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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 has larger effects on securities whose valuations are highly subjective and difficult to arbitrage. Consistent with this prediction, we find that when beginning-of-period proxies for sentiment are low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. When sentiment is high, on the other hand, these categories of stock earn relatively low subsequent returns.

CLASSICAL FINANCE THEORY LEAVES NO ROLE FOR INVESTOR SENTIMENT. Rather, this theory argues that competition among rational investors, who diversify to optimize the statistical properties of their portfolios, will lead 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 and thus have 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, we predict that a broad-based wave of sentiment has cross-sectional effects (that is, does not simply raise or lower all prices equally) when sentiment-based demands *or* arbitrage

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

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 shares of certain firms—newer, smaller, more volatile, unprofitable, non-dividend paying, distressed or with extreme growth potential, and firms with analogous characteristics—are likely to be 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 the rises and falls in U.S. market sentiment from 1961 through the Internet bubble. This summary is based on anecdotal accounts and thus 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 examine whether cross-sectional predictability patterns in stock returns depend upon proxies for beginning-of-period sentiment. 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 the ex ante relative overvaluation of young firms. 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 that we can use as time-series conditioning variables. Since there are no perfect and/or uncontroversial proxies for investor sentiment, our approach is necessarily practical. Specifically, we consider a number of proxies suggested in recent work and form a composite sentiment index based on their first principal component. To reduce the likelihood that these proxies are connected to systematic risk, 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. Using monthly stock returns between 1963 and 2001, we start by forming equal-weighted decile portfolios based on several firm characteristics. (Our theory predicts, and the empirical results confirm, that large firms will be less affected by sentiment, and hence value weighting will tend to obscure the relevant patterns.) We then look for patterns in the average returns across deciles conditional upon the beginning-of-period level of sentiment. 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 we sort on other firm characteristics. When sentiment is low, subsequent returns are higher on very young (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 are not as rich, some 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 the 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 the middle deciles are less affected by sentiment. (The result is not statistically significant for book-to-market, however.) This U-shaped pattern in the conditional difference is also broadly consistent with theoretical predictions: both extreme growth and distressed firms have relatively subjective valuations and are relatively hard to arbitrage, and so they should be expected to be most affected by sentiment. Again, note that this intriguing conditional pattern would be averaged away in an unconditional study.

We then consider a regression approach, which allows us to control for comovement in size and book-to-market-sorted stocks using the Fama-French (1993) factors. We use the sentiment indexes to forecast the returns of various high-minus-low portfolios (in terms of sensitivity to sentiment). Not surprisingly, given that our decile portfolios are equal-weighted and several of the characteristics we examine are correlated with size, the inclusion of *SMB* as a control tends to reduce the magnitude of the predictability, although some predictive power generally remains.

We then turn to the classical alternative explanation, namely, that they simply reflect a complex pattern of compensation for systematic risk. This explanation would account for the predictability evidence by either time variation in rational, market-wide risk premia or time variation in the cross-sectional pattern of risk, that is, beta loadings. Further tests cast doubt on these hypotheses. 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 also changes in sign. Put simply, it would require that in half of our sample period (when sentiment is relatively low), older, less volatile, profitable, and/or dividend-paying firms actually require a risk premium over very young, highly volatile, unprofitable, and/or nonpayers. This is counterintuitive. Other aspects of the results also suggest that systematic risk is not a complete explanation.

The results challenge the classical view of the cross-section of stock prices and, in doing so, build on several recent themes. First, the results complement earlier work that shows sentiment helps to explain the time series of returns (Kothari and Shanken (1997), Neal and Wheatley (1998), Shiller (1981, 2000), 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; here we condition on investor sentiment. Daniel and Titman (1997) test a characteristics-based model for the cross-section of expected returns; we extend their specification into a *conditional* characteristics-based model. 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), Neal and Wheatley (1998)).

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

I. Theoretical Effects of Sentiment on the Cross-Section

A mispricing is the result of both 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 therefore 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? We suggest that the main factor is the subjectivity of their valuations. For instance, consider a canonical young, unprofitable, extreme growth 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. During a bubble period, when the propensity to speculate is 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

[2] Aghion and Stein (2004) develop a model with both rational expectations and bounded rationality in which 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.

stable dividends is much less subjective, and thus its stock is likely to be less affected by fluctuations in the propensity to speculate.[3]

While the above channel suggests how variation in the propensity to speculate may generally affect the cross-section, it does not take a stand on 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, investors 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 essentially taken to define 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

One might also define investor sentiment 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. First, their high idiosyncratic risk makes relative-value arbitrage especially risky (Wurgler and Zhuravskaya (2002)). Moreover, such stocks 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

[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 are 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, see, for example, 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 episodes such as the late 1960s growth stocks bubble and the Internet bubble. In other words, the term "Internet bubble" is interesting, but it does not make for a useful or testable theory. The key is to examine the recurring underlying characteristics.

Pedersen (2002), Lamont and Thaler (2003), Mitchell, Pulvino, and Stafford (2002)). Further, their lower liquidity also exposes would-be arbitrageurs to predatory attacks (Brunnermeier and Pedersen (2005)).

The key point of this discussion is that, in practice, *the same stocks that are the hardest to arbitrage also tend to be the most difficult to value*. While for expositional purposes we have outlined the two channels separately, they are likely to have overlapping effects. This may make them difficult to distinguish empirically; however, it only strengthens our predictions about what region of the cross-section is 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 generates a noise-trader risk that further deters short-horizon arbitrageurs (De Long et al. (1990), Shleifer and Vishny (1997)).[6]

II. An Anecdotal History of Investor Sentiment, 1961–2002

Here we briefly summarize the most prominent U.S. stock market bubbles between 1961 and 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 allows 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.

We distill our brief history of sentiment 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 those themes that appear repeatedly.

