# Does Sentiment Matter?*

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**Abstract**

Whether investor sentiment has any bearing on asset returns has long been a topic of interest in finance. I examine a sentiment measure based on the University of Michigan Consumer Sentiment Index. I find that changes in consumer sentiment are positively related to contemporaneous excess market returns. They are negatively related to future excess market returns at one-month horizon and one-year horizon over 1979-2003 and 1955-2003 periods. Change in consumer sentiment is a strong economic and statistical predictor of returns compared to other known market return predictors. Change in consumer sentiment performs better than an AR(1) benchmark model in out-of-sample forecasting tests. Change in consumer sentiment may predict returns because it measures time-varying rational beliefs that cause time-varying expected returns or is related economic cycles. To test this proposition, I include a myriad of well-known predictors of time-varying expected returns and contemporaneous measures of economic cycles in the analysis. Test results suggest that the predictive power of change in consumer sentiment is unrelated to time-varying expected returns or economic cycles.

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# I. Introduction

Rational asset pricing theories, such as the Capital Asset Pricing Model (CAPM), Merton's intertemporal CAPM, and Ross's APT, posit that non-diversifiable risks and their risk premiums determine asset prices. In these models, investors' beliefs affect price through perception of risk and expected returns, and a measure of aggregate risk aversion, which determines the risk-return trade off. In the rational expectation framework, investors' perceptions are correct on average, allowing researchers to test asset pricing models with realized risk and return in place of investors' ex ante perceptions or expectations. However, much of the empirical evidence has not been supportive of these rational models.[1] To reconcile theory and empirical evidence, two lines of inquiries have emerged: development of more dynamic asset pricing models and development of behavioral pricing models.[2]

In the first line of inquiry, the rational investor assumption is maintained. The theoretical advances have been in 1) identifying other risks to better capture investors' perception of risk (e.g., Lettau and Ludvigson, 2001), 2) improving methods to account for time-varying risks and risk premiums (e.g., Ferson and Harvey, 1991), and 3) using alternative risk-return trade off models, modifying assumptions about what kinds of risks are insurable, and having heterogeneous consumers/investors (e.g., Constantinides 1990, and Constantinides and Duffie, 1996). In the second line of inquiry, the behavioral finance literature allows investors' beliefs to deviate from those of rational investors. These deviations are attributed to psychological biases, such as overconfidence or self attribution, documented in the psychology literature (Hirshleifer, 2001). Misvaluations by irrational investors can affect

[1] Examples include the inability of traditional models to explain high equity premium (Mehra and Prescott, 1985) or returns of the momentum strategy (Jegadeesh and Titman, 1993).

[2] A third line of inquiry is to investigate whether these empirical findings are results of misspecification of econometric methods or data snooping.

stock prices when coupled with limits on arbitrage activities of rational investors, which would otherwise eliminate the pricing effect of irrational investors (Shleifer and Vishny, 1997). These two lines of inquiries generate a heated debate concerning a fundamental issue in asset pricing: are stock returns determined solely by risk factors and risk premia or instead are stock returns determined by risk factors and risk premia plus the valuation of irrational investors who misperceive the distribution of asset values?

As in much of the literature, I will refer to the beliefs of irrational investors as *sentiment*. The objective of this paper is to examine whether sentiment affects individual stock prices, and whether these effects are correlated across stocks such that they impact the aggregate market.

Existing empirical work has analyzed various proxies for sentiment. In the closed-end fund literature, some researchers argue that investor sentiment can be measured by the discount on closed-end funds, and investigate its relation to the return generating process of individual stocks or portfolio of stocks grouped by size (market capitalization).[3] However, these studies find conflicting evidence. Lee, Shleifer, and Thaler (1991), Chopra, Lee, Shleifer, and Thaler (1993) report that closed-end fund discounts are a determinant of returns of small capitalization stocks, while Chen, Kan, and Miller (1993) and Elton, Gruber, and Busse (1998) conclude that the discount on closed-end funds is not a determinant of stock returns.[4] Neal and Wheatley (1998) examine the relation of three proxies of sentiment

[3] The closed-end fund discount refers to the empirical finding that closed-end fund shares typically sell at prices lower than the per share market value of assets the fund holds.

[4] Lee, Shleifer, and Thaler (1991) report that retail investors own a large portion of close-end funds and small capitalization stocks. They show that when the price of small stocks with high proportion of retail investors increase, the discount on close-end funds narrow. Based on this evidence, they argue that the discount on close-end funds is a measure of retail investor sentiment. On the contrary, Chen, Kan, and Miller (1993) report that a closer look at Lee, Shleifer, and Thaler (1991) data reveals that the returns of smaller capitalization stocks are not strongly related to closed-end funds in any absolute sense and not substantially more strongly so than are the returns of most larger capitalization stocks. Chopra, Lee, Shleifer, and Thaler (1993), in turn, present

with long-term returns and find inconclusive results. They find that net fund redemption can forecast portfolio returns of small capitalization stocks and the size premium, while closed-end fund discounts do not. They also report that the ratio of odd lot sales to purchases has forecasting power but the sign is counterintuitive.

Brown and Cliff (2005) develop a sentiment measure constructed from the number of bull, bear, and neutral market newsletters. They investigate the relation of this measure and returns of size and book-to-market sorted portfolios, and find that high sentiment levels are followed by lower returns at horizons of two and three years for portfolios with large size and low book-to-market firms. Brown and Cliff (2004) use principal component analysis to extract a composite measure of sentiment from various sentiment measures that have been previously proposed, such as fund flows to mutual funds, the ratio of advance over declining issues, and the number of bull, bear, and neutral market newsletters. They investigate the relation of this composite sentiment measure and monthly and weekly stock returns, but find it does not predict near-term returns.[5]

The prior literature review highlights the lack of consensus on the best measure of sentiment or on whether sentiment in fact affects stock prices. While existing studies test the impact of sentiment on individual stocks and small portfolios of stocks, this paper takes a different approach. I propose a different measure of sentiment, and examine whether sentiment affects stock prices focusing on whether sentiment affects the aggregate market returns. Understanding whether sentiment affects the aggregate stock market is important in

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evidence that counter Chen, Kan, and Miller (1993). More recently, Elton, Gruber, and Busse (1998) test the time series relation of returns of portfolios of stocks grouped by their capitalization and the close-end fund discount. They conclude that the discount on closed-end funds is not a determinant of stock returns.

[5] In a related literature, Hirshleifer and Shumway (2003) argue that the level of sunshine alters mood and sentiment of investors. They test the relation between daily weather and daily stock returns across a large number of stock exchanges and find a significant relation. They conclude that sentiment affects stock prices. Kamstra, Kramer, and Levi (2003) find a seasonal affective disorder (SAD) in the seasonal cycle of stock returns.

a number of dimensions. First, if sentiment is correlated across stocks, then its effects can not be diversified away by holding a large portfolio of stocks. Second, if sentiment affects the aggregate market, then the uncertainty of sentiment (time-variation) may have real risk consequences. DeLong, Shleifer, Summers, and Waldmann (1990) show that the unpredictable nature of noise traders beliefs create a pricing risk in the market. Lastly, it sheds light on the issue of whether a market-wide stock price bubble is possible, which Alan Greenspan, the chairman of the federal reserved board, suggested could explain the rapid rise and fall of the stock market prices during the late 1990s, coining the phrase irrational exuberance.[6]

The sentiment measure used here is based on the University of Michigan Consumer Sentiment Index (hereafter referred to as consumer sentiment).[7] This index is a weighted average of responses to five survey questions that ask respondents about their views on current and future financial conditions. There are various reasons why this consumer sentiment index is a natural candidate for analysis in studies of sentiment. First, both economists and investors agree that the consumer sentiment index, closely watched by economists and individual investors, conveys information relevant to the stock market. It has been claimed by the financial press to move daily market returns.[8] The influence of this index is also illustrated in a March 2004 Federal Bureau of Investigation and Securities Exchange Commission investigation on a possible early leak of the index.[9] Second, the consumer sentiment index is based on a direct survey of public perceptions about current

[6] From the remarks by Alan Greenspan in his speech at the Annual Dinner and Francis Boyer lecture of the American Enterprise Institute for public policy research on December 5, 1996.
[7] The term 'consumer sentiment' is not used to imply that the consumer sentiment index measures only beliefs of irrational investors.
[8] In March 2002, for example, stocks and bonds rose on the news that consumer confidence had jumped to its highest level since August (Reuters, March 26, 2002).
[9] This investigation is reported in the New York Times on March 17, 2004.

and expected economic conditions that should be more closely aligned with the beliefs of typical retail investors. Behavioral finance theories often attribute irrational beliefs to small less sophisticated investors (Shleifer, 2000). Qiu and Welch (2004) report that for the short period of 4 years when the UBS/Gallop survey of investor sentiment (monthly survey of 10,000 retail investors) is available, only the consumer sentiment correlates well with investor sentiment, in a test of various sentiment measures.[10] Lastly, the consumer sentiment index has a long time-series starting in the 1950s. Other sentiment survey data represent significantly shorter time spand starting in the late 1970s or 1980s.

I develop the relation between sentiment and stock prices using the model proposed by Daniel, Hirshleifer, and Subrahmanyam (1998); its implications are consistent with a large number of other empirical studies.[11] In this model, investors' overconfidence about their noisy private signals of future dividends causes stocks to be over (under) priced when the arrival of private news is good (bad). Subsequently, when the true dividend outcome is revealed or limits on arbitrage decline, mispriced stocks adjust to rational expectation values. Thus, if sentiment affects stock prices, changes in sentiment should be positively correlated with contemporaneous stock returns, and overly optimistic sentiment should predict lower stock returns than their market required returns based on risks.

I test the relation between change in consumer sentiment with contemporaneous returns, and with future aggregate stock market returns at one-month horizon and one-year horizon for the periods of 1978-2003 and 1955-2003, respectively. I find that changes in consumer sentiment are positively related to contemporaneous returns and negatively related to future

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[10] Qui and Welch (2004) test the closed-end fund discount, the University of Michigan consumer sentiment index, the Conference Board confidence index, Shiller's index, and Baker and Wurgler index.
[11] See also Daniel, Hirshleifer, and Subrahmanyam (2001).

returns. Changes in consumer sentiment predict value-weighted and equal-weighted aggregate stock market returns at one-month and one-year horizons. The predictive power of change in consumer sentiment is economically significant; a one standard deviation improvement in consumer sentiment predicts a 5 percentage points a year lower excess return relative to the unconditional mean. Changes in consumer sentiment also out performs the benchmark AR(1) model in out-of-sample forecasts of market returns.

Because the consumer sentiment index may capture beliefs of irrational as well as rational investors, an alternative explanation for the relation between changes in consumer sentiment and future returns is that it proxies for rational beliefs that are time-varying. That is to say, changes in consumer sentiment are related to time-varying expected returns. If as investors become more optimistic, they also become less risk averse and require lower returns, then a rise in consumer sentiment will predict lower expected returns.

The second hypothesis I examine is whether change in sentiment predicts market returns because it is related to time-varying expected returns. To test this hypothesis, I include variables that are known to predict time-varying expected returns in the analysis. These are dividend yield, the book-to-market ratio of the Dow Jones Industrial Average (DJIA), the slope of the term structure, the yield spread between Baa and Aaa bonds, the short rate yield, lagged excess market returns, and the consumption-wealth ratio. To further test if consumer sentiment predicts returns because it is related to economic cycles that is not captured by traditional predictors of expected returns, I include contemporaneous measures of economic conditions, such as real gross domestic product growth and consumption growth, in the analysis.[12] Together, all test results lead to the conclusion that the predictive power of change in consumer sentiment is unrelated to time-varying expected return or economic cycles. However, this conclusion should be tempered by the fact that these tests are tests of joint hypotheses, thus the above conclusion depends on having an accurate model and proxies for for time-varying expected returns and economic cycles.

