795.
17. 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.
18. 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.
19. Brown G.W. and Cliff, M.T 2005. Investor Sentiment and Asset Valuation, *Journal of Business*, January.
20. 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.
21. Brunnermeier, M. and Nagel, S., 2005. Hedge Funds and the Technology Bubble, *Journal of Finance*, forthcoming
22. Bulan, L.T., Subramanian, N., and Tanlu, L.D., 2004. On the timing of dividend initiations. Working paper, Brandies University, International Business School.
23. Cassidy, D., 2002. *Trading on Volume: The Key to Identifying and Profiting from Stock Price Reversals*, New York, McGraw-Hill.
24. Chan, L.K.C. and Lakonishok, J., 1992. Robust Measurement of Beta Risk, *Journal of Financial and Quantitative Analysis*, 27, pp. 265-282.
25. Cornelli, Goldreich and Ljunqqvist, 2005. Investor sentiment and pre-IPO markets, Working paper, London Business School
26. Daniel, K., and Titman, S., 2005. Testing Factor-Model Explanations of Market Anomalies, Northwestern University, Working Paper
27. D'Avolio, G., 2002. The Market for Borrowing Stock, *Journal of Financial Economics*, vol. 66(2-3)
28. 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.
29. 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.
30. Deuskar, P., 2004. Aggregate liquidity and Investor Sentiment: Empirical Connection, Working paper, Stern School of Business, New York University.
31. Diether, K., Malloy C., and Scherbina, A. 2002. Differences of Opinion and the Cross-Section of Stock Returns. *Journal of Finance* 57, no. 5, pp. 2113-2141.
32. Dorn, D., 2003. Does sentiment drive the retail demand for IPOs? Working Paper, Drexel University.
33. 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.
34. Easley, D., Hvidkjaer, S., and O'Hara, M. 2002. Is information risk a determinant of asset returns? *Journal of Finance*, 57.
35. 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.
36. Fama, E.F., 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49, 283-306.
37. 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.
38. 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..

39. Flynn, S.M., 2004. Arbitrage in Closed-end Funds: New Evidence, Working paper, Vassar College.
40. Frazzini, A., and Lamont, O., 2006. Dumb Money: Mutual Fund flows and the cross-section of stock returns, working paper, Yale University
41. Hughen C.J, and McDonald C., 2004. Who are the noise traders? *Journal of Financial Research,* forthcoming
42. Indro, D., 2004. Does Mutual Fund Flow Reflect Investor Sentiment? *Journal of Behavioral Finance*, vol. 5, No. 2, pp. 105-115/
43. Jackson, A., 2003a. The Aggregate Behavior of Individual Investors, Working paper, London Business School.
44. Jackson, A., 2003b. The noise trader risk exists…but the noise traders are not who you think they are, Working paper, London Business School.
45. 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.
46. Jorion, P., 1986. Bayes-Stein Estimation for Portfolio Analysis, *Journal of Financial and Quantitative Analysis*, Vol. 21, No. 3, Columbia University, pp. 279-292.
47. Gabaix, X., Gopikrishnan, P., Plerou, V., and Stanley, E. 2005. Institutional Investors and Stock Market Volatility, Working Paper, Massachusetts Institute of Techonology.
48. 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)
49. 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.
50. Griffin, J.M., 2002. Are the Fama and French Factors Global or Country-Specific? *Review of Financial Studies*, 15, pp. 783-803.
51. Griffin, J.M., Harris, J.H., and Topaloglu, S. 2003. The Dynamics of Institutional and Individual Trading, *Journal of Finance* 6, December.
52. 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.
53. 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.
54. Kan, R., and Zhang, C., 1999. Two-Pass Tests of Asset Pricing Models with Useless Factors, *Journal of Finance*, 54, 203-235
55. Kaniel, R., Saar, G., and Titman S., 2006. Individual Investor Trading and Stock Returns, working paper, Johnson School of Management, Cornell University.
56. Klibanoff, P., Lamont, O., and Wizman, T.A., 1999. Investor reaction to salient news in closed-end country funds, *Journal of Finance* 53, 673–699.
57. Kothari, S.P., and Shanken, J., 1997. Book-to-market, dividend yield, and expected market returns: a time-series analysis, *Journal of Financial Economics* 44, 169-203.
58. Kumar, A. and Lee, C., 2006. Retail Investor Sentiment and Return Comovements, *Journal of Finance*, Vol. LXI, No. 5.
59. Lee, Jiang and Indro, 2002. Stock market volatility, excess returns and the role of investor sentiment, *Journal of Banking and Finance*, 26.
60. Lee, C., Shleifer, A. and Thaler, R., 1991. Investor Sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75-109.
61. Lemmon, M. and Portniaguina, E., 2006. Consumer Confidence and Asset Prices: Some Empirical Evidence, *Review of Financial Studies*, 19(4), pp. 1499-1529.

62. Neal, R. and Wheatley, S.M., 1998. Do measures of investor sentiment predict returns? *Journal of Financial and Quantitative Analysis* 33, pp. 523-547.
63. O'Brien, Patricia C. and Ravi Bhushan, 1990, Analyst following and institutional ownership, *Journal of Accounting Research,* 28, Supplement, pp. 55-76.
64. Pastor, L, and Stambaugh, R., 2003. Liquidity risk and Expected Stock Returns, *Journal of Political Economy*, 111, pp.642-685.
65. Pearson, Neil D, 1992, Determinants of the production of information, Mimeo, University of Rochester.
66. Pirinsky and Wang, 2004. Institutional Investors and the Comovement of Equity Prices, Working paper, Texas A&M University.
67. Reilly, F.K., Brown, K.C., 1997. Investment Analysis and Portfolio Management, fifth ed. The Dryden Press, USA.
68. Qiu, L., and Welch, I., 2004. Investor Sentiment Measures, Working paper, Brown University.
69. Scholes, M. and Williams, J., 1977. Estimating betas from non-synchronous data, *Journal of Financial Economics*, vol. 5, No 3.
70. Shleifer, A. and Vishny R., 1997. The limits of arbitrage. *Journal of Finance*, 52, pp. 35-55.
71. Sias, R.W., 1996. Volatility and the Institutional Investor, *Financial Analysts Journal*, Mar/Apr
72. Sias, R.W., 2004. Institutional herding, *Review of Financial Studies*, Vol. 17, No.1.
73. Sias R.W., Starks, L., and Tinic, S.M, 2001. Is noise trader risk priced? *Journal of Financial Research*, Vol. XXIV, No. 3, pp.311-329.
74. Siegel, J.J., 1992. Equity risk premia, corporate profit forecasts, and investor sentiment around the stock crash of October 1987, *Journal of Business* 65 (4), 557-570.
75. Shefrin, H., and Statman, M., 1994. Behavioral Capital Asset Pricing Theory, *Journal of Financial and Quantitative Analysis* 29, No. 3 pp. 323-349.
76. 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.
77. Warther, V.A., 1995. Aggregate Mutual Fund Flow and Security Returns. *Journal of Financial Economics,* 39, pp. 209-235.

Appendix A. A Simple model of investor sentiment

This section outlines a simple general equilibrium model which can be viewed as a stylized version of DSSW (1990). The model provides theoretical justification for the empirical measure of sentiment at the individual stock level.

Model setup: at each time t, the market is assumed to be populated by the two types of traders: boundedly rational sentiment 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 irrational sentiment are assumed to be uncorrelated with changes in* *the fundamental value, as we are interested in sentiment changes that are orthogonal to fundamentals*)[60].

- $z_t^{i,h}$ 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.[61]

The sentiment factor may enter into the optimal demand of the irrational traders with either positive or negative sign depending on whether they positive or negative feedback trade on the sentiment. There is some empirical evidence[62] 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 sentiment traders to extrapolate past performance too far into the future and behave like momentum investors as well.

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

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

Plugging in the expressions for the demand of rational and sentiment 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:

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

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

---

[60] 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.

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

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

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

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 sentiment traders, on average, are neither bullish nor bearish. The price change is 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 irrational sentiment traders in a stock should increase the correlation of the stock with the common sentiment factor. Multiplying price change by change in sentiment factor, applying covariance operator yields and taking into account that sentiment changes are orthogonal to changes in fundamental value, we obtain

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

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:

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

Appendix B. Definitions of stock characteristics

I subdivide the characteristics into several categories. First category includes 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.

I use two dividend characteristics, dividend yield (DivYield) and dividend to equity (DivToEq). First 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 (Compustat item 6) reported anytime during the fiscal year t divided by market value at the end of the calendar year. The market value is equal to market equity at calendar year end (Item 24 times Item 25) plus book debt (Item 6 minus book equity). Book equity is defined as stockholder's equity (Item 216) [or first available of common equity (60) plus preferred stock par value (130) or book assets (6) minus liabilities (181)] minus preferred stock liquidating value (10) [or first available of redemption value (56) or par value (130)] plus balance sheet deferred taxes and investment tax credit (35) if available and minus post retirement assets (330) if available. 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 stock 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 59 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 positive dividend yield variables are winsorized at 1% and 99% levels to eliminate outliers.

Appendix C. Calculation of analysts' earnings forecasts dispersion

Since split adjusted I/B/E/S data set is unsuitable for computing dispersion due to the rounding issues (Diether et al., 2002) I compute dispersion using the raw forecast data, unadjusted for stock splits. Month-end averages and standard deviations are computed from the fiscal year one individual earnings estimates in the Detail History file by extending each forecast until its revision date. If revision date precedes the estimate date, the former is replaced with the reported announcement date. For example, if the forecast was made in May and was last confirmed as accurate in July, it will be used in the computations of averages and standard deviations for May, June and July. If an analyst makes more than one forecast in a given month, only the last forecast is used in calculations. Obviously, each stock must be covered by two or more analysts during that month, since I define dispersion as the standard deviation of earnings forecasts scaled by the absolute value of the mean earnings forecast. For robustness, I also use the mean and standard deviations of forecasts from IBES Summary History file.

Table 1. Monthly correlations between different sentiment proxies and macroeconomic variables (from April 1965 till December 2003 in levels).

