Is “Sentiment” Sentimental?

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Abstract

Previous studies have shown that the “sentiment index” constructed by Baker and Wurgler (2006) is a powerful predictor of cross-sectional stock returns. We find that investor sentiment is strongly correlated with contemporaneous business cycle variables. About 63% percent of the total variation in the investor sentiment index can be explained by well-known, contemporaneous business cycle variables. We decompose the widely used investor sentiment index into two components: one related to standard business cycle variables and the other unrelated to those variables. We show that the power of the sentiment index to predict cross-sectional stock returns is mainly driven by the business cycle component, while the component unrelated to business cycle conditions has little significance in predicting cross-sectional stock returns. Our results cast doubt on the notion of “sentiment” as a pure behavioral predictive factor.

Keywords: investor sentiment index, return predictability, conditioning information.

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"Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand."

Baker and Wurgler (2007)

I. Introduction

Traditional asset pricing models leave essentially no role for investor sentiment. In a standard asset pricing model, investors maximize their expected utility (or in a prospect theory framework, maximize their value function) according to their own preferences. Asset prices are determined in equilibrium, reflecting their exposure to systematic risks. Nevertheless, there is a long literature on investor sentiment, dating back as early as Keynes (1936). The presence of sentiment-driven investors could potentially have an important price impact, driving prices away from their fundamental values and leading to mispricing. This effect might be particularly severe when rational investors face high arbitrage costs and cannot fully exploit the profit opportunities caused by mispricing.

The first obstacle for research on sentiment is that sentiment is not observable. The innovative and influential study of Baker and Wurgler (2006) develop a sentiment index from six proxies of investor sentiment: closed-end fund discount, market turnover, number of IPOs, first day return on IPOs, new equity issuances, and difference in book-to-market ratios between dividend payers and dividend non-payers. To be consistent with the notion of sentiment cited at the beginning of the paper, Baker and Wurgler (2006) orthogonalize the sentiment index with respect to the NBER recession indicator, consumption growth and industrial production growth, in an attempt to define a "pure" sentiment index rather than a proxy for business cycle.

Since the creation of the sentiment index in Baker and Wurgler (2006), the use of the sentiment index has grown rapidly, with the main focus on using the sentiment index to predict stock returns. For instance, Baker and Wurgler (2006) argue that market-wide sentiment should exert stronger impacts on stocks that are difficult to value, hard to arbitrage, or both. Consistent with their hypothesis, they find that the investor sentiment index can significantly predict the performance of a broad set of cross-sectional stock trading strategies, especially those involving small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Baker, Wurgler and Yuan (2012) present evidence that global sentiment is a contrarian predictor of country-level returns and that United States' sentiment index has predictive power in countries linked to the United States through significant capital flows. Stambaugh, Yu and Yuan (2012a) relate the idea of sentiment having the potential to influence asset prices to the possibility that arbitrage costs and/or short sales constraints might prevent rational investors from exploiting mispricing. They find that the short legs of eleven anomaly-based trading strategies are more profitable following periods of high sentiment, while the long legs of the strategies are unrelated to sentiment. Stambaugh, Yu and Yuan (2012b) show that the strong predictive power of sentiment is not spuriously caused by the high persistence of the sentiment index, as suggested by Novy-Marx (2012). Meanwhile, Yu and Yuan (2011) find that the sentiment index in Baker and Wurgler (2006) significantly affects mean-variance tradeoff. Yu (2012) documents the fact that the same sentiment index helps explain the forward premium.

Most of the above papers treat the Baker and Wurgler sentiment index as a behavioral variable and interpret their empirical results as consistent with the idea that investors' sentiments, unrelated to economic fundamentals, drive prices and returns in the market. Nevertheless, there are alternative explanations for the strong predictive power of sentiment on the prices and returns. It is possible that the sentiment index is not completely purged of business cycle influences and contains information about rational risk premia or expectations of future cash flows. Therefore, we define our research question accordingly: is the predictability of sentiment index coming from economic fundamentals or coming from investors' true sentiment defined as "belief not justified by the facts at hand" (Baker and Wurgler (2007))? The answer to the above research question is especially important for how to interpret previous findings using the sentiment index.

We answer the question in three steps. First, we project both the original sentiment index and its orthogonalized counterpart on a set of contemporaneous, commonly-used business cycle variables, such as the T-bill rate, the unemployment rate, industrial production growth, the term spread, the dividend yield, and a liquidity proxy, etc. Our empirical results clearly show that both sentiment indices are strongly correlated with contemporaneous business cycle variables.

Approximately 63% of the total variations in both sentiment indices can be attributed to these business cycle variables, especially the T-bill rate and market liquidity proxy. At the same time, this regression naturally decomposes the investor sentiment index into two orthogonal components: one component contains information related to economic fundamentals, and the other one does not.

Second, we re-examine the predictive ability of investor sentiment in order to identify which of the two orthogonal components drives the results of previous studies. Following the existing literature, we collect the returns on the long legs, short legs and long-short spreads of the 16 strategies used in Baker and Wurgler (2006) as well as the 12 strategies used in Stambaugh, Yu and Yuan (2012a). The sentiment index significantly predicts the return spread in 19 of 28 cases. When we decompose the sentiment index into the business cycle component and the residual component, the business cycle component significantly predicts spread portfolio returns in 16 of 28 cases, while the residual component of sentiment index significantly predicts spread portfolio returns in only 3 of 28 cases. The sentiment index significantly predicts the short leg of the portfolio returns in 25 of 28 cases. The business cycle component significantly predicts returns in 26 of 28 cases, while the residual component does not significantly predict any short leg returns of the 28 portfolios. A direct implication of these results is that the business cycle component of the sentiment index seems to be the main driver of the predictive power of the sentiment index. All above results are confirmed with simulations to address concerns about spurious regressions due to persistent regressors.

Finally, we formally evaluate the importance of the sentiment index and the two orthogonal components as conditioning variables in an asset pricing test. According to Merton (1973), all state variables that define the future investment opportunity set should be included in the pricing model. Campbell (1996) demonstrates that any variable that helps to predict future market returns should be included in the state variable set. Given that Baker and Wurgler (2006) and Baker, Wurgler and Yuan (2012) present direct evidence that the sentiment index helps to predict future market returns, we follow Cochrane (1996) and allow the risk prices to fluctuate with the sentiment index as a conditioning state variable. Our empirical results show that sentiment is significantly priced, and the inclusion of the sentiment index substantially improves the performances of both the CAPM and Fama and French models when pricing the 25 Fama and

French size and BM portfolios. This clearly indicates that the sentiment index is an important state variable. Between the two components of the sentiment index, our estimation shows that the business cycle related component is a significant and important conditioning variable, while the residual component barely shows any significance.

In summary, our empirical results suggest that the widely-used investor sentiment index contains rich information about economic fundamentals and might not be a pure behavioral measure of sentiment. Our paper clearly provides new insights about the nature of the widely-used Baker-Wurgler sentiment index. It still remains a challenge to measure pure investor sentiment. On the other hand, we do not rule out the possibility that sentiment could be a general equilibrium phenomenon that might cause business cycle variables such as interest rates and liquidity to fluctuate. Nevertheless, without a full-fledged general equilibrium model, it is empirically difficult to test the direction of causality between sentiment measures and business cycle variables, and we leave this agenda for future research.

