Sentiment beta

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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 several related hypotheses. First hypothesis postulates that sentiment affects stocks of some firms more than others mainly due to differences in firm characteristics. Second hypothesis predicts that sentiment is a priced factor, i.e., stocks with greater exposure to sentiment earn higher returns. 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. However, after accounting for size and volatility, stocks with more extreme values of sentiment beta tend to have more of an analyst following, greater institutional ownership and investors' disagreement, a higher likelihood of S&P500 membership, higher turnover and lower book-to-market ratios. The relationship between sentiment beta and returns has an inverse U-shape: stocks with extreme values of sentiment beta earn lower future returns relative to their near-zero sentiment beta counterparts. This is inconsistent with the risk factor interpretation of investor sentiment.

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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.

Recent work by Baker and Wurgler (BW, 2006) provides indirect evidence that investor sentiment is an important determinant of stock returns. Specifically, they extend characteristics-based approach of Daniel and Titman (1997) and find 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. If returns of stocks with certain characteristics tend to exhibit these sentiment-conditional patterns and BW's result is robust to the use of various methodologies, then we should expect that certain firm characteristics also affect the degree of stock returns comovement with investor sentiment after accounting for other factors shown to explain returns.

First, motivated by this idea, 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, not only should 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 exhibit sentiment-conditional patterns documented in BW, but also are predicted to comove with sentiment changes more because such characteristics make these stocks hard to value and difficult to arbitrage. Alternatively, classic finance theory postulates that investor sentiment has no systematic impact on the valuation process and asset prices regardless of firm characteristics, i.e., there is no systematic link between firm characteristics and the degree of stock comovement with sentiment.

If firm characteristics play an important role in explaining how investor sentiment affects returns, the next logical step is to see whether the exposure to sentiment is a priced factor. BW do not directly focus on this question. Therefore, the second goal of the paper is to test the hypothesis that the exposure of stocks to shifts in investor sentiment is priced in the cross-section, i.e., whether, on average, investors demand premium for holding stocks that are more exposed to investor sentiment. To address this question, the paper adopts a firm-level factor model approach. The advantage of using this method is twofold. Firstly, it is well rooted in theory on the subject as it directly comes out as an implication of the "noise trade theory" proposed by De Long et al. (1990) whose main prediction is that, in equilibrium, "noise traders" trading on sentiment demand compensation for bearing the risk they themselves create. Secondly, the factor approach makes it straightforward to apply the well-known two-step procedure (a-la Fama-MacBeth) to test whether sentiment is a priced factor. If the exposure to sentiment factor (estimated in the first step) is priced, we should observe that portfolios with higher sentiment betas should earn higher future returns and lower sentiment beta stocks should earn low returns (second step of the procedure).

To explore the predictions of these hypotheses, this study utilizes the following empirical design. First, it develops an aggregate measure of investor sentiment (sentiment factor) constructed as the first principal component of several investor sentiment measures. 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 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.

To mitigate the possibility that the sentiment factor may represent an active economic factor, all sentiment measures are orthogonalized with respect to several variables that may be correlated with fundamentals. 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 BW measure and UMich Consumer Confidence Index (UMCCI) do not predict aggregate market returns. The constructed 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. I also demonstrate that this sentiment proxy has an incremental explanatory power for time-series of individual stock returns (as much as Pastor and Stambaugh (2003) liquidity factor).

Using the constructed sentiment beta measure, I perform unconditional and conditional sorts on sentiment sensitivity and several control characteristics 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 valuations of small stocks.

To alleviate the concern that the relationship between sentiment beta and firm characteristics is confounded by variation of size and volatility across sentiment beta deciles, I explicitly control for these characteristics in conditional sorts. Results of these sorts suggest that more sentiment sensitive stocks tend to be younger growth stocks that have higher total and idiosyncratic volatility, higher turnover, lower dividend yields, greater short-sales constraints and lower book-to-market ratios[1]. Most of the differences are both statistically and economically significant. For example, the difference between average dividend yields of least extreme vs. most extreme 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.

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 preceding five years. 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.

However, there are also intriguing results which run counter to the predictions of HV-DA story. After controlling for differences in size and volatility, most extreme 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. Nor does empirical evidence support the result of BW that broad waves of sentiment influence unprofitable stocks more than profitable stocks once effects of size and volatility are accounted for. In fact, during 1989-2003 stocks with higher sentiment sensitivities appeared to be more profitable relative to their least extreme

[1] 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.

sentiment beta counterparts in terms of their return on assets (on average, by about 0.5% on the annual basis).

I then proceed to test whether more sentiment sensitive stocks earn higher returns. I find that the relationship between sentiment beta and stock returns has an inverse U-shape. Stocks with greater exposure to investor sentiment (regardless of the sign of this exposure) tend to underperform stocks with low (near-zero) exposure. Investors will fare better in the future by holding the portfolio of stocks with near-zero loadings on the sentiment factor: a zero-cost long-short equal-weighted portfolio that is long in near-zero sentiment beta stocks and short in extreme (both most positive and most negative) sentiment beta stocks produces higher raw and risk-adjusted excess returns (27 bp and 38 bp per month respectively). The result is qualitatively similar in sub-periods and robust to the horizons over which returns are measured: over a year horizon near-zero sentiment beta portfolio continues to deliver cumulative risk-adjusted returns that are 250 basis points higher than returns of extreme sentiment beta portfolio. This evidence is inconsistent with the risk-factor interpretation of investor sentiment which implies a linear relationship between sentiment beta and stock returns, but appears to be in line with the findings of Ang et al. (2006) who find that stocks with high idiosyncratic volatility relative to Fama and French (1993) model (as I show later, these stocks tend to have extreme sentiment betas) have abysmally low average returns. Tests also show 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.

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 the exposure to these changes is related to stock returns. The closest in spirit to this paper is Baker and Wurgler (2006). 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[2].

Second, in contrast to BW, sentiment in this paper is treated not as a conditioning variable in the characteristics-based model of returns, 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 in greater detail the relationship between institutional ownership and sentiment.

[2]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 (2006) 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), notably, 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 the 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. This study reveals several new findings not documented in BW: a) such characteristics as 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 and Brown and Cliff (2005)) predominantly used proxies based on a single time series such as closed-end fund discounts, equity share of new issues or survey measures, which captured different dimensions of variation in unobserved sentiment factor[3]. To proxy for sentiment at the individual stock level, literature used buy-and-sell imbalance (Kumar and Lee (2006), Barber et al. (2006), 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 literature: 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 describes the data, the methodology of constructing the sentiment index and details of sentiment beta estimation. Section 2 contains empirical results, analysis and interpretation. Robustness checks and measure validation results are presented in Section 3. Economic significance and discussion are the topics of Section 4. The last section concludes the paper.

1. Data and methodology

Stock returns, market capitalization and turnover are from the CRSP Monthly Stocks Combined File, which includes NYSE, AMEX, and NASDAQ stocks. Throughout, ADRs, REITs, closed-end funds, and primes and scores are excluded– that is, stocks that do not have a CRSP share type code of 10 or 11. Volatility is computed using daily CRSP files. Firm characteristics are from CRPS/Compustat Merged

[3]For aggregate sentiment measures see: CEF discounts - 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)

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.

