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INVESTOR SENTIMENT IN THE STOCK MARKET

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ABSTRACT

Real investors and markets are too complicated to be neatly summarized by a few selected biases and trading frictions. The "top down" approach to behavioral finance focuses on the measurement of reduced form, aggregate sentiment and traces its effects to stock returns. It builds on the two broader and more irrefutable assumptions of behavioral finance -- sentiment and the limits to arbitrage -- to explain which stocks are likely to be most affected by sentiment. In particular, stocks of low capitalization, younger, unprofitable, high volatility, non-dividend paying, growth companies, or stocks of firms in financial distress, are likely to be disproportionately sensitive to broad waves of investor sentiment. We review the theoretical and empirical evidence for these predictions.

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The history of the stock market is full of events striking enough to earn their own names: the Great Crash of 1929, the 'Tronics Boom of the early 1960s, the Go-Go Years of the late 1960s, the Nifty Fifty bubble of the early 1970s, and the Black Monday crash of October 1987. Each of these events refers to a dramatic level or change in stock prices that seems to defy explanation. The standard finance model, where unemotional investors always force capital market prices to equal to the rational present value of expected future cash flows, has considerably difficulty fitting these patterns. Researchers in behavioral finance have been working to augment the standard model with an alternative model built on two basic assumptions.[1]

The first assumption is that investors are subject to sentiment. Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand. The second assumption is that betting against sentimental investors is costly and risky. And so, rational investors, or arbitrageurs as they are often called, are not as aggressive in forcing prices to fundamentals as the standard model would suggest. In the language of modern behavioral finance, there are limits to arbitrage. Recent stock market history has cooperated nicely, providing the Internet bubble and the ensuing Nasdaq and telecom crashes and thus validating the two premises of behavioral finance. A period of extraordinary investor sentiment pushed the prices of speculative and difficult-to-value technology stocks to unfathomable levels in the late 1990s. Instead of creating opportunity for contrarian arbitrageurs, the period forced many out of business, as prices that were merely high went higher still before an eventual crash.

Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects. One

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[1] See De Long et al. (1990) and Shleifer and Vishny (1997) for this conception.

approach is "bottom up," using biases in individual investor psychology, such as overconfidence, representativeness, and conservatism, to explain how individual investors underreact or overreact to past returns or fundamentals.[2] A related class of models, discussed by Hong and Stein in this issue, relies on differences of opinion across investors, often combined with short sales constraints to generate misvaluation. When aggregated, these models make predictions about patterns in market wide investor sentiment, stock prices, and volume.

The investor sentiment approach that we develop in this paper is, by contrast, distinctly "top down" and macroeconomic. The starting point for this approach is that many of the bottom up models lead to a similar reduced form of variation over time in mass psychology, and certainly none is uniquely true. Real investors and markets are too complicated to be neatly summarized by a few selected biases and trading frictions. The top down approach focuses on the measurement of reduced form, aggregate sentiment and traces its effects to market returns and individual stocks. The new directions in this top down approach build on the two broader and more irrefutable assumptions of behavioral finance—sentiment and the limits to arbitrage—to explain *which* stocks are likely to be *most* affected by sentiment, rather than simply pointing out that the level of stock prices in the aggregate depends on sentiment.[3]

In particular, stocks of low capitalization, younger, unprofitable, high volatility, non-dividend paying, growth companies, or stocks of firms in financial distress, are likely to be disproportionately sensitive to broad waves of investor sentiment. As the reader will recall, small startup firms represented a majority of the excitement and subsequent carnage of the Internet bubble, so this statement may ring true already. Theoretically, it follows because these groups of

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[2] See Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyman (1998) for models of this sort.

[3] As an analogy, aggregate risk aversion is another one-dimensional variable that will affect all stocks to some degree but will also affect some more than others.

stocks tend to be harder to arbitrage, for example they have higher transaction costs, and because they are more difficult to value, making biases more insidious and valuation mistakes more likely.

The remainder of the paper develops these theoretical predictions in more detail, shows how one might measure sentiment explicitly, and finally how to use the sentiment measures to validate the key predictions of the top down approach. Certainly, both the bottom up and top down approaches to investor sentiment deserve continued attention. The advantage of the top down approach is its potential to encompass bubbles, crashes, and more everyday patterns in stock prices in a simple, intuitive and comprehensive way. The advantage of the bottom up model is in providing microfoundations for the variation in investor sentiment that the top down model takes as exogenous.

Theoretical Effects of Investor Sentiment on Stocks

A pioneering and well-known set of studies of sentiment and aggregate stock returns appeared in the 1980s. They were largely atheoretical, testing in various ways whether the stock market as a whole could be mispriced. Authors looked for: the tendency of aggregate returns to mean revert; volatility in aggregate stock index returns that could not be justified by volatility in fundamentals, which is in fact another way of characterizing mean reversion in returns; or

predictability of aggregate returns using simple valuation ratios like the ratio of aggregate

dividends to stock market value.[4]

In these studies, the role of sentiment was left implicit, and the statistical evidence was

not usually very strong. Practically speaking, it is hard to distinguish a random walk from a long-

lived bubble, especially in a short time series containing at best a few bubbles. Even when

statistical inferences seemed robust, the economic interpretation was still unclear. Predictability

of stock returns could reflect the correction of sentiment-induced mispricings or, arguably, time-

varying risk or risk aversion that causes time variation in expected stock returns.

The more recent studies, such as Baker and Wurgler (2006), utilize interim advances in

behavioral finance theory to provide sharper tests for the effects of sentiment. In particular, in the

many behavioral models of securities markets inspired by De Long et al. (1990), investors are of

two types: rational arbitrageurs who are sentiment-free and irrational traders prone to exogenous

sentiment. They compete in the market and set prices and expected returns. But, arbitrageurs are

limited in various ways. These limits come from short horizons or costs and risks of trading and

short selling. So, prices are not always at their fundamental values. In such models, mispricing

arises out of the combination of two factors: a change in sentiment on the part of the irrational

traders, and a limit to arbitrage from the rational ones.

The key predictions of this framework come from its two moving parts. Consider first the

possibility that sentiment-based demand shocks vary across firms, while arbitrage is equally

difficult across firms. For example, suppose one thinks about investor sentiment as the

propensity to speculate by the marginal investor, akin to a propensity to play the lottery. Then

sentiment is almost by definition a higher demand for more speculative securities, and when

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[4] See Shiller (1981) on excess volatility, Fama and French (1988) and Poterba and Summers (1988) on mean
reversion, and Campbell and Shiller (1988) and Fama and French (1989) on valuation ratios.

sentiment increases we expect such "speculative" stocks to have contemporaneously higher returns.

What makes some stocks more speculative than others? We believe that the crucial characteristic is the difficulty and subjectivity of determining their true values. For instance, in the case of a young, currently unprofitable but potentially extremely profitable growth firm, the combination of no earnings history and a highly uncertain future allows investors to defend valuations ranging from much too low to much too high, as befits their prevailing sentiment. During a bubble, when the propensity to speculate is high, investment bankers can join the chorus arguing for high valuations. By contrast, a firm with a long earnings history, tangible assets, and stable dividends is much less subjective to value, and thus its stock is likely to be less sensitive to sentiment. One could appeal to psychological foundations here. Uncertainty means that the effect of overconfidence (Daniel, Hirshleifer, and Subrahmanyman, 1998), representativeness, and conservatism (Barberis, Shleifer, and Vishny, 1998) is more pronounced. And, differences of opinion (Miller, 1977), even when investors have the same basic information, can be large. The changes over time in these biases, we would call shifts in the propensity to speculate.

Now suppose instead that we view investor sentiment as simply optimism or pessimism about stocks in general, and we allow the limits to arbitrage to vary across stocks. A large body of research shows that arbitrage tends to be particularly risky and costly for certain stocks: namely those that are young, small, unprofitable, or experiencing extreme growth. Such stocks tend to be more costly to buy and to sell short (D'Avolio, 2002). Such stocks have a high degree of idiosyncratic variation in their returns, which makes betting on them riskier (Wurgler and Zhuravskaya, 2002). Such stocks' higher volatility may lead to second-guessing by the investors

who provide funds to the arbitrageur, ultimately leading to withdrawals from contrarian arbitrageurs just when the mispricing is greatest (Shleifer and Vishny, 1997). By not paying dividends, such stocks' fundamentals remain far in the future and therefore subject to speculation (Pontiff, 1996). Thus, again, we might expect that sentiment has a greater effect on such stocks.