The literature on investor sentiment is large and diverse. For instance, Lemmon and Portniaguina (2006) present evidence that their consumer confidence based measure of sentiment negatively predicts future size premiums. They also show that the residual component of consumer confidence that is orthogonal to business cycle variables still has significant predictive power for the future size premium. Glushkov (2006) finds that sentiment is not priced using a set of portfolios sorted on their loadings on the sentiment index. Hwang (2012) finds that measures of a country's popularity in the United States are inversely correlated with the discounts of single country closed-end funds and ADRs. Our paper suggests that one should be cautious about interpreting the information content of investor sentiment measures.

Our results also challenge the argument that asset pricing anomalies must be driven by mispricing just because the sentiment index predicts returns. Asset pricing anomalies could reflect mispricing, as suggested by Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012a, 2012b), but they could also result from rational equilibrium models. For instance, in recent years, researchers have shown that q-theory based asset pricing models can explain many cross-sectional asset pricing anomalies. Zhang (2005), Liu, Whited and Zhang (2010), and Chen, Novy-Marx and Zhang (2010) are a few examples of those who illustrate implications from q-theory based models with respect to asset pricing anomalies. Our results show that it is the common business cycle component and not the pure sentiment component of the investor sentiment index that can predict cross-sectional stock returns. This is consistent with the classical finance theory.

The rest of the paper is organized as follows. We introduce data in Section II. In Section III, we report decomposition results. Section IV contains predictability tests. Section V reports asset pricing tests. Section VI concludes.

II. Data

This section discusses the data we use. We first introduce the sentiment indices constructed by Baker and Wurgler (2006) and then discuss the business cycle variables we use in our decomposition.

Baker and Wurgler (2006) construct the investor sentiment index, $SENTIMENT$, as the first principal component of 6 different proxies for investor sentiment as suggested by prior literature. Specifically, these proxies are the closed-end fund discount, the lagged and detrended natural log of the raw turnover ratio, the number of IPOs, the lagged average first-day return on IPOs, the equity share of new issues, and the log of the difference between average market-to-book ratio for dividend payers and non-payers. To address concerns that each of these proxies for sentiment might contain common information about economic fundamentals, Baker and Wurgler orthogonalize each of the proxies to the NBER recession dummy, growth in consumer durables, non-durables and services as well as growth in the industrial production index prior to the construction of the orthogonalized sentiment index, $SENTIMENT_{\perp}$. Baker and Wurgler (2006) normalize both sentiment indices to have a mean of zero and a variance of one. (More details can be found in the original paper.) We obtain the sentiment data from Wurgler's website. Due to sentiment data availability, we restrict our sample to July 1965 to December 2010.

We obtain four widely used pricing factors from Ken French's website: the market excess return (MKT), the size factor (SMB), the value factor (HML) and the momentum factor (WML). Summary statistics are presented in Panel A of Table 1. As noted by Novy-Marx (2012), both sentiment indices are highly persistent, with auto-correlation of nearly 0.99. The correlations between sentiment indices and MKT, HML and WML are not particularly high and are not statistically significant. However, it is interesting to note that the correlations between the sentiment indices and SMB are significant at the 5% level. The two sentiment indices are highly correlated at 97%.

To determine whether *SENTIMENT* is related to the state of the business cycle, we regress *SENTIMENT* on a variety of business cycle indicators. We choose business cycle variables based on previous literature and data availability. We start with six macroeconomic variables: the U.S. unemployment rate (Unemp) as in Lemmon and Portniaguina (2006); the change in inflation (dCPI) computed from CPI as in Fama and Schwert (1977); the consumption growth rate (dCons) as in Chen, Roll, and Ross (1986); the growth rate of disposable personal income (dSPI) as in Lemmon and Portniaguina (2006); the growth rate of industrial production (dInd) as in Chen, Roll, and Ross (1986); and the NBER recession dummy (NBER) as in Baker and Wurgler (2006). Additionally, we include several variables from financial markets that have been frequently used as indicators for the business cycle: the 3-month Treasury Bill rate (Tbill) as in Campbell (1987) and Hodrick (1992); the default spread (Def) defined as the difference in yields between Baa-rated corporate bonds and AAA-rated corporate bonds as in Fama and French (1989); the term spread (Term) defined as the difference in yields between the 10-year Treasury bond and the 3-month T-bill as in Chen, Roll, and Ross (1986); the dividend yield (Div) on CRSP market return as in Campbell and Shiller (1988a, 1988b); the return (VWRETD) on CRSP all market index as in Campbell (1996); the stock market volatility (MktVol) computed as the annualized standard deviation of market daily return within each month, as in Bollerslev and Zhou (2011), and the average percentage of zero return days (PctZero) as a market liquidity proxy introduced by Lesmond, Ogden and Trzcinka (1999)[1].

Data sources for each variable are provided alongside the summary statistics in Panel B of Table 1. The summary statistics include the means, standard deviations, and serial auto-correlations of the macroeconomic variables, as well as their correlations with the two sentiment indices. One common feature of these business variables is that many are highly persistent, much as are the

[1] We also investigate other market aggregate liquidity measures, such as bid-ask spread, turnover and Amihud price impact measures. The empirical results using alternative liquidity proxies are quantitatively similar and are available upon request.

sentiment indices. $SENTIMENT_{\perp}$ is constructed by Baker and Wurgler (2006) to be orthogonal to business cycle conditions. However, we see that $SENTIMENT_{\perp}$ is significantly correlated with many of the business cycle variables. At the 5% significance level, $SENTIMENT_{\perp}$ is correlated with inflation (dCPI), consumption growth rate (dCons), industrial production growth rate (dInd), T-bill rate (Tbill), default spread (Def), NBER dummy, dividend yield (Div), market volatility (MktVol) and market liquidity proxy (PctZero). In particular, the correlation between $SENTIMENT_{\perp}$ and Tbill is 27.72%, and it has a correlation of -22.09% with our market liquidity proxy, PctZero. Simply judging by the correlation between $SENTIMENT_{\perp}$ and these business cycle variables, it is hard to draw the conclusion that $SENTIMENT_{\perp}$ is unrelated to business cycle conditions.

In Figure 1, we plot the $SENTIMENT_{\perp}$ together with the T-bill rate and PctZero. For easy comparison, we normalize T-bill and PctZero to have zero mean and unit standard deviations. The co-movement between the T-bill rate and the sentiment index is striking. Both the sentiment index and the T-bill rate reach a peak between 1968 and 1969, both are high during 1978-1987, and both reach another peak around 1999-2001 during the Internet bubble period. For most of our sample period, the sentiment index and T-bill rate share the same trends of ups and downs, while PctZero is negatively correlated with the sentiment index. During 1973-1980 and 1989-1992, when sentiment is low, PctZero is high.

