How Does Investor Sentiment Affect the Cross-Section of Stock Returns?

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ABSTRACT

Broad waves of investor sentiment should have larger impacts on securities that are more difficult to value and to arbitrage. Consistent with this intuition, we find that when an index of investor sentiment takes low values, small, young, high volatility, unprofitable, non-dividend-paying, extreme growth, and distressed stocks earn relatively higher subsequent returns. When sentiment is high, the aforementioned categories of stocks earn relatively lower subsequent returns.

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1. Introduction

In this paper, an updated version of Baker and Wurgler (2006), we present evidence that broad waves of investor sentiment have significantly effects on the cross-section of stock prices.

These effects can take place through two complementary channels. On one hand, if all stocks are equally difficult to arbitrage, the current sentiment level may cause investors to demand certain stocks because such stocks are more compatible with current investor tastes. That is, suppose that we define investor sentiment as the aggregate inclination to speculate. When sentiment is high, investor demand for speculative investments is also high. Conversely, when sentiment is low, investor demand for speculative investments is also low. Because speculative opportunity is high for some stocks and low for others, sentiment affects the cross-section of stock returns even if arbitrage forces are constant across stocks.

On the other hand, if some stocks are more difficult to arbitrage than others, even indiscriminate waves of sentiment will affect the cross-section of stock prices. Suppose we define investor sentiment is optimism or pessimism about stocks in general. Then, to the extent that some stocks are more costly to arbitrage than others, the same waves of sentiment will affect the cross-section of stocks differently, driving up the prices of stocks that are more costly to arbitrage because arbitrageurs cannot step in to take advantage of uninformed sentiment.

In our recent academic paper, Baker and Wurgler ("we" henceforth) studied whether sentiment affected the cross-section of stock returns. A guiding principle for the tests was that while the two ways sentiment affects pricing outlined above operate separately, they give very similar empirical predictions. This is because the stocks that are most sensitive to speculative demand, namely those that are most difficult to value, also tend to be the riskiest to arbitrage. These include stocks of small, young, highly volatile, unprofitable, non-dividend-paying, distressed, and extreme growth potential firms. Thus, we predicted that these stocks would be most affected by shifts in sentiment, and we looked for evidence whether this was the case. It was.

2. An Anecdotal History of Investor Sentiment, 1961 to the present

To give some intuition, we first discussed how U.S. market sentiment rose and fell in recent decades, according to anecdotal reports. Graham (1973), Malkiel (1990), Brown (1991), and Dreman (1979) note during 1961, investors strongly demanded small, young, growth stocks. Malkiel writes about a "new-issue mania" that spread among new "tronics" firms. "… The tronics boom came back to earth in 1962. The tailspin started early in the year and exploded in a horrendous selling wave … Growth stocks took the brunt of the decline, falling much further than the general market" (p. 54-57).

The next major market bubble developed in 1967 and 1968 and was popularly associated with "growth" stocks. Brown remarks "scores of franchises, computer firms, and mobile home manufactures seemed to promise overnight wealth … [while] quality was pretty much forgotten" (p. 90). Malkiel and Dreman also remarked on how the market focused on strong earnings potential to the exclusion of the major industrial giants.

Dividends were apparently out of favor. According to the New York Times, “during the speculative market of the late 1960s many brokers told customers that it didn’t matter whether a company paid a dividend—just so long as its stock kept going up” (9/13/1976). But “after 1968, as it became clear that capital losses were possible, investors came to value dividends” (10/7/1999). Graham summarizes the cross-section of returns during this period by stating “comparative results undoubtedly reflect the tendency of smaller issues of inferior quality to be relatively overvalued in bull markets, and not only to suffer more serious declines than the stronger issues in the ensuing price collapse, but also to delay their full recovery—in many cases indefinitely” (p. 212).

The early 1970s was generally marked by a bear market with low investor enthusiasm. Nonetheless, a set of large, established, and profitable stocks known as the “nifty fifty” performed well. Siegel (1998) remarks, “All of these stocks had proven growth records, continual increases in dividends … and high market capitalization” (p. 106). What happened to the “nifty fifty” stocks in this *low* sentiment period is similar to the typical experience of small, young, unprofitable, growth stocks in bull markets.

Reagan-era optimism is sometimes cited as the cause of rising sentiment from the late 1970s through the mid 1980s. This period saw a series of episodes marked by high speculative demand. Dreman notes a bubble in gambling issues in 1977 and 1978. Ritter (1984) describes a hot market of natural resource startups in 1980. Malkiel (p.74-75) writes that “the high technology new-issue boom of the first half of 1983 was an almost perfect replica of the 1960’s episodes … The bubble appears to have burst early in the second half of 1983 … the carnage in the small company and new issue markets was truly catastrophic.” Of biotech, Malkiel says, “What electronics was to the 1960s, biotechnology became to the 1980s … new issues of biotech companies were eagerly gobbled up … having positive sales and earnings was actually considered a drawback" (p. 77-79). However, by 1987, "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" (p. 79).