The key point is that *in practice, the same securities that are difficult to value also tend to be difficult to arbitrage*. Therefore we are left with a very robust and testable conclusion: The stocks most sensitive to investor sentiment will be those of companies that are younger, smaller, more volatile, unprofitable, non-dividend paying, distressed or with extreme growth potential, or having analogous characteristics. Whereas "bond-like" stocks will be less driven by sentiment. Again, note that this assessment does not depend on specifying a fine definition of investor sentiment or rely on just one arbitrage mechanism such as short-sales constraints.

The Sentiment Seesaw

Figure 1 summarizes this into a simple, unified view of the effects of sentiment on stocks. The x-axis orders stocks according to how difficult they are to value and arbitrage. Bond-like stocks, such as regulated utilities, are toward the left; stocks of companies that are newer, smaller, more volatile, distressed or extreme growth are toward the right. The y-axis measures prices, with P* denoting fundamental values which, of course, can vary over time. The lines then illustrate the basic hypotheses about how stock valuations are affected by swings in sentiment. High sentiment should be associated with high stock valuations, particularly for the hardest to value and arbitrage stocks. Low sentiment works in the reverse direction. In the absence of sentiment, stocks are, on average, assumed to be correctly priced at P*.

An empirical question that arises in the drawing of Figure 1 is where to locate the crossing point of this seesaw. One case (not in Figure 1) is that no crossing point exists: the upward-sloping high sentiment line lies entirely above the no sentiment P line, which in turn lies entirely above the downward-sloping low sentiment line. That is, when sentiment increases, all stocks' prices go up, but some more than others. In this case, the *aggregate* effects of sentiment will be strong, because aggregate stock indexes are simply averages of the underlying stocks.

As drawn, Figure 1 reflects the more complex case where the prices of particularly safe, easy-to-arbitrage stocks actually are inversely related to sentiment. This could occur if sentiment fluctuations induce substantial changes in the demand for speculative securities, for example engendering "flights to quality" *within* the stock market. Such episodes may, controlling for any changes in fundamentals, reduce the prices of speculative stocks and at the same time increase the prices of bond-like stocks. In this case, the effect of sentiment on aggregate returns will be muted, as stocks are not all moving in the same direction.

Behavioral theory thus delivers clear cross-sectional predictions about the effects of sentiment—but the aggregate predictions are somewhat less clear, which may help to explain why the 1980s studies did not always reach strong statistical conclusions. The rest of the paper reviews some empirical evidence regarding three critical aspects of Figure 1. First, we discuss how investor sentiment can be empirically measured.

Second, we ask whether more speculative and harder to arbitrage stocks are indeed more sensitive to sentiment, in the sense that their prices comove more with an index of sentiment changes. In finance parlance, we ask whether speculative and harder to arbitrage stocks have higher "sentiment betas." (The term is by analogy to the famous concept of market beta, which measures the exposure of a stock to returns on the stock market as a whole. A stock with a

market beta of 1.0 appreciates by 1 percentage point, on average, when the market return is one percentage point. Market betas above 1.0 indicate relatively high market risk exposure.) We also test whether bond-like stocks have negative sentiment betas, i.e. their returns are negatively related to changes in sentiment, as represented in Figure 1.

Third, we investigate whether current investor sentiment levels predict future returns as sentiment wanes (perhaps spurred by fundamental news or an absence thereof) or as arbitrage forces eventually accumulate to correct mispricings. This is an important test, because sentiment measures may, despite our best efforts, be contaminated by economic fundamentals, and fundamentals should of course affect stock returns contemporaneously. In other words, the comovement patterns are subject to a correlated omitted variables critique. Return predictability helps to address this concern because it suggests a profitable trading strategy, which by definition cannot exist if stocks are priced correctly.

Ruling Out Other Explanations

Contrasting Figure 1 with some other finance frameworks helps to clarify the unique predictions of the sentiment model. The classical risk-based and the behavioral disagreement models make distinct predictions about the slope of the thick, or overall, valuation line. Neither makes predictions about the dashed valuations, conditional on sentiment.

In the risk-based asset pricing models, such as the capital-asset pricing model, a stock's expected return depends on its risk exposure, measured by market beta, times the market risk premium, which is the expected return on the stock market as a whole. Furthermore, since investors are rational and risk averse in these models, the market risk premium is always

positive, though it may change over time. See Fama and French (2004) and Perold (2004) for introductions to this model.

What does this imply for tests of return predictability? Even if speculative and hard-to-arbitrage securities have higher market betas, as is likely the case, classical models predict that such stocks always have higher expected returns than bond-like stocks. In fact, as we will see below, this is not true. When sentiment is measured to be high, speculative and hard-to-arbitrage stocks have lower future returns, on average, than bond-like stocks. This is a powerful confirmation of the sentiment-driven mispricing view.

In a behavioral model of disagreement among regular investors combined with short-sales constraints by arbitrageurs, on the other hand, hard to short stocks can become overvalued. As fundamentals are revealed, this mispricing will disappear, so the future returns of such stocks will be relatively low on average. The sentiment seesaw in Figure 1 makes a distinct and testable prediction that hard to arbitrage stocks can, conditional on the state of sentiment, be undervalued as well. We will also investigate this point.

Measuring Investor Sentiment

Investor sentiment is not straightforward to measure, but there is no fundamental reason why one cannot find imperfect proxies that remain useful over time. We discuss some generic issues involved in measuring sentiment and describe proxies for sentiment that have come into use. We then describe a sentiment index which combines several of these proxies, and we show that it fluctuates with the major speculative episodes of the past 40 years.

Potential Sentiment Proxies

An exogenous shock in investor sentiment can lead to a chain of events, and the shock itself could in principle be observed at any or every part of this chain. For example, it might show up first in investor beliefs, which could be surveyed. These beliefs might then translate to observable patterns of securities trades, which are recorded. Limited arbitrage implies that these demand pressures might cause some mispricings, which might be observed using benchmarks for fundamental value like the book-to-market ratio. These mispricings might engender an informed response by insiders, such as corporate executives, who may have both the superior information and the incentive to take advantage of it, and the patterns of firms in whether they choose to adjust their balance of equity or debt could be observed.

The bad news is that each part of this chain is also subject to confounding influences. Economists always treat surveys with some degree of suspicion, because of the potential gap between how people respond to a survey and how they actually behave. Trades net to zero, so measuring sentiment with trading activity means taking a stand on the identity of irrational investors. Market prices of securities normally reflect fundamentals, by and large, with sentiment playing a lesser role. And, corporations may alter their financial structure for many reasons, including a change in business fundamentals, rather than simply acting as corporate arbitrageurs.

Such considerations suggest that the practical approach is to combine several imperfect measures. Candidate ways of measuring sentiment, ordered from origins in investor psychology to responses by corporate insiders, include: surveys, mood proxies, retail investor trades, mutual fund flows, trading volume, dividend premia, closed-end fund discounts, option implied volatility, first-day returns on initial public offerings, volume of initial public offerings, new

equity issues, and insider trading. We comment on these sentiment proxies and then choose among them.

Investor Surveys. Perhaps just by asking investors how optimistic they are, we can gain insight into the marginal irrational investor. Robert Shiller has conducted investor attitude surveys since 1989. UBS/Gallup surveys randomly-selected investor households, and Investors Intelligence surveys financial newsletter writers. Qiu and Welch (2006) point out that although consumers polled for the University of Michigan Consumer Confidence Index are not asked directly for their views on securities prices, changes in that consumer confidence index nonetheless correlate highly with changes in the UBS/Gallup index. They show that changes in the consumer confidence measure correlate especially strongly with small stock returns and the returns of firms held disproportionately by retail investors.

Investor Mood. Some papers have creatively tried to connect stock prices to exogenous changes in human emotions. Kamstra, Kramer, and Levi (2003) find that market returns are on average lower through the fall and winter, which they attribute to the onset of seasonal affective disorder, a depressive disorder associated with declining hours of daylight. Patterns at different latitudes and both hemispheres also are consistent with this interpretation. Edmans, Garcia, and Norli (2006) use international soccer results as a mood variable and find that losses in major games predict poor returns in the losing country the next day, particularly among small stocks.

Retail investor trades. The inexperienced retail or individual investor is more likely than the professional to be subject to sentiment. Greenwood and Nagel (2006) find that younger investors were more likely than older investors to buy stocks at the peak of the Internet bubble. More generally, Barber, Odean, and Zhu (2003) and Kumar and Lee (2006) find in micro-level trading data that retail investors buy and sell stocks in concert, which is consistent with

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systematic sentiment. Kumar and Lee suggest constructing sentiment measures for retail

investors based on whether such investors are buying or selling.