Some researchers raise a concern that a variable may appear to predict market returns due to spurious regression bias.[13] Spurious regression bias can arise when the explanatory variables are highly persistent, especially in a small sample. However, spurious bias does not drive the results here. I find the strongest predictive power in the one-year returns sample where change in consumer sentiment index is not persistent. Moreover, the outcomes of a number of robustness tests reinforce the main results.

This study contributes to the current literature in three dimensions. First, it employs a direct survey of sentiment instead of proxies such as the closed-end fund discount. I am not aware of other studies of *yearly* changes in the University of Michigan Consumer Sentiment Index or studies that examine the relation of this index and long-horizon returns. The use of yearly changes is important because the consumer sentiment index time series exhibits strong seasonality at the monthly frequency. Otoo (2000) examines log of *monthly* consumer sentiment index and finds that they do not predict one-month-ahead returns.

Second, this study finds that one measure of sentiment can predict the aggregate stock market and all portfolios ranked by size and book-to-market. This result is significantly different from the existing evidence that a proxy for sentiment is able to forecast either small

[12] Carroll, Fuhrer, and Wilcox (1994) find that consumer sentiment helps predict future household spending. Howrey (2001) finds that consumer sentiment has some incremental predictive power relative to other economic variables for predicting recession and recovery.

[13] See for example, Yule (1926), Granger and Newbold (1974), Nelson and Kim (1993), Kothari and Shanken (1997), Kirby (1997), Stambaugh (1999), and Ferson, Sarkissian, and Simin (2003).

or large firm returns, but never both. For example, the close-end-fund discount only predicts small firm returns. Information in market news letter predicts returns of large and low book-to-market firms.

Lastly, outside the debate of whether sentiment affects stock prices, identifying a strong predictor of stock market returns has important implications for the area of asset allocation. Stock market return predictability is relevant to investors' optimal dynamic asset allocation among stocks, bonds, and other assets; accurate predictions of conditional stock market returns assist investors in managing their portfolios to obtain higher returns.

The remainder of this paper is organized as follows. In section II, I develop the hypotheses on the relation of sentiment and stock prices. Section III describes the data employed in the analysis. Section IV presents the main test results. Section V offers concluding remarks.

## II. Sentiment and asset prices

In this section, I develop the hypotheses for the relation of sentiment and stock market returns first from the behavioral finance view and later from the rational expectation view.

I use the model proposed by Daniel, Hirshleifer, and Subrahmanyam (1998) to develop the relationship between sentiment and stock market prices. The model is based on findings in the psychology literature that people are overconfident. In the model, each member of a continuous mass of investors is overconfident in the sense that if he receives a private signal, he over estimates its precision. These signals can be thought of as private information or personal beliefs about the stock market. Those who receive the signal are referred to as the informed (*I*) and those who do not the uninformed (*U*). It is assumed that the uninformed are risk averse and that the informed are risk neutral. Each investor is endowed with a risky security, which is assumed here to be the market portfolio, and a risk-free asset that is a claim to one unit of terminal-period wealth.

There are three dates in the model. At date 0, investors start of with identical beliefs. They trade their endowments for the purpose of risk sharing. At date 1, investors *I* receive a common noisy private signal. The signal changes their beliefs, and they update the risky security price. Investors *I* then trade with *U*. At date 2, a noisy public news arrives, and further trade occurs. At date 3, definitive pubic information arrives, and the risky security pays dividend. All random variables in the model are assumed to be independent and normally distributed.

The risky security generates a terminal dividend of $\theta \sim N(\overline{\theta}, \sigma_\theta^2)$. The private signal received by *I* at date 1 is $s_1 = \theta + \varepsilon$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. Thus, the signal precision is $1/\sigma_\varepsilon^2$. *U* correctly assesses the error variance, but *I* under estimates it to be $\sigma_C^2 < \sigma_\varepsilon^2$. The date 2 noisy public news is $s_2 = \theta + \eta$, where $\eta \sim N(0, \sigma_p^2)$ and is independent of $\varepsilon$ and $\theta$. Its variance is correctly estimate by all investors. Daniel, Hirshleifer, and Subrahmanyam (1998) show that the equilibrium prices of the risky security at dates 1 and 2 are

$$P_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_C^2}(\theta + \varepsilon),$$

$$P_2 = \frac{\sigma_\theta^2(\sigma_C^2 + \sigma_p^2)}{D}\theta + \frac{\sigma_\theta^2\sigma_p^2}{D}\varepsilon + \frac{\sigma_\theta^2\sigma_C^2}{D}\eta, \tag{1}$$

where $D = \sigma_\theta^2(\sigma_C^2 + \sigma_p^2) + \sigma_p^2\sigma_C^2$.

The price path of the risky security is illustrated in Figure I, which is the same as in Daniel, Hirshleifer, and Subrahmanyam (1998). The dark thick line shows the average price path following a positive signal (upper curve) or negative signal (lower curve) at date 1, and the lighter line shows the rational expected values. Overconfident in the precision of their private signals, $\sigma_C^2 < \sigma_\varepsilon^2$, causes invertors to be overly optimistic when good signals arrive and overly pessimistic when bad signals arrive. Thus, time 1 prices are higher (lower) than the rational expected values when good (bad) signals arrive. At date 2 when noisy public signal arrives, the price is partially corrected. At date 3, when the true dividend value is revealed, the security price equals its rational expectation value. For deviations from rational expectation values to persist for a period of time, the model also assumes that there are limits to arbitrage in the sense of Shleifer and Vishny (1997) and that overconfident investors are able to survive in the long run.[14] Daniel, Hirshleifer, and Subrahmanyam (1998) and Hirshleifer (2001) offer explanations on how overconfident investors survive in the long run.

[Insert Figure I here]

The price paths in figure I indicate that, a variable that measures innovation or change in the beliefs of investors *I* between date 0 and 1, should be positively correlated with the return of the risky asset over this same period and it should predict returns that are lower than returns from the rational expectation values in periods 1 to 2 and 2 to 3. That is, overreaction to good signal (bad signal) at date 1 predicts future returns that are lower (higher) than the intrinsic returns based on risks.

**Hypothesis 1**: If sentiment affects the aggregate market returns, changes in sentiment

[14] A number of factors limit arbitrage. First is the possibility that arbitrageurs are forced to liquidate their investment position when it is detrimental to do so. This can happen if markets become even more over or under valued when at the same time arbitrageurs cannot borrow (or borrowing cost is too high) to cover their margin calls. Second, arbitrageurs often have a short-term performance measure that forces them to be myopic and not take long-term arbitrage positions. Third, short-sale constraints also put additional limit on arbitrage for over priced markets. See Shleifer and Vishny (1997) for other limits on arbitrage.

should be positively related to contemporaneous stock market returns, and negatively related to future stock market returns.

As argued earlier in the introduction, the consumer sentiment index is likely to capture beliefs of some irrational investors, thus, hypothesis 1 is tested using changes in the consumer sentiment. According to the model above, future asset prices revert to rational expectation values when the true information about the private signal is revealed. The consumer sentiment index is constructed from five survey questions that ask respondents two questions about current financial situation, two questions about financial and economic condition expected over the next year, and one question about financial condition expected over the next five years. Consequently, a large portion of the information about the financial situation and economic condition reflected in investors' beliefs and in the consumer sentiment index is revealed during the year following the survey. Therefore, most of the stock price adjustment towards rational expectation values should occur during the year following the survey. This motivates the examination of the relation between changes in consumer sentiment and future one-month and one-year returns.[15]

Existing literature examine both the predictability of levels of sentiment and changes in sentiment; the studies of these two variables complement each other. Some studies on sentiment, such as Brown and Cliff (2005), test the levels. Other studies of survey data, such as Otoo (2000), test changes in sentiment. Studies of the closed-end fund discount also examine changes in the close-end fund discount, which is argued to proxy for sentiment. Here, I examine changes in sentiment because using changes in sentiment helps mitigate econometric problems that arise due to the persistence and seasonality patterns in the time

[15] Some of the information in the index may be resolved over five years following the survey, but examining return periods longer than one-year is infeasible due to the small number of non-overlapping sample points.

series of the index levels.

In this model, the security prices are set by the informed risk neutral investor. The rationale for assuming that informed investors are overconfident is that the investor has personal attachment to his own signal. Relaxing some of these assumptions does not change the outcome of the model. Daniel, Hirshleifer, and Subrahmanyam (1998) report that if both groups of investors are risk averse, as long as the uninformed are not risk neutral price setters, overconfident investors still affect prices, and price paths are similar to Figure I. The model also assumes prices are initially unbiased. Relaxing this assumption causes hypothesis 1 not to hold every period, but to hold on average. Thus, in a time series regression, changes in sentiment should be negative related to future market returns.

Hypothesis 1 is a common prediction generated by several behavioral asset pricing models other than Daniel, Hirshleifer, and Subrahmanyam (1998). For example, Barberis, Shleifer, and Vishny (1998) propose a model of under- and overreactions of investors based on a learning model of the earnings process. The actual earnings process follows a random walk, but investors believe that earnings follow a steady growth or revert to the mean. Investors' trading based on wrong beliefs causes returns to be predictable in similar patterns.

*Consumer sentiment and time-varying expected returns*

Change in consumer sentiment may also capture time variation in beliefs consistent with rational expectations. In this case, changes in consumer sentiment predict market returns because they predict time-varying expected market returns. Consider the consumption-based asset pricing model and assume a standard power utility function. The conditional excess expected return of the market portfolio is given as (Cochrane 2001):

$$E_t[R_{m,t+1}] - r_{f,t} = -r_{f,t} Cov_t(\beta_t (c_{t+1}/c_t)^{-\gamma_t}, R_{m,t+1}), \tag{2}$$

where $R_m$ denotes the market return, $\beta$ denotes a discount factor, $c$ denotes consumption, and $\gamma$ denotes the risk aversion level. Change in consumer sentiment may predict excess market returns because it is related to time variation in consumption growth, in aggregate risk aversion level, and in the discount factor. For example, if the period when consumers become more optimistic about future economic growth coincides with the time when investors become less risk averse, then investors should demand lower return on their investment. This creates a negative relation between changes in consumer sentiment and future aggregate market returns.

**Hypothesis 2**: Changes in consumer sentiment predict market returns because it predicts time-varying expected return.

To test hypothesis 2, I include in the analysis variables that are known to predict time-varying expected market return and contemporaneous measures of economic cycles.

## III. Data

Excess market returns are calculated using the Center for Research in Security Prices (CRSP) market indices minus the one-month return of the Treasury bill that is closest to 30 days to maturity. The indices include firms from the Amex, NYSE, and the NASDAQ.

The University of Michigan Consumer Sentiment Index (CSI) is an average of scores from five survey questions that ask respondents about their current financial situations, the expected changes in their financial situations over the next year, their views on expected business conditions in the next year and the next five years, and whether they think this is a good time or a bad time to make big-ticket household purchases. The actual survey questions and construction method of the index are presented in the Appendix.

Most published academic research on consumer sentiment focuses on the CSI because of its long history. Quarterly CSI survey data begin in November 1952, and monthly data begin in January 1978. Quarterly data are available for months 2, 5, 8, and 11, with some missing quarters in the 1950s. Figure II shows the time series of the level of the CSI for the entire sample from November 1952 through December 2003. An alternative index from the Conference Board began as a bimonthly survey only in 1967.

