

Investor sentiment and the cross-section of stock returns

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ABSTRACT

We study how investor sentiment affects the cross-section of stock returns. We predict that a wave of investor sentiment disproportionately affects securities whose valuations are highly subjective and are difficult to arbitrage. We find that when beginning-of-period proxies for investor sentiment are low, subsequent returns are relatively high on small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme-growth stocks, and distressed stocks, suggesting that such stocks are relatively underpriced in low-sentiment states. When sentiment is high, on the other hand, the patterns largely reverse, suggesting that these categories of stocks are relatively overpriced in high-sentiment states.

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Classical finance theory leaves no role for investor sentiment. In this theory, most investors are rational and diversify to optimize the statistical properties of their portfolios. Competition among them leads to an equilibrium in which prices equal the rationally discounted value of expected cash flows, and in which the cross-section of expected returns depends only on the cross-section of systematic risks.¹ Even if some investors are irrational, classical theory argues, their demands are offset by arbitrageurs with no significant impact on prices.

In this paper, we present evidence that investor sentiment may have significant effects on the cross-section of stock prices. We start with simple theoretical predictions. Because a mispricing is the result of an uninformed demand shock in the presence of a binding arbitrage constraint, a broad-based wave of sentiment is predicted to have cross-sectional effects, not simply to raise or lower all prices equally, when sentiment-based demands vary across stocks or when arbitrage constraints vary across stocks. In practice, these two distinct channels lead to quite similar predictions, because stocks that are likely to be most sensitive to speculative demand – those with highly subjective valuations – also tend to be the riskiest and costliest to arbitrage. Concretely, then, theory suggests two distinct channels through which the stocks of newer, smaller, highly volatile firms, firms in distress or with extreme growth potential, firms without dividends, and firms with like characteristics, are expected to be relatively more affected by shifts in investor sentiment.

To investigate this prediction empirically, and to get a more tangible sense of the intrinsically elusive concept of investor sentiment, we start with a summary of rises and falls in U.S. market sentiment from 1961 through the Internet bubble. This summary is based on anecdotal accounts and by its nature can only be a suggestive, ex-post characterization of fluctuations in sentiment. Nonetheless, its basic message appears broadly consistent with our theoretical predictions, and suggests that more rigorous tests are warranted.

Our main empirical approach is as follows. Because cross-sectional patterns of sentiment-driven mispricing would be difficult to identify directly, we look for the hypothesized patterns in *subsequent* stock returns that appear when one conditions on proxies for beginning-of-period investor sentiment. The idea is that conditional cross-sectional patterns in subsequent returns may represent the initial patterns of mispricing correcting themselves over time. For example, low future returns on young firms relative to old firms, conditional on high values for proxies for beginning-of-period sentiment, would be consistent with young firms being relatively overvalued *ex ante*. As usual, we are mindful of the joint hypothesis problem that any predictability patterns we find actually reflect compensation for systematic risks.

The first step is to gather proxies for investor sentiment to use as time series conditioning variables. There are no perfect and/or uncontroversial proxies for investor sentiment, so our approach is necessarily practical. We consider a number of proxies suggested in recent work and form them into a composite sentiment index based on their first principal component. To reduce the likelihood that these proxies are connected to systematic risks, we also form an index based on sentiment proxies that have been orthogonalized to several macroeconomic conditions. The sentiment indexes visibly line up with historical accounts of bubbles and crashes.

We then test how the cross-section of subsequent stock returns varies with beginning-of-period sentiment. We use monthly stock returns between 1963 and 2001. We start by simply sorting firm-month observations according to the level of sentiment, first, and then the decile rank of a given firm characteristic, second. We find that when sentiment is low (below sample average), small stocks earn particularly high subsequent returns, but when sentiment is high (above average), there is no size effect at all. Conditional patterns are even sharper when sorting on other characteristics. When sentiment is low subsequent returns are higher on very young (or newly listed) stocks than older stocks, high-return volatility than low-return volatility stocks, unprofitable stocks than profitable ones, and nonpayers than dividend payers. When sentiment is

high, these patterns completely reverse. In other words, several characteristics that do not have any unconditional predictive power actually display sign-flipping predictive ability, in the hypothesized directions, once one conditions on sentiment. These are our most striking findings. Although earlier data is not as rich, most of these patterns are also apparent in a sample that covers 1935 through 1961.

The sorts also suggest that sentiment affects extreme growth and distressed firms in similar ways. Note that when stocks are sorted into deciles by sales growth, book-to-market, or external financing activity, growth and distress firms tend to lie at opposing extremes, with more “stable” firms in middle deciles. We find that when sentiment is low, the subsequent returns on stocks at both extremes are especially high relative to their unconditional average, while stocks in middle deciles are less affected by sentiment. (The result is not statistically significant for book-to-market, however.) This U-shaped pattern in *conditional difference* of returns also appears broadly consistent with theoretical predictions: both extreme-growth and distressed firms have relatively subjective valuations and are relatively hard to arbitrage, and so should be expected to be most affected by sentiment. Again, note that this intriguing conditional pattern would be averaged away in an unconditional study.

After confirming these patterns with a regression approach, we turn to the classical alternative explanation that they simply reflect a complex pattern of compensation for systematic risk. For instance, it would require either time variation in rational, market-wide risk premia or time variation in the cross-sectional pattern of risk, i.e., beta loadings. The results cast doubt on these notions. We test the second possibility directly and find no link between the patterns in predictability and patterns in betas with market returns or consumption growth. If risk is not changing over time, then the first possibility requires not just time-variation in risk premia but changes in sign. Put simply, it would require that in half of our sample period (when sentiment is relatively low), that older, less volatile, profitable, dividend-paying firms actually require a risk

premium over very young, highly volatile, unprofitable, nonpayers. This is counterintuitive. Other results also suggest that systematic risk is at best a partial explanation.

The results challenge the classical view of the cross-section of stock prices. In doing so, it builds on several recent themes. In particular, our results complement earlier work that sentiment also helps to explain the time series of returns (Kothari and Shanken (1997), Neal and Wheatley (1998), Shiller (1981, 2000), and Baker and Wurgler (2000)). Campbell and Cochrane (2000), Wachter (2000), Lettau and Ludvigson (2001), and Menzly, Santos, and Veronesi (2004) examine the effects of conditional systematic risks; we condition on sentiment. Daniel and Titman (1997) test a characteristics-based model for the cross-section of expected returns; we extend their specification and provide it with a specific, conditional motivation. Shleifer (2000) surveys early work on sentiment and limited arbitrage, two key ingredients here. Barberis and Shleifer (2003), Barberis, Shleifer, and Wurgler (2005), and Peng and Xiong (2004) discuss category-level trading, and Fama and French (1993) document comovement of stocks of similar sizes and book-to-market ratios; uninformed demand shocks for categories of stocks with similar characteristics are central to our results. Finally, we extend and unify known relationships among sentiment, IPOs, and small stock returns (Lee, Shleifer, and Thaler (1991), Swaminathan (1996), and Neal and Wheatley (1998)).

Section I discusses theoretical predictions. Section II provides a qualitative history of recent speculative episodes. Section III describes the empirical hypotheses and the data, and the main empirical tests are contained in Section IV. Section V concludes.

I. Theoretical effects of sentiment on the cross-section

A mispricing is the result of an uninformed demand shock and a limit on arbitrage. One can therefore think of two distinct channels through which investor sentiment, as defined more

precisely below, might affect the cross-section of stock prices. In the first channel, sentimental demand shocks vary in the cross-section, while arbitrage limits are constant. In the second, the difficulty of arbitrage varies across stocks but sentiment is generic. We discuss these in turn.

A. *Cross-sectional variation in sentiment*

One possible definition of investor sentiment is the propensity to speculate.² Under this definition, sentiment drives the relative demand for speculative investments, and so causes cross-sectional effects even if arbitrage forces are the same across stocks.

What makes some stocks more vulnerable to broad shifts in the propensity to speculate? Perhaps the main factor is the subjectivity of their valuations. For instance, consider a canonical young, unprofitable, extreme-growth potential stock. The lack of an earnings history combined with the presence of apparently unlimited growth opportunities allows unsophisticated investors to defend, with equal plausibility, a wide spectrum of valuations, from much too low to much too high, as suits their sentiment. In a bubble period, when the propensity to speculate is apparently high, this profile of characteristics also allows investment bankers (or swindlers) to further argue for the high end of valuations. By contrast, the value of a firm with a long earnings history, tangible assets, and stable dividends is much less subjective, and so its stock is likely to be less affected by fluctuations in the propensity to speculate.³

This channel suggests how variation in the propensity to speculate may generally affect the cross-section, but not how sentimental investors actually choose stocks. We suggest that they simply demand stocks that have the bundle of salient characteristics that is compatible with their sentiment.⁴ That is, those with a low propensity to speculate may demand profitable, dividend-paying stocks not because profitability and dividends are correlated with some unobservable firm property that defines safety to the investor, but precisely because the salient characteristics “profitability” and “dividends” are used to infer safety.⁵ Likewise, the salient characteristics “no

earnings,” “young age,” and “no dividends” mark the stock as speculative. Casual observation suggests that such an investment process may be a more accurate description of how typical investors pick stocks than the process outlined by Markowitz (1959), in which investors view individual securities purely in terms of their statistical properties.

B. Cross-sectional variation in arbitrage

Investor sentiment might also be reasonably defined as optimism or pessimism about stocks in general. Indiscriminate waves of sentiment still affect the cross-section, however, if arbitrage forces are relatively weaker in a subset of stocks.

This channel is better understood than the cross-sectional variation in sentiment channel. A body of theoretical and empirical research shows that arbitrage tends to be particularly risky and costly for young, small, unprofitable extreme-growth or distressed stocks. Their high idiosyncratic risk makes relative-value arbitrage especially risky (Wurgler and Zhuravskaya (2002)). They tend to be more costly to trade (Amihud and Mendelsohn (1986)) and particularly expensive, sometimes impossible, to sell short (D’Avolio (2002), Geczy, Musto, and Reed (2002), Jones and Lamont (2002), Duffie, Garleanu, and Pedersen (2002), Lamont and Thaler (2003), and Mitchell, Pulvino, and Stafford (2002)). Further, their lower liquidity also exposes would-be arbitrageurs to predatory attacks (Brunnermeier and Pedersen (2004)).

Note that, in practice, the same stocks that are the hardest to arbitrage also tend to be the most difficult to value. So although for expositional purposes we have outlined the two channels separately, they are likely to have overlapping effects. And while this makes them difficult to distinguish empirically, it only strengthens the predictions about what region of the cross-section are most affected by sentiment. Indeed, the two channels can reinforce each other. For example, the fact that investors can convince themselves of a wide range of valuations in some regions of

the cross-section is a noise-trader risk that further deters short-horizon arbitrageurs (De Long et al. (1990) and Shleifer and Vishny (1997)).⁶

II. An anecdotal history of investor sentiment, 1961 to 2002

Here we briefly summarize the most prominent U.S. stock market bubbles between 1961 to 2002 (matching the period of our main data). The reader eager to see results may skip this section, but it is useful for three reasons. First, despite great interest in the effects of investor sentiment, the academic literature does not contain even the most basic, ex-post characterization of most of the recent speculative episodes. Second, a knowledge of the rough timing of these episodes allow us to make a preliminary judgment about the accuracy of the quantitative proxies for sentiment that we develop later. Third, the discussion sheds some initial, albeit anecdotal light on the plausibility of our theoretical predictions.

