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# A More Predictive Index of Market Sentiment

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Recently, finance literature has turned to non-economic factors such as investor sentiment as possible determinants of asset prices. Using mutual fund data, I calculate a new sentiment measure, a perceived loss index. The advantage of the loss index is that it can determine perceived risk for different categories of equities, including market capitalization, style and sector. Results provide evidence that the perceived loss index outperforms all other sentiment and systematic risk measures in predicting future medium run returns, especially for one- and two-year horizons. This evidence pertains not just to broad market returns but also to capitalization-style and sector specific indice returns as well. In addition, I provide evidence that the loss index can be used as a quantitative measure to detect bubbles and financial crises in financial markets.

***Keywords:*** Financial markets, Behavioral finance

## INTRODUCTION

The motivation to study the effects of investor sentiment on asset prices comes from the fact that fundamental based models do not fully explain asset price movement in the short to medium term. Flood and Rose [2007] find that a random walk model of stock prices performs as well as any estimated model at 1–12-month horizons, even though they base their forecasts on actual future fundamentals. In response, researchers have explored the possible effect of investor sentiment on asset prices. Brown and Cliff [2005] find evidence that investor sentiment affects future asset prices in the long run. Baek, Bandopadhyaya and Du [2005] suggest that shifts in investor sentiment may explain short-term movements in asset prices better than any other set of fundamental factors. However, because traditional finance theory leaves no role for investor sentiment, the issue is still open to debate.

In this paper, I test a new sentiment measure, created by Friedman and Abraham [2008]. The sentiment measure was developed using two insights from behavioral finance. The first insight is that investors are loss averse. Loss aversion, developed by Tversky and Kahneman [1979], means investors are more affected by losses than by gains. Loss aversion kicks in when investors (or their acquaintances) are hit by losses, so they become more pessimistic about the reward/risk prospects. Loss aversion subsides when investors (or their acquaintances) experience gains.

The second insight is that investors place greater weight on the most current performance. Investors remember the most current loss and forget losses far in the past. Friedman and Abraham model this insight by using an exponential average of losses.

Based on the ideas of loss aversion and exponential averaging, Friedman and Abraham calculate a sentiment measure and use it in a computer-simulated stock market. The computer-generated model involves a population of investors who make allocation decisions between a market index and risk-free security based on the tradeoff between expected return and sentiment where sentiment is calculated in three steps. First, losses of each simulated investor are tabulated (positive returns are set to zero). Second, an exponential average of those losses is calculated. Third, for each time period the exponential average of investor losses are averaged across all investors. This creates a sentiment index for each date such that when losses of the investors are high, bearish sentiment is strong. When investors experience gains bearish sentiment is weak. In addition, the sentiment index follows the intuition of loss aversion where losses and gains are treated asymmetrically. For example, if two investors earn positive returns for the week, 0.1% and 50%, their positive returns are treated equally because they are both set to zero. Therefore, their returns contribute to the sentiment index by lowering bearish sentiment equally. However, if two investors

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experience losses for the week, $-.1\%$ and $-50\%$, the $-0.1\%$ loss contributes little to increasing bearish sentiment, but a $-50\%$ loss contributes greatly to increasing bearish sentiment. Moreover, once losses become widespread, bearish sentiment can increase quickly.

I contribute to the literature by calculating Friedman and Abraham's index (called the perceived loss index) using real financial market data. More specifically, I use mutual fund data for two reasons. First, portfolio managers handle the majority of money in industrialized countries either through pension funds, mutual funds, hedge funds or other types of vehicles. Second, the focus is on fund losses because an increase in losses leads to higher investor bearish sentiment. The higher level of bearish sentiment provides an incentive for investors to pull their money out of the fund, which induces the fund manager to sell to raise cash. This creates a feedback loop among losses, redemptions and selling that can generate financial crises. Even though I use mutual fund returns, I also calculate the perceived loss index using specific stock returns to test whether there exist a measurable difference between the two data sets.

The purpose of this paper is to test how the perceived loss index performs in explaining contemporaneous and future medium run returns. Running computer simulations of Friedman and Abraham's model, I find a feedback exists between selling and mounting losses. The feedback persists when losses occur, and the more exposed investors get hit the hardest and sell the fastest. This puts downward pressure on asset prices, increasing losses and further increasing the level of perceived risk, potentially creating vicious cycles. During these cycles, losses today lead to more losses in the future. Therefore, I test whether the index has significant predictive power using real market data.

Even though there has been a fair amount of research in this area, there exist three underlying distinctions between my paper and other research. First, I calculate a new index using a data set consisting of weekly individual mutual fund returns from more than 14,000 domestic mutual funds. Other authors use monthly survey data and aggregate sentiment proxies to measure investor sentiment. Second, I test how the perceived loss index performs against other popular measures of investor sentiment in explaining contemporaneous and future returns. These other measures include the University of Michigan's consumer confidence index, Baker Wrugler sentiment index, VIX, put call ratio and advance to decline ratio. Many researchers test different sentiment measures but none test their relative performance. Lastly, unlike other measures, I measure investor sentiment for portfolios of capitalization-style and sector-specific stocks in addition to the broad market. No such measure has been created that has been able to measure sentiment, for example, in a portfolio of small growth or financial stocks.

My first hypothesis is that the perceived loss index should be a priced factor in an asset pricing equation. It has been recognized that investor sentiment may be an important component of the market pricing process.[1] I test this hypothesis by including the perceived loss index as a factor in the Fama French three-factor asset pricing regression.

My second hypothesis is that the perceived loss index outperforms other sentiment measures in predicting future medium-run returns. Intuitively, this hypothesis is appealing because the feedback between selling and losses (or buying and positive returns) can build overtime. Therefore, today's sentiment level might be able to forecast future returns in the medium run. In addition, I study medium- to long-run returns since it makes sense that the index has no predictive power in the short-term since short-run predictability would lead to trading strategies that generate high returns. However, it is reasonable that investor sentiment can predict returns over longer periods in a way that is not easy to arbitrage. I test this hypothesis by regressing future k-period log returns on both sentiment and control variables. I choose control variables that remove economic fundamentals because the sentiment proxies already reflect economic fundamentals to a degree. These control variables may simply control for the level of actual risk rather than provide any indication of perceived risk. Controlling for economic fundamentals should then capture the gap between perceived and actual risk rather than changes in the underlying risk.

My third hypothesis is that the capitalization-style and sector perceived loss indices outperform the broad based perceived loss index in explaining asset price portfolio returns formed by capitalization, style and sector. Brown and Cliff [2005] find broad-based sentiment levels have a greater effect on large capitalization stocks than small cap stocks, even though theory concludes that smaller firms are more difficult to value and thus should be affected more by investor sentiment. I retest this result using an index that measures the perceived risk of small capitalization stocks.