1.1. Sentiment measures and index construction

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:

1. SENT - Investors Intelligence Index (Siegel, 1992; Brown and Cliff, 2005). This is a survey-based measure which reflects the outlook of over 100 independent financial market newsletter writers and has been compiled since 1964. Following Brown and Cliff (2005), I use the difference between bulls and bears ("bull-bear" spread) as a direct measure of sentiment.

2. DIVPREM - the dividend premium (Baker and Wurgler, 2004; Bulan et al.,2004). It is defined as 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. 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-paying firms and, hence, DIVPREM is low.

3. CEFD - the closed-end fund discount (Lee et al.,1991). CEFD for any given fund is defined as the equal-weighted average difference between the market price and the NAV of closed-end stock fund shares. Previous research argued that the fluctuations in the discount of these funds reflect the changing sentiment of retail, less sophisticated investors who are more prone to sentiment.

4. MARGIN - aggregate market level and ΔMARGIN - the percent change in margin borrowing (Brown and Cliff, 2005). 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.

5. SPECIAL - the ratio of specialists' short sales to total short sales (Brown and Cliff, 2005). Specialists tend to be considered as better informed and more sophisticated investors, so when their short-selling activity is relatively large, the market is believed to be more likely to decline.

6. FUNDFLOW - the net new cash flows of US equity mutual funds (Warther, 1995; Neal and Wheatley, 1998; Indro, 2004). Mutual fund flows are a logical place to look for indicators of unsophisticated investor sentiment as most of mutual fund investors are generally considered to be the least informed investors in the market because they delegate their investment management to fund managers.

7-8. IPON – the number of IPOs in a given month and IPORETS - average monthly first-day returns on IPOs (Baker and Wurgler, 2000; Dorn, 2003). IPO activity is often associated with market tops and is considered as a measure of sentiment because of information asymmetries between managers and investors[4].

Table 1 presents the summary statistics and the contemporaneous monthly correlations between the sentiment measures and business cycle variables (in levels) between April 1965 and Dec 2003. Figures 1a plots all eight proxies at the annual frequency over the same time period. 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.

Following the methodology outlined in Baker and Wurgler (2006), I proceed to construct a single index of investor sentiment as the first principal component of these eight measures. In addition to orthogonalizing sentiment proxies with respect to macro variables used in BW, I add term and credit spreads as well as the returns of the long-short factor-mimicking portfolio which is constructed to have the highest exposure to the fluctuations in aggregate consumption growth as control macro-related variables. The statistical procedure yields the first principal component which explains 29% of the total variation in changes and 37% of variation in levels[5]:

$$\Delta SENTINDEX(t)=0.45\Delta SENT(t-1)-0.16\Delta DIVPREM(t)+0.17\Delta CEFD(t-1)+0.55\Delta MARGIN(t)+$$
$$+0.26\Delta SPECIAL(t-1)-0.32\Delta FUNDFLOW(t)+0.42\Delta IPORETS(t-1)+0.30\Delta IPON(t).$$

The correlation between raw and orthogonalized SENTINDEX is 0.88 and between raw and "net of fundamentals" ΔSENTINDEX is 0.95 (see figure 1b). This suggests that macroeconomic risk factors are of secondary importance in influencing time variation in sentiment measures. Signs and timing are generally as expected and consistent with the evidence provided in BW: positive changes in sentiment are associated with positive changes in specialist short-selling, more active IPO market and an increase in the margin borrowing. Notably, the negative sign on the fund flow variable indicates that fund flow data

[4] I would like to thank Meir Statman for generously providing data on Investor Intelligence Index and Ivo Welch for providing data on CEFDs. Margin debt and Specialist short-selling are from Pinnacle Data Corp http://www.pinnacledata.com/. FUNDFLOW is from Investment Company Institute (international funds are excluded). IPO–related variables are from Jay Ritter's website. DIVPREM is constructed as in BW (2004).

[5] To address 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.

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.

For the purpose of estimating sentiment betas ΔSENTINDEX is constructed repeatedly over five-year rolling windows. This estimation yields 136 time-series. The loadings on II Index, CEFD, IPO and FUNDLOW are relatively stable over time, whereas the loadings on the specialist short-selling and dividend premium vary over time. The time-series loadings (averaged across 136 estimation periods) of the first principal component on inputs are 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 over the entire estimation period with the exception of the specialist short sales. This suggests a generally robust covariance structure among all sentiment index components over time. Now armed with the proxy for sentiment factor, I proceed to estimate sentiment proxy at the individual stock level: the sentiment beta.

1.2. Estimation of sentiment betas

One of the empirical implications of the theory outlined in appendix A is that the relative proportion of sentiment traders can be proxied by the regression coefficient of individual stock returns on changes in sentiment. In this sense, the 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, as the reader will see later, sentiment betas should not be interpreted in the same manner as in Shefrin and Statman, because sentiment factor is not returns-based.

Sentiment beta estimation methodology is based on the following model:

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

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

where ΔSENTINDEX is constructed over the same five years in which returns are measured to avoid look-ahead bias, 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 (mean=0, std=1) sentiment factor proxy. Following Fama and French (1993), the model (1) is estimated using a five-year window rolled forward every 3 months to obtain sentiment beta estimate $\beta_{SENT,i}$ for individual stocks. To mitigate the impact of the estimation error on the precision of point estimates which arises from the use of noisy individual stock returns, I use Bayes-Stein "shrinkage" approach to improve statistical precision of sentiment beta estimates (details are in the appendix B)[6].

The correlations of sentiment factor (in levels and changes) with the other factors used in model (1) suggest that multi-collinearity is not a serious issue in sentiment beta estimation:

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

Correlations over the entire time period (464 months)					
	Δ SENTINDEX	SMB	HML	MARKET	LIQUIDITY
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

2. Empirical Results

2.1. 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., more extreme values of 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 and sentiment exposure.

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 with decile 1 containing stocks with least extreme values of sentiment beta and decile 10 consisting of stocks with most extreme sentiment betas. Results are in the table 2. The 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

[6] For instance, Chan et al. (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.

as the average sentiment factor exposure rises from the lowest to the highest. The decreasing trend is observed for earnings, dividend yields and age, and an increasing trend for short-sales constraints, asset growth and share turnover.

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. For instance, unreported tests suggest that for positive sentiment beta stocks the average (median) size of most positive sentiment beta portfolio is around 11 (13) times smaller than that of its near-zero sentiment beta counterpart. The same ratio for stocks with the lowest negative sentiment betas vs stocks with near-zero sentiment betas is just 3.5:1 for the mean and 4.5:1 for the median size. 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 size.

In summary, the main takeaway from this unconditional analysis is that small stocks are more sensitive to changes in investor sentiment than large stocks. 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.

2.2. 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 sensitivities of small stocks' returns to 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 3 reports the results of conditional sorts on volatility-adjusted sentiment betas excluding extreme portfolios 1 and 10 to mitigate the influence of outliers[7]. Results demonstrate 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.

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,

[7] 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.

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 4 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; 2) they also are more likely to be more volatile and have higher turnover[8].

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 least and most extreme 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 the relation between sentiment beta and growth/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. This result is, however, 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.