The tech bubble of the late 1990s is most likely still fresh on the minds of most readers. Investor sentiment was, by all accounts, very high before the bubble burst in 2000. Cochrane (2003) and Ofek and Richardson (2002) look at some of the reasons behind the bubble. Even before the crash, Asness et al. (2000) and Chan, Karceski, and Lakonishok (2000) argued the surging stock prices cannot be attributed to rational expected earnings. Malkiel (1999) likens this episode to those in the 1960s, 1970s, and 1980s. Shiller (2000) draws parallels between what happened in the late 1920s to this period. One similarity between the recent bubble period and earlier bubble periods is that demand for dividend paying firms was lower than that during non-bubble periods (New York Times, 1/6/1998). Ljungqvist and Wilhelm (2003) find 80% of the 1999 and 2000 IPO cohorts reported negative earnings per share. Moreover, the median age of 1999 IPOs was 4 years. This is much different from non-bubble periods: According to Ritter (2003), the average age of IPOs is 9 years prior to the tech bubble, and over 12 years after.

This anecdotal evidence seems consistent with the hypothesis that sentiment increases the relative price of stocks most subjective to value and hardest to arbitrage. We proceeded to more formal tests of this hypothesis.

3. Sample data and summary characteristics

A. Characteristics and Returns

Our data came from the merged CRSP-Compustat database. In our updated tests, we include all common stocks (share codes 10 and 11) between 1962 and 2005. If possible we followed variable definitions from Fama and French (1992) when we matched accounting data to CRSP stock data.

Table 1 gives data summary statistics. Panel A contains return variables, raw and momentum returns. MOM was defined as the cumulative raw return for the 11-month period from 12 through 2 months prior to the observation return. We used momentum merely as a control variable here (Jegadeesh and Titman 1993).

The remaining panels review the other firm and stock characteristics that seemed likely, according to our hypotheses, to identify stocks more and less affected by sentiment. We roughly grouped them according to whether they relate to firm size and age, profitability, dividends, asset tangibility, and growth opportunities and/or distress.

Size and age characteristics included market equity (ME), age, and firm return volatility (sigma). Market equity was measured as price multiplied by the number of shares outstanding. As stated, we followed the timing convention of Fama and French (1992). Firm age was defined as the number of years since CRSP started tracking the firm, measured to the nearest month. Firm return volatility (Sigma), which prior work has argued reflects both the difficulty in valuing and the difficulty in arbitraging a firm's stock, was calculated as the standard deviation of monthly returns over the 12 months ending in a month at least 6 months before the return observation month. We required at least 9 monthly returns when we estimated Sigma.

[TABLE 1 HERE]

Our profitability characteristics were return on equity (E+/BE) and whether earnings were positive last period (E>0). We calculated earnings as income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19). Book equity (BE) was defined as shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35). And return on equity was defined as earnings divided by book equity if the quotient is positive; it is zero otherwise.

Our dividend characteristics were dividends to equity (D/BE) and whether dividends were positive last period (D>0). Dividends to equity was calculated as dividend per share at the ex date (Item 26) multiplied by the number of shares outstanding (Item 25) divided by book equity. Some have argued that asset tangibility proxies for difficulty in valuation. Our asset tangibility characteristics included property, plant and equipment (Item 7) over assets (PPE/A) and research and development expense (item 46) over assets (RD/A).

Finally, we included characteristics capturing growth opportunities and/or distress. We looked at book-to-market equity (BE/ME), external finance (EF/A), and sales growth (GS). BE/ME was calculated using variables detailed above. External finance was calculated as change in assets (Item 6) minus the change in retained earnings (Item 36) divided by assets. Sales growth (GS) was calculated as the change in net sales (Item 12) divided by prior-year net sales.

One has to be careful interpreting the variables capturing growth and/or distress. For example, book-to-market captures at least three effects. High values are more likely to indicate distress; low values are more likely to indicate growth opportunities; and, it is also a generic indicator of mispricing and rational expected returns.

B. Investor Sentiment

Capturing investor sentiment is not an easy task. We turned to previous work for a number of proxies. Each has its own strengths and weaknesses. We therefore formed a composite index of sentiment based on the common variation in six underlying proxies. The six proxies we use are the closed-end fund discount, NYSE share turnover, the number of and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. In our updated data here, we measure these variables annually from 1962 to 2004.

The closed-end fund discount (CEFD) was calculated as the average difference between closed-end funds net asset values (NAV) and their market values. Previous research suggests that sentiment is inversely related to CEFD. Zweig (1973) uses CEFD to forecast Dow Jones stock reversions. Lee et al. (1991) argue sentiment is the cause behind many features of closed-end fund discounts. We took the value-weighted average discount on closed-end stock funds for the period between 1962 and 1993 from Neal and Wheatley (1998), for the period between 1994 and 1998 from CDA/Wiesenberger, and for the period between 1999 and 2004 from turn-of-the-year issues of the Wall Street Journal.

We calculated NYSE share turnover based on the ratio of reported share volume to average shares listed from the NYSE Fact Book. Baker and Stein (2004) suggest turnover, which may proxy for liquidity, captures sentiment. Lending credence to this view, Jones (2001) finds high turnover forecasts low market returns. In our study, we defined TURN as the natural log of the raw turnover ratio, detrended by its five-year moving average.

The condition of IPO market is usually thought to be closely related to investor sentiment. High first-day IPO returns can be seen as a sign of investors being enthusiastic about the investing environment. Also, as pointed out by Stigler (1964) and Ritter (1991), low idiosyncratic returns can be interpreted as a symptom of market timing. We took the number of IPOs (NIPO) and their average first day returns (RIPO) from Ritter's website.

Our fifth measure was the share of equity issues in total equity and debt issues. It captures financing activity and thus may capture sentiment. Baker and Wurgler (2000) report high values of equity share predict low market returns. Using data from the Federal Reserve Bulletin, we calculated equity share as gross equity issuance divided by gross equity plus gross long-term debt issuance.