Statistical analysis yields three important results. First, neither the perceived loss index, VIX, put call ratio, Consumer Confidence index, Baker Wrugler Index nor the advance to decline ratio provide any significant power in explaining contemporaneous returns. Second, the perceived loss index outperforms all other measures in explaining future medium-run returns. The perceived loss index has significant predictive power in all horizons, especially for the one- and two-year horizons. The statistical significance of the perceived loss index after controlling for fundamental risk factors provides evidence a gap between actual and perceived risk may exist meaning prices can deviate from fundamental value in ways that are difficult to arbitrage. In addition, the statistical significance of the index provides evidence that the feedback mechanism between selling and losses holds in actual data.

Third, I find that the perceived loss index can be used to detect financial crises in real time. Figure 1 shows that the index crosses its threshold at the beginning of every crisis since 1984. Therefore, the index is not so much a leading indicator predicting a crisis months before the onset.

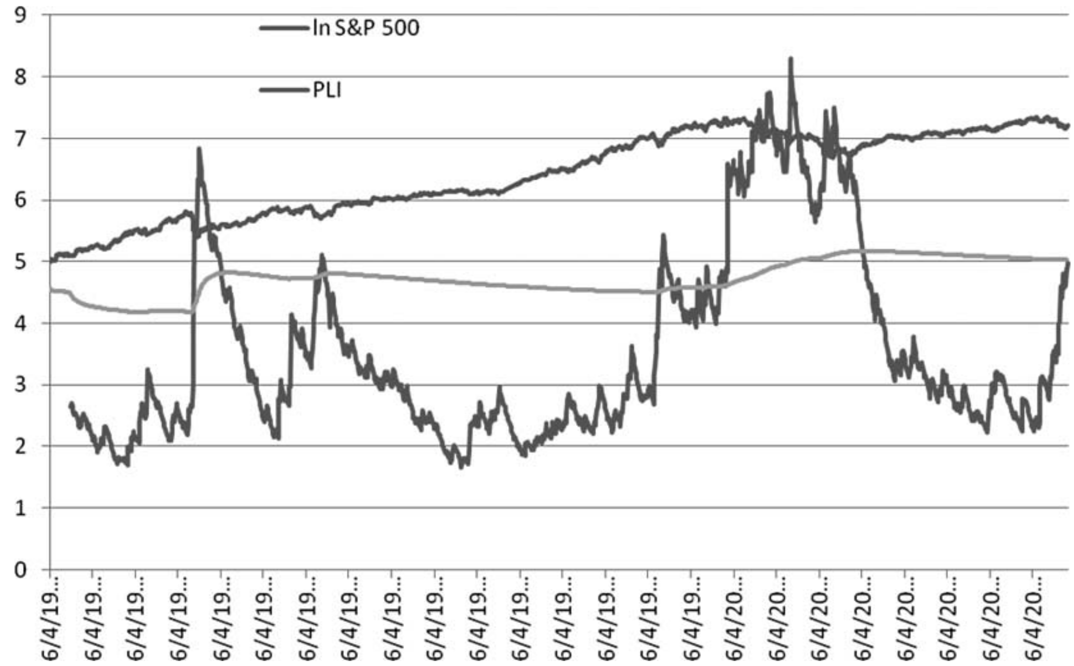


FIGURE 1 S&P 500 vs. Perceived loss index.

However, it identifies the emergence of a crisis in real time. For example, the index detects the tech crash as of April 2000. As of that date, investors were uncertain whether there was a bump in the road of an increasing stock market or the start of a crisis. This index clearly identifies a crisis. Moreover, the index can provide some indication of how long a crisis will last. The greater the magnitude of the crisis, the longer it takes for the crisis to end. Today's crisis is one and half times greater in magnitude than the tech crash; therefore, the stock market should take one and half more time than the tech crash to bottom out. In addition, the perceived loss index for value related stocks is consistently below the perceived loss index for growth-related stocks. The finance literature has shown that value stocks outperform growth stocks in the long run even though value stocks have lower betas, called the value premium puzzle. The behavioral finance literature suggests that stocks with lower perceived risk should earn higher returns. Therefore, the above result may indicate that

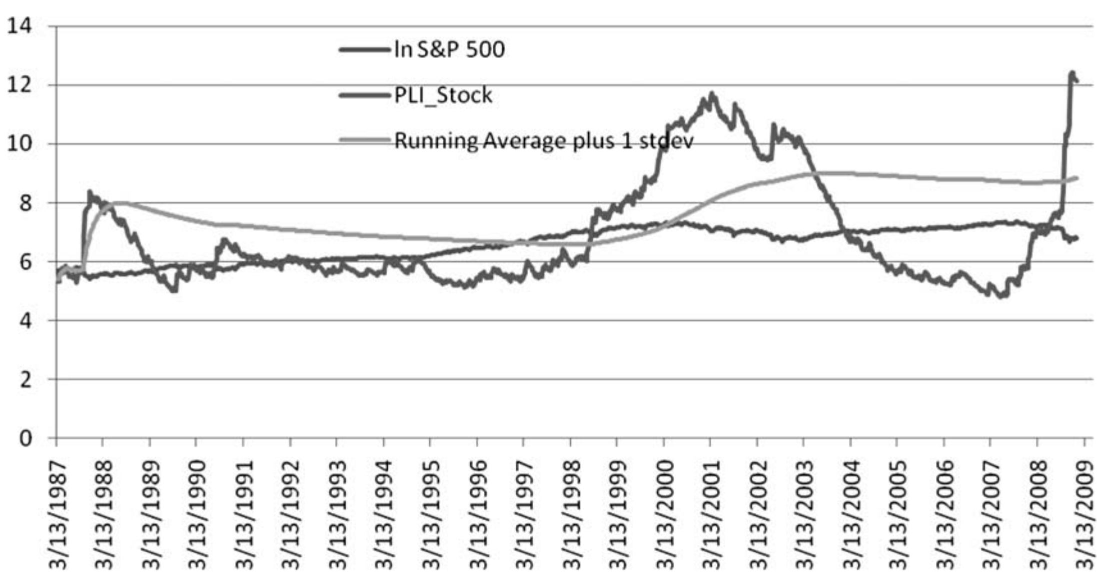


FIGURE 2 S&P 500 vs. stock perceived loss index.

TABLE 1
Summary Statistics.