More sentiment-sensitive stocks have lower dividend yields, ceteris paribus. They monotonically fall from 3.1% to 2 as we move from decile 1 to decile 10. The difference of about 1% is economically significant by any conventional standards as it constitutes around 45% of the average dividend yield of 2.3% during 1975-2003 and around 80% of the average dividend yield of 1.4% during 1989-2003. Sales growth exhibits an upward trend as we move from decile 1 to decile 10, with sales growth being reliably higher among stocks with more extreme values of sentiment beta. In contrast to Baker and Wurgler

[8] 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 (2006).

(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.

Several findings are seemingly counter to the predictions of HV-DA and deserve closer attention. Unconditional sorts in table 2 show that analyst coverage, S&P membership and institutional ownership (IO) display a decreasing trend as sentiment beta increases. However, this is mainly driven by the negative relationship between size and extremity of sentiment beta. Conditional sorts in table 4 which control for size and past volatility reveal a novel result: for two portfolios in the same "size-volatility" group a portfolio of stocks with more extreme sentiment betas tends to have greater analyst coverage than the one with near-zero sentiment beta. The difference in analyst 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, "in spotlight" stocks during the 90s or it is also possible that stocks attracted attention of sentiment traders exactly because there were widely covered and talked about 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%[9]. This result seems to run counter to the conventional wisdom that stocks more prone to shifts in sentiment are primarily held by retail investors. To investigate this finding further and to control for other characteristics which were shown to affect institutional ownership (Gompers et al, 2001) I also performed multivariate analysis. Unreported tests show that throughout the 80's institutions indeed avoided exposure to more-sentiment sensitive stocks, however, in the 90's they appear to have changed their behavior by shifting their preferences towards stocks with higher sentiment risk as indicated by the positive loading of institutional ownership on absolute value of sentiment beta during that sample period.

To uncover the "sentiment beta-IO" relationship better, 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)[10]. Unreported tests show that the coefficient on sentiment beta

[9] 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.

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

for banks and investment advisors is more negative than for other types of institutions during 80's, suggesting that these types of institutions tended to be more conservative in their investments during the 80's.

In the 90's, however, I find that all types of institutions shifted their preferences, but in different degrees: less conservative investment companies (mutual funds) and other (unclassified) institutional investors such as endowments tilted their portfolios towards more extreme sentiment beta stocks compared to banks, insurance and independent investment advisors. Note that this 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: institutional investors (especially, mutual funds) seem to have been seeking exposure to particular type of return volatility - volatility associated with fluctuations in investor sentiment.

Finally, in order to avoid loss of information stemming from the use of absolute sentiment betas, 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. In unreported tests I find that stocks with positive sentiment beta stocks 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 some of these differences 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.

2.3. Sentiment beta and investors' disagreement

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 the fact that certain stock characteristics make 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 has valid grounds, we should expect that stocks with greater disagreement will, on average, have higher sensitivity to investor sentiment.

Building on the existing "differences-of-opinion" literature (e.g., Diether et al. 2002) I use analysts' earnings forecast dispersion as a proxy for investors' disagreement about the stock value. Table 5 reports time-series average of Fama-MacBeth coefficients in predictive regressions of next period forecast

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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) dispersion on current sentiment beta (Panel A) and next period sentiment beta on the current forecast dispersion (Panel B). More sentiment-sensitive stocks appear to have greater dispersion of analysts' forecasts with causality running both ways. In summary, this analysis shows that sentiment beta is a reliable predictor of analyst forecast dispersion reflecting the degree of investors' differences of opinion above and beyond such fundamental characteristics as size and volatility.

2.4. Sentiment beta and future returns

Recent work by Baker and Wurgler (2006) provides strong indirect evidence that investor sentiment is an important determinant of stock returns. Specifically, BW extend characteristics-based approach of Daniel and Titman (1997) and find 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. However, their approach does not allow one to directly test whether exposure of stocks to shifts in investor sentiment is priced in the cross-section, i.e., whether investors, on average, demand premium for holding stocks that exhibit greater degree of comovement with sentiment. Firm-level factor model approach adopted in this paper enables me to address this question. If the exposure to sentiment factor is priced, we should observe that portfolios with higher sentiment betas should earn higher average returns in the future and lower sentiment beta stocks should earn low returns.

To test this prediction, each month I match excess returns to the last available sentiment betas stock-by-stock and form equal-weighted quintile portfolios on the basis of sentiment betas. The tables 6a and 6b show the cumulative excess returns of these portfolios as well as returns of zero-net investment portfolio which is long stocks with the lowest sentiment sensitivity (near-zero betas) and short stocks with the highest sentiment sensitivity (most extreme sentiment betas).

The key result is that the relationship between sentiment beta and returns is inverse U-shaped, i.e., stocks with extreme values of sentiment betas (most positive and most negative) tend to underperform stocks which have near-zero loadings on sentiment index. Investors lose money by holding more sentiment-sensitive stocks. This finding is inconsistent with the risk factor interpretation of investor sentiment which implies a linear relationship between sentiment beta and stock returns. I find that there is no significant difference between returns of stocks with the lowest and highest sentiment beta, but both of these portfolios underperform near-zero sentiment beta portfolio.

For example, from the table 6a 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). This suggests that even though the strategy of buying least extreme sentiment beta and shorting most extreme 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 which includes momentum factor. The reason for this is that the zero-cost portfolio 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)[11]. Figure 2 demonstrates that underperformance of stocks with extreme values of sentiment beta is not driven by occasional outliers: the difference between moving 12-month geometrically compounded returns of near-zero sentiment beta stocks and stocks with extreme sentiment betas tends to be consistently above zero, on average, with the exception of the period of 1999-2000 when sentiment-sensitive stocks outperformed their lower sentiment-sensitive counterparts by around 15% per year. This is consistent with the anecdotal evidence regarding the performance of "hot" stocks during that period.

Further analysis shows that underperformance of stocks with high sentiment factor exposure is mainly attributable to low future returns of stocks that tend to covary *positively* with sentiment changes. "Stocks with positive sent.betas" section of table 6a 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 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 extreme sentiment beta stocks versus their near-zero sentiment beta counterparts is robust in sub-periods and whether size-adjusted or market-adjusted returns are used. For additional robustness, I excluded small stocks below 20% NYSE/AMEX breakpoints and computed cumulative returns over longer time horizons. Results are qualitatively similar. Results in table 6b 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. Table 7 demonstrates that the relationship between sentiment beta and stock returns is not driven by the loadings on lagged market returns: stocks with extreme values of sentiment beta continue to exhibit lower future returns even though there is no significant difference in the average lagged market betas of portfolios with extreme and near-zero sentiment betas.

[11] This zero-investment 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.

In summary, the "sentiment beta – future returns" analysis provides evidence inconsistent with the risk factor interpretation of investor sentiment as the relationship between loadings on sentiment factor and returns is not linear, but rather has an inverse U-shape. 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. I provide several potential explanations for this result in "Economic significance and discussion" section.