Our brief history of sentiment is distilled from several sources. Kindleberger (2001) draws general lessons from bubbles and crashes over the past few hundred years, while Brown (1991), Dreman (1979), Graham (1973), Malkiel (1990, 1999), Shiller (2000), and Siegel (1998) focus more specifically on recent U.S. stock market episodes. We take each of these accounts with a grain of salt, and emphasize only themes that appear repeatedly.

We start in 1961, a year in which Graham (1973), Malkiel (1990) and Brown (1991) note a high demand for small, young, growth stocks. Dreman (1979, p. 70) confirms their accounts. Malkiel writes of a “new-issue mania” that was concentrated on 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 bubble develops in 1967 and 1968. Brown writes that “scores of franchisers, computer firms, and mobile home manufactures seemed to promise overnight wealth. ... [while] quality was pretty much forgotten” (p. 90). Malkiel and Dreman also note this pattern—a focus on firms with strong earnings growth or potential, and an avoidance of “the major industrial giants, ‘buggywhip companies,’ as they were sometimes contemptuously called” (Dreman 1979, p. 74-75). Another characteristic apparently out of favor was dividends. According to the *New York Times*, “during the speculative market of the late 1960’s 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). In summarizing the performance of stocks from the end of 1968 through August 1971, Graham (1973) writes: “[our] 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).

Anecdotal accounts invariably describe the early 1970’s as a bear market, with sentiment at a low level. However, a set of established, large, stable, consistently profitable stocks known as the “nifty fifty” enjoyed notably high valuations. Brown, Malkiel, and Siegel (1998) each highlight this episode. Siegel writes, “All of these stocks had proven growth records, continual increases in dividends ... and high market capitalization” (p. 106). Note that this speculative episode is a mirror image of those described above (and below). They center on small, young, unprofitable growth stocks in periods of *high* sentiment, while the nifty fifty episode appears to be a bubble in a set of firms with an opposite set of characteristics (old, large, and continuous earnings and dividend growth) and happens in a period of *low* sentiment.

The late 1970’s through mid-1980’s are described as a period of generally high sentiment, perhaps associated with Reagan-era optimism, and saw a series of speculative

episodes. Dreman describes a bubble in gambling issues in 1977 and 1978. Ritter (1984) studies the hot issue market of 1980, finding greater initial returns on IPOs of natural resource start-ups than on larger, mature, profitable offerings. Of 1983, 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.” Brown confirms this account. Of the mid-1980’s, Malkiel writes that “What electronics was to the 1960’s, biotechnology became to the 1980’s. ... new issues of biotech companies were eagerly gobbled up. ... having positive sales and earnings was actually considered a drawback” (p. 77-79). But by 1987 and 1988, “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 late-1990’s bubble in technology stocks is familiar. By all accounts, investor sentiment was broadly high before the bubble started to burst in 2000. Cochrane (2003) and Ofek and Richardson (2002) offer *ex post* perspectives on the bubble, while Asness et al. (2000) and Chan, Karceski, and Lakonishok (2000) were arguing even before the crash that late-1990’s growth stock valuations were difficult to ascribe to rationally expected earnings growth. Malkiel draws parallels to episodes in the 1960’s, 1970’s, and 1980’s, and Shiller (2000) compares the Internet bubble to the late 1920’s. As in earlier speculative episodes that occurred in high sentiment periods, demand for dividend payers seems to have been low (*New York Times*, 1/6/1998). Ljungqvist and Wilhelm (2003) find that 80% of 1999 and 2000 IPOs had negative earnings per share and that the median age of 1999 IPOs was 4 years. This contrasts with an average age of over 9 years just prior to the emergence of the bubble, and of over 12 years by 2001 and 2002 (Ritter, 2003).

These anecdotes suggest some regular patterns in the effect of investor sentiment on the cross-section. For instance, canonical extreme-growth stocks seem to be especially prone to

bubbles (and subsequent crashes), consistent with the observation that they are more appealing to speculators and optimists and at the same time hard to arbitrage. The “nifty fifty” bubble is a notable exception. However, anecdotal accounts suggest that this bubble occurred in a period of broadly low sentiment, so it may still be consistent with the cross-sectional prediction that an increase in sentiment increases the *relative* price of stocks that are most subjective to value and hardest to arbitrage. We now turn to formal tests of this prediction.

III. Empirical approach and data

A. Empirical approach

Theory and historical anecdote both suggest that sentiment may cause systematic patterns of mispricing. Because mispricing is hard to identify directly, however, our approach is to look for systematic patterns of *correction* of mispricing. For example, a pattern in which returns on young and unprofitable growth firms are (on average) especially low when beginning-of-period sentiment is estimated to be high may represent the correction of a bubble in growth stocks.

More specifically, to identify sentiment-driven changes in cross-sectional predictability patterns, we need to control for two more basic effects: the generic impact of investor sentiment on all stocks and the generic impact of characteristics across all time periods. Thus, our analysis is organized loosely around the following predictive specification:

$$E_{t-1}[R_{it}] = a + a_1 T_{t-1} + \mathbf{b}_1' \mathbf{x}_{it-1} + \mathbf{b}_2' T_{t-1} \mathbf{x}_{it-1} \quad (1)$$

where i indexes firms, t is time, $\mathbf{x}$ is a vector of characteristics, and T is a proxy for sentiment. a_1 picks up the generic effect of sentiment and $\mathbf{b}_1$ the generic effect of characteristics. Our interest centers on $\mathbf{b}_2$. The null is that $\mathbf{b}_2$ is zero or, more precisely, that any nonzero effect is rational compensation for systematic risk. The alternative is that $\mathbf{b}_2$ is nonzero and reveals cross-sectional

patterns in sentiment-driven mispricing. Eq. (1) is a “conditional characteristics model” because it adds conditional terms to the characteristics model of Daniel and Titman (1997).

B. Characteristics and returns

The firm-level data is from the merged CRSP-Compustat database. The sample includes all common stock (share codes 10 and 11) between 1962 through 2001. Following Fama and French (1992), we match accounting data for fiscal year-ends in calendar year $t-1$ to (monthly) returns from July t through June $t+1$, and we use their variable definitions when possible.

Table 1 shows summary statistics. Panel A summarizes returns variables. Following common practice, momentum *MOM* is defined as the cumulative raw return for the eleven-month period from 12 through two months prior to the observation return. Because momentum is not mentioned as a salient characteristic in historical anecdote, nor does theory suggest a direct connection between momentum and the difficulty of valuation or arbitrage, we use momentum merely as a control variable, to establish the robustness of other patterns.

The remaining panels summarize the firm and security characteristics that we consider. The previous sections’ discussions point us directly to several variables. To that list, we add a few more characteristics that, by introspection, seem likely to be salient to investors. Overall, we roughly group characteristics as pertaining to firm size and age, profitability, dividends, asset tangibility, and growth opportunities and/or distress.

Size and age characteristics include market equity *ME* from June of year t , measured as price times shares outstanding from CRSP. *ME* is matched to monthly returns from July of year t through June of year $t+1$. *Age* is the number of years since the firm’s first appearance on CRSP, measured to the nearest month.⁷ *Sigma* is the standard deviation of monthly returns over the twelve months ending in June of year t . If there are at least nine returns to estimate it, *Sigma* is then matched to monthly returns from July of year t through June of year $t+1$. While historical

anecdote doesn't identify stock volatility itself as a salient investment characteristic, it seems likely to serve as a good proxy for both the difficulty of valuation and of arbitrage.

[TABLE 1 HERE]

Profitability characteristics include the return on equity $E+/BE$, which is positive for profitable firms and zero for unprofitable firms. Earnings (E) is income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), if earnings are positive; book equity (BE) is shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35). $E>0$ is a dummy variable for profitability that takes the value one for profitable firms and zero for unprofitable firms.

Dividend characteristics include dividends to equity D/BE , which is dividends per share at the ex date (Item 26) times Compustat shares outstanding (Item 25) divided by book equity. $D>0$ is a dummy for positive dividends per share by the ex date. The decline in the percentage of firms that pay dividends noted by Fama and French (2001) is apparent.

Asset tangibility characteristics are measured by property, plant and equipment (Item 7) over assets PPE/A and research and development expense over assets (Item 46) RD/A . The referee suggests that asset tangibility may proxy for the difficulty of valuation. One concern is the coverage of the R&D variable. We do not consider this variable prior to 1972, because FASB did not require R&D to be expensed until 1974 and Compustat coverage prior to 1972 is very poor. Also, even in recent years less than half of the sample reports positive R&D.

Characteristics indicating growth opportunities, distress, or both include book-to-market equity BE/ME , whose elements are defined above. External finance EF/A is the change in assets (Item 6) minus the change in retained earnings (Item 36) divided by assets. Sales growth (GS) is the change in net sales (Item 12) divided by prior-year net sales. Sales growth $GS/10$ is the decile of the firm's sales growth in the prior year relative to NYSE firms' decile breakpoints.

As we shall see, one must understand the multidimensional nature of the growth and distress variables in order to understand how they interact with sentiment. In particular, book-to-market wears at least three hats: high values may indicate distress; low values may indicate high growth opportunities; and, as a scaled-price variable, book-to-market is also a generic valuation indicator, varying with any source of mispricing or rational expected returns. Sales growth and external finance wear at least two hats: low values (which are negative) may indicate distress; high values may reflect growth opportunities. Further, to the extent that market timing motives drive external finance, EF/A also serves as a generic misvaluation indicator.

All explanatory variables are Winsorized each year at their 0.5 and 99.5 percentiles. Finally, in Panels C through F, the accounting data for fiscal years ending in calendar year $t-1$ are matched to monthly returns from July of year t through June of year $t+1$.

C. *Investor sentiment*

Prior work suggests a number of proxies for sentiment to use as time-series conditioning variables. There are no definitive or uncontroversial measures, however. We form a composite index of sentiment. It is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The sentiment proxies are measured annually from 1962 to 2001. We first introduce each one of them, and then discuss how they are formed into overall sentiment indexes.

The closed-end fund discount $CEFD$ is the average difference between the NAV of closed-end stock fund shares and their market prices. Prior work suggests that $CEFD$ is inversely related to sentiment. Zweig (1973) uses it to forecast reversion in Dow Jones stocks, and Lee, Shleifer, and Thaler (1991) argue that sentiment is behind various features of closed-end fund discounts. We take the value-weighted average discount on closed-end stock funds for 1962

through 1993 from Neal and Wheatley (1998), for 1994 through 1998 from CDA/Wiesenberger, and for 1999 through 2001 from turn-of-the-year issues of the *Wall Street Journal*.

NYSE share turnover is based on the ratio of reported share volume to average shares listed from the *NYSE Fact Book*. Baker and Stein (2004) suggest that turnover, or more generally liquidity, can serve as a sentiment index. In a market with short-sales constraints, irrational investors participate, and thus add liquidity, only when they are optimistic. Hence high liquidity is a symptom of overvaluation. Supporting this, Jones (2001) finds that high turnover forecasts low market returns. Turnover displays an exponential positive trend over our period and the May 1975 elimination of fixed commissions also has a visible effect. As a partial solution, we define *TURN* as the natural log of the raw turnover ratio, detrended by the five-year moving average.