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| UMCSENT | 93.64 | 8.93 | 72.69 | 112.82 | 762 |
| BWSENT | 0.13 | 0.65 | -0.91 | 3.03 | 709 |
| Put Call | 0.78 | 0.2 | 0.3 | 1.47 | 814 |
| ADV_DEC | 1.09 | 0.45 | 0.29 | 4.3 | 814 |
| VIX | 18.8 | 6.67 | 9.04 | 44.92 | 814 |
| PLI_all | 0.04 | 0.01 | 0.02 | 0.07 | 814 |

*Note.* Table 1 is a summary table of sentiment variables. UMCSENT is the Michigan consumer confidence index. BWSENT is the Baker Wrugler sentiment index. Put_call is the put to call ratio. Adv_dec is the advance to decline ratio. VIX is the weekly implied volatility. PLI_all is the weekly perceived loss index for all U.S. common stock mutual funds.

the behavioral finance approach offers an explanation of the value premium puzzle. In addition, I find that the perceived loss index for sector-related stocks, including housing and financial stocks, has predictive power for portfolios of sector stocks.

The implications of these results could be profound from both a policy and asset allocation perspective. First, major policy decisions usually occur after a financial crisis. The perceived loss index could be used to capture the level of risk in the market, allowing policy makers to act in a timely manner to mitigate major crises. Second, the index could have a major influence on how funds and banks manage their portfolios.

## LITERATURE REVIEW

Most of the literature has used two types of investor sentiment measures: survey data and sentiment proxies. Some of the most prominent sentiment proxies include the Consumer Confidence Index, VIX, the put call ratio, mutual fund cash positions, mutual fund redemptions, closed-end fund discount and advance to decline ratio. All of these measures are determined differently and may represent sentiment level for different horizons and segments of the stock market. However, all these measures at some level represent the amount of bullishness and bearishness in the stock market. The VIX is also known as the “fear index.” The greater the amount of fear of financial loss, the more the “fear factor” is priced into the cost of puts and consequently VIX tends to go up. The put call ratio is the ratio of the trading volume of put options to call options, where a high volume of puts compared to calls indicates a bearish sentiment in the market. The Consumer Confidence Index is based on survey data and represents the degree of optimism on the state of the economy. It is not a stock market measure, but it does represent sentiment. The differences that exist could be that some are real time measures of sentiment, some are lagged measures and some are leading indicators. The purpose of this paper is to test which of these measures along with the perceived loss index is the best predictor of future stock market returns. Most of the previous literature has concentrated on three types of analysis.

First, the literature has examined whether sentiment levels should be a priced factor in a standard asset pricing regression. Since numerous tests of the original CAPM model indicate that it does not do well in explaining the cross-section of stock returns, Fama and French [1993] present a three-factor model that includes factors for size and relative value in addition to the original market factor. Durand, Lim and Zumwalt [2007] examine how investors’ expectation of the total risk of the market, captured by the VIX, affects U.S. stocks. They find the VIX is priced in a five-factor model of returns. However, when considering the adequacy of the model, they argue that further work remains to be done in the area.

Second, researchers have examined whether investor sentiment has short-term predictive power. Using survey data, Brown and Cliff [2004] investigate investor sentiment and its relation to near-term stock market returns. They find that sentiment levels and changes are strongly correlated with contemporaneous market returns but find little predictive power for near-term future stock returns. In addition, they find no evidence that investor sentiment affects small stocks.

TABLE 2
Correlation Matrix.

| | Rm_Rf | Baa_Aaa | UMCSENT | BWSENT | Put_Call | ADV_DEC | VIX | PLI_all |
|---|---|---|---|---|---|---|---|---|
| Rm_Rf | 1 | | | | | | | |
| Baa_Aaa | −0.023 | 1 | | | | | | |
| UMCSENT | 0 | −0.304 | 1 | | | | | |
| BWSENT | −0.116 | −0.212 | 0.39 | 1 | | | | |
| Put_Call | 0.022 | 0.209 | −0.51 | −0.293 | 1 | | | |
| ADV_DEC | 0.042 | 0.118 | −0.06 | 0.003 | 0.331 | 1 | | |
| VIX | −0.177 | 0.323 | 0.307 | 0.245 | −0.201 | 0.034 | 1 | |
| PLI_all | −0.085 | 0.645 | 0.011 | 0.211 | −0.147 | 0.139 | 0.643 | 1 |

*Note.* Table 2 is a correlation matrix of market risk premium, Rm_Rf, spread between Baa and Aaa corporate bonds, Baa_Aaa and sentiment variables.

TABLE 3
Contemporaneous Asset Price Regression with Four Factors.

| Variable | Small Value | Small Neutral | Small Growth | Large Value | Large Neutral | Large Growth |
|---|---|---|---|---|---|---|
| | | | Sentiment Estimates | | | |
| ln_UMCSENT | −0.68 | 0.11 | 0.19 | 0.25 | 0.01 | −0.02 |
| | (0.23) | (0.16) | (0.14) | (0.17) | (2.3) | (0.21) |
| BWSENT | 0.08 | 0.14 | 0.06 | 0.07 | 0.12 | 0.02 |
| | (0.42) | (0.03)** | (0.02)** | (0.02)** | (0.04)** | (0.04) |
| ln_Put_Call | −0.2 | 0.02 | −0.14 | −0.08 | −0.1 | −0.15 |
| | (0.1) | (0.08) | (0.07)** | (0.07)** | (0.11) | (0.1) |
| ln_ADV_DEC | −0.28 | 0.06 | −0.02 | 0.08 | −0.07 | −0.21 |
| | (0.07) | (0.05) | (0.04) | (0.03) | (0.06) | (0.07) |
| VIX | 0.03 | 0.04 | 0.002 | 0.02 | 0.03 | 0.03 |
| | (0.04) | (0.03) | (0.02) | (0.02) | (0.04) | (0.04) |
| ln_PLI_all | −0.23 | 0.03 | 0 | −0.01 | −0.05 | −0.08 |
| | (0.21) | (0.05) | (0.03) | (0.04) | (0.07) | (0.09) |
| | | | F Statistics | | | |
| No Sentiment | 1634 | 2096 | 3135 | 3544 | 1043 | 1472 |
| ln_UMCSENT | 1081 | 1403 | 1818 | 2339 | 908 | 1103 |
| BWSENT | 929 | 1316 | 1755 | 2398 | 821 | 1041 |
| ln_Put_Call | 1158 | 1515 | 2176 | 2246 | 733 | 1000 |
| ln_ADV_DEC | 1364 | 1632 | 2060 | 2144 | 735 | 1033 |
| VIX | 1132 | 1485 | 2063 | 2187 | 745 | 1003 |
| ln_PLI_all | 1228 | 1581 | 2396 | 2684 | 813 | 1132 |

*Note.* This table shows the estimates on sentiment with its standard errors in parentheses and F statistics from regressing $R_i-R_f$ on three and four factors. The dependent variable, R_i-R_f, is the current weekly excess return on six portfolios formed based on the the Fama and French (1993) procedure where portfolio i (i=1,2,3,4,5,6) is constructed by size and style. R_m-R_f is the market risk premium. SMB is the size premium. HML is the style premium. Sentiment_i is the ith sentiment index. No Sentiment refers to the three factor baseline regression below without the sentiment factor. The regression is run using Newey standard errors with six lags. There are 814 observations from May 29, 1992 to December 28, 2007. * significant at 5%; ** significant at 1%

Third, researchers have studied the relationship between sentiment and future long-run returns. Neal and Wheatley [1998] examine the forecast power of three measures of individual investor sentiment: the level of discounts on closed-end funds, the ratio of odd-lot sales to purchases and net mutual fund redemptions. Using data from 1933–1993, they find evidence that fund discounts and net redemptions predict the size premiums. In addition, they find the difference between small and large firm returns provides little evidence that the odd-lot is useful in predicting returns. Brown and Cliff [2005] find that sentiment, as measured by surveys, is in fact significantly related to long-run stock returns. Specifically, sentiment levels one standard deviation above its mean result in significantly lower returns over the next two or three years. This effect is concentrated in large-capitalization growth stocks.