3. Robustness checks and measure validation

I perform robustness checks along two dimensions: the validation of a) sentiment index and b) sentiment beta measure. Figure 3 presents SENTINDEX plotted alongside the BW measure and the University of Michigan Consumer Confidence Index (UMCCI). My measure has higher (and statistically significant) correlations with UMCCI, whereas BW measure is not related to UMCCI index by any conventional statistical standards. Furthermore, unreported results suggest that ΔSENTINDEX helps contemporaneously explain the variation in the small and retail stock return spreads, whereas ΔBW (the measure of sentiment used in Baker and Wurgler (2006)) does not, once both measures are included simultaneously. Adjusted R-squared in the regression where small stock return spread is a dependent variable doubles from 6% to 12% when 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. The fact that sentiment factor is able to explain time-series variation of these return spreads is a favorable feature of any sentiment measure because many financial anomalies were found to be more pronounced in smaller stocks with higher individual ownership. I also find that ΔSENTINDEX has predictive power for the market-wide returns: the inclusion of ΔSENTINDEX increases adjusted R-square of the predictive regression by 0.8%, which is economically significant given that the overall R-squared in predicting market returns is around 1.8%.

To address the concern that estimation error in sentiment beta drives the results, several checks are performed. First, 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 likely to be due to the differences in stock returns sensitivities to *sentiment* changes, not to estimation error issues.

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%.

Finally, 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 and sales growth exhibit similar trends from the lowest to the highest sentiment beta decile portfolio. In addition, these robustness checks confirm the finding that given size and volatility, profitable stocks are just as likely to be affected by swings in investor sentiment as unprofitable ones.

4. 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 8. 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 sentiment-sensitive stocks became more pronounced 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.

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[12], 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.

Besides, 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-cut pattern 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. 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

[12] 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.

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)[13]. 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?

The inverse U-shaped relationship between sentiment beta and returns remains to be more explored in order to be better understood. At this point, I offer but do not explicitly test a potential (albeit, speculative) explanation for this finding which hinges on the "short-sales constraints" argument. Tests demonstrate that it is not the sign of sentiment beta but rather its absolute magnitude is what matters for future returns: stocks with more extreme values of sentiment sensitivities tend to have lower future returns. It is reasonable to conjecture that prices of these types of stocks (with extreme degrees of comovement with investor sentiment) are more likely to be pushed further away from fundamental values and potentially remain mispriced for relatively longer periods of time compared to their near-zero sentiment beta counterparts. As a result of this sentiment-driven mispricing, future price revisions will lead to negative returns for overpriced stocks and positive returns for underpriced stocks. However, the price correction for underpriced stocks is more likely to occur sooner and to be smaller in magnitude relative to that of overpriced stocks due the short-sales constraints investors are facing in the latter case. The net effect is that, on average, more extreme sentiment beta stocks earn lower returns, consistent with the results in the paper.

5. Conclusions

Recent work Baker and Wurgler (2006) provides indirect evidence that investor sentiment is an important determinant of stock returns. In this paper I subject their findings to further scrutiny by developing and validating a novel measure of sentiment at the individual stock level which I call sentiment beta. This is done in three steps. First, I construct the sentiment index as the first principal component of several sentiment proxies and, second, by using firm-level factor model approach I estimate sentiment beta stock-by-stock as a sensitivity of stock returns to a composite sentiment index constructed in the first step. Third, using this measure I test two related hypotheses. The first hypothesis which I call "Hard-to-Value, Difficult-to-Arbitrage" (HV-DA) hypothesis postulates that investor sentiment affects

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

stocks of some firms more than others due to the differences in firm characteristics. The second hypothesis posits that stocks with higher sentiment sensitivities earn higher average returns.

Unconditionally, my primary findings are that 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, more extreme sentiment beta stocks tend to be younger, have higher subsequent turnover, volatility and sales growth, lower dividend yields and book-to-market ratios which is consistent with the predictions of HV-DA. However, counter to HV-DA story, stocks with extreme sentiment betas tend to have more of an 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 most and least extreme sentiment beta stocks are both statistically significant and economically important. This evidence suggests that firm characteristics play an important role in how sentiment affects stock returns. Evidence with respect to second hypothesis is intriguing: the relationship between sentiment beta and returns turns out to be inverse U-shaped. Specifically, 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. Existence of short-sales constraints may offer a potential explanation for why extreme sentiment beta stocks experience lower returns.

These findings are potentially important for investors' portfolio allocation because it may help them understand in a) which types of stocks sentiment effects are most pronounced (if any), b) which firm characteristics play a determining role in how large the effects and c) what the potential implications for portfolio performance could be. 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.

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 sentiment beta.

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*)[14].

- $z_t^{i,h}$ 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

[14] 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.

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.[15]

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[16] 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:

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

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

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

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

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

[16] See Kaniel et al. (2006) and Jackson (2005).

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

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. Bayes-Stein shrinkage of sentiment beta estimates

In the first stage of shrinkage procedure, sentiments betas are estimated separately for each stock using the traditional rolling OLS regression approach (model (1)). The 5-year period monthly regressions are run for each stock that has no fewer than 58 months of successive returns history and Bayesian updating is performed each quarter. Parameters of prior distribution are determined 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:

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

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

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, 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), 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 negative original sentiment betas allegedly indicate that contrarian sentiment traders, who tend to sell when sentiment goes up and vice versa, are affecting stock prices relatively more than momentum sentiment traders, who tend to 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. 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 model 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, 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 of potential loss of information from using absolute values, I also perform tests without resorting to the concept of unsigned sentiment betas.

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Table 1. Monthly correlations between different sentiment proxies and macroeconomic variables

SENT- bull minus bear spread of Investor Intelligence Index, DivPrem - dividend premium, Cefd Vw - value-weighted average closed-end fund discount, Cefd Ew - equal-weighted average closed-end fund discount, Margin - level of margin borrowing de-trended 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 - average first-day IPO return, IPON - number of IPOs, 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. All variables are from April 1965 till December 2003, except for ES which goes to Jun 2003.

			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*** **	

Table 2. 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	219.64093	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
t-stat	-2.52	3.21	-9.33	10.99	6.39	-3.00	4.26	-3.80	-1.65

Table 3. Sentiment and firm characteristics: conditional sort on volatility-adjusted sentiment betas

(definitions are the same as in table 2)

1975-2003

	Sent.Beta	Size (in '$mil)	Idiosyn. sima	Market beta	SMB	HML	DivYield	Earnings ($Mil)	ROA
2	0.009	1,270	0.116	1.042	0.001	0.059	0.022	82.46	0.052
3	0.010	1,171	0.120	1.045	0.022	0.063	0.021	76.31	0.051
4	0.011	1,067	0.121	1.037	0.050	0.078	0.021	67.15	0.052
5	0.012	1,077	0.121	1.043	0.050	0.015	0.020	64.32	0.052
6	0.013	1,064	0.120	1.054	0.067	0.020	0.020	68.96	0.053
7	0.015	1,020	0.118	1.039	0.102	-0.024	0.020	63.36	0.052
8	0.017	903	0.117	1.046	0.112	0.005	0.021	61.99	0.052
9	0.021	719	0.117	1.030	0.211	-0.076	0.020	48.71	0.051
2-9	-0.012	551	0.000	0.012	-0.210	0.135	0.003	33.753	0.001
t-stat	-8.87	2.32	-0.1	0.44	-2.34	1.80	2.39	2.99	1.47