Our sixth and last measure is the "dividend premium" ($P^{D\text{-}ND}$). It is calculated as the log difference of the average market-to-book ratios of payers and non-payers. Baker and Wurgler (2004) argue that the dividend premium proxies for investor demand for dividend-paying stocks relative to other stocks.

Each of the aforementioned sentiment proxies doubtless includes a sentiment component and a non-sentiment component. To isolate the common sentiment component, we used principal component analysis to form an overall sentiment index.[1] Before doing so however, we first determined the relative "timing" of the variables. Ibbotson and Jaffe (1975), Lowry and Schwert (2002), and Benveniste et al. (2003) all report IPO volume lags the first-day returns on IPOs. More generally, it is reasonable to expect some among our proxies to take longer to reveal common sentiment as compared to others. Thus we started by estimating the first principal component of the six proxies and their lags. This process gave us a first-stage index consisted of 12 loadings. We then computed the correlation between the first-stage index and the current and lagged values for each proxy. For each of the six proxies, we took either the lead or the lag of each variable depending on which is more correlated with the first-stage index. Finally, we defined the second-stage SENTIMENT index as the first principal component of the correlation matrix of the six variables chosen, rescaling the coefficients so SENTIMENT has unit variance.

The above procedure led to a parsimonious index,

$$\begin{aligned} SENTIMENT_t \; = \; & -0.252CEFD_t + 0.248TURN_{t-1} + 0.249NIPO_t \\ & + 0.263RIPO_{t-1} + 0.100S_t - 0.299P_{t-1}^{D-ND}, \end{aligned} \tag{1}$$

where each of the index components was first standardized. The first principal component explained about half of the total sample variance of the raw sentiment proxies, indicating one factor captures much of the common variation. The correlation between the first-stage index and the second-stage index is above 0.9. Thus we lost little by dropping either the lead or lag of each of the six sentiment proxies. Two comments should be made about the sentiment index. First, each individual proxy entered the combined index with the expected sign. Second, the index ironed out outlier observations.

An objection about the above index may be that it does not distinguish between a common sentiment component, which is what we were after, and a common business cycle component. For example, the number of IPOs clearly varies with the business cycle. For our purposes, we wanted to identify when the number of IPOs is high because of sentiment, i.e. because of no good reason. We thus constructed an index that explicitly removed identifiable business components. Specifically, we regressed each of the six proxies on growth in industrial production index (Federal Reserve Statistical Release

G.17), growth in consumer durables, non-durables, and services (all from BEA national Income Accounts Table 2.10), and a dummy variable for NBER recessions. We took the residuals from these six regressions, labeled with a superscript ⊥, and constructed a sentiment index, also labeled with a superscript ⊥. The resulting index,

$$SENTIMENT^{\perp}{}_{t} = -0.215 CEFD_{t}^{\perp} + 0.232 TURN_{t-1}^{\perp} + 0.229 NIPO_{t}^{\perp} + 0.273 RIPO_{t-1}^{\perp} + 0.211 S_{t}^{\perp} - 0.264 P_{t-1}^{\perp, D-ND}. \quad (2)$$

is orthogonal to common business cycle effects. The first principal component again explained about half of the sample variance of the residuals, and $SENTIMENT^{\perp}$ retains all of the appealing properties of *SENTIMENT*. Because $SENTIMENT^{\perp}$ may be a cleaner measure of sentiment, we use it as our index for the rest of this paper.

Figure 1 shows that the sentiment measures we used roughly line up with anecdotal accounts of sentiment fluctuations (except for turnover which is confounded by deregulation). Most individual proxies indicate low sentiment in the early years of the sample, after the 1961 crash in growth stocks. Each variable then points to a sentiment spike in 1968 and 1969. Sentiment then tails off. By the mid 1970s, sentiment resided at a very low level by most measures. Sentiment then rebounded from the late 1970s through the mid 1980s. In fact, sentiment has stayed above its medium level since 1980. Overall, $SENTIMENT^{\perp}$ is positive during the periods of 1968-1970, 1972, 1979-1987, 1994, 1996-1997, and 1999-2003. Again, this pattern matches the anecdotes of market sentiment previously discussed.

[FIGURE 1 HERE]

4. Empirical Tests

We tested our prediction that an increase in sentiment increases the relative price of stocks most subjective to value and hardest to arbitrage using two methods. First, we performed nonparametric tests based on sorting. Second, we performed multivariate time-series regression analysis.

A. Sorts

For each month, we first sorted monthly returns of all stocks into deciles based on values a certain characteristic takes at the beginning of that month. To keep the definition of the deciles similar over time, we chose the decile cutoffs based on NYSE firms. Then we further segregated the return deciles based on the level of $SENTIMENT^{\perp}$ at the end of the previous calendar year. We computed the equal-weighted average monthly return for each bin and looked for patterns.

[TABLE 2 HERE]

Table 2 shows the sorts. The first set of results focus on the size effect, conditional on investor sentiment. Strikingly, the size effect of Banz (1981) appears in low sentiment periods only. When sentiment is low, the smallest stocks return on average 2.33% per month; the largest stocks return on average 1.08% per month. Swaminathan (1996) notes a similar link between the size effect and closed-end fund discounts, which is one of our six sentiment proxies used to construct our sentiment index. Our result is consistent with other previous results. Namely, Keim (1983) and Blume and Stambaugh (1983) argue the size effect is essentially a January effect; and according to Reinganum

(1983), the January effect is stronger after a period of low returns, which is also when sentiment is likely to be low.