We start in 1961, a year that Graham (1973), Malkiel (1990) and Brown (1991) note as characterized by a high demand for small, young, growth stocks; Dreman (1979, p. 70) confirms their accounts. For instance, 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 major bubble developed in 1967 and 1968. Brown writes that "scores of franchisers, computer firms, and mobile home manufactures seemed

[6] We do not incorporate the equilibrium prediction of DeLong et al. (1990), 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 a sentiment factor constructed from daily mutual fund flows is a priced factor in the United States and Japan.

to promise overnight wealth . . . . [while] quality was pretty much forgotten" (p. 90). Malkiel and Dreman also note this pattern of 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 1960s many brokers told customers that it didn't matter whether a company paid a dividend—just so long as its stock kept going up" (9/13/1976). But "after 1968, as it became clear that capital losses were possible, investors came to value dividends" (10/7/1999). 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 1970s 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 (1991), Malkiel (1990), 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). That is, the bubbles associated with high sentiment periods centered on small, young, unprofitable growth stocks, whereas 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) that happened in a period of *low* sentiment.

The late 1970s through mid 1980s are described as a period of generally high sentiment, perhaps associated with Reagan-era optimism. This period witnessed 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, and finds greater initial returns on IPOs of natural resource start-ups than on large, 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 1980s, Malkiel writes that "What electronics was to the 1960s, biotechnology became to the 1980s . . . . new issues of biotech companies were eagerly gobbled up . . . . having positive sales and earnings was actually considered a drawback" (p. 77–79). 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 1990s 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 1990s growth stock valuations were difficult to ascribe to rationally expected earnings growth. Malkiel draws parallels to episodes in the 1960s, 1970s, and 1980s, and Shiller (2000) draws parallels to the late 1920s. 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 the 1999 and 2000 IPO cohorts 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, but anecdotal accounts suggest that this bubble occurred during 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 those stocks that are the most subjective to value and the 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 mispricing *correction*. 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.

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

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

where i indexes firms, t denotes time, $\mathbf{x}$ is a vector of characteristics, and T is a proxy for sentiment. The coefficient a_1 picks up the generic effect of sentiment, and the vector $\mathbf{b}_1$ the generic effect of characteristics. Our interest centers on $\mathbf{b}_2$. The null is that $\mathbf{b}_2$ equals 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. We call Equation (1) 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 are 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 I shows summary statistics. Panel A summarizes returns variables. Following common practice, we define momentum, *MOM*, as the cumulative raw return for the 11-month period from 12 through 2 months prior to the observation return. Because momentum is not mentioned as a salient characteristic in historical anecdote, and theory does not suggest a direct connection between momentum and the difficulty of valuation or arbitrage, we use momentum merely as a control variable to understand the independence of our results from known mispricing 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. We match *ME* to monthly returns from July of year t through June of year $t+1$. Firm age, *Age*, is the number of years since the firm's first appearance on CRSP, measured to the nearest month,[7] and *Sigma* is the standard deviation of monthly returns over the 12 months ending in June of year t. If there are at least nine returns available to estimate it, *Sigma* is then matched to monthly returns from July of year t through June of year $t+1$. While historical anecdote does not identify stock volatility itself as a salient characteristic, prior work argues that it is likely to be a good proxy for the difficulty of both valuation and arbitrage.

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). The profitability dummy variable $E > 0$ 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. The dividend payer dummy $D > 0$ takes the value one for firms with positive dividends per share by the ex date. The decline noted by Fama and French (2001) in the percentage of firms that pay dividends is apparent.

[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 Nasdaq coverage begins. Excluding these firms from our analyses of age does not change any of our inferences.

Table I

Summary Statistics, 1963–2001

Panel A summarizes the returns variables. Returns are measured monthly. Momentum (*MOM*) is defined as the cumulative return for the 11-month period between 12 and 2 months prior to t. Panel B summarizes the size, age, and risk characteristics. Size is the log of market equity. Market equity (*ME*) is price times shares outstanding from CRSP in the June prior to t. Age is the number of years between the firm's first appearance on CRSP and t. Total risk (σ) is the annual standard deviation in monthly returns from CRSP for the 12 months ending in the June prior to t. Panel C summarizes profitability variables. The earnings-book equity ratio is defined for firms with positive earnings. Earnings (E) is defined as income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19). Book equity (*BE*) is defined as shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35). We also report an indicator variable equal to one for firms with positive earnings. Panel D reports dividend variables. Dividends (D) are equal to dividends per share at the ex date (Item 26) times shares outstanding (Item 25). We scale dividends by assets and report an indicator variable equal to one for firms with positive dividends. Panel E shows tangibility measures. Plant, property, and equipment (Item 7) and research and development (Item 46) are scaled by assets. We only record research and development when it is widely available after 1971; for that period, a missing value is set to zero. Panel F reports variables used as proxies for growth opportunities and distress. The book-to-market ratio is the log of the ratio of book equity to market equity. External finance (*EF*) is equal to the change in assets (Item 6) less the change in retained earnings (Item 36). When the change in retained earnings is not available we use net income (Item 172) less common dividends (Item 21) instead. Sales growth decile is formed using NYSE breakpoints for sales growth. Sales growth is the percentage change in net sales (Item 12). In Panels C through F, accounting data from the fiscal year ending in $t-1$ are matched to monthly returns from July of year t through June of year $t+1$. All variables are Winsorized at 99.5 and 0.5%.

	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	2,400.00	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_{t-1} (%)	1,476,109	54.66	37.15	0.00	187.69	70.21	59.14	55.49	51.28	45.49
RD/A_{t-1} (%)	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

The referee suggests that asset tangibility may proxy for the difficulty of valuation. 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*. One concern is the coverage of the R&D variable. We do not consider this variable prior to 1972, because the Financial Accounting Standards Board 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 will become clear below, one must grasp 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 that varies with any source of mispricing or rational expected returns. Similarly, sales growth and external finance wear at least two hats: Low values (which are negative) may indicate distress, and high values may reflect growth opportunities. Further, to the extent that market timing motives drive external finance, *EF/A* also wears a third hat 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 therefore form a composite index of sentiment that 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 proxy separately, and then discuss how they are formed into overall sentiment indexes.

