Investor Sentiment and Asset Valuation*

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Abstract

The link between asset valuations and investor sentiment is the subject of considerable debate in the profession. We address this question by examining how survey data on investor sentiment relates to i) long-horizon returns, and ii) asset valuations. If excessive optimism drives prices above intrinsic values, periods of high sentiment should be followed by low returns as market prices revert to fundamental values. We find this to be the case for the overall stock market at horizons of two to three years. The relation is strongest for large-capitalization, low book-to-market (growth) portfolios. We also examine the relation between sentiment levels and deviations from intrinsic value. Using errors from an independent pricing model, we find sentiment is positively related to valuation errors using a variety of tests. All of our results are robust to the inclusion of other factors that have been shown to forecast stock returns, including past returns.

1 Introduction

A long-running debate in financial economics concerns the possible effect of investor sentiment on asset prices. For example, respected researchers have entered on both sides of the argument as to whether the stock price run-up and subsequent market collapse of 1929 was rational or not [see DeLong and Shleifer (1991) and White (1990)]. Perhaps "irrational exuberance" [Shiller (2000)] drove prices above fundamental values. More recently, some commentators have suggested the rapid rise and fall of technology stocks was due to excessively bullish sentiments that started returning to more typical levels in the spring of 2000. Indeed, even before the massive devaluation of technology stocks, Malkiel (1999) wrote

> *The spreading philosophy of the day traders that "fundamentals don't matter" may well have contributed to valuations of Internet stocks that can only be described in terms of a financial bubble.*

The existence of systematic mispricing in the market remains contentious because of the difficulty in examining the issue empirically.[1] The absence of precise valuation models for stocks makes it is difficult to measure deviations from theoretical prices. Similar problems arise from the difficulty in measuring investor sentiment.

Several recent papers identify examples which are difficult to reconcile with rational pricing. Lamont and Thaler (2001) examine 3Com's spinoff of Palm. In this transaction, the market valuations of the companies implied the 3Com "stub" (a 3Com share less the claim on Palm) was –$63, a violation of the law of one price. Rashes (2001) discusses the heavy trading in Massmutual Corporate Investors (ticker MCI) around Worldcom's acquisition of MCI Communications (ticker MCIC). Apparently these investors were unable to determine the correct ticker symbol and mistakenly placed trades in Massmutual, and their trading drove the price away from its intrinsic value. Ofek and Richardson (2001) discuss a variety of examples from the Internet sector in developing a "strong, circumstantial case against

[1] See Fama (1998) for a recent review from the rational camp, or Hirshleifer (2001) for a review from the behavioral side.

market efficiency." While these papers provide interesting evidence of misvaluation, they are specific to either a few companies or to an industry which is admittedly difficult to value. Our focus in this paper is at the level of broad market indices.

We shed new light on the issue of investor rationality by bringing new data and techniques to the question. Specifically, we use a direct survey measure of investor sentiment instead of relying on other proxies such as closed-end fund discounts [see Lee, Shleifer, and Thaler (1991), Swaminathan (1996), and Neal and Wheatley (1998)]. Unlike prior researchers, our empirical tests concentrate on the long-run effects of sentiment on stock returns and on relating sentiment levels directly to stock price deviations from fundamental value.[2]

Intuitively, looking at the relation between long-run market returns and sentiment is more appealing for two reasons. First, it seems natural to view sentiment as a persistent variable. People become more optimistic as they are reinforced by others joining on the bandwagon. Thus, the importance of sentiment may build over time. Second, arbitrage forces are likely to eliminate short-run mispricing, but may break down at longer horizons. Two examples of the limits to arbitrage are the noise trader risk of DeLong, Shleifer, Summers, and Waldmann (1990) and the interaction of agency costs and capital constraints in Shleifer and Vishny (1997). Indeed, sentiment appears to have little predictive power for subsequent near-term returns (see the papers cited in Footnote 2). This result is not surprising since predictability would lead to a simple trading strategy generating excess returns. However, the lack of predictability in the short run does not imply that sentiment has no affect on prices. Sentiment may drive asset prices away from intrinsic value for extended periods of time, yet this would be difficult to detect over short horizons [see Summers (1986)]. Whether sentiment does affect asset valuations in this way is an important open question which we address in this paper.

We test two main hypotheses. The first is that excessive optimism leads to periods of market overvaluation. If so, this leads to the second hypothesis that high current sentiment is

[2]Solt and Statman (1988), Clarke and Statman (1998), Otoo (1999), Fisher and Statman (2000), and Brown and Cliff (2001) also use survey data, but focus on the short-run implications.

followed by low cumulative long-run returns as the market price reverts to its intrinsic value. If the price correction were quick and predictable, there would be a potentially profitable trading strategy. However, a gradual correction over some unknown horizon is possible if there are limits to arbitrage. For example, an arbitrageur may believe with high confidence that the market is overvalued, but be unwilling to take a short position for fear the market may become more overvalued before reverting to its intrinsic value. Frequent performance evaluation exacerbates this problem since investors may withdraw capital precisely at the time when it is needed to meet margin calls.

To test our first hypothesis we relate the level of sentiment to a measure of market mispricing. Bakshi and Chen (2001) derive and estimate a model for stock prices based on a discounted cash flow approach. Their model embeds mean-reverting processes for earnings growth and interest rates. We use their out-of-sample model errors as a proxy for market mispricing. Estimating the relation between sentiment and mispricing is econometrically challenging because both time series are highly persistent. We undertake two types of tests each of which yields similar conclusions in support of the hypothesis that sentiment is related to market mispricing.

One test of our first hypothesis uses the level of sentiment to explain pricing errors. This test is complicated by strongly autocorrelated residuals so we use a variety of methods (Newey-West, Cochrane Orcutt, and Maximum Likelihood with AR(1) residuals) to assure the validity of our results. Regardless of the method used we find a significantly positive coefficient on the sentiment variable. In our analysis we are careful to control for other factors predicting market returns (e.g., past returns, the dividend yield, the term spread, Fama-French factors, a momentum factor, etc.). Our sentiment variable is correlated with many of these factors, but sentiment provides incremental explanatory power. The impulse response functions implied by these estimates reveal that after a bullish shock to sentiment there is an economically significant positive effect on prices in the first few months which is then nearly completely reversed over the next three years. This pattern is consistent with the short-run underreaction and long-run overreaction implied by many of the behavioral models [see Hirshleifer (2001, page 1566)].

The other test of our first hypothesis treats the market and model valuations as a cointegrated system.[3] We first establish that the model and market prices are cointegrated. Next, we show that sentiment is a significant explanatory variable for the error correction version of the cointegrating regression. In the error correction model, when the market becomes overvalued subsequent changes in the market bring the valuation level back towards intrinsic value. Again, sentiment explains pricing errors above and beyond the information contained in our control variables.

In the test of our second hypothesis we find that sentiment is in fact significantly related to long-run stock returns in the manner predicted. Specifically, high levels of sentiment result in significantly lower returns over the next two or three years. While this effect is present for the aggregate stock market, it is concentrated in large capitalization growth stocks. The economic significance of this result is also plausible. For example, a one standard deviation (bullish) shock to sentiment results in a predicted 7% underperformance of the market over the next three years. These results are robust to inclusion of the control variables and the econometric issues related to overlapping observations

Together these tests provide strong and consistent support for the hypothesis that asset values are affected by investor sentiment. Each of the tests provides both statistically and economically significant results all pointing in the same direction. Namely, that overly optimistic (pessimistic) investors drive prices above (below) fundamental values and that these pricing errors tend to revert over a multi-year horizon. This pattern is consistent with the predictions of many behavioral models that prices underreact in the short run and overreact in the long run.

The remainder of the paper is organized as follows. Section 2 provides some motivation for the paper and our approach. Section 3 discusses the data we use. The next two sections

[3] A cointegrated system is one in which two (or more) variables are individually integrated, but a linear combination of the variables is not integrated.

contain our analysis. Section 4 covers the long-horizon regressions and Section 5 examines the relation between sentiment and the mispricing implied by the Bakshi and Chen (2001) model. Some conclusions are in Section 6. An Appendix contains the details of the simulation used with the long-horizon regressions.

2 Motivation

In this section we develop our hypotheses by discussing an environment where sentiment can affect asset valuation. Our approach makes three main assumptions. First, we assume that a subset of investors makes biased asset valuations. Second, we assume that this bias is persistent. Finally, we assume that there are limits to arbitrage which hinder the exploitation of asset mispricing. These assumptions lead to an environment where market prices can differ from intrinsic value for protracted periods of time. Excessive optimism leads to overvaluation of assets. Arbitrage forces can eliminate profitable short-term trading strategies, but not longer run mispricing. Over longer horizons, the high sentiment that leads to overvaluation would be associated with low long-run returns as asset values eventually revert to intrinsic values.

We begin by partitioning the universe of investors into two groups. The first group, which we can think of as rational investors, we refer to as *fundamentalists*. This group has the property that they make an unbiased assessment of an asset's intrinsic value. The second group of investors are swayed by episodes of excessive optimism or pessimism. For convenience, we refer to this group as *speculators*. As a group, they tend to overvalue assets during times of extreme optimism, or high sentiment. When their sentiment is especially low, the group tends to undervalue assets.