## SENTIMENT INDEX

The loss index is created in several stages. First, I calculate Friday weekly returns for each fund, $R_{Gi}$. I use Thursday prices when markets are closed on Friday holidays. In addition, I add back distributions because they reduce the fund's net asset value. Second, I only pick up negative returns for each fund setting positive ones to zero, such that, $L_i = \max\{0, -R_{Gi}\}$. Third, I calculate an exponential average of $L_i$ for each fund, $\acute{L}_i(t)$. Investors seem to judge managers by the overall historical track record of the fund, with greater emphasis on more recent results. Taking an exponential average of historical data is a common practice among financial analysts. In the following analysis, I average fund losses using a half life of one year.[2] Lastly, once I calculate the exponential average of each fund's losses, I calculate PLI for each time period by taking the weighted average of $\acute{L}_i$ (t). for each fund i, weighting by its total assets. Therefore, I start with a cross sectional time series of returns for various U.S. mutual funds and end up with a time series of sentiment values.[3] The intuition behind the index is that portfolio managers trade based on the level of perceived risk. Therefore, a sharp increase in the index may lead to selling, putting downward pressure on asset prices, further increasing the loss index and continuing the cycle.

The loss index is determined by using mutual fund data found in the Center for Research in Security Prices (CRSP) and Bloomberg. I use daily NAV, monthly total assets and distributions for 14,242 mutual funds from January 1, 1984, to December 31, 2007. The 14,242 funds include all funds found in the CRSP database that invest in U.S. stocks. Bond and international funds were excluded. The space of funds includes all styles, market capitalizations, intersection of market cap and style and sectors as defined by Lipper. The

TABLE 4
Forecasting Asset Price Regression.

| Variable | 6mth | 12mth | 24mth | 36mth |
|---|---|---|---|---|
| | | Sentiment Estimates | | |
| ln_UMCSENT | −0.56 | −0.4 | −0.41 | −0.62 |
| | (0.27)** | (0.16)** | (0.13)** | (0.13)** |
| BWSENT | −0.12 | −0.1 | −0.11 | −0.06 |
| | (0.01)** | (0.02)** | (0.02)** | (0.02)** |
| ln_Put_Call | 0.23 | 0.19 | 0.19 | 0.16 |
| | (0.05)** | (0.05)** | (0.03)** | (0.03)** |
| ln_ADV_DEC | −0.01 | −0.02 | −0.02 | −0.01 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| VIX | 0.05 | 0.02 | −0.01 | −0.04 |
| | (0.03) | (0.02) | (0.02) | (0.02) |
| ln_PLI_all | −0.24 | −0.31 | −0.38 | −0.33 |
| | (0.05)** | (0.05)** | (0.03)** | (0.03)** |
| | | F Statistics | | |
| baseline | 0.19 | 0.24 | 0.26 | 0.24 |
| ln_UMCSENT | 0.24 | 0.28 | 0.32 | 0.49 |
| BWSENT | 0.28 | 0.34 | 0.44 | 0.4 |
| ln_Put_Call | 0.13 | 0.15 | 0.25 | 0.27 |
| ln_ADV_DEC | 0.19 | 0.22 | 0.27 | 0.28 |
| VIX | 0.2 | 0.24 | 0.26 | 0.36 |
| ln_PLI_all | 0.25 | 0.4 | 0.6 | 0.63 |

*Note.* This table shows the estimates on sentiment and spread between Baa and Aaa corporate bonds with its standard errors in parentheses and F statistics from a regression of k-period log returns, R_i,t+k where is the weekly return for k ahead period returns for the All Investable MSCI Index. The control variables are: detrended 1 month Treasury bill rate, Tbill_1mth, spread between the three-month and one-month Treasury bill rate, Tbill_3_1mth, spread between the ten-year and three-month Treasury bill rate, Tbill_10yr-3mth, the inflation rate, market risk premium, R_m-R_f, size premium, SMB, style premium, HML and an indicator variable that equals one for a recession as determined by NBER and 0 otherwise, Recession. Sentiment_i is the ith sentiment index. The regression is run using Newey standard errors with six lags. There are 814 observations from May 29, 1992 to December 28, 2007. **significant at 5%;**significant at 1%.

sector fund data includes financial, housing, biotech and environmental funds. Using this data, I calculate $PLI_i$ where i is the classification of the fund. The most common measure used in the paper is $PLI_{all}$ where "all" signifies every fund classified by either capitalization, style or the intersection of capitalization and style.[4]

Figure 1 displays the natural log S&P 500, the loss index and a threshold line.[5] I calculate the threshold as a running one standard deviation above the mean. Figure 1 detects the onset of crises in real time when the index crosses its threshold. As seen in the figure, no crisis is detected when a crisis does not exist. The advantage of the level loss index is one can determine the magnitude of the crisis relative to the magnitude of past crises. It can been seen in Figure 1 the current financial crisis is one and half times greater than the tech crash and two times greater than the 87 crash.

One good question is why use mutual fund data and not stock prices? For comparison purposes I also calculate the index using stock prices. I use all U.S. common stocks in the CRSP database. However, I use market capitalization to weight losses instead of total assets. It can be seen that the perceived loss index calculated with mutual fund and stock market data is similar by comparing Figure 2 with Figure 1. One noticeable difference is that the peak of bearish sentiment for the current crisis is relatively larger than the tech bust using mutual fund data; however, they reach approximately the same peak using stock-specific data.

## DEPENDENT VARIABLE

### Contemporaneous Regressions

I use six Fama and French [1993] portfolios, which are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on style or the ratio of book equity to market equity (BE/ME). Returns are calculated on a weekly basis and then annualized.[6]

### Forecasting Regressions

I use MSCI Barra indices for future return data. MSCI Barra calculates more than 100,000 equity, REIT and hedge fund indices daily. Past research has used the Fama and French portfolios formed on the basis of size and style. I use MSCI Barra index levels to find percentage returns that update on a weekly basis.[7] For each index I calculate 6-, 12-, 24-, and 36-month future returns.[8]

## CONTROL VARIABLES

### Contemporaneous Regressions

I run a contemporaneous regression that includes the three most popular factors in the asset pricing literature. These are the excess return on the value-weighted market portfolio, the premium on a portfolio of small stocks relative to large stocks (SMB) and the premium on a portfolio of high book/market stocks relative to low book/market stocks (HML).