The closed-end fund discount, *CEFD*, is the average difference between the net asset values (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 et al. (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 5-year moving average.

The IPO market is often viewed as sensitive to sentiment, with high first-day returns on IPOs cited as a measure of investor enthusiasm, and the low idiosyncratic returns on IPOs often interpreted as a symptom 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 sentiment. Baker and Wurgler (2000) find that high values of the equity share predict low 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]

Our 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 generally larger, more profitable firms with weaker growth opportunities (Fama and French (2001)), the dividend premium may proxy for the relative demand for this correlated bundle of characteristics.

Each sentiment proxy is likely to include a sentiment component as well as idiosyncratic, non-sentiment-related components. We use principal components analysis to isolate the common component. Another issue in forming an index is determining the relative timing of the variables—that is, 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 partly behind the high first-day returns, and this attracts additional IPO volume with a lag. More generally, proxies that involve firm supply responses (*S* and *NIPO*) can be expected to lag behind proxies

[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.

that are based directly on investor demand or investor behavior (*RIPO*, P^{D-ND}, *TURN*, and *CEFD*).

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 12 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

$$SENTIMENT_t = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t + 0.257RIPO_{t-1} + 0.112S_t - 0.283P^{D-ND}_{t-1}, \tag{2}$$

where each of the index components 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 12-term first-stage index and the *SENTIMENT* index is 0.95, suggesting that little information is lost in dropping the six terms with other time subscripts.

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 equation (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 IPOs varies with the business cycle in part for entirely rational reasons. We want to identify when the number of IPOs 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.

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

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

$$SENTIMENT_t^{\perp} = -0.198CEFD_t^{\perp} + 0.225TURN_{t-1}^{\perp} + 0.234NIPO_t^{\perp} + 0.263RIPO_{t-1}^{\perp} + 0.211S_t^{\perp} - 0.243P_{t-1}^{D-ND,\perp}. \quad (3)$$

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 II 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 or the overall index (see Panel E). Indeed, Table II suggests that on balance the orthogonalized proxies are 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. Specifically, 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 1970s, it is low by most measures (recall that for turnover this is confounded by deregulation). The late 1970s through mid 1980s 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 1968–1970, 1972, 1979–1987, 1994, 1996–1997, and 1999–2001. This correspondence with anecdotal accounts seems to confirm that the measures capture the intended variation.

There are other variables that one might reasonably wish to include in a sentiment index. The main constraint is availability and consistent measurement over the 1962–2001 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. However, Nejat Seyhun shared with us 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 average Seyhun's series across months to obtain 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.

Table II

Investor Sentiment Data, 1962–2000

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 5-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 1 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. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

					Correlations with Sentiment		Correlations with Sentiment Components					
	Mean	SD	Min	Max	*SENTIMENT*	$SENTIMENT^{\perp}$	*CEFD*	*TURN*	*NIPO*	*RIPO*	S	P^{D-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^{D-ND}_{t-1}	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							
$CEFD^{\perp}_t$	0.00	6.25	−18.32	9.60	-0.62^a	-0.63^a	1.00					
$TURN^{\perp}_{t-1}$	0.00	15.49	−26.03	26.37	0.69^a	0.71^a	−0.26	1.00				
$NIPO^{\perp}_t$	0.00	226.30	−435.98	484.15	0.73^a	0.74^a	-0.45^a	0.39^b	1.00			
$RIPO^{\perp}_{t-1}$	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		
$S^{\perp}_t$	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	
$P^{D-ND\perp}_{t-1}$	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

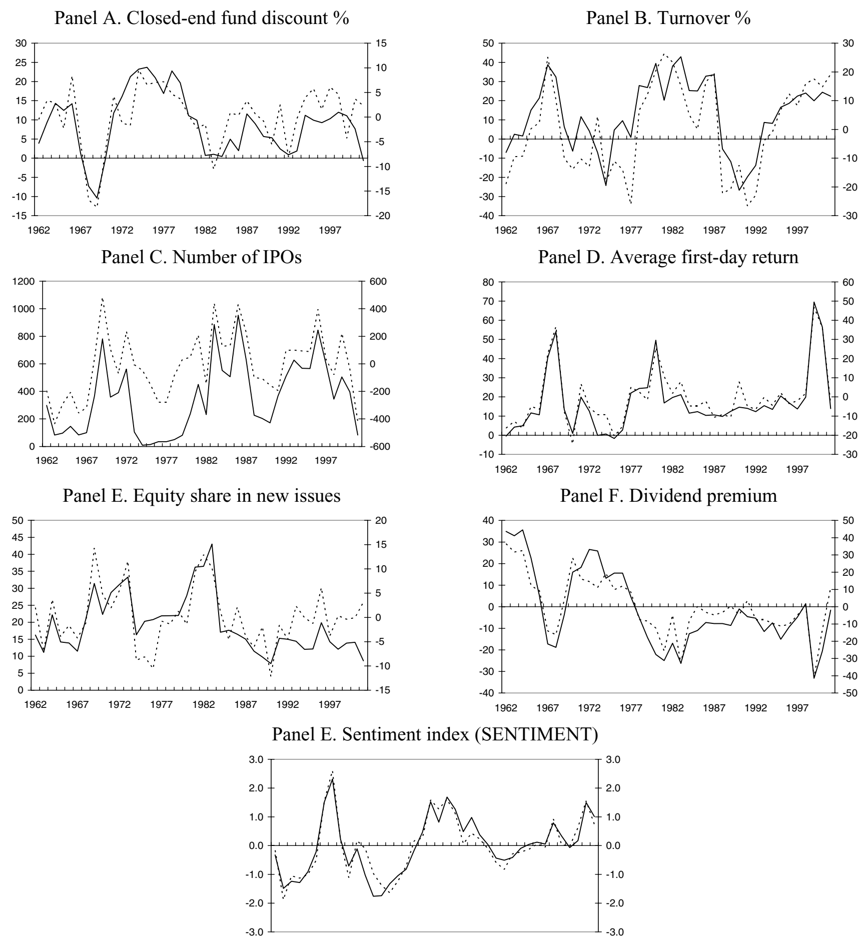

Figure 1. Investor sentiment, 1962–2001. The first panel shows the year-end, value-weighted average discount on closed-end mutual funds. The data on prices and net asset values (NAVs) come from Neal and Wheatley (1998) for 1962 through 1993, CDA/Wiesenberger for 1994 through 1998, and turn-of-the-year 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 5-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 1 year relative to the other three measures, as discussed in the text.