Intuitively, we can think of the market price of an asset as reflecting a weighted average of the valuations of these two groups. More formally, this can come from a model such as Lintner (1969). In that model, the heterogeneous judgments of investors aggregate to form market prices as we describe. Our setup amounts to a way of partitioning the investor universe in the Lintner model. In particular, for a set of assets in unit supply, the vector of asset prices is

$$\mathbf{P} = \frac{1}{R_f}\left[w_S\left(\boldsymbol{\mu}_S - \alpha\boldsymbol{\Omega}\boldsymbol{\iota}\right) + w_F\left(\boldsymbol{\mu}_F - \alpha\boldsymbol{\Omega}\boldsymbol{\iota}\right)\right] = w_S\mathbf{P}_S + w_F\mathbf{P}_F \tag{1}$$

where R_f is the gross riskless return, α is the coefficient of absolute risk aversion, $\boldsymbol{\Omega}$ is the belief of the variance-covariance matrix of asset returns, and $\boldsymbol{\mu}_i$ is the belief of the vector of asset payoffs ($i = S$ for the speculators and F for the fundamentalists). We focus on the simplest case where both types of investors have identical risk aversion and estimates of $\boldsymbol{\Omega}$, but have different expectations of asset payoffs.[4]

Under these assumptions, the weights w_S and w_F are determined by the fraction of investors that are speculators versus fundamentalists. Clearly, if there are any speculators in the market and $\boldsymbol{\mu}_S > \boldsymbol{\mu}_F$ then $\mathbf{P} > \mathbf{P}_F$. Interpreting the fundamentalists as properly valuing the assets, this says the market price is above fundamentals when the speculators are overoptimistic. Our point in introducing this model is not to take it literally, but just to show that the simple idea we posit is supported by formal models.

One question that arises is how the speculators can survive if they systematically misvalue assets. Here we appeal to limits to arbitrage. In the context of DeLong, Shleifer, Summers, and Waldmann (1990), our fundamentalists may recognize the market is overvalued, but still be unwilling to try to exploit the mispricing. For example, portfolio managers may be evaluated annually, so they would be unwilling to take a position that may take longer to payoff. There is not a pure arbitrage opportunity since it is unknown when the market prices will converge back to the intrinsic value. Shleifer and Vishny (1997) show how agency problems between an arbitrageur and his source of capital can also hinder arbitrage. In their model, if a position moves against the arbitrageur the investors will withdraw some capital. But this is precisely when the arbitrageur needs capital to meet margin calls. The arbitrageur is potentially forced to liquidate the position at a loss, even though the expected

[4] Generalizing to allow differences in risk aversion or covariance estimates complicates the algebra but the important features remain.

return is even more attractive than when the position was initiated.

There are two main implications of the environment we describe. First, we should see market overvaluation when sentiment is high. The second implication is that, as the market price reverts to its intrinsic value, long-horizon returns following periods of high sentiment should be abnormally low. These predictions are a common thread in many models. DeLong, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997) are two examples, although they have exogenous noise or sentiment traders. Several recent behavioral models model the source of noise more formally. In Daniel, Hirshleifer, and Subrahmanyam (1998) investors are overconfident about their private signals and they incorrectly attribute successful outcomes to their own abilities, while blaming bad outcomes on chance ("biased self-attribution"). Barberis, Shleifer, and Vishny (1998) have a model where earnings are a random walk, but investors mistakenly believe earnings switch between a mean-reverting regime and a growth regime. The investors are slow to update their beliefs about the regime in the face of new evidence ("conservatism"). At the same time, these investors think they see patterns where none exist ("representativeness"). Hong and Stein (1999) posit two groups of boundedly rational agents, "newswatchers" and "momentum traders." Newswatchers get private signals but ignore information in market prices. Slow transmittal of information causes prices to underreact in the short run. This underreaction leads to trading by the momentum investors. Overreaction results when the momentum investors have gone too far.

The aim of our paper is not to distinguish one of these theories from another. Instead, our goal is to evaluate the broad predictions of behavioral theories relative to the null of rational pricing. We make reference to the theories primarily to justify the hypotheses we test. In the analyses to follow we present three main tests of the implications laid out above. In each case we find strong support of these hypotheses. The tests are robust to controlling for rational factors that may be correlated with sentiment, and to modifications to the methodology. Where appropriate, we make connections to specific behavioral models.

3 Data

The main results in the paper are based on a sample of monthly data. For the long-horizon regressions, the data start in January 1963 and end in December 2000 for a total of 456 observations. The analysis involving pricing errors is limited to the shorter sample of 235 observations from January 1979 to July 1998.

3.1 Sentiment

A key variable used in the analysis is survey data on investor sentiment, denoted S_t. These data are from Investor's Intelligence, who track the number of market newsletters that are bullish, bearish, or neutral. Our sentiment variable is the "bull-bear spread" a common measure of sentiment in the popular press. Summary statistics for S_t are in Table 1. One important feature of the variable is its strong persistence. In either sample the first-order autocorrelation is about 0.7. The series is plotted in Figure 1.

3.2 Dependent Variables

For the long-horizon regressions we cumulate monthly log returns over various horizons. We use the 25 Fama and French (1993) portfolios formed on the basis of size and book/market sorts, in addition to the 5 portfolios from univariate size sorts, the 5 portfolios from univariate book/market sorts, and the overall market portfolio. This collection of 36 portfolios allows an opportunity to see if predictability due to sentiment is affected by the size or value effects. Table 2 contains summary statistics for the 36 portfolios. In our sample the value stocks had higher average returns and lower standard deviations than growth stocks. Small stocks generally had both high average returns and standard deviations.

In the pricing error analysis, we have data from Bakshi and Chen (2001) on the mispricing of each of the 30 stocks in the Dow Jones Industrial Average (DJIA) as of July 1998.[5] As the composition of the Dow has changed over time, the stocks for which we have pricing errors

[5]We thank Gurdip Bakshi and Zhiwu Chen for providing these data.

do not exactly represent the actual DJIA. In addition, not all the pricing errors are available back to January 1979. Consequently, we form an index which we call the "quasi-Dow" that uses the available stocks from this group. In particular, for each month we value-weight the pricing errors on the stocks with pricing errors in that month. We also calculate the returns on this value-weighted index. The returns and pricing error series are then used to determine the log level of the market's valuation (p) and the log valuation level according to the Bakshi and Chen (2001) model (p^*). The working assumption is that the model valuation is a proxy for the intrinsic value of the index, and the market's deviation from this intrinsic value is a pricing error. It is of course possible that the "pricing error" is actually model misspecification, not mispricing. However, we will present some evidence that this does not seem to be the predominant explanation for our results.

Figure 2 shows the (log) valuations for the market and the model. Both clearly move together over the long run, but there are substantial deviations for a year or more. Figure 1 shows the percentage pricing error along with the level of sentiment. The pricing errors make persistent swings around zero. The average pricing error is near zero, and the summary statistics in Panel B of Table 1 show that it is volatile and persistent. Figure 3 shows some properties of the pricing error and its relation to sentiment in the frequency domain. Panel A is the spectral density of $p - p^*$ over various frequencies. This shows that most of the variability in the pricing errors is due to movements over the two to four year horizon. This is consistent with the swings in the pricing errors shown in Figure 1 lasting for several years. Panel B of Figure 3 shows the cospectrum of $p - p^*$ and S_t. This can be thought of as showing the comovement between the two series at various horizons. The plot indicates that most of the comovement comes from the two year horizon. The negative values at the four year horizon are consistent with a reversal correcting prior valuation errors. Although the figures do not provide formal tests that optimism (pessimism) drives market overvalutions (undervaluations), they are consistent with this interpretation.

3.3 Control Variables

In order to interpret our results as sentiment influencing future market valuations, we need to control for the information our sentiment variable may contain about rational factors. Indeed, our sentiment variable will partially contain rational expectations based on risk factors and other variables that have been shown to predict future performance. When someone says they are bullish on the market, this can be a rational reflection of prosperous times to come, an irrational hope of the future, or some combination of the two. We want to focus on the irrational part of sentiment, so we include a set of control variables designed to capture this rational predictability. We acknowledge that it is possible we are missing some important rational factor, but we feel our set of control variables is a reasonable effort in mitigating this problem.

Our set of control variables are motivated by the conditional asset pricing literature. We use the stochastically detrended one month US Treasury bill return [RFx; Campbell (1991), Hodrick (1992)], the difference in monthly returns on three month and one month T-bills [$HB3$; Campbell (1987), Ferson and Harvey (1991)], the term spread as measured by the spread in yields on the 10 year US Treasury bond vs. three month T-bill [TS; Fama and French (1989)], the default spread measured as the difference in yields on Baa and Aaa corporate bonds [DS; Keim and Stambaugh (1986) or Fama (1990)], the dividend yield for the value-weighted CRSP index over the past twelve months [DY; Fama and French (1988b), Campbell and Shiller (1988a, 1988b)], and the rate of inflation [$Infl$].

In addition to these variables, we include several of the popular factors in asset pricing models. Specifically, we also include the excess return on the value-weighted market portfolio, the premium on a portfolio of small stocks relative to large stocks (SMB), the premium on a portfolio of high book/market stocks relative to low book/market stocks (HML), and the premium on a portfolio of past winners relative to losers (UMD). The market factor is based on the CAPM, while Fama and French (1993) show the SMB and HML factors are incrementally useful. The momentum factor is based on Jegadeesh and Titman (1993) and

Carhart (1997).

Summary statistics for the control variables are in Table 1. The last column of the table shows the correlation with sentiment. Several of the variables have correlations of 0.2 or higher (in magnitude) with sentiment, but none is larger than 0.33. Thus, it appears that sentiment does share common information with the control variables, but also contains incremental information.