III. Decomposition of Sentiment Index

We now decompose the sentiment index into two orthogonal components: one is related to business cycle variables reflecting economic fundamentals, and the other is not. For this purpose, we estimate the following regression:

$$SENTIMENT_t = a + b'X_t + e_t, \tag{1}$$

where X_t is a vector of business cycle variables[2], and e_t is the regression residual. Based on the estimated coefficients, $\hat{b}$, we decompose the sentiment index into two parts:

$$SENTIMENT_t = SENTHAT_t + SENTRES_t,$$

where $SENTHAT_t$ is equal to $\hat{a} + \hat{b}' X_t$ and $SENTRES_t$ is simply the residual term e_t. By construction, the two components, SENTHAT and SENTRES are orthogonal to each other. We interpret SENTHAT as the part of the sentiment index that is directly related to economic fundamentals and SENTRES as the pure sentiment measure.

The decomposition results for both $SENTIMENT$ and $SENTIMENT_{\perp}$ are reported in Table 2, Panel A. For both decompositions, we present the coefficient estimates, OLS t-stats, and Newey-West t-stats adjusted for 24 lags. Additionally, we decompose the R-squared into the variance explained by each of the individual macroeconomic variables. The left panel presents results on $SENTIMENT$, and the right panel presents results on $SENTIMENT_{\perp}$. For both sentiment indices, business cycle variables are able to explain a large part of their total variation. The adjusted R-squares for $SENTIMENT$ and $SENTIMENT_{\perp}$ are 62.97% and 62.56%, respectively. Among the independent variables, Tbill, Term and PctZero show up with the highest t-statistics, significant at the 1% level for both sentiment indices. The bulk of the explained variance of both sentiment indices comes from two business cycle variables: Tbill and PctZero. For $SENTIMENT$, almost half of the adjusted R-square (62.97%) comes from the contribution of Tbill (29.24%) and for $SENTIMENT_{\perp}$, around two-thirds of the adjusted R-square (62.56%) is due to the contribution of Tbill (39.3%). $SENTIMENT$ is high when interest rates are high, when the term structure is steeper, and when market liquidity conditions (measured by PctZero) are good.

T-bill has been shown in many previous studies to be an important business cycle variable. In fact, Ang and Bekaert (2007) show that the short rate is the only robust and significant predictor for future market returns. Meanwhile, since the NYSE turnover is one of the sentiment proxies used for constructing the sentiment index, the significance on PctZero might not be surprising. Previous studies, such as Pastor and Stambaugh (2003), which show that liquidity is a systematic

[2] In results not reported, we estimate equation (1) using X_{t-1}. We find results are qualitatively similar to those reported in the paper.

risk factor that affects the cross-section of stock returns, and Sadka and Korajczyk (2008) with similar evidence, convince us that market liquidity is an important business cycle variable.

Novy-Marx (2012) points out the danger of using highly persistent variables on the right hand side of a predictive regression. He finds that the standard deviation of test statistics depends on the persistence of the expected return process, signal-to-noise ratio, and the autocorrelation of independent variables. A high standard deviation of the test statistic means that the precision of the slope coefficient in the predictive regression is overstated. As a result, Novy-Marx (2012) suggests scaling the standard OLS t-statistics by the standard deviation of the empirical distribution of t-statistics using simulated regressors with similar autocorrelations.

In our decomposition procedure, even though it is not a predictive regression as discussed in Novy-Marx (2012), both dependent and independent variables are highly persistent. To ensure that the significant coefficients on Tbill, PctZero and Term are not a result of a spurious regression, we conduct the following simulation to address the bias in both coefficients and t-statistics: First, we estimate a vector autoregressive (VAR) model of order 1 to fit the data, as follows:

$$X_t = \rho(X_{t-1} - \mu) + \Sigma\varepsilon_t,$$

where X_t is the vector of business cycle variables used in the decomposition procedure, μ is a vector of the means of these variables, ρ is a matrix of VAR coefficients, Σ is the variance-covariance matrix of the disturbance terms, and ε_t is a vector of normally-distributed error terms[3]. After estimating the parameters of the VAR(1) model, we simulate 100,000 series of artificial macroeconomic variables, matching the variables' means, variances, and auto-correlations. Third, for each simulated series, we estimate the decomposition regression using both original and orthogonal sentiment and record coefficient estimates $\hat{b}$ as in Equation (1) and OLS t-stats.

In the first two columns of Table 2 Panel B, we report the 2.5th and 97.5th percentile of coefficient estimates from the simulations. The third column reports a one-sided p-value for the

[3] The idea of VAR(1) is to describe the data dynamics. In terms of whether order 1 is the best order, we examine BIC and SIC, and order 1 is most of the time the optimal lag for our variables.

coefficients. Additionally, following Novy-Marx (2012), we report OLS t-stats scaled by the standard deviation of the t-statistics over the 100,000 simulations in the last column, labeled "NM t-stat." We find that the Tbill, Term, and PctZero variables remain significantly related to both of the investor sentiment indices in this simulation. This robustness check alleviates concerns that our decomposition results might be spuriously driven by the persistence of either the sentiment index or the independent variables.

In Panel C of Table 2 we report the summary statistics of the two orthogonal components: SENTHAT and SENTRES. Note that both sentiment indices are constructed to have a mean of zero and volatility of one. SENTHAT, by construction, shares the same mean as the dependent variable, and SENTRES by definition, has a mean of zero. All series remain highly persistent with above 90% auto-correlations for both SENTHAT and SENTRES. Given the high correlation between $SENTIMENT$ and $SENTIMENT_{\perp}$ (0.97), it is not surprising that SENTHAT constructed from $SENTIMENT$ is highly correlated with SENTHAT constructed from $SENTIMENT_{\perp}$, with a correlation of 0.98. The correlation between the two SENTRES series is also high (0.95). Interestingly, we observe that SENTHAT is more related to the original (orthogonal) sentiment index with a correlation coefficient of 0.80 (0.78), compared to the 0.60 (0.57) correlation between original (orthogonal) sentiment index and SENTRES. Since the results for the original sentiment index and the orthogonal sentiment index are similar throughout our tests, from this point on, we focus our discussions on the orthogonal sentiment index. All results using the original sentiment index are available on request.

To examine how the two sentiment components are related to risk pricing factors, we report correlations between SENTHAT (SENTRES) and contemporaneous and future Fama and French factors in Panel D of Table 2. SENTHAT is significantly negatively correlated with contemporaneous excess market return with a correlation coefficient of -0.09 and p-value of 0.04. Interestingly, SENTHAT is also significantly correlated with the Fama and French size factor, SMB, at time t+1. The correlation coefficient between SENTHAT at time t and SMB at t+1 is -0.10 with a p-value of 0.02. In stark contrast, SENTRES is not significantly correlated with any Fama and French factors either at time t or at time t+1. As mentioned earlier, the sentiment index is significantly correlated with SMB; the decomposition shows us that this correlation is solely coming from the common business cycle component of the sentiment index.