[Insert Figure II here]

Change in the Consumer Sentiment (CCSI) is defined as CSI of the current month minus CSI of the same month in the previous year over CSI of the same month in the previous year. Figure III shows the time series of CCSI. The yearly change in consumer sentiment is used to mitigate econometric problems arising form persistent in the time series of the index level and noise from seasonal patterns. Figure IV shows the monthly averages of the CSI, which reveal some seasonality; the CSI is lower in the last three months of the year.

[Insert Figures III and IV here]

The Center for Survey Research at the University of Michigan releases the index data at the end of each month. According to the available release dates during 1997-2001, approximately 10% of the CSI is released one to five days after the end of the survey month. To assure that that CCSI is available before the return period it predicts, current-period returns, both $VWRET_t$ and $EWRET_t$, are matched with lagged CCSI from two months prior to the return period, skipping one month in between. This lagged variable is denoted $CCSI_{t-1}$. For example, the change in consumer sentiment for May of this year is matched with the July return of this year in the one-month returns sample. Change in consumer sentiment for

May of this year is matched with the one-year compounded return from July of this year through June of next year in the one-year returns sample.[16]

Other variables documented to predict aggregate market returns are included in the analysis. They are the short rate yield (Fama and Schwert, 1977), the slope of the term structure (Keim and Stambaugh, 1986), the dividend yield (Campbell and Shiller, 1988, Fama and French, 1988) , the yield spread between Aaa and Baa bonds (Fama, 1990) , the aggregate book-to-market ratio of the DJIA (Kothari and Shanken, 1997, Pontiff and Schall, 1998) , and the consumption-wealth ratio (cay) (Lettau and Ludvigson, 2001).

The three-month T-bill rate from the Fama-Bliss file (CRSP database) is used as the short rate yield (YLD3). The term structure slope (TERM) is the difference between the long-term bond yield and the yield on the three-month T-bill. Dividend yield (DIV) is constructed using the same method as in Fama and French (1988). Dividends are obtained from CRSP value-weighted returns, and the end-of-year market price is used as the denominator. The bond spread (DEF) is the difference between the Baa-rated bond yield and the Aaa-rated bond yield. Long-term bond yields, Aaa-rated bond yields, and Baa-rated bond yields are from data provided by the Federal Reserve Bank of St. Louis.[17] The book-to-market value of the DJIA (BM) is constructed as in Pontiff and Schall (1998).[18] The quarterly consumption-wealth ratio data from 1952 quarter 1 through 2001 quarter 4 are provided by Ludvigson. For monthly return tests, consumption-wealth ratio is constant for the quarter until the next

[16] All the main empirical tests are also performed using changes in consumer sentiment matched with returns of the next month (without skipping one month). The results are largely the same, with minor differences in statistical significance levels.

[17] These data can be obtained from http://www.stls.frb.org/fred/.

[18] For the DJIA book-to-market, I use the December year-end book value of the DJIA from the Value Line Publication, "A Long Term Perspective." The monthly BM is constructed by dividing the most recent DJIA book value by the contemporaneous monthly DJIA level. To make sure that BM is available before the return period, the book value from December of year $t-1$ is matched with the market value of March of year $t$ to February of year $t+1$.

consumption-wealth ratio is available. Unlike $CCSI_{t-1}$, the lagged variable subscript *t – 1* for these other variables denotes the values of the variables for the month immediately prior to the return period. As some existing studies use log value of these variables, I also use log dividends and log book-to-market and find qualitatively the same results (not reported here).

*Descriptive statistics*

Panel A of Table 1 reports the summary statistics for the one-month returns sample from 1979 through 2003. Monthly consumer sentiment index series starts in 1978, and thus the yearly change series begins in 1979. During this period, $CCSI_{t-1}$ has a mean of 1.1% and a standard deviation of 12.8%, and it is positively skewed. The greatest positive and greatest negative values of the $CCSI_{t-1}$ occur in May 1981 and in October 1990.

[Insert Table 1 here]

Panel A of Table 1 also reports the autocorrelations. The variable $CCSI_{t-1}$ at monthly intervals is not as persistent as other variables. The Dickey-Fuller test, which includes an intercept term, rejects, at the 1% significance level, the hypothesis that $CCSI_{t-1}$ has a unit root. This hypothesis cannot be rejected for dividend yield, book-to-market, yield spread, short rate yield, or consumption-wealth ratio. Panel B reports the cross-correlations. $CCSI_{t-1}$ is not contemporaneously correlated with any other predictor variable except for the short rate yield. The correlation between $CCSI_{t-1}$ and short rate yield is low at 0.15.

Table 2 reports summary statistics, autocorrelations, and cross-correlations for the one-year returns sample. This sample covers 1955 through 2003. The market excess returns are non-overlapping one-year compounded excess returns from July through June of the following year. $CCSI_{t-1}$ is from May of each year, and the other lagged variables are from

June of each year.[19] The mean of $CCSI_{t-1}$ is 1.1%, and the standard deviation is 13.0%. Change in consumer sentiment is not persistent. The Dickey-Fuller test rejects, at the 1% significance level, the hypothesis that $CCSI_{t-1}$ has a unit root.

[Insert Table 2 here]

# IV. Results

The relation between changes in consumer sentiment and contemporaneous returns is estimated as:

$$r_t = e + f\,CCSI_t + n_t, \tag{3}$$

where $r_t$ denotes excess market returns, and $n_t$ denotes a residual term. The sample includes 48 non-overlapping data points of one-year returns and $CCSI_t$. Since $CCSI_t$ is the change of CSI over one year, the return, $r_t$ , is the compounded return over the exact same one-year period. The slope estimate of the regression, $f$, is 0.924 for equal-weighted returns and 0.618 for value-weighted returns. Both are statistically significant at lower than the 1% level. The R-square of the regressions are above 25% in both cases. These results confirm that changes in consumer sentiment are positively related to contemporaneous market returns.

*Predictive univariate regressions*

The relation between change in consumer sentiment and future excess market returns is examined by estimating the following least squares (LS) regressions of excess market returns

[19] The May CCSI time series is available continuously starting from 1955. In the main tests of this study, I use only non-overlapping time series of continuous non-missing data to avoid any potential biases related to overlapping data. I also perform the same tests using every quarterly and monthly CCSI from 1952 through 2003. The results are presented in Table A1 in the Appendix. Missing data points during the earlier years in the 1950s are skipped over. In the one-year return tests, yearly return periods are overlapping, but the results reported are corrected for heteroskedasticity and autocorrelation in the error term. The results are qualitatively the same as those reported in the main text.

on lagged change in consumer sentiment ($CCSI_{t-1}$):

$$r_t = a + b\, CCSI_{t-1} + u_t\,, \tag{4}$$

where $r_t$ denotes excess market returns, and $u_t$ denotes a residual term.

[Insert Table 3 here]

Panel A of Table 3 reports regression estimates of one-month returns, and Panel B reports the regression estimates of one-year returns. These results show that the relation between lagged change in consumer sentiment and excess market returns is negative and statistically significant for the one-month and one-year return horizons. The magnitude of the slope estimates of $CCSI_{t-1}$ is also economically significant. A one-standard deviation rise (drop) in consumer sentiment (12.8% from Table 1) predicts a decline (rise) of 0.52 percentage points (equivalent to 6.3 percentage points annually) in one-month value-weighted excess market returns from its unconditional mean. A one-standard deviation rise (drop) predicts a decline (rise) of 5.0 (38.6% x 0.13) percentage points in one-year value-weighted returns and 9.1 percentage points in one-year equal-weighted returns. These magnitudes are large compared to the average one-year value-weighted and equal-weighted excess returns of 6 and 9.7 percentage points (Table 2).

Table 3 also reports regression results for other selected variables. Dividend yield and consumption-wealth-ratio predict one-year market returns. These results are similar to those reported by Fama and French (1988), Campbell and Shiller, (1988), and Lettau and Ludvigson, (2001).

*Robustness checks*

It has been noted that the slope coefficients of a least squares regression are subject to small-sample biases when regression disturbances are correlated with future values of the independent variables (See Yule, 1926; Granger and Newbold, 1974; Nelson and Kim, 1993; Kothari and Shanken, 1997; Kirby, 1997; Stambaugh, 1999; and Ferson, Sarkissian, and Simin, 2003). The fact that I find strong predictability in the one-year returns sample where CCSI is not persistent suggests that spurious regression bias is not driving the results here. Nonetheless, I conduct two robustness checks: one using a correction method as in Stambaugh (1999), and another using a simulation (bootstrap) method proposed by Nelson and Kim (1993). Details of the implementation of these tests are described in the appendix.

The Stambaugh-bias-adjusted estimates of the slope coefficients are reported in Table 3. For the regressions of consumer sentiment, all the Stambaugh-bias-adjusted estimates of *b* are virtually identical to their corresponding LS estimates. As expected, the Stambaugh-bias-adjusted estimate is lower than the LS estimate for persistent variables such as dividend yield.

The distribution of the parameter estimates from the Nelson and Kim (1993) simulation method accounts for small-sample bias, for the correlation between residuals *u* and the shocks to the time series of the explanatory variable, and for residual terms that are not normally distributed. Table 3 reports the p-value from the distribution obtained using this simulation for the LS estimates *b*. The p-value for the slope estimates of change in consumer sentiment are below the 5% significance level in every case. The small sample bias appears to affect the slope estimates of other persistent variables such as dividend yield and the consumption-wealth-ratio. Their statistical significance levels decline when using the p-values from the simulation. Nelson and Kim (1993) find similar results for dividend yield.

*Controlling for other predictors*

The incremental predictive power of change in consumer sentiment is examined in multiple regressions of return on lagged change in consumer sentiment controlling for lagged values of dividend yield ($DIV_{t-1}$) , yield spread between Baa and Aaa bonds ($DEF_{t-1}$) , term structure slope ($TERM_{t-1}$) , short rate yield ($YLD3_{t-1}$) , book-to-market ratio of the DJIA ($BM_{t-1}$) , consumption-wealth ratio ($cay_{t-1}$) , and excess market returns ($r_{t-1}$):

$$r_t = a + b_1\, CCSI_{t-1} + b_2\, DIV_{t-1} + b_3\, DEF_{t-1} + b_4\, TERM_{t-1} + b_5\, YLD3_{t-1} + b_6\, BM_{t-1} + b_7\, r_{t-1} + b_8\, cay_{t-1} + u\,. \qquad (5)$$

The lagged value of excess market return is included in the regression to control for autocorrelation in returns.

[Insert Table 4 here]

Table 4 presents the results for one-month returns. I report both the Newey-West t-statistics and the p-value from the simulation method proposed by Nelson and Kim (1993). YLD3 and other variables are tested in separate multiple regressions because of a multicolinearity problem.[20]

In Table 4, the slope coefficient estimates of $CCSI_{t-1}$ range from –0.035 to –0.055 and they are significant at the 5% level in all regressions. The slope estimates of $CCSI_{t-1}$ are economically and statistically significant after controlling for other predictors. Dividend yield predicts one-month value-weighted returns and lagged returns predict equal-weighted returns, but other control variables do not have any predictive power.

[20] When YLD3 is included with other variables in the regression, DIV, DEF, TERM, and YLD3 are all highly statistically significant. The condition index is 24.96. A value of more than 20 suggests potential problems (Greene, 2003). By merely excluding YLD3 from the regression eliminates the significance of DIV and DEF, which are not significant in the univariate regressions to begin with. Moreover, the short rate yield is highly contemporaneously correlated with book-to-market (correlation is 0.82) and dividend yield (correlation is 0.77).