SENT- bull minus bear spread of Investor Intelligence Index, DivPrem - monthly dividend premium, Cefd Vw - value-weighted average monthly closed-end fund discount, Cefd Ew - equal-weighted average monthly closed-end fund discount, Margin - level of margin borrowing detrended by its 12-month moving average, Special – the ratio of specialist short-sales to total short-sales, Fund Flow - net fund flows into equity mutual funds, Iporets - monthly average first-day IPO return, IPON - number of IPOs in a given month, Turn - aggregate NYSE turnover detrended by its six-month moving average, ES - equity share of new issues. Macro variables (in levels): IP - Industrial Production index, Dur - consumer durables, Nondur - consumer nondurables, Serv - services, Emp - aggregate employment, Recess - NBER recession dummy, TS - term spreads, CS - credit spreads; UMI - level of the University of Michigan Consumer Confidence index

			Premium to NAV																		
	SENT	DivPrem	Cefd Vw	Cefd Ew	Margin	Special	Fund Flow	Iporets	IPON	Turn	ES	IP	Dur	Nondur	Serv	Emp	Recess	TS	CS	UMI
Mean	10.49	-0.56	-8.73	-8.36	2,077	0.45	0.29	18.03	29.42	0.02	0.21	71.80	383	965	1,679	97,057	0.14	1.48	1.04	86.87
Std	21.26	0.45	7.02	7.22	12,435	0.08	0.90	21.38	25.34	0.16	0.11	21.81	273	598	1,342	21,370	0.35	1.31	0.43	12.28
N	465	465	465	465	465	465	465	465	465	465	459	465	465	465	465	465	465	465	465	465
SENT	1.00																			
DivPrem	**0.16*****	1.00																		
Cefd Vw	-0.04	**0.12*****	1.00																	
Cefd Ew	-0.05	0.06	0.93***	1.00																
Margin	**0.08***	**-0.03**	-0.05	-0.05	1.00															
Special	**0.14*****	**0.3*****	0.00	0.11**	-0.06	1.00														
Fund Flow	**0.17*****	-0.07	**0.41*****	**0.48*****	**0.22*****	**-0.17*****	1.00													
Iporets	0.06	-0.1**	-0.02	0.04	**0.31*****	**0.19*****	0.07	1.00												
IPON	0.08*	**-0.25*****	**0.32*****	**0.36*****	**0.33*****	**-0.15*****	0.5***	0.07	1.00											
Turn	**0.27*****	0.00	-0.01	-0.02	0.00	0.11**	0.05	0.16***	-0.07	1.00										
ES	-0.04	**-0.25*****	0.00	0.01	**0.13*****	0.06	-0.03	0.01	**0.34*****	-0.1**	1.00									
IP	0.08*	0.00	0.06	0.00	0.15***	-0.54***	0.23***	0.17***	0.11**	-0.02	-0.36***	1.00								
Dur	0.11**	-0.01	0.11**	0.07	0.12***	-0.54***	0.29***	0.14***	0.13***	-0.02	-0.39***	0.99***	1.00							
Nondur	0.09*	-0.05	0.11**	0.06	0.11**	-0.59***	0.31***	0.13***	0.14***	-0.01	-0.36***	0.98***	0.99***	1.00						
Serv	0.1**	0.02	0.14***	0.1**	0.11**	-0.53***	0.31***	0.13***	0.13***	-0.01	-0.4***	0.98***	1***	0.99***	1.00					
Emp	0.05	-0.11**	0.05	-0.01	0.13***	-0.63***	0.28***	0.13	0.17***	-0.02	-0.33***	0.98***	0.98***	0.99***	0.97***	1.00				
Recess	**-0.27*****	-0.01	0.04	-0.01	-0.28***	-0.05	-0.14***	-0.16***	-0.25***	0.03	0.00	-0.12***	-0.14***	-0.11***	-0.12***	-0.11**	1.00			
TS	**0.31*****	0.06	0.24***	0.17***	-0.04	-0.38***	0.21***	-0.19***	0.16***	0.06	-0.04	0.19***	0.26***	0.29***	0.27***	0.26***	-0.1**	1.00		
CS	0.09*	-0.37***	-0.1**	-0.14***	-0.15***	-0.18***	-0.16***	-0.07	-0.06	0.12***	0.37***	-0.18***	-0.17***	-0.12**	-0.18***	-0.11**	0.33***	0.23***	1.00	
UMI	**0.26*****	0.03	0.13***	0.24***	**0.31*****	0.05	**0.3*****	**0.23*****	**0.31*****	-0.04	**-0.22*****	0.38***	0.42***	0.35***	0.39***	0.32***	-0.54***	0.08*	**-0.52*****	

Table2a. Summary statistics for the time-series averages of sentiment betas

Descriptive statistics		Extreme observations							
		Lowest				Highest			
N	11663								
Mean	0.002								
Median	0.001	Value	Company name	Exchange	SIC code	Value	Company name	Exchange	SIC code
Std	0.021	-0.171	Teletek Inc	Nasdaq	3660	0.151	Citrix Systems	Nasdaq	7370
Skewness	0.554	-0.148	Innovet Inc	Nasdaq	2830	0.151	PENN treaty American Corp	NYSE	6310
Kurtosis	6.990	-0.143	Antares Oil Corp	Nasdaq	1311	0.154	AXS One Inc	Amex	7372
Interquartile Range	0.018	-0.129	Metal Recovery Technologies	Nasdaq	3710	0.162	Sport of Kings	Nasdaq	7394
t-stat for mean=0	8.270	-0.125	P E T X Petroleum Corp	Nasdaq	1311	0.172	Storage Computer Corp	Amex	3572

Quantiles

100% Max	0.172
90%	0.024
75% Q3	0.010
50% Median	0.001
25% Q1	-0.008
10%	-0.019
0% Min	-0.171

Table 2b. Summary statistics for the time-series averages of the "shrunk" sentiment betas

Descriptive statistics		Extreme observations							
		Lowest				Highest			
N	11665								
Mean	0.013								
Median	0.013	Value	Company name	Exchange	SIC code	Value	Company name	Exchange	SIC code
Std	0.004	0.001	QCF Bancorp Inc	Nasdaq	6030	0.040	Family Golf Centers	Nasdaq	7990
Skewness	1.290	0.001	Chase Capital V	NYSE	6021	0.041	Davel Communications	Nasdaq	4810
Kurtosis	5.990	0.002	First Busey Corp	Nasdaq	6020	0.045	Trism Inc	Nasdaq	4210
Interquartile Range	0.005	0.002	Noth Land S & L ASSN WI	Nasdaq	6120	0.053	Texoil Inc New	Nasdaq	1310
t-stat for mean=0	342.3	0.003	Florida Glass Inds	Nasdaq	5030	0.068	Vitalcom Inc	Nasdaq	7373

Quantiles

100% Max	0.0682
90%	0.0184

Table 3a. Sentiment sensitivity and stock returns

Every month individual excess stock returns are matched to the last available Bayes-Stein estimate of sentiment beta and, then five equal-weighted portfolios are formed on the basis of sentiment beta sort. Left part of the table presents equal-weighted average monthly excess returns on the quintile portfolios formed on sentiment beta over the period 1975-2003 and two sub-periods. 1- portfolio with the lowest Bayes-Stein estimate of sentiment beta, 5 – portfolio with the highest Bayes-Stein estimate of sentiment beta. Size-adjusted returns are computed as the difference between individual stock returns and the average return of the corresponding size portfolio (20 size portfolios are constructed using NYSE/AMEX breakpoints every month). Market-adjusted returns represent the difference between individual stock returns and CRSP value-weighted market index. Carhart alphas are intercepts in the Carhart (1997) time-series regression of portfolio returns on the market, size, book-to-market and momentum factors. "Stocks with positive (negative) sentiment beta" raw reports returns of quintile portfolios that contain only stocks with positive (negative) loadings on sentiment factor with 1 being the portfolio of stocks with the lowest positive (largest negative) and 5 being the portfolio of stocks with the highest positive (lowest negative) value of original sentiment beta. T-stats on portfolio returns are adjusted for serial correlation. The last column "average R" contains the difference between returns of portfolio 1 and 5 and the corresponding t-stat.

	Average returns (%/month)					T-statistics						t-stat
	1	2	3	4	5	1	2	3	4	5	1-5	
						Full Sample (April 1975- Dec 2003)						
raw	0.98	0.84	0.74	0.68	0.70	4.19	2.83	2.28	2.04	2.07	0.27	1.75
size-adjusted	0.17	0.04	-0.05	-0.11	-0.09	1.67	1.57	-1.27	-2.28	-1.58	0.26	1.69
market-adjusted	0.36	0.22	0.14	0.07	0.09	2.68	1.55	0.83	0.42	0.54	0.27	1.72
Carhart alphas	0.20	0.01	-0.11	-0.17	-0.19	2.56	0.12	-1.11	-1.58	-2.02	**0.38**	**4.14**
						First half (Apr 1975 - Jun 1989)						
raw	1.06	0.91	0.79	0.81	0.83	2.96	2.10	1.71	1.71	1.76	0.23	1.60
size-adjusted	0.15	0.04	-0.08	-0.07	-0.06	1.57	1.62	-1.87	-1.41	-1.15	0.21	1.49
market-adjusted	0.39	0.24	0.12	0.13	0.16	2.61	1.35	0.61	0.63	0.77	0.23	1.60
Carhart alphas	0.17	-0.15	-0.36	-0.39	-0.32	2.26	-2.04	-4.36	-4.77	-4.15	**0.49**	**5.58**
						Second half (Jul 1989 - Dec 2003)						
raw	0.89	0.76	0.69	0.56	0.58	2.99	1.90	1.50	1.17	1.17	0.32	1.13
size-adjusted	0.19	0.05	-0.02	-0.15	-0.13	1.05	0.93	-0.31	-1.81	-1.19	0.32	1.13
market-adjusted	0.34	0.21	0.15	0.01	0.03	1.48	0.92	0.57	0.04	0.12	0.30	1.10
Carhart alphas	0.35	0.25	0.18	0.08	-0.02	3.49	2.14	1.27	0.50	-0.15	**0.38**	**2.61**
						Stocks with positive sent.beta						
raw	0.98	0.81	0.75	0.63	0.59	4.14	2.69	2.22	1.76	1.63	0.38	2.04
size-adjusted	0.18	0.01	-0.05	-0.17	-0.20	1.70	0.21	-0.85	-2.20	-2.21	0.38	2.08
market-adjusted	0.36	0.20	0.14	0.01	-0.01	2.62	1.32	0.83	0.07	-0.06	0.37	1.98
Carhart alphas	0.21	0.03	-0.06	-0.13	-0.19	2.69	0.31	-0.51	-0.83	-1.34	**0.40**	**2.94**
						First half (Apr 1975 - Jun 1989)						
Carhart alphas	0.21	-0.17	-0.37	-0.38	-0.38	2.50	-1.92	-3.57	-3.82	-3.68	**0.58**	**5.49**
						Second half (Jul 1989 - Dec 2003)						
Carhart alphas	0.33	0.31	0.27	0.10	-0.05	2.89	2.00	1.51	0.40	-0.20	**0.38**	**1.75**
						Stocks with negative sent. Betas						
raw	0.99	0.83	0.76	0.73	0.83	4.23	2.84	2.34	2.26	2.54	0.16	1.13
size-adjusted	0.18	0.04	-0.03	-0.07	0.03	1.74	1.19	-0.71	-1.30	0.36	0.16	1.04
market-adjusted	0.38	0.22	0.14	0.12	0.22	2.76	1.51	0.86	0.73	1.27	0.16	1.13
Carhart alphas	0.20	-0.03	-0.15	-0.21	-0.17	2.36	-0.36	-1.65	-2.54	-1.89	**0.37**	**3.79**
						First half (Apr 1975 - Jun 1989)						
Carhart alphas	0.15	-0.18	-0.32	-0.41	-0.27	1.73	-2.20	-3.62	-4.56	-2.40	**0.42**	**3.36**
						Second half (Jul 1989 - Dec 2003)						
Carhart alphas	0.39	0.21	0.09	0.05	0.02	3.32	1.88	0.68	0.37	0.12	**0.38**	**2.55**

Table 3b. Sentiment sensitivity and stock returns (continued)

Every month cumulative excess stock returns (computed over 3, 6, 12, 24, 36 and 60 months) are matched to the last available Bayes-Stein estimate of sentiment beta stock by stock and then five equal-weighted portfolios are formed on the basis of sentiment beta sort. The definitions are the same as in the table 3a.