Mutual fund flows. Data are easily available on how mutual fund investors allocate across

fund categories. Brown, Goetzmann, Hirkai, Shiraishi, and Watanabe (2002) propose an overall

market sentiment measure based on how fund investors are moving into and out of, for example,

"safe" government bond funds to "risky" growth stocks funds. Mutual fund investors are well-

known to chase investments with high recent returns (e.g. Warther, 1995), so whether the

causality also goes the other direction—whether their allocation decisions actually lead to

mispricing—is a tricky question. Frazzini and Lamont (2005) find some affirmative evidence by

using fund flows to proxy for sentiment for individual stocks. They find that when funds that

hold a particular stock experience strong inflows, the subsequent performance of that stock is

relatively poor.

Trading volume. Trading volume, or more generally liquidity, can be viewed as an

investor sentiment index. For instance, Baker and Stein (2004) note that if short-selling is costlier

than opening and closing long positions (as it is, in practice), irrational investors are more likely

to trade, and thus add liquidity, when they are optimistic and betting on rising stocks rather than

when they are pessimistic and betting on falling stocks. In Scheinkman and Xiong (2003),

volume reveals underlying difference of opinion, which are in turn related to valuation levels

when short selling is difficult. Market turnover, the ratio of trading volume to the number of

shares listed on the New York Stock Exchange, is a simple proxy for this concept.

Dividend premium. Dividend-paying stocks resemble bonds in that their predictable

income stream represents a salient characteristic of safety. The first price-based measure we

mention here is therefore the relative "premium" for dividend-paying stocks, which may be

inversely related to sentiment. Baker and Wurgler (2004a, b) define the dividend premium as the difference between the average market-to-book-value ratios of dividend payers and nonpayers. The dividend premium explains well the major historical trends in firms' propensity to pay dividends, such as the post-1977 decline documented by Fama and French (2001)—that is, when dividends are at a premium, firms are more likely to pay them, and less so when they are discounted. On the margin, firms appear to cater to prevailing sentiment for or against "safety" when deciding whether to pay dividends.

Closed-end Fund Discount. Closed-end funds are investment companies who issue a fixed number of shares, which then trade on stock exchanges. The closed-end fund "discount" (or occasionally premium) is the difference between the net asset value of a fund's actual security holdings and the fund's market price. Many authors, including Zweig (1973), Lee, Shleifer, and Thaler (1991), and Neal and Wheatley (1998), have argued that if closed-end funds are disproportionately held by retail investors, the average discount on closed-end equity funds may be a sentiment index, with the discount increasing when retail investors are bearish.

Option implied volatility. Options prices rise when the value of the underlying asset has greater expected volatility, and options pricing models such as the Black-Scholes formula can be inverted to yield implied volatility as a function of options prices. The Market Volatility Index ("VIX"), which measures the implied volatility of options on the Standard and Poor's 100 stock index, is often called the "investor fear gauge" by practitioners. Whaley (2000) discusses the spikes in the VIX series since its 1986 inception, which include the crash of October 1987 and the 1998 Long Term Capital Management crisis.

IPO First-Day Returns. Initial public offerings sometimes earn such remarkable returns on their first trading day that it is difficult to find an explanation that does not involve investor

enthusiasm. For example, Netscape's return on the day of its August 1995 IPO was 108 percent. Interestingly, IPO first-day returns are not idiosyncratic. Average first-day returns display peaks and troughs which are highly correlated with IPO volume (below) and other sentiment proxies that are not fundamentally related.[5]

IPO Volume. The underlying demand for initial public offerings is often said to be extremely sensitive to investor sentiment. Investment bankers speak of "windows of opportunity" for an initial public offering that capriciously open and close. Such caprice could explain the fact that IPO volume displays wild fluctuations, with a rate of over 100 issues per month in some periods and zero issues per month in others.

Equity Issues Over Total New Issues. A broader measure of equity financing activity is the equity share of total equity and debt issues by all corporations. This measures all equity offerings, not just IPOs. Baker and Wurgler (2000) find that high values of the equity share portend low stock market returns, and suggest that this pattern reflects firms shifting successfully between equity and debt to reduce the overall cost of capital. This pattern need not imply that individual firms or their managers can predict prices on the market as a whole. Rather, correlated mispricings across firms may lead to correlated managerial actions, which may then forecast correlated corrections of mispricings – that is, it will forecast market returns.

Insider Trading. Corporate executives have better information about the true value of their firms than outside investors. Thus, legalities aside, executives' personal portfolio decisions may also reveal their views about the mispricing of their firm. If sentiment leads to correlated

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[5] Why IPOs are "underpriced" to such an extreme degree is still a puzzle, since the prices are set in consultation with investment bankers well-informed about market conditions. The extreme unpredictability of investor sentiment may be a factor. The offer price is typically set in advance and indications of interest are then gathered from potential investors. It may be better to issue shares at a likely discount to first day prices than risk an undersubscribed offering in a period of generally high sentiment and valuations. This raises the question of why companies do not simply auction their shares. See Ritter (2003) for a discussion of underpricing and Ljungqvist, Nanda, and Singh (2006) for a sentiment-based model.

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mispricings across firms, insider trading patterns may contain a systematic sentiment component. See Seyhun (1998) for evidence on the ability of insider trading patterns to predict stock returns.

An Operational Sentiment Index

Which of the above measures to choose? Data availability narrows the list considerably. Sentiment may vary daily, but major episodes occur over years, and the most convincing tests of the effects of sentiment are those in which it is used to actually predict long-horizon returns— tests which suggest a contrarian trading strategy. This rules out using data that do not go back as far as our stock returns data (i.e. to the 1960s), for example including insider trading, micro-level data on trading behavior, and implied volatility series.

Instead, we construct an index based on the six proxies used by Baker and Wurgler (2006): trading volume as measured by NYSE turnover; the dividend premium; the closed-end fund discount; the number and first-day returns on IPOs; and the equity share in new issues. All these data are available at www.stern.nyu.edu/~jwurgler. Later on, we will also consider some mutual fund series.

Although these six proxies are highly correlated in the expected directions, some of them also contain idiosyncratic components that are unrelated to sentiment. For example, the 1975 deregulation of brokerage commissions and the subsequent long decline in trading costs has led to a decades-long upward trend in turnover, so we use the log of turnover minus a five-year moving average. With respect to closed-end fund discounts, if the majority of individual investors have come to prefer open-end funds in recent years, the discount provides a less useful summary of the opinion of the marginal investor than it once did. And the evolution of public

debt markets has made the equity share less useful in recent years. But, no obvious patch suggests itself in these cases.

Also, some of the sentiment proxies reflect economic fundamentals to some extent. For instance, IPO volume depends, in part, on prevailing investment opportunities. To remove such influences, at least partially, we regress each proxy on a set of macroeconomic indicators—growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator—and use the residuals from these regressions as our sentiment proxies.

Since the six sentiment proxies, especially given that major macroeconomic influences have been removed, will have a common sentiment component, we can iron out the remaining idiosyncracies by averaging them together into an index. We form a sentiment levels index to test for return predictability conditional on the state of sentiment and also a sentiment changes index to test for return comovement patterns associated with changes in sentiment. The levels index is simply the first principal component of the six proxies.[6] The changes index is the first principal component of the changes in the six proxies.[7]

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[6] Brown and Cliff (2004) also use a principal components methodology to define a sentiment index. The first principal component of a set of time series variables is simply the linear combination of the variables with the coefficients chosen to capture as much of the joint variation across the series as possible. The second principal component performs the same analysis but defines the relevant series as the residuals from the first principal component, etc. A decision with defining which of our six series to include in the analysis is timing. Some variables may reflect the same shift in sentiment before others. In general, proxies that involve firm supply decisions are further down the chain of events and likely to lag behind proxies that are based directly on investor trading patterns or prices. Baker and Wurgler (2006) find that the best combination to capture the common variation in annual series includes the current values of the closed-end fund discount, the equity share, and IPO volume, and one-year-lagged versions of the three other variables. We are using monthly data here, but for simplicity we also adopt this convention.

[7] While we could simply take the changes in the sentiment levels index, a better approach is to form a second index based on the first principal component of the *changes* in the six proxies. The reason for this preference is that the proxies have differential noisiness in going from levels to changes. E.g., turnover has low frequency error related to falling transaction costs, but high frequency changes are more informative; the equity share, on the other hand, has low frequency error related to long-term shifts in financing patterns plus high frequency error because corporations can respond to sentiment only with a lag (which itself is unlikely to be consistent enough to try to align the changes

Figure 2 shows the sentiment indexes graphically. As expected, variables positively associated with sentiment levels include share turnover, IPO volume and first-day returns, and the equity share in new issues, and those negatively associated are the closed-end fund discount and the dividend premium. The bottom panel reports the changes index. The coefficients all have the same signs as in the levels index, with the exception of the equity share. We regard its unexpected sign as a chance event made possible by the fact that its changes at high frequencies are largely unrelated to sentiment, but we retain it to avoid data mining.