	Assets Growth	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	Average N
2	0.126	2.92	0.202	0.150	0.246	0.064	181.8	0.032	327
3	0.124	2.66	0.206	0.139	0.235	0.065	179.5	0.036	327
4	0.119	2.62	0.208	0.135	0.232	0.066	177.5	0.039	327
5	0.123	2.63	0.210	0.131	0.231	0.067	175.2	0.040	327
6	0.122	2.68	0.211	0.133	0.235	0.067	175.6	0.041	327
7	0.124	2.58	0.211	0.129	0.232	0.066	174.8	0.041	327
8	0.137	2.70	0.214	0.130	0.236	0.066	176.1	0.040	327
9	0.121	2.81	0.219	0.115	0.236	0.068	173.3	0.045	327
2-9	0.005	0.115	-0.016	0.036	0.010	-0.003	8.432	-0.012	
t-stat	1.03	0.61	-4.35	2.85	1.37	-1.00	2.20	-2.86	

1989-2003

	Sent. Beta	Size (in '$mil)	Idiosyn. sima	Market beta	SMB	HML	DivYield	Earnings ($Mil)	ROA
2	0.009	2,039	0.127	1.051	-0.073	0.046	0.014	111.90	0.046
3	0.010	1,857	0.133	1.056	-0.024	0.080	0.013	99.84	0.045
4	0.012	1,685	0.134	1.054	0.024	0.097	0.012	85.66	0.045
5	0.013	1,719	0.135	1.051	-0.014	-0.017	0.012	85.43	0.046
6	0.014	1,680	0.134	1.112	0.010	-0.006	0.011	87.61	0.046
7	0.016	1,610	0.132	1.057	0.057	-0.106	0.011	79.87	0.045
8	0.018	1,395	0.132	1.046	0.130	-0.013	0.011	77.70	0.046
9	0.024	1,060	0.133	1.036	0.235	-0.182	0.010	56.19	0.046
2-9	-0.015	979	-0.006	0.015	-0.308	0.228	0.004	55.709	0.000
t-stat	-11.11	3.89	-1.29	0.34	-2.55	3.42	5.94	4.19	-0.39

	Assets Growth	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	Average N
2	0.135	4.05	0.196	0.135	0.293	0.085	203.3	0.038	367
3	0.135	3.69	0.200	0.119	0.281	0.087	199.6	0.043	367
4	0.124	3.63	0.202	0.111	0.276	0.089	196.4	0.048	367
5	0.130	3.60	0.205	0.106	0.276	0.090	191.5	0.049	367
6	0.131	3.71	0.205	0.109	0.281	0.091	192.0	0.049	367
7	0.132	3.51	0.207	0.101	0.277	0.088	190.0	0.052	367
8	0.160	3.68	0.212	0.097	0.282	0.089	191.1	0.048	367
9	0.124	3.84	0.217	0.081	0.286	0.094	186.4	0.055	367
2-9	0.010	0.215	-0.022	0.054	0.007	-0.009	16.983	-0.018	
t-stat	1.38	0.81	-8.44	3.43	0.88	-1.78	3.90	-4.92	

Table 4. 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	B/M	Market beta	SMB	HML	Div Yield	Earnings ($Mil)	ROA	Past 6 months return
1	0.006	1.018	0.970	-0.130	0.127	0.031	98.06	0.050	0.110
2	0.008	0.979	0.995	-0.066	0.073	0.025	85.85	0.051	0.099
3	0.009	0.962	1.024	-0.042	0.064	0.022	81.66	0.052	0.105
4	0.010	0.956	1.041	-0.009	0.072	0.022	80.44	0.052	0.105
5	0.011	0.943	1.040	0.000	0.093	0.022	81.29	0.053	0.105
6	0.012	0.951	1.032	0.016	0.051	0.021	75.21	0.053	0.106
7	0.013	0.957	1.054	0.011	0.023	0.021	76.36	0.053	0.101
8	0.015	0.966	1.037	0.014	-0.005	0.021	75.80	0.053	0.103
9	0.017	0.972	1.028	-0.004	-0.041	0.021	78.05	0.054	0.103
10	0.021	0.969	1.029	0.055	-0.076	0.020	80.47	0.054	0.100
1-10	-0.015	0.049	-0.059	-0.185	0.203	0.010	17.60	-0.003	0.010
t-stat	-10.91	3.07	-2.10	-2.25	3.74	9.30	4.15	-2.46	1.90

	Sales growth	Analysts	PIN	SP500	IO	Turnover	Age	Short Sales	Average number of firms
1	0.096	2.290	0.203	0.133	0.220	0.049	189.77	0.022	315
2	0.095	2.647	0.204	0.148	0.238	0.057	185.07	0.024	328
3	0.105	2.785	0.204	0.149	0.241	0.063	182.04	0.032	326
4	0.108	2.825	0.204	0.149	0.241	0.065	180.73	0.034	329
5	0.108	2.834	0.203	0.151	0.240	0.067	180.51	0.039	331
6	0.108	2.837	0.206	0.148	0.239	0.067	178.94	0.038	323
7	0.109	2.937	0.205	0.149	0.242	0.067	178.95	0.038	326
8	0.111	2.936	0.205	0.153	0.245	0.066	179.21	0.039	329
9	0.106	3.018	0.207	0.153	0.249	0.067	179.88	0.037	325
10	0.110	3.454	0.207	0.158	0.256	0.071	179.56	0.042	339
1-10	-0.01	-1.16	0.00	-0.02	-0.04	-0.02	10.21	-0.02	-24.00
t-stat	-3.37	-3.65	-1.64	-3.10	-3.06	-3.76	2.09	-2.46	

1989-2003

	Sent Beta	B/M	DivYield	Analysts	SP500	IO	Turnover	Age	Short Sales
1	0.006	0.903	0.022	3.080	0.114	0.258	0.064	216.86	0.027
2	0.008	0.853	0.017	3.545	0.127	0.280	0.075	208.76	0.028
3	0.009	0.838	0.014	3.726	0.126	0.282	0.083	203.00	0.038
4	0.010	0.830	0.014	3.803	0.126	0.286	0.087	200.27	0.040
5	0.011	0.813	0.014	3.870	0.128	0.285	0.091	199.87	0.047
6	0.013	0.816	0.013	3.831	0.122	0.284	0.089	196.35	0.046
7	0.014	0.837	0.013	3.992	0.126	0.290	0.090	196.91	0.047
8	0.016	0.841	0.012	4.033	0.129	0.292	0.089	196.26	0.049
9	0.018	0.836	0.012	4.158	0.127	0.299	0.090	197.06	0.045
10	0.023	0.825	0.011	4.866	0.133	0.312	0.099	194.93	0.052
1-10	-0.018	0.078	0.012	-1.79	-0.019	-0.054	-0.035	21.94	-0.025
t-stat	-10.91	3.07	9.83	-9.39	-1.99	-6.32	7.55	6.27	-2.57