	Average cumulative 3-month returns (%/quarter)					**T-statistics**						**t-stat**
	1	2	3	4	5	1	2	3	4	5	1-5	
raw	2.62	2.25	1.91	1.83	1.91	3.98	2.87	2.25	2.09	2.18	0.71	1.77
size-adjusted	0.46	0.10	-0.20	-0.26	-0.20	1.79	1.88	-2.45	-2.09	-1.36	0.66	1.70
market-adjusted	0.95	0.45	0.07	-0.03	0.04	2.01	1.02	0.16	-0.06	0.07	0.91	2.27
Carhart alphas	0.08	-0.47	-0.92	-1.07	-0.94	0.41	-2.50	-4.91	-6.01	-5.26	**1.02**	**5.18**
	Average cumulative 6-month returns					**T-statistics**						**t-stat**
raw	5.18	4.51	3.85	3.66	3.87	4.52	3.33	2.65	2.46	2.58	1.31	1.72
size-adjusted	0.89	0.25	-0.39	-0.55	-0.35	1.92	2.35	-2.70	-2.56	-1.30	1.24	1.72
market-adjusted	1.91	1.03	0.29	0.08	0.25	2.15	1.26	0.35	0.09	0.30	1.66	2.30
Carhart alphas											**1.72**	**4.29**
	Average cumulative 12-month returns					**T-statistics**						**t-stat**
raw	9.86	8.39	7.21	6.98	7.17	4.92	3.85	3.09	2.98	3.00	2.69	2.00
size-adjusted	1.81	0.42	-0.70	-0.94	-0.79	2.18	1.90	-2.79	-2.41	-1.53	2.60	1.95
market-adjusted	3.88	2.26	0.95	0.65	0.74	1.90	1.24	0.56	0.40	0.46	3.14	2.21
Carhart alphas											**2.53**	**3.35**
	Average cumulative 24-month returns					**T-statistics**						**t-stat**
raw	18.70	16.01	14.19	13.86	14.23	5.96	5.13	4.45	4.48	4.36	4.47	1.98
size-adjusted	3.21	0.58	-1.21	-1.53	-1.24	2.28	1.56	-2.70	-2.17	-1.46	4.45	2.01
market-adjusted	7.65	4.73	2.80	2.40	2.54	1.63	1.15	0.73	0.67	0.73	5.11	2.11
Carhart alphas											**3.96**	**2.39**
	Average cumulative 36-month returns					**T-statistics**						**t-stat**
raw	28.33	24.50	22.55	21.82	22.71	5.44	4.95	4.37	4.26	4.29	5.62	1.83
size-adjusted	4.33	0.55	-1.55	-2.27	-1.34	2.07	1.32	-1.82	-2.19	-1.34	5.67	1.88
market-adjusted	9.58	5.85	4.04	3.15	3.64	1.28	0.87	0.61	0.49	0.60	5.94	1.89
Carhart alphas											**5.82**	**2.01**
	Average cumulative 60-month returns					**T-statistics**						**t-stat**
raw	49.36	43.62	40.06	39.71	39.73	5.49	5.21	4.75	4.50	4.65	9.63	2.17
size-adjusted	6.89	1.10	-2.65	-3.10	-2.84	2.05	2.25	-2.13	-1.80	-2.41	9.74	2.23
market-adjusted	10.03	5.62	3.24	3.18	2.47	1.34	0.75	0.41	0.39	0.33	7.56	2.44
Carhart alphas											**11.59**	**3.30**

Table 4. Sentiment beta and firm characteristics: unconditional sentiment beta sort, 1975-2003

Every quarter average firm characteristics are matched to the last available Bayes-Stein estimate of sentiment beta (Sent.Beta) obtained from formula (1). The table reports the time-series averages of cross-sectional means. Idiosyn.sigma is the standard deviation of residuals in the regression of individual stock returns on Fama-French (1993) factors. Market/SMB/HML betas are the value-weighted averages of the corresponding betas of individual stocks. ROA is the return on assets. PIN is the probability of informed trading from Easley et al. (2002), SP500 is the probability of being an S&P 500 member, IO is the aggregate institutional ownership, Turnover is the volume by lagged shares outstanding, Age is the number of months since the stock's appearance on CRSP tapes, Past 6 Months Ret is the cumulative return over six months prior to the beginning of the quarter, "Short-Sales" is the proxy for short-sales constraints from Ali et al. (2003) and represents the probability that the loan fee for a stock is relatively high. All variables are winsorized at 1 and 99%. T-statistics were adjusted for serial correlation using Newey-West (1987) algorithm.

	Sent.Beta	Size (in '$mil)	Idiosyn. sigma	Market beta	SMB	HML	DivYield	Earnings ($Mil)	ROA
1	0.005	2,824	0.059	0.940	-0.214	0.118	0.043	251.30	0.061
2	0.007	1,904	0.075	1.019	-0.085	0.090	0.033	143.97	0.060
3	0.009	1,589	0.089	1.036	-0.017	0.050	0.027	105.70	0.058
4	0.010	1,158	0.104	1.033	0.050	0.052	0.023	73.53	0.055
5	0.011	956	0.119	1.068	0.096	-0.009	0.020	57.30	0.051
6	0.012	887	0.133	1.090	0.134	0.021	0.018	53.56	0.050
7	0.014	819	0.144	1.108	0.203	0.002	0.016	48.30	0.049
8	0.015	741	0.148	1.100	0.224	-0.051	0.016	45.87	0.048
9	0.017	630	0.144	1.090	0.260	-0.094	0.016	41.37	0.048
10	0.022	493	0.138	1.108	0.405	-0.080	0.014	31.66	0.048
1-10	-0.017	2,331	-0.079	-0.167	-0.619	0.198	0.029	219.6409	0.013
t-stat	-10.41	3.52	-8.35	-8.36	-6.28	2.23	11.29	7.28	6.97

	Assets Growth	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	Past 6 months return
1	0.100	4.06	0.177	0.291	0.288	0.039	225	0.005	0.084
2	0.107	3.87	0.191	0.239	0.300	0.050	209	0.011	0.088
3	0.112	3.56	0.200	0.192	0.284	0.058	196	0.019	0.092
4	0.116	3.01	0.206	0.153	0.259	0.064	184	0.029	0.096
5	0.121	2.64	0.212	0.127	0.237	0.067	174	0.040	0.105
6	0.126	2.44	0.214	0.115	0.220	0.070	169	0.049	0.106
7	0.144	2.25	0.215	0.103	0.210	0.072	166	0.050	0.115
8	0.138	2.16	0.218	0.097	0.202	0.072	165	0.054	0.119
9	0.133	2.23	0.222	0.093	0.206	0.075	164	0.055	0.116
10	0.147	2.38	0.224	0.081	0.207	0.074	163	0.060	0.114
1-10	-0.047	1.69	-0.047	0.210	0.081	-0.035	62	-0.054	-0.029

Table 5. Sentiment and firm characteristics: conditional sort on volatility-adjusted sentiment betas,

(definitions are the same as in table 4)

1975-2003

	Sent.Beta	Size (in '$mil)	Past sigma	Idiosyn. sima	B/M	Market beta	SMB	HML	DivYield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Tobin Q	Past 6 months return
2	0.009	1,270	0.136	0.116	0.956	1.042	0.001	0.059	0.022	82.46	0.045	0.063	0.052	1.548	0.105
3	0.010	1,171	0.139	0.120	0.953	1.045	0.022	0.063	0.021	76.31	0.046	0.061	0.051	1.576	0.106
4	0.011	1,067	0.140	0.121	0.959	1.037	0.050	0.078	0.021	67.15	0.044	0.059	0.052	1.557	0.105
5	0.012	1,077	0.140	0.121	0.959	1.043	0.050	0.015	0.020	64.32	0.043	0.061	0.052	1.572	0.105
6	0.013	1,064	0.139	0.120	0.970	1.054	0.067	0.020	0.020	68.96	0.043	0.058	0.053	1.549	0.102
7	0.015	1,020	0.137	0.118	0.981	1.039	0.102	-0.024	0.020	63.36	0.042	0.060	0.052	1.528	0.099
8	0.017	903	0.136	0.117	0.991	1.046	0.112	0.005	0.021	61.99	0.042	0.055	0.052	1.543	0.101
9	0.021	719	0.136	0.117	1.011	1.030	0.211	-0.076	0.020	48.71	0.043	0.054	0.051	1.580	0.097
2-9	-0.012	551	0.000	0.000	-0.055	0.012	-0.210	0.135	0.003	33.753	0.003	0.009	0.001	-0.033	0.009
t-stat	-8.87	2.32	0.12	-0.1	-6.11	0.44	-2.34	1.80	2.39	2.99	5.13	5.83	1.47	-0.56	1.77