### Future Return Regressions

I run regressions using one of the sentiment measures controlling for actual risk factors. According to financial theory, once actual risk factors are controlled for, sentiment indicators should not have any predictive power. My control variables are motivated by the conditional asset pricing literature. I use the 1-month U.S. Treasury bill return (RFx; Campbell [1991], Hodrick [1992]), the difference in monthly returns on 3-month and 1-month T-bills (HB3; Campbell [1987]), the term spread as measured by the spread in yields on the 10-year U.S. Treasury bond versus the 3-month T-bill (Fama and French [1989]), the default spread measured as the difference in yields on Baa and Aaa corporate bonds (Fama [1990]) and the rate of inflation (Fama and Schwert [1977], Sharpe

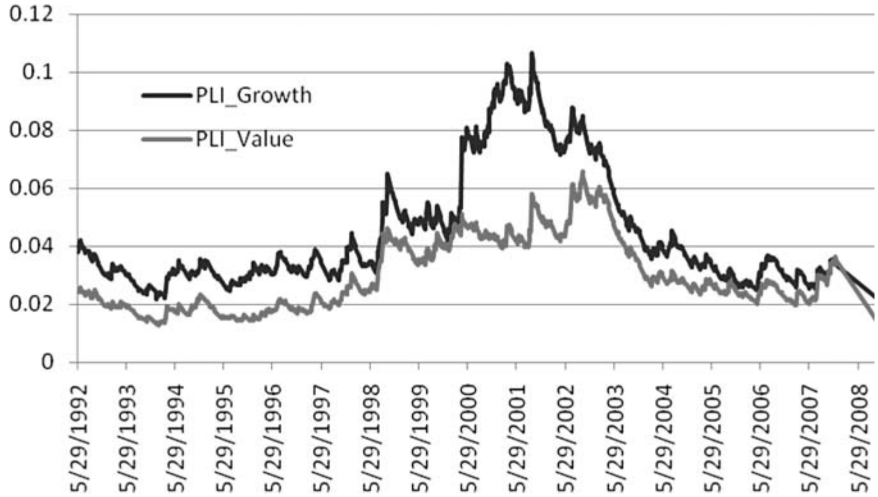


FIGURE 3 Growth vs. value.

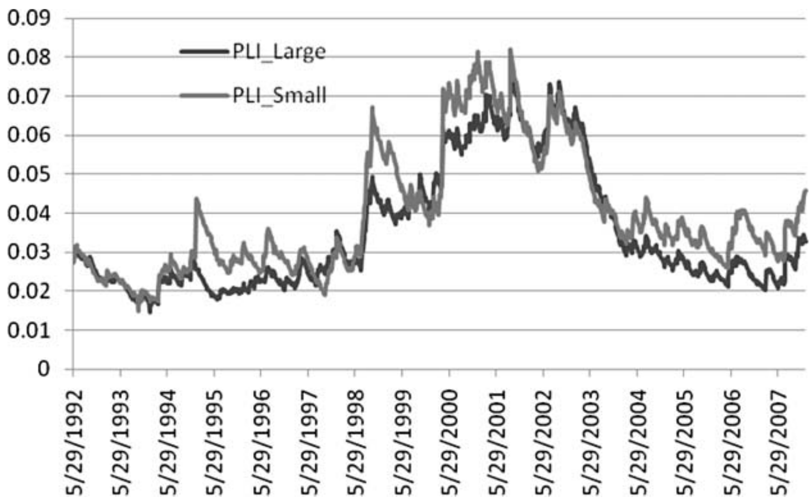


FIGURE 4 Large vs. small.

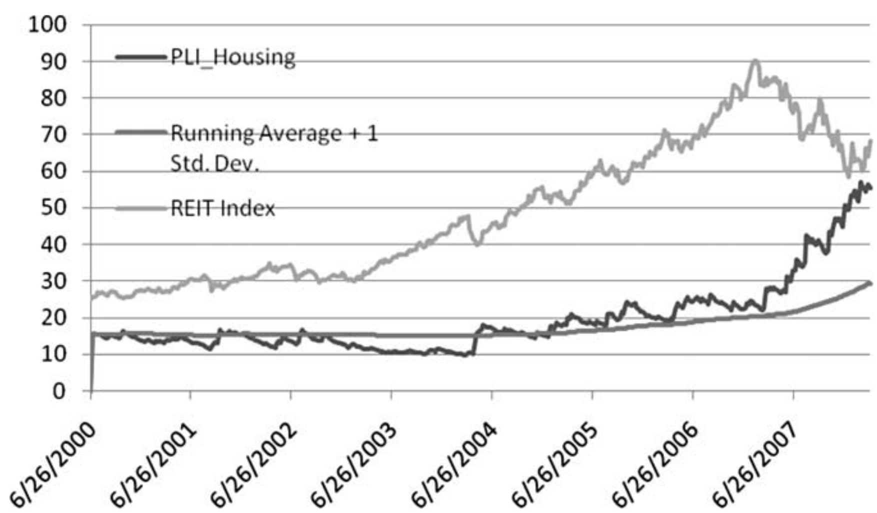


FIGURE 5 Housing.

TABLE 5
Asset Pricing Regression: Broad Based vs Specific Perceived Loss Indices.