4 Sentiment and Long-Horizon Returns

Our first step in examining the impact of investor sentiment on asset valuations is to regress future k-period log returns on sentiment and the control variables ($\mathbf{z}_t$),

$$(r_{t+1} + \cdots + r_{t+k})/k = \alpha(k) + \mathbf{\Theta}'\mathbf{z}_t + \beta(k)S_t + \varepsilon_t^{(k)}. \quad (2)$$

As the length of the horizon increases, the number of observations in the regression drops, as do the number of independent observations.

$\beta(k)$ indicates the sensitivity of expected monthly returns over the horizon to investor sentiment. Under the null hypothesis that asset valuations are not influenced by behavioral forces, sentiment should not enter the regression significantly. Under the alternative hypothesis that optimism drives asset values above fundamental values and prices subsequently correct, β should be negative. Current optimism results in overvaluation, so future returns over the horizon would be lower than normal as the market valuation returns to its intrinsic value.

It turns out that carefully implementing this simple test is complicated. Long-horizon regressions are plagued by several econometric problems. The process of cumulating monthly returns, then running a regression with overlapping observations generates strong correlation in the residuals. Hansen and Hodrick (1980) provide standard errors that correct for this problem, but this correction does not perform well in finite samples [see Richardson and Stock (1989), Richardson and Smith (1991), Hodrick (1992), or Boudoukh and Richardson

(1994)]. A second problem is that the inclusion of persistent independent variables can bias the coefficient estimates since they are predetermined but not strictly endogenous. [see Stambaugh (1999)]. To circumvent these problems we use a bootstrap simulation. Details of the simulation are provided in the Appendix. In short, the simulations allow us to correct for the bias and use the appropriate critical values for inferences.

The results from the long-horizon regression are collected in Tables 3 through 5. Each table contains four panels, corresponding to horizons of 6, 12, 24, or 36 months. Within each panel are the results for each of the 36 portfolios, estimated separately.

Table 3 reports the bias-adjusted coefficient estimates. They are almost universally negative as predicted by the alternative hypothesis and tend to be most negative for the larger firms and low book/market (growth) firms. A comparison of the panels shows that coefficients for horizons of a year or more are almost always more negative than those for the six month horizon. This pattern is consistent with limits to arbitrage hindering the ability of investors from profiting on mispricing that might persist for a significant amount of time.

Table 4 gauges the statistical significance of the sentiment variable. These p-values are based on the empirical distributions obtained from the simulation. The test statistic is constructed as the bias-adjusted coefficient divided by the *standard deviation* (across simulations) of the coefficient estimate. We find these statistics adhere very closely to the standard normal distribution.

The pattern of significance basically matches the magnitude of the coefficients. For larger firms or low book/market firms, sentiment is a significant predictor of future returns at the one-, two-, or three-year horizon. Since these portfolios represent most of the market capitalization,[6] the market portfolio is also significantly affected by sentiment (10% level for one year, 5% level for two years, and 1% level for three years). That these portfolios are the ones most influenced by sentiment is interesting in light of the conventional wisdom that sentiment would most affect smaller stocks. Perhaps one reason for the lack of significance

[6] Fama and French (1993, Table 1) report that the two portfolios with the stocks in largest capitalization quintile and lowest two book/market quintiles account for 46% of the overall market capitalization.

for smaller stocks is that the sentiment variable we use applies to the market as a whole: the newsletters on which our variable is based are forecasts for the overall market. Thus, it may be the case that sentiment does more strongly affect small stocks, just that our sentiment data do not allow us to address this. It seems plausible that growth firms are more influenced by sentiment than value firms since they are typically more difficult to value. If there are not well-established valuation benchmarks then investors may be more likely to follow the pack.

In order to understand the economic magnitude of the coefficients on sentiment, it is helpful to refer to Table 5. This table takes the bias-adjusted coefficient and multiplies it by the horizon and the standard deviation of sentiment (22%). The values in the table indicate the effect of a one standard deviation increase in sentiment on the return over the indicated horizon (in percent). For example, a one standard deviation increase in sentiment is associated with a reduction in the return on the large size, low book/market portfolio of 7.1% over a two-year period. The average (simple) two-year return for this portfolio is about 25%, so this is an economically significant reduction. Moreover, it is not so severe as to be implausible. Even if institutional investors are aware that future returns may be reduced by 7%, they may not be willing to try to exploit this mispricing since this is *not* an arbitrage opportunity. There is a very real chance the position may move against them in the interim, and they are likely to have their performance evaluated before this "convergence" strategy is expected to payoff.

In unreported tables we also examine the regression R^2 and conventional t-statistics for the long-horizon regression. For R^2, the general patterns are that predictability increases with horizon, although most of the increase comes in moving from 6 to 12 months. Predictability tends to be lowest for small and/or low book/market firms, although there is not a monotonic size or book/market relation. If we use Hansen and Hodrick (1980) standard errors to form conventional t-statistics, the overall patterns of significance are similar to those reported in Table 4. We find these t-statistics to be less reliable since the standard errors are often poorly behaved. This results in many extreme statistics in the simulation, which make the empirical critical values large in magnitude. Still, the large size, low book/market firms and the overall market portfolio have significant coefficients at the 5–10% level. These tables are not reported to conserve space, but are available upon request.

5 Sentiment and Pricing Errors

In this section we perform two types of analyses to examine the impact of sentiment on asset valuation. Both analyses rely on the pricing errors from the Bakshi and Chen (2001) model which we use to form a market valuation and model valuation for a quasi-Dow index. The first test is simply to regress the pricing errors $e_t = P_t - P_t^*$ (market minus model) on sentiment and the control variables. The second test exploits the fact that the market and model valuations should be cointegrated.

5.1 Pricing Errors Regressions

The simple question we have in mind is, "Can sentiment explain the pricing errors?" We start by regressing the pricing errors on a constant, sentiment, and the return on the quasi-Dow,

$$e_t = \alpha + \beta S_t + R_{\mathrm{Dow},t} + \varepsilon_t \tag{3}$$

The last variable is used as a control to pick up misspecification of the model. For example, if the model inputs such as earnings growth forecasts are delayed due to reporting lags, the market price might react to that information before the model. This would show up in both the pricing error and the return.

As the pricing errors are highly persistent (autocorrelation of 0.9), serial correlation in the regression residuals is a problem. We correct for this serial correlation in three ways. First, we use a Newey and West (1987) correction with 24 lags. This type of correction may not be adequate when the residuals are highly autocorrelated so we also use the Cochrane-Orcutt procedure and maximum likelihood with AR(1) errors.

The results of these regression are in Table 6. The row labeled ρ indicates the autocorrelation of the residuals for the Newey-West regression, and the estimated autocorrelation coefficient in the other two regressions. For all three of these regressions ρ is 0.89, and the t-stats of 29 indicate it is highly significant. Additional tests estimating various ARMA(p,q) models for the residuals from OLS indicates the AR(1) specification is appropriate, so most of the discussion below focuses on the Cochrane-Orcutt regression (the maximum likelihood regression is nearly identical). For all three regressions the coefficient on sentiment is positive and significant (t-stat of 3.5, or 1.8 for the Newey-West regression). The positive sign is as expected. When investors are optimistic, the market valuation is higher than the intrinsic value.

The first three regressions leave open the possibility that the sentiment variable is simply picking up some other rational factors. We therefore include the set of control variables from the long-horizon regressions,

$$e_t = \alpha + \beta S_t + R_{\mathrm{Dow},t} + \boldsymbol{\Theta}'\mathbf{z}_t + \varepsilon_t. \tag{4}$$

Even in the presence of the control variables, the coefficient on sentiment is positive and significant in all three regressions (t-stat is 2.8, or 2.2 for the Newey-West regression). Although we don't interpret the control variables individually, they do increase the adjusted R^2 and the default spread and dividend yield enter significantly.

To aid in interpreting the economic magnitude of the sentiment coefficient we construct the impulse response function. Ideally, we would like to know how a shock to sentiment affects the future pricing errors. There are several effects that come into play. First is the direct effect on the contemporaneous pricing error, determined by the regression coefficient, β. There are also several indirect effects. Since sentiment is highly persistent, a shock to sentiment today will also affect sentiment in subsequent periods. If we model sentiment as an AR(1) process with persistence parameter ϕ_S, then the shock at time t affects S_{t+k} by ϕ_S^k, which in turn affects the pricing error at time $t+k$. Another indirect effect comes from the persistence of pricing errors. The shock to sentiment at time t will give rise to a shock to e_t, but since e has persistence ρ the effect on e_{t+k} is ρ^k. The impulse response is

$$\frac{\partial e_{t+k}}{\partial S_t} = \beta \phi_S^k + \rho \frac{\partial e_{t+k-1}}{\partial S_t}$$

with $\partial e_\tau / \partial S_t = 0$ for $\tau < t$. Since ρ is about 0.9 these shocks do not die out quickly. We make the assumption that the control variables are exogenous with respect to sentiment. This makes sense from the point of view that the shocks to sentiment we have in mind reflect irrationality. Admittedly, our sentiment variable potentially measures in part rational information about future economic conditions. Our exogeneity assumption means we are focusing on shocks that are not related to the rational factors we use as control variables. Therefore we do not need to account for indirect effects where sentiment affects the control variables, which in turn affect the pricing errors. This assumption has the effect of reducing the magnitude of the effects we report so it is a conservative assumption.