The next rows give results on conditional cross-sectional effect of age. Investors seem to demand younger stocks when sentiment is high and older stocks when sentiment is low. For example, when sentiment is low, the oldest firms return 0.38% per month less than the youngest firms. However, the oldest firms return 0.55% per month more than the youngest firms when sentiment is high. Also, when sentiment is high, the age effect is concentrated in the youngest stocks, which are the recent IPOs. Overall, one can see a nearly monotonic pattern in the difference of returns. Because age has no unconditional effect, one would miss this result if one does not condition on previous period's investor sentiment. The strong conditional effects would average out to nearly nothing across high and low sentiment periods.

The third set of rows shows how sentiment affects firms with different return volatility. The results match our prediction. Specifically, when sentiment is low, investors avoid highly volatile stocks as they have to promise returns of 2.23% per month over the next year. When sentiment is high, highly volatile stocks earn lower returns. We interpret these results to say that highly volatile stocks, like young stocks, are relatively more difficult to value and to arbitrage. Thus they move with fluctuations in investor sentiment.

The next two sets of rows look at how sentiment affects stocks sorted based on profitability and dividends. When the average investor chooses her investments, her most salient comparisons are probably between profitable (E>0) and unprofitable (E<=0) firms or between dividend payers (D>0) and dividend non-payers (D=0). Sentiment again significantly affects returns sorted based on these characteristics. When sentiment is high, over the next year, monthly returns for profitable firms are 0.22% higher than that for unprofitable firms; monthly returns for dividend payers are 0.39% higher than that for dividend non-payers. When sentiment is low, over the next year, monthly returns for profitable firms are 0.67% lower than that for unprofitable ones; monthly returns for dividend payers are also 0.67% lower than that for dividend non-payers. The left column of these rows shows that these patterns are driven mostly by the conditional variation in returns of unprofitable and nonpaying firms. All these results are consistent with the likely scenario that unprofitable and non-dividend-paying firms are more difficult to value and arbitrage, thus exposing them more to changes in sentiment.

The next two sets of results examine how sentiment affects stocks sorted based on tangibility characteristics under the notion that firms with fewer tangible assets are probably more difficult to value. The patterns here are not as strong as the previous characteristics, possibly because these characteristics do not sharply separate firms according to their difficultly of valuation and arbitrage.

The remaining sets of variables, book-to-market, external finance, and sales growth, capture distress and/or extreme growth potential. Each of them has some unconditional explanatory power. High BE/ME, lower EF/A, low GS stocks generally give higher future returns. The unconditional EF/A result echos results from Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995, 1999), and the GS result is mentioned in Lakonishok, Shleifer, and Vishny (1994).

Conditional on sentiment level however, an interesting U-shaped pattern emerges for the distress and/or extreme growth potential variables. For example, for the bottom-decile GS firms, the difference in returns between high and low sentiment is -1.11% per month. For the fifth-decile firms, the difference is -0.41% per month. For the tenth-decile firms, the difference is -1.52% per month. This U-shaped pattern also shows up for BE/ME and EF/A results. Thus for these sorting variables, firms landing in the extreme bins react more to sentiment than those that land in the middle bins.

The U-pattern probably reflects the multidimensional nature of these variables. Take GS firms as examples. High GS-firms are high-flying growth firms; low-GS firms are distressed firms with shrinking sales; middle-GS firms are more likely to be steady and established. Thus firms falling into the extreme bins are more difficult to value and arbitrage and hence are more affected by sentiment, consistent with the hypothesis.

B. Predictive Regressions for Long-Short Portfolios

While our sorting results are telling, they do not control for some factors previously shown to affect expected stock returns. Another way to test conditional effects of sentiment is to use sentiment to forecast returns from an equal-weighted portfolio, formed by buying stocks that fall into the top decile of a characteristic while selling stocks that fall into the bottom decile. We used a regression framework to test this prediction. This approach allowed us to take into account the continuous nature of our sentiment index and determine how characteristics of interest affect returns once we condition on investor sentiment.

We ran regressions of the type

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = c + dSENTIMENT^{\perp}_{t-1} + \varepsilon_{it}\,. \qquad (3)$$

The dependent variable is the monthly returns series from a long-short portfolio based a characteristic such as size; returns from year t are regressed on the sentiment index of year t-1. We further tested our sentiment predictive power by controlling for other factors well known to affect the cross-section of stock returns. Specifically, we ran

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = c + dSENTIMENT_{t-1}^{\perp} + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + \varepsilon_{it}\,. \tag{4}$$

The additional independent variables in this regression are the well-known Fama and French (1993) three factors and Carhart's (1997) momentum factor.[2] Note when we used the long-short portfolio based on size and book-to-market, namely SMB and HML, we exclude them from the right hand side of the regression. We used bootstrap methods to correct for any bias present in the standard errors.

The results from these regressions are shown in Table 3, and they concur with results from our sorts. When sentiment is high, returns on small, young, and high volatility firms are relatively lower over the next year. Adding additional controls does reduce sentiment's effects, but sentiment nonetheless remains statistically and economically significant. Under the multivariate specification in Table III, a one standard deviation increase in sentiment is associated with a -0.4% decrease in monthly return for the SMB portfolio.[3]

[TABLE 3 HERE]

Results show sentiment has significant predictive power for portfolios formed based on profitability and dividend payment. Higher sentiment forecasts relatively higher returns on profitable and dividend paying firms. Forecasting power for tangibility portfolios is weak, consistent with the results of the sorts.