We plot the time-series of SENTHAT, SENTRES and $SENTIMENT_{\perp}$ in Figure 2. As evident in the plot, the two components of sentiment are distinct from each other and in fact often have different signs. During some periods, SENTHAT closely tracks the sentiment index (e.g. 1980-1982, 2008-2010), while during other periods, SENTRES more closely tracks the sentiment index (e.g. 1967-1972, 1999-2000). As we noted earlier, SENTHAT has a higher correlation with the sentiment index than does SENTRES.

The result from the simple decomposition has strong implications with respect to how we should interpret the sentiment index. Does the sentiment index truly reflect investors' beliefs, unjustified by the prevailing economic conditions? Our results show that both sentiment indices share a substantial common business cycle component. In particular, it is strongly related to the Tbill rate and stock market average liquidity conditions.

IV. Predictive Power of Sentiment

In this section, we re-examine the ability of investor sentiment to predict cross-sectional stock returns in a fashion similar to that of Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012a). Baker and Wurgler (2006) challenges the traditional view in finance theory that investor sentiment does not play any role in the cross-section of stock returns by showing that investor sentiment indices have significant predictive power on future cross-sectional stock returns. Stambaugh, Yu, and Yuan (2012a) find that anomalous long-short strategies are more profitable following periods of high sentiment, and further, that sentiment affects the short leg of the long-short strategy but not the long leg. To disentangle what information component in the investor sentiment index is responsible for its predictive power, we re-investigate the findings from the above two papers using our SENTHAT and SENTRES. We start by describing anomalies in section IV.A. We discuss the empirical design in section IV.B. In section IV.C, we discuss results for the spread portfolios. In section IV.D, we present results for the long and short legs. Finally, in section IV.E, we check the robustness of our results.

A. The Anomalies

To be comparable with original results in the literature, we adopt the exact 16 spread portfolios from Baker and Wurgler (2006) as well as 11 anomalies from Stambaugh, Yu, and Yuan (2012a). We denote them “the 16 Baker and Wurgler (2006) portfolios” and “the 11 Stambaugh, Yu and Yuan (2012a) anomalies.”

Baker and Wurgler (2006) suggest that the stocks most likely to be sensitive to investor sentiment are those stocks that are difficult to value, hard to arbitrage, or both. The authors form decile portfolios by sorting on several firm characteristics that might be indicative of difficulty in valuation or arbitrage. To be specific, Baker and Wurgler (2006) investigate spread portfolios based on firm age (age), dividend to book equity (D/BE), external finance to assets (EF/A), earnings to book equity (E/BE), growth in sales (GS), property, plant and equipment to total assets (PPE/A), R&D to total assets (RD/A), stock return volatility (sigma), market equity(ME), and book to market equity(B/M). We form spread portfolios following these exact procedures documented in Baker and Wurgler (2006), and we refer readers to Appendix A for more details.

Stambaugh, Yu, and Yuan (2012a) investigate the extent to which investor sentiment predicts the returns of 11 previously documented anomalies that are unexplained by the Fama and French 3-factor model. Citing Miller (1977), the authors suggest that in the presence of short-sales constraints, some stocks might be overvalued. If this is the case and sentiment is the cause of the mispricing, then most of the anomalous returns should arise from the short leg following periods of high investor sentiment. The 11 anomalies include Campbell, Hilscher and Szilagyi (2008) financial distress (distress), Ohlson (1980) O-score (O-score), net stock issue (NSI), composite equity issues (CEI), accruals anomaly (Accruals), net operating assets (NOA), momentum (MOM), gross profitability (GP), asset growth anomaly (AG), return on assets anomaly (ROA) and investment to assets anomaly (INV). As in Stambaugh, Yu, and Yuan (2012a), we also study the returns on a “combination” portfolio formed as an equally weighted portfolio of all 11 anomaly portfolios. We refer readers to Appendix B for more details on portfolio construction.

Returns on the 16 Baker and Wurgler (2006) portfolios span our entire sample period from August 1965 to January 2011. However, the data for 8 of the 11 Stambaugh, Yu and Yuan (2012a) anomalies span the period from August 1965 to January 2008. For the O-score and the

ROA anomalies, data are available beginning in January 1972, while the failure-probability data begin in December 1974.

We would like to point out that there are a few differences between the Baker and Wurgler (2006) and the Stambaugh, Yu and Yuan (2012a) portfolios. First is the weighting scheme. The returns on the Baker and Wurgler (2006) 16 spread portfolios are constructed as equally weighted average returns. The Stambaugh, Yu and Yuan (2012a) portfolio returns, however, are value-weighted. Baker and Wurgler (2006) argue that theory predicts (and empirical results confirm) that large firms are likely less affected by investors' sentiment. Consequently, using value-weighting might obscure some results. To facilitate easy comparison of our results to those of the previous papers, we use the original method of data construction in Baker and Wurgler (2006) and use the original data from Stambaugh, Yu and Yuan (2012a)[4]. That is, we report results using equally weighted Baker and Wurgler (2006) portfolio returns and value-weighted Stambaugh, Yu and Yuan (2012a) portfolio returns.

The second difference between the Baker and Wurgler (2006) portfolios and Stambaugh, Yu and Yuan (2012a) portfolios is that the Baker and Wurgler (2006) portfolios are defined as "high minus low," and thus returns on the spread portfolios could be either positive or negative, depending on the characteristic on which the portfolio is formed. In contrast, Stambaugh, Yu and Yuan (2012a) define the spread portfolio as the "long minus short" portfolio, which goes long the extreme decile with the highest average return and short the extreme decile with the lowest average return. Thus, the spread portfolios always have positive average returns.

The third difference between Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2012a) portfolios is how the long and short legs are defined. In Baker and Wurgler (2006), "high" is defined as the top three deciles, and "low" is defined as the bottom three deciles, using NYSE breakpoints. So the "High" in BM portfolios is therefore an equally weighted average of the top three deciles and the "Low" is the equally weighted average of the bottom three deciles. Stambaugh, Yu and Yuan (2012a) define the long and short leg of an anomaly by the most profitable versus the least profitable decile. We later conduct robustness checks using various other methods of portfolio construction.

[4] We thank Stambaugh, Yu and Yuan for providing us with their original data.

Table 3 reports the summary statistics for these 28 trading strategies. We report mean returns, CAPM alphas and the four-factor Fama and French factor model alphas, together with the Newey-West adjusted t-statistics (24 lags) for the alphas. Among the 16 Baker and Wurgler (2006) spread portfolios, ten have significant alphas using a momentum-augmented Fama and French factor model. The ten spread portfolios are based on external finance (High-Low, High-Medium, Medium-Low), sales growth (High-Low, High-Medium), and R&D over asset, Size and book-to-market ratio (High-Low, High-Medium, Medium-Low). Note that Baker and Wurgler (2006) do not choose cross-sectional strategies that cannot be priced by Fama French models, but rather choose cross-sectional sorts that are theoretically reflective of investor sentiment's impact. For instance, there is a strong conditional effect of sentiment on age, but the effects average out across high and low sentiment periods. Stambaugh, Yu and Yuan (2012a) have chosen 11 portfolios that have been shown to be difficult for the Fama and French model to price. Consequently, all 11 portfolios and the equal-weighted combination of them have highly significant positive alphas.