[Insert Table 5 here]

Table 5 presents the regression estimates for the one-year returns sample. Dividend yield is tested separately from other variables due to its high correlation with other variables such as book-to-market (correlation of 0.9) and the yield spread (correlation of 0.5). In various multiple regressions, the slope estimates of $CCSI_{t-1}$ range from -0.323 to -0.528. The slope estimates of $CCSI_{t-1}$ are statistically significant at the 5% level in all regression specifications, and their magnitudes are economically significant. These results show that the predictive power of change in consumer sentiment is unrelated to time-varying expected returns (conditioned on these variables being affective proxies), thus rejecting hypothesis 2.

In the one-year returns sample, yield spread and the consumption-wealth ratio predict value-weighted returns. Existing studies suggest that yield spread and the consumption-wealth ratio predict returns because they predict time-variation in expected returns, which is related to business cycles (Fama, 1990; and Lettau and Ludvigson, 2001). The predictive power of the yield spread diminishes when the consumption-wealth ratio is included in the regression suggesting that, in this sample, the consumption-wealth ratio is the stronger predictor of business cycles. As in previous studies, the term structure and the dividend yield appear to predict market returns. But the statistic significance of their slope estimates disappears when the results are corrected for small sample bias. After controlling for small sample bias, the book-to-market does not predict returns in my sample (1955-2003) – consistent with Pontiff and Schall (1998) who report that book-to-market does not predict market returns in the post 1960's period.

*Out-of sample predictions*

Next, I evaluate the out-of-sample forecasting power of CCSI compared to the AR(1) model. The AR(1) model is employed as the benchmark model because this study and other existing studies, such as Jegadeesh and Titman (1993), find that lagged return is a strong predictor. For the one-month returns sample, I use 11-year rolling window regressions to predict one-month-ahead returns. The mean squared error (MSE) between the predicted return and realized return is calculated for each model. For the one-year returns sample, I use 20-year rolling window regressions to predict one-year-ahead returns. This gives 28 one-year return predictions. Again, the mean squared error (MSE) between the predicted return and realized return is calculated for each model. Table 6 reports the MSE of each forecasting model. The CCSI model performs better than the AR(1) model in predicting returns in all cases except for the one-month equal-weighted returns.

[Insert Table 6 here]

*Predicting size and book-to-market sorted portfolios*

I test one-year cumulative returns of 25 size and book-to-market sorted portfolios. Monthly returns of these portfolios are constructed as in Fama and French (1993).[21] The portfolios are value-weighted. The one-year return is the cumulative return from July of year *t* through June of year *t+1*. In the univariate tests, not reported here, the slope coefficient estimates of $CCSI_{t-1}$ are statistically significant at the 5% level or below for all 25 portfolios. Table 7 reports the coefficient estimates of $CCSI_{t-1}$ in regressions of returns on $CCSI_{t-1}$, $TERM_{t-1}$, $YLD3_{t-1}$, $BM_{t-1,}$ and $cay_{t-1}$.[22] Earlier results in this article show that the t-statistics

[21]The portfolio returns are from Kenneth French's website.

[22] As discussed earlier, dividend yield is not included in the regression due to multicolinearity.

and the p-value from simulation give similar statistical significance for the slope coefficient estimates of $CCSI_{t-1}$, therefore from this point on, I report only the Newey-West t-statistics.

The slope coefficients of $CCSI_{t-1}$ are statistically significant at the 5% level for 21 portfolios and significant at the 10% level for 3 portfolios. Changes in consumer sentiment lack incremental predictive power for the portfolio consisting of the largest firms and firms with highest book-to-market ratio. These are very interesting results since sentiment measures in other studies do not predict returns of both small and large capitalization stocks.

[Insert Table 7 here]

*Change in consumer sentiment and economic cycles*

This section examines whether consumer sentiment predicts market returns because it predicts economic cycles and consumption growth beyond the control variables included above by including contemporaneous measures of economic cycles in the analysis. In the one-year sample, I use change in the logarithm of the real GDP (Gross Domestic Product) to measure economic growth (ECONG). In the one-month sample, I use change in the logarithm of the coincidence index to measure economic growth since GDP data is available quarterly. The coincidence index is widely used as an indicator of current economic conditions. Consumption growth (CONG) is the change in the logarithm consumption. The contemporaneous variables match the period of the market returns exactly. For example, in the one-year sample, excess returns from July of year $t$ through June of year $t+1$ are matched with $ECONG_t$ and $CONG_t$ over the period from July of year $t$ through June of year $t+1$.

[Insert Table 8 here]

Table 8 shows that change in consumer sentiment is a statistically and economically significant predictor of value-weighted and equal-weighted returns at one-month and one-year horizons after including $ECONG_t$ and $CONG_t$ in the regressions. In regressions that include YLD3 and DIV separately (not reported in the table), the slope coefficient estimates of $CCSI_{t-1}$ are significant at the 5% level as well. These results indicate that the predictive power of change in consumer sentiment is unrelated to economic or business cycles.

## V. Concluding Remarks

This study examines whether sentiment affects stock prices focusing on its effects on the aggregate stock market returns. The yearly change in the University of Michigan consumer sentiment index is employed as a measure of sentiment. The overall results indicate that change in consumer sentiment is positively related to contemporaneous excess market returns and negatively related to future excess market returns. Changes in sentiment predict value-weighted and equal-weighted excess market returns at one-month and one-year horizons. In out-of-sample forecasting tests, change in consumer sentiment out performs the benchmark AR(1) model. In multiple regressions, changes in consumer sentiment predict future excess stock returns after controlling for time-varying expected return using dividend yield, book-to-market ratio of the DJIA, slope of the term structure, yield spread, short rate yield, consumption-wealth ratio, and lagged excess market returns. Test results also show that the predictive power of change in consumer sentiment appears to be unrelated to economic growth or business cycles.

These results are interesting whether they are interpreted from a rational expectation view or a behavioral finance view. From the rational expectation view, a potential explanation is that respondents to the surveys posses relevant information about the time-varying expected returns and expected future cash flows that is not available in other widely known predictors. The interpretation in this context is surprising and counter intuitive which makes it unlikely. Another potential explanation is that consumer beliefs affect spending that drives economic conditions, thus beliefs predict the aggregate stock market. Although currently this explanation is only mildly supported because of the weak link between consumer sentiment and consumer spending, it has important implications for economic policy.

From a behavioral finance view, these findings suggest that investor sentiment affects stock prices, and their effects are systematically correlated such that they impact the aggregate stock market. The predictability at both the one-month and one-year horizon and the finding that the magnitude of the slope estimates of change in consumer in the one-year returns sample is approximately 10 times the magnitude in the one-month returns sample suggest that prices adjust to fundamental values slowly over a period of time.

Testing why change in consumer sentiment predicts return is limited by the accuracy of the model and empirical proxies of time-varying expected returns. Therefore, while our results favor a behavioral finance explanation, a rational expectation based explanation cannot be ruled out. However, a rational expectation based explanation must contend with the puzzling question of why the array of variables that should predict expected returns proposed by the literature miss so much of the return predictability that is captured by the change in consumer sentiment.

# Appendix

*A1. University of Michigan consumer sentiment index*

Historical data for the University of Michigan Consumer Sentiment Index are available at http://www.athena.sca.isr.umich.edu and http://www.stls.frb.org/fred/. The procedure used to calculate the Consumer Sentiment Index (CSI) as described in Howrey (2001) is as follows:

To calculate the Consumer Sentiment Index (CSI), first compute the relative scores (the percent giving favorable replies minus the percent giving unfavorable replies, plus 100) for each of the five index questions. Round each relative score to the nearest whole number. Using the formula shown below, sum the five relative scores , divide by the 1966 base period total of 6.7558 , and add 2.0 (a constant to correct for sample design changes since the 1950s).

$$CSI = \frac{COM_1 + COM_2 + COM_3 + COM_4 + COM_5}{6.7558} + 2.0$$

$COM_1$ = "We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago?"

$COM_2$ = "Now, looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

$COM_3$ = "Now, turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

$COM_4$ = "Looking ahead, which would you say is more likely—that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

$COM_5$ = "About the big things people buy for their homes—such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or a bad time for people to buy major household items?"

*A2. Robustness check procedures*

I conduct two robustness checks: one using a correction method as in Stambaugh (1999) and another using a simulation (bootstrap) method proposed by Nelson and Kim (1993). In the system:

$$r_t = a + b\,X_{t-1} + u_t, \tag{A1}$$

$$X_t = c + d\,X_{t-1} + v_t\ , \tag{A2}$$

Stambaugh (1999) shows that the bias in the LS estimate of *b* depends on the contemporaneous covariance between *u* and *v* and the magnitude of *d*. The more persistent the variable *X*, the higher *d,* and the more biased is the LS estimate of *b*.

Following Stambaugh (1999) the bias in the LS estimate is calculated as

$$E[\hat{b} - b] = \frac{\sigma_{uv}}{\sigma_v^2} E[\hat{d} - d]\,, \tag{A3}$$

where variables with hats denote LS estimates. The bias in the LS estimate of *d* is calculated as (Kendall, 1954)

$$E[\hat{d} - d] = -(1 + 3d)/n + O(n^{-2})\,. \tag{A4}$$

The bias term in (A3) is calculated substituting (A4) into (A3). The Stambaugh-bias-adjusted estimate equals the LS estimate subtracted by this bias term. This adjustment provides better estimates than the LS estimates but may still be size distorted (Campbell and Yogo, 2003).

I also use the simulation method proposed by Nelson and Kim (1993) to deal with the potential small sample bias.[23] I estimate Equations (A1) and (A2) using LS. I impose no

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[23] This method is also employed in Kothari and Shanken (1997). Similar simulation methods have been extensively employed to correct for small sample bias.

predictability to generate new series of returns and $X$ using residuals (*u, v*). Each pair (*u, v*) is randomly selected with replacement.[24] The starting value for $X$ is randomly selected from historical values. This procedure creates series of returns and $X$ under the null hypothesis that returns are not predictable. The simulated return series is then regressed on the simulated time series of $X$. This procedure is iterated 1000 times.[25]

As in any bootstrapping method, it is assumed that the observations are representative of the underlying distribution of the variable of interest. Without a theory that suggests what the underlying distribution of the variable should be, it is difficult to assess exactly how well this assumption holds. But we can gauge how well the 48 observations in the one-year returns sample spread out over the tails of the distribution. In the sample, 30% of the observations are further than one standard deviation away from the mean, and 3 out of 48 observations are two standard deviations away from the mean. This indicates that the sample carries reasonable amount of information about the tails of the distribution, which is important in the analysis.

In the bootstrap simulation of the multiple regression, the error term $v$ from the estimate of equation (A2) for each independent variable and the residual $u$ are paired up and randomized separately for each independent variable to construct a randomized series of the independent variable while preserving the joint distribution of each $(u,v)$. This procedure creates series of returns, and other independent variables under the null hypothesis that returns are not predictable by each individual independent variable in the multiple regression.

[24] Nelson and Kim (1993) randomly select the residual pairs without replacement, while Kothari and Shanken (1997) select them with replacement.

[25] I also performed the simulation iterating 1050 times and discarding the first 50 data points to check for any start up effects. The results remain qualitatively the same.