The IPO market is often viewed as sensitive to sentiment, and high first-day returns on IPOs are cited as a measure of investor enthusiasm. Likewise, the low idiosyncratic returns on IPOs are often interpreted as the result of market timing (Stigler (1964), Ritter (1991)). We take the number of IPOs *NIPO* and the average first-day returns *RIPO* from Jay Ritter's website, which updates the sample in Ibbotson, Sindelar, and Ritter (1994).

The share of equity issues in total equity and debt issues is another measure of financing activity that may capture some aspect of sentiment. Baker and Wurgler (2000) find that the equity share is inversely related to subsequent market returns. The equity share is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance using data from the *Federal Reserve Bulletin*.⁸

The sixth and last sentiment proxy is the dividend premium P^{D-ND} , the log difference of the average market-to-book ratios of payers and nonpayers. Baker and Wurgler (2004) use this variable to proxy for relative investor demand for dividend-paying stocks. Given that payers are larger, more profitable, and have weaker growth opportunities (Fama and French (2001)), this variable may proxy for the relative demand for this correlated bundle of characteristics.

Each sentiment proxy is likely to include a sentiment component and as well as idiosyncratic or non-sentiment-related components. We use principal components analysis to isolate the common component. Another issue in forming an index is deciding on the relative timing of the variables—i.e., if they exhibit lead-lag relationships, some variables may reflect a given shift in sentiment earlier than others. For instance, Ibbotson and Jaffe (1975), Lowry and Schwert (2002), and Benveniste et al. (2003) find that IPO volume lags the first-day returns on IPOs. Perhaps sentiment is in part behind the high first-day returns, and this attracts additional IPO volume with a lag. More generally, one suspects that proxies that involve firm supply responses (S and $NIPO$) would lag behind proxies that are based directly on investor demand or investor behavior ($RIPO$, P^{D-ND} , $TURN$, and $CEFD$).

[TABLE 2 HERE]

We form a composite index that captures the common component in the six proxies and incorporates the fact that some variables take longer to reveal the same sentiment.⁹ We start by estimating the first principal component of the six proxies and their lags. This gives us a first-stage index with twelve loadings, one for each of the current and lagged proxies. We then compute the correlation between the first-stage index and the current and lagged values of each of the proxies. Finally, we define $SENTIMENT$ as the first principal component of the correlation matrix of six variables—each respective proxy’s lead or lag, whichever has higher correlation with the first-stage index—rescaling the coefficients so that the index has unit variance.

This procedure leads to a parsimonious index:

$$\begin{aligned} SENTIMENT_t = & -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t \\ & + 0.257RIPO_{t-1} + 0.112S_t - 0.283P_{t-1}^{D-ND} \end{aligned} \quad (2)$$

where each of the components of the index has first been standardized. The first principal component explains 49% of the sample variance, so we conclude that one factor captures much

of the common variation. The correlation between the twelve-term first-stage index and the *SENTIMENT* index is 0.95, suggesting that little information is lost in dropping the six terms.

The *SENTIMENT* index has several appealing properties. First, each individual proxy enters with the expected sign. Second, all but one enters with the expected timing—with the exception of *CEFD*, price and investor behavior variables lead firm supply variables. Third, the index irons out some extreme observations. The dividend premium and the first-day IPO returns reached unprecedented levels in 1999, so for these proxies to work as individual predictors in the full sample, these levels must be matched exactly to extreme future returns.

One might object to Eq. (2) as a measure of sentiment on the grounds that the principal components analysis cannot distinguish between a common sentiment component and a common business-cycle component. For instance, the number of IPO's varies with the business cycle in part for entirely rational reasons. We want to identify when the number of IPO's is high for *no* good reason. We therefore construct a second index that explicitly removes business-cycle variation from each of the proxies prior to the principal components analysis.

[FIGURE 1 HERE]

Specifically, we regress each of the six raw proxies on growth in the industrial production index (Federal Reserve Statistical Release G.17), growth in consumer durables, nondurables, and services (all from BEA National Income Accounts Table 2.10), and a dummy variable for NBER recessions. The residuals from these regressions, labeled with a superscript $\perp$, may be cleaner proxies for investor sentiment. We form an index of the orthogonalized proxies following the same procedure as before. The resulting index is:

$$\begin{aligned} \text{SENTIMENT}_t^\perp = & -0.198\text{CEFD}_t^\perp + 0.225\text{TURN}_{t-1}^\perp + 0.234\text{NIPO}_t^\perp \\ & + 0.263\text{RIPO}_{t-1}^\perp + 0.211\text{S}_t^\perp - 0.243\text{P}_{t-1}^{\perp, D-ND} \end{aligned} \quad (3)$$

Here, the first principal component explains 53% of the sample variance of the orthogonalized variables. Moreover, only the first eigenvalue is above 1.00. In terms of the signs and the timing of the components, $SENTIMENT^\perp$ retains all of the appealing properties of $SENTIMENT$.

Table 2 summarizes and correlates the sentiment measures, and Figure 1 plots them. The figure shows immediately that orthogonalizing to macro variables is a second-order issue. It does not qualitatively affect any component of the index, and so it does not qualitatively affect the overall index (see Panel E). Indeed, Table 2 suggests that the orthogonalized proxies are on balance slightly *more* correlated with each other than are the raw proxies. If the raw variables were driven by common macroeconomic conditions (that we failed to remove through orthogonalization) instead of common investor sentiment, one would expect the opposite. In any case, to demonstrate robustness we present results for both indexes in our main analysis.

More importantly, Figure 1 shows that the sentiment measures roughly line up with anecdotal accounts of fluctuations in sentiment. Most proxies point to low sentiment in the first few years of the sample, after the 1961 crash in growth stocks—the closed-end fund discount and dividend premium are high, while turnover and equity issuance-related variables are low. Each variable identifies a spike in sentiment in 1968 and 1969, again matching anecdotal accounts. Sentiment then tails off until, by the mid-1970's, it is low by most measures (recall that for turnover this is confounded by deregulation). The late 1970's through mid-1980's sees generally rising sentiment, and, according to the composite index, sentiment has not dropped far below a medium level since 1980. At the end of 1999, near the peak of the Internet bubble, sentiment is high by most proxies. Overall, $SENTIMENT^\perp$ is positive for the years 1968 to 1970, 1972, 1979 to 1987, 1994, 1996 to 1997, and 1999 to 2001. This correspondence with anecdotal accounts seems to confirm that the measures capture the intended variation.

There are many other variables one might wish include in a sentiment index. The main constraint is availability and consistent measurement over the 1962 to 2001 period. We have

considered insider trading as a sentiment measure. Unfortunately, a consistent series does not appear to be available for the whole sample period. Nejat Seyhun shared his monthly series, which spans 1975 to 1994, on the fraction of public firms with net insider buying, as plotted in Seyhun (1998, p. 117). Lakonishok and Lee (2001) study a similar series. We averaged Seyhun's series across months to get an annual series. Over the overlapping 20-year period, insider buying has a significant negative correlation with both the raw and orthogonalized sentiment indexes, and also correlates with the six underlying components as expected.

IV. Empirical tests

A. *Sorts*

Table 3 looks for conditional characteristics effects in a simple, nonparametric way. We place each monthly return observation into a bin according to the decile rank that a characteristic takes at the beginning of that month, and then according to the level of $SENTIMENT^{\perp}$ at the end of the previous calendar year. To keep the meaning of the deciles similar over time, we define them based on NYSE firms. The tradeoff is that there is not a uniform distribution of firms across bins in any given month. We compute the average monthly return for each bin and look for patterns. In particular, we can identify time-series changes in cross-sectional effects from the conditional *difference* of average returns across characteristics deciles.

The first rows of Table 3 show the effect of size, as measured by ME , conditional on sentiment. They reveal that the size effect of Banz (1981) appears in low-sentiment periods only. Specifically, Table 3 shows that when $SENTIMENT^{\perp}$ is negative, returns average 2.37% per month for the bottom ME decile and 0.92 for the top decile. A similar pattern is apparent when conditioning on $CEFD$ (not reported); a link between the size effect and closed-end fund discounts was noted before by Swaminathan (1996). This pattern is consistent with some long-

known results. Namely, the size effect is essentially a January effect (Keim (1983), Blume and Stambaugh (1983)), and the January effect, in turn, is stronger after a period of low returns (Reinganum (1983)), which is also when sentiment is likely to be low.

As an aside, note that the average returns across the first two rows of Table 3 illustrate that subsequent returns tend to be higher, across most of the cross-section, when sentiment is low. This is consistent with prior results that the equity share and turnover, for example, forecast market returns. More generally, it supports our premise that sentiment has broad effects, and so the existence of richer patterns within the cross-section is not surprising.

[TABLE 3 HERE]

The conditional cross-sectional effect of *Age* is striking. In general, investors appear to demand young stocks when $SENTIMENT^{\perp}$ is positive and prefer older stocks when sentiment is negative. For example, when sentiment is pessimistic, top-decile *Age* firms return 0.54% per month *less* than bottom-decile *Age* firms. However, they return 0.85% *more* when sentiment is optimistic. When sentiment is positive, the effect is concentrated in the very youngest stocks, which are recent IPOs; when it is negative, the contrast is between the bottom several deciles of age and the top several deciles. Overall, there is a nearly monotonic effect in the conditional difference of returns. This result is intriguing because *Age* has no unconditional effect.¹⁰ This is because the strong conditional effects, of opposite sign, will average out across high and low sentiment periods.

The next rows of Table 3 indicate that the cross-sectional effect of return volatility is conditional on sentiment in the hypothesized manner. In particular, high *Sigma* stocks appear to be out of favor when sentiment is low—they subsequently earn returns of 2.41% per month over the next year. However, just as with *Age*, the cross-sectional effect of *Sigma* fully reverses in low sentiment conditions. Loosely speaking, when sentiment is high, “riskier” stocks earn *lower* returns. When sentiment is low, they earn *higher* returns. A natural interpretation is that highly

volatile stocks are, like young stocks, relatively hard to value and relatively hard to arbitrage. Both of these features make them especially prone to fluctuations in sentiment.

Figure 2 shows the results of Table 3 graphically. Panel C, for example, shows the unconditional average monthly returns across *Sigma* deciles (dashed line), which is essentially flat; the average monthly return in high-sentiment periods (solid bar), which is decreasing with risk decile; the average monthly return in low-sentiment periods (clear bars), which is increasing with risk deciles; and the difference in conditional returns (solid line). The solid line summarizes the difference in the relationship between *Sigma* and future returns across the two regimes and clearly illustrates that the future returns on high-*Sigma* stocks are more sensitive to sentiment.

[FIGURE 2 HERE]

The next rows examine profitability and dividends. For average investors, perhaps the most salient comparison is simply between profitable and unprofitable ($E < 0$) firms and payers and nonpayers ($D = 0$). These contrasts are in the extreme right column, where we average returns across profitable firms and compare them to unprofitable firms (analogously for dividends). These characteristics again display intriguing conditional sign-flip patterns. When sentiment is positive, monthly returns over the next year are 0.61% higher on profitable than unprofitable firms and 0.75% higher on payers than nonpayers. When it is negative, however, returns are 0.95% per month *lower* on profitable firms and 0.89% lower on payers. The left column shows that these patterns are driven mostly by conditional variation in the returns of unprofitable and nonpaying firms, although there are also some differences across levels of dividend payments and profitability. Again, this is consistent with unprofitable, nonpaying firms being generally both harder to value and harder to arbitrage.