B. Empirical Approach

Following Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012a), the benchmark predictive regression takes the following forms:

$$R_t = a + bSENTMENT_{t-1} + u_t,$$

The dependent variable, R_t, is the return on a trading strategy at time *t*. It could be the long leg, the short leg or the return spread between long and short. $SENTIMENT_{t-1}$ is the sentiment index at time t-1. If the sentiment index can predict future returns, then the coefficient *b* should be significantly different from zero. Given our decomposition, the benchmark regression is modified as:

$$R_t = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + u_t, \qquad (2)$$

where SENTHAT is the business cycle component in sentiment, and SENTRES is the residual component unrelated to the business cycle. For either component to significantly predict future returns, the corresponding coefficient should be significantly different from zero.

To test the predictive power of sentiment for future returns with the presence of other asset pricing factors, we specify the following predictive regressions. Following Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2012a), our $FACTOR$ vector includes the market factor (MKT), size factor (SMB), value factor (HML) and momentum factor (WML)[5]. To be "strictly" predictive, we use factors from t-1.

$$R_t = a + bSENTIMENT_{t-1} + c'FACTOR_{t-1} + u_t,$$

$$R_t = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + d'FACTOR_{t-1} + u_t. \qquad (3)$$

For controls, Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2012a) include on the right hand side factors observed at time t, which is the same time as the dependent variable.

$$R_t = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + d'FACTOR_t + u_t. \qquad (4)$$

The statistical significance with respect to sentiment could change due to its correlation with either current or future asset pricing factors. Because of this, we report results for both regressions (3) and (4). Regressions (2) and (4) are exactly the same regressions as in Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2012a), which allows for easy comparison of results.

As discussed earlier, Novy-Marx (2012) points out that the OLS t-statistics in a predictive regression with highly persistent regressors can be overstated. In fact, Novy-Marx finds that after correcting for this bias, the predictive ability of the original sentiment index, as in Stambaugh, Yu, and Yuan (2012a), seems to be spurious in several cases. Since we use similarly persistent dependent and independent variables, we conduct the same simulations as in Novy-Marx (2012) in order to ease this concern. We first estimate an AR(1) model for both SENTHAT and

[5] Following Stambaugh, Yu, and Yuan (2012a), we do not include WML as a control in regressions involving the 11 Stambaugh, Yu and Yuang (2012a) anomalies. In addition, the SMB is omitted when analyzing the returns of the portfolio formed on market equity, and HML is omitted when analyzing returns of the three portfolios formed on book-to-market ratios.

SENTRES. Using the parameter estimates, we simulate 100,000 artificial time-series of SENTHAT and SENTRES, maintaining the orthogonality of the two variables and also matching means, variances, and auto-correlation coefficients. Next, we re-estimate the benchmark predictive regressions, replacing the SENTHAT and SENTRES series with the simulated series of these variables. We do this for the 100,000 series of simulated data, and then scale the OLS t-stats by the standard deviation of t-stats from these simulations, as suggested in Novy-Marx (2012). The Novy-Marx t-statistics, denoted as "NM t-stat", are always reported in our tables. In addition, we present empirical p-values for the coefficient estimates. These p-values represent the percentage of coefficient estimates from regressions using simulated SENTHAT or SENTRES series that are greater than (less than) the estimate using the actual SENTHAT or SENTRES series, in the case of positive (negative) actual coefficient estimates. For instance, if the coefficient estimate on SENTHAT is positive, then the empirical p-value is the percentage of coefficient estimates from simulated SENTHAT series that are greater than the coefficient estimates using actual SENTHAT.

We would like to point out that the predictive regressions in Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2012a) are not econometrically "predictive" in nature, because the sentiment index is constructed using full sample data and therefore contains look-ahead bias. Our decomposition procedure also uses full sample data and is subject to the same criticism. Nevertheless, given that our focus is to account for the sources of sentiment's predictive ability as documented in the literature, our methodology is consistent with the original studies and does not adjust for this look-ahead bias.

C. Predictive Regression on Spread Portfolios

Table 4 reports the results of using the two components of sentiment as a predictor of long-short spread portfolio returns. Given that all sentiment variables are highly persistent, we report both OLS t-stats and Novy-Marx adjusted t-statistics.[6] Panel A reports results without the Fama and French factors as controls, as in Equation (2). As a benchmark, in results not reported, the orthogonal sentiment index in Baker and Wurgler (2006) is statistically significant in predicting 19 of the 28 spread returns. In our findings, SENTHAT demonstrates significant predictive

[6] Results using Newey-West adjusted t-statistics are very similar. These results are available upon request.

ability in 16 out of the 28 spread-portfolios considered. In sharp contrast, SENTRES is significant in only 3.

Baker and Wurgler (2006) find that when sentiment is high, returns on small, young, and high volatility firms are relatively low over the following coming year. The signs of the coefficients on Size, Age and Sigma in Panel A of Table 4 are consistent with the signs documented by Baker and Wurgler. For all three of these spread portfolios, SENTHAT is significant while SENTRES is not. The fact that only the business cycle component of the sentiment index significantly predicts spread portfolio returns on Size, Age and Sigma indicates that, it is not when sentiment is high that returns on these stocks are relatively low, but rather it is when interest rates are high, liquidity is high (or transaction costs are low) that the returns on small, young and high volatility firms are lower. Baker and Wurgler (2006) also find that spread portfolios formed on dividend payout, profitability, external finance (High-Medium, Medium-Low), and sales growth (High-Medium, Medium-Low) can be significantly predicted by the beginning of period sentiment index. We find that all of these portfolios can be significantly predicted by the common business component of sentiment, SENTHAT, but cannot be predicted by SENTRES, the part of sentiment unrelated to the business cycle. In addition to these spread portfolios where Baker and Wurgler (2006) find significant predictability, we also find that SENTHAT significantly predicts book-to-market spread portfolios (High-Medium, Medium-Low). One reason for this might be that Baker and Wurgler (2006)'s sample ends in 2001 and our sample ends in 2010, and the value effect is stronger over the final ten years. Out of the 16 portfolios that Baker and Wurgler (2006) considered, only one spread portfolio formed on external finance can be significantly predicted by SENTRES, the pure sentiment component of the sentiment index.

The results also show that when SENTHAT is high, subsequent returns on both low and high sales growth, external finance, and book-to-market ratio portfolios are relatively low compared to the returns on firms with medium levels of these variables. These results are exactly the same as those documented in Baker and Wurgler (2006)[7].

[7] In unreported results, we also use more extreme cutoff points in constructing the 16 Baker and Wurgler (2006) portfolios. Specifically, we define High as the top decile, Low as the bottom decile, and Medium as the 6th decile.