**Table A1: Predictive regressions using all quarterly and monthly data**

This table reports the univariate regression $r_t = a + b\ CCSI_{t-1} + u_{t,}$, where $r_t$ denotes return and $CCSI_{t-1}$ denotes lagged change in consumer sentiment. The sample includes all quarterly and monthly data from 1952 through 2003. Quarterly data of CCSI starts in 1952 with some missing quarters. Monthly data of CCSI starts in January 1978. In the regressions, missing data points are skipped. In the regression of one-year returns on lagged CCSI, returns periods are overlapping. This table reports the Newey-West t-statistic, which corrects for heteroskedasticity and autocorrelations in the residual term. The 'simulation p-value' is the p-value from a distribution obtained using the simulation (bootstrapping) method proposed by Nelson and Kim (1993), which account for small-sample bias and non-normality and autocorrelation of the residual term. **, and *** denote parameter significance levels at 5%, and 1% with respect to the simulated distribution.

| | VWRET t | | EWRET t | |
|---|---|---|---|---|
| | one-month return | one-year return | one-month return | one-year return |
| Intercept | 0.01 | 0.071 | 0.011 | 0.102 |
| Newey-West t | [2.97] | [5.99] | [3.54] | [3.99] |
| Simulation p-value | (0.468) | (0.398) | (0.404) | (0.299) |
| b | -0.037*** | -0.195*** | -0.06*** | -0.557*** |
| Newey-West t | [-2.03] | [-2.17] | [-2.32] | [-3.46] |
| Simulation p-value | (0.004) | (0.001) | (0.002) | (0.001) |
| N | 386 | 375 | 386 | 375 |

**References**


Barberis, N., A. Shleifer and R. Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Brown, G. W. and M. T. Cliff, 2005, Investor Sentiment and Asset Valuation, *Journal of Business* forthcoming.

Brown, G. W. and M. T. Cliff, 2004, Investor Sentiment and the Near-Term Stock Market, *Journal of Empirical Finance*, 11, 1-27.

Campbell, J. Y. and R. J. Shiller, 1998, Valuation Ratios and the Long-Run Stock Market Outlook, *Journal of Portfolio Management,* 24, 11-26.

Campbell, J. Y. and M. Yogo, 2003, Efficient Tests of Stock Return Predictability, Working paper, Harvard University.

Carroll, C. D., J. C. Fuhrer, and D. W. Wilcox, 1994, Does Consumer Sentiment Forecast Household Spending? If so, why?, *American Economic Review,* 84, 1397-1408.

Chen, N., R. Kan, and M. H. Miller, 1993, Are the Discounts on Closed-End Funds a Sentiment Index?, *Journal of Finance,* 48, p. 795-800.

Chopra, N., C. M. C. Lee, A. Shleifer, and R. H. Thaler, 1993, Yes, Discounts on Closed-End Funds Are a Sentiment Index**,** *Journal of Finance,* 48*,* 801-808.

Cochrane, J. H., 2001, *Asset Pricing,* Princeton University Press, Princeton, N.J.

Constantinides, G. M., 1990, Habit Formation: A Resolution of the Equity Premium Puzzle, *Journal of Political Economy*, 98, 519-543.

Constantinides, G. M., and D. Duffie, 1996, Asset Pricing with Heterogeneous Consumers, *Journal of Political Economy*, 104, 219-241.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor Psychology and Security market Under- and Overreactions, *Journal of Finance,* 53*,* 1839-1885.

Daniel, K.. D. Hirshleifer, and A. Subrahmanyam, 2001, Overconfidence, Arbitrage, and Equilibrium Asset Pricing, *Journal of Finance,* 56*,* 921-965.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann, 1990, Noise Trader Risk in Financial Markets, *Journal of Political Economy*, 98, 703-738.

Elton, E. J., M. J. Gruber, and J. A. Busse, 1998, Do Investors Care About Sentiment?, *Journal of Business,* 71, 477-500.

Fama, E. F., 1990, Stock Returns, Expected Returns and Real Activity, *Journal of Finance,* 45, 1089-1108.

Fama, E. F., and G. W. Schwert, 1977, Asset Returns and Inflation, *Journal of Financial Economics,* 5, 115-146.

Fama, E. F., and K. R. French, 1988, Dividend Yields and Expected Stock Returns, *Journal of Financial Economics,* 22, 3-25.

Fama, E. F., and K. R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Ferson, W. E., and C. Harvey, 1991, The Variation of Economic Risk Premiums, *Journal of Political Economy*, 99, 385-416.

Ferson, W. E., S. Sarkissian, and T. Simin, 2003, Spurious Regressions in Financial Economics?, *Journal of Finance*, 58, 1393-1413.

Granger, C. W. J., and P. Newbold, 1974, Spurious Regressions in Economics, *Journal of Econometrics*, 2, 111-120.

Greene, W. H, 2003, *Econometric Analysis*, Prentice Hall Inc., New Jersey.

Hirshleifer, D., 2001, Investor Psychology and Asset Pricing, *Journal of Finance*, 56, 1533-1597.

Hirshleifer, D., and T. Shumway, 2003, Good Day Sunshine: Stock Returns and the Weather, *Journal of Finance*, 58, 1009-1032.

Howrey, E. P., 2001, The Predictive Power of the Index of Consumer Sentiment, *Brookings Papers on Economic Activity,* 1, 175-216.

Jegadeesh, N. and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance,* 48, 65-91.

Kamstra, M., L. Kramer, and M. Levi, 2003, Winter blues: Seasonal Affective Disorder (SAD) and stock market returns, *American Economic Review* 93, 324-343.

Keim, D. B., and R. F. Stambaugh, 1986, Predicting Returns in Bond and Stock Markets, *Journal of Financial Economics,* 17, 357-390.

Kendall, M. G., 1954, Note on Bias in the Estimation of Autocorrelation, *Biometrika,* 41, 403-404.

Kirby, C., 1997, Measuring the Predictability in Stock and Bond Returns, *Review of Financial Studies,* 10, 579-630.

Kothari, S. P., and J. Shanken, 1997, Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis, *Journal of Financial Economics,* 44, 169-203.

Lee, C. M. C., A. Shleifer, and, R. H. Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *Journal of Finance***,** 46, 75-109.

Lettau, M., and S. Ludvigson, 2001, Consumption, Aggregate Wealth, and Expected Stock Returns, *Journal of Finance,* 56, 815-849.

Mehra, R., and E. C. Prescott, 1985, The Equity Premium: A Puzzle, *Journal of Monetary Economics*, 15, 145-157.

Neal, R., and S. M. Wheatley, 1998, Do Measures of Investor Sentiment Predict Returns?, *Journal of Financial and Quantitative Analysis,* 33, 523-547.

Nelson, C. R., and M. J. Kim, 1993, Predictable Stock Returns: The Role of Small Sample Bias, *Journal of Finance,* 48, 641-661.

Newey, W. K., and K. D. West, 1987, Hypothesis Testing with Efficient Method of Moments Estimate, *International Economic Review,* 28, 777-788.

Otoo, M. W., 2000, Consumer Sentiment and the Stock Market, Working paper, Board of Governors of the Federal Reserve System.

Pontiff, J., and L. D. Schall, 1998, Book-to-Market Ratios as Predictors of Market Returns, *Journal of Financial Economics,* 49, 141-160.

Qiu, L. and I. Welch, 2004, Investment Sentiment Measures, NBER working paper.

Shleifer, A., 2000, *Inefficient Markets: An Introduction to Behavioral Finance*, Oxford University Press, Inc., New York.

Shleifer, A., and R. W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance,* 52, 35-55.

Stambaugh, R. F., 1999, Predictive Regressions, *Journal of Financial Economics,* 54, 375-421.

Yule, G. U., 1926, Why Do We Sometimes Get Nonsense Correlations Between Time Series?: A Study in Sampling and the Nature of Time Series, *Journal of the Royal Statistical Society*, 89, 111-64.

**Figure I. Price path of the risky security when investors are overconfident**

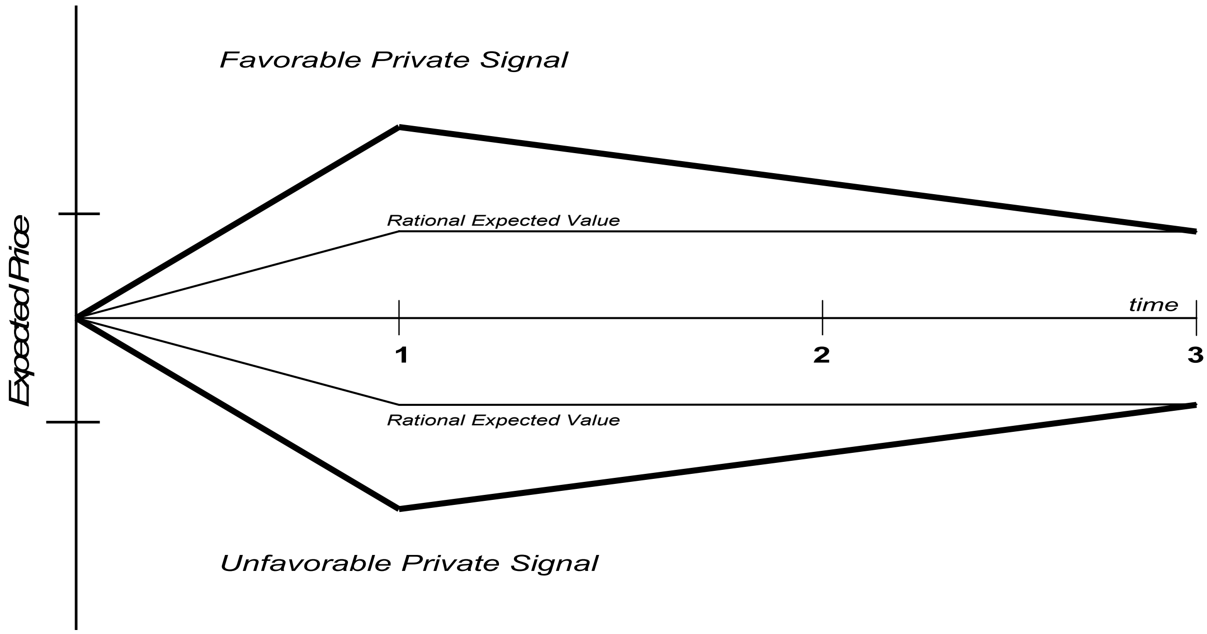


**Figure II. Time series of consumer sentiment index**
Time series of consumer sentiment from November 1952 through December 2003. Quarterly data begin November 1952, and monthly data begin January 1978.