IV. Empirical Tests

A. Sorts

Table III 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 trade-off is that there is not a uniform distribution of firms across bins in any given month. We compute the equal-weighted average monthly return for each bin and look for patterns. In particular, we identify time-series changes in cross-sectional effects from the conditional *difference* of average returns across deciles.

The first rows of Table III show the effect of size, as measured by *ME*, conditional on sentiment. These rows reveal that the size effect of Banz (1981) appears in low sentiment periods only. Specifically, Table III 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 is also noted 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 III 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.

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 and top several deciles of age. Overall, there is a nearly monotonic effect in the conditional difference of returns. This result is intriguing because *Age* has no unconditional effect.[10] *The strong conditional effects, of opposite sign, average out across high and low sentiment periods*.

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

Table III
Future Returns by Sentiment Index and Firm Characteristics, 1963–2001

For each month, we form 10 equal-weighted portfolios according to the NYSE breakpoints of firm size (*ME*), *age*, total risk, earnings-book ratio for profitable firms (*E/BE*), dividend-book ratio for dividend payers (*D/BE*), fixed assets (*PPE/A*), research and development (*RD/A*), book-to-market ratio (*BE/ME*), external finance over assets (*EF/A*), and sales growth (*GS*). We also calculate portfolio returns for unprofitable firms, nonpayers, zero-PP&E firms, and zero-R&D firms. We then report average portfolio returns over months in which $SENTIMENT^{\perp}$ from the previous year-end is positive, months in which it is negative, and the difference between these two averages. $SENTIMENT^{\perp}$ is positive for 1968–1970, 1972, 1979–1987, 1994, 1996–1997, and 1999–2001 (the return series ends in 2001, so the last value used is 2000).

		Decile											Comparisons			
	$SENTIMENT^{\perp}_{t-1}$	≤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	

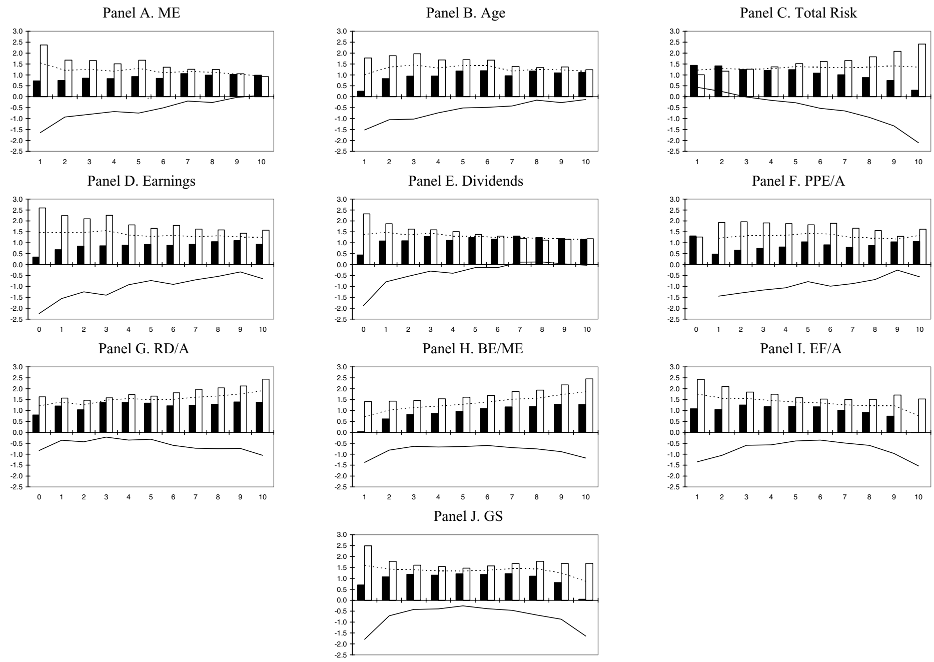

Figure 2. Two-way sorts: Future returns by sentiment index and firm characteristics, 1963–2001. For each month, we form 10 portfolios according to the NYSE breakpoints of firm size (*ME*), age, total risk, earnings-book ratio for profitable firms (*E/BE*), dividend-book ratio for payers (*D/BE*), fixed 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 $SENTIMENT^{\perp}$ 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. $SENTIMENT^{\perp}$ is positive for 1968–1970, 1972, 1979–1987, 1994, 1996–1997, and 1999–2001 (returns end in 2001, so the last value used is 2000).

The next rows of Table III 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, as they 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, making them especially prone to fluctuations in sentiment.

Figure 2 shows the results of Table III 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.

The next rows examine profitability and dividends. For average investors, perhaps the most salient comparisons are simply those 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 (paying) firms and compare them to unprofitable (nonpaying) firms. 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 harder both to value and to arbitrage, thus exposing them more to sentiment fluctuations.

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–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? It reflects the multidimensional nature of the growth and distress variables. Consider *GS*. 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 the 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 sort returns not just on positive and negative values of $SENTIMENT^{\perp}$ but also on >1 and <-1 standard deviation 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 nonorthogonalized 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 10-year history of sentiment, one loses a little more than one-quarter of the sample. The results are qualitatively identical to those in Table III, 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 equal-weighted portfolios that are long on stocks with high values of a characteristic and short on stocks with low values. Above we see 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, incorporate the continuous nature of the sentiment indexes, and determine which characteristics have conditional effects that are distinct from well-known unconditional effects.