Figure 4 shows our impulse response function for the pricing errors. The graph tracks the effect on the pricing error of a one standard deviation (18.5% for this subsample) shock to sentiment. This shock leads to a contemporaneous increase in the pricing error of about 1.5%. For the first several periods after the shock, the pricing error builds up. This is due to the indirect effects mentioned above. As time goes by the shock decays. Within about six months the pricing error begins to reverse. At the peak, the shock to sentiment led to about a 3.5% valuation error. Over the next two years, the mispricing due to the sentiment shock declines to about one percent. This pattern is consistent with short-run underreaction and long-run overreaction, a common theme in many of the behavioral models. In fact, our impulse response function follows the same pattern as Figure 2 in Daniel, Hirshleifer, and Subrahmanyam (1998). Overall, the estimated effect of a shock to sentiment is very similar to that suggested by the long-horizon regression results. The impulse response function presented in the figure is based on the Cochrane-Orcutt regression with the control variables, but is very similar if the control variables are not included in the regression.

The pricing error regressions show that, even controlling for common factors associated with rational asset pricing, some mispricing is explained by investor sentiment. This finding is robust to various forms of serial correlation correction and to alternative regression specifications. We next explore this issue with another approach to see if we obtain the same conclusions.

5.2 Cointegration

A cointegrated system is one in which two (or more) variables are individually integrated, but a linear combination of those variables is not integrated. We have a very natural environment for such a system. Since the market value of an index can be viewed as the sum of permanent shocks (and a drift), it is reasonable to expect that it is integrated. By the same logic the intrinsic (model) value of the index should be integrated as well. Yet the difference of the log series should not have permanent components. That is $p - p^*$ should be integrated of order zero, making p and p^* cointegrated with cointegrating vector $[1 \quad -1]'$. The error correction interpretation of cointegration says that when the market is overvalued, it will adjust toward its equilibrium value based on the sensitivity to the error $p - p^*$.

In this section we explore this idea. We first establish that p and p^* are cointegrated, then estimate the error correction representation of the cointegrating regressions. In these regressions we include sentiment and the control variables to see if sentiment can explain any of the deviations from intrinsic value.

To test for the integration of p and p^* we estimate augmented Dickey-Fuller regressions including a constant, a time trend, and twelve lags of changes to the dependent variable to correct for serial correlation.[7] Panel A of Table 7 contains the results for this test. The null of integration is not rejected for p. For p^* the null of integration is rejected at the 10% level, although integration is not rejected at alternative lag lengths in the ADF test. Given the strong *a priori* theoretical reasoning for integration of p^* and the sensitivity to the choice of lags, we proceed assuming that the intrinsic value series is also integrated.

We next test for cointegration in two ways. Given our strong theoretical prior on the

[7] In testing for the number of lags, there is evidence that lags 12 and 24 are significant for p^*. We present the more parsimonious regression here, although the tests still fail to reject the null with the additional lags.

cointegrating vector we follow the recommendation of Hamilton (1994, p. 582) and estimate the ADF regressions for $p - p^*$. In this regression a time trend is not included since the errors do not appear to drift up over time (see Figure 1) and only one lagged change in the dependent variable is included based on specification tests (although the results are robust to other lag choices). Panel A shows that the null of integration is strongly rejected, indicating the two series are cointegrated. We also check our assumption about the cointegrating vector by rerunning the ADF test using the cointegrating vector $[1 \quad -0.83]'$ as estimated in the second column of Table 8.[8] In this regression a time trend is included since this linear combination of p and p^* does trend upward over time. Once again, the null of integration is rejected at the 5% level, meaning the two series are cointegrated.

The second test of cointegration uses Johansen's trace and eigenvalue statistics. The tests are of the null hypothesis that there are zero cointegrating relationships. A rejection of the null is evidence that p and p^* are cointegrated. The results of these tests are reported in Panel B of Table 8. We report the test for VAR lags from one to four, although the conclusions are the same in all cases.[9] For each lag order and for either test the null is rejected at the 5% level in favor of the alternative that p and p^* are cointegrated.[10] Having established the cointegration of these series, we then assess whether sentiment is marginally significant when added to the error correction version of the cointegrating regression. In particular, we estimate

$$\Delta p_t = \alpha_1 + \beta_1 S_t + \mathbf{\Theta}_1' \mathbf{z}_t + \phi_1 \Delta p_t^* + \gamma_1 (p_{t-1} - \theta_1 p_{t-1}^*) + \varepsilon_{1,t} \tag{5}$$

and

$$\Delta p_t^* = \alpha_2 + \beta_2 S_t + \mathbf{\Theta}_2' \mathbf{z}_t + \phi_2 \Delta p_t + \gamma_2 (p_{t-1}^* - \theta_2 p_{t-1}) + \varepsilon_{2,t} \tag{6}$$

[8]The cointegrating vectors for the other regressions in Table 8 are not materially different from $[1 \quad -1]'$ so they are not reported.

[9]Likelihood ratio or AIC tests for model order of the VAR indicate one lag is appropriate. The BIC test favors two lags.

[10]We do not report the Johansen test for the null of less than one cointegrating relationship. Rejection of this null would mean both variables are I(0). In every instance we fail to reject this hypothesis, supporting cointegration of p and p^*.

The coefficient γ_1 represents the correction of p_{t+1} to the error $p_t - \theta_1 p_t^*$ and $[1 \quad \theta_1]'$ is the cointegrating vector.

The results of these regressions are in Table 8. One pair of regressions excludes the control variables, the other pair includes them.[11] The first two columns are for the regressions with Δp as the dependent variable. In either case sentiment is positive and highly significant. This indicates that when investors are optimistic the market valuation tends to be high, controlling for the intrinsic value and (possibly) other variables to control for rational factors.

The last two columns in the table are for the regressions with Δp^* as the dependent variable. Here the question is whether the sentiment variable can explain the level of the model valuation. If we could perfectly measure sentiment and intrinsic value, we should not find a significant relation. Excessive optimism or pessimism should be unrelated to the intrinsic value. However, a significant relation may indicate our proxy for intrinsic value is plagued by misspecification. The regression without controls shows the sentiment coefficient is negative and significant, but we already have seen that sentiment captures some of the information in the control variables. Thus, the negative relation may simply be due to the information in these control variables, which *should* be related to the intrinsic value. When we include the controls in the regression, there is no longer a significant relation. Therefore we conclude that the ability of sentiment to explain pricing errors is driven by its relation with p and not p^*. We again make use of an impulse response function for interpretation, but it is qualitatively similar to Figure 4 so we do not report it to conserve space.

In summary, this section attacks from two fronts the issue of whether sentiment affects the level of asset values. We find strong evidence that sentiment can explain deviations from intrinsic value even when controlling for rational factors. In addition, we show in a cointegration framework that sentiment is significantly related to the level of market valuation. In either approach, the results indicate that when investors are optimistic, the market valuation often exceeds the intrinsic value. The hump-shaped pattern we document in the

[11] Note that we lag the excess market return by one period since it can explain almost all the variation in Δp by construction.

impulse response function is consistent with the patterns of short-run underreaction followed by long-run overreaction predicted by most of the recent behavioral models.

6 Conclusions

Our analysis shows that a direct survey measure of investor sentiment predicts market returns over the next one to three years and that this measure has the ability to explain deviations from intrinsic value as measured by other researchers' models of stock prices. In all cases, the significance of our results is robust to controlling for rational factors and to changes in the methodology.

There are (at least) two ways to interpret these findings. The more conservative interpretation is that we have identified some new factor related to asset valuation. This factor may be derived from investors' outlook for the market or from some other origin altogether, for example, unidentified risk factors. Regardless of the interpretation, our sentiment variable forecasts market returns over the next several years and helps to explain mispricings from a rigorous valuation model.

The bolder interpretation is that we have actually used an accurate measure of investor sentiment and this measure is related to the level of stock prices. This finding has several important implications. First and foremost, our results support the important yet controversial behavioral theories that predict the irrational sentiments of investors do in fact affect asset price levels. Second, this suggests asset pricing models should consider the role of investor sentiment. Third, market regulators and government officials *should* be concerned about the potential for market bubbles or "irrational exuberance" if a sudden change in sentiment translates into a negative wealth shock that depresses economic activity. Finally, individual investors should be aware of the impact sentiment can have on both their own and money managers' investment strategies.

Appendix A Simulation

We regress k-period returns on sentiment and control variables,

$$(r_{t+1} + \cdots + r_{t+k})/k = \alpha(k) + \beta(k) SENT_t^p + \mathbf{\Theta}'(k)\mathbf{z}_t + \varepsilon_{t+k}^{(k)}. \tag{A.1}$$

r_{t+1} is the log return from month t to $t+1$ and $\mathbf{z}_t$ is the vector of predictive variables known at time t. The use of overlapping observations induces a MA$(k-1)$ structure in the residuals under the null that $\varepsilon^{(1)}$ is serially uncorrelated. Hansen and Hodrick (1980) propose a correction for this induced correlation.

There are two main problems with the regression in (A.1). First, there is a bias in the coefficient estimates. Second, Hansen and Hodrick (1980) standard errors do not perform well when the degree of overlap is "large" relative to the sample size. Therefore, we perform a simulation to account for the bias and to adjust the critical values used in inference.

The simulation estimates a VAR(1) for $\mathbf{y}_t = [r_t \quad S_t \quad \mathbf{z}_t']'$.[12] The null hypothesis that sentiment does not predict returns is imposed on the coefficient matrix by setting the appropriate element to zero. The constant in the constrained model is adjusted to restore the original mean, and the residuals from the constrained model are saved. We bootstrap the residuals from the calibration regressions to account for heteroskedasticity and generate and discard an additional 100 observations to remove any start-up effects. At each replication the simulated data are used to form long-horizon returns and estimate (A.1) at each of the horizons. The coefficients at iteration i are saved along with the corresponding Hansen and Hodrick (1980) standard errors. This process is repeated for 10,000 artificial datasets to get a distribution of the $\hat{\beta}(k)$'s.