| Variable | scv | scg | lcv | leg | growth | value |
|---|---|---|---|---|---|---|
| | | | 6 Month | | | |
| $lnPLI_{scv}$ | 0.03 ± (0.03) | | | | | |
| $lnPLI_{scg}$ | | −0.08 ± (0.04) | | | | |
| $lnPLI_{lcv}$ | | | −0.05*± (0.02) | | | |
| $lnPLI_{lcg}$ | | | | −0.26**± (0.05) | | |
| $lnPLI_{growth}$ | | | | | −0.28 ± (0.06) | |
| $lnPLI_{value}$ | | | | | | −0.07* ± (0.03) |
| $lnPLI_{all}$ | 0.08 ± (0.03)** | −0.06 ± (0.06) | −0.06**± (0.02) | −0.17**± (0.03) | −0.25** ± (0.06) | −0.09** ± (0.03) |
| | | | 12 Month | | | |
| $lnPLI_{scv}$ | 0.004 ± (0.04) | | | | | |
| $lnPLI_{scg}$ | | −0.13* ± (0.07) | | | | |
| $lnPLI_{lcv}$ | | | −0.15** ± (0.04) | | | |
| $lnPLI_{lcg}$ | | | | −0.60** ± (0.08) | | |
| $lnPLI_{growth}$ | | | | | −0.31**± (0.04) | |
| $lnPLI_{value}$ | | | | | | −0.10** ± (0.02) |
| $lnPLI_{all}$ | 0.11*± (0.04) | −0.12* ± (O.O8) | −0.16**± (0.04) | −0.53** ± (0.07) | −0.31** ± (0.04) | −0.10**± (0.03) |
| | | | 24 Month | | | |
| $lnPLI_{scv}$ | −0.005 ± (0.02) | | | | | |
| $lnPLI_{scg}$ | | −0.16**± (0.04) | | | | |
| $lnPLI_{lcv}$ | | | −0.26**± (0.03) | | | |
| $lnPLI_{lcg}$ | | | | −0.65** ± (0.05) | | |
| $lnPLI_{growth}$ | | | | | −0.39** ± (0.03) | |
| $lnPLI_{value}$ | | | | | | −0.17**± (0.01) |
| $lnPLI_{all}$ | 0.00 ± (0.04) | −0.28**± (0.04) | −0.27** ± (0.03) | −0.60** ± (0.05) | −8.1**± (0.80) | −0.15**± (0.02) |
| | | | 36 Month | | | |
| $lnPLI_{scv}$ | 0.01 ± (0.02) | | | | | |
| $lnPLI_{scg}$ | | −0.05 ± (0.03) | | | | |
| $lnPLI_{lcv}$ | | | −0.24**± (0.02) | | | |
| $lnPLI_{lcg}$ | | | | −0.55** ± (0.06) | | |
| $lnPLI_{growth}$ | | | | | −0.30** ± (0.02) | |
| $lnPLI_{value}$ | | | | | | −0.17**± (0.01) |
| $lnPLI_{all}$ | −0.006 ± (0.02) | −0.22** ± (0.04) | −0.24** ± (0.02) | −0.54** ± (0.05) | −9.0**± (0.71) | −0.13** ± (0.02) |

*Note.* This table shows the coefficients on various perceived loss indices with its standard errors in parentheses. The dependent variable is $k$-period ahead log returns, $R_i, t+k$, where $i =$ (MSCI Small Value, Small Growth, Small Cap. Large Value. Large Growth, Large Cap, Growth, Value). The control variables are: detrended 1 month Treasury bill rate, $Tbill_{1mth}$, spread between the three month and one month treasury bill rate, $Tbill_{3\_1mth}$, spread between the ten year and three month treasury bill rate, $Tbill_{10yr-3mth}$, the inflation rate, market risk premium, $R_m$—$R_f$, size premium, *SMB,* style premium, $HML$, and an indicator variable that equals one for a recession as determined by NBER and 0 otherwise, *Recession. Sentiment*$_i$ is the ith sentiment index. The regression is run using Newey standard errors with four lags. There are 814 observations from 05/29/1992 to 12/28/2007. †significant at 10%; * significant at 5%; **significant at 1%

$$R_i, t+k = \beta_0 + \beta_1 * Tbill_{1\,mth} + \beta_2 * Tbill_{3\_1mth} + \beta_3 * Tbill\_spread_{10yr-3mth} + \beta_4 * inflation + \\ \beta_5 * (R_m - R_f) + \beta_6 * SMB + \beta_7 * HML + \beta_8 * recession + \beta_9 * sentiment_i + \epsilon$$

[2002]). In addition to these variables, I 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 a recession indicator variable.

$$\begin{aligned} &R_i, t+k = \\ &\beta_0 + \beta_1 * Tbill_{1\,mth} + \beta_2 * Tbill_{3\_1mth} + \\ &\beta_3 * Tbill_{10yr-3mth} + \beta_4 * inflation + \\ &\beta_5 * (R_m - R_f) + \beta_6 * SMB + \beta_7 * HML + \\ &\beta_8 * recession + \beta_9 * sentiment_i + \varepsilon \end{aligned} \tag{1}$$

Before using sentiment as an explanatory variable, I run a baseline regression using only control variables. I then add a sentiment measure, as in Equation 2, to analyze whether it adds any explanatory power relative to the baseline regression. I take the log of the perceived loss index, put call ratio, advance to decline ratio, VIX, Baker Wrugler Index and Consumer Confidence Index to determine how a percentage change in the sentiment level leads to a change in the k-period ahead annualized return.

Table 1 uses a data set that covers the period from May 29, 1992, to December 31, 2008. Even though I calculate the perceived loss index starting from 1984, I run regressions

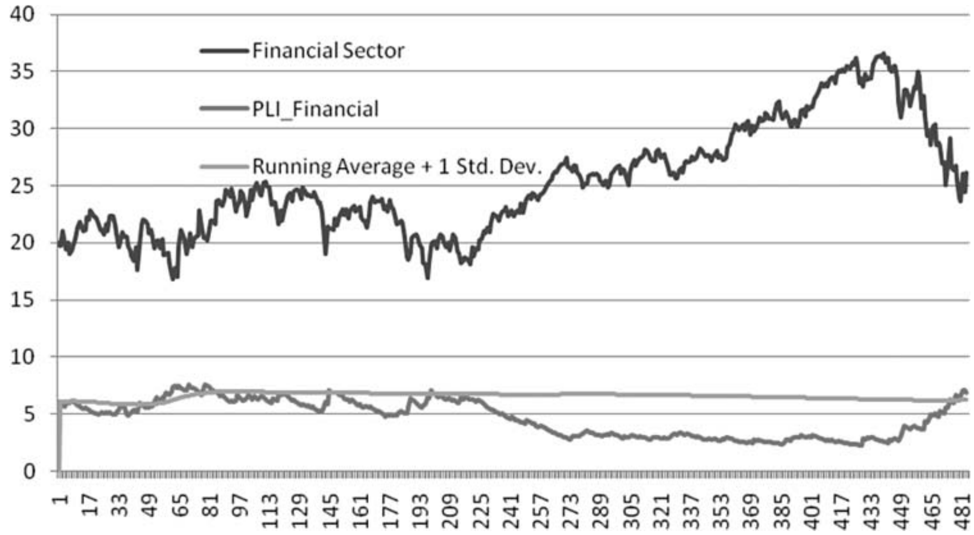


FIGURE 6 Financial sector.

using data from 1992 onward because the MSCI Barra indices and VIX began in 1992.

I calculate the perceived loss index, PLI, using a half life of one year in all regressions. In addition, to allow for serial correlation and heteroskedasticity in the residuals from the estimated regressions I rely on Newey and West [1987] robust t-statistics based on five lags.[9] The Newey-West standard errors assume the error structure is heteroskedastic and possibly autocorrelated up to some lag. Lastly, the table only shows the estimates and standard errors for the sentiment and Baa-Aaa spread. All other estimates and standard errors are available upon request.