The next two rows look at asset tangibility characteristics, under the notion that firms with less tangible assets may be more difficult to value. The patterns here are not so strong, but there is a suggestion that firms with more intangible assets, as measured by less PPE/A , are more

sensitive to fluctuations in sentiment. (This pattern is only apparent within firms that report positive *PPE/A*.) The clearest pattern in *RD/A* is a modest unconditional effect in which higher *RD/A* firms earn higher returns.

The remaining variables—book-to-market, external finance, and sales growth—also display intriguing patterns. Most simply, running across rows, one can see that each of them has some unconditional explanatory power. Future returns are generally higher for high *BE/ME* stocks, low *EF/A* stocks, and low *GS* decile stocks. The *EF/A* result is reminiscent of Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995, 1999), while the *GS* result is suggested in Lakonishok, Shleifer, and Vishny (1994).

A closer look reveals that after controlling for these unconditional effects, a conditional pattern emerges. Specifically, there is a U-shaped pattern in the conditional difference. Consider the *GS* variable. The difference in returns on bottom-decile *GS* firms is -1.79% per month. For fifth-decile firms, the difference is only -0.26% per month. But for tenth-decile firms, the difference is again large, -1.64% per month. U-shaped patterns also appear in the conditional difference row for *BE/ME* and *EF/A*. The solid lines in Panels H, I, and J of Figure 2 show these “frowns” graphically. The figure illustrates why one must control for the strong unconditional effects in these variables in order to see the conditional effects.

Thus, in all three of these growth and distress variables, firms with extreme values react more to sentiment than firms with middle values. What does the U reflect? We believe it reflects the multidimensional nature of these particular characteristics. In particular, high-*GS* firms include high-flying growth firms, low-*GS* firms are often distressed firms with shrinking sales, and middle-*GS* firms are steady, slow-growth firms. Thus, relative to firms in middle deciles, firms with extreme values of *GS* are harder to value, and perhaps to arbitrage, and thus may be more sensitive to sentiment. Put differently, firms with extreme values of *GS* are likely to seem “riskier,” in a salient sense, than firms in the middle. The same explanation may help to explain

the U-shaped patterns in the conditional difference row of EF/A and BE/ME . There again, low- EF/A firms and high- BE/ME firms include distressed firms, high- EF/A and low- BE/ME firms include high-flyers, and the middle deciles tend to be populated by the most “stable” firms.

In unreported results, we have sorted returns not just on positive and negative values of $SENTIMENT^\perp$ but also compared >1 SD and <-1 SD values. Not surprisingly, conditioning on more extreme values of sentiment leads to stronger results. We take more formal account of the continuous nature of the sentiment indexes in the next subsection. Also, for brevity, we omit sorts on $SENTIMENT$ (the non-orthogonalized version), which give similar results. We present results for both indexes in the next section. Finally, we have also sorted returns on positive and negative $SENTIMENT^\perp$ where positive and negative are defined relative to a 10-year average. By requiring a ten-year history of sentiment, one loses a little more than a quarter of the sample. The results are qualitatively identical to those in Table 3, although slightly weaker except for Age , which is slightly stronger.

B. Predictive regressions for long-short portfolios

Another way to look for conditional characteristics effects is to use sentiment to forecast portfolios that are long on stocks with high values of a characteristic and short on stocks with low values. We have just seen that the average payer, for example, earns higher returns than the average nonpayer when sentiment is high, so sentiment seems likely to forecast a long-short portfolio formed on dividend payment. But a regression approach allows us to conduct formal significance tests, to incorporate the continuous nature of the sentiment indexes, and to determine which characteristics have conditional effects that are distinct from well-known unconditional effects.

Table 4 starts by plotting the average monthly returns on various long-short portfolios over time. The first several rows show that, not surprisingly, long-short portfolios formed on size

(*SMB*), age, volatility, profitability, dividend payment, and (to a lesser extent) tangibility are typically highly correlated. Thus, a good question, which we address in subsequent tables, is whether the results from the sorts are all part of the same pattern or are somewhat distinct. In the last several rows of Table 4, we break the growth and distress variables into “high minus medium” and “medium minus low” portfolios. In the case of the *GS* variable, for example, these portfolios are highly *negatively* correlated with each other, at -0.63, indicating that high- and low-*GS* firms actually move together relative to middle-*GS* firms. Likewise, the correlation between “high minus medium” and “medium minus low” *EF/A* is -0.60. Simple “high minus low” analyses of these variables would thus be omitting crucial aspects of the cross-section.

[TABLE 4 HERE]

The question is whether sentiment can predict the various long-short portfolios analyzed in Table 4. We run regressions of this type:¹¹

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = c + dSENTIMENT_{t-1} + \varepsilon_{it}. \quad (4)$$

The dependent variable is the monthly return on a long-short portfolio, such as *SMB*, and the monthly returns from January through December of *t* are regressed on the sentiment index that prevailed at the end of the prior year. We also distinguish novel predictability effects from well-known comovement using a multivariate regression:

$$\begin{aligned} R_{X_{it}=High,t} - R_{X_{it}=Low,t} = & c + dSENTIMENT_{t-1} + \beta RMKT_t + sSMB_t \\ & + hHML_t + mUMD_t + \varepsilon_{it}. \end{aligned} \quad (5)$$

RMRF is the excess return of the value-weighted market over the risk-free rate. *UMD* is the return on high-momentum stocks minus the return on low-momentum stocks, where momentum is measured over months [-12, -2]. As described in Fama and French (1993), *SMB* is the return on portfolios of small and big *ME* stocks that is separate from returns on *HML*, and *HML* is constructed to isolate the difference between high- and low-*BE/ME* portfolios.¹² We exclude *SMB* and *HML* from the right side when they are being forecast. Standard errors are bootstrapped

to correct for the bias induced if the autocorrelated sentiment index has innovations that are correlated with innovations in portfolio returns, as in Stambaugh (1999).

Table 5 shows the results. The results provide formal support to the preliminary impressions from the sorts. In particular, the first panel shows that when sentiment is high, returns on small, young, and high-volatility firms are relatively low over the coming year. The coefficient on sentiment diminishes once we control for *RMRF*, *SMB*, *HML*, and *UMD*, but in most cases the significance of the predictive effect does not depend on including or excluding these controls. In terms of magnitudes, the coefficient for predicting *SMB*, for example, indicates that a one unit increase in sentiment (which equals a one-SD increase, because the indexes have been standardized) is associated with -0.40% per month lower return on the small minus large portfolio.¹³

[TABLE 5 HERE]

Table 5 also shows that the coefficients on *SENTIMENT* and $SENTIMENT^{\perp}$ are very similar. Keep in mind that the coefficients on $SENTIMENT^{\perp}$ are essentially the same as one would get from regressing long-short portfolio returns directly on a raw sentiment index and controls for contemporaneous macroeconomic conditions—i.e., regressing X on Z and using the residuals to predict Y is equivalent to regressing Y on X and Z . The similarity of the results on *SENTIMENT* and $SENTIMENT^{\perp}$ thus suggests that macroeconomic conditions play a minor role.

For profitability and dividend payment, we run regressions to predict the difference between the profitable and paying portfolios and the unprofitable and nonpaying portfolios, respectively, because the sorts suggest that these are likely to capture the main contrasts. The results show that sentiment indeed has significant predictive power for these portfolios, with higher sentiment forecasting relatively higher returns on payers and profitable firms. These results are quite separate from *RMRF*, *SMB*, *HML*, and *UMD*.

As we found in the sorts, the tangibility characteristics do not exhibit strong conditional effects. Sentiment does have marginal predictive power for the *PPE/A* portfolio, with high sentiment associated with relatively low future returns on low-*PPE/A* stocks, but this disappears after controlling for *RMRF*, *SMB*, *HML*, and *UMD*. The coefficients on the *RD/A* portfolio forecasts are not consistent in sign or magnitude.

Also as we found in the sorts, the “growth and distress” variables do not have simple monotonic relationships with sentiment. Panel D shows that sentiment does not predict simple high minus low portfolios formed on any of *BE/ME*, *EF/A*, or *GS*. However, Panels E and F show that when the multidimensional nature of these variables is incorporated, there is much stronger evidence of predictive power. We separate extreme growth opportunities effects from distress effects by constructing High, Medium, and Low portfolios based on the top three, middle four, and bottom three NYSE decile breakpoints, respectively.

The results show that when sentiment is high, subsequent returns on both low- and high-sales growth firms are low relative to returns on medium-growth firms. This illustrates the U-shaped pattern in Table 3 in a different way, and shows that it is statistically significant. An equally significant U-shaped pattern is apparent with external finance; when sentiment is high, subsequent returns on both low- and high-external finance firms are low relative to more typical firms. In the case of *BE/ME*, however, although sentiment predicts the high minus medium and medium minus low portfolios with opposite signs, neither coefficient is reliably significant. This matches the sorts, where we saw that the U-shaped pattern in the conditional difference for *BE/ME* was somewhat weaker than for *EF/A* and *GS*.

Equations (4) and (5) offer a simple framework in which to address some robustness issues. To test whether the results are driven by an overall trend, we have included a post-1982 dummy in the regressions, with no change in inferences from those in the last column of Table 5. Also, the results are slightly stronger when returns from January and December are removed

from the sample. This indicates that tax-motivated trading and associated fluctuations in liquidity around the turn of the year are not driving the main results. Finally, while we omit the results for brevity, the six individual sentiment components generally predict the portfolio returns with the expected sign. The number of IPOs *NIPO* and the closed-end fund discount *CEFD* offer the best individual performance, followed by the equity share *S*, turnover *TURN*, the average first-day return *RIPO*, and the dividend premium P^{D-ND} . Those results are reported in the NBER working paper version of this paper.

In summary, the regressions essentially confirm the significance of the patterns suggested in the sorts. When sentiment is high, future returns are relatively low for small firms, the youngest firms, firms with volatile stock returns, unprofitable firms, non-dividend-paying firms, high growth firms, and distressed firms. And vice-versa. In general, the results support predictions that sentiment most affects stocks that are hard to value and hard to arbitrage.

C. *A brief look at earlier data*

Reliable accounting information, especially on the sorts of firms most affected by sentiment, is not easy to obtain for the pre-Compustat era. Some of our sentiment proxies also are not available. However, using CRSP data, we can perform a reduced set of tests over a longer period. Specifically, we form a sentiment index from 1935 to 2001 using the first principal component of *CEFD*, *S*, and *TURN*, where *TURN* is lagged relative to the others, in the spirit of Eq. (2).¹⁴ We also orthogonalize these sentiment proxies with respect to consumption growth variables and NBER recessions (industrial production is not available over the full period, however) to form an index in the spirit of Eq. (3). We use these indexes to forecast the return on *SMB* and long-short portfolios formed on *Age*, *Sigma*, and dividend payer status.