As we found in our sorting results, our variables capturing distress and/or extreme growth potential do not vary linearly with sentiment. Panel D shows sentiment does not forecast “high minus low” portfolios formed based on BE/ME, EF/A, or GS. Panel E and F, however, show that once we took the multidimensional nature of these variables into consideration, sentiment revealed its predictive power. That is, for each of these characteristics, we first constructed High, Medium, and Low portfolios using the top three, middle four, and bottom three NYSE decile breakpoints. Then instead of using High-Low, we constructed long-short portfolios of High-Medium and Medium-Low. Using these portfolios as our dependent variables, sentiment has strong predictive power for long-short portfolios formed based on EF/A and GS; it remains statistically insignificant for BE/ME.

Several comments are worth making about the robustness of the results in Table 3. First, they are robust to controlling for an overall time trend. Second, the results are stronger when January and December returns are excluded from the sample. This says the sentiment effects we find are not motivated by tax-motivated trading and the induced liquidity fluctuations. Third, we use equal weighted portfolios because we predicted that sentiment has large effects on small firms. Value weighting the portfolios would obscure some of the results. Nonetheless, by including SMB in specification (4), we controlled for the size effect in some sense. Fourth, we extended our sample back to 1935. Because of data availability, we lost two of our sentiment proxies and several firm characteristics in the process. Nonetheless, using the remaining data, we confirmed our results in this longer period qualitatively match the results already discussed. Finally, we showed that our results do not reflect time variation in systematic risks.

Thus the regression results confirm our sorting results. When sentiment is high, future returns of small, young, highly volatile, unprofitable, non-dividend-paying, distressed, and extreme growth firms are relatively low. The opposite is also generally true. As predicted, sentiment most strongly affects stocks that are more difficult to value and arbitrage.

5. Conclusion

Investor sentiment affects the cross-section of stock returns. For practitioners, the main takeaway is that the cross-section of future stock returns varies with beginning-of-period investor sentiment. The patterns are intuitive and consistent with economic theory. When sentiment is high, stocks that are prone to speculation and difficult to arbitrage, namely stocks of young, small, unprofitable, non-dividend-paying, highly volatile, distressed, and extreme growth firms, tend to earn relatively lower subsequent returns. When sentiment is low, the reverse mostly holds. Most strikingly, several characteristics that exhibit no unconditional predictive power actually exhibit predictive power once we condition on beginning-of-period investor sentiment. These results suggest there is much to be done in terms of understanding more about investor sentiment and its effects.

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Table I

Summary Statistics, 1963 to 2005

Panel A summarizes the returns variables. Returns are measured monthly. Momentum (MOM) is defined as the cumulative return for the 11-month period between 12 and two months prior to *t*. Panel B summarizes the size, age, and risk characteristics. Size is the log of market equity. Market equity (ME) is price times shares outstanding from CRSP in the June prior to *t*. Age is the number of years between the firm's first appearance on CRSP and *t*. Total risk (σ) is the annual standard deviation in monthly returns from CRSP for the 12 months ending in the June prior to *t*. Panel C summarizes profitability variables. The earnings-book equity ratio is defined for firms with positive earnings. Earnings (E) is defined as income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19). Book equity (BE) is defined as shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35). We also report an indicator variable equal to one for firms with positive earnings. Panel D reports dividend variables. Dividends (D) are equal to dividends per share at the ex date (Item 26) times shares outstanding (Item 25). We scale dividends by assets and report an indicator variable equal to one for firms with positive dividends. Panel E shows tangibility measures. Plant, property, and equipment (Item 7) and research and development (Item 46) are scaled by assets. We only record research and development when it is widely available after 1971; for that period, a missing value is set to zero. Panel F reports variables used as proxies for growth opportunities and distress. The book-to-market ratio is the log of the ratio of book equity to market equity. External finance (EF) is equal to the change in assets (Item 6) less the change in retained earnings (Item 36). When the change in retained earnings is not available we use net income (Item 172) less common dividends (Item 21) instead. Sales growth decile is formed using NYSE breakpoints for sales growth. Sales growth is the percentage change in net sales (Item 12). In Panels C through F, accounting data from the fiscal year ending in *t*-1 are matched to monthly returns from July of year *t* through June of year *t*+1. All variables are Winsorized at 99.5 and 0.5 percent.