We now turn to the 12 Stambaugh, Yu and Yuan (2012a) portfolios. SENTHAT is significant for 4 out of the 12 portfolios considered, and SENTRES shows up significantly twice in predicting spread portfolio returns. In particular, SENTHAT is significant in predicting the spread returns of portfolios formed on the Campbell, Hilscher, and Szilagyi (2008) distress probability, return on assets, net operating assets, and the combination strategy. SENTRES is significant in forecasting spread returns of two strategies: return on assets and net stock issuance. Given that SENTHAT contains only information in the sentiment index related to common business cycle variables, the significance on SENTHAT for future long-short strategy returns could simply reflect the fact that SENTHAT is related to the future investment opportunity set or underlying business cycle conditions.

In Panel B of Table 4, we report the predictive regression results as in Equation (3) for the long-short spread portfolio returns when the t-1 Fama and French factors are included to predict returns at time t. In general, the coefficient on SENTHAT slightly diminishes in magnitude and the significance of SENTHAT is also somewhat reduced. Out of 28 spread portfolios, SENTHAT is significant for 13, while SENTRES is significant for only 3. Basically, including contemporaneous Fama and French factors with SENTHAT and SENTRES does not change the predictability of either variable.

Panel C of Table 4 reports the predictive regression Equation (4) as in Baker and Wurgler (2006) and Stambaugh, Yu and Yan (2012a), in which the time t Fama and French factors are added on the right hand side when predicting returns at time t. We find that the coefficient on SENTHAT further decreases in magnitude and that the significance of SENTHAT is substantially reduced. Out of 28 spread portfolios, SENTHAT is significant for 9, while SENTRES is significant for 5. Baker and Wurgler (2006) observe that the predictive power of sentiment diminishes as the Fama and French factors are used as controls. They attribute this to the fact that they use equally weighted portfolios, and some characteristics they examine are correlated with size. Recall from Panel D of Table 2: SENTHAT is significantly correlated with the SMB from the next period with a correlation coefficient of -0.10 and a p-value of 0.02, while SENTRES is not significantly correlated with any future asset pricing factors. The decrease in significance of SENTHAT as a

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Using these alternate cutoffs, we find that of the 16 Baker and Wurgler (2006) portfolios, SENTHAT is significant in predicting 10 of the spread returns, while the coefficient on SENTRES is never significant.

predictor of returns is primarily driven by the fact that SENTHAT predicts the next period SMB. In other words, the drop in the significance of SENTHAT shows that part of the predictive power of SENTHAT is driven by its correlation with future asset pricing factors, particularly SMB.

This finding sheds some light on the source of the predictive power of the common business cycle component in the sentiment index. For SENTRES, since it is put side-by-side with SENTHAT in regression (3), we also see its significance change due to the correlation of SENTHAT with future SMB. We estimate an alternative regression (not reported but available on request), where SENTRES is put alone with next period Fama and French factors to predict portfolio spread. The result here is that SENTRES is significant for only 2 out of the 28 spreads considered.

To summarize, the results in this section show that it is SENTHAT, the component of the sentiment index related to macroeconomic fundamentals, rather than SENTRES, the pure sentiment component of the Baker and Wurgler (2006) sentiment index, that is the dominant driving force of the sentiment index's ability to forecast future cross-sectional portfolio spread returns. In particular, part of the predictive power of SENTHAT arises from the fact that it is significantly correlated with the future Fama and French size factor.

D. Predictive Regression Results on Long and Short Portfolios

Stambaugh, Yu and Yuan (2012a) argue that overpricing in the cross-section of stocks should be more prevalent than underpricing due to short-sale constraints. They find that each anomaly is stronger following high levels of sentiment, because high sentiment leads to overpricing rather than underpricing, and overpricing is difficult to correct when there are short-sale constraints. They consistently find that the short leg of each strategy is more profitable following high sentiment, while sentiment exhibits no relation to returns on the long legs of the strategies. In other words, there is a strong negative relation between investor sentiment and the returns on the short leg of the anomalies, and long leg returns of the anomalies are not related to the sentiment index.

Table 5 reports results of predictive regressions involving the long and short legs of the spread portfolios. Panel A reports results without the Fama and French factors as controls. In Panel B and C, we report results with time t-1 Fama and French factors, and time t Fama and French factors as controls, respectively. For both the short and long legs, we report regression coefficients on SENTHAT and SENTRES, the Novy-Marx adjusted t-statistic, and the empirical p-value. Again, note there is a difference between Baker and Wurgler (2006) and Stambaugh, Yu and Yuan (2012a) in terms of what defines long and short: a long (short) leg in a Baker and Wurgler (2006) portfolio is an equally weighted portfolio of the top three (bottom three) deciles, while for Stambaugh, Yu and Yuan (2012a) portfolios, the most profitable (least profitable) decile is the long (short) leg.

We first examine the results for short legs. The coefficient on SENTHAT is always negative for the short leg, which is consistent with Stambaugh, Yu and Yuan (2012a), indicating that the return on the short leg is lower after high SENTHAT. The coefficient on SENTRES is mostly negative except for 7 cases. For the 28 trading strategies, SENTHAT is significant for all short legs except for volatility (Sigma) and gross profitability (GP). In striking contrast, SENTRES is only marginally significant in the case of gross profitability. This finding clearly implies that SENTHAT is more relevant for predicting future short leg returns than is SENTRES.

Next we turn to the long legs. For the 16 Baker and Wurgler (2006) strategies, SENTHAT is equally important in predicting the return on the long leg. It carries a significant negative sign for all 16 long legs with two exceptions: D/BE and Size. Stambaugh, Yu and Yuan (2012a) find that the sentiment index is only significant in predicting the long-leg returns of the momentum and the investment-to-asset ratio strategies. We find that SENTHAT is indeed statistically significant in predicting the long-leg return of those two strategies, and in addition, it also significantly predicts the long return of the Campbell, Hilscher, and Szilagyi (2008) distress strategy. SENTRES is not significant for any of the long-leg returns.

Combining the results for the short and long legs, we make several observations. First and most importantly, sentiment’s ability to predict either the short or the long leg returns comes solely from the common business cycle component in the sentiment index, and this is overwhelmingly the case. We do not see a single case of significance from SENTRES, the pure sentiment component of the sentiment index, in predicting either the long or short leg returns of the 28 strategies considered in total.

Second, we do find that SENTHAT much more strongly predicts the returns of the short legs than those of the long legs for each of the Stambaugh, Yu and Yuan (2012a) portfolios. Nevertheless, this conclusion can only be drawn based on those specific portfolios used in Stambaugh, Yu and Yuan (2012a). Our findings are consistent with their prediction that, if sentiment-driven mispricing and short-sales constraints are the driving force behind the anomaly returns, short leg returns should be lower following periods of high investor sentiment while long leg returns should be unaffected. However, the fact that much of the sentiment index's predictive power comes from the component related to the business cycle challenges the assertion that irrational investor sentiment leads to mispricing. For the Stambaugh, Yu and Yuan (2012a) strategies, SENTHAT is significant in predicting the short leg of all strategies except for gross profitability, but it is only significant in predicting 3 long-leg returns. We also note that the negative coefficient on SENTHAT is larger in magnitude on the short leg returns than on the long leg returns, which is consistent with findings in Stambaugh, Yu and Yuan (2012a). However, the result is very different for the Baker and Wurgler (2006) strategies. Judging from the 16 Baker and Wurgler (2006) strategies, we see that SENTHAT is significant in predicting both the long and short-leg returns.