The results are in Table 6. With the exception of the *Age* portfolio, where the results are not significant, the results from the full 1935 to 2001 period and the “out-of-sample” 1935 to

1961 period are similar to those in more recent data.¹⁵ One possibility for the insignificant results on the *Age* portfolio is that we measure age as the number of months for which CRSP data is available. Anecdotal evidence suggests that in these early data, there are fewer truly “young” firms listing on the NYSE. By contrast, in recent years, many genuinely young IPOs start trading on Nasdaq, and so our way of measuring age may be more meaningful.

[TABLE 6 HERE]

The longer time series make it possible to conduct an out-of-sample test. In unreported results, we compare the in-sample reduction in root mean squared error (RMSE) in Table 6 to the reduction in RMSE that an investor might see using only past data. The results suggest that a substantial fraction of the portfolio predictability would have been “knowable” in advance. The exceptions are the *Age* portfolio and the *SMB* portfolio in the post-1980 period (where the in-sample predictive power for *SMB* is also modest). A table is available on request.

Together, the longer-sample results and the out-of-sample exercise help to rule out the possibility that a spurious correlation is behind the main results. The fact that there are at least several fluctuations in sentiment, and the fact that the cross-sectional patterns tend to work in the predicted directions, cast further doubt on that notion.

D. Systematic risk

At face value, the conditional characteristics effects seem unlikely to be compensation for systematic risk. Among other considerations, the index $SENTIMENT^{\perp}$ is orthogonalized to macroeconomic conditions; the patterns match predictions as to where sentiment *should* matter most; and the patterns line up with anecdotal accounts of bubbles and crashes. Intuitively, the systematic risk explanation requires that older, profitable, less volatile, dividend-paying firms often require higher returns than younger, unprofitable, more volatile, nonpaying firms, and are

recognized as riskier in the relevant sense by the marginal investor. While this proposition already seems counterintuitive, we can attempt to rule it out more rigorously.

Systematic risk explanations come in two basic flavors. One is that the systematic risks (beta loadings) of stocks with certain characteristics vary with the sentiment proxies, despite our effort to isolate them from macroeconomic conditions. Table 7 investigates this directly. It asks whether sentiment coincides with time-variation in market betas in a way that could at least qualitatively reconcile the earlier results with a conditional CAPM. Specifically, we predict returns on the characteristics portfolios:

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = c + dSENTIMENT_{t-1} + \beta(e + fSENTIMENT_{t-1})RMRF_t + \varepsilon_{it}. \quad (6)$$

The time-varying betas story predicts that the composite coefficient βf , reported in Table 7, is of the same sign as the estimates of d in Table 5. However, it turns out that when the coefficient βf is significant, it is typically of the wrong sign. We obtain similar results when we replace $RMRF$ by aggregate consumption growth. A table is available upon request.

[TABLE 7 HERE]

The second systematic risk story keeps stocks' betas fixed, but allows the risk premium to vary with sentiment, which means that the difference in required returns between the high- and low-beta stocks varies in proportion. However, this story runs into trouble with the simple fact that the predicted effect of several characteristics does not just vary in magnitude over time, but in direction. It would seem then that the bulk of the results do not reflect compensation for classical systematic risks.

E. Predictive regressions for earnings announcement returns

Our last test is whether there are conditional characteristics effects in the returns around earnings announcements. La Porta et al. (1997) find that low book-to-market stocks have lower average returns at earnings announcements than high book-to-market stocks, suggesting

systematic errors in earnings expectations. Likewise, if errors in earnings expectations account for some of our results, we might expect that the average earnings announcement return on small, young, volatile, unprofitable, nonpaying, extreme growth and/or distress stocks would tend to be inversely related to sentiment.

This methodology, while appealing at first glance, has only limited power to detect how expectational errors affect our results. That is, our results are driven by the *correlated* correction of mispricing, but a firm's announcement event return picks up the expectational corrections that occur only to it alone and within its own announcement window. Malkiel (1999) illustrates the problem: "The music slowed drastically for the conglomerates on January 19, 1968. On that day, the granddaddy of the conglomerates, Litton Industries, announced that earnings for the second quarter of that year would be substantially less than forecast. ... the announcement was greeted with disbelief and shock. In the selling wave that followed, conglomerate stocks declined by roughly 40 percent ..." (p. 67). So although a study of announcement event returns captures the corrective effect of Litton Industries' announcement on its own stock, it picks up none of its broader effects, which appear to be important to our main results. Nevertheless, an analysis of earnings announcements may provide a lower bound on the effect that sentiment-driven expectational errors have on our results.

We gather quarterly earnings announcement dates from the merged CRSP-Compustat file. These dates are available beginning in January 1971. The quarterly earnings announcement sample represents approximately 75% of the firm-quarters (firm-months) analyzed in the main tables, so coverage is fairly complete. For each firm-quarter observation, we compute the cumulative abnormal return over the value-weighted market index over trading days [-1, +1] around the report date. We then construct a quarterly series of average announcement effects for each characteristic decile, and attempt to predict it with the composite sentiment index:

$$CAR_{X_{it}=Decile,t} = c + dSENTIMENT_{t-1}^{\perp} + u_t. \quad (7)$$

Table 8 reports the coefficient estimates for each characteristic decile using the orthogonalized sentiment index. The results for the raw index are very similar.

[TABLE 8 HERE]

Perhaps the most striking feature of Table 8 is that most coefficients are negative, thus earnings announcement effects are in general lower following high sentiment periods. A very crude comparison can be made between the cross-sectional patterns in Table 8 and those in Table 3. In Table 8, 12 of the 104 coefficients are significant at the 5% level. In Table 3, 9 of the 104 estimated conditional differences are larger than 1.5% per month in absolute value. The intersection of the two tables' "strong results" is six cells, and the signs of the effects are congruent in all cases.

Overall, this suggests that some portion of the conditional characteristics effects may reflect the correction of errors in earnings expectations. However, as noted above, this test is not powerful and provides only a lower bound on the contribution of expectational errors.

V. Conclusion

In classical finance theory, investor sentiment does not play any role in the cross-section of stock prices, returns, or expected returns. This paper challenges that view. We use simple theoretical arguments, historical accounts of speculative episodes, and most importantly a set of novel empirical results to argue that investor sentiment, broadly defined, has significant cross-sectional effects.

Our main empirical finding is that the cross-section of future stock returns is conditional upon beginning-of-period proxies for sentiment. The patterns are rich but intuitive. In particular, when sentiment is estimated to be high, stocks that are attractive to optimists and speculators and at the same time unattractive to arbitrageurs—younger stocks, small stocks, unprofitable stocks,

non-dividend paying stocks, high-volatility stocks, extreme-growth stocks, and distressed stocks—tend to earn relatively low subsequent returns. Conditional on low sentiment, however, these cross-sectional patterns attenuate or *completely reverse*. The most striking finding is that several firm characteristics which display no unconditional predictive power are actually hiding strong conditional patterns which become visible only after conditioning on sentiment. We consider the classical explanation that the results reflect compensation for systematic risks, but several aspects of the results are inconsistent with this explanation.

The results suggest several avenues for future work. In corporate finance, a better understanding of sentiment may shed light on time-series patterns in security issuance and the supply of firm characteristics that seem to be conditionally relevant to share price. In asset pricing, the results suggest that descriptively accurate models of prices and expected returns need to incorporate a prominent role for investor sentiment.

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Table 1. Summary Statistics, 1963 to 2001. Panel A summarizes the returns variables. Returns are measured monthly. Momentum (MOM) is defined as the cumulative return for the eleven-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; in 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	2000-1
Panel A. Returns										
R_t (%)	1,600,383	1.39	18.11	-98.13	2400.00	1.08	1.56	1.25	1.46	1.28
MOM_{t-1} (%)	1,600,383	13.67	58.13	-85.56	343.90	21.62	12.24	15.02	13.06	11.02
Panel B. Size, Age, and Risk										
ME_{t-1} (\$M)	1,600,383	621	2,319	1	23,302	388	238	395	862	1,438
Age_t (Years)	1,600,383	13.36	13.41	0.03	68.42	15.90	12.62	13.61	13.26	13.47
σ_{t-1} (%)	1,574,981	13.70	8.73	0.00	60.77	9.44	12.51	13.32	13.89	19.55
Panel C. Profitability										
$E+/BE_{t-1}$ (%)	1,600,383	10.70	10.03	0.00	65.14	12.10	12.05	11.37	9.54	9.49
$E>0_{t-1}$	1,600,383	0.78	0.41	0.00	1.00	0.95	0.91	0.78	0.71	0.68
Panel D. Dividend Policy										
D/BE_{t-1} (%)	1,600,383	2.08	2.98	0.00	17.94	4.42	2.75	2.11	1.58	1.43
$D>0_{t-1}$	1,600,383	0.48	0.50	0.00	1.00	0.77	0.66	0.50	0.37	0.33
Panel E. Tangibility										
PPE/A (%)	1,476,109	54.66	37.15	0.00	187.69	70.21	59.14	55.49	51.28	45.49
RD/A (%)	1,452,840	2.97	7.27	0.00	54.75		1.22	2.29	3.86	4.68
Panel F. Growth Opportunities and Distress										
BE/ME_{t-1}	1,600,383	0.94	0.86	0.02	5.90	0.70	1.37	0.95	0.76	0.82
EF/A_{t-1} (%)	1,549,817	11.44	24.24	-71.23	127.30	7.17	6.45	10.59	13.97	17.71
GS_{t-1} (Decile)	1,529,508	5.94	3.16	1.00	10.00	5.67	5.66	6.01	6.08	5.91

Table 2. Investor Sentiment Data, 1962 to 2000. Means, standard deviations, and correlations for measures of investor sentiment. In the first panel, we present raw sentiment proxies. The first (CEFD) is 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 and 2000. The second measure (TURN) is detrended natural 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 measure (NIPO) is the annual number of initial public offerings. The fourth measure (RIPO) is the average annual first-day returns of initial public offerings. Both IPO series come from Jay Ritter, updating data analyzed in Ibbotson, Sindelar, and Ritter (1994). The fifth measure (S) is gross annual equity issuance divided by gross annual equity plus debt issuance from Baker and Wurgler (2000). The sixth measure (P^{D-ND}) is the year-end log ratio of the value-weighted average market-to-book ratios of payers and nonpayers from Baker and Wurgler (2004). Turnover, the average annual first-day return, and the dividend premium are lagged one year relative to the other three measures. SENTIMENT is the first principal component of the six sentiment proxies. In the second panel, we regress each of the six proxies 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 orthogonalized proxies, labeled with a $\perp$, are the residuals from these regressions. SENTIMENT $\perp$ is the first principal component of the six orthogonalized proxies. a, b, and c denote statistical significance at 1%, 5%, and 10%.