While data availability is the key constraint, some judgment has entered this approach to measuring sentiment. Robustness is a natural question. We offer two remarks in response. First, the process of averaging the six proxies is not crucial. They are strongly correlated and if they were each studied as independent sentiment indexes, some would display empirical results even stronger (i.e., more consistent with a strong role for sentiment) than those we present below. We pursue the index approach so as not to arbitrarily elevate individual proxies and to iron out idiosyncratic variation. Second, Baker and Wurgler (2006) find that macro fundamentals explain little of the common variation in the six series. In other words, indexes formed from the "raw" series would look and perform almost identically to those used here. Nonetheless we include this step to illustrate an approach to controlling for fundamentals.

Does This Index Capture Major Fluctuations In Sentiment? An Eyeball Test

Perhaps the best evidence that the index generally succeeds in capturing sentiment is simply that it lines up fairly well with the anecdotal accounts of bubbles and crashes written by

in the series). Hence, equity share fluctuations will feature prominently in a changes in the levels index, but will likely drop out in an index based on changes.

authors such as Brown (1991), Dreman (1979), Graham (1973), Malkiel (1999), Shiller (2000), and Siegel (1998). The first major bubble in our data period developed in 1967 and 1968. Brown (1991, p. 90) writes that "scores of franchisers, computer firms, and mobile home manufactures seemed to promise overnight wealth. … [while] quality was pretty much forgotten." The early 1970s, on the other hand, are invariably described in bear market terms. Yet a set of established, large, stable, consistently profitable stocks known as the "Nifty Fifty" enjoyed extreme price-earnings ratios. Siegel (1998, p. 106) writes, "All of these stocks had proven growth records, continual increases in dividends … and high market capitalization." The Nifty Fifty is a mirror image of the speculative episodes that occurred before and after it, which generally involved small, young, unprofitable growth stocks in high sentiment periods.

The late 1970s through mid-1980s are described anecdotally as a period of generally high sentiment and witnessed a series of speculative episodes involving gambling issues in 1977 and 1978 and—more apparent in the levels index—natural resource startups in 1980 on the heels of the second oil crisis (Ritter, 1984) and the high-tech and biotech booms in the first half of 1983. But by 1987 and 1988, Malkiel (p. 80) writes, "market sentiment had changed from an acceptance of an exciting story … to a desire to stay closer to earth with low-multiple stocks that actually pay dividends." Consistent with this view, the overall index shows sentiment at a high level during the early 1980s and tailing off somewhat toward the end of the decade.

The late-1990s bubble in technology stocks will be familiar to many readers. By all accounts, sentiment was broadly high before the bubble started to burst in 2000. Malkiel draws parallels to episodes in the 1960s, 1970s, and 1980s, and Shiller and others compare the Internet bubble to that of the late 1920s. The sentiment index flags 1999 as a high-sentiment year, and the dividend premium and first-day returns on IPOs hit record levels that year.

The sentiment changes index in the bottom of Figure 2 is harder to decipher in an eyeball test. However, when the series is viewed in light of major speculative episodes, one pattern does appear: The volatility of sentiment rises in a speculative episode. This suggests that the relative influence of fundamentals and sentiment on aggregate market returns changes over time.

Mutual Fund Flows

Detailed data on mutual fund flows are not available back to the 1960s, so we do not include these in our main indexes. However, we use the period of overlap to correlate patterns in fund flows and the indexes. This is useful because fund flows provide a transparent measure of decisions made by a large set of investors who are, on average, less sophisticated and more likely to display sentiment. Moreover, the fund flows data help us to investigate the precise mechanism through which sentiment affects stock prices, as we explain.

The Investment Company Institute offers monthly data on flows into various categories of funds. We look at net flows into the eight stock-oriented fund categories for which data exist back to January 1990. The categories vary from speculative "Aggressive Growth" funds to safer, dividend-paying "Income" funds.

Figure 3 shows the results of a principal components analysis of changes in fund flows, as in Goetzmann et al. (2000). Once more, the principal components analysis helps us detect general patterns across several time series while ironing out distracting idiosyncratic fluctuations. The results in the figure show that across the eight stock fund categories, the first principal component is a "general demand" effect. It reflects the fact that investors often shift in and out of stock funds en masse. In contrast, the second principal component shows that the next most important effect is shifts between more speculative funds and safer funds. Thus we call this the

"speculative demand" component. Therefore, controlling for the overall generic equity fund demand, when flows fall in the more speculative categories they tend to rise in the less speculative categories. Barberis and Shleifer (2003) would call this "style investing."

With these two principal components in hand, we can construct monthly time series of the two most important sources of changes in mutual fund flows: one reflecting general demand and another reflecting speculative demand. We then correlate these with the sentiment changes index. During the period of overlap, the sentiment changes index has a marginally significant correlation of 0.16 with general fund demand and, perhaps more interestingly, a highly significant correlation of 0.36 with speculative demand. This latter correlation is particularly suggestive that our overall sentiment indexes do, to a large extent, capture a prevailing "greed" versus "fear" or "bullish" versus "bearish" notion.

Finally, recall that there are essentially two distinct channels by which sentiment will have cross-sectional effects: when general investor demand for risky assets is uniform but stocks differ in the costs and risks arbitrage, and when investor demand focuses on relatively speculative stocks and the difficulty of arbitrage is held constant. The fairly clean empirical break of fund flows into general and speculative demand components suggests the possibility of empirically separating the two channels. Of course, both can operate at the same time.

Using Sentiment to Explain Current Returns

With the index of sentiment changes and the fund flow series in hand, we now turn to testing the key hypotheses about how sentiment affects stocks. We start by asking whether

speculative and harder-to-arbitrage stocks are relatively more affected by sentiment changes. At the end of the section, we briefly consider effects on the aggregate market.

Defining Speculative, Difficult-to-arbitrage Stocks

To study the differential effects of investor sentiment across firms, we first need to settle on a way of sorting stocks according to their speculative appeal and their difficulty of arbitrage. A natural proxy for speculative appeal would be the dispersion of professional analysts'earnings forecasts for that company, but such forecasts are not available for all stocks back to the mid-1960s. A possible proxy for difficulty of arbitrage could be a direct measure of transaction costs for given stocks, but those too are unavailable for a long time series.

We simply sort stocks according to their recent return volatility, specifically the standard deviation of monthly returns over the prior year. Returns data are from the Center for Research in Securities Prices (CRSP). High volatility is characteristic of stocks with strong speculative appeal; low volatility is a bond-like feature. Moreover, highly volatile stocks are generally riskier to arbitrage, so an arbitrageur with limited risk-bearing capacity will hesitate before making large bets against mispricing. Each month, we place each stock into one of ten portfolios according to the decile of their return volatility of the previous year, and we use the returns on the resulting portfolios to represent the cross-section of stock returns.[8]

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[8] Baker and Wurgler (2006) divide stocks in several other ways, including firm age, market capitalization, dividend payment, and profitability. These are natural given an intuition that larger, older, dividend paying and profitable firms tend to be more bond-like and generally easier to arbitrage. They also sort stocks on growth and distress indicators such as the market-to-book equity ratio, asset growth, and sales growth. When sorted this way, bond-like stocks now lie in the middle deciles while speculative stocks, whether due to their extreme growth potential or risk of financial distress, are found at both extremes. These other sorting methods produce qualitatively similar results, so we report results only for volatility portfolios here.

Sentiment Betas: Cross-Sectional Effects of Sentiment Changes

Figure 4 shows the relationship between sentiment changes and the returns on the ten volatility portfolios. The dependent variable is the monthly return on one of the ten volatility portfolios. For each one of these ten portfolios, we run three time-series regressions. In Panel A, we plot the coefficients on the general or speculative mutual fund demand factors. In Panel B, we plot the coefficients on the sentiment changes index. Each of the regressions also includes the value-weighted market return as a control variable, because high volatility stocks are likely to have higher market betas, an effect that we do not want to contaminate the sentiment betas.

The results are as expected. The effect of general demand for stock funds on monthly returns is higher for higher volatility portfolios, presumably because stocks therein are harder to arbitrage. In addition, the effect of speculative demand is also increasing, presumably reflecting the more speculative nature of volatile stocks. The convex pattern in the coefficients is intriguing—stocks in the extreme volatility decile, which are often small, rapidly growing, or in financial distress, are disproportionately more sensitive to both components of fund flows.