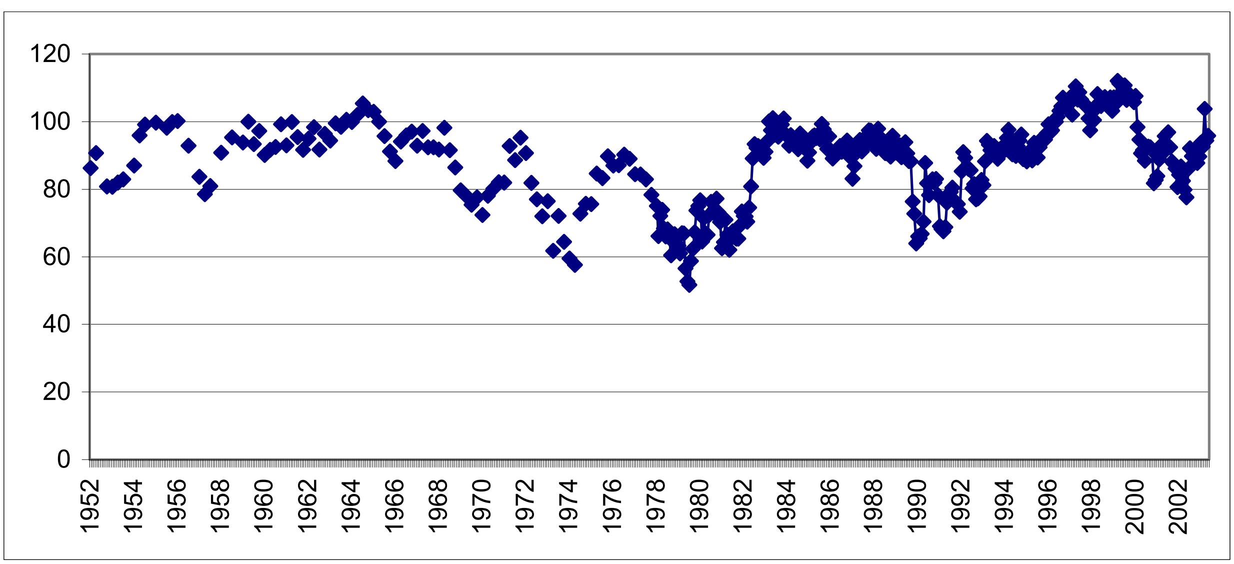

**Figure III. Time series of the change in consumer sentiment index**

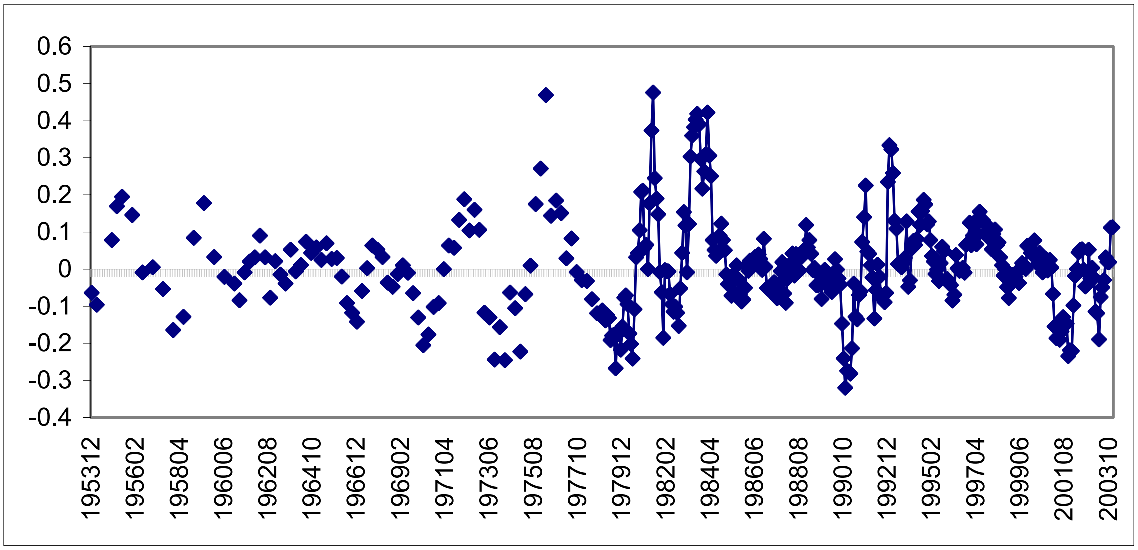


**Figure IV. Monthly averages of the consumer sentiment index 11/1956 - 12/2003**

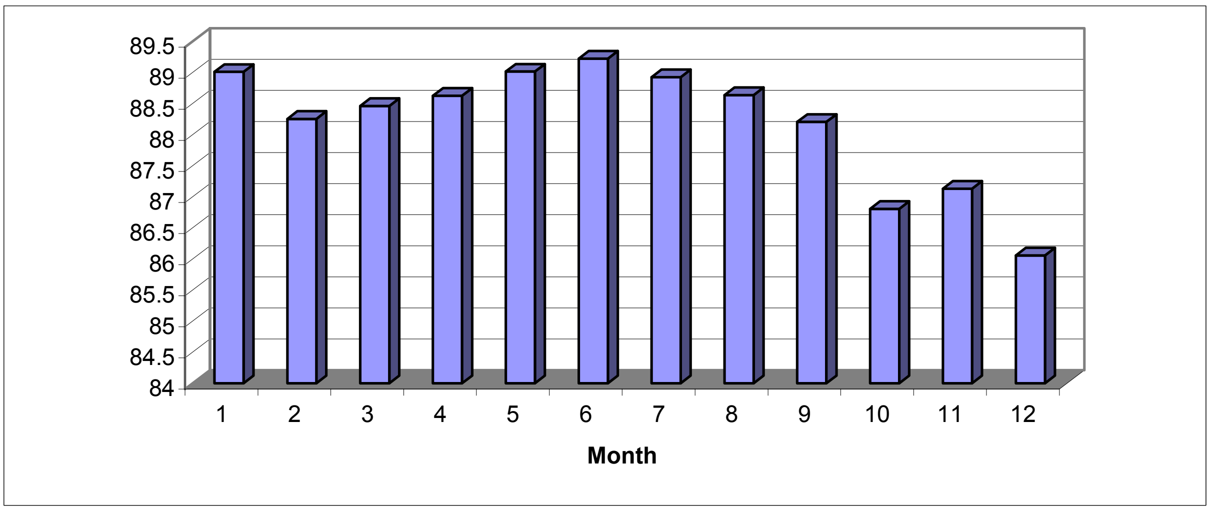

**Table 1: Summary statistics for one-month returns sample**

Panel A presents summary statistics for variables in the one-month returns sample, their autocorrelations, and the Dicky-Fuller unit root test that includes an intercept term. Panel B presents correlations between $CCSI_{t-1}$ and other variables. The variables VWRET and EWRET denote excess CRSP value-weighted portfolio returns and excess CRSP equal-weighted portfolio returns. Excess returns are portfolio returns minus one-month T-bill rate. Returns are from March 1979 through December 2003. DIV is the dividend yield payment accruing to the CRSP value-weighted index over the previous 12 months divided by the index level of the previous month. BM is the book-to-market ratio of the DJIA. DEF is the average yield of Baa bonds minus the average yield of Aaa bonds. TERM is the average yield of Treasury bonds with maturity greater than 10 years minus the three-month T-bill rate. YLD3 is the three-month T-bill rate. CCSI denotes yearly change in consumer sentiment index. The variable cay is the consumption-wealth ratio from Lettau and Ludvigson (2001). CONG denotes monthly consumption growth. ECONG denotes monthly economic growth.

Panel A: Summary statistics, autocorrelations, and Dicky-Fuller test

| | | | | | | | Autocorrelation | | | | Dicky-Fuller |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Std. Dev. | Skewness | Min. | Max. | 1 | 3 | 6 | 12 | p value |
| $VWRET_t$ | 298 | 0.007 | 0.046 | -0.761 | -0.228 | 0.124 | 0.05 | -0.04 | 0.04 | -0.04 | 0.00 |
| $EWRET_t$ | 298 | 0.008 | 0.055 | -0.590 | -0.274 | 0.221 | 0.24 | -0.08 | 0.02 | -0.05 | 0.00 |
| $DIV_{t-1}$ | 298 | 0.029 | 0.012 | 0.208 | 0.010 | 0.060 | 0.99 | 0.95 | 0.91 | 0.82 | 0.55 |
| $BM_{t-1}$ | 298 | 0.476 | 0.296 | 0.853 | 0.121 | 1.207 | 0.99 | 0.97 | 0.93 | 0.84 | 0.30 |
| $DEF_{t-1}$ | 298 | 0.011 | 0.005 | 1.185 | 0.005 | 0.027 | 0.96 | 0.89 | 0.82 | 0.68 | 0.28 |
| $TERM_{t-1}$ | 298 | 0.018 | 0.017 | -0.866 | -0.035 | 0.044 | 0.94 | 0.82 | 0.68 | 0.45 | 0.04 |
| $YLD3_{t-1}$ | 298 | 0.065 | 0.032 | 0.759 | 0.009 | 0.160 | 0.98 | 0.92 | 0.85 | 0.72 | 0.56 |
| $CCSI_{t-1}$ | 298 | 0.011 | 0.128 | 0.694 | -0.319 | 0.476 | 0.87 | 0.59 | 0.35 | -0.14 | 0.00 |
| $cay_{t-1}$ | 275 | 0.002 | 0.014 | -1.005 | -0.040 | 0.026 | 0.96 | 0.88 | 0.81 | 0.65 | 0.33 |
| $CONG_t$ | 298 | 0.006 | 0.004 | 0.372 | -0.008 | 0.018 | -0.05 | 0.27 | 0.10 | -0.01 | 0.00 |
| $ECONG_t$ | 298 | 0.319 | 0.810 | -0.420 | -2.500 | 2.300 | 0.27 | 0.25 | 0.14 | 0.05 | 0.00 |

Panel B: Correlations between change in consumer sentiment and other variables and corresponding p-values (in italics)

| | $VWRET_t$ | $EWRET_t$ | $DIV_{t-1}$ | $BM_{t-1}$ | $DEF_{t-1}$ | $TERM_{t-1}$ | $YLD3_{t-1}$ | $cay_{t-1}$ | $CONG_t$ | $ECONG_t$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $CCSI_{t-1}$ | -0.12 | -0.15 | -0.05 | 0.00 | -0.03 | -0.01 | 0.15 | 0.05 | 0.02 | 0.36 |
| | *0.05* | *0.01* | *0.35* | *0.99* | *0.57* | *0.80* | *0.01* | *0.43* | *0.78* | *0.00* |

**Table 2: Summary statistics for one-year returns sample**

Panel A presents summary statistics for variables in the one-year returns sample, their autocorrelations, and the Dicky-Fuller unit root test that includes an intercept term. Panel B presents correlations between $CCSI_{t-1}$ and other variables. The variables VWRET and EWRET denote excess CRSP value-weighted portfolio returns and excess CRSP equal-weighted portfolio returns. Excess returns are portfolio returns minus the one-month T-bill rate. One-year returns are compounded portfolio returns from July through June of the following year. The return series consists of 48 observations from 1955 through 2003. DIV is the dividend yield payment accruing to the CRSP value-weighted index over the previous 12 months divided by the index level of the previous month. BM is the book-to-market ratio of the DJIA. DEF is the average yield of Baa bonds minus the average yield of Aaa bonds. TERM is the average yield of Treasury bonds with maturity greater than 10 years minus the three-month T-bill rate. YLD3 is the three-month T-bill rate. The variable cay is the consumption-wealth ratio from Lettau and Ludvigson (2001). These variables are for June of each year. The variable CCSI denotes yearly change in consumer sentiment index. It is for May of each year. CONG denotes monthly consumption growth. ECONG denotes monthly economic growth.