We calculate t-stats for the test that $\beta(k) = 0$ by subtracting the bias and dividing by the *standard deviation* of the coefficient estimates. That is, the t-stat at the i^{th} iteration for horizon k is

$$t^i(k) = \frac{\hat{\beta}^i(k) - \overline{\beta^i(k)}}{\mathrm{std}(\hat{\beta}^i(k))}$$

[12] AIC and BIC model selection criteria indicate the VAR(1) specification is appropriate.

where $\overline{\beta^i(k)}$ and $\text{std}(\hat{\beta}^i(k))$ indicate the mean and standard deviation of the $\hat{\beta}^i(k)$'s across the 10,000 simulations. We find that t-statistics constructed in this fashion perform much better than those obtained by using the standard error of the coefficient. The empirical distribution of the t-stats provides small sample critical values for inference. Each of the 36 portfolios has its own simulation for bias- and size-adjustments.

References

Bakshi, Gurdip, and Zhiwu Chen, 2001, Stock valuation in dynamic economies, Working Paper.

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

Boudoukh, Jacob, and Matthew Richardson, 1994, The statistics of long-horizon regressions revisited, *Mathematical Finance* 4, 103–119.

Brown, Gregory W., and Michael T. Cliff, 2001, Investor sentiment and the near-term stock market, Working Paper, The University of North Carolina at Chapel Hill.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.

———, 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157–179.

———, and Robert J. Shiller, 1988a, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–228.

———, 1988b, Stock prices, earnings, and expected dividends, *Journal of Finance* 43, 661–676.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Clarke, Roger G., and Meir Statman, 1998, Bullish or bearish?, *Financial Analysts Journal* May/June, 63–72.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839–1886.

DeLong, J. Bradford, and Andrei Shleifer, 1991, The bubble of 1929: Evidence from closed-end funds, *Journal of Economic History* 51, 675–700.

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

Fama, Eugene, 1990, Term-structure forecasts of interest rates, inflation, and real returns, *Journal of Monetary Economics* 25, 59–76.

———, 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

——— , and Kenneth French, 1988b, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

——— , 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

——— , 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation in economic risk premiums, *Journal of Political Economy* 99, 385–415.

Fisher, Kenneth L., and Meir Statman, 2000, Investor sentiment and stock returns, *Financial Analysts Journal* March/April, 16–23.

Hamilton, 1994, *Time Series Analysis* (Princeton University Press: Princeton, NJ).

Hansen, Lars Peter, and Robert J. Hodrick, 1980, Forward exchage rates as optimal predictors of future spot rates: An empirical analysis, *Journal of Political Economy* 88, 829–853.

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1598.

Hodrick, Robert J., 1992, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, *Review of Financial Studies* 5, 357–386.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the bond and stock markets, *Journal of Financial Economics* 17, 357–390.

Lamont, Owen A., and Richard H. Thaler, 2001, Can the market add and subtract? Mispricing in tech stock carve-outs, University of Chicago Working Paper.

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

Lintner, John, 1969, The aggregation of investor's diverse judgements and preferences in purely competitive security markets, *Journal of Financial and Quantitative Analysis* 4, 347–400.

Malkiel, Burton G., 1999, Day trading, and its dangers, *Wall Street Journal* p. A22.

Neal, Robert, and Simon M. Wheatley, 1998, Do measures of investor sentiment predict returns?, *Journal of Financial and Quantitative Analysis* 33, 523–547.

Newey, Whitney, and Kenneth West, 1987, A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Ofek, Eli, and Matthew Richardson, 2001, DotCom mania: A survey of market efficiency in the Internet sector, New York University Working Paper.

Otoo, Maria Ward, 1999, Consumer sentiment and the stock market, Federal Reserve Board of Governors Working Paper.

Rashes, Michael S., 2001, Massively confused investors making conspicuously ignorant choices (MCI-MCIC), *Journal of Finance* 56, 1911–1927.

Richardson, Matthew, and Tom Smith, 1991, Tests of financial models in the presence of overlapping observations, *Review of Financial Studies* 4, 227–254.

Richardson, Matthew, and James H. Stock, 1989, Drawing inferences from statistics based on multiyear asset returns, *Journal of Financial Economics* 25, 323–348.

Shiller, Robert J., 2000, *Irrational Exuberance* (Princeton University Press: Princeton, NJ).

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

Solt, Michael E., and Meir Statman, 1988, How useful is the sentiment index, *Financial Analysts Journal* September/October, 45–55.

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

Summers, Lawrence H., 1986, Does the stock market rationally reflect fundamental values?, *Journal of Finance* 41, 591–601.

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

White, Eugene, 1990, The stock market boom and crash of 1929 revisited, *Journal of Economic Perspectives* 4, 67–83.

Table 1: Summary Statistics

Panel A contains summary statistics for sentiment and the control variables used in the long-horizon regressions. Panel B contains the summary statistics for sentiment, the log pricing error on the "quasi-Dow" ($p - p^*$), and the monthly return on the quasi-Dow (R_{Dow}) for a shorter subsample. Panel B data are used in the pricing error regressions and cointegration regressions. The quasi-Dow is a value-weighted index we create using all available firms for which Bakshi and Chen (2001) have pricing errors. The variables are sentiment (S), the detrended interest rate (RFx), the difference in returns on three- and one-month T-bills (HB3), term spread (TS), default spread (DS), inflation (Infl), the Fama and French (1993) factors (ExMkt, SMB, and HML) and a momentum factor (UMD). See the text for additional variable descriptions.

	Mean	Std Dev	Skewness	Ex Kurt	ρ_1	$\rho_{S,i}$
Panel A: 456 Observations from 01/1963 to 12/2000						
S	10.8890	22.0475	0.0428	−0.3606	0.7110	1.0000
Tbill	0.0037	0.0989	−0.1284	3.2788	0.7755	−0.2406
HB3	0.0717	0.1013	2.3729	10.1190	0.3265	−0.1202
TS	1.2339	1.2952	−0.1419	−0.3162	0.9316	0.2485
DS	1.0073	0.4529	1.1951	1.2728	0.9711	−0.0302
DY	3.2349	0.9970	−0.0703	−0.2224	0.9865	−0.2579
Infl	0.3845	0.3041	0.9932	1.6812	0.6468	−0.2815
ExMkt	0.5280	4.3997	−0.5107	2.3572	0.0416	0.2828
SMB	0.1596	3.2425	0.5493	5.8565	0.0956	0.1822
HML	0.4210	2.8878	−0.0149	2.0385	0.1657	−0.0126
UMD	0.9276	3.6184	−0.0375	3.3080	0.0392	0.0039
Panel B: 235 Observations from 01/1979 to 07/1998						
S	7.1694	18.4963	−0.0171	−0.4220	0.7059	1.0000
Tbill	−0.0055	0.1189	0.0562	2.2936	0.7570	−0.2634
HB3	0.0856	0.1186	2.2201	8.0713	0.3666	−0.1006
TS	1.6073	1.4289	−0.6903	0.1779	0.9272	0.2104
DS	1.1466	0.4912	1.0046	0.5091	0.9656	−0.1016
DY	3.3521	1.0210	0.0320	−0.6550	0.9873	−0.2909
Infl	0.3743	0.3130	1.0573	1.3300	0.7631	−0.3221
ExMkt	0.8067	4.2627	−0.8068	3.9041	0.0270	0.3068
SMB	−0.0008	2.5002	0.0369	0.6324	0.1441	0.1402
HML	0.3631	2.5691	0.1598	0.3153	0.1930	−0.0599
UMD	0.9203	3.1796	−0.1080	2.0910	0.0989	0.0173
$p - p^*$	−0.0040	0.1117	−0.1062	−0.3174	0.8834	0.2044
R_{DOW}	1.7008	4.2046	−0.4424	2.7785	−0.0279	0.2429

Table 2: Summary Statistics Returns

Summary statistics for monthly returns on portfolios formed on size and book/market values. Portfolio formation follows the Fama and French (1993) procedure. Portfolios in the row labeled All are univariate book/market sorts. Portfolios in the All column are univariate size sorts. The portfolio in the All row and All column contains all available firms. These portfolios are used in the long-horizon regression by converting to multi-period log returns. There are 456 observations from January 1963 through December 2000.