Table IV 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. This question is also relevant given that our portfolios are equal-weighted. By controlling for *SMB* in portfolio forecasting regressions, we can examine the extent to which the conditional predictability patterns are independent of size.

Table IV

Correlations of Portfolio Returns, 1963–2001

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, and medium is defined as a firm in the middle four NYSE deciles. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10%, level, respectively.

		Size, Age, and Risk			Profitability, Dividends		Tangibility		Growth Opportunities and Distress			Growth Opportunities			Distress		
		ME	*Age*	σ	*E*	*D*	*PPE/A*	*RD/A*	*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

In the last several rows of Table IV, 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. Thus, simple "high minus low" analyses of these variables would omit crucial aspects of the cross-section.

The question is whether sentiment can predict the various long–short portfolios analyzed in Table IV. We run regressions of the type[11]

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

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 the multivariate regression

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = c + dSENTIMENT_{t-1} + \beta RMKT_t + sSMB_t + hHML_t + mUMD_t + u_{it}. \qquad (5)$$

The variable *RMRF* is the excess return of the value-weighted market over the risk-free rate. The variable *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*, where *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 the portfolios 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 V shows the results. The results provide formal support to our 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 are standardized) is associated with a −0.40% lower monthly return on the small minus large portfolio.

[11] Intuitively, in terms of equation (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.

Table V 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 find from regressing long–short portfolio returns directly on a raw sentiment index and controls for contemporaneous macroeconomic conditions—that is, 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. The patterns are little affected by controlling for *RMRF*, *SMB*, *HML*, and *UMD*.

As we find with 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 find with 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 III 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 our inferences from the sorts, where we see that the U-shaped pattern in the conditional difference for *BE/ME* is 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 include a post-1982 dummy in the regressions, with no change in inferences from those in the last column of Table V. Also, the results are slightly stronger when returns from January and December are removed from the sample. This

Table V

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, and medium is defined as a firm in the middle four NYSE deciles. Average monthly returns are matched to *SENTIMENT* from the previous year-end. $SENTIMENT^{\perp}$ index is based on six sentiment proxies that 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. Bootstrapped p-values are in brackets.

		$SENTIMENT_{t-1}$		$SENTIMENT_{t-1}$ Controlling for *RMRF*, *SMB*, *HML*, *UMD*		$SENTIMENT^{\perp}_{t-1}$		$SENTIMENT^{\perp}_{t-1}$ Controlling for *RMRF*, *SMB*, *HML*, *UMD*	
		d	**p(*d*)**	***d***	**p(*d*)**	***d***	**p(*d*)**	***d***	**p(*d*)**
				Panel A: Size, Age, and Risk					
ME	***SMB***	−0.4	[0.04]	−0.3	[0.08]	−0.4	[0.06]	−0.3	[0.15]
Age	**High-Low**	0.5	[0.02]	0.2	[0.08]	0.5	[0.01]	0.2	[0.04]
σ	**High-Low**	−1.0	[0.01]	−0.5	[0.01]	−0.9	[0.00]	−0.4	[0.01]
				Panel B: Profitability and Dividend Policy					
E	**>0 – <0**	0.8	[0.00]	0.5	[0.02]	0.8	[0.00]	0.4	[0.02]
D	**>0 – =0**	0.8	[0.00]	0.4	[0.00]	0.8	[0.00]	0.4	[0.00]

(continued)

Table V—*Continued*

		$SENTIMENT_{t-1}$		$SENTIMENT_{t-1}$ Controlling for *RMRF*, *SMB*, *HML*, *UMD*		$SENTIMENT^{\perp}_{t-1}$		$SENTIMENT^{\perp}_{t-1}$ Controlling for *RMRF*, *SMB*, *HML*, *UMD*	
		d	**p(*d*)**	***d***	**p(*d*)**	***d***	**p(*d*)**	***d***	**p(*d*)**
Panel C: Tangibility									
PPE/A	**High-Low**	0.4	[0.12]	0.1	[0.65]	0.4	[0.07]	0.1	[0.53]
RD/A	**High-Low**	−0.3	[0.25]	0.0	[0.77]	−0.3	[0.24]	0.1	[0.62]
Panel D: Growth Opportunities and Distress									
BE/ME	***HML***	0.1	[0.47]	0.0	[1.00]	0.2	[0.25]	0.1	[0.68]
EF/A	**High-Low**	−0.1	[0.24]	−0.1	[0.46]	−0.2	[0.13]	−0.1	[0.40]
GS	**High-Low**	−0.1	[0.53]	−0.0	[0.67]	−0.1	[0.23]	−0.1	[0.51]
Panel E: Growth Opportunities									
BE/ME	**Medium-Low**	0.2	[0.11]	0.1	[0.39]	0.3	[0.06]	0.1	[0.35]
EF/A	**High-Medium**	−0.4	[0.00]	−0.2	[0.01]	−0.4	[0.00]	−0.2	[0.00]
GS	**High-Medium**	−0.4	[0.00]	−0.2	[0.00]	−0.4	[0.00]	−0.2	[0.00]
Panel F: Distress									
BE/ME	**High-Medium**	−0.1	[0.21]	−0.1	[0.49]	−0.1	[0.30]	−0.1	[0.53]
EF/A	**Medium-Low**	0.3	[0.00]	0.2	[0.01]	0.2	[0.00]	0.2	[0.00]
GS	**Medium-Low**	0.3	[0.01]	0.2	[0.04]	0.3	[0.01]	0.2	[0.07]

indicates that tax-motivated trading and associated fluctuations in liquidity around the turn of the year do not drive the main results. Further, our portfolios are equal-weighted. As mentioned previously, the purpose of this is that theory predicts that small firms will be most affected by sentiment, and hence value weighting will obscure the relevant patterns. Yet by sorting on characteristics that are correlated with size, as several of our characteristics are, and then equal-weighting these characteristics portfolios, one worries that we are just picking up the size effect once again. By controlling for *SMB* in portfolio forecasting regressions, we can see that several of the conditional predictability patterns are distinguishable from size, though as theory predicts the predictive coefficient is attenuated. 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 and the closed-end fund discount offer the best individual performance, followed by the equity share, turnover, the average first-day return, and the dividend premium. (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 has stronger effects on 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 equation (2).[13] We also orthogonalize these sentiment proxies with respect to consumption growth variables and NBER recessions (industrial production is not available over the full period) to form an index in the spirit of equation (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 VI. With the exception of the *Age* portfolio, for which the results are not significant, the results from the full 1935–2001 period and the "out-of-sample" 1935–1961 period are similar to those in more

[13] 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 VI change when we use a longer sample period and a sentiment index based on these two variables alone.