## RESULTS

### Summary Table and Figures

Table 2 reports correlations between all the sentiment indicators, spread between Baa and Aaa corporate bonds, and the market premium. The perceived loss index is highly correlated to the VIX and spread between Baa and Aaa corporate bonds with a correlation of 0.645 and 0.643. It is moderately correlated with the Baker Wrugler index with a correlation of 0.211 and has a low correlation with all other sentiment variables.

### Contemporaneous Factor Regression

Results shown in Table 3 confirm that none of the sentiment indicators adds any power in explaining contemporaneous returns. On the other hand, the indicators reduce the explanatory power. This evidence dispels the notion that sentiment should be a priced factor. Using the percentage change in the sentiment level, I find similar non-significant results. Intuitively, as explained by Cochrane and Piazzesi [2005], this is because the contemporaneous returns are heavily influenced by the noises and not the fundamentals.

### Asset Pricing Forecast Regressions

I run a baseline regression regressing future returns at four different horizons as the dependent variable and fundamental risk factors as control variables. I then add one of the sentiment risk factors as an explanatory variable. Results from Table 4 indicate that the perceived loss index is a significant predictive of future asset price returns, contributing to the predicator power relative to the baseline regression for all horizons. The market perceived loss index performs the strongest in the one- and two-year horizons and outperforms the Consumer Confidence Index, VIX, put call ratio and advance to decline ratio in all horizons. The Baker Wrugler index has a greatest R-square for the six month horizon; however, according to an F test, it is not significantly different to the perceived loss index's R-square. These results provide evidence to the testable hypotheses mentioned above. First, the perceived loss index has the greatest predictive power over the medium horizon among all the sentiment proxies tested. Second, the statistical significance of the perceived loss index controlling for fundamental risk factors provides evidence a gap between actual and perceived risk exists. Third, the additional predictive power obtained from adding the perceived loss index to the baseline regression provides evidence that the feedback mechanism between selling and losses also exists. Therefore, the implication is that perceived risk should be included in asset pricing regressions because actual risks do not explain the entire story.

TABLE 6
Adjusted R-Squared of Asset Pricing Regression using Broad and Specific Perceived Loss Indices.

| Variable | sm value | sm growth | lg growth | 1 growth | growth | value |
|---|---|---|---|---|---|---|
| | | | 6 Month | | | |
| $lnPLI_{scv}$ | 0.06 | | | | | |
| $lnPLI_{scg}$ | | 0.12 | | | | |
| $lnPLI_{lcv}$ | | | 13.63 | | | |
| $lnPLI_{lcg}$ | | | | 29.61 | | |
| $lnPLI_{growth}$ | | | | | 22.63 | |
| $lnPLI_{value}$ | | | | | | 8.62 |
| $lnPLI_{all}$ | 0.09 | 0.11 | 14.74 | 27.66 | 22.14 | 9.16 |
| | | | 12 Month | | | |
| $lnPLI_{scv}$ | 0.11 | | | | | |
| $lnPLI_{scg}$ | | 0.18 | | | | |
| $lnPLI_{lcv}$ | | | 25.67 | | | |
| $lnPLI_{lcg}$ | | | | 52.37 | | |
| $lnPLI_{growth}$ | | | | | 43.74 | |
| $lnPLI_{value}$ | | | | | | 18.11 |
| $lnPLI_{all}$ | 0.13 | 0.19 | 25.88 | 53.66 | 44.49 | 18.24 |
| | | | 24 Month | | | |
| $lnPLI_{scv}$ | 0.24 | | | | | |
| $lnPLI_{scg}$ | | 0.31 | | | | |
| $lnPLI_{lcv}$ | | | 124.43 | | | |
| $lnPLI_{lcg}$ | | | | 95.85 | | |
| $lnPLI_{growth}$ | | | | | 79.12 | |
| $lnPLI_{value}$ | | | | | | 82.54 |
| $lnPLI_{all}$ | 0.24 | 0.20 | 130.10 | 95.07 | 84.49 | 88.24 |
| | | | 36 Month | | | |
| $lnPLI_{scv}$ | 0.37 | | | | | |
| $lnPLI_{scg}$ | | 0.30 | | | | |
| $lnPLI_{lcv}$ | | | 116.37 | | | |
| $lnPLI_{lcg}$ | | | | 89.54 | | |
| $lnPLI_{growth}$ | | | | | 87.88 | |
| $lnPLI_{value}$ | | | | | | 90.29 |
| $lnPLI_{all}$ | 0.37 | 0.45 | 100.08 | 97.58 | 83.52 | 78.22 |

*Note*. This table shows the F statistics on regressing future returns on various perceived loss indices witl its standard errors in parentheses. The dependent variable is k-period ahead log returns. $R_i$, $t + k$, where $i =$ (MSCI Small Value, Small Growth, Small Cap, Large Value, Large Growth. Large Cap, Growth, Value). The control variables are: detrended 1 month Treasury bill rate. $Tbill_{1mth}$, spread between the three month and one month treasury bill rate, $Tbill_{3\_1mth}$, spread between the ten year and three month treasury bill rate, T*bill*_10yr - 3mth the inflation rate, market risk premium, $R_m - R_f$, size premium, $SMB$, style premium, $HML$, and an indicator variable that equls one for a recession as determined by NBER and 0 otherwise, *Recession*, *Sentiment*, is the ith sentiment index. The regression is run using; Newey standard errors with four lags. There are 814 observations from 05/29/1992 to 12/28/2007, †significant at 10%; *significant at 5%; **significant at 1%

$$R_i, t + k = \beta_0 + \beta_1 * Tbill_{1\,mth} + \beta_2 * Tbill_{3\_1mth} + \beta_3 * Tbill_{10yr-3mth} + \beta_4 * inflation +$$
$$\beta_5 * (R_m - R_f) + \beta_6 * SMB + \beta_7 * HML + \beta_8 * recession + \beta_9 * sentiment_i + \varepsilon$$

## Sentiment and Cap-Style and Sector Returns

Given evidence that the perceived loss index out predicts other measures of investor sentiment, I proceed to test whether the capitalization-style specific perceived loss indices outperform the broad based index. For example, does the small capitalization-growth stock perceived loss index out predict the broad market perceived loss index for a portfolio formed by small capitalization-growth stocks? To answer this question, I regress future k period returns on the log broad market perceived loss index and on each capitalization-style log perceived loss index controlling for fundamental risk factors. According to results from Tables 5 and 6, there is no significant difference in regressions with control variables. In addition, there is no significant difference in the predictive power between the small cap value, small cap, large value, large cap, value loss and broad market perceived loss indices. The implication here is that the broad based perceived loss index is just as good as the cap-style loss indices in explaining future returns of cap-style portfolios of stock returns.