Panel A: Means

	Low	BM 2	BM 3	BM 4	High	All
Small	0.7807	1.2724	1.3053	1.5025	1.6061	1.1995
Size 2	0.8984	1.1530	1.3927	1.4536	1.5312	1.2288
Size 3	0.9240	1.2557	1.2338	1.3820	1.5423	1.1982
Size 4	1.0742	1.0184	1.2598	1.4314	1.4682	1.1646
Large	1.0390	1.0043	1.0402	1.1479	1.2169	1.0252
All	1.0096	1.0181	1.1026	1.2738	1.4126	1.0352

Panel B: Standard Deviations

	Low	BM 2	BM 3	BM 4	High	All
Small	8.0397	6.9855	6.0499	5.6533	5.8785	6.2894
Size 2	7.3342	5.9717	5.3282	5.0690	5.6048	5.8295
Size 3	6.7469	5.4185	4.9084	4.6638	5.2517	5.3003
Size 4	5.9466	5.1468	4.8414	4.5864	5.3428	4.9721
Large	4.7450	4.5314	4.3135	4.2734	4.5935	4.2223
All	4.9110	4.5888	4.2527	4.2147	4.7004	4.3795

Panel C: Autocorrelations

	Low	BM 2	BM 3	BM 4	High	All
Small	0.2128	0.1813	0.1861	0.2000	0.2359	0.2179
Size 2	0.1399	0.1559	0.1658	0.1514	0.1360	0.1513
Size 3	0.1055	0.1424	0.1384	0.1455	0.1403	0.1283
Size 4	0.0757	0.1031	0.0668	0.0665	0.0375	0.0752
Large	0.0256	0.0077	−0.0566	−0.0556	0.0136	−0.0175
All	0.0487	0.0487	−0.0033	0.0120	0.0746	0.0352

Table 3: Sentiment Coefficient in Long-horizon Regressions

Coefficients on sentiment from regression of k-period log returns on lagged predictive variables. Explanatory variables are a constant, RFx, HB3, TS, DS, DY, Infl, ExMkt, SMB, HML, UMD and sentiment. The full dataset is 456 observations from 1/1963 to 12/2000. Each panel has k fewer observations due to construction of long-horizon returns. The reported coefficients are bias-adjusted from a simulation. See the Appendix for additional details.

$$(r_{t+1} + \cdots + r_{t+k})/k = \alpha + \boldsymbol{\Theta}'\mathbf{z}_t + \beta S_t + \varepsilon_t^{(k)}$$

Panel A: 6 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	−0.0044	−0.0114	−0.0114	−0.0074	−0.0088	−0.0074
Sz 2	−0.0157	−0.0126	−0.0141	−0.0107	−0.0076	−0.0168
Sz 3	−0.0194	−0.0147	−0.0087	−0.0096	−0.0082	−0.0159
Sz 4	−0.0144	−0.0123	−0.0097	−0.0059	−0.0056	−0.0124
Big	−0.0125	−0.0125	−0.0067	−0.0057	−0.0070	−0.0082
All	−0.0130	−0.0136	−0.0076	−0.0051	−0.0060	−0.0067

Panel B: 12 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	−0.0055	−0.0116	−0.0114	−0.0085	−0.0094	−0.0081
Sz 2	−0.0137	−0.0113	−0.0125	−0.0117	−0.0086	−0.0127
Sz 3	−0.0155	−0.0114	−0.0091	−0.0108	−0.0104	−0.0128
Sz 4	−0.0140	−0.0116	−0.0105	−0.0087	−0.0082	−0.0122
Big	−0.0154	−0.0142	−0.0090	−0.0110	−0.0096	−0.0130
All	−0.0153	−0.0143	−0.0095	−0.0093	−0.0083	−0.0109

Panel C: 24 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	0.0032	−0.0035	−0.0030	−0.0023	−0.0016	−0.0003
Sz 2	−0.0066	−0.0031	−0.0037	−0.0045	−0.0016	−0.0038
Sz 3	−0.0075	−0.0053	−0.0028	−0.0033	−0.0043	−0.0049
Sz 4	−0.0101	−0.0081	−0.0053	−0.0034	−0.0027	−0.0071
Big	−0.0134	−0.0132	−0.0070	−0.0066	−0.0093	−0.0115
All	−0.0122	−0.0120	−0.0065	−0.0044	−0.0050	−0.0088

Panel D: 36 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	0.0073	0.0009	−0.0010	−0.0006	0.0005	0.0021
Sz 2	−0.0029	−0.0013	−0.0020	−0.0038	−0.0004	−0.0018
Sz 3	−0.0055	−0.0044	−0.0030	−0.0023	−0.0012	−0.0036
Sz 4	−0.0095	−0.0074	−0.0059	−0.0032	−0.0015	−0.0065
Big	−0.0145	−0.0136	−0.0079	−0.0069	−0.0082	−0.0122
All	−0.0129	−0.0119	−0.0071	−0.0046	−0.0037	−0.0092

Table 4: Significance of Sentiment in Long-horizon Regressions

Significance of sentiment from regression of k-period log returns on lagged predictive variables. Explanatory variables are a constant, RFx, HB3, TS, DS, DY, Infl, ExMkt, SMB, HML, UMD and sentiment. The full dataset is 456 observations from 1/1963 to 12/2000. Each panel has k fewer observations due to construction of long-horizon returns. p-values are constructed from the distribution of the bias-adjusted coefficient estimates obtained by simulation to correct for problems associated with overlapping observations. See the Appendix for additional details.

$$(r_{t+1} + \cdots + r_{t+k})/k = \alpha + \mathbf{\Theta}'\mathbf{z}_t + \beta S_t + \varepsilon_t^{(k)}$$

Panel A: 6 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	0.7819	0.3857	0.3053	0.4874	0.4326	0.5505
Sz 2	0.2600	0.2545	0.1610	0.2481	0.4501	0.1264
Sz 3	0.1122	0.1421	0.3531	0.2722	0.4031	0.1078
Sz 4	0.1791	0.2011	0.2645	0.4684	0.5458	0.1683
Big	0.1425	0.1107	0.3366	0.4151	0.3686	0.2282
All	0.1375	0.0927	0.2883	0.4799	0.4732	0.3641

Panel B: 12 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	0.6375	0.2323	0.1694	0.2869	0.2663	0.3701
Sz 2	0.1920	0.1717	0.0956	0.0913	0.2447	0.1261
Sz 3	0.0924	0.1341	0.1930	0.0964	0.1590	0.0828
Sz 4	0.0908	0.1126	0.1026	0.1588	0.2334	0.0706
Big	0.0168	0.0187	0.0832	0.0375	0.1107	0.0124
All	0.0230	0.0201	0.0759	0.0821	0.1839	0.0488

Panel C: 24 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	0.6908	0.5993	0.5919	0.6682	0.7793	0.9587
Sz 2	0.3446	0.5612	0.4615	0.3421	0.7367	0.4925
Sz 3	0.2226	0.2942	0.5417	0.4556	0.3871	0.3295
Sz 4	0.0798	0.1012	0.2306	0.4268	0.5651	0.1377
Big	0.0068	0.0029	0.0537	0.0683	0.0317	0.0025
All	0.0130	0.0051	0.0772	0.2250	0.2448	0.0174

Panel D: 36 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	0.2400	0.8476	0.8077	0.8841	0.8996	0.6473
Sz 2	0.5842	0.7538	0.5985	0.2957	0.9192	0.6627
Sz 3	0.2283	0.2536	0.4017	0.4945	0.7450	0.3388
Sz 4	0.0386	0.0561	0.0886	0.3346	0.6642	0.0695
Big	0.0002	0.0000	0.0094	0.0181	0.0222	0.0001
All	0.0023	0.0011	0.0136	0.1082	0.2574	0.0024

Table 5: Economic Magnitude of Sentiment in Long-horizon Regressions

Economic magnitude of a one standard deviation shock to sentiment. Results are based on bias-adjusted coefficients from regression of k-period log returns on lagged predictive variables. Explanatory variables are a constant, RFx, HB3, TS, DS, DY, Infl, ExMkt, SMB, HML, UMD and sentiment. The full dataset is 456 observations from 1/1963 to 12/2000. Each panel has k fewer observations due to construction of long-horizon returns.

$$(r_{t+1} + \cdots + r_{t+k})/k = \alpha + \mathbf{\Theta}'\mathbf{z}_t + \beta S_t + \varepsilon_t^{(k)}$$

Panel A: 6 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	−0.5813	−1.5083	−1.5078	−0.9744	−1.1666	−0.9730
Sz 2	−2.0732	−1.6726	−1.8688	−1.4203	−1.0086	−2.2173
Sz 3	−2.5638	−1.9474	−1.1534	−1.2637	−1.0789	−2.1002
Sz 4	−1.9060	−1.6271	−1.2853	−0.7842	−0.7370	−1.6362
Big	−1.6470	−1.6534	−0.8804	−0.7516	−0.9270	−1.0823
All	−1.7163	−1.7979	−1.0089	−0.6719	−0.7904	−0.8827

Panel B: 12 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	−1.4654	−3.0780	−3.0152	−2.2438	−2.4911	−2.1405
Sz 2	−3.6275	−2.9783	−3.3157	−3.1062	−2.2751	−3.3678
Sz 3	−4.1012	−3.0040	−2.4188	−2.8594	−2.7443	−3.3868
Sz 4	−3.7089	−3.0808	−2.7841	−2.2960	−2.1600	−3.2273
Big	−4.0816	−3.7470	−2.3749	−2.8996	−2.5298	−3.4356
All	−4.0407	−3.7810	−2.5033	−2.4549	−2.1970	−2.8876

Panel C: 24 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	1.7001	−1.8312	−1.5772	−1.2013	−0.8389	−0.1674
Sz 2	−3.4881	−1.6368	−1.9659	−2.3615	−0.8695	−2.0242
Sz 3	−3.9523	−2.7919	−1.4633	−1.7279	−2.2887	−2.5667
Sz 4	−5.3420	−4.3023	−2.8291	−1.7783	−1.4246	−3.7407
Big	−7.0956	−6.9960	−3.7013	−3.4996	−4.9130	−6.0747
All	−6.4753	−6.3615	−3.4144	−2.3485	−2.6283	−4.6366

Panel D: 36 Month Horizon

	Low	BM 2	BM 3	BM 4	High	All
Small	5.8137	0.7265	−0.8132	−0.4687	0.4073	1.6572
Sz 2	−2.2929	−1.0253	−1.5830	−2.9952	−0.3093	−1.4269
Sz 3	−4.3351	−3.5078	−2.3530	−1.8079	−0.9725	−2.8248
Sz 4	−7.5164	−5.8887	−4.7149	−2.5762	−1.2163	−5.1949
Big	−11.4882	−10.7701	−6.2452	−5.5144	−6.4960	−9.6798
All	−10.2198	−9.4140	−5.6136	−3.6188	−2.9194	−7.2917

Table 6: Dow Pricing Error Analysis

Results of regressing pricing errors for the "quasi-Dow" on sentiment and contol variables. Three methods of correcting for the strong autocorrelation in pricing errors are used: Newey-West with 24 lags, Cochrane-Orcutt, and maximum likelihood with AR(1) residuals. Regressions use 235 observations from January 1979 trough July 1998. t-statistics are reported in parenthesis. For the Newey-West regressions, ρ is the autocorrelation of the residuals.