	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
2	0.009	0.186	107.17	0.051	0.105	0.126	0.033	2.92	0.202	0.150	0.246	0.064	181.8	0.032	327
3	0.010	0.183	95.17	0.053	0.107	0.124	0.035	2.66	0.206	0.139	0.235	0.065	179.5	0.036	327
4	0.011	0.184	79.65	0.054	0.105	0.119	0.035	2.62	0.208	0.135	0.232	0.066	177.5	0.039	327
5	0.012	0.184	80.57	0.054	0.107	0.123	0.035	2.63	0.210	0.131	0.231	0.067	175.2	0.040	327
6	0.013	0.185	84.45	0.053	0.111	0.122	0.035	2.68	0.211	0.133	0.235	0.067	175.6	0.041	327
7	0.015	0.184	74.60	0.053	0.108	0.124	0.035	2.58	0.211	0.129	0.232	0.066	174.8	0.041	327
8	0.017	0.190	77.61	0.051	0.107	0.137	0.035	2.70	0.214	0.130	0.236	0.066	176.1	0.040	327
9	0.021	0.190	61.08	0.048	0.103	0.121	0.035	2.81	0.219	0.115	0.236	0.068	173.3	0.045	327
2-9	-0.012	-0.004	46.092	0.003	0.002	0.005	-0.002	0.115	-0.016	0.036	0.010	-0.003	8.432	-0.012	
t-stat	-8.87	-0.93	3.05	0.04	0.36	1.03	-1.17	0.61	-4.35	2.85	1.37	-1.00	2.20	-2.86	

1989-2003

	Sent. Beta	Size (in '$mil)	Past sigma	Idiosyn. sima	B/M	Market beta	SMB	HML	DivYield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Tobin Q	Past 6 months return
2	0.009	2,039	0.143	0.127	0.821	1.051	-0.073	0.046	0.014	111.90	0.024	0.071	0.046	1.815	0.090
3	0.010	1,857	0.149	0.133	0.824	1.056	-0.024	0.080	0.013	99.84	0.023	0.069	0.045	1.863	0.091
4	0.012	1,685	0.150	0.134	0.836	1.054	0.024	0.097	0.012	85.66	0.023	0.065	0.045	1.801	0.090
5	0.013	1,719	0.152	0.135	0.823	1.051	-0.014	-0.017	0.012	85.43	0.030	0.071	0.046	1.866	0.091
6	0.014	1,680	0.151	0.134	0.846	1.112	0.010	-0.006	0.011	87.61	0.027	0.065	0.046	1.813	0.083
7	0.016	1,610	0.148	0.132	0.856	1.057	0.057	-0.106	0.011	79.87	0.018	0.067	0.045	1.793	0.083
8	0.018	1,395	0.148	0.132	0.861	1.046	0.130	-0.013	0.011	77.70	0.020	0.063	0.046	1.828	0.085
9	0.024	1,060	0.149	0.133	0.876	1.036	0.235	-0.182	0.010	56.19	0.016	0.061	0.046	1.733	0.077
2-9	-0.015	979	-0.006	-0.006	-0.055	0.015	-0.308	0.228	0.004	55.709	0.008	0.010	0.000	0.082	0.014
t-stat	-11.11	3.89	-1.28	-1.29	-3.93	0.34	-2.55	3.42	5.94	4.19	2.46	4.00	-0.39	2.65	1.67

	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
2	0.009	0.176	144.46	0.071	0.105	0.135	0.040	4.05	0.196	0.135	0.293	0.085	203.3	0.038	367
3	0.010	0.172	121.88	0.074	0.106	0.135	0.042	3.69	0.200	0.119	0.281	0.087	199.6	0.043	367
4	0.012	0.173	96.68	0.076	0.106	0.124	0.043	3.63	0.202	0.111	0.276	0.089	196.4	0.048	367
5	0.013	0.172	105.28	0.076	0.107	0.130	0.043	3.60	0.205	0.106	0.276	0.090	191.5	0.049	367
6	0.014	0.174	103.94	0.076	0.108	0.131	0.043	3.71	0.205	0.109	0.281	0.091	192.0	0.049	367
7	0.016	0.172	89.75	0.077	0.109	0.132	0.043	3.51	0.207	0.101	0.277	0.088	190.0	0.052	367
8	0.018	0.182	96.24	0.073	0.106	0.160	0.043	3.68	0.212	0.097	0.282	0.089	191.1	0.048	367
9	0.024	0.179	69.27	0.069	0.104	0.124	0.043	3.84	0.217	0.081	0.286	0.094	186.4	0.055	367
2-9	-0.015	-0.003	75.194	-0.004	0.001	0.010	-0.003	0.215	-0.022	0.054	0.007	-0.009	16.983	-0.018	
t-stat	-11.11	-1.00	3.86	-0.72	0.11	1.38	-1.93	0.81	-8.44	3.43	0.88	-1.78	3.90	-4.92	

Table 6. Sentiment and firm characteristics: conditional sort (controlling for size and volatility)

Each quarter (from march 1975 till March 2004) firm characteristics are matched to the firm's last available Bayes-Stein estimate of sentiment beta. Then stocks are placed into 25 size groups based on their average market capitalization in a given quarter. Within each size group stocks are ranked into deciles conditional on their volatility-adjusted sentiment betas. After portfolio formation, the times series averages of the cross-sectional means are calculated. All variables are winsorized at 1% and 99% levels

1975-2003

	Sent. Beta	Size (in '$mil)	Past sigma	Idiosyn. sima	B/M	Market beta	SMB	HML	Div Yield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Tobin Q	Past 6 months return
1	0.006	1,199	0.134	0.115	1.018	0.970	-0.130	0.127	0.031	98.06	0.035	0.061	0.050	1.538	0.110
2	0.008	1,225	0.132	0.112	0.979	0.995	-0.066	0.073	0.025	85.85	0.029	0.059	0.051	1.489	0.099
3	0.009	1,200	0.136	0.116	0.962	1.024	-0.042	0.064	0.022	81.66	0.028	0.061	0.052	1.523	0.105
4	0.010	1,172	0.137	0.117	0.956	1.041	-0.009	0.072	0.022	80.44	0.027	0.061	0.052	1.564	0.105
5	0.011	1,213	0.137	0.118	0.943	1.040	0.000	0.093	0.022	81.29	0.029	0.061	0.053	1.559	0.105
6	0.012	1,167	0.137	0.118	0.951	1.032	0.016	0.051	0.021	75.21	0.028	0.061	0.053	1.569	0.106
7	0.013	1,160	0.136	0.117	0.957	1.054	0.011	0.023	0.021	76.36	0.031	0.059	0.053	1.532	0.101
8	0.015	1,206	0.134	0.115	0.966	1.037	0.014	-0.005	0.021	75.80	0.027	0.061	0.053	1.554	0.103
9	0.017	1,185	0.133	0.114	0.972	1.028	-0.004	-0.041	0.021	78.05	0.026	0.056	0.054	1.552	0.103
10	0.021	1,267	0.132	0.113	0.969	1.029	0.055	-0.076	0.020	80.47	0.024	0.056	0.054	1.626	0.100
1-10	-0.015	-68	0.002	0.002	0.049	-0.059	-0.185	0.203	0.010	17.60	0.011	0.005	-0.003	-0.089	0.010
t-stat	-10.91	-0.76	0.75	0.67	3.07	-2.10	-2.25	3.74	9.30	4.15	5.19	1.83	-2.46	-1.05	1.90

	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	0.183	133.80	0.048	0.096	0.129	0.030	2.290	0.203	0.133	0.220	0.049	189.77	0.022	315
2	0.008	0.183	113.75	0.051	0.095	0.116	0.032	2.647	0.204	0.148	0.238	0.057	185.07	0.024	328
3	0.009	0.184	104.99	0.051	0.105	0.119	0.034	2.785	0.204	0.149	0.241	0.063	182.04	0.032	326
4	0.010	0.185	101.97	0.053	0.108	0.120	0.034	2.825	0.204	0.149	0.241	0.065	180.73	0.034	329
5	0.011	0.184	101.53	0.054	0.108	0.123	0.034	2.834	0.203	0.151	0.240	0.067	180.51	0.039	331
6	0.012	0.184	93.69	0.054	0.108	0.121	0.034	2.837	0.206	0.148	0.239	0.067	178.94	0.038	323
7	0.013	0.186	95.85	0.053	0.109	0.124	0.034	2.937	0.205	0.149	0.242	0.067	178.95	0.038	326
8	0.015	0.186	90.38	0.053	0.111	0.127	0.034	2.936	0.205	0.153	0.245	0.066	179.21	0.039	329
9	0.017	0.190	98.82	0.051	0.106	0.137	0.033	3.018	0.207	0.153	0.249	0.067	179.88	0.037	325
10	0.021	0.189	103.48	0.048	0.110	0.126	0.034	3.454	0.207	0.158	0.256	0.071	179.56	0.042	339
1-10	-0.015	-0.01	30.31	0.00	-0.01	0.00	0.00	-1.16	0.00	-0.02	-0.04	-0.02	10.21	-0.02	-24.00
t-stat	-10.91	-0.76	5.00	0.04	-3.37	0.24	-3.94	-3.65	-1.64	-3.10	-3.06	-3.76	2.09	-2.46	

1989-2003

	Sent Beta	B/M	DivYield	Earnings ($Mil)	DivToEq	External Financing Activity	ROA	Cash flow ($Mil)	Sales growth	Sigma	Analysts	SP500	IO	Turnover	Age	Short Sales
1	0.006	0.903	0.022	122.29	0.033	0.071	0.044	133.80	0.091	0.034	3.080	0.114	0.258	0.064	216.86	0.027
2	0.008	0.853	0.017	109.00	0.025	0.066	0.045	113.75	0.093	0.037	3.545	0.127	0.280	0.075	208.76	0.028
3	0.009	0.838	0.014	107.70	0.023	0.067	0.045	104.99	0.102	0.038	3.726	0.126	0.282	0.083	203.00	0.038
4	0.010	0.830	0.014	104.67	0.023	0.066	0.046	101.97	0.103	0.039	3.803	0.126	0.286	0.087	200.27	0.040
5	0.011	0.813	0.014	106.21	0.028	0.070	0.046	101.53	0.109	0.039	3.870	0.128	0.285	0.091	199.87	0.047
6	0.013	0.816	0.013	96.79	0.025	0.070	0.046	93.69	0.109	0.039	3.831	0.122	0.284	0.089	196.35	0.046
7	0.014	0.837	0.013	97.89	0.030	0.065	0.046	95.85	0.107	0.039	3.992	0.126	0.290	0.090	196.91	0.047
8	0.016	0.841	0.012	95.63	0.023	0.068	0.046	90.38	0.112	0.039	4.033	0.129	0.292	0.089	196.26	0.049
9	0.018	0.836	0.012	98.75	0.021	0.063	0.048	98.82	0.106	0.039	4.158	0.127	0.299	0.090	197.06	0.045
10	0.023	0.825	0.011	104.25	0.019	0.063	0.049	103.48	0.109	0.039	4.866	0.133	0.312	0.099	194.93	0.052
1-10	-0.018	0.078	0.012	18.041	0.014	0.008	-0.005	30.314	-0.018	-0.005	-1.79	-0.019	-0.054	-0.035	21.94	-0.025
t-stat	-10.91	3.07	9.83	3.05	4.32	2.06	-6.13	5.00	-2.67	-7.88	-9.39	-1.99	-6.32	7.55	6.27	-2.57