	Full Sample					*Subsample Means*				
	N	**Mean**	**SD**	**Min**	**Max**	**1960s**	**1970s**	**1980s**	**1990s**	**2000-5**
					Panel A. Returns					
R_t (%)	1,807,218	1.42	18.02	-98.13	2400.00	1.08	1.56	1.25	1.46	1.48
MOM_{t-1} (%)	1,807,218	14.35	59.32	-85.87	357.14	21.68	12.28	15.07	13.11	16.10
					Panel B. Size, Age, and Risk					
ME_{t-1} ($M)	1,807,218	779	2,990	1	30,154	393	240	398	901	1,688
Age_t (Years)	1,807,218	13.56	13.47	0.03	70.58	15.78	12.55	13.55	13.25	14.66
σ_{t-1} (%)	1,780,620	13.87	9.01	0.00	61.80	9.45	12.53	13.33	13.89	16.77
					Panel C. Profitability					
$E+/BE_{t-1}$ (%)	1,807,218	10.50	10.22	0.00	68.13	12.12	12.07	11.39	9.55	9.10
$E>0_{t-1}$	1,807,218	0.77	0.42	0.00	1.00	0.95	0.91	0.78	0.71	0.67
					Panel D. Dividend Policy					
D/BE_{t-1} (%)	1,807,218	2.01	2.99	0.00	18.43	4.44	2.75	2.11	1.58	1.44
$D>0_{t-1}$	1,807,218	0.47	0.50	0.00	1.00	0.77	0.66	0.50	0.37	0.35
					Panel E. Tangibility					
PPE/A_{t-1} (%)	1,650,539	53.80	37.32	0.00	187.32	70.08	59.09	55.47	51.34	46.28
RD/A_{t-1} (%)	1,660,280	3.24	7.81	0.00	57.93		1.23	2.31	3.88	4.85
					Panel F. Growth Opportunities and Distress					
BE/ME_{t-1}	1,807,218	0.92	0.86	0.02	5.96	0.70	1.37	0.95	0.76	0.80
EF/A_{t-1} (%)	1,756,471	11.29	24.62	-72.53	129.93	7.18	6.44	10.58	13.94	13.03
GS_{t-1} (Decile)	1,734,102	5.89	3.17	1.00	10.00	5.67	5.67	6.02	6.09	5.64

Table II

Future Returns by Sentiment Index and Firm Characteristics, 1963 to 2005

For each month, we form ten portfolios according to the NYSE breakpoints of firm size (ME), age, total risk, earnings-book ratio for profitable firms (E/BE), dividend-book ratio for dividend payers (D/BE), fixed assets (PPE/A), research and development (RD/A), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth (GS). We also calculate portfolio returns for unprofitable firms, nonpayers, zero-PP&E firms, and zero-R&D firms. We then report average portfolio returns over months in which SENTIMENT$^{\perp}$ from the previous year-end is positive, months in which it is negative, and the difference between these two averages. SENTIMENT$^{\perp}$ is positive for 1968 to 1970, 1972, 1979 to 1987, 1994, 1996 to 1997, and 1999 to 2003.

	$SENTIMENT^{\perp}_{t-1}$	*Decile*											*Comparisons*			
		≤0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**	**10-5**	**5-1**	**>0-≤0**
ME	**Positive**		1.00	0.81	0.77	0.76	0.82	0.68	0.90	0.83	0.80	0.73	-0.27	-0.08	-0.19	
	Negative		2.33	1.66	1.77	1.61	1.77	1.52	1.43	1.35	1.25	1.08	-1.25	-0.69	-0.56	
	Difference		-1.32	-0.85	-1.01	-0.86	-0.95	-0.84	-0.53	-0.52	-0.45	-0.35	0.98	0.61	0.37	
Age	**Positive**		0.38	1.12	1.02	1.08	1.20	1.20	1.01	1.02	0.94	0.93	0.55	-0.27	0.83	
	Negative		1.80	1.80	1.95	1.79	1.68	1.72	1.48	1.53	1.55	1.42	-0.38	-0.26	-0.11	
	Difference		-1.42	-0.68	-0.93	-0.71	-0.48	-0.51	-0.47	-0.51	-0.61	-0.49	0.93	-0.01	0.94	
σ	**Positive**		1.23	1.23	1.13	1.08	1.11	0.94	0.99	0.93	0.93	0.68	-0.55	-0.43	-0.12	
	Negative		1.23	1.38	1.42	1.52	1.68	1.81	1.77	1.91	2.05	2.23	1.00	0.55	0.45	
	Difference		0.00	-0.15	-0.29	-0.44	-0.57	-0.87	-0.77	-0.98	-1.12	-1.55	-1.55	-0.98	-0.57	
E/BE	**Positive**	0.70	0.81	0.90	1.00	0.97	0.99	0.90	0.92	0.98	0.99	0.82	0.01	-0.17	0.18	0.22
	Negative	2.42	2.31	2.06	2.22	1.90	1.67	1.87	1.79	1.74	1.62	1.73	-0.58	0.06	-0.64	-0.67
	Difference	-1.72	-1.50	-1.16	-1.22	-0.93	-0.69	-0.96	-0.87	-0.76	-0.62	-0.92	0.58	-0.23	0.82	0.88
D/BE	**Positive**	0.65	0.99	1.00	1.17	0.99	1.11	1.02	1.08	1.02	0.92	0.92	-0.06	-0.18	0.12	0.39
	Negative	2.27	2.02	1.81	1.74	1.67	1.55	1.47	1.38	1.29	1.38	1.39	-0.63	-0.16	-0.47	-0.67
	Difference	-1.62	-1.04	-0.80	-0.57	-0.68	-0.45	-0.45	-0.29	-0.27	-0.46	-0.47	0.57	-0.02	0.59	1.06
PPE/A	**Positive**	1.14	0.56	0.85	0.94	0.91	1.10	0.95	0.88	0.92	0.99	1.14	0.59	0.04	0.54	-0.25
	Negative	1.49	1.92	1.87	1.88	1.84	1.85	1.97	1.79	1.56	1.44	1.76	-0.16	-0.09	-0.07	0.31
	Difference	-0.36	-1.36	-1.02	-0.94	-0.93	-0.75	-1.01	-0.92	-0.64	-0.45	-0.62	0.74	0.13	0.61	-0.56
RD/A	**Positive**	0.79	1.20	0.97	1.23	1.30	1.20	1.11	1.20	1.35	1.55	1.74	0.54	0.55	-0.01	0.73
	Negative	1.76	1.68	1.63	1.82	1.85	1.79	1.84	2.00	2.02	1.92	2.01	0.34	0.23	0.11	0.09
	Difference	-0.97	-0.47	-0.66	-0.59	-0.56	-0.59	-0.74	-0.80	-0.66	-0.37	-0.27	0.20	0.32	-0.12	0.63
BE/ME	**Positive**		0.18	0.66	0.79	0.85	0.96	1.09	1.17	1.18	1.35	1.53	1.35	0.57	0.78	
	Negative		1.32	1.43	1.53	1.61	1.68	1.77	1.96	2.05	2.27	2.48	1.16	0.80	0.37	
	Difference		-1.14	-0.77	-0.74	-0.76	-0.72	-0.68	-0.79	-0.87	-0.91	-0.94	0.19	-0.23	0.42	
EF/A	**Positive**		1.34	1.20	1.28	1.26	1.21	1.16	1.05	0.92	0.80	0.15	-1.20	-1.06	-0.13	
	Negative		2.32	2.09	1.91	1.76	1.68	1.60	1.59	1.64	1.78	1.50	-0.82	-0.18	-0.64	
	Difference		-0.98	-0.89	-0.63	-0.51	-0.47	-0.44	-0.54	-0.72	-0.98	-1.35	-0.38	-0.88	0.50	
GS	**Positive**		1.13	1.28	1.15	1.14	1.18	1.11	1.15	1.07	0.87	0.19	-0.94	-0.99	0.05	
	Negative		2.24	1.73	1.71	1.66	1.59	1.65	1.83	1.87	1.76	1.71	-0.53	0.12	-0.65	
	Difference		-1.11	-0.45	-0.56	-0.52	-0.41	-0.54	-0.68	-0.80	-0.88	-1.52	-0.41	-1.11	0.70	