	Newey-West (24 lags)		Cochrane-Orcutt		ML AR(1)	
Const	−0.6299	−992.0765	0.0255	−62.8978	−0.2544	−70.9781
	(−0.3155)	(−1.6475)	(0.0085)	(−0.3911)	(−0.0912)	(−0.4411)
S	0.1302	0.1338	0.0854	0.0767	0.0857	0.0789
	(1.8383)	(2.1532)	(3.4560)	(2.8437)	(3.4698)	(2.9305)
R_{Dow}	−0.0504	1.1872	−0.0026	0.1234	−0.0029	0.1180
	(−0.2550)	(2.5469)	(−0.0445)	(0.6911)	(−0.0487)	(0.6602)
RFx		9.0546		−2.3794		−2.4532
		(1.3752)		(−0.5729)		(−0.5897)
HB3		4.3642		1.4280		1.4567
		(0.5060)		(0.4145)		(0.4231)
TS		0.0116		0.0120		0.0113
		(0.8165)		(1.4743)		(1.3982)
DS		0.1746		−0.0576		−0.0570
		(6.1171)		(−2.0908)		(−2.0835)
DY		−8.8921		−7.1731		−6.2479
		(−3.3788)		(−2.6379)		(−2.4605)
CPI		9.9456		0.8963		0.9592
		(1.6519)		(0.5598)		(0.5985)
ExMkt		−1.7101		−0.3076		−0.2855
		(−4.4358)		(−1.6101)		(−1.5082)
SMB		0.1795		−0.1001		−0.0971
		(0.4682)		(−0.7710)		(−0.7462)
HML		−0.3505		−0.1628		−0.1595
		(−1.2787)		(−1.2870)		(−1.2592)
UMD		0.1611		−0.0427		−0.0433
		(0.6348)		(−0.5047)		(−0.5104)
ρ	0.8863	0.7530	0.8896	0.9449	0.8859	0.9372
			(29.7311)	(44.0527)	(29.1533)	(41.0272)
$\bar{R}^2$	0.0368	0.2426	0.0421	0.0863	0.0422	0.0818

Table 7: Tests for Integration and Cointegration

Panel A reports augmented Dickey-Fuller tests of the hypothesis that the variable is integrated of order one. The ADF regressions for $p - p^*$ contains a constant. The other ADF regressions include a contant and time trend. The ADF regressions for p and p^* include twelve lagged changes of the dependent variable to account for serial correlation. The $p - p^*$ and $p - \theta p^*$ regressions include a single lag. The critical values shown for $p - \theta p^*$ assume θ is known. The asymptotic critical values accounting for the estimation of θ are –4.32, –3.78, and –3.50. Tests that fail to reject the null indicate the variable is integrated, so for $p - p^*$ and $p - \theta p^*$ rejection of the null indicates cointegration. Panel B reports the trace and eigenvalue statistics for Johansen's tests of cointegration using one to four lags. LR and AIC tests indicate one lag, which BIC suggests two lags are needed. The data are 234 observations from February 1979 through July 1998.

Panel A: ADF Tests					
			Critical Values		
Variable	Z_t		1%	5%	10%
p	−2.1001		−3.9942	−3.4229	−3.1398
p^*	−3.2709		−3.9942	−3.4229	−3.1398
$p - p^*$	−3.8531		−3.4456	−2.8418	−2.5731
$p - \theta p^*$	−3.6782		−3.9914	−3.4154	−3.1359
Panel B: Johansen Tests $p - p^*$					
			Critical Values		
Lags	Trace	Eig	1%	5%	10%
1	15.0823		19.9349	15.4943	13.4294
1		14.6439	18.5200	14.2639	12.2971
2	17.3196		19.9349	15.4943	13.4294
2		16.7486	18.5200	14.2639	12.2971
3	16.6898		19.9349	15.4943	13.4294
3		16.0755	18.5200	14.2639	12.2971
4	18.8019		19.9349	15.4943	13.4294
4		18.1525	18.5200	14.2639	12.2971

Table 8: Cointegration Regressions

Results from estimating cointegration regressions with additional explanatory variables. The regressions use 234 observations from February 1979 through July 1998. t-statistics are reported in parenthesis. The cointegrating vector is $[1 \quad \theta]'$. The coefficient on the own-lagged level is the error correction. $L(\cdot)$ indicates the lag of a variable.

	Δp		Δp^*	
Const	0.0060	0.0201	0.0052	3.4344
	(1.3621)	(0.0205)	(0.8108)	(2.0220)
Sent	0.0006	0.0003	−0.0004	−0.0003
	(4.5498)	(2.1903)	(−2.1045)	(−1.1945)
RFx		−0.0390		0.0440
		(−1.8184)		(1.1653)
HB3		0.0512		−0.0114
		(2.7996)		(−0.3496)
TS		−0.0000		−0.0000
		(−1.0419)		(−0.3458)
DS		0.0003		−0.0002
		(3.2170)		(−1.4117)
DY		−0.0314		0.0171
		(−4.0993)		(1.2321)
CPI		0.0009		−0.0345
		(0.0924)		(−2.0579)
L(ExMkt)		−0.0004		−0.0010
		(−0.8421)		(−1.0894)
SMB		−0.0018		0.0004
		(−2.1155)		(0.2577)
HML		−0.0063		0.0057
		(−7.9258)		(3.7019)
UMD		0.0004		0.0003
		(0.6547)		(0.2977)
$\Delta(p^*)$	0.3563	0.3122		
	(9.3280)	(9.6831)		
$\Delta(p)$			0.7728	0.9601
			(9.3280)	(9.6831)
$L(p)$	−0.0726	−0.0933	0.1181	0.1226
	(−3.4734)	(−4.6891)	(3.8581)	(3.4384)
$L(p^*)$	0.0727	0.0775	−0.1174	−0.1201
	(3.4949)	(4.0623)	(−3.8542)	(−3.5635)
θ	−1.0008	−0.8300	−1.0061	−1.0207
$\bar{R}^2$	0.3166	0.5500	0.2818	0.3296

Figure 1: Pricing Errors and Sentiment

This figure shows the pricing error on the "quasi-Dow" index and investor sentiment, measured as percentages. The quasi-Dow is a value-weighted index we create using all available firms for which Bakshi and Chen (2001) have pricing errors. Data are monthly from January 1979 through July 1998.

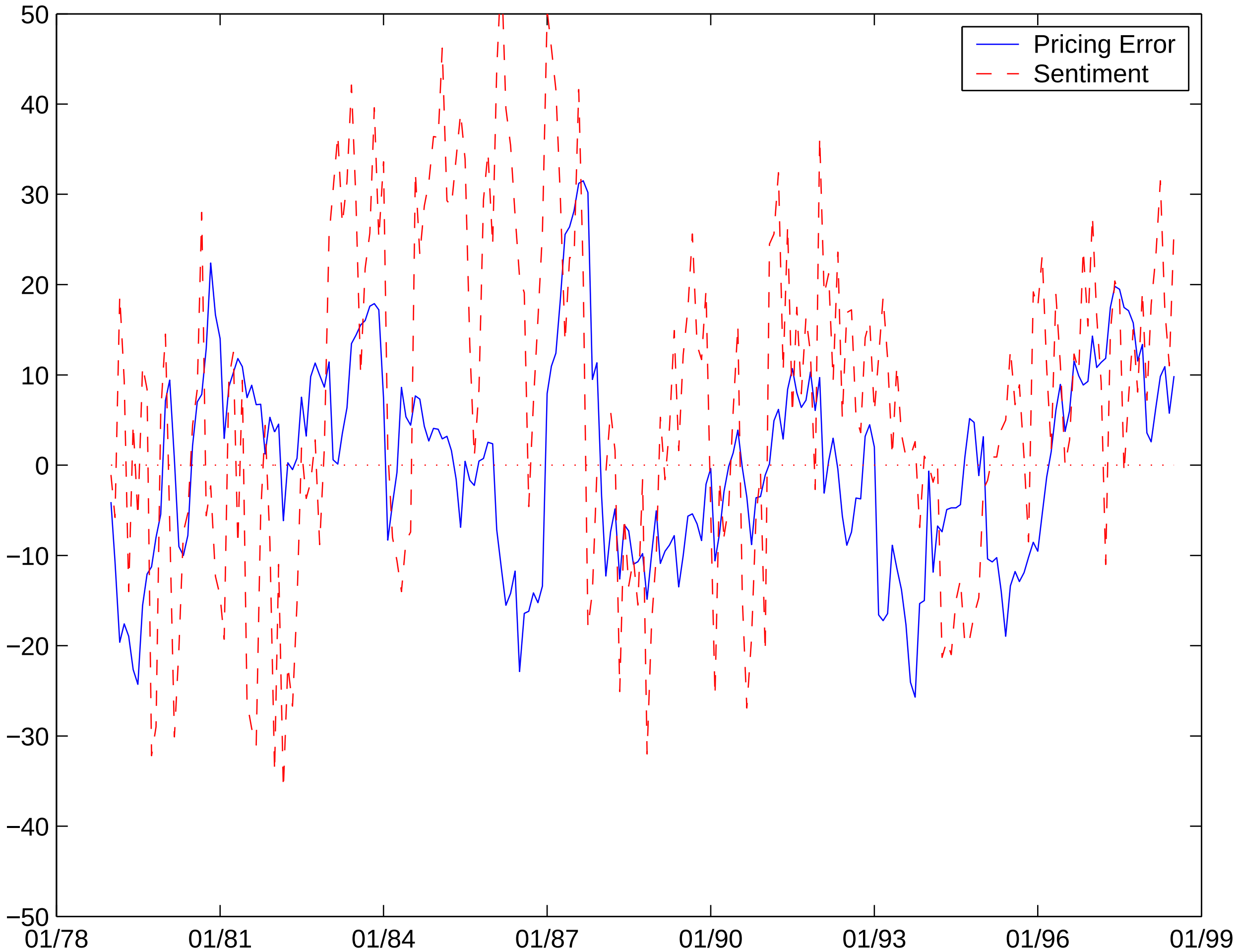

Figure 2: Market and Model Valuations

This figure shows the logs of the market valuation for the quasi-Dow (p) and the corresponding intrinsic value from the Bakshi and Chen (2001) model (p^*). The quasi-Dow is a value-weighted index we create using all available firms for which Bakshi and Chen (2001) have pricing errors. Data are monthly from January 1979 through July 1998.