Table 7. Analyst's forecast dispersion and sentiment beta

This table presents average coefficients of Fama-MacBeth regressions. In Panel A the dependent variable DISP is the dispersion of analysts' earnings forecasts in month t (its calculation is described in Appendix C). In Panel B the dependent variable is volatility-adjusted ($\beta_{sent.vol\_adj}$) and unadjusted (β_{sent}) sentiment beta. β_{sent} is sentiment beta estimated over five years preceding month t; $\beta_{sent.vol\_adj}$ is β_{sent} adjusted for volatility; $I_{\beta sent>0}$ and $I_{\beta sent.vol\_adj>0}$) are a dummy variables equal to 1 if β_{sent} and $\beta_{sent.vol\_adj}$ are positive respectively and 0 otherwise; "Volatility" is idiosyncratic volatility of monthly stock returns over five years preceding month t; NumEst is the number of analyst estimates used in estimation of earnings forecast dispersion in month t; Size is market capitalization of the stock in month t-1.

Panel A

	Dispersion (DISP)					
β_{sent}	**4.95**	**1.42**	**0.95**	**1.26**		
	(19.35)	**(7.64)**	**(5.38)**	**(5.56)**		
$\beta_{sent}*I_{\beta sent>0}$				-0.57		
				(-1.41)		
$\beta_{sent.vol\_adj}$					**0.69**	**1.25**
					(4.05)	**(4.52)**
$\beta_{sent.vol\_adj}*I_{\beta sent.vol\_adj>0}$						-1.05
						(-1.31)
Volatility		0.96	0.75	0.74		
		(7.89)	(7.68)	(7.37)		
NumEst			0.04	0.04	0.047	0.047
			(14.93)	(15.00)	(15.97)	(16.25)
Size			-0.027	-0.026	-0.04	-0.04
			(-17.00)	(-17.19)	(-18.48)	(-18.30)
R-sq	0.018	0.056	0.074	0.077	0.048	0.049
Average Nobs	1757	1757	1757	1757	1757	1757

Panel B

	$\beta_{sent.vol\_adj}$	$\beta_{sent.vol\_adj}$	$\beta_{sent.vol\_adj}$	β_{sent}	β_{sent}	β_{sent}	β_{sent}
DISP (x100)	**0.10**	**0.097**	**0.0611**	**0.38**	**0.11**	**0.11**	**0.0835**
	(3.38)	**(2.99)**	**(1.99)**	**(8.74)**	**(3.57)**	**(3.52)**	**(3.00)**
Numest (x100)		-0.023	0.031			-0.028	0.0346
		(-3.80)	(4.94)			(-3.69)	(6.33)
Size (x100)			-0.035				-0.045
			(-13.54)				(-14.37)
Volatility					0.049	0.048	0.044
					(5.51)	(5.47)	(5.47)
R-sq	0.002	0.005	0.01	0.016	0.19	0.2	0.21
Average Nobs	1847	1847	1847	1847	1847	1847	1847

Table 8. Sentiment sensitivity and institutional ownership

The table reports time-series averages from quarterly cross-sectional regressions of (log) aggregate institutions ownership on sentiment sensitivity (beta) and a set of controls. Sent. beta is the last available (prior to the first month of the quarter) log of Bayes-Stein estimate of sentiment sensitivity from formula (2), Ind is the dummy equal one if sentiment beta is positive, BM is the lagged (log) book-to-market ratio, Size is the (log) average market capitalization over the previous quarter, Volatility is the standard deviation of monthly excess returns over the last 5 years, Turnover is the average share turnover over the previous quarter, Price is the average (log) price over the previous quarter, SP500 is a dummy equal to 1 if the stock was a member of S&P 500 Index at the beginning of the quarter, Return is the compounded stock return over the previous quarter, Age is the (log) number of months since the month the stock appeared on CRPS tapes since Dec 1972, DivYield is the lagged (log) dividend yield, Nobs is the average number of cross-sectional observations. Model 8(9) includes only stocks with positive (negative) sentiment betas. Penny stocks (with price below $5) are excluded. All variables are winsorized at 1% and 99%. T-statistics of average Fama-MacBeth coefficients are Newey-West adjusted for serial correlation and reported in parentheses

1980-1989	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
								sent.beta>0	sent.beta<0
Sent. beta	**-0.838**	**-1.182**	**-1.376**	**-1.217**	**-1.227**		**-1.030**	**-1.530**	**-0.598**
	(-1.60)	**(-2.50)**	**(-2.41)**	**(-2.34)**	**(-2.52)**		**(-1.91)**	**(-5.63)**	**(-0.83)**
Ind*Sent.beta							-0.479		
							(-2.61)		
BM		0.002	-0.006	0.006	-0.003	-0.003	-0.005	-0.010	-0.006
		(0.76)	(-1.06)	(1.36)	(-0.56)	(-0.52)	(-0.88)	(-2.20)	(-0.64)
Size	0.039	0.037	0.033	0.023	0.018	0.018	0.018	0.017	0.021
	(35.25)	(34.76)	(28.95)	(20.87)	(10.55)	(10.32)	(10.97)	(7.19)	(9.93)
Volatility	-0.392	-0.520	-0.797	-0.561	-0.550	-0.598	-0.538	-0.587	-0.459
	(-3.32)	(-4.95)	(-5.66)	(-3.65)	(-3.55)	(-3.52)	(-4.14)	(-3.79)	(-4.13)
Turnover			0.251	0.232	0.229	0.227	0.223	0.238	0.230
			(5.95)	(4.87)	(4.83)	(4.43)	(4.14)	(6.05)	(3.37)
Price				0.043	0.043	0.044	0.043	0.043	0.041
				(15.8)	(17.79)	(16.24)	(17.39)	(18.3)	(10.18)
S&P500					0.023	0.023	0.023	0.023	0.018
					(3.98)	(3.88)	(4.07)	(5.19)	(1.75)
Past Return	-0.008	-0.006	-0.012	-0.029	-0.028	-0.028	-0.028	-0.022	-0.026
	(-1.16)	(-0.82)	(-1.51)	(-3.63)	(-3.53)	(-3.64)	(-3.58)	(-3.21)	(-2.57)
Age					0.005	0.006	0.005	-0.002	0.012
					(1.39)	(1.53)	(1.4)	(-0.51)	(2.81)
Dividend yield	-1.159	-1.360	-1.423	-1.320	-1.286	-1.296	-1.281	-0.900	-1.349
	(-15.88)	(-13.46)	(-21.55)	(-16.77)	(-13.82)	(-17.12)	(-13.86)	(-3.85)	(-20.14)
Nobs	2036	1761	1573	1573	1572	1576	1571	744	826
Adjusted R-sq	0.201	0.021	0.205	0.217	0.220	0.218	0.220	0.214	0.231

Table 8. Sentiment sensitivity and institutional ownership (continued): 1990-2003

1990-2003	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
								sent.beta>0	sent.beta<0
Sent. beta	**1.193**	**1.001**	**0.959**	**1.058**	**1.023**		**1.285**	**0.516**	**1.270**
	(4.26)	**(3.11)**	**(3.11)**	**(3.32)**	**(3.05)**		**(3.36)**	**(1.40)**	**(2.68)**
Ind*Sent.beta							-0.643		
							(-3.32)		
BM		0.032	0.037	0.054	0.051	0.053	0.050	0.019	0.087
		(4.10)	(4.34)	(6.24)	(4.04)	(4.41)	(4.05)	(0.86)	(8.36)
Size	0.040	0.041	0.037	0.023	0.025	0.025	0.025	0.022	0.029
	(21.84)	(24.37)	(37.31)	(8.44)	(4.68)	(4.84)	(4.81)	(3.31)	(8.81)
Volatility	-0.293	-0.360	-0.610	-0.364	-0.367	-0.337	-0.371	-0.438	-0.326
	(-2.16)	(-3.05)	(-5.30)	(-3.11)	(-3.05)	(-3.01)	(-3.23)	(-2.91)	(-3.44)
Turnover			0.207	0.172	0.184	0.180	0.181	0.167	0.211
			(9.95)	(8.79)	(7.56)	(7.15)	(7.18)	(8.63)	(7.46)
Price				0.058	0.056	0.056	0.056	0.053	0.056
				(12.93)	(11.05)	(11.38)	(10.8)	(22.59)	(7.08)
S&P500					-0.015	-0.016	-0.015	-0.004	-0.031
					(-1.40)	(-1.44)	(-1.44)	(-0.20)	(-3.09)
Past Return	0.000	0.000	-0.005	-0.020	-0.020	-0.020	-0.020	-0.018	-0.019
	(-0.02)	(0.04)	(-0.76)	(-3.09)	(-3.07)	(-3.07)	(-3.09)	(-2.18)	(-3.30)
Age					0.007	0.006	0.011	0.011	0.004
					(0.57)	(0.55)	(0.61)	(0.82)	(0.46)
Dividend yield	-1.85	-2.08	-2.04	-2.01	-1.98	-2.01	-1.98	-2.17	-1.69
	(-10.19)	(-10.35)	(-9.56)	(-9.52)	(-7.54)	(-7.65)	(-7.75)	(-6.9)	(-11.6)
Nobs	2222	1834	1834	1834	1833	1834	1832	908	923
Adjusted R-sq	0.163	0.154	0.169	0.183	0.187	0.187	0.187	0.195	0.186

Table 9. Sentiment beta and ownership by different types of institutions

The table reports the average Fama-MacBeth coefficients in the regression of institutional ownership by different types of institutional investors (as classified by Thomson Financial) on past sentiment sensitivity and a set of controls (definitions are in table 8).