	Mean	SD	Min	Max	Correlations with Sentiment		Correlations with Sentiment Components					
					SENTIMENT	SENTIMENT [⊥]	CEFD	TURN	NIPO	RIPO	S	PD-ND
Panel A. Raw data												
CEFD _t	9.03	8.12	-10.41	23.70	-0.71 ^a	-0.60 ^a	1.00					
TURN _{t-1}	11.99	18.27	-26.70	42.96	0.71 ^a	0.68 ^a	-0.29 ^c	1.00				
NIPO _t	358.41	262.76	9.00	953.00	0.74 ^a	0.66 ^a	-0.55 ^a	0.38 ^b	1.00			
RIPO _{t-1}	16.94	14.93	-1.67	69.53	0.76 ^a	0.80 ^a	-0.42 ^a	0.50 ^a	0.35 ^b	1.00		
S _t	19.53	8.34	7.83	43.00	0.33 ^b	0.44 ^a	-0.01	0.30 ^c	0.16	0.26	1.00	
P _{t-1} ^{D-ND}	0.20	18.67	-33.17	36.06	-0.83 ^a	-0.76 ^a	0.52 ^a	-0.50 ^a	-0.56 ^a	-0.58 ^a	-0.12	1.00
Panel B. Controlling for macroeconomic conditions												
CEFD _t [⊥]	0.00	6.25	-18.32	9.60	-0.62 ^a	-0.63 ^a	1.00					
TURN _{t-1} [⊥]	0.00	15.49	-26.03	26.37	0.69 ^a	0.71 ^a	-0.26	1.00				
NIPO _t [⊥]	0.00	226.30	-435.98	484.15	0.73 ^a	0.74 ^a	-0.45 ^a	0.39 ^b	1.00			
RIPO _{t-1} [⊥]	0.00	14.31	-23.55	46.54	0.77 ^a	0.83 ^a	-0.46 ^a	0.53 ^a	0.44 ^a	1.00		
S _t [⊥]	0.00	6.15	-12.17	14.29	0.55 ^a	0.67 ^a	-0.41 ^a	0.32 ^b	0.50 ^a	0.47 ^a	1.00	
P _{t-1} ^{D-ND} [⊥]	0.00	16.89	-43.20	35.96	-0.78 ^a	-0.77 ^a	0.26	-0.60 ^a	-0.46 ^a	-0.68 ^a	-0.28 ^c	1.00

Table 3. Future Returns by Sentiment Index and Firm Characteristics, 1963 to 2001. 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 where $\text{SENTIMENT}^\perp$ from the previous year end is positive, negative, and the difference between the two averages. $\text{SENTIMENT}^\perp$ is positive for 1968 to 1970, 1972, 1979 to 1987, 1994, 1996 to 1997, and 1999 to 2001 (the return series ends in 2001, so the last value used is 2000).

SENTIMENT [⊥] _{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		0.73	0.74	0.85	0.83	0.92	0.84	1.06	0.99	1.02	0.98	0.26	0.06	0.20	
	Negative		2.37	1.68	1.66	1.51	1.67	1.35	1.26	1.25	1.05	0.92	-1.45	-0.75	-0.70	
	Difference		-1.65	-0.93	-0.81	-0.68	-0.75	-0.51	-0.20	-0.26	-0.03	0.06	1.71	0.81	0.90	
Age	Positive		0.25	0.83	0.94	0.95	1.18	1.19	0.96	1.18	1.09	1.11	0.85	-0.07	0.93	
	Negative		1.77	1.88	1.97	1.68	1.70	1.68	1.38	1.34	1.36	1.24	-0.54	-0.46	-0.08	
	Difference		-1.52	-1.05	-1.03	-0.74	-0.51	-0.49	-0.42	-0.16	-0.27	-0.13	1.39	0.39	1.00	
σ	Positive		1.44	1.41	1.25	1.20	1.24	1.08	1.01	0.88	0.75	0.30	-1.14	-0.94	-0.20	
	Negative		1.01	1.17	1.26	1.37	1.52	1.61	1.65	1.83	2.08	2.41	1.40	0.89	0.51	
	Difference		0.43	0.24	-0.01	-0.16	-0.28	-0.53	-0.65	-0.95	-1.33	-2.11	-2.54	-1.84	-0.71	
E/BE	Positive	0.35	0.68	0.85	0.86	0.89	0.92	0.88	0.92	1.05	1.10	0.93	0.24	0.01	0.24	0.61
	Negative	2.59	2.24	2.10	2.26	1.82	1.65	1.79	1.62	1.59	1.43	1.57	-0.67	-0.08	-0.59	-0.95
	Difference	-2.25	-1.56	-1.25	-1.40	-0.93	-0.73	-0.91	-0.70	-0.54	-0.34	-0.65	0.91	0.09	0.82	1.56
D/BE	Positive	0.44	1.08	1.09	1.29	1.11	1.24	1.17	1.31	1.24	1.19	1.15	0.07	-0.09	0.16	0.75
	Negative	2.32	1.87	1.63	1.59	1.51	1.38	1.30	1.20	1.12	1.16	1.18	-0.69	-0.19	-0.49	-0.89
	Difference	-1.88	-0.79	-0.54	-0.30	-0.40	-0.14	-0.14	0.11	0.12	0.03	-0.03	0.76	0.11	0.65	1.64
PPE/A	Positive	1.31	0.48	0.66	0.74	0.81	1.04	0.90	0.79	0.87	1.04	1.05	0.57	0.02	0.56	-0.53
	Negative	1.26	1.93	1.96	1.90	1.87	1.82	1.89	1.66	1.56	1.29	1.62	-0.31	-0.20	-0.11	0.53
	Difference	0.05	-1.45	-1.31	-1.17	-1.07	-0.78	-0.99	-0.87	-0.69	-0.25	-0.56	0.88	0.22	0.67	-1.05
RD/A	Positive	0.80	1.21	1.04	1.37	1.37	1.34	1.22	1.24	1.29	1.39	1.38	0.17	0.04	0.13	0.55
	Negative	1.63	1.57	1.47	1.58	1.73	1.66	1.81	1.97	2.04	2.13	2.44	0.87	0.78	0.09	0.43
	Difference	-0.83	-0.36	-0.43	-0.22	-0.36	-0.32	-0.60	-0.73	-0.75	-0.74	-1.05	-0.69	-0.74	0.04	0.12
BE/ME	Positive		0.03	0.61	0.82	0.87	0.96	1.09	1.17	1.18	1.29	1.27	1.24	0.31	0.93	
	Negative		1.41	1.43	1.46	1.54	1.61	1.69	1.87	1.94	2.18	2.45	1.04	0.84	0.20	
	Difference		-1.38	-0.81	-0.64	-0.67	-0.65	-0.60	-0.70	-0.76	-0.88	-1.18	0.20	-0.53	0.73	
EF/A	Positive		1.08	1.04	1.25	1.18	1.19	1.17	1.02	0.92	0.75	-0.01	-1.09	-1.20	0.11	
	Negative		2.43	2.09	1.85	1.75	1.59	1.53	1.51	1.51	1.71	1.53	-0.90	-0.06	-0.84	
	Difference		-1.35	-1.05	-0.59	-0.57	-0.40	-0.35	-0.49	-0.60	-0.96	-1.54	-0.18	-1.14	0.96	
GS	Positive		0.70	1.07	1.19	1.15	1.21	1.18	1.22	1.10	0.81	0.05	-0.65	-1.16	0.51	
	Negative		2.49	1.78	1.61	1.54	1.47	1.57	1.68	1.78	1.68	1.69	-0.80	0.22	-1.02	
	Difference		-1.79	-0.71	-0.42	-0.40	-0.26	-0.39	-0.46	-0.68	-0.87	-1.64	0.15	-1.38	1.53	

Table 4. Correlations of Portfolio Returns, 1963 to 2001. Correlations among characteristics-based portfolios. The sample period includes monthly returns from 1963 to 2001. The long-short portfolios are formed based on firm characteristics: 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; medium is defined as a firm in the middle four NYSE deciles. a, b, and c denote statistical significance at 1%, 5%, and 10%.

		Size, Age, and Risk			Profitability, Dividends		Tangibility		Growth Opportunities and Distress			Growth Opportunities			Distress		
		ME	Age	σ	E	D	PPE	RD	BE/ ME	EF/A	GS	BE/ ME	EF/A	GS	BE/ ME	EF/A	GS
ME	SMB	1.00															
Age	High-Low	-0.78 ^a	1.00														
σ	High-Low	0.77 ^a	-0.92 ^a	1.00													
E	>0 – <0	-0.64 ^a	0.85 ^a	-0.85 ^a	1.00												
D	>0 – =0	-0.76 ^a	0.94 ^a	-0.96 ^a	0.91 ^a	1.00											
PPE/A	High-Low	-0.74 ^a	0.85 ^a	-0.87 ^a	0.71 ^a	0.84 ^a	1.00										
RD/A	High-Low	0.61 ^a	-0.78 ^a	0.82 ^a	-0.69 ^a	-0.80 ^a	-0.79 ^a	1.00									
BE/ME	HML	0.09 ^a	0.47 ^a	-0.46 ^a	0.23 ^a	0.43 ^a	0.51 ^a	-0.73 ^a	1.00								
EF/A	High-Low	0.33 ^a	-0.55 ^a	0.56 ^a	-0.34 ^a	-0.51 ^a	-0.59 ^a	0.66 ^a	-0.65 ^a	1.00							
GS	High-Low	0.14 ^a	-0.17 ^a	0.23 ^a	0.10 ^b	-0.15 ^a	-0.34 ^a	0.29 ^a	-0.57 ^a	0.73 ^a	1.00						
BE/ME	Medium-Low	-0.37 ^a	0.66 ^a	-0.68 ^a	0.48 ^a	0.64 ^a	0.61 ^a	-0.80 ^a	0.81 ^a	-0.74 ^a	-0.49 ^a	1.00					
EF/A	High-Medium	0.65 ^a	-0.87 ^a	0.90 ^a	-0.76 ^a	-0.88 ^a	-0.83 ^a	0.76 ^a	-0.51 ^a	0.77 ^a	0.42 ^a	-0.73 ^a	1.00				
GS	High-Medium	0.65 ^a	-0.84 ^a	0.88 ^a	-0.69 ^a	-0.86 ^a	-0.81 ^a	0.80 ^a	-0.62 ^a	0.78 ^a	0.55 ^a	-0.77 ^a	0.92 ^a	1.00			
BE/ME	High-Medium	0.31 ^a	-0.30 ^a	0.29 ^a	-0.50 ^a	-0.35 ^a	-0.22 ^a	-0.01	0.40 ^a	-0.31 ^a	-0.53 ^a	0.16 ^a	0.14 ^a	0.03	1.00		
EF/A	Medium-Low	-0.61 ^a	0.69 ^a	-0.70 ^a	0.77 ^a	0.74 ^a	0.56 ^a	-0.39 ^a	-0.01	0.04	0.26 ^a	0.23 ^a	-0.60 ^a	-0.47 ^a	-0.61 ^a	1.00	
GS	Medium-Low	-0.61 ^a	0.80 ^a	-0.79 ^a	0.88 ^a	0.83 ^a	0.60 ^a	-0.62 ^a	0.17 ^a	-0.20 ^a	0.31 ^a	0.42 ^a	-0.65 ^a	-0.63 ^a	-0.53 ^a	0.77 ^a	1.00

Table 5. Time Series Regressions of Portfolio Returns, 1963 to 2001. 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 2001. 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; 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[⊥] 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. Bootstrap p-values are in braces.