Sentiment betas also increase as stocks become more speculative and harder to arbitrage.[9] The figure shows that controlling for market returns, a one-standard-deviation increase in the sentiment changes index increases returns on the eighth volatility decile portfolio, for example, by about one percentage point. The effect on the tenth decile portfolio is over two percentage points. For particularly bond-like stocks, on the other hand, the effect is slightly negative. This is consistent with the most bond-like stocks actually having slightly negative sentiment betas, i.e. as conjectured in Figure 1. Once again, there is a convex pattern in the sentiment betas.

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[9] See Glushkov (2005) for sentiment betas for portfolios sorted on other characteristics as well (as opposed to only volatility). All of his results are closely consistent with the argument that hard to arbitrage and value stocks are more sensitive to sentiment.

Although these results are all highly consistent with the seesaw diagram, there are other interpretations. For example, perhaps speculative flows are highly correlated with the returns of speculative stocks simply because mutual fund investors chase returns, not because their trading has any causal effect on its own. Or, the sentiment changes index may include components, such as the dividend premium, which lead to mechanical differences in the correlations between sentiment changes and different stocks (e.g., dividend paying and nonpaying stocks).[10] Or, the sentiment index may, despite our best efforts, be contaminated by economic fundamentals, which should of course affect returns independently. The fact that sentiment actually helps to predict returns, as we illustrate below, suggests that these considerations cannot fully account for the patterns in Figure 4.

Aggregate Effects

Although our main focus is on cross-sectional differences, a positive correlation will exist between aggregate market returns and sentiment changes if the average stock is affected by sentiment. Indeed, the correlation between an equal-weighted market return index and the sentiment changes index is a highly significant 0.43. The correlation between equal-weighted returns and speculative demand estimated from fund flows is 0.26, and the correlation between equal-weighted returns and general demand from fund flows is 0.48. Using capitalization-weighted market returns, which give more weight to large firms, the respective correlations are 0.32, 0.29, and 0.39, again all highly significant.

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[10] Excluding any particular component from the sentiment indexes, including the dividend premium, does not alter our conclusions.

Using Sentiment to Predict Stock Returns

We have perhaps saved the best for last. The strongest tests of the effects of sentiment involve return predictability. If high sentiment indeed causes overvaluation, we may be able to document low future returns on sentiment-prone stocks as sentiment wanes and fundamentals are revealed. But predictability is not a natural implication of, for example, the skeptical view that the correlation between returns and sentiment arises because the latter is contaminated by fundamentals, for example.

Cross-sectional Predictability

To test these ideas further, we create an empirical version of the sentiment seesaw and compare it to the predictions in Figure 1. We use the same volatility-based characterization of stocks to identify those that are speculative and difficult to arbitrage. Next, we split the time series into high- and low- sentiment periods using the previous month's measure of the sentiment level. Finally, we compute average returns for each of the ten volatility portfolios, for the two separate periods and overall. As with the calculation of sentiment betas, we control for the value-weighted market return.

The resulting picture, in Figure 5, is strikingly similar to the predictions of the seesaw diagram. When sentiment is low, the average future returns of speculative stocks exceed those of bond-like stocks. When sentiment is high, the average future returns of speculative stocks are on average lower than the returns of bond-like stocks. This is a telling pattern—the fact that riskier stocks (at least, stocks that are riskier by all outward appearances) sometimes have *lower*

expected returns is inconsistent with classical asset pricing in which investors bear risk because they are compensated by higher expected return.

The unconditional average returns are slightly lower for speculative stocks, consistent with behavioral models of disagreement among investors combined with short-sales constraints such Hong and Stein (2003) and others they discuss in this volume. The market-adjusted returns are on average positive because of the well-known size effect—in January, small capitalization stocks earn high returns, on average—which increases the average return of our equally-weighted portfolios. Controlling for equal-weighted market returns instead of value-weighted returns shifts the market-adjusted returns down across all ten portfolios, but the overall similarity to Figure 1 remains intact.

Aggregate Predictability

When sentiment is high, subsequent market returns are low. Figure 6 shows that when the sentiment level is more than one standard deviation above its historical average, monthly returns average -0.34 percentage points for value-weighted market index returns and -0.41 percentage points for equal-weighted returns. And when the investor sentiment level is very low, for example more than one standard deviation below its historical average, monthly returns average 1.18 and 2.75 percentage points for value- and equal-weighted indexes, respectively.[11] Therefore, just as the correlation between sentiment changes and returns is higher for an equal-weighted index of returns, so is the correlation between sentiment levels and subsequent equal-

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[11] Figure 6 breaks the historical time series into four sentiment states, while Figure 5 conditions breaks it into only two. We made the latter choice to allow for an easier comparison to the seesaw diagram. If Figure 5 were to display results for four sentiment states, it would display all of the expected patterns, e.g. when sentiment is *very* high, the highest-volatility stocks subsequently earn *particularly* low returns, and so on.

weighted stock returns. The gap between equal-weighted and value-weighted market returns again demonstrates that the impact of sentiment is stronger on small stocks, as predicted.

While Figure 6 indicates economically important gaps, the statistical significance is modest, as is the case with other non-sentiment predictors of aggregate returns such as the dividend-price ratio. Put another way, market crashes tend to occur in high sentiment periods, but the timing of the crashes within these periods is very hard to predict.

Conclusion

This paper takes a "top down" approach to behavioral finance and the stock market, whereby we take the origin of investor sentiment as exogenous and instead focus on its empirical effects. We show that it is quite possible to measure investor sentiment, and that waves of sentiment have clearly discernible, important, and regular effects on individual firms and on the stock market as a whole. In particular, stocks that are difficult to arbitrage or to value are most affected by sentiment. The seesaw diagram in Figure 1 summarizes our approach.

Looking forward, the investor sentiment approach faces a number of challenges: characterizing and measuring uninformed demand or investor sentiment; understanding the foundations and variation in investor sentiment over time; and determining which particular stocks attract speculators or have limited arbitrage potential. Much remains to be done in terms of spelling out this framework, but the potential payoffs of an improved understanding of investor sentiment are substantial. For example, the standard methodology for estimating fundamental market betas, an input to long-term capital budgeting and other important financial

decisions, does not account for sentiment; doing so might improve estimates and clarify their interpretation. Finally, we have seen that sentiment affects the cost of capital. Therefore it may have real consequences for the allocation of corporate investment capital across safer and more speculative firms.

Acknowledgements

References

Baker, Malcolm, and Jeremy Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271-299.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219-2257.

Baker, Malcolm, and Jeffrey Wurgler, 2004a, A catering theory of dividends, *Journal of Finance* 59, 1125-1165.

Baker, Malcolm, and Jeffrey Wurgler, 2004b, Appearing and disappearing dividends: The link to catering incentives, *Journal of Financial Economics* 73, 271-288.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Barber, Brad, Terrance Odean, and Ning Zhu, 2003, Systematic noise, Unversity of California at Davis working paper.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161-199.

Brown, John Dennis, 1991, *101 Years on Wall Street*, Prentice Hall.

Brown, Gregory W., and Michael T. Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1-27.

Brown, Stephen J., William N. Goetzmann, Takato Hiraki, Noriyoshi Shiraishi, and Masahiro Watanabe, 2005, Investor sentiment in Japanese and U.S. daily mutual fund flows, New York University working paper.

D'Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271-306.

Dreman, David, 1979, *Contrarian Investment Strategy*, Dreman Contrarian Group.

Daniel, Kent, David Hirshleifer, and Avanidhar Subramanyam. 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839-85.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98:4, 703-738.

Edmans, Alex, Diego Garcia, and Oyvind Norli, 2006, Sports sentiment and stock returns, *Journal of Finance*, forthcoming.

Fama, Eugene F., and Kenneth R. French, 1988, Permanent and termporary components of stock prices, *Journal of Political Economy* 96, 246-73.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fama, Eugene F., and Kenneth R. French, 2001, Disappearing dividends: Changing firm characteristics or lower propensity to pay?, *Journal of Financial Economics* 60, 3-44.

Fama, Eugene F., and Kenneth R. French, 2004, The capital asset pricing model: Theory and evidence, *Journal of Economic Perspectives* 18:3, 25-46.

Glushkov, Denys, 2005, Sentiment betas, University of Texas working paper.

Graham, Benjamin, 1973, *The Intelligent Investor*, 4th ed., Harper & Row.

Greenwood, Robin, and Stefan Nagel, 2006, Inexperienced investors and bubbles, Harvard University working paper.

Hong, Harrison, and Jeremy Stein, 2003, Differences of opinion, short-sales constraints and market crashes, *Review of Financial Studies* 16, 487-525.

Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, 2003, Winter blues: Seasonal Affective Disorder (SAD) and stock market returns, *American Economic Review* 92, 1257-63.

Kumar, Alok, and Charles Lee, 2006, Retail investor sentiment and return comovement, *Journal of Finance*, forthcoming.

Lee, Charles, Andrei Shleifer and Richard H. Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *Journal of Finance,* 46, 75-109.

Ljungqvist, Alexander, Vikram Nanda and Rajdeep Singh, 2006, Hot markets, investor sentiment, and IPO pricing, *Journal of Business*, forthcoming.

Malkiel, Burton, 1999, *A Random Walk Down Wall Street*, W.W. Norton.

Neal, Robert and Simon M. Wheatley, (1998), Do Measures of Investor Sentiment Predict Returns?, *Journal of Financial & Quantitative Analysis*, Vol. 33, Issue 4, 523-548.

Perold, Andre F., 2004, The capital asset pricing model, *Journal of Economic Perspectives* 18:3, 3-24.

Pontiff, Jeffrey, 1996, Costly arbitrage: Evidence from closed-end funds, *Quarterly Journal of Economics* 111, 1135-51.

Poterba, James M., and Lawrench H. Summers, 1988, Mean reversion in stock prices: Evidence and implications, *Journal of Financial Economics* 22, 27-59.

Ritter, Jay, 1984, The 'hot issue' market of 1980, *The Journal of Business* 57, 215-40.

Ritter, Jay, 2003, Investment banking and securities issuance, in Constantinides, George, Milton Harris, and Rene Stulz, editors, *Handbook of the Economics of Finance*, Elsevier Science.

Scheinkman, Jose, and Wei Xiong, 2003, Overconfidence and speculative bubbles, *Journal of Political Economy* 111, 1183-1219.

Seyhun, H. Nejat, 1998, *Investment Intelligence from Insider Trading*, (Cambridge, MA: MIT Press).

Shiller, Robert J., 2000, *Irrational Exuberance*, Princeton University Press.

Shleifer, Andrei, and Robert Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Warther, Vincent A., 1995, Aggregate mutual fund flows and security returns, *Journal of Financial Economics* 39, 209-235.

Whaley, Robert E., 2000, The investor fear gauge, *Journal of Portfolio Management*, Vol. 26, Issue 3.

Wurgler, Jeffrey, and Katia Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *Journal of Business* 75, 583-608.

Zweig, Martin E., 1973, An investor expectations stock price predictive model using closed-end fund premiums, *Journal of Finance* 28, 67-87.

Figure 1. Cross-sectional effects of investor sentiment. Stocks that are speculative and difficult to value and arbitrage will have higher relative valuations when sentiment is high.
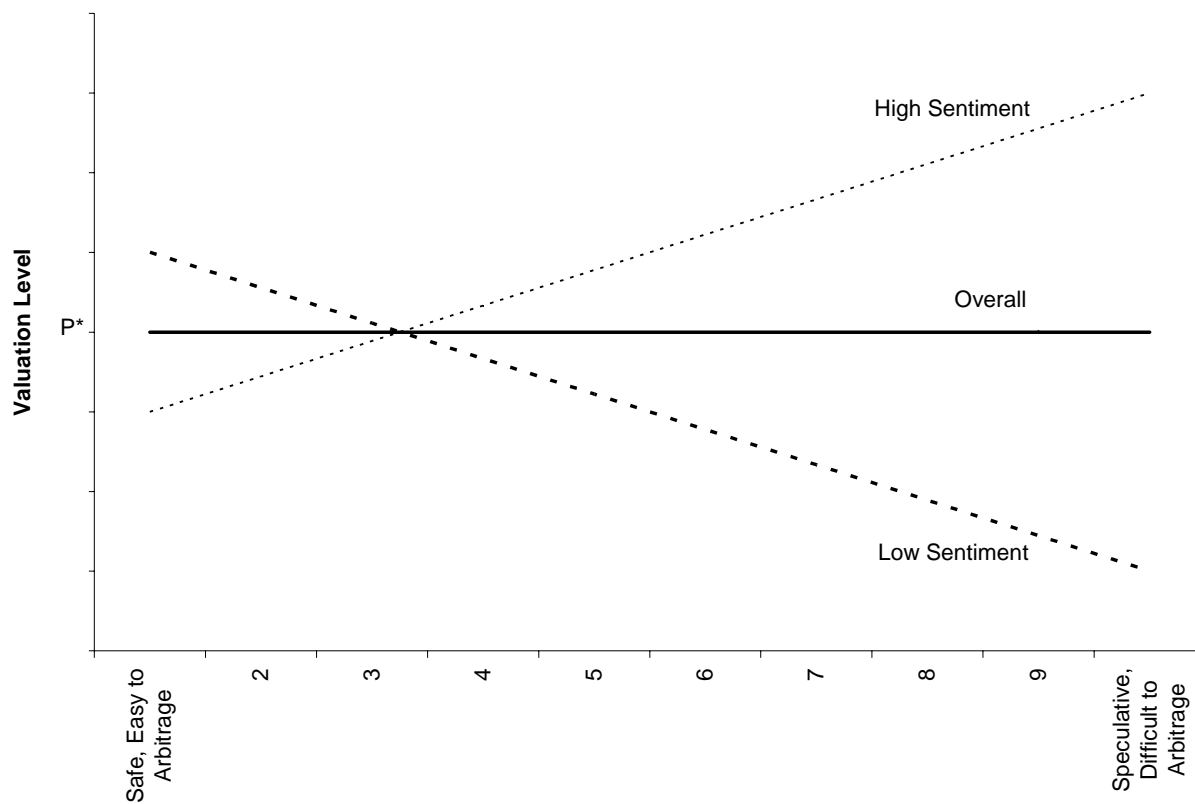
Figure 2. A sentiment index, January 1966 through December 2005. The first principal component of levels and changes in six measures of sentiment: the closed-end fund discount (CEFD), detrended log turnover (TURN), the number of IPOs (NIPO), the first-day return on IPOs (RIPO), the dividend premium (PDND), and the equity share in new issues (S), each standardized and with the effect of macroeconomic conditions removed. In the levels index, turnover, the first-day return on IPOs, and the dividend premium are lagged 12 months. Both indices are standardized to have zero mean and unit variance over the 40 year period.

Panel A. Index of sentiment levels

$$SENT = -0.23CEFD + 0.23TURN + 0.24NIPO + 0.29RIPO - 0.32PDND + 0.23S$$
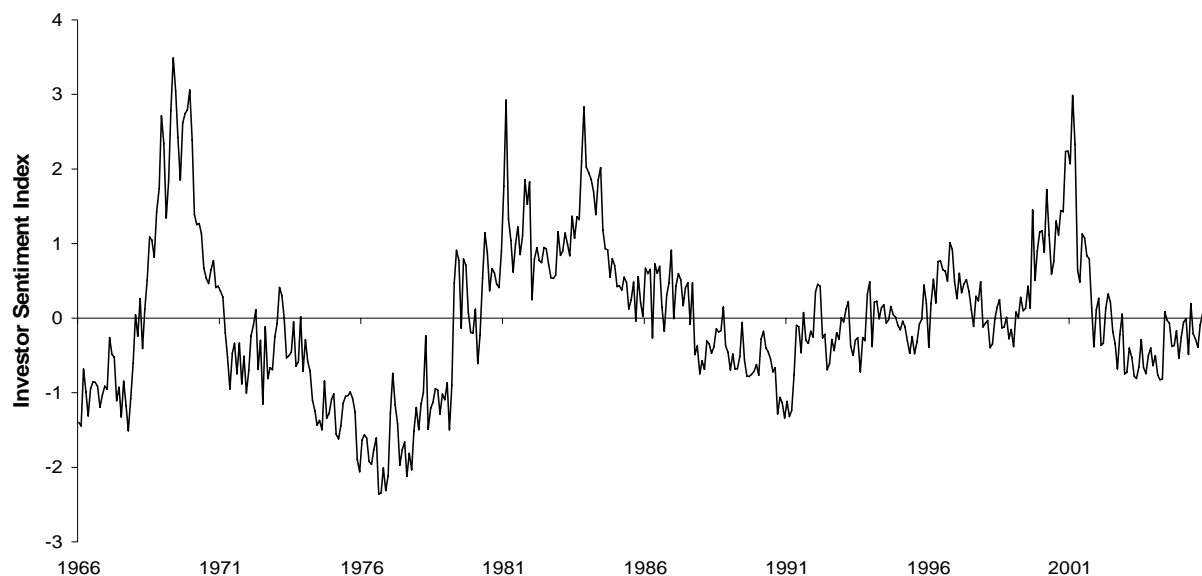
Panel B. Index of sentiment changes