	1980-1989					1990-2003				
	Banks	Insurance companies	Investment companies	Investment advisors	Other	Banks	Insurance companies	Investment companies	Investment advisors	Other
Ind*Sent. Beta	0.000	-0.088	-0.110	-0.408	0.022	-0.170	-0.170	-0.275	-0.371	-0.304
	(0.01)	(-2.88)	(-1.67)	(-7.32)	(0.42)	(-1.56)	(-1.65)	(-3.13)	(-1.86)	(-4.55)
Sent.beta	**-0.475**	**-0.053**	**-0.082**	**-0.319**	**-0.155**	**0.126**	**0.167**	**0.470**	**0.599**	**0.633**
	(-1.86)	**(-0.44)**	**(-0.86)**	**(-3.44)**	**(-1.62)**	**(0.83)**	**(1.77)**	**(2.65)**	**(1.75)**	**(3.34)**
BM	-0.016	-0.001	0.001	0.010	0.001	-0.015	0.007	0.014	0.031	0.027
	(-5.69)	(-0.93)	(0.48)	(1.83)	(0.78)	(-2.32)	(5.38)	(2.63)	(4.25)	(1.88)
Size	0.007	0.004	0.002	0.005	0.003	0.006	0.005	0.006	0.002	0.015
	(12.25)	(8.38)	(2.89)	(6.27)	(17.7)	(7.99)	(5.53)	(3.39)	(1.32)	(3.37)
Volatility	-0.314	-0.043	-0.077	-0.158	-0.026	-0.151	-0.024	0.001	-0.088	-0.125
	(-4.64)	(-1.91)	(-7.00)	(-2.96)	(-1.98)	(-3.98)	(-1.52)	(0.02)	(-1.01)	(-1.92)
Turnover	-0.039	0.025	0.053	0.244	-0.009	-0.002	0.016	0.064	0.148	0.055
	(-2.66)	(5.00)	(8.82)	(7.36)	(-0.77)	(-0.29)	(4.26)	(3.15)	(2.32)	(2.16)
Price	0.014	0.003	0.006	0.023	0.004	0.015	0.007	0.015	0.032	0.015
	(13.41)	(3.45)	(5.63)	(17.42)	(12.9)	(3.23)	(4.36)	(3.19)	(3.21)	(2.26)
SP&500	0.019	0.002	0.002	-0.006	0.014	0.020	-0.001	-0.006	-0.006	-0.006
	(15.81)	(0.87)	(1.62)	(-1.74)	(9.53)	(3.02)	(-1.70)	(-3.59)	(-2.59)	(-0.39)
Return	-0.004	-0.005	-0.003	-0.014	-0.007	-0.005	-0.004	0.003	-0.002	-0.015
	(-1.34)	(-3.90)	(-2.05)	(-3.56)	(-4.94)	(-2.90)	(-3.67)	(1.28)	(-0.42)	(-3.50)
Age	0.003	0.001	-0.001	0.003	0.002	0.009	0.004	0.001	0.005	-0.006
	(1.39)	(0.93)	(-1.89)	(1.76)	(1.54)	(2.67)	(2.21)	(0.45)	(1.37)	(-1.16)
Dividend yield	-0.360	-0.138	-0.152	-0.679	-0.131	-0.150	-0.248	-0.345	-1.107	-0.702
	(-11.00)	(-26.14)	(-9.77)	(-6.41)	(-24.68)	(-1.90)	(-4.18)	(-2.76)	(-3.09)	(-2.97)
Nobs	1570	1570	1570	1570	1570	1831	1831	1831	1831	1831
Adjusted R-sq	0.197	0.119	0.090	0.153	0.144	0.225	0.118	0.149	0.106	0.192

Table 10. Small/retail stock return spread and sentiment index

The dependent variables are in the top row (EW/VW stands for equal-weighted/value-weighted returns). The regressions are estimated from May 1965 till Dec 2003 for the small stock return spreads and from Apr 1980 till Dec 2003 for the retail stock return spreads. 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 follows. Within each non-zero institutional holdings decile portfolio and within the zero-institutional holdings portfolio, stocks are sorted by dollar trading volume. The retail stock return spread is the return of the portfolio long in the low-trading volume zero-institutional holding stocks and short in the high-trading volume high-institutional holding stock portfolio. ΔSENTINDEX is the principal component of the changes in eight sentiment proxies (SENT, 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 (2006). Δ(Michindex) is the change in the University of Michigan Consumer Confidence Index. "Market" is the value-weighted CRSP market return. Coefficients on ΔSENTINDEX, Δ BW measure and Δ(Michindex) are multiplied by 100. T-statistics are in the parentheses and adjusted for serial correlation using Newey-West (1987) standard errors with 3 lags.

	EW small stock		VW small stock		Value-weighted retail stock spread					
Constant	0.64	0.59	0.31	0.25	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
	(-2.44)	(-2.16)	(-1.21)	(-0.96)	(-12.79)	(-12.44)	(-11.8)	(-12.6)	(-12.17)	(-12.49)
Δ (SENTINDEX)	**1.19**		**1.17**		**0.40**	**0.50**			**0.64**	**0.55**
	(4.86)		**(5.29)**		**(1.84)**	**(2.18)**			**(3.39)**	**(2.87)**
Δ (BW measure)	0.46	1.00	0.20	0.74	0.21	0.23		0.38		
	(1.44)	(3.77)	(0.80)	(3.41)	(0.65)	(0.73)		(1.39)		
Market	-0.06	0.01	0.05	0.12	-0.41	-0.38	-0.35	-0.39	-0.38	-0.41
	(-0.84)	(0.18)	(0.78)	(1.74)	(-6.62)	(-6.5)	(-5.85)	(-6.41)	(-6.51)	(-6.64)
Δ (Michindex)	0.21	0.22	0.17	0.18	0.20			0.21		0.20
	(2.48)	(2.38)	(2.23)	(2.15)	(4.12)			(4.19)		(4.23)
Adj. R-square	0.12	0.06	0.12	0.05	0.23	0.19	0.16	0.18	0.19	0.22
Nobs	458	458	458	458	279	279	285	279	285	285

Table 11. Sentiment measure and aggregate monthly market returns (1965 –2003)

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 (2006). Δ(Michindex) is the change in the University of Michigan Consumer Confidence Index. DivYield is the aggregate value-weighted dividend yield. T-statistics are in the parentheses and adjusted for serial correlation using Newey-West (1987) standard errors with 3 lags.

	Lead CRSP value-weighted returns (t+1)					
Constant	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(-1.01)	(-1.01)	(-0.95)	(-0.95)	(-0.93)	(-1.05)
Δ (SENT measure)			**-0.004**	**-0.004**	**-0.004**	**-0.004**
			(-2.19)	**(-2.04)**	**(-2.03)**	**(-1.89)**
Market t	0.050	0.050	0.020	0.020	0.020	0.020
	(-0.96)	(-1.00)	(-0.40)	(-0.45)	(-0.44)	(-0.43)
Market t-1	-0.060	-0.060	0.050	0.050	0.050	0.040
	(-1.37)	(-1.16)	(-0.78)	(-0.75)	(-0.73)	(-0.55)
Market t-2	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.08)	(-0.08)	(-0.11)	(-0.12)	(-0.13)	(-0.13)
Market t-3	-0.030	-0.040	-0.060	-0.060	-0.060	-0.050
	(-0.75)	(-0.79)	(-1.16)	(-1.17)	(-1.16)	(-1.18)
Term spreads (t)	0.210	0.190	0.210	0.190	0.190	0.200
	(-1.24)	(-1.11)	(-1.25)	(-1.13)	(-1.11)	(-1.18)
Credit spreads (t)	1.090	1.090	1.010	1.020	1.020	1.010
	(-2.13)	(-2.13)	(-1.98)	(-1.98)	(-1.98)	(-2.06)
Δ(BW measure)		-0.001		-0.001	-0.001	-0.001
		(-0.73)		(-0.36)	(-0.37)	(-0.29)
Δ (MichIndex)					0.001	
					(-0.05)	
Divyield(t)						0.001
						(-0.34)
Adjusted R-squared	0.010	0.009	0.018	0.016	0.014	0.013
Nobs	461	456	460	455	455	457

Table 12. Economic significance

"diff" raw reports the difference between the average values (value-weighted for market and HML betas) of the selected characteristic in bottom (1) and top (10) portfolios formed on the basis of Bayes-Stein sentiment beta, conditional on size and volatility. "average" raw reports the average value of characteristic within the sample period. "diff/average" is a fraction that the difference constitutes in the average value of the characteristic (i.e., ratio of "diff" raw to "average" raw). Book-to-market, tobin Q, sales growth and dividend yields are winsorized at 1% and 99% levels.

1975-2003

	MRKT beta	HML beta	B/M	DivYield	Earnings ($Mil)	DivToEq	ROA	Tobin Q	Cash flow ($Mil)
diff	-0.059	0.203	0.049	0.010	17.60	0.011	-0.003	-0.09	30.31
average	1.019	0.033	0.965	0.023	81.95	0.024	0.067	1.45	78.792
diff/average	**5.79%**		**5.08%**	**44.45%**	**21.47%**	**45.26%**	**5.11%**	**6.10%**	**38.47%**

	Sales growth	Future quarterly volatility	Analysts	PIN	SP500	IO	Turnover	Age	Short sales
diff	-0.013	-0.004	-1.16	-0.003	-0.02	-0.036	-0.021	10.21	-0.019
average	0.105	0.033	2.86	0.204	0.149	0.298	0.061	181.4	0.031
diff/average	**12.50%**	**11.76%**	**40.69%**	**1.60%**	**16.64%**	**12.10%**	**34.86%**	**5.63%**	**62.75%**

1989-2003

	MRKT beta	HML beta	B/M	DivYield	Earnings ($Mil)	DivToEq	ROA	Tobin Q	Cash flow ($Mil)
diff	-0.063	0.292	0.078	0.012	18.04	0.014	-0.005	-0.073	33.24
average	1.032	0.014	0.838	0.014	103.90	0.025	0.046	1.79	130.57
diff/average	**6.10%**		**9.28%**	**82.26%**	**17.36%**	**54.41%**	**11.85%**	**4.09%**	**25.46%**

	Sales growth	Future quarterly volatility	Analysts	SP500	IO	Turnover	Age	Past Idiosyn. sigma	Short sales
diff	-0.018	-0.005	-1.79	-0.019	-0.054	-0.035	21.94	0.001	-0.025
average	0.104	0.040	3.93	0.126	0.287	0.086	200.97	0.013	0.042
diff/average	**16.93%**	**12.93%**	**45.54%**	**15.12%**	**18.98%**	**40.16%**	**10.92%**	**6.51%**	**58.95%**

Figure 1a. Sentiment Proxies

Average monthly values of 8 raw (not orthogonalized) sentiment proxies: Investors Intelligence Index, Closed-end Fund Discount, Net Fund Flow into equity mutual funds, level of aggregate margin borrowing (de-trended by its 5-year moving average), dividend premium, number of IPOs, average first day IPO returns and ratio of specialist short-selling to total shortselling.