In addition, I find several interesting results regarding the relationship between the perceived loss index and cap-style asset prices. First, I find evidence, similar to Brown and Cliff [2004], that the large cap portfolios are more influenced by sentiment than are the small cap portfolios. However, unlike Brown and Cliff who find no significant estimates to explain future small cap stock returns, I find significant negative estimates for the two- and three-year horizons. In addition, Brown and Cliff assign this result to using a broad based sentiment measure. I use a small cap sentiment measure and still find a similar result. This may be due to the fact that small-cap stocks are more exposed to idiosyncratic rather than the systematic risks.

Second, growth stocks are more influenced by sentiment than value stocks. This makes sense since growth stocks are harder to value than value stocks.

Third, according to Figure 3, the perceived risk of value stocks is always lower than the perceived risk of growth stocks. Even during the late 1990s when growth outperformed value stocks, the perceived risk of growth stocks was still larger. The figure helps explain the value-premium puzzle and provide evidence that the behavioral finance approach to measuring risk can explain what we see in the real world. According to behavioral finance, the higher the perceived risk the lower the return. As seen in Figure 3, growth stocks have a higher perceived risk and thus should have a lower return than value stock which is what we see in real markets.

## CONCLUSION

Using data from more than 14,000 mutual funds, I calculate a new sentiment index. The sentiment focuses on an exponential average of current and realized losses. Using this index, as well as other popular sentiment measures, reveals several interesting results. First, none of the sentiment measure adds explanatory power relative to the baseline contemporaneous three-factor regression. This result reinforces Durand et al. [2007], who find ambiguous results in determining whether sentiment should be a priced risk factor.

Second, the broad based perceived loss index has predictive power in forecasting asset price returns for both medium- and long-run horizons, especially for the one- and two-year horizons. This result holds even when controlling for fundamental economic and structural risk factors. The implication is that there may be a gap between perceived and actual risk exists. In addition, the perceived loss index outperforms the Consumer Confidence index, Baker Wrugler Index, VIX, put-call ratio and advance to decline ratio in forecasting future returns for all horizons.

Third, the perceived loss index for value stocks, at an all-time low versus the perceived loss index for growth stocks, may provide insight into the value premium puzzle. We know from the finance literature that value stocks, which are considered less risky, outperform growth in the long run. According to the perceived loss theory, a lower perceived loss index should lead to higher returns. Therefore, if value outperforms growth than its loss index should be lower than the loss index for growth stocks, which is the exact result I find. The upshot is that standard deviation may not be the best way to measure risk because it leads to puzzling results. Perhaps we need a different mainstream measure to define risk.

Lastly, I find the housing and financial sector perceived loss index has predictive power for portfolios of housing and financial stocks. As of August 2007 and January 2008, the index indicates we are in a housing and financial crisis. This is obvious now but not a year ago when these indices were suggesting crises.

These results suggest several extensions to the analysis. One extension is to use the loss index for international and fixed income portfolios. International perceived loss indices could not only have predictive power for international stocks but they could have predictive power for correlations of markets. Another extension would be to integrate the perceived loss index into an asset allocation framework. The beauty of the index is that it can calculate the perceived risk not only for the broad market but also for sectors and perhaps fixed income and international assets.

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## NOTES

1. See Fischer and Statman [2000] and Baker and Wurgler [2006].
2. In the regressions below I use PLI calculated with various half lives. The PLI with a half life of one year returned the highest R-square.
3. See Appendix for a more detailed explanation.
4. More specifically, this index uses all funds classified as growth, value, core, small cap, mid cap, large cap, small growth, small value, small core, mid growth, mid value, mid core, large growth, large value and large core.
5. Due to the recent financial crisis I have updated the figures to include the level of the index up until January 1, 2009.
6. The data are taken from Kenneth French's website, ttp://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
7. The MSCI index levels I use include the US Investable Market 2500, Small Cap Value, Small Cap Growth, Large Cap Value, Large Cap Growth, Growth, Value, Small Cap 1750, Large Cap 300, and MSCI REIT Index.

8. For graphical analysis I use the S & P 500 data because it goes back farther in time, where as, the MSCI Indices start in 1992.
9. Using the benchmarkrecommended by Newey and West [1987] that the number of lags chosen should equal 4(n/100) {2/9} and suggested by others that n {1/4} I obtain a lag equal to six.

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## APPENDIX

### Sentiment Variables

The put call ratio is determined as the volume of put option contracts to the volume of call option contracts. I use the data collected by the Chicago Board of Exchange. During strong markets the number of calls bought typically outweighs the number of puts. During weak markets the number of puts bought outnumbers the purchase of calls. Markets are considered strong when the ratio falls below 0.7 and weak when the ratio rises above 1.1. The VIX is constructed by using implied volatilities of options on equities in the S&P 100 index. The implied volatilities of eighth-day near the money, nearby and second nearby options from the S&P 100 index are first computed using the Black-Scholes option pricing model. These volatilities are then weighted to characterize the implied volatility of a 22 trading day at the money option contract on the index. I use VIX data computed by the CBOE. The advance and decline index is the ratio between the number of stocks closing higher to the number of stocks closing lower each day. It can be used as a measure of market strength as it moves higher when the there are more advancing issues than declining issues.

The Baker Wrugler index is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on initial public offerings (IPOs), the equity share in new issues and the dividend premium.

The closed-end fund discount (CEFD) is the average difference between the net asset value (NAV) of closed-end stock fund shares and their market prices. NYSE share turnover is based on the ratio of reported share volume to average shares listed from the NYSE Fact Book. Turnover displays an exponential positive trend over their period. As a partial solution, they define TURN as the natural log of the raw turnover ratio, detrended by the five-year moving average. The IPO market is often viewed as sensitive to sentiment, and high first-day returns on IPOs are cited as a measure of investor enthusiasm. Likewise, the low idiosyncratic returns on IPOs are often interpreted as the result of market timing. They take the number of IPOs (NIPO) and the average first-day return of IPOs (RIPO) from Jay Ritter's Web site, which updates the sample in Ibbotson, Sindelar and Ritter ([1994] http://bear.warrington.ufl.edu/ritter/ipodata.htm). The share of equity issues in total equity and debt issues is another measure of financing activity that may capture some aspect of sentiment. The equity share is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance using data from the Federal Reserve Bulletin. The sixth and last sentiment proxy is the dividend premium PD-ND, the log difference of the average market-to-book ratios of payers and nonpayers.

## Perceived Loss Index

1. Calculate the weekly return for each mutual fund in the sample.
2. Set positive returns to zero for each fund.
3. Take the absolute value of the negative returns for each fund.
4. Calculate an exponential average of each fund's losses. Use a weighting scheme such that the half live equals one year. Therefore, loss older than two years old is not used in the calculation.
5. Perform a cross-sectional average, by averaging over each fund's exponential average of losses weighting by their total assets. This average equals the perceived loss index for that date.