Table VI

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, and 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*), the equity share (S), and the lag of detrended log turnover (*TURN*). Average monthly returns are matched to *SENTIMENT* from the previous year-end. $SENTIMENT^{\perp}$ index is based on six sentiment proxies that 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. Bootstrapped p-values are in brackets.

		$SENTIMENT_{t-1}$		$SENTIMENT_{t-1}$ Controlling for *RMRF*, *SMB*, *HML*, *UMD*		$SENTIMENT^{\perp}_{t-1}$		$SENTIMENT^{\perp}_{t-1}$ Controlling for *RMRF*, *SMB*, *HML*, *UMD*	
		d	**p(*d*)**	***d***	**p(*d*)**	***d***	**p(*d*)**	***d***	**p(*d*)**
				Panel A: 1935–2001					
ME	***SMB***	−0.3	[0.03]	−0.2	[0.07]	−0.3	[0.04]	−0.2	[0.07]
Age	**High-Low**	0.2	[0.18]	0.1	[0.38]	0.2	[0.10]	0.1	[0.26]
σ	**High-Low**	−1.0	[0.00]	−0.4	[0.00]	−0.8	[0.00]	−0.4	[0.00]
D	$>$ **0 – = 0**	0.9	[0.00]	0.5	[0.01]	0.7	[0.00]	0.4	[0.01]
				Panel B: 1935–1961					
ME	**SMB**	−0.3	[0.05]	−0.3	[0.05]	−0.1	[0.33]	−0.1	[0.33]
Age	**High-Low**	−0.1	[0.41]	−0.1	[0.41]	−0.1	[0.04]	−0.1	[0.05]
σ	**High-Low**	−0.8	[0.01]	−0.8	[0.01]	−0.4	[0.14]	−0.4	[0.16]
D	$>$**0 – = 0**	0.9	[0.01]	0.9	[0.01]	0.5	[0.10]	0.5	[0.11]

recent data.[14] One possibility for the insignificant results on the *Age* portfolio is that we measure age as the number of months for which CRSP data are available. Anecdotal evidence suggests that in these early data, there are fewer truly "young" firms listing on the NYSE. In contrast, in recent years, many genuinely young IPOs start trading on Nasdaq, so our way of measuring age may be more meaningful.

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

[14] 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, that is, shifts in the term structure of discount rates. This is similar to our notion of sentiment as a shift in the propensity to speculate.

error (RMSE) in Table VI 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 (for which 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 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 about 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 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. We investigate this directly in Table VII, where we ask 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

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

The time-varying betas story predicts that the composite coefficient βf, reported in Table VII, has the same sign as the estimates of d in Table V. 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.

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 varies not just in magnitude over time, but also in sign. It would seem then that the bulk of the results do not reflect compensation for classical systematic risks.

Table VII

Conditional Market Betas, 1963–2001

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, and medium is defined as a firm in the middle four NYSE deciles. Monthly returns are matched to *SENTIMENT* from the previous year-end. $SENTIMENT^{\perp}$ index is based on six sentiment proxies that 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 brackets. A superscript "a" indicates a statistically significant βf that matches the sign of the return predictability from Table V; "b" indicates a statistically significant βf that does not match.

		$SENTIMENT_{t-1}$		$SENTIMENT^{\perp}_{t-1}$	
		βf	$t(\beta f)$	βf	$t(\beta f)$
		Panel A: Size, Age, and Risk			
ME	***SMB***	−0.03	[0.48]	−0.02	[0.62]
Age	**High-Low**	−0.05	[0.19]	−0.07	[0.09]
σ	**High-Low**	0.00	[0.98]	0.03	[0.58]
		Panel B: Profitability and Dividend Policy			
E	**>0 – <0**	−0.04	[0.47]	−0.00	[0.98]
D	**>0 – = 0**	−0.01	[0.75]	−0.04	[0.35]
		Panel C: Tangibility			
PPE/*A*	**High-Low**	−0.00	[0.94]	−0.01	[0.76]
RD/*A*	**High-Low**	0.12[b]	[0.01]	0.17[b]	[0.00]
		Panel D: Growth Opportunities and Distress			
BE/*ME*	***HML***	−0.10[b]	[0.02]	−0.12[b]	[0.00]
EF/*A*	**High-Low**	0.06[b]	[0.00]	0.07[b]	[0.00]
GS	**High-Low**	0.42	[0.06]	0.37	[0.08]
		Panel E: Growth Opportunities			
BE/*ME*	**Medium-Low**	−0.06	[0.05]	−0.09[b]	[0.01]
EF/*A*	**High-Medium**	0.03	[0.13]	0.04	[0.05]
GS	**High-Medium**	0.05[b]	[0.02]	0.06[b]	[0.01]
		Panel F: Distress			
BE/*ME*	**High-Medium**	−0.07[a]	[0.00]	−0.07[a]	[0.00]
EF/*A*	**Medium-Low**	0.03	[0.08]	0.02	[0.17]
GS	**Medium-Low**	−0.01	[0.62]	−0.02	[0.27]

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, within its own announcement window. An anecdote from 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, that is,

$$CAR_{X_{it}=Decile,t} = c + dSENTIMENT^{\perp}_{t-1} + u_t. \tag{7}$$

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

Perhaps the most striking feature of Table VIII 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 VIII and those in Table III. In Table VIII, 12 of the 104 coefficients are significant at the 5% level. In Table III, 9 of the 104 estimated conditional differences are larger than 1.5% per month in absolute

Table VIII

Earnings Announcement Effects, 1973–2001

Regressions of average quarterly earnings announcement effects on lagged *SENTIMENT*.