Table 5. 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. 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)					
Size			-0.04 (-18.48)	-0.04 (-18.30)	-0.027 (-17.00)	-0.026 (-17.19)
NumEst			0.047 (15.97)	0.047 (16.25)	0.04 (14.93)	0.04 (15.00)
Volatility		0.96 (7.89)			0.75 (7.68)	0.74 (7.37)
β_{sent}	4.95 (19.35)	1.42 (7.64)			0.95 (5.38)	1.26 (5.56)
$\beta_{sent}*I_{\beta sent>0}$						-0.57 (-1.41)
$\beta_{sent.vol\_adj}$			0.69 (4.05)	1.25 (4.52)		
$\beta_{sent.vol\_adj}*I_{\beta sent.vol\_adj>0}$				-1.05 (-1.31)		
R-sq	0.018	0.056	0.048	0.049	0.074	0.077
Average Nobs	1,757	1,757	1,757	1,757	1,757	1,757

Panel B

	$\beta_{sent.vol\_adj}$	$\beta_{sent.vol\_adj}$	$\beta_{sent.vol\_adj}$	β_{sent}	β_{sent}	β_{sent}
DISP (x100)	0.10 (3.38)	0.097 (2.99)	0.0611 (1.99)	0.38 (8.74)	0.11 (3.52)	0.0835 (3.00)
Volatility					0.048 (5.47)	0.044 (5.47)
Numest (x100)		-0.023 (-3.80)	0.031 (4.94)		-0.028 (-3.69)	0.0346 (6.33)
Size (x100)			-0.035 (-13.54)			-0.045 (-14.37)
R-sq	0.002	0.005	0.01	0.016	0.2	0.21
Average Nobs	1,847	1,847	1,847	1,847	1,847	1,847

Table 6a. Sentiment Sensitivity and Stock Returns: Short Horizons

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. 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					Diff	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**

Table 6a (cont'd). Sentiment Sensitivity and Stock Returns: Short Horizons

Every month individual excess stock returns are matched to the last available signed 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. "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					Diff	T-stat
	1	2	3	4	5	1	2	3	4	5	1-5	
						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 6b. Sentiment Sensitivity and Stock Returns: Longer Horizons

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					Diff	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 7. Sentiment Beta and Stock Returns Controlling for Lagged Market Betas

Every month individual excess stock returns are matched to the last available signed sentiment beta and then five equal-weighted portfolios are formed on the basis of dependent double sort on a) lagged market betas and then on b) sentiment beta. In the upper (lower) part of the table 1 is the portfolio of stocks with the lowest positive (largest negative) and 5 is the portfolio of stocks with the highest positive (lowest negative) values of sentiment beta. T-stats on portfolio returns are adjusted for serial correlation and reported in parentheses. The raw 1-5 contains raw returns, four-factor risk-adjusted alpha and loadings (on market, SMB, HML, and Momentum factors) of the portfolio that buys portfolio 1 and (short) sells portfolio 5.

Positive Sentiment Beta vs Near-Zero Sentiment Beta Portfolio

Sentiment Beta Quintile	EW returns	Bayes-Stein Sentiment Beta	Sentiment beta	Size ($ Mil.)	Lagged market beta (mean)	Lagged market beta (median)	Alpha	Market	SMB	HML	Momentum	# of firms
1	0.847%	0.007	0.003	1,096	0.222	0.214	0.17% (1.94)	0.880	0.480	0.390	-0.150	318
2	0.741%	0.010	0.008	855	0.234	0.233	0.01% (0.11)	0.960	0.630	0.360	-0.180	319
3	0.744%	0.012	0.013	652	0.231	0.229	-0.004% (-0.03)	1.020	0.780	0.310	-0.210	317
4	0.638%	0.014	0.019	516	0.223	0.219	-0.135% (-1.07)	1.020	0.890	0.290	-0.210	315
5	0.570%	0.019	0.030	372	0.223	0.219	-0.19% (-1.49)	1.020	0.970	0.220	-0.210	319
1-5	0.28% (1.77)						0.36% (3.78)	-0.135 (-4.59)	-0.49 (-12.70)	0.17 (2.61)	0.06 (1.70)	

Negative Sentiment Beta vs Near-Zero Sentiment Beta Portfolio

Sentiment Beta Quintile	EW returns	Bayes-Stein Sentiment Beta	Sentiment beta	Size ($ Mil.)	Lagged market beta (mean)	Lagged market beta (median)	Alpha	Market	SMB	HML	Momentum	# of firms
1	0.869%	0.007	-0.003	1,278	-0.134	-0.138	0.12% (1.74)	0.890	0.400	0.410	-0.060	306
2	0.858%	0.010	-0.007	908	-0.134	-0.140	0.023% (0.32)	0.970	0.620	0.410	-0.080	307
3	0.784%	0.012	-0.011	743	-0.126	-0.139	-0.1% (-0.92)	1.000	0.790	0.410	-0.130	306
4	0.706%	0.014	-0.018	661	-0.124	-0.133	-0.216% (-2.39)	1.060	0.830	0.480	-0.110	304
5	0.736%	0.018	-0.029	528	-0.139	-0.147	-0.22% (-2.23)	1.040	0.950	0.410	-0.100	308
1-5	0.13% (0.88)						0.34 % (3.71)	-0.15 (-5.59)	-0.55 (-11.68)	-0.001 (-0.17)	0.04 (1.69)	

Table 8. 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, 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 annual 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 the ratio of specialist short-selling to total short-selling.