Table III

Time Series Regressions of Portfolio Returns, 1963 to 2005

Regressions of long-short portfolio returns on lagged SENTIMENT, the market risk premium (RMRF), the Fama-French factors (HML and SMB), and a momentum factor (UMD).

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = c + dSENTIMENT_{t-1} + \beta RMRF_t + sSMB_t + hHML_t + mUMD_t + u_t \, .$$

The sample period includes monthly returns from 1963 to 2005. The long-short portfolios are formed based on firm characteristics (X): firm size (ME), age, total risk (σ), profitability (E), dividends (D), fixed assets (PPE), research and development (RD), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth decile (GS). High is defined as a firm in the top three NYSE deciles, low is defined as a firm in the bottom three NYSE deciles, and medium is defined as a firm in the middle four NYSE deciles. Average monthly returns are matched to SENTIMENT from the previous year-end. SENTIMENT$^{\perp}$ index is based on six sentiment proxies which have been orthogonalized to growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment, and a flag for NBER recessions; the components of SENTIMENT are not orthogonalized. The first and third sets of columns show univariate regression results, while the second and the fourth columns include RMRF, SMB, HML, and UMD as control variables. SMB (HML) is not included as a control variable when SMB (HML) is the dependent variable. T-statistics are in brackets.

		$SENTIMENT^{\perp}_{t-1}$		$SENTIMENT^{\perp}_{t-1}$ *Controlling for RMRF, SMB, HML,and UMD*	
		d	**t(d)**	**d**	**t(d)**
		Panel A. Size, Age, and Risk			
ME	**SMB**	-0.4	[-2.8]	-0.3	[-2.3]
Age	**High-Low**	0.5	[3.1]	0.2	[2.0]
σ	**High-Low**	-0.9	[-3.7]	-0.4	[-3.2]
		Panel B. Profitability and Dividend Policy			
E	**>0 – <0**	0.7	[3.6]	0.5	[2.9]
D	**>0 – =0**	0.8	[3.9]	0.4	[3.3]
		Panel C. Tangibility			
PPE/A	**High-Low**	0.4	[2.3]	0.1	[0.9]
RD/A	**High-Low**	-0.3	[-1.2]	-0.0	[-0.1]
		Panel D. Growth Opportunities and Distress			
BE/ME	**HML**	0.2	[1.7]	0.1	[0.6]
EF/A	**High-Low**	-0.2	[-2.0]	-0.1	[-1.6]
GS	**High-Low**	-0.2	[-1.7]	-0.1	[-1.1]
		Panel E. Growth Opportunities			
BE/ME	**Medium-Low**	0.3	[2.2]	0.1	[1.4]
EF/A	**High-Medium**	-0.4	[-3.7]	-0.2	[-3.6]
GS	**High-Medium**	-0.4	[-4.0]	-0.3	[-3.9]
		Panel F. Distress			
BE/ME	**High-Medium**	-0.1	[-1.1]	-0.0	[-0.7]
EF/A	**Medium-Low**	0.2	[3.6]	0.2	[3.1]
GS	**Medium-Low**	0.3	[3.5]	0.2	[2.9]