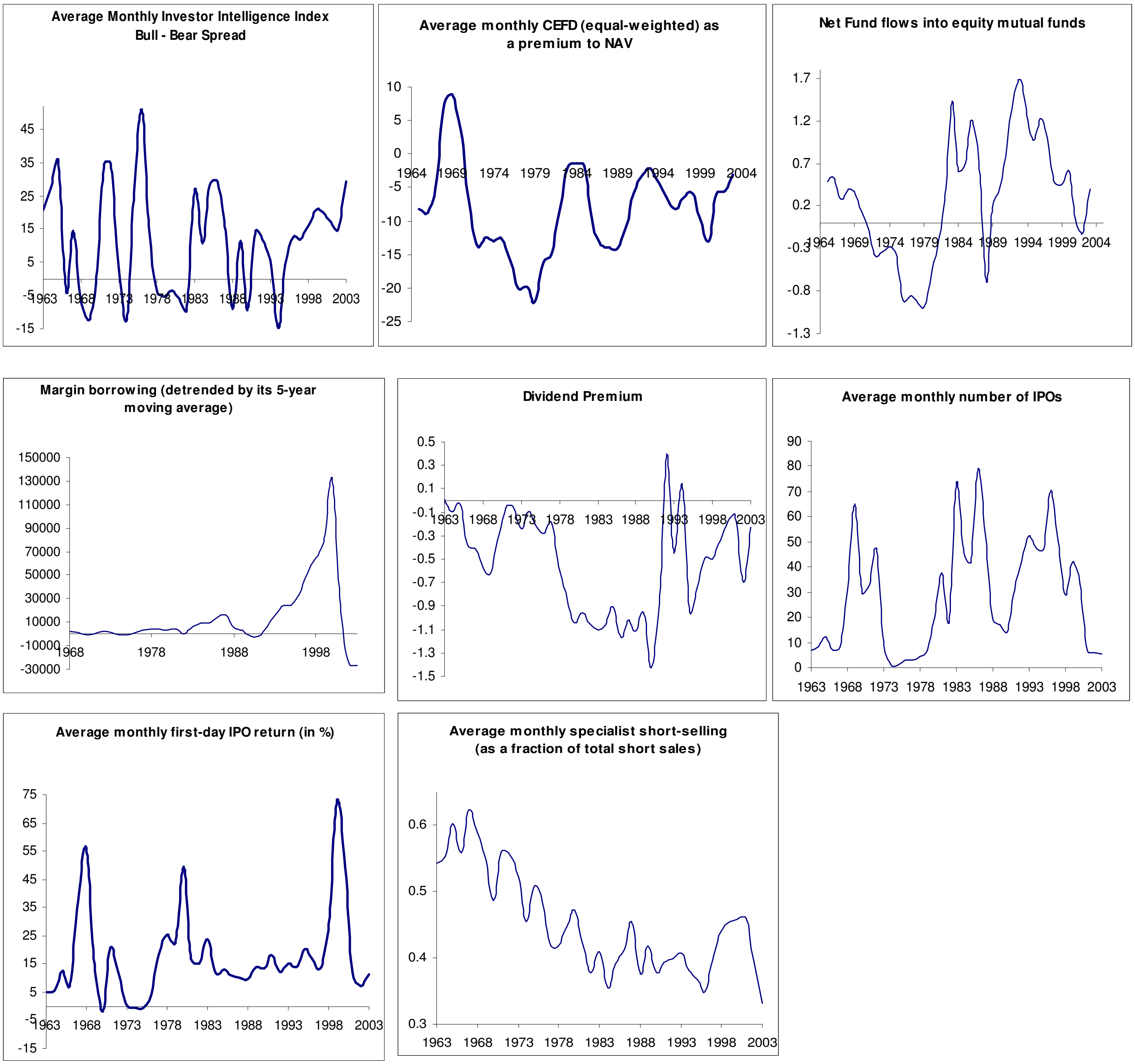
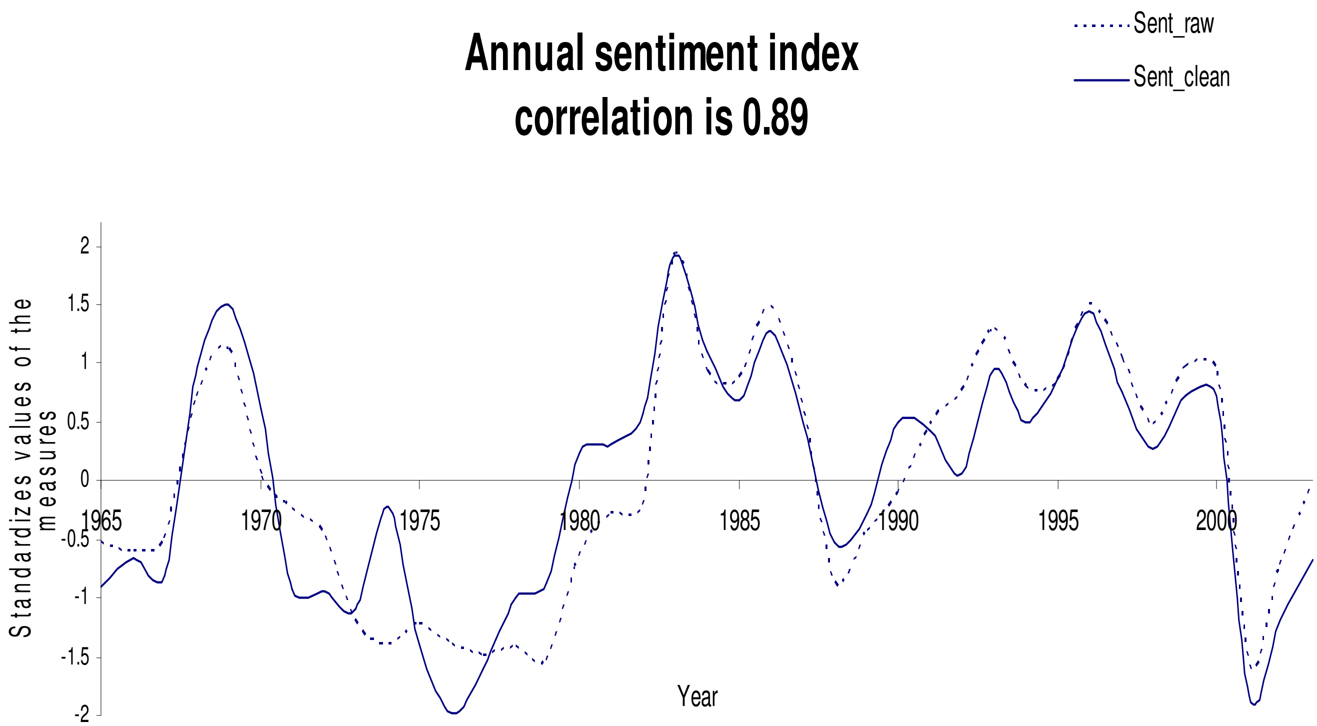


Figure 1b. Annual and monthly sentiment index.

Index obtained as the first principal component of eight sentiment proxies from figure 1. Sent_raw represents the raw index, not orthogonalized with respect to macro variables. Sent_clean is the index net of macro conditions. Both measures are standardized to have mean 0, std 1. Macro variables are innovations in growth of industrial production, durables and non-durables consumption, services, employment, NBER recession dummy, term and credit spreads



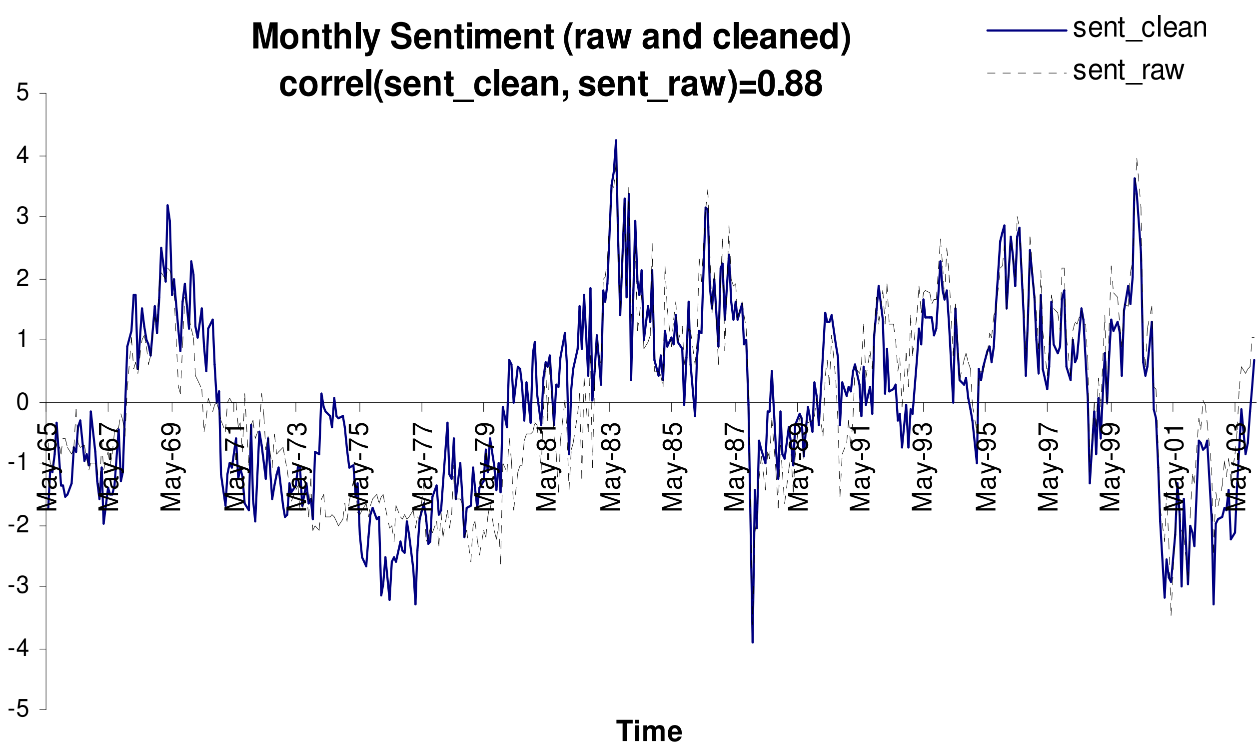


Figure 2a. The empirical distribution of sentiment betas from model (1)