$$\Delta SENT = -0.17\Delta CEFD + 0.32\Delta TURN + 0.17\Delta NIPO + 0.41\Delta RIPO - 0.49\Delta PDND - 0.28\Delta S$$
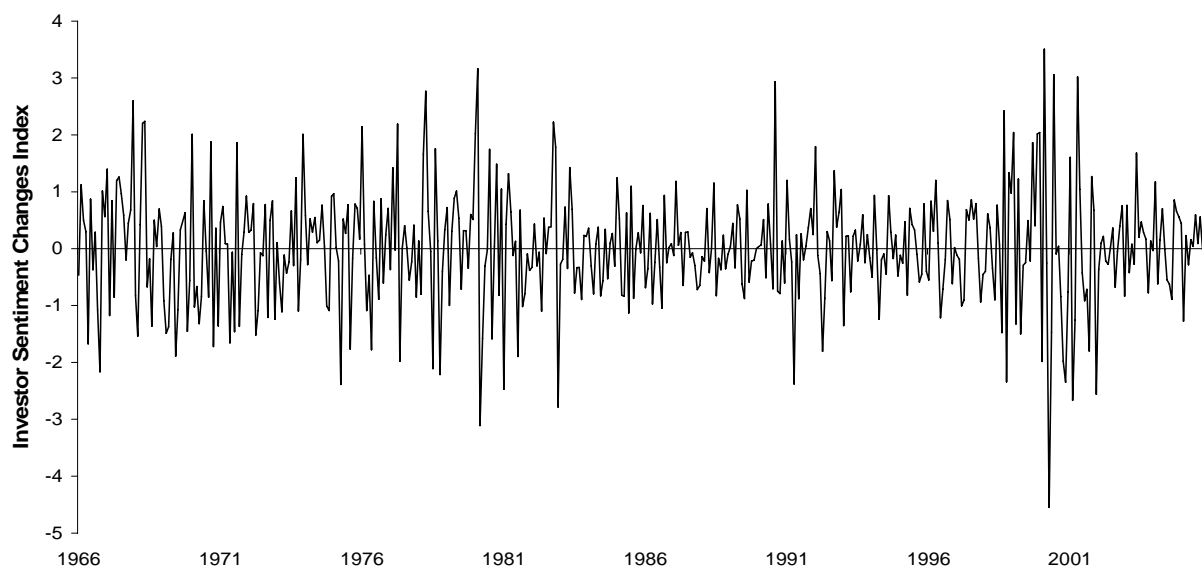
Figure 3. Principal components of equity mutual fund flow changes, January 1990 through December 2005.
The contribution of a one standard deviation change in each equity-oriented mutual fund category to the first two principal components of changes in mutual fund flows, which we label general and speculative demand components. Each bar shows the impact of a one standard deviation change in mutual fund flow. For example, a one standard deviation change in flows into Aggressive Growth funds increases the first principal component by 0.23 and the second principal component by 0.29. Flows are net sales minus redemptions by category, scaled by total mutual fund assets across categories.

Panel A. Generic demand: The first principal component of flow changes
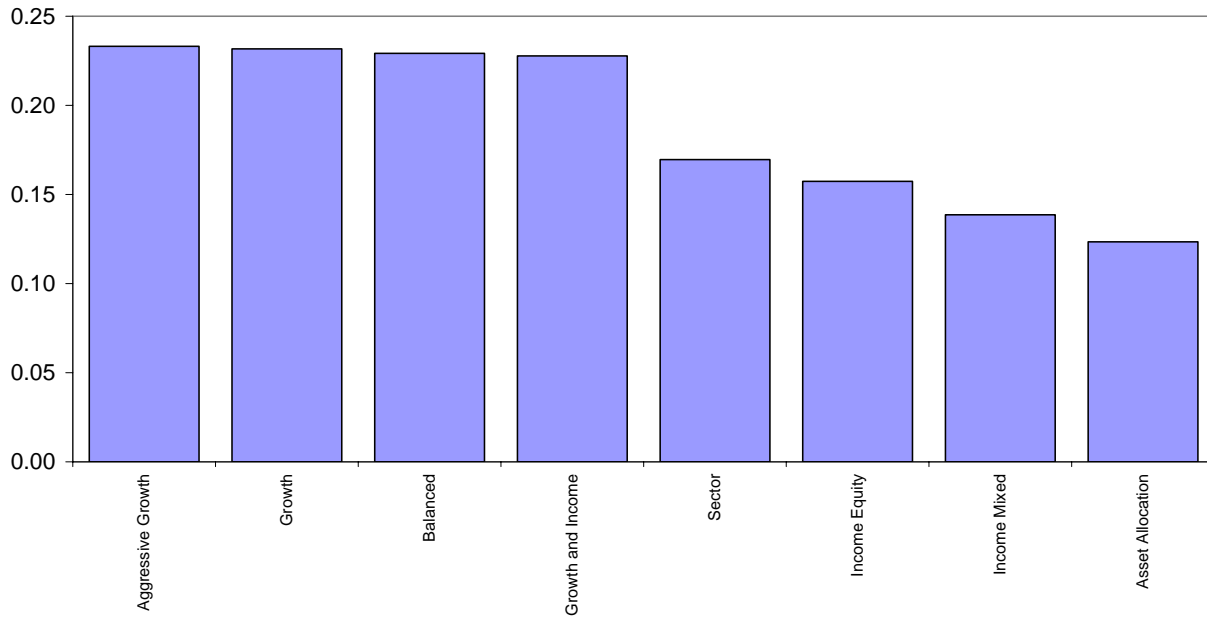
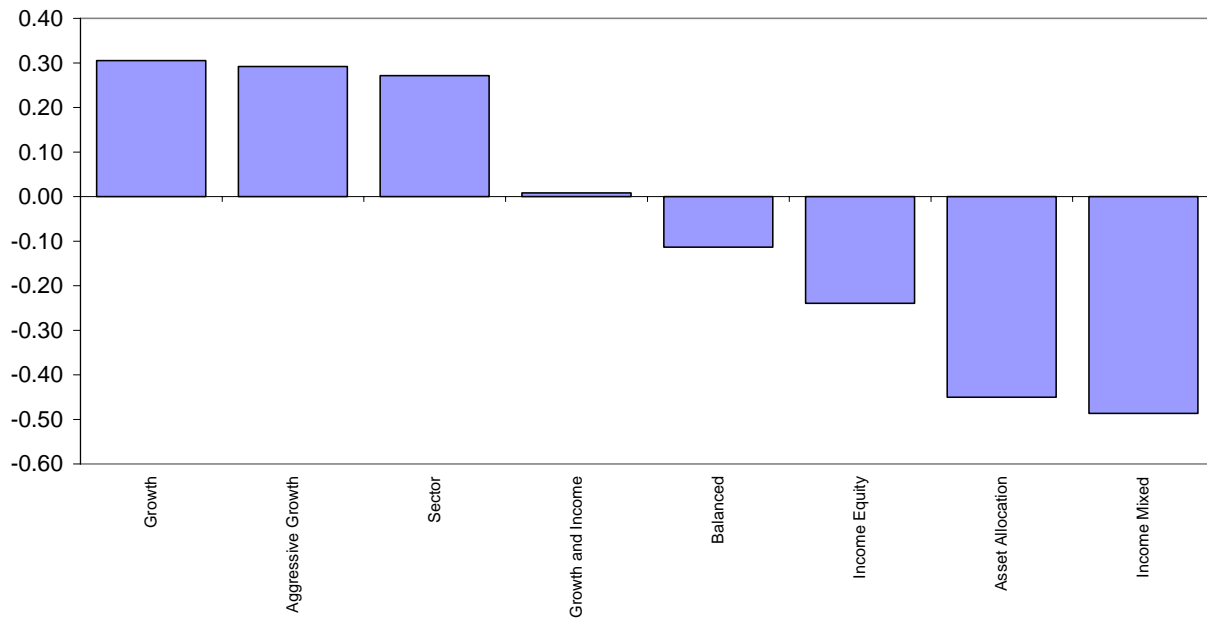Panel B. Speculative demand: The second principal component of flow changes

Figure 4. The sensitivity of stock returns to investor sentiment. The monthly returns of volatility sorted portfolios are regressed on general and speculative demand components of mutual fund flow changes (Panel A) and the index of sentiment changes (Panel B). The coefficients, or sentiment betas, show the effect of a one standard deviation difference in the sentiment measure on average returns in percentage points. The regressions control for the value-weighted stock market return.