In Panel B of Table 5, we report predictive regressions when we also include time t-1 Fama and French factors as control variables, as in regression (3) in predicting time t returns. The controls marginally reduce the magnitude of all coefficients. For the short leg, SENTHAT is still significant in 23 out of 28 cases, while SENTRES is never significant. For the long leg, SENTHAT is significant in 14 out of 28 cases, while once again, SENTRES is never significant. Clearly, including contemporaneous Fama and French factors with sentiment variables does not significantly change their predictive power

In Panel C of Table 5, however, the significance of SENTHAT in predicting both the long leg and short leg in the Baker and Wurgler (2006) portfolios almost completely disappears once we add in the Fama and French factors from the next period. As discussed earlier, SENTHAT is significantly correlated with the next period SMB. The change in significance of SENTHAT, therefore, primarily reflects the fact that it contains information about the future realization of an important asset pricing factor, namely, SMB. For Stambaugh, Yu and Yuan (2012a) portfolios, the drop in the significance of SENTHAT for the short leg is less striking. After controlling for Fama and French factors, we still see SENTHAT as significant in predicting the short leg for 5 out of 12 portfolios. SENTRES, which is not significant at all in predicting the short end when Fama and French factors are absent, is now significant in forecasting the short leg 6 out of 12 times.

To summarize, we find that the predictive power of sentiment on the short leg is predominantly driven by the common business component in sentiment, SENTHAT, while the component that is unrelated to the business cycle, SENTRES, has little ability to predict either the short or long leg returns. Furthermore, the asymmetric effect of SENTHAT on the short and long leg of anomalies is not universal beyond the Stambaugh, Yu and Yuan (2012a) 12 value-weighted strategies.

E. *Robustness*

Equally weighted returns in Stambaugh, Yu, and Yuan (2012)

The previous section shows that SENTHAT is equally important in predicting both long and short leg returns for the Baker and Wurgler (2006) portfolios. However, SENTHAT is a much stronger predictor for the short leg returns than for the long leg returns when it comes to the 12 Stambaugh, Yu and Yuan (2012a) strategies. One natural conjecture is that this might be due to the fact that Baker and Wurgler (2006) portfolios are equally weighted, whereas Stambaugh, Yu and Yuan (2012a) portfolios are value weighted. Baker and Wurgler (2006) argue in page 1646 that “Our theory predicts, and the empirical results confirm, that large firms will be less affected by sentiment, and hence value weighting will tend to obscure the relevant patterns.” In order to align our analysis closer to theirs, we re-examine the predictability issue using equally weighted Stambaugh, Yu and Yuan (2012a) strategies.

Since Stambaugh, Yu and Yuan (2012a) do not use equally weighted portfolios, we start with predictability tests using the original Baker and Wurgler (2006) sentiment index, reported in

Appendix Table A1. Panel A of Table A1 shows the results using only the sentiment index in predicting the spread, long leg and short leg returns. We see that the sentiment index is statistically significant in forecasting 5 out of 12 equally weighted Stambaugh, Yu and Yuan (2012a) strategies, 7 out of 12 short leg returns, and 6 out of 12 long leg returns. It does not appear that sentiment more strongly predicts the short leg than the long leg when equally weighted portfolios are used. In Panel B of Table A1, we see that when Fama and French factors from the next period are added as controls, much of the predictive power disappears. In this case, the sentiment index is significant in forecasting 3 out of 12 spread returns, 3 out of 12 short leg returns, and 1 out of 12 long leg returns. This drop in significance when Fama and French factors from the next period are added as controls is not surprising, and is consistent with our earlier findings.

In Table 6, we report predictability tests using both SENTHAT and SENTRES on the spread returns, the long leg returns and the short leg returns for the equally weighted Stambaugh, Yu and Yuan (2012a) portfolios. In Panel A of Table 6, when using equally-weighted Stambaugh, Yu and Yuan (2012a) portfolios, SENTHAT significantly predicts 3 spread returns, while SENTRES is never significant in predicting any of the 12 Stambaugh, Yu and Yuan (2012a) spread portfolio returns. Comparing the ability to predict both short and long legs in Panel B, we see that SENTRES is insignificant in predicting any long or short leg returns, while SENTHAT is significant in forecasting 8 short leg returns and 8 long leg returns. Unlike the asymmetric effect as in Stambaugh, Yu and Yuan (2012a), SENTHAT is equally important for both the short leg and long leg, consistent with the Baker and Wurgler (2006) portfolio results in Table 5. Clearly, the weighting scheme has quite an impact on the asymmetric effect of sentiment on long and short leg returns.[8]

The Long of It

Following Novy-Marx's critique, Stambaugh, Yu and Yuan (2012b) propose a set of simulations for sign consistence and t-statistics magnitudes and conclude that the sentiment index's

[8] From unreported results, if we include lagged Fama and French factors, the predictability of both SENTHAT and SENTRES stay about the same as in Panels A and B of Table 6. These findings are consistent with our previous results, and we exclude them to conserve space.

predictive power does not result from its persistence. The idea is that if the sentiment index is a random persistent variable with no predictive information, then we should not observe the consistency in signs or magnitude of t-statistics across all anomalies.

We conduct the same simulations as a robustness check, using only the 11 Stambaugh, Yu and Yuan (2012a) anomalies and combination portfolio. Using the same simulation of SENTHAT and SENTRES as described above in Section II (but increasing the number of simulations to 500,000), we follow Stambaugh, Yu and Yuan (2012b) in determining whether a simulated series predicts returns as strongly as SENTHAT or SENTES. The simulation procedure is described in detail in Appendix C.

Table 6 Panel C reports the results from this simulation exercise. The numbers in the short, long, and spread columns represent the reciprocal of the frequency with which a simulated regressor outperforms its respective component of sentiment for j anomalies. Only 1 in 5,682 simulated regressors performs as well as SENTHAT across all 11 anomaly spread portfolios, while 1 in 443 does as well as SENTRES. For the short legs, only once in 6,329 generated random series did the simulated series predict the short leg as strongly as did the SENTHAT. It takes 166,667 generated series to produce one random series that predicts spread portfolio and short leg returns as strongly as SENTHAT. The odds for a randomly generated persistent series to have predictive ability as strong as SENTRES is much higher, as one in every 443 generated series will predict returns as strongly as SENTRES for the spread portfolios and only one in every 21 for the short legs.

The simulation exercise clearly demonstrates that there are long odds for a randomly generated variable with similar persistence as SENTHAT to have predictive power as strong as that of SENTHAT on portfolio spread returns and the short-leg returns.