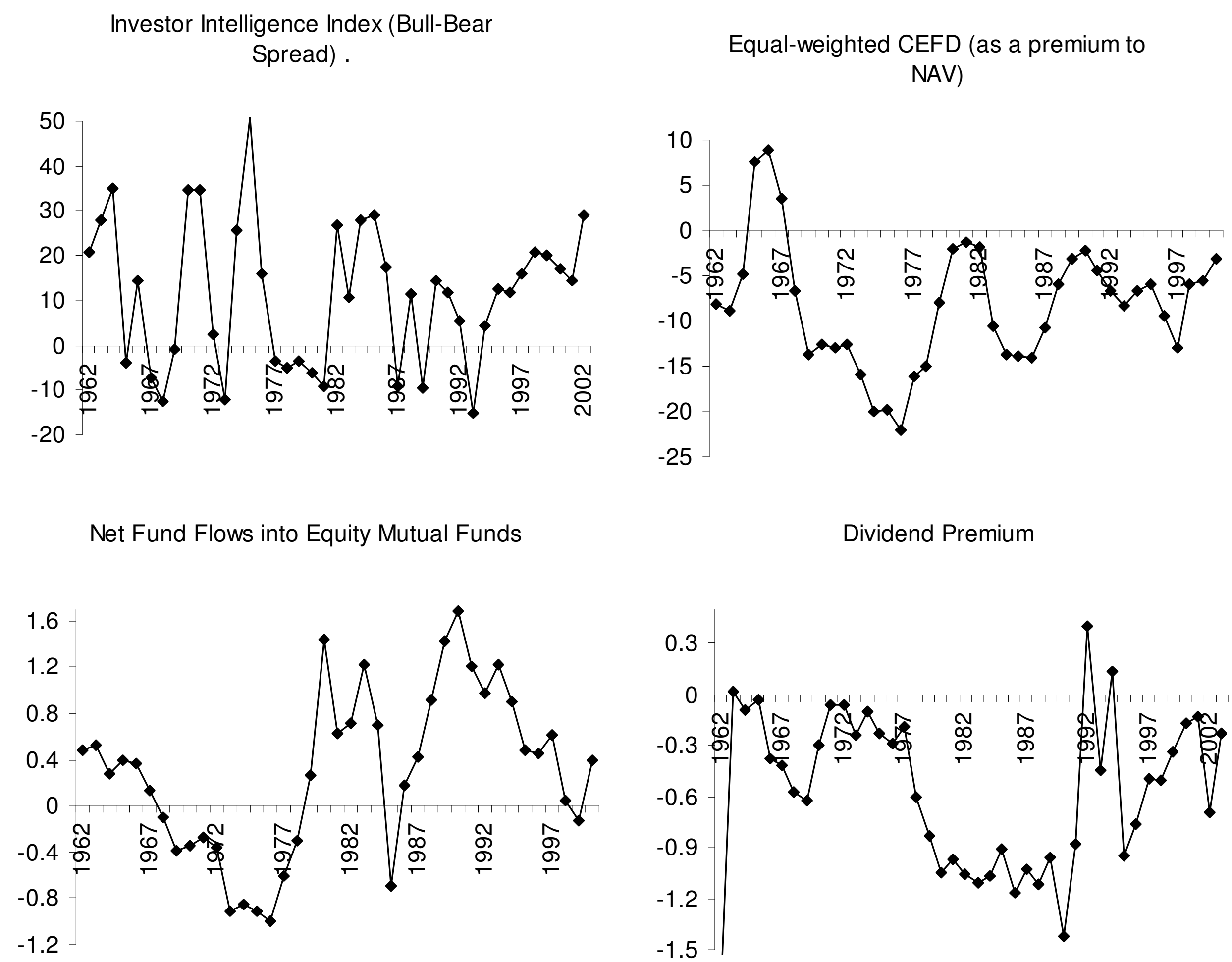


Figure 1a (continued)