Regression (1) is run every 3 months using 60 months rolling window from March 1970 till Dec 2003. Sentiment betas for each stock are averaged over 116 overlapping time intervals. The figure represents the empirical cross-sectional distribution of the time-series averages

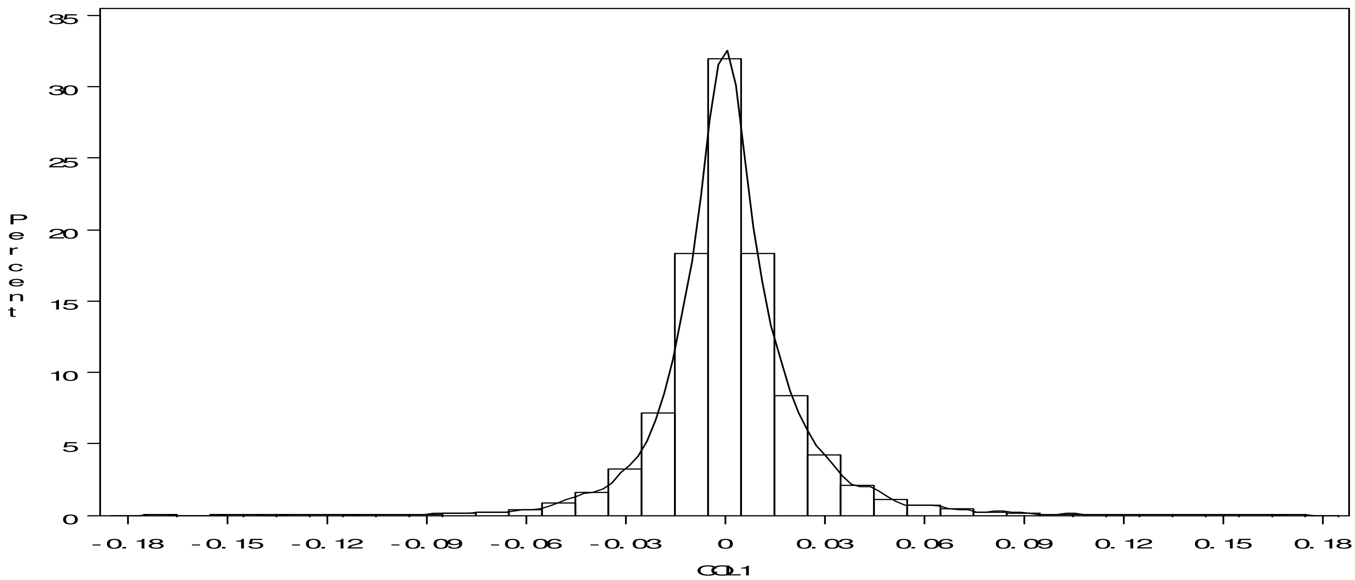


Figure 2b. Empirical distribution of “shrunk” Bayes-Stein estimates of sentiment betas

Regression (1) is run using 60 months window rolled every quarter from March 1970 to Dec 2003. Obtained sentiment betas are “shrunk” using Bayes-Stein procedure. For each stock the “shrunk” estimates are averaged out over 116 overlapping estimation periods. The figure represents the empirical cross-sectional distribution of the time-series averages

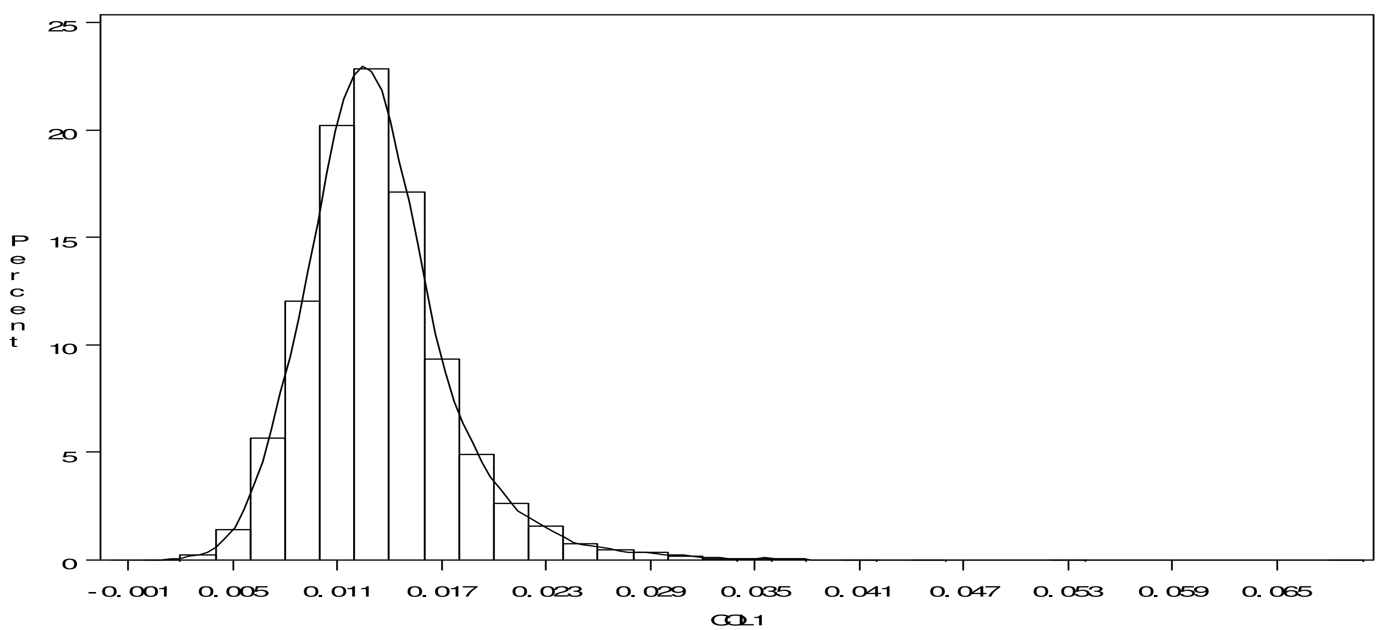


Figure 3. Sentiment beta and Institutional Ownership

The table presents the time-series of Fama-MacBeth coefficients in the cross-sectional regressions of aggregate institutional ownership on sentiment sensitivities and a set of controls (see model 4) from March 1980 till Dec 2003, where *both* dependent and all independent variables in the model 4 were standardized to mean 0 and standard deviation 1 to make coefficients comparable over time.

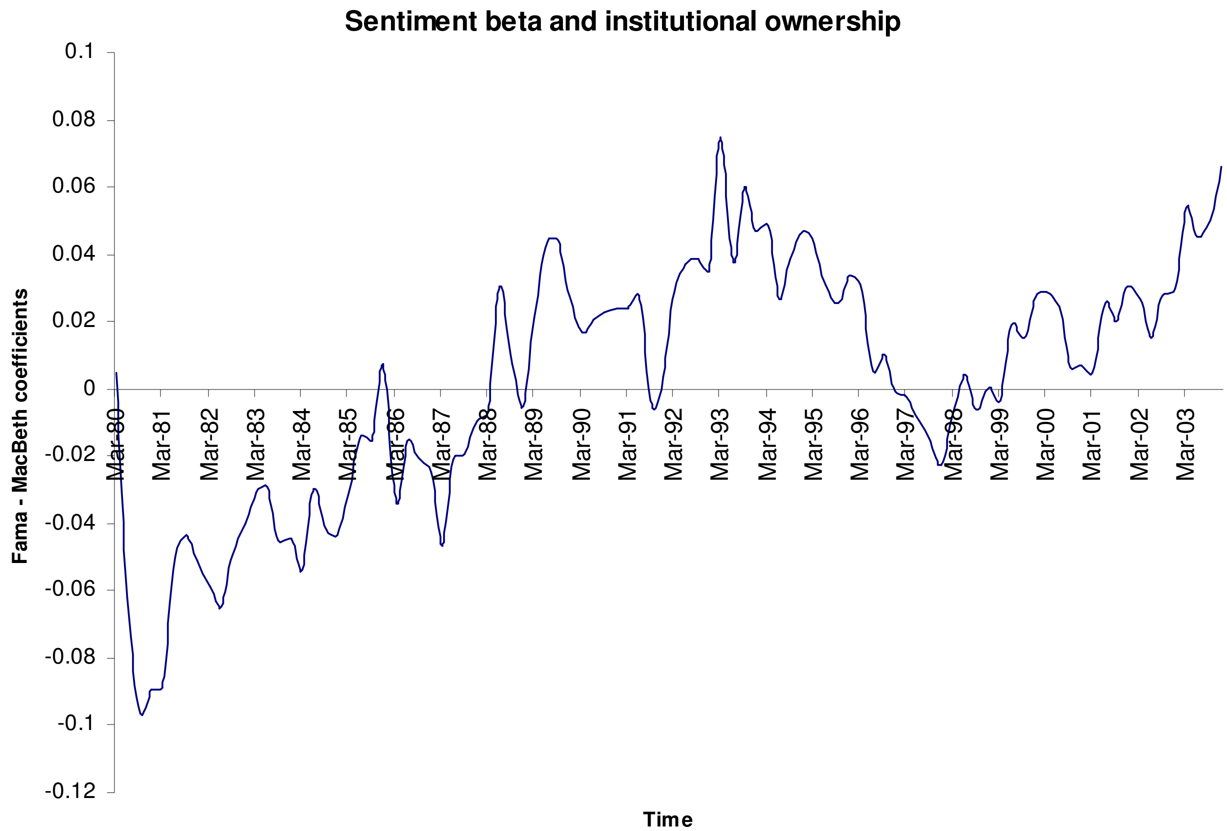


Figure 4. Annual SENTINDEX, Baker&Wurgler measure vs University of Michigan Index (UMCCI)

SENTINDEX is the principal component of eight sentiment proxies in figure 1 net of macro variables (innovations in growth of industrial production, consumer durables and non-durables, services, employment; recession dummy, term and credit spreads). Baker and Wurgler (2006) is a sf2 measure (the first principal component of closed-end fund discount, dividend premium, equity share of new issues, detrended NYSE turnover, average first-day IPO returns and number of IPOs) from Wurgler's website. Umich is the University of Michigan Consumer Confidence Index. All measures are standardized to have mean 0 and standard deviation 1.