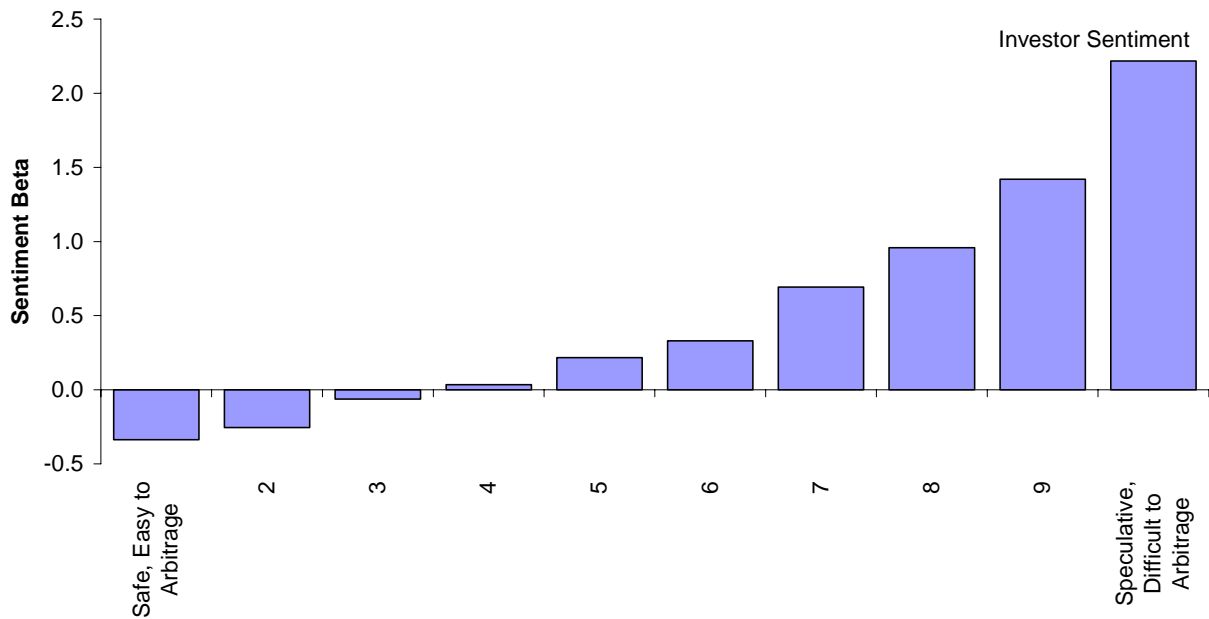Panel A. Mutual fund flow betas
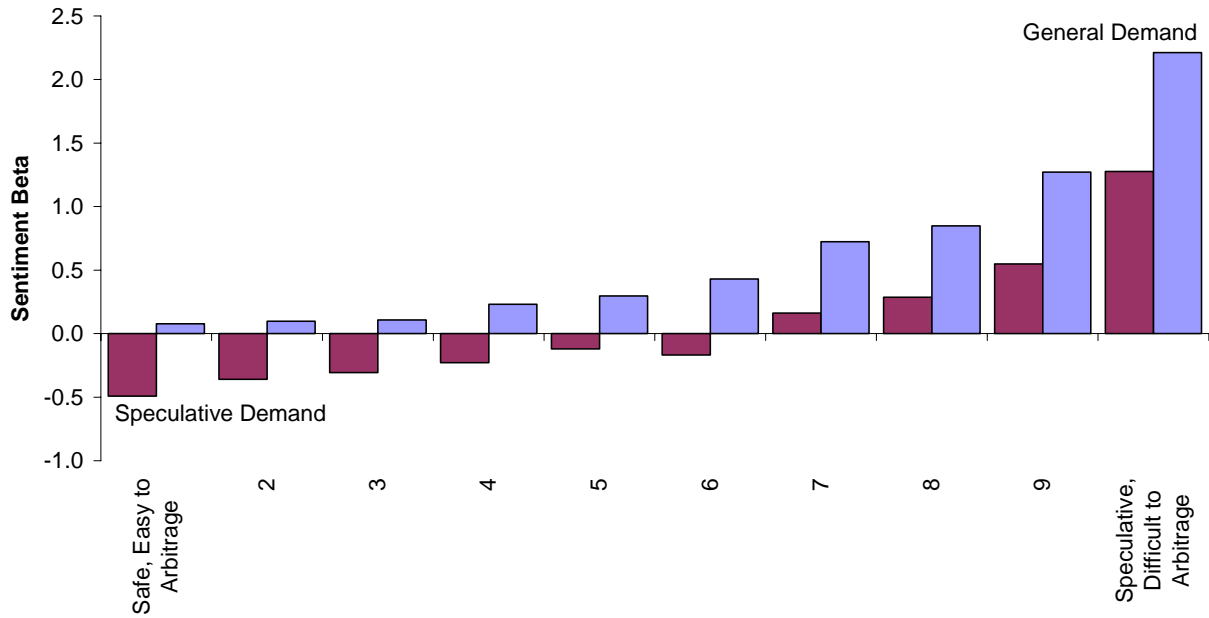
Panel B. Sentiment index betas

Figure 5. Sentiment and future returns. Average monthly returns over the value-weighted market index for volatility sorted portfolios following a month with a positive sentiment level (short dash); a negative level (long dash); and the overall average market-adjusted return. The latter are positive because of the small firm effect over this period: the volatility portfolios are equal weighted while the market index is value weighted.
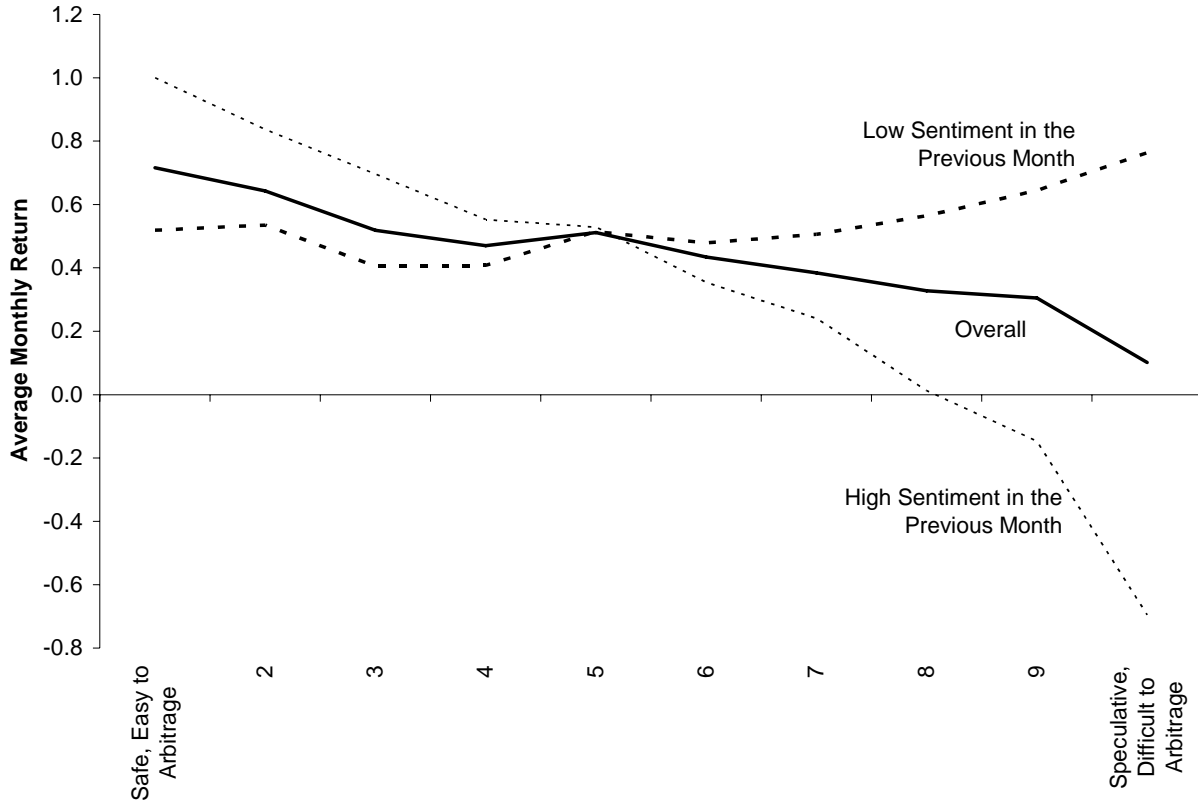
Figure 6. Sentiment and market returns. Average monthly returns in percentage points on the equal- and value-weighted market portfolios. The sample is divided into four groups according to the sentiment level in the preceding month.