		<i>SENTIMENT_{t-1}</i>		<i>SENTIMENT_{t-1} Controlling for RMRF, SMB, HML, UMD</i>		<i>SENTIMENT_{t-1}[⊥]</i>		<i>SENTIMENT_{t-1}[⊥] Controlling for RMRF, SMB, HML, UMD</i>	
		<i>d</i>	<i>p(d)</i>	<i>d</i>	<i>p(d)</i>	<i>d</i>	<i>p(d)</i>	<i>d</i>	<i>p(d)</i>
Panel A. Size, Age, and Risk									
ME	SMB	-0.4	[.04]	-0.3	[.08]	-0.4	[.06]	-0.3	[.15]
Age	High-Low	0.5	[.02]	0.2	[.08]	0.5	[.01]	0.2	[.04]
σ	High-Low	-1.0	[.01]	-0.5	[.01]	-0.9	[.00]	-0.4	[.01]
Panel B. Profitability and Dividend Policy									
E	>0 – <0	0.8	[.00]	0.5	[.02]	0.8	[.00]	0.4	[.02]
D	>0 – =0	0.8	[.00]	0.4	[.00]	0.8	[.00]	0.4	[.00]
Panel C. Tangibility									
PPE/A	High-Low	0.4	[.12]	0.1	[.65]	0.4	[.07]	0.1	[.53]
RD/A	High-Low	-0.3	[.25]	0.0	[.77]	-0.3	[.24]	0.1	[.62]
Panel D. Growth Opportunities and Distress									
BE/ME	HML	0.1	[.47]	0.0	[1.00]	0.2	[.25]	0.1	[.68]
EF/A	High-Low	-0.1	[.24]	-0.1	[.46]	-0.2	[.13]	-0.1	[.40]
GS	High-Low	-0.1	[.53]	-0.0	[.67]	-0.1	[.23]	-0.1	[.51]
Panel E. Growth Opportunities									
BE/ME	Medium-Low	0.2	[.11]	0.1	[.39]	0.3	[.06]	0.1	[.35]
EF/A	High-Medium	-0.4	[.00]	-0.2	[.01]	-0.4	[.00]	-0.2	[.00]
GS	High-Medium	-0.4	[.00]	-0.2	[.00]	-0.4	[.00]	-0.2	[.00]
Panel F. Distress									
BE/ME	High-Medium	-0.1	[.21]	-0.1	[.49]	-0.1	[.30]	-0.1	[.53]
EF/A	Medium-Low	0.3	[.00]	0.2	[.01]	0.2	[.00]	0.2	[.00]
GS	Medium-Low	0.3	[.01]	0.2	[.04]	0.3	[.01]	0.2	[.07]

Table 6. Time Series Regressions of Portfolio Returns, 1935 to 2001. 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 long-short portfolios are formed based on firm characteristics (X): firm size (ME), age, total risk (σ), and dividends (D). High is defined as a firm in the top three NYSE deciles; low is defined as a firm in the bottom three NYSE deciles. The sentiment index is the first principal component of the closed-end fund discount (CEFD) and the equity share (S) for the calendar year one year before t and detrended log turnover (TURN) for the calendar year two years before t . Average monthly returns are matched to SENTIMENT from the previous year end. SENTIMENT[⊥] 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. Bootstrap p-values are in braces.

		<i>SENTIMENT_{t-1}</i>		<i>SENTIMENT_{t-1} Controlling for RMRF, SMB, HML, UMD</i>		<i>SENTIMENT_{t-1}[⊥]</i>		<i>SENTIMENT_{t-1}[⊥] Controlling for RMRF, SMB, HML, UMD</i>	
		<i>d</i>	<i>p(d)</i>	<i>d</i>	<i>p(d)</i>	<i>d</i>	<i>p(d)</i>	<i>d</i>	<i>p(d)</i>
Panel A. 1935 to 2001									
ME	SMB	-0.3	[.03]	-0.2	[.07]	-0.3	[.04]	-0.2	[.07]
Age	High-Low	0.2	[.18]	0.1	[.38]	0.2	[.10]	0.1	[.26]
σ	High-Low	-1.0	[.00]	-0.4	[.00]	-0.8	[.00]	-0.4	[.00]
D	>0 – =0	0.9	[.00]	0.5	[.01]	0.7	[.00]	0.4	[.01]
Panel B. 1935 to 1961									
ME	SMB	-0.3	[.05]	-0.3	[.05]	-0.1	[.33]	-0.1	[.33]
Age	High-Low	-0.1	[.41]	-0.1	[.41]	-0.1	[.04]	-0.1	[.05]
σ	High-Low	-0.8	[.01]	-0.8	[.01]	-0.4	[.14]	-0.4	[.16]
D	>0 – =0	0.9	[.01]	0.9	[.01]	0.5	[.10]	0.5	[.11]

Table 7. Conditional Market Betas, 1963 to 2001. Regressions of long-short portfolio returns on the market risk premium (RMRF) and the market risk premium interacted with SENTIMENT.

$$R_{X_{it}=high,t} - R_{X_{it}=low,t} = c + dSENTIMENT_{t-1} + \beta(e + fSENTIMENT_{t-1})RMRF_t + u_t$$

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; medium is defined as a firm in the middle four NYSE deciles. Monthly returns are matched to SENTIMENT from the previous year end. SENTIMENT[⊥] 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. Heteroskedasticity robust p-values are in braces. a indicates a statistically significant βf that matches the sign of the return predictability from Table 5; b indicates a statistically significant βf that does not match.

		$SENTIMENT_{t-1}$		$SENTIMENT_{t-1}^{\perp}$	
		βf	$t(\beta f)$	βf	$t(\beta f)$
Panel A. Size, Age, and Risk					
ME	SMB	-0.03	[.48]	-.02	[.62]
Age	High-Low	-0.05	[.19]	-.07	[.09]
σ	High-Low	0.00	[.98]	.03	[.58]
Panel B. Profitability and Dividend Policy					
E	>0 – <0	-0.04	[.47]	-.00	[.98]
D	>0 – =0	-0.01	[.75]	-.04	[.35]
Panel C. Tangibility					
PPE/A	High-Low	-0.00	[.94]	-.01	[.76]
RD/A	High-Low	0.12 ^b	[.01]	.17 ^b	[.00]
Panel D. Growth Opportunities and Distress					
BE/ME	HML	-0.10 ^b	[.02]	-.12 ^b	[.00]
EF/A	High-Low	0.06 ^b	[.00]	.07 ^b	[.00]
GS	High-Low	0.42	[.06]	.37	[.08]
Panel E. Growth Opportunities					
BE/ME	Medium-Low	-0.06	[.05]	-.09 ^b	[.01]
EF/A	High-Medium	0.03	[.13]	.04	[.05]
GS	High-Medium	0.05 ^b	[.02]	.06 ^b	[.01]
Panel F. Distress					
BE/ME	High-Medium	-0.07 ^a	[.00]	-.07 ^a	[.00]
EF/A	Medium-Low	0.03	[.08]	.02	[.17]
GS	Medium-Low	-0.01	[.62]	-.02	[.27]

Table 8. Earnings Announcement Effects, 1973 to 2001. Regressions of average quarterly earnings announcement effects on lagged SENTIMENT[⊥].

$$CAR_{X_{it}=Decile,t} = c + dSENTIMENT_{t-1}^{\perp} + u_t$$

We report *b*. For each calendar quarter, 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 average announcement effects for unprofitable firms, nonpayers, zero PP&E firms, and zero R&D firms. Quarterly average announcement effects are matched to SENTIMENT[⊥] from the previous year end. SENTIMENT[⊥] 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 Heteroskedasticity robust p-values are in braces.

	Decile										
	≤0	1	2	3	4	5	6	7	8	9	10
ME		-0.18 [.03]	-0.05 [.35]	-0.02 [.76]	-0.07 [.27]	-0.02 [.64]	-0.05 [.36]	0.00 [.99]	-0.03 [.50]	0.01 [.90]	-0.03 [.48]
Age		-0.11 [.20]	0.02 [.79]	-0.06 [.27]	-0.06 [.35]	-0.12 [.08]	0.00 [1.00]	0.06 [.21]	-0.03 [.64]	0.00 [1.00]	-0.12 [.01]
σ		0.10 [.05]	0.05 [.23]	0.05 [.26]	0.05 [.32]	-0.04 [.45]	-0.03 [.59]	0.03 [.69]	-0.02 [.79]	-0.08 [.27]	-0.30 [.00]
E/BE	-0.31 [.00]	-0.24 [.01]	0.01 [.92]	0.11 [.24]	-0.08 [.31]	-0.09 [.23]	-0.02 [.73]	-0.01 [.85]	0.04 [.54]	0.04 [.47]	0.10 [.08]
D/BE	-0.18 [.02]	0.00 [.94]	-0.05 [.43]	-0.02 [.72]	0.01 [.80]	0.00 [1.00]	0.03 [.56]	-0.03 [.60]	-0.08 [.07]	0.04 [.43]	-0.10 [.16]
PPE/A	-0.12 [.14]	-0.12 [.12]	-0.12 [.14]	-0.14 [.05]	-0.02 [.75]	0.01 [.87]	0.00 [.97]	-0.12 [.07]	-0.10 [.09]	-0.06 [.28]	-0.05 [.41]
RD/A	-0.05 [.32]	-0.10 [.45]	-0.07 [.46]	-0.04 [.66]	-0.10 [.22]	-0.15 [.12]	-0.28 [.00]	-0.29 [.01]	-0.14 [.10]	-0.11 [.21]	-0.08 [.42]
BE/ME		-0.11 [.06]	-0.03 [.67]	0.03 [.62]	-0.04 [.38]	-0.04 [.43]	0.04 [.54]	-0.05 [.37]	0.01 [.87]	-0.14 [.05]	-0.12 [.24]
EF/A		-0.07 [.38]	-0.01 [.95]	0.05 [.40]	-0.06 [.31]	0.03 [.57]	-0.04 [.51]	-0.10 [.07]	0.01 [.90]	-0.11 [.06]	-0.09 [.20]
GS		-0.20 [.02]	0.00 [.99]	-0.08 [.23]	-0.02 [.68]	-0.03 [.60]	0.04 [.51]	-0.03 [.56]	0.03 [.60]	0.00 [.94]	-0.11 [.15]

Figure 1. Investor Sentiment, 1962 to 2001. 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.