Panel A: Summary statistics, autocorrelations, and Dicky-Fuller test

| | | | | | | | Autocorrelation | | | | Dicky-Fuller |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Std. Dev. | Skewness | Min. | Max. | lag 1 | lag 3 | lag 6 | lag 12 | p value |
| $VWRET_t$ | 48 | 0.060 | 0.166 | 0.162 | -0.304 | 0.547 | -0.21 | 0.00 | -0.12 | 0.37 | 0.12 |
| $EWRET_t$ | 48 | 0.097 | 0.229 | 0.599 | -0.425 | 0.921 | -0.30 | 0.05 | -0.14 | 0.29 | 0.02 |
| $DIV_{t-1}$ | 48 | 0.032 | 0.010 | -0.082 | 0.011 | 0.056 | 0.78 | 0.60 | 0.25 | -0.16 | 0.89 |
| $BM_{t-1}$ | 48 | 0.567 | 0.255 | 0.332 | 0.125 | 1.202 | 0.89 | 0.74 | 0.40 | -0.06 | 0.80 |
| $DEF_{t-1}$ | 48 | 0.010 | 0.004 | 1.397 | 0.004 | 0.022 | 0.74 | 0.45 | 0.28 | -0.23 | 0.47 |
| $TERM_{t-1}$ | 48 | 0.012 | 0.013 | -0.006 | -0.023 | 0.041 | 0.45 | 0.10 | 0.12 | -0.16 | 0.10 |
| $YLD3_{t-1}$ | 48 | 0.055 | 0.028 | 1.127 | 0.007 | 0.147 | 0.75 | 0.51 | 0.29 | -0.14 | 0.20 |
| $CCSI_{t-1}$ | 48 | 0.011 | 0.130 | 1.237 | -0.241 | 0.476 | -0.24 | -0.19 | -0.02 | 0.14 | 0.00 |
| $cay_{t-1}$ | 47 | -0.001 | 0.013 | -0.704 | -0.040 | 0.026 | 0.59 | 0.00 | -0.05 | 0.00 | 0.03 |
| $CONG_t$ | 48 | 0.072 | 0.021 | 0.614 | 0.039 | 0.119 | 0.85 | 0.64 | 0.40 | -0.25 | 0.67 |
| $ECONG_t$ | 48 | 0.033 | 0.020 | -0.296 | -0.017 | 0.074 | 0.23 | -0.12 | 0.01 | 0.11 | 0.00 |

Panel B: Correlations between change in consumer sentiment and other variables and corresponding p-values (in italics)

| | $VWRET_t$ | $EWRET_t$ | $DIV_{t-1}$ | $BM_{t-1}$ | $DEF_{t-1}$ | $TERM_{t-1}$ | $YLD3_{t-1}$ | $cay_{t-1}$ | $CONG_t$ | $ECONG_t$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $CCSI_{t-1}$ | -0.30 | -0.40 | -0.12 | -0.08 | 0.09 | -0.04 | 0.12 | 0.43 | 0.28 | -0.42 |
| | *0.04* | *0.01* | *0.40* | *0.57* | *0.53* | *0.77* | *0.42* | *0.00* | *0.06* | *0.00* |

**Table 3: Univariate regressions of one-month value-weighted and equal-weighted returns on change in consumer sentiment and other variables**

This table presents the least square regressions of one-month and one-year value-weighted (VWRET) and equal-weighted (EWRET) excess returns, $r_t$, on various lagged explanatory variables, $X_{t-1}$: $r_t = a + b X_{t-1} + u_t$. Excess returns are calculated from CRSP market indices minus the one-month T-bill rate. CCSI denotes change in consumer sentiment. DIV denotes dividend yield. YLD3 is the yield of a T-bill that matures in 3 months. The variable cay is the consumption-wealth ratio from Lettau and Ludvigson (2001). Newey-West t-statistics (1987) are reported in brackets. Stambaugh-bias-adjusted *b* is the LS regression adjusted for estimation bias as in Stambaugh (1999). The 'simulation p-value' is the p-value from a distribution obtained using the simulation (bootstrapping) method proposed by Nelson and Kim (1993), which account for small-sample bias and the non-normality and autocorrelation of the residual term. The Adj. R-square simulation at the 95% level is also obtained from this simulated distribution. **, and *** denote parameter significance levels at 5%, and 1% with respect to the simulated distribution.

Panel A: Regressions of one-month returns

| Dependent variable | $VWRET_t$ | $VWRET_t$ | $VWRET_t$ | $EWRET_t$ | $EWRET_t$ | $EWRET_t$ |
|---|---|---|---|---|---|---|
| Independent variable | $CCSI_{t-1}$ | $DIV_{t-1}$ | $YLD3_{t-1}$ | $CCSI_{t-1}$ | $DIV_{t-1}$ | $YLD3_{t-1}$ |
| Intercept a | 0.007 | -0.002 | 0.012** | 0.009 | 0.002 | 0.021 |
| Newey-West t | [2.69] | [-0.27] | [2.08] | [2.67] | [0.22] | [2.87] |
| Simulation p-value | (0.408) | (0.264) | (0.237) | (0.365) | (0.359) | (0.103) |
| Slope b | -0.041** | 0.295 | -0.083 | -0.066*** | 0.220 | -0.192 |
| Stambaugh-bias-adjusted b | -0.041** | 0.282 | -0.092 | -0.065 | 0.132 | -0.197 |
| Newey-West t | [-2.6] | [1.26] | [-1.07] | [-2.96] | [0.74] | [-1.96] |
| Simulation p-value | (0.013) | (0.352) | (0.313) | (0.001) | (0.358) | (0.179) |
| Adj. R-square LS | 0.010 | 0.003 | 0.000 | 0.020 | -0.001 | 0.010 |
| Simulation Adj. R-square 95% | 0.012 | 0.017 | 0.013 | 0.016 | 0.013 | 0.018 |
| N | 298 | 298 | 298 | 298 | 298 | 298 |

Panel B: Regressions of one-year returns

| Dependent variable | $VWRET_t$ | $VWRET_t$ | $VWRET_t$ | $EWRET_t$ | $EWRET_t$ | $EWRET_t$ |
|---|---|---|---|---|---|---|
| Independent variable | $CCSI_{t-1}$ | $CAY_{t-1}$ | $DIV_{t-1}$ | $CCSI_{t-1}$ | $CAY_{t-1}$ | $DIV_{t-1}$ |
| Intercept a | 0.065*** | 0.065*** | -0.109 | 0.105*** | 0.098*** | -0.162 |
| Newey-West t | [2.73] | [3.53] | [-1.14] | [3.41] | [3.72] | [-1.45] |
| Simulation p-value | (0.416) | (0.469) | (0.127) | (0.359) | (0) | (0.208) |
| Slope b | -0.386*** | 4.18** | 5.336 | -0.697*** | 3.256 | 8.168 |
| Stambaugh-bias-adjusted b | -0.383*** | 4.023** | 3.660 | -0.694*** | 3.100 | 6.493 |
| Newey-West t | [-2.11] | [3.04] | [1.94] | [-3.37] | [1.96] | [2.43] |
| Simulation p-value | (0.002) | (0.041) | (0.196) | (0.001) | (0.155) | (0.259) |
| Adj. R-square LS | 0.072 | 0.091 | 0.087 | 0.140 | 0.014 | 0.114 |
| Simulation Adj. R-square 95% | 0.061 | 0.209 | 0.156 | 0.038 | 0.140 | 0.195 |
| N | 48 | 47 | 48 | 48 | 47 | 48 |

**Table 4: Multiple regressions for predicting one-month excess market returns**

This table presents estimates from regressions of one-year value-weighted and equal-weighted excess market returns on multiple predictors
$r_t = a + b_1\, CCSI_{t-1} + b_2\, DIV_{t-1} + b_3\, DEF_{t-1} + b_4\, TERM_{t-1} + b_5\, YLD3_{t-1} + b_6\, BM_{t-1} + b_7\, cay_{t-1} + b_8\, r_{t-1} + u,$
where $r_t$ denotes one-month value-weighted (VWRET) and equal-weighted (EWRET) excess returns calculated from CRSP market indices minus the one-month T-bill rate. CCSI denotes change in consumer sentiment. DIV denotes dividend yield. DEF is the average yield of Baa bonds minus the average yield of Aaa bonds. TERM is the average yield of Treasury bonds with maturity greater than 10 years minus the yield of T-bills that mature in 3 months. YLD3 denotes the yield of a T-bill that matures in 3 months. BM denotes the book-to-market value of the DJIA. The variable cay is the consumption-wealth ratio. Lagged returns are one-month lagged return corresponding to the dependent variable. Newey-West t-statistics (1987) are reported in brackets. The 'simulation p-value' is the p-value from a distribution obtained using the simulation (bootstrapping) method proposed by Nelson and Kim (1993), which account for small-sample bias and the non-normality and autocorrelation of the residual term. *, **, and *** denote parameter significance levels at 10%, 5%, and 1% with respect to the simulated distribution.

| Independent variable | $VWRET_t$ | $VWRET_t$ | $VWRET_t$ | $VWRET_t$ | $EWRET_t$ | $EWRET_t$ | $EWRET_t$ | $EWRET_t$ |
|---|---|---|---|---|---|---|---|---|
| Column number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| **Intercept** | -0.012 | 0.011 | -0.011 | -0.006 | -0.006 | 0.016 | -0.008 | -0.001 |
| Newey-West t | [-1.15] | [1.83] | [-1.1] | [-0.62] | [-0.85] | [2.62] | [-1.1] | [-0.45] |
| Simulation p-value | (0.255) | (0.303) | (0.254) | (0.367) | (0.222) | (0.205) | (0.303) | (0.451) |
| **$CCSI_{t-1}$** | -0.035** | -0.038** | | -0.039** | -0.055*** | -0.052** | | -0.055** |
| Newey-West t | [-2.38] | [-2.46] | | [-2.51] | [-3.05] | [-2.75] | | [-2.99] |
| Simulation p-value | (0.05) | (0.029) | | (0.047) | (0.01) | (0.012) | | (0.028) |
| **$DIV_{t-1}$** | 1.072** | | 0.824* | 0.402 | 0.218 | | 0.315 | -0.292 |
| Newey-West t | [1.69] | | [1.25] | [0.57] | [0.31] | | [0.4] | [-0.35] |
| Simulation p-value | (0.042) | | (0.094) | (0.3) | (0.4) | | (0.332) | (0.217) |
| **$DEF_{t-1}$** | -0.017 | | 0.676 | 0.833 | 0.711 | | 1.086 | 1.332 |
| Newey-West t | [-0.02] | | [0.61] | [0.77] | [0.7] | | [0.74] | [0.97] |
| Simulation p-value | (0.267) | | (0.49) | (0.307) | (0.333) | | (0.206) | (0.153) |
| **$TERM_{t-1}$** | 0.177 | | 0.14 | 0.146 | 0.285* | | 0.237 | 0.245 |
| Newey-West t | [1.12] | | [0.8] | [0.89] | [1.6] | | [1.16] | [1.27] |
| Simulation p-value | (0.116) | | (0.221) | (0.2) | (0.133) | | (0.2) | (0.179) |
| **$YLD3_{t-1}$** | | -0.057 | | | | -0.134 | | |
| Newey-West t | | [-0.77] | | | | [-1.63] | | |
| Simulation p-value | | (0.405) | | | | (0.247) | | |
| **$BM_{t-1}$** | -0.032 | | -0.034 | -0.021 | -0.005 | | -0.015 | 0.004 |
| Newey-West t | [-1.15] | | [-1.22] | [-0.77] | [-0.16] | | [-0.41] | [0.11] |
| Simulation p-value | (0.137) | | (0.137) | (0.199) | (0.44) | | (0.232) | (0.5) |
| **$cay_{t-1}$** | | | 0.166 | 0.275 | | | 0.06 | 0.219 |
| Newey-West t | | | [0.7] | [1.17] | | | [0.21] | [0.76] |
| Simulation p-value | | | (0.376) | (0.24) | | | (0.461) | (0.305) |
| **lagged return** | 0.007 | 0.033 | 0.003 | -0.001 | 0.209*** | 0.257*** | 0.207*** | 0.198*** |
| Newey-West t | [0.11] | [0.58] | [0.04] | [-0.01] | [3.78] | [4.51] | [3.72] | [3.4] |
| Simulation p-value | (0.476) | (0.404) | (0.493) | (0.45) | (0.005) | (0.001) | (0.012) | (0.016) |
| R-Square | 0.031 | 0.016 | 0.022 | 0.033 | 0.083 | 0.078 | 0.063 | 0.080 |
| N | 298 | 298 | 275 | 275 | 298 | 298 | 275 | 275 |

**Table 5: multiple regressions for predicting one-year excess market returns**

This table presents estimates from regressions of one-year value-weighted and equal-weighted excess market returns on multiple predictors

$r_t = a + b_1\, CCSI_{t-1} + b_2\, DIV_{t-1} + b_3\, DEF_{t-1} + b_4\, TERM_{t-1} + b_5\, YLD3_{t-1} + b_6\, BM_{t-1} + b_7\, cay_{t-1} + b_8\, r_{t-1} + u,$

where $r_t$ denotes one-year value-weighted (VWRET) and equal-weighted (EWRET) excess returns calculated from CRSP market indices minus the one-month T-bill rate. CCSI denotes change in consumer sentiment. DIV denotes dividend yield. DEF is the average yield of Baa bonds minus the average yield of Aaa bonds. TERM is the average yield of Treasury bonds with maturity greater than 10 years minus the yield of T-bills that mature in 3 months. YLD3 denotes the yield of a T-bill that matures in 3 months. BM denotes the book-to-market value of the DJIA. The variable cay is the consumption-wealth ratio. Lagged returns are one-year lagged return corresponding to the dependent variable. Newey-West t-statistics (1987) are reported in brackets. The 'simulation p-value' is the p-value from a distribution obtained using the simulation (bootstrapping) method proposed by Nelson and Kim (1993), which account for small-sample bias and the non-normality and autocorrelation of the residual term. *, **, and *** denote parameter significance levels at 10%, 5%, and 1% with respect to the simulated distribution.