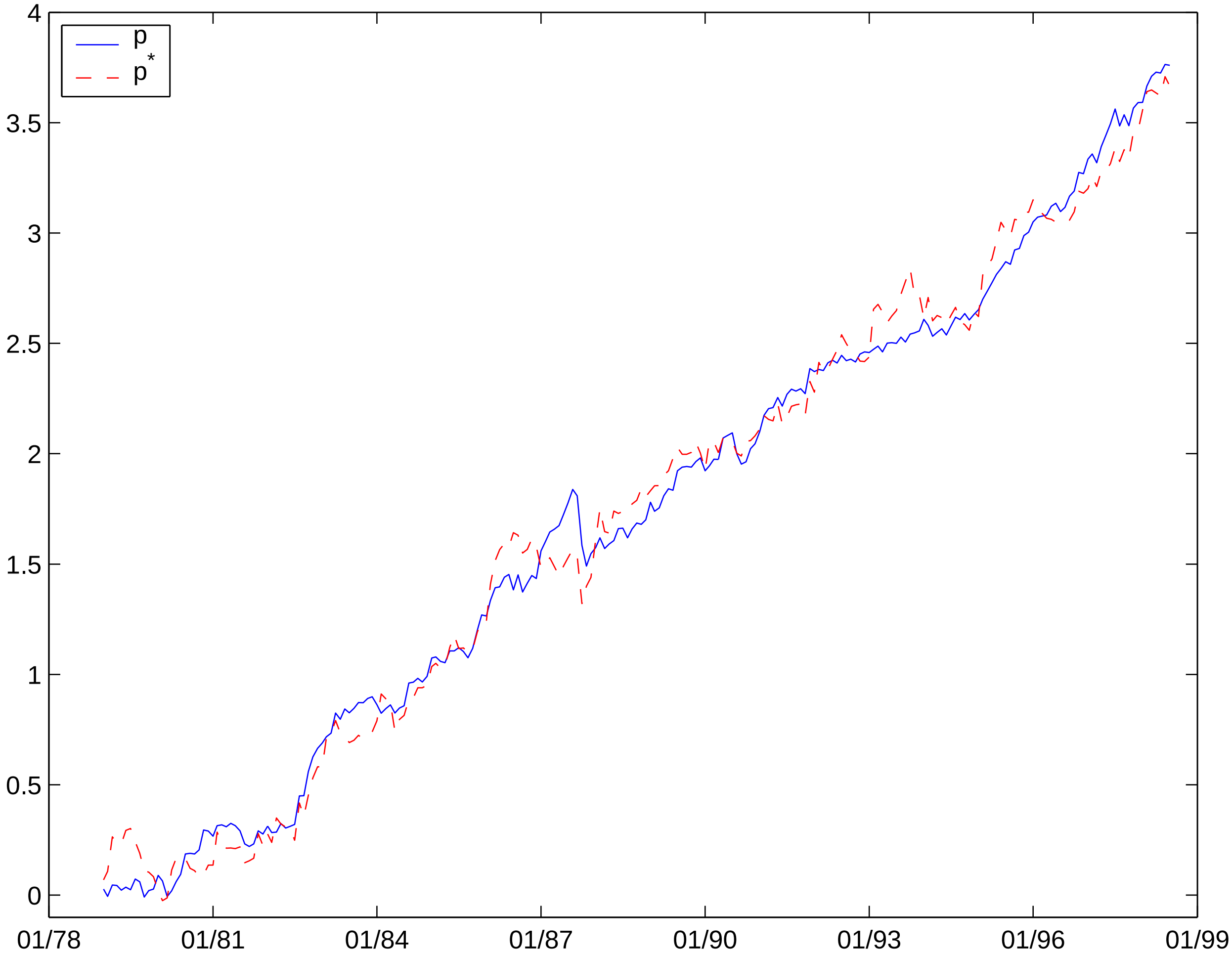

Figure 3: Frequency Domain Representation

Panel A plots the spectral density of the pricing error $p - p^*$ for the quasi-Dow index. It shows the importance of various frequencies in the variation of $p - p^*$. Panel B shows the cospectrum of $p - p^*$ and sentiment, which indicates the importance of various frequencies in the covariation between the two series.

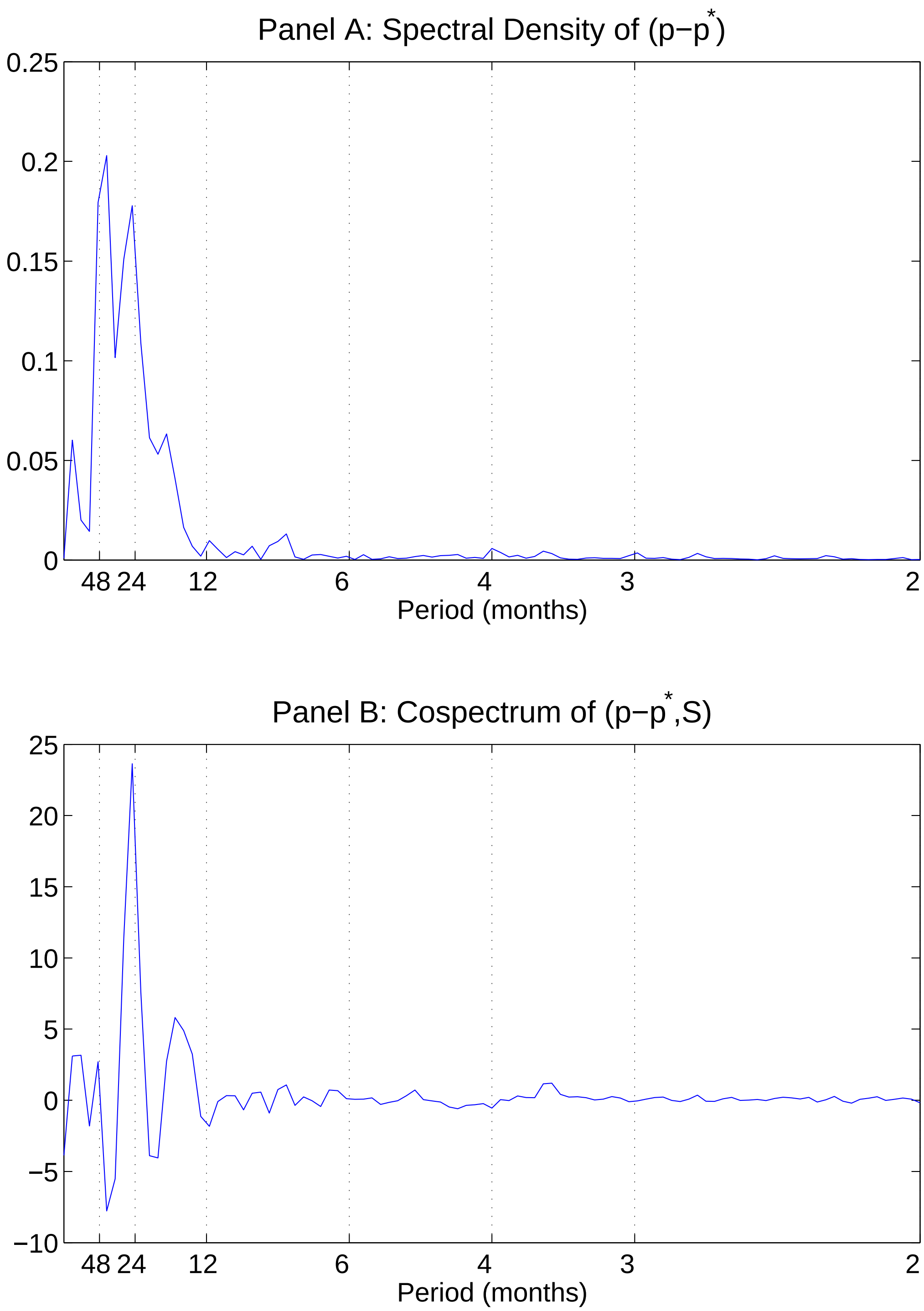

Figure 4: Impulse Response for Pricing Error

This figure shows the effect of a one standard deviation shock to sentiment on the pricing error. The impulse response function (IRF) is based on the results of the Cochrane-Orcutt regression with the control variables in Table 6 and an AR(1) model for sentiment. The IRF assumes the shock to sentiment does not affect the control variables.