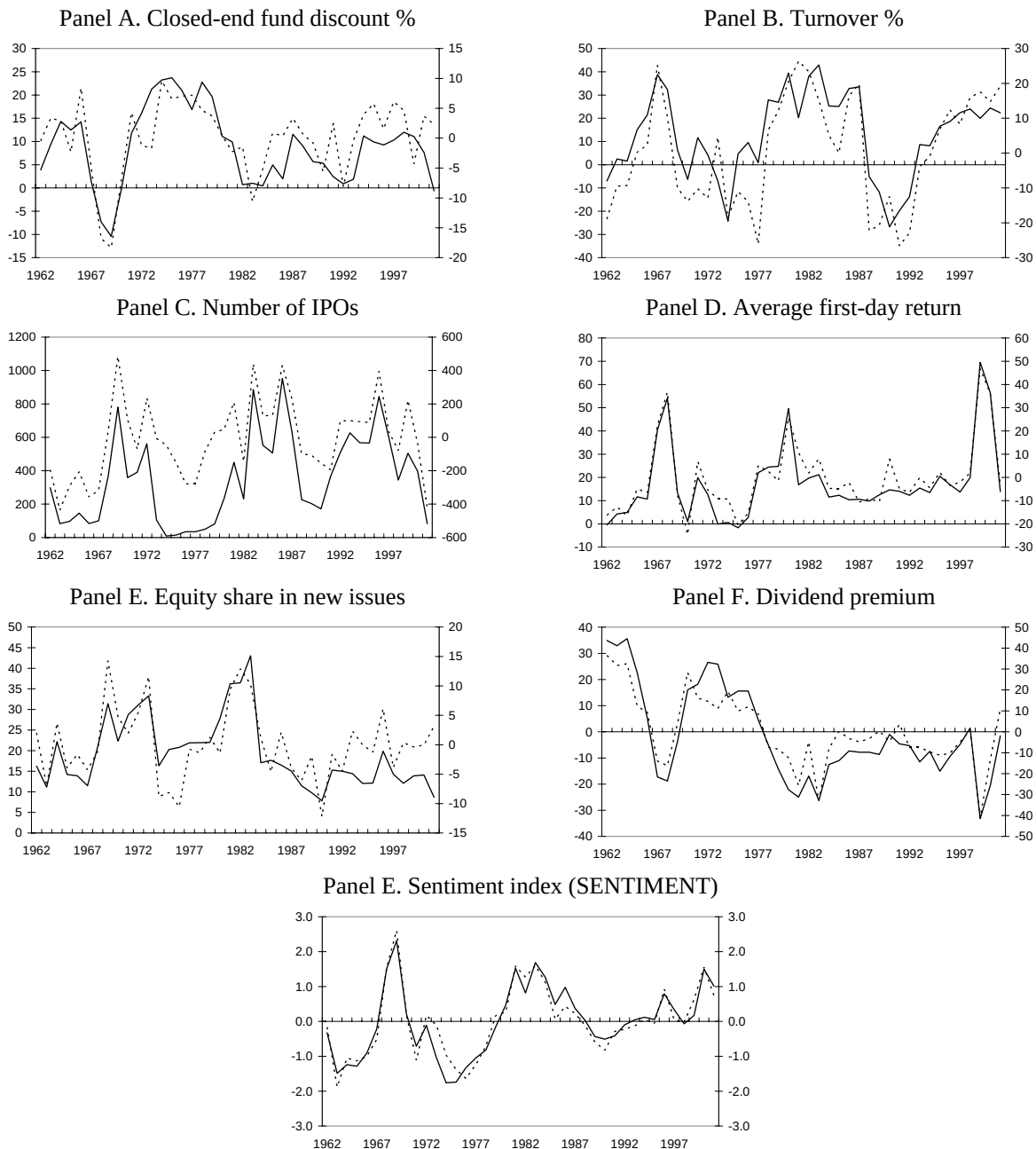
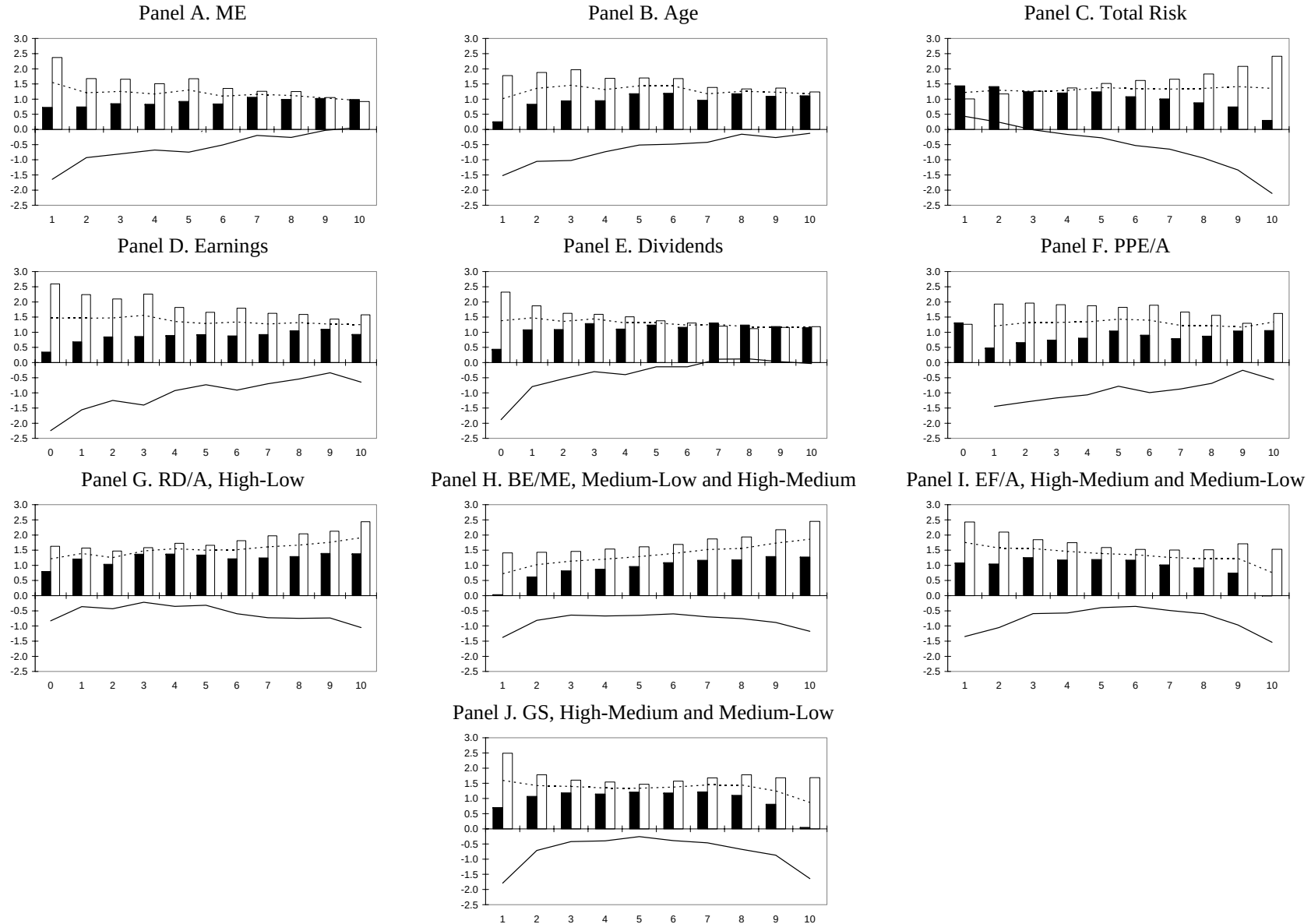


Figure 2. Two-way Sorts: Future Returns by Sentiment Index and Firm Characteristics, 1963 to 2001. For each month, we form ten portfolios according to the NYSE breakpoints of firm size (ME), age, total risk, earnings-book ratio for profitable firms (E/BE), dividend-book ratio for payers (D/BE), fixed 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, nonpaying, zero PP&E, and zero R&D firms. The solid bars are returns following positive SENTIMENT⁺ periods, and the clear bars are returns following negative sentiment periods. The dashed line is the average across both periods and the solid line is the difference. SENTIMENT⁺ is positive for 1968 to 1970, 1972, 1979 to 1987, 1994, 1996 to 1997, and 1999 to 2001 (returns end in 2001, so the last value used is 2000).



¹ See Gomes, Kogan, and Zhang (2003) for a recent model in this tradition.

² Aghion and Stein (2004) develop a model with both rational expectations and bounded rationality where investors periodically emphasize growth over profitability. While the emphasis is on the corporate and macroeconomic effects, the bounded-rationality version of the model offers some similar predictions for the cross-section of returns.

³ The favorite-longshot bias in racetrack betting is a static illustration of the notion that investors with a high propensity to speculate (racetrack bettors) have a relatively high demand for the most speculative bets (longshots have the most negative expected returns; see Hausch and Ziemba (1995)).

⁴ The idea that investors view securities as a vector of salient characteristics borrows from Lancaster (1966, 1971), who views consumer demand theory from the perspective that the utility of a consumer good (e.g. oranges) derives from more primitive characteristics (fiber and vitamin C).

⁵ The implications of categorization for finance have recently been explored by Baker and Wurgler (2003), Barberis and Shleifer (2003), Barberis, Shleifer, and Wurgler (2005), Greenwood and Sosner (2003), and Peng and Xiong (2004). Note that if investors infer category membership from salient characteristics (some psychologists propose that category membership is determined by the presence of defining or characteristic features, e.g. Smith, Shoben, and Rips (1974)), then sentiment-driven demand will be directly connected to characteristics even if sentimental investors undertake an intervening process of categorization and trade entirely at the category level. It is also empirically convenient to boil key investment categories down into vectors of stable and measurable characteristics: one can use the same empirical framework to study such episodes as the late-1960's growth stocks bubble and the Internet bubble. In other words, "Internet bubble" is interesting, but it doesn't make a useful theory. The key is to examine the recurring underlying characteristics.

⁶ We do not incorporate the equilibrium prediction of DeLong et al., namely that securities with more exposure to sentiment have higher unconditional expected returns. Elton, Gruber, and Busse (1998) argue that expected returns are not higher on stocks that have higher sensitivities to the closed-end fund discount. However, Brown et al. (2003) argue that exposure to daily mutual fund flows is a priced factor in the U.S. and Japan.

⁷ Barry and Brown (1984) use the more accurate term “period of listing.” A large number of firms appear on CRSP for the first time in December 1972, when coverage of NASDAQ begins. Excluding these firms from our analyses of age does not change any of our inferences.

⁸ While they both reflect equity issues, the number of IPOs and the equity share have important differences. The equity share includes seasoned offerings, predicts market returns, and scales by total external finance to isolate the composition of finance from the level. On the other hand, the IPO variables may better reflect demand for certain IPO-like regions of the cross-section that theory and historical anecdote suggest are most sensitive to sentiment.

⁹ See Brown and Cliff (2004) for a similar approach to extracting a sentiment factor from a set of noisy proxies.

¹⁰ This conclusion is in seeming contrast to Barry and Brown (1984)’s evidence of an unconditional negative period-of-listing effect, however their sample excludes stocks listed for fewer than 61 months.

¹¹ Intuitively, in terms of Eq. (1), this amounts to a regression of $(b_1\Delta X + b_2T_{t-1}\Delta X)$ on sentiment proxies T_{t-1} , where ΔX is the difference between “high” and “low” levels of a characteristic.

¹² These portfolios are taken from Ken French’s website and are described there.

¹³ The patterns with *ME* in Table 3 and the fact that sentiment predicts *SMB* suggests 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 significant predictors for equal-weighted returns but not 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.

¹⁴ The closed-end fund discount is first available in 1933 from Neal and Wheatley (1998): “Wiesenberger’s survey has published end-of-year fund prices and net asset values since 1943. Moreover, the first edition of the survey contains end-of-year data from 1933 to 1942.” Turnover and the equity share in new issues are available in earlier years. None of our inferences in Panel A of Table 6 change when we use a longer sample period and a sentiment index based on these two variables alone.

¹⁵ For a more detailed look at earlier data, see Gruber (1966). He documents changes in the cross-sectional determinants of stock prices between 1951 and 1963, and argues that they are connected to changes in the average investor's time horizon, i.e., shifts in the term structure of discount rates. This is similar to our notion of a shift in the propensity to speculate.