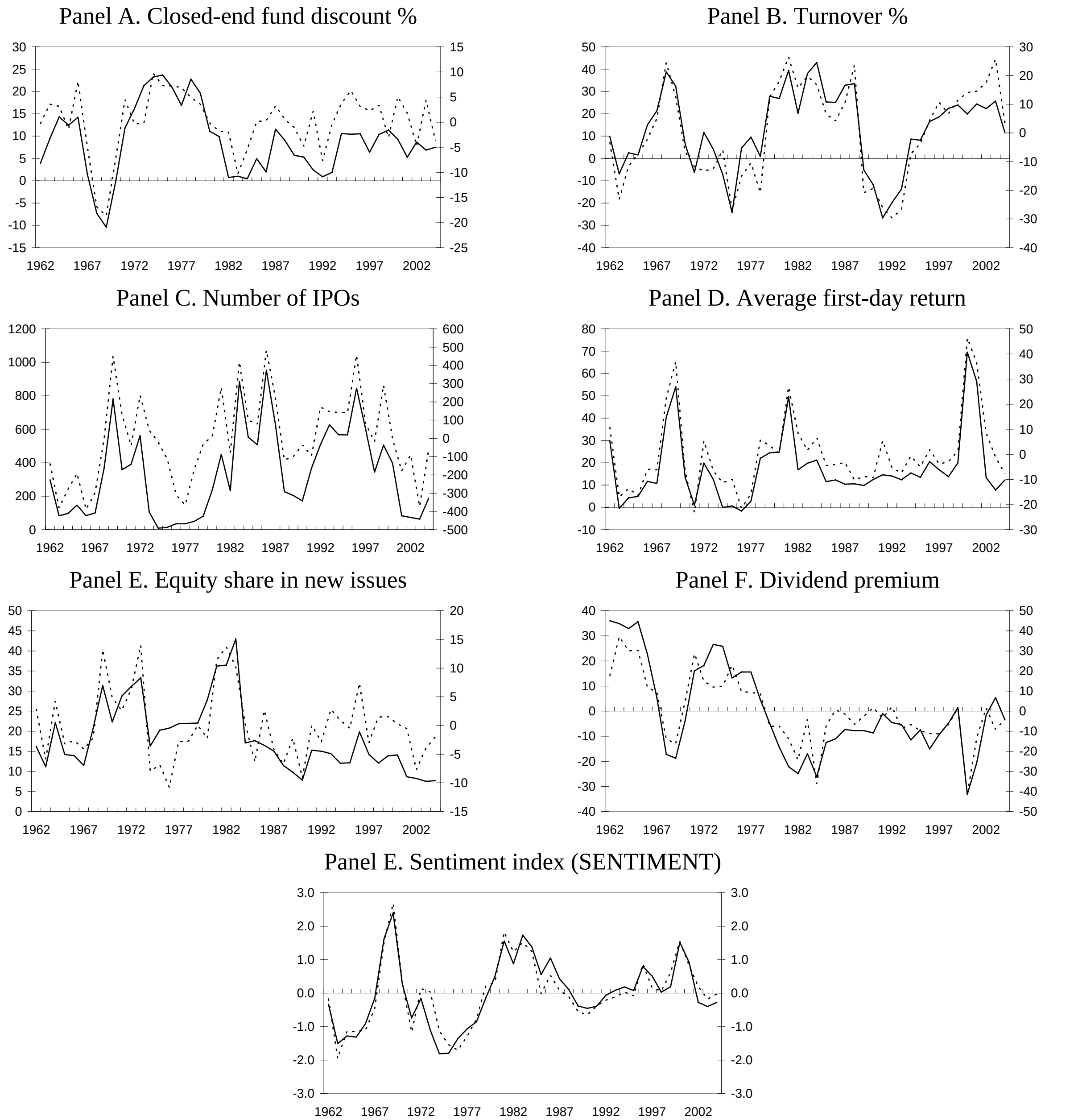

Figure 1. Investor Sentiment, 1962 to 2004. The first panel shows the year-end, value-weighted average discount on closed-end mutual funds. The data on prices and net asset values (NAVs) come from Neal and Wheatley (1998) for 1962 through 1993, CDA/Wiesenberger for 1994 through 1998, and turn-of-the-year issues of the *Wall Street Journal* for 1999 through 2001. The second panel shows detrended log turnover. Turnover is the ratio of reported share volume to average shares listed from the NYSE Fact Book. We detrend using the past five-year average. The third panel shows the annual number of initial public offerings. The fourth panel shows the average annual first-day returns of initial public offerings. Both series come from Jay Ritter, updating data analyzed in Ibbotson, Sindelar, and Ritter (1994). The fifth panel shows gross annual equity issuance divided by gross annual equity plus debt issuance from Baker and Wurgler (2000). The sixth panel shows the year-end log ratio of the value-weighted average market-to-book ratios of payers and nonpayers from Baker and Wurgler (2004). The solid line (left axis) is raw data. We regress each measure on the growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment, and a flag for NBER recessions. The dashed line (right axis) is the residuals from this regression. The solid (dashed) line in the final panel is a first principal component index of the six raw (orthogonalized) measures. Both are standardized to have zero mean and unit variance. In the index, turnover, the average annual first-day return, and the dividend premium are lagged one year relative to the other three measures, as discussed in the text.

Notes

[1] See Brown and Cliff (2004) for a similar approach to extracting a sentiment factor from a set of noisy proxies.

[2] These portfolios are taken from Ken French's website and are described there.

[3] The patterns with *ME* in Table 3 and the fact that sentiment predicts *SMB* suggest that sentiment proxies will predict equal-weighted market returns better than value-weighted market returns. We have briefly explored this and found that the sentiment indexes are stronger predictors of equal-weighted than value-weighted returns. Likewise, in Baker and Wurgler (2000), the equity share significantly forecasts both equal- and value-weighted returns, but the former coefficient is considerably larger. This is consistent with the prediction that sentiment has stronger effects on small stocks.