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

We report the coefficient b below. For each calendar quarter, we form 10 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 $SENTIMENT^{\perp}$ from the previous year-end. $SENTIMENT^{\perp}$ index is based on six sentiment proxies that 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 brackets.

	Decile										
	≤0	1	2	3	4	5	6	7	8	9	10
ME		−0.18	−0.05	−0.02	−0.07	−0.02	−0.05	0.00	−0.03	0.01	−0.03
		[0.03]	[0.35]	[0.76]	[0.27]	[0.64]	[0.36]	[0.99]	[0.50]	[0.90]	[0.48]
Age		−0.11	0.02	−0.06	−0.06	−0.12	0.00	0.06	−0.03	0.00	−0.12
		[0.20]	[0.79]	[0.27]	[0.35]	[0.08]	[1.00]	[0.21]	[0.64]	[1.00]	[0.01]
σ		0.10	0.05	0.05	0.05	−0.04	−0.03	0.03	−0.02	−0.08	−0.30
		[0.05]	[0.23]	[0.26]	[0.32]	[0.45]	[0.59]	[0.69]	[0.79]	[0.27]	[0.00]
E/BE	−0.31	−0.24	0.01	0.11	−0.08	−0.09	−0.02	−0.01	0.04	0.04	0.10
	[0.00]	[0.01]	[0.92]	[0.24]	[0.31]	[0.23]	[0.73]	[0.85]	[0.54]	[0.47]	[0.08]
D/BE	−0.18	0.00	−0.05	−0.02	0.01	0.00	0.03	−0.03	−0.08	0.04	−0.10
	[0.02]	[0.94]	[0.43]	[0.72]	[0.80]	[1.00]	[0.56]	[0.60]	[0.07]	[0.43]	[0.16]
PPE/A	−0.12	−0.12	−0.12	−0.14	−0.02	0.01	0.00	−0.12	−0.10	−0.06	−0.05
	[0.14]	[0.12]	[0.14]	[0.05]	[0.75]	[0.87]	[0.97]	[0.07]	[0.09]	[0.28]	[0.41]
RD/A	−0.05	−0.10	−0.07	−0.04	−0.10	−0.15	−0.28	−0.29	−0.14	−0.11	−0.08
	[0.32]	[0.45]	[0.46]	[0.66]	[0.22]	[0.12]	[0.00]	[0.01]	[0.10]	[0.21]	[0.42]
BE/ME		−0.11	−0.03	0.03	−0.04	−0.04	0.04	−0.05	0.01	−0.14	−0.12
		[0.06]	[0.67]	[0.62]	[0.38]	[0.43]	[0.54]	[0.37]	[0.87]	[0.05]	[0.24]
EF/A		−0.07	−0.01	0.05	−0.06	0.03	−0.04	−0.10	0.01	−0.11	−0.09
		[0.38]	[0.95]	[0.40]	[0.31]	[0.57]	[0.51]	[0.07]	[0.90]	[0.06]	[0.20]
GS		−0.20	0.00	−0.08	−0.02	−0.03	0.04	−0.03	0.03	0.00	−0.11
		[0.02]	[0.99]	[0.23]	[0.68]	[0.60]	[0.51]	[0.56]	[0.60]	[0.94]	[0.15]

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, realized 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 demonstrate 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 on beginning-of-period proxies for sentiment. The patterns are rich but intuitive. 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 that display no unconditional predictive power actually hide strong conditional patterns that 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 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.

REFERENCES

Aghion, Philippe, and Jeremy Stein, 2004, Growth versus margins: The destabilizing consequences of giving the stock market what it wants, Working paper, Harvard University.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223–249.

Asness, Clifford S., Jacques A. Friedman, Robert J. Krail, and John M. Liew, 2000, Style timing: Value versus growth, *Journal of Portfolio Management* 26, 50–60.

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

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

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

Banz, Rolf, 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

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

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–318.

Barry, Christopher B., and Stephen J. Brown, 1984, Differential information and the small firm effect, *Journal of Financial Economics* 13, 283–294.

Benveniste, Lawrence M., Alexander P. Ljungqvist, William J. Wilhelm, Jr., and Xiaoyun Yu, 2003, Evidence of information spillovers in the production of investment banking services, *Journal of Finance* 58, 577–608.

Blume, Marshall, and Robert Stambaugh, 1983, Biases in computed returns: An application to the size effect, *Journal of Financial Economics* 12, 387–404.

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

Brown, John Dennis, 1991, *101 Years on Wall Street* (Prentice Hall, Englewood Cliffs, NJ).

Brown, Stephen J., William N. Goetzmann, Takato Hiraki, Noriyoshi Shiraishi, and Masahiro Watanabe, 2003, Investor sentiment in Japanese and U.S. daily mutual fund flows, Working paper, Yale University.

Brunnermeier, Markus, and Lasse Pedersen, 2005, Predatory trading, *Journal of Finance* 60, 1825–1863.

Campbell, John Y., and John H. Cochrane, 2000, Explaining the poor performance of consumption-based asset pricing models, *Journal of Finance* 55, 2863–2878.

Chan, Louis K.C., Jason Karceski, and Josef Lakonishok, 2000, New paradigm or same old hype in equity investing? *Financial Analysts Journal* 56, 23–36.

Cochrane, John H., 2003, Stocks as money: Convenience yield and the tech-stock bubble, in William C. Hunter, George G. Kaufman, and Michael Pomerleano, eds.: *Asset Price Bubbles* (MIT Press, Cambridge).

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

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross-sectional variation in stock returns, *Journal of Finance* 46, 1739–1764.