.

| Independent variable | $VWRET_t$ | $VWRET_t$ | $VWRET_t$ | $VWRET_t$ | $EWRET_t$ | $EWRET_t$ | $EWRET_t$ | $EWRET_t$ |
|---|---|---|---|---|---|---|---|---|
| Column number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| **Intercept** | -0.036 | -0.088 | -0.047 | -0.063 | -0.117 | -0.112 | -0.025 | -0.038 |
| Newey-West t | [-0.44] | [-0.88] | [-0.46] | [-0.62] | [-0.97] | [-1.08] | [-0.2] | [-0.31] |
| Simulation p-value | (0.372) | (0.179) | (0.39) | (0.309) | (0.208) | (0.2) | (0.411) | (0.362) |
| **$CCSI_{t-1}$** | -0.324** | -0.342** | | -0.323** | -0.469** | -0.528*** | | -0.386** |
| Newey-West t | [-2.2] | [-1.87] | | [-2.1] | [-2.41] | [-2.58] | | [-2.14] |
| Simulation p-value | (0.023) | (0.02) | | (0.032) | (0.022) | (0.009) | | (0.044) |
| **$DIV_{t-1}$** | | 4.803 | | | | 7.124 | | |
| Newey-West t | | [1.68] | | | | [2.26] | | |
| Simulation p-value | | (0.166) | | | | (0.13) | | |
| **$DEF_{t-1}$** | -12.996** | | -6.226* | -6.316 | -2.995 | | -1.647 | -2.448 |
| Newey-West t | [-1.97] | | [-0.87] | [-0.84] | [-0.47] | | [-0.23] | [-0.35] |
| Simulation p-value | (0.02) | | (0.06) | (0.117) | (0.297) | | (0.203) | (0.319) |
| **$TERM_{t-1}$** | 4.618* | | 4.475 | 4.202 | 5.2 | | 3.479 | 3.391 |
| Newey-West t | [2.69] | | [1.87] | [2.21] | [2.28] | | [1.17] | [1.39] |
| Simulation p-value | (0.053) | | (0.133) | (0.162) | (0.129) | | (0.285) | (0.329) |
| **$YLD3_{t-1}$** | 1.583 | | 0.227 | 0.653 | -0.353 | | -1.780 | -1.134 |
| Newey-West t | [1.4] | | [0.21] | [0.54] | [-0.26] | | [-1.35] | [-0.89] |
| Simulation p-value | (0.115) | | (0.33) | (0.245) | (0.44) | | (0.372) | (0.436) |
| **$BM_{t-1}$** | 0.182 | | 0.204 | 0.185 | 0.381* | | 0.415* | 0.374* |
| Newey-West t | [1.24] | | [1.22] | [1.15] | [2.9] | | [2.57] | [2.42] |
| Simulation p-value | (0.219) | | (0.169) | (0.195) | (0.1) | | (0.096) | (0.1) |
| **$cay_{t-1}$** | | | 2.323** | 2.533** | | | 0.796 | 0.865 |
| Newey-West t | | | [0.23] | [1.49] | | | [0.3] | [0.36] |
| Simulation p-value | | | (0.023) | (0.028) | | | (0.219) | (0.192) |
| **lagged return** | -0.025 | 0.004 | -0.164 | -0.032 | -0.133 | -0.106 | -0.304* | -0.185 |
| Newey-West t | [-0.18] | [0.03] | [-0.98] | [-0.21] | [-0.94] | [-0.76] | [-2.23] | [-1.49] |
| Simulation p-value | (0.5) | (0.489) | (0.26) | (0.429) | (0.358) | (0.346) | (0.052) | (0.282) |
| R-Square | 0.319 | 0.176 | 0.227 | 0.270 | 0.304 | 0.267 | 0.250 | 0.298 |
| N | 48 | 48 | 47 | 47 | 48 | 48 | 47 | 47 |

**Table 6: Out-of-sample forecast**

The out-of-sample predictive power of change in consumer sentiment is compared to the benchmark AR(1) model. For monthly returns, an estimation period of 132 months (11 years) is used to forecast one-month-ahead returns in a rolling window forecast. For yearly returns, an estimation period of 20 years is used to forecast one-year-ahead returns in a rolling window forecast. This table reports the mean squared error (MSE) between the predicted returns and realized returns for the change in consumer sentiment model and the AR(1) model.

Panel A: Value-weighted market returns

| | MSE | |
|---|---|---|
| Model | $VWRET_t = a + b\ CCSI_{t-1}$ | $VWRET_t = a + b\ VWRET_{t-1}$ |
| Monthly returns | 0.00196 | 0.00197 |
| Yearly returns | 0.02729 | 0.03238 |

Panel B: Equal-weighted market returns

| | MSE | |
|---|---|---|
| Model | $EWRET_t = a + b\ CCSI_{t-1}$ | $EWRET_t = a + b\ EWRET_{t-1}$ |
| Monthly returns | 0.0030 | 0.0029 |
| Yearly returns | 0.0413 | 0.0454 |

**Table 7: Multiple regression of size and book-to-market portfolios**

This table presents the slope coefficients of change in consumer sentiment ($CCSI_{t-1}$) in the multiple regressions of one-year returns of 25 portfolios formed based on size (log capitalization) and book-to-market on the following lagged variables: $CCSI_{t-1}$, $DEF_{t-1}$, $TERM_{t-1}$, $YLD3_{t-1}$, $cay_{t-1}$. The one-year returns are compounded monthly returns from July of year *t* through June of year *t+1*. The Newey-West t-statistics (1987) are reported in brackets. **, and *** denote parameter significance levels at 5% and 1% respectively.

| Book-to-market | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|
| Size | | | | | |
| Small | -0.762*** | -0.62*** | -0.795*** | -0.54*** | -0.429** |
| Newey-West t | [-2.69] | [-2.79] | [-3.96] | [-2.81] | [-2.34] |
| 2 | -0.745*** | -0.555** | -0.473** | -0.405*** | -0.335** |
| Newey-West t | [-2.88] | [-2.6] | [-2.52] | [-2.69] | [-2.35] |
| 3 | -0.599** | -0.564*** | -0.39** | -0.368** | -0.372** |
| Newey-West t | [-2.34] | [-2.71] | [-2.2] | [-2.5] | [-2.32] |
| 4 | -0.689*** | -0.501*** | -0.509*** | -0.389** | -0.378** |
| Newey-West t | [-3.08] | [-2.78] | [-3.05] | [-2.28] | [-2.24] |
| Large | -0.378* | -0.397** | -0.301* | -0.288* | -0.21 |
| Newey-West t | [-1.68] | [-2.36] | [-1.86] | [-1.78] | [-1] |

**Table 8: Change in consumer sentiment and economic cycles**

This table presents estimates from multiple regressions of value-weighted (VWRET) and equal-weighted (EWRET) excess one-month and one-year returns on $CCSI_{t-1,}$ controlling for contemporaneous values of economic growth ($ECONG_t$) and consumption growth ($CONG_t$) and lagged variables of other predictors. CONG is change in logarithm of consumption. In the one-month sample, ECONG is the change in the logarithm of the coincidence index. In the one-year sample, ECONG is the change in the logarithm of the real GDP. Variables CONG and ECONG are calculated over the exact same period as returns. For example, in regressions of one-year returns, returns are from July of year *t* through June of year *t+1*, and CONG and ECONG are also from July of year *t* through June of year *t+1*. The excess returns are from CRSP market indices minus the one-month T-bill rate. CCSI denotes change in consumer sentiment. DIV denotes dividend yield. DEF is the average yield of Baa bonds minus the average yield of Aaa bonds. TERM is the average yield of Treasury bonds with maturity greater than 10 years minus the yield of T-bills that mature in 3 months. YLD3 denotes the yield of a T-bill that matures in 3 months. BM denotes the book-to-market value of the DJIA. The variable cay is the consumption wealth ratio from Lettau and Ludvigson (2001). The Newey-West t-statistics (1987) are reported in brackets. **, and *** denote parameter significance levels at 5% and 1% respectively.

| Independent variable<br>column number | one month<br>$VWRET_t$<br>1 | one month<br>$EWRET_t$<br>2 | one year<br>$VWRET_t$<br>3 | one year<br>$EWRET_t$<br>4 |
|---|---|---|---|---|
| **Intercept** | -0.010 | -0.009 | 0.042 | 0.007 |
| Newey-West t | [-0.87] | [-0.72] | [0.48] | [0.06] |
| **$CCSI_{t-1}$** | -0.033** | -0.044** | -0.468** | -0.594** |
| Newey-West t | [-1.96] | [-2.15] | [-2.42] | [-2.14] |
| **$DIV_{t-1}$** | 0.177 | -0.726 | | |
| Newey-West t | [0.25] | [-0.91] | | |
| **$DEF_{t-1}$** | 1.060 | 1.605 | -8.372 | -6.082 |
| Newey-West t | [0.97] | [1.16] | [-1.23] | [-0.78] |
| **$TERM_{t-1}$** | 0.192 | 0.331* | 3.902** | 4.531 |
| Newey-West t | [1.23] | [1.83] | [2.03] | [1.52] |
| **$YLD3_{t-1}$** | | | 2.120 | 0.806 |
| Newey-West t | | | [1.76] | [0.39] |
| **$BM_{t-1}$** | -0.025 | 0.000 | 0.424** | 0.558** |
| Newey-West t | [-0.91] | [0.01] | [2.46] | [2.3] |
| **$cay_{t-1}$** | 0.383 | 0.392 | 0.821 | 0.064 |
| Newey-West t | [1.57] | [1.42] | [0.48] | [0.02] |
| **Lagged return** | -0.019 | 0.187** | -0.005 | -0.062 |
| Newey-West t | [-0.25] | [3.3] | [-0.04] | [-0.43] |
| **$CONG_t$** | 1.83** | 2.86*** | -4.877*** | -3.743 |
| Newey-West t | [2.09] | [2.91] | [-2.86] | [-1.2] |
| **$ECONG_t$** | -0.004 | -0.008 | 1.479 | 0.278 |
| Newey-West t | [-0.9] | [-1.51] | [1.06] | [0.13] |
| R-Square | 0.051 | 0.111 | 0.398 | 0.350 |
| N | 275 | 275 | 47 | 47 |