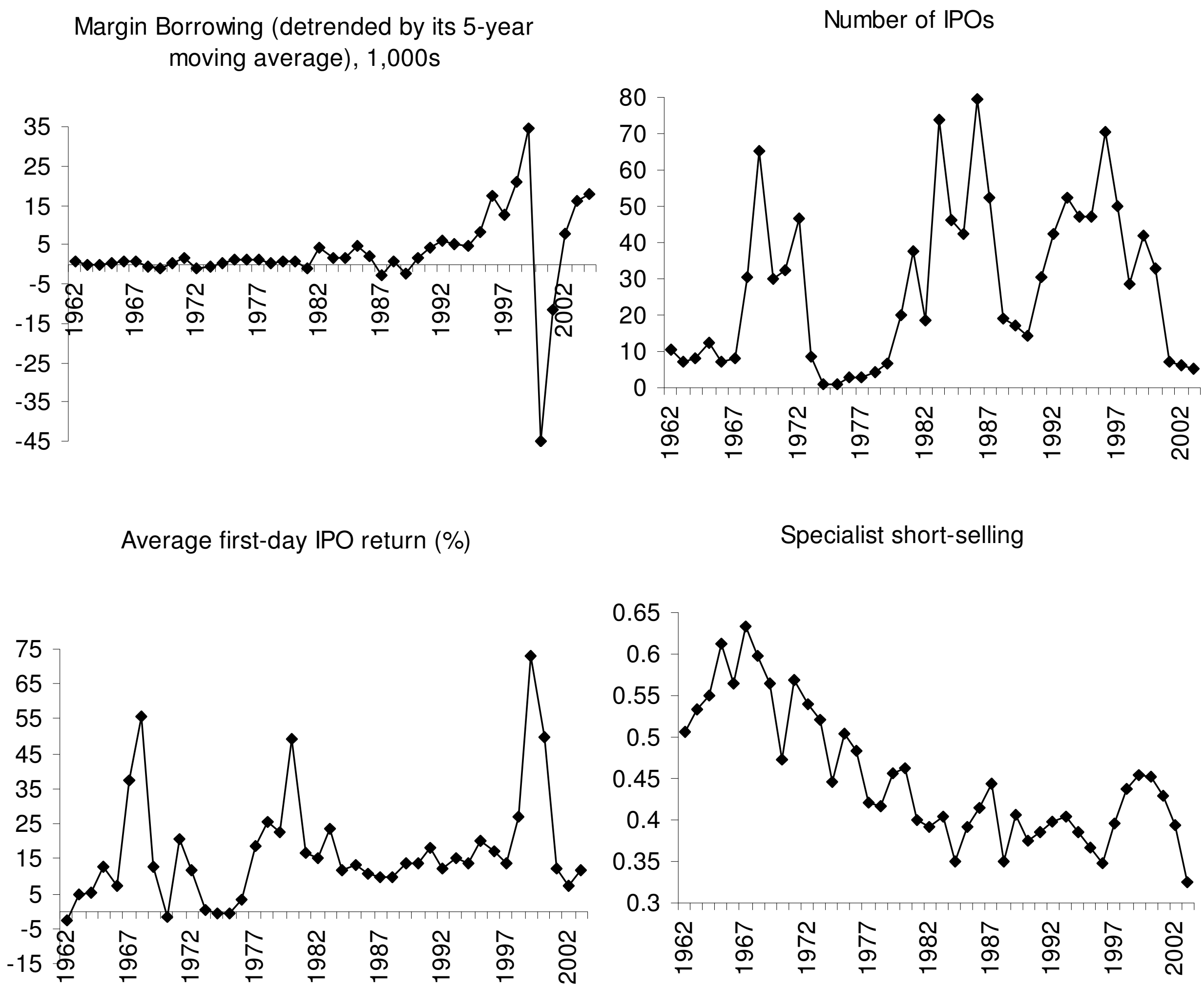


Figure 1b. Annual and monthly sentiment index

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

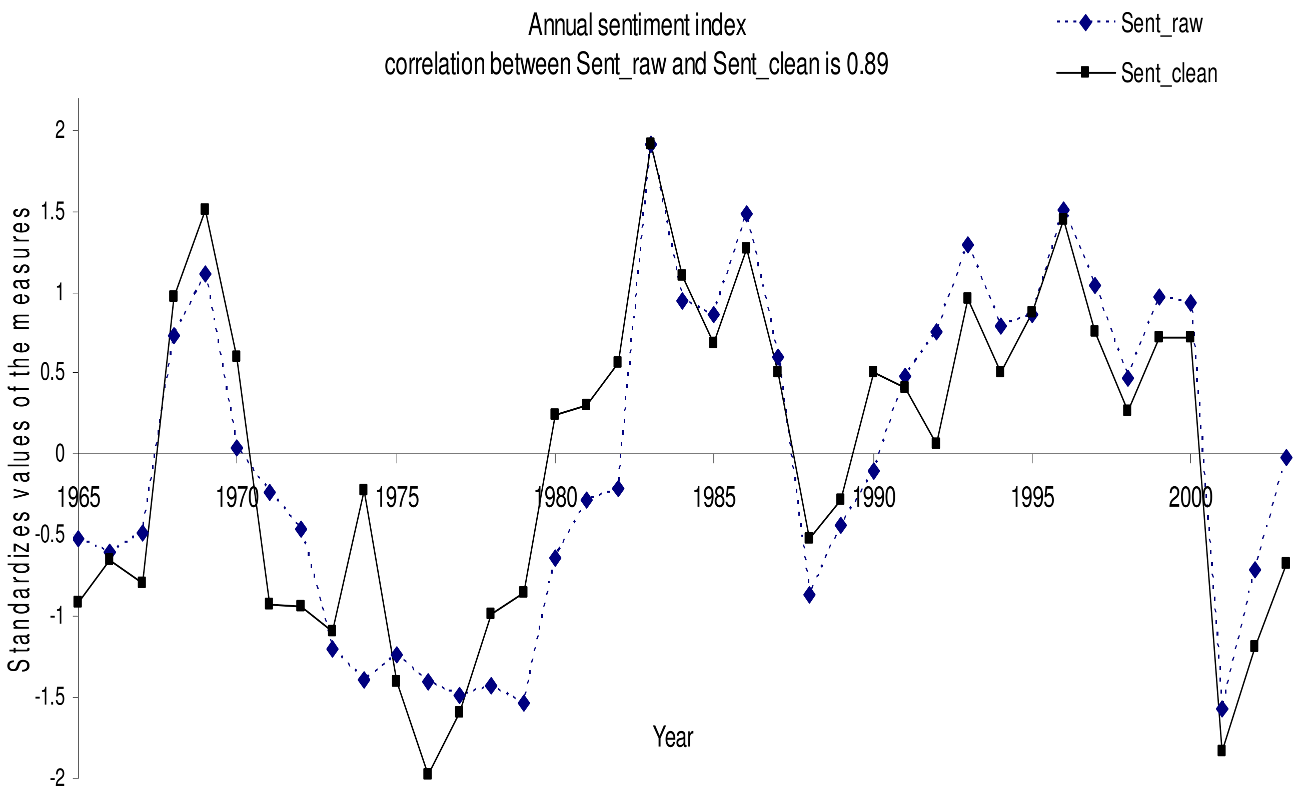
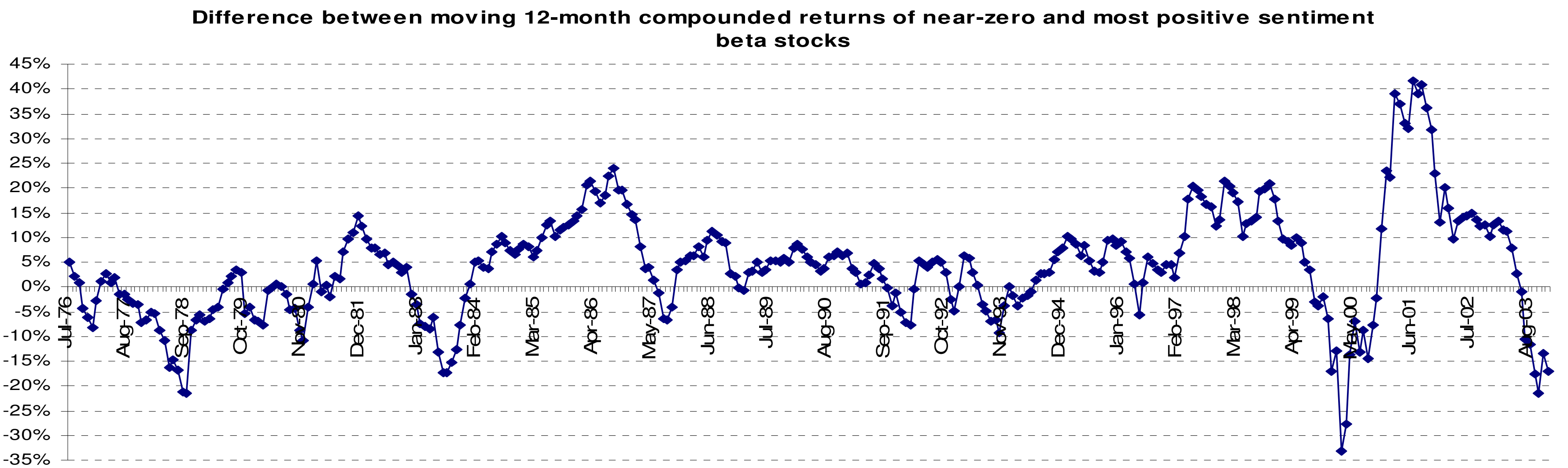


Figure 2. Difference between returns of near-zero and extreme value sentiment beta stocks

The upper (lower) part of figure depicts monthly differences between moving twelve-month geometrically compounded returns of the zero-investment portfolio that is long in quintile of stocks with the lowest positive (largest negative) sentiment beta and short in quintile stocks with the most positive (most negative) values of sentiment beta. There is no statistically significant difference between betas on lagged market returns between long and short portfolios.



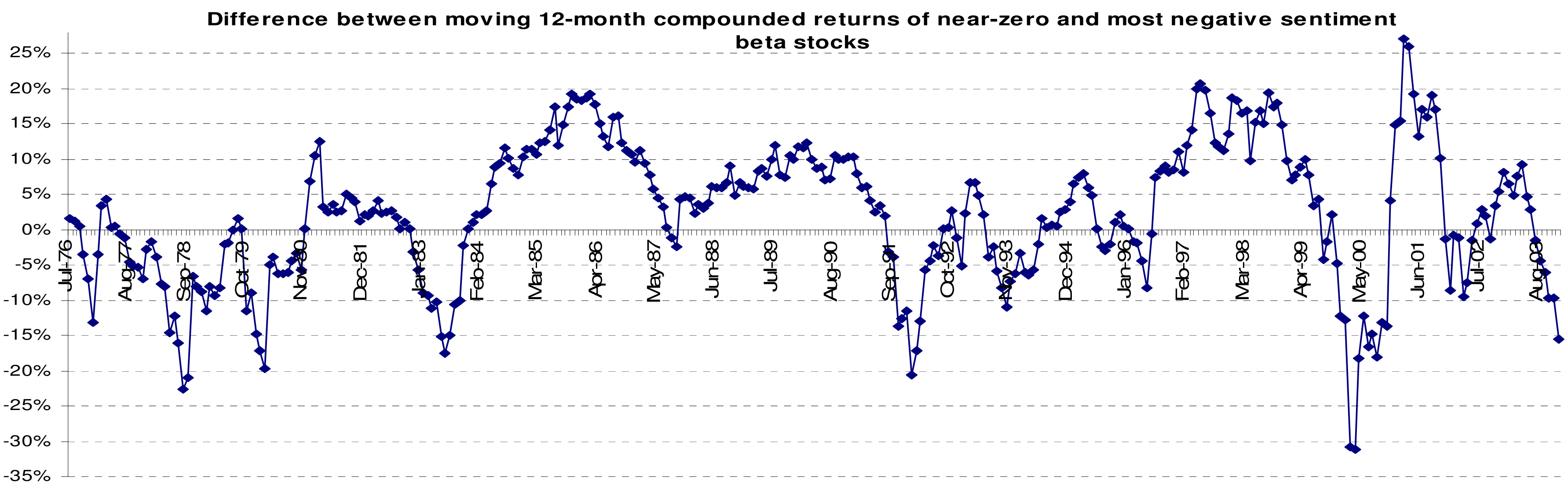


Figure 3. Annual SENTINDEX, Baker&Wurgler measure vs University of Michigan CC Index

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.