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

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

Duffie, Darrell, Nicolae Garleanu, and Lasse H. Pedersen, 2002, Securities lending, shorting, and pricing, *Journal of Financial Economics* 66, 307–339.

Elton, Edwin J., Martin J. Gruber, and Jeffrey A. Busse, 1998, Do investors care about sentiment?, *Journal of Business* 71, 477–500.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

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

Geczy, Christopher C., David K. Musto, and Adam V. Reed, 2002, Stocks are special too: An analysis of the equity lending market, *Journal of Financial Economics* 66, 241–269.

Gomes, Joao, Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

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

Greenwood, Robin, and Nathan Sosner, 2003, Trade and the comovement of stock returns: Evidence from Japan, Working paper, Harvard University.

Gruber, Martin J., 1966, The determinants of common stock prices, Ph.D. dissertation, Columbia University.

Hausch, Donald, and William Ziemba, 1995, Efficiency of sports and lottery betting markets, In: *Handbooks in Operations Research and Management Science*, Volume 9, Elsevier, New York, NY.

Ibbotson, Roger, and Jeffrey F. Jaffe, 1975, 'Hot issue' markets, *Journal of Finance* 30, 1027–1042.

Ibbotson, Roger, Jody Sindelar, and Jay Ritter, 1994, The market's problems with the pricing of initial public offerings, *Journal of Applied Corporate Finance* 7, 66–74.

Jones, Charles, 2001, A century of stock market liquidity and trading costs, Working paper, Columbia University.

Jones, Charles, and Owen Lamont, 2002, Short sale constraints and stock returns, *Journal of Financial Economics* 66, 207–239.

Keim, Donald, 1983, Size-related anomalies and stock return seasonality: Further empirical evidence, *Journal of Financial Economics* 12, 13–32.

Kothari, S. P., and Jay Shanken, 1997, Book-to-market, dividend yield, and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169–203.

Kindleberger, Charles, 2001, *Manias, Panics, and Crashes* (Wiley, New York).

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert W. Vishny, 1997, Good news for value stocks: Further evidence on market efficiency, *Journal of Finance* 52, 859–874.

Lakonishok, Josef, and Inmoo Lee, 2001, Are insider trades informative?, *Review of Financial Studies* 14, 79–111.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Lamont, Owen A., and Richard H. Thaler, 2003, Can the market add and subtract? Mispricing and tech stock carve-outs, *Journal of Political Economy* 111, 227–268.

Lancaster, Kelvin J., 1966, A new approach to consumer theory, *Journal of Political Economy* 74, 132–157.

Lancaster, Kelvin J., 1971, *Consumer Demand: A New Approach* (Columbia UP, New York).

Lee, Charles, Andrei Shleifer, and Richard H. Thaler, 1991, Investor sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75–109.

Lettau, Martin, and Sydney Ludvigson, 2001, Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* 109, 1238–1287.

Ljungqvist, Alexander, and William Wilhelm, 2003, IPO pricing in the dot-com bubble, *Journal of Finance* 58, 723–752.

Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

Lowry, Michelle, and G. William Schwert, 2002, IPO market cycles: Bubbles or sequential learning?, *Journal of Finance* 57, 1171–1200.

Malkiel, Burton, 1990, *A Random Walk Down Wall Street* (W.W. Norton, New York).

Malkiel, Burton, 1999, *A Random Walk Down Wall Street* (W.W. Norton, New York).

Markowitz, Harry, 1959, *Portfolio Selection: Efficient Diversification of Investments* (Wiley, New York).

Menzly, Lior, Tano Santos, and Pietro Veronesi, 2004, Understanding predictability, *Journal of Political Economy* 112, 1–47.

Mitchell, Mark L., Todd Pulvino, and Erik Stafford, 2002, Limited arbitrage and equity markets, *Journal of Finance* 57, 551–584.

Neal, Robert, and Simon Wheatley, 1998, Do measures of investor sentiment predict stock returns, *Journal of Financial and Quantitative Analysis* 34, 523–547.

Ofek, Eli, and Matthew Richardson, 2002, DotCom mania: The rise and fall of internet stocks, *Journal of Finance* 58, 1113–1138.

Peng, Lin, and Wei Xiong, 2004, Limited attention and asset prices, Working paper, Princeton University.

Reinganum, Marc R., 1983, The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects, *Journal of Financial Economics* 12, 89–104.

Ritter, Jay, 1984, The 'hot issue' market of 1980, *The Journal of Business* 57, 215–240.

Ritter, Jay, 1991, The long-run performance of initial public offerings, *Journal of Finance* 46, 3–27.

Ritter, Jay, 2003, Some factoids about the 2002 IPO market, Working paper, University of Florida.

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

Shiller, Robert J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* 71, 421–436.

Shiller, Robert J., 2000, *Irrational Exuberance* (Princeton UP, Princeton).

Shleifer, Andrei, 2000, *Inefficient Markets* (Oxford UP, Oxford).

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

Siegel, Jeremy, 1998, *Stocks for the Long Run* (McGraw-Hill, New York).

Smith, E. E., E. J. Shoben, and L. J. Rips, 1974, Structure and process in semantic memory: A featural model for semantic decisions, *Psychological Review* 81, 214–241.

Speiss, D. Katherine, and John Affleck-Graves, 1995, Underperformance in long-run stock returns following seasoned equity offerings, *Journal of Financial Economics* 38, 243–267.

Spiess, Katherine, and John Affleck-Graves, 1999, The long-run performance of stock returns following debt offerings, *Journal of Financial Economics* 54, 45–73.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Stigler, George J., 1964, Public regulation of the securities markets, *Journal of Business* 37, 117–142.

Swaminathan, Bhaskaran, 1996, Time-varying expected small firm returns and closed-end fund discounts, *Review of Financial Studies* 9, 845–887.

Wachter, Jessica, 2000, Habit formation and the cross-section of asset returns, Chapter 4 of Ph.D. dissertation, Harvard University.

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

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