The Michigan Consumer Sentiment Index

An alternative sentiment measure is the Michigan Consumer Sentiment Index. Lemmon and Portniaguina (2006) show that the component that is related to investor sentiment can significantly forecast returns of small stocks. We apply our decomposition procedure to the Michigan consumer sentiment index and find 74% of its variation can be contributed to business cycle variables, with disposable personal income growth and unemployment rate explaining largest portions of its total variations. On the other hand, the Michigan Consumer Sentiment Index is not as powerful a predictor for cross-sectional stock returns as the Baker and Wurger (2006) sentiment index. After decomposing the Michigan Consumer Sentiment Index intoa business cycle component and a pure sentiment component, we find the business cycle component can predict 5 of the 28 spread portfolios used in our paper and the pure sentiment component can forecast only the size spread portfolio return. For the sake of brevity, we do not report our results using Michigan Consumer Sentiment index, but they are available upon request.

V. Sentiment as a Conditioning Variable for Asset Pricing Models

As shown in previous sections, the inclusion of the Fama and French factors from the next period as controls reduces the significance of lagged SENTHAT as a predictor of future anomaly returns. One implication from this result is that SENTHAT might contain information that predicts future realizations of the asset pricing factor SMB[9], which supports the notion that SENTHAT is a relevant state variable. In this section, we conduct rigorous asset pricing tests to examine whether the sentiment index contains relevant information for asset pricing models, and furthermore, to determine which of the two components of the sentiment index is important for asset pricing in general. We describe our approach in section IV.A. In section IV.B, we examine the relevance and importance of the original sentiment index and the two components SENTHAT and SENTRES as state variables in asset pricing models.

A. Empirical Approach

Campbell (1996) argues that any variable that helps to predict the future investment opportunity set can be a state variable. Given the strong power of the sentiment index to predict the market

[9] Some asserting that SMB is behavioral in nature might argue that the drop in significance of SENTHAT when SMB is included as a control, and the high correlation between the two variables, suggests that SENTHAT, too, is a behavioral indicator. We disagree. First, SENTHAT is constructed from fundamental macroeconomic variables. Secondly, Vassalou (2003) presents evidence that SMB predicts future GDP growth, and Petkova (2005) demonstrates that SMB is correlated with innovations in state variables shown to predict the excess market return.

return as documented in Baker, Wurgler and Yuan (2012), it is natural to consider the sentiment index as a state variable that is relevant for asset pricing. Our empirical approach aims to answer two questions: whether sentiment variables are important conditioning variables in formal asset pricing test; and which component of sentiment, SENTHAT or SENTRES, is more important as a state variable.

We set up our asset pricing test in the stochastic discount factor (SDF) framework. Each asset pricing model has a corresponding SDF. For instance, the CAPM's and FF's SDFs are defined as:

$$m_t^{CAPM} = a + bMKT_t,$$

$$m_t^{FF} = a + bMKT_t + cSMB_t + dHML_t.$$

To make use of the potential state variable, the sentiment index, $SENTIMENT_{t-1}$, we adopt Cochrane's (1996) conditional model approach and make the risk prices linear functions of the state variable from the previous period. In this sense, the model becomes a conditional model and the state variable becomes a conditioning variable. For the conditional CAPM and conditional FF, the SDFs take the following forms:

$$m_t^{CAPM*SENTIMENT} = (a + bSENTIMENT_{t-1}) + (c + dSENTIMENT_{t-1})MKT_t,$$

$$m_t^{FF*SENTIMENT} = (a + bSENTIMENT_{t-1}) + (c + dSENTIMENT_{t-1})MKT_t$$

$$+(e + fSENTIMENT_{t-1})SMB_t + (g + hSENTIMENT_{t-1})HML_t.$$

In the case of the decomposed sentiment index, we can easily replace the conditioning variable $SENTIMENT_{t-1}$ by either $SENTHAT_{t-1}$ or $SENTRES_{t-1}$, and form corresponding SDFs.

To evaluate the above models' performances, we follow the standard in the asset pricing literature and require those models to price the Fama and French 25 size and BM portfolios. That is, a good model should be able to obtain zero pricing errors on the size and BM portfolios. We estimate the above unconditional models and conditional models using two approaches, the optimal GMM and the Hansen-Jagannathan distance. The two tests are well documented in the literature, so we refer readers to Hodrick and Zhang (2001) and Xing (2008) for more details.

The inferences from the above exercises can be drawn in multiple ways. First, if the coefficient for the state variable is statistically significant, then the state variable is relevant for asset pricing. For instance, we can compare the significance of $SENTHAT_{t-1}$ or $SENTRES_{t-1}$ and examine which one is more important. Second, if the model can pass either the J-test from optimal GMM or the zero HJ-distance test, then the model is considered adequate. The HJ-distance can be directly compared across different models, and the model with the minimum HJ-distance is considered the best performing model. We can then judge whether $SENTHAT_{t-1}$ or $SENTRES_{t-1}$ reduces the pricing errors more. Finally, the pricing errors from different models directly provide evidence on which assets can be priced by each model.

B. The Sentiment Index as a Conditioning Variable

We report the asset pricing test results for the sentiment index as a conditioning variable in Table 7. Panel A presents risk prices. We start with the unconditional CAPM and Fama and French model as benchmarks. For both models, MKT and HML are significantly priced. When we include the sentiment index as a conditioning variable, the sentiment index is always highly significant with a negative price in both models, which indicates that assets with high correlations with sentiment receive high returns, consistent with the Baker and Wurgler (2006) finding. However, their focus is on the price of MKT*SENTIMENT, which is only marginally significant. Baker and Wurgler (2006) interpret this finding as indicating that the time-varying market risk price conditioning on sentiment index is not important for asset pricing, and thus a risk story is an unlikely explanation for why sentiment predicts future cross-sectional returns. Our finding confirms that sentiment is not important because of its interaction with the market factor. Instead, the term $(a + bSENTIMENT_{t-1})$ in both conditional models helps to pin down the time-varying interest rate or the return on the zero beta portfolio, and this is how the sentiment index improves both asset pricing models by setting the right interest rate level. In that sense, we can still put sentiment in a systematic risk setting.

Next we include both SENTHAT and SENTRES as conditioning variables. From the risk prices, SENTHAT is significant with a negative price, while SENTRES is marginally significant for a conditional Fama and French model with a negative price. The above findings show that all sentiment variables can be important state variables.

Table 7 Panel B reports specification test results. Without conditioning information, the original unconditional CAPM and FF fail to pass both the optimal GMM J-test and Hansen-Jagannathan distance test with p-values less than 1%. When the risk prices are allowed to fluctuate with the sentiment index, the performances of both models are significantly improved, and both are able to pass specification tests at 1%. The decreases in J-stat and HJ-distance are much larger using SENTHAT than using SENTRES. For instance, the J-stat decreases from 58.47 for unconditional CAPM, to 38.37 for CAPM*SENTHAT, to 47.87 for CAPM*SENTRES, and to 36.49 for CAPM*SENTIMENT. This clearly indicates that the improvement of the models by including SENTIMENT as a conditioning variable is derived primarily from SENTHAT rather than SENTRES. Similar patterns are observed in HJ-distance and all p-values.

Finally, in Panel D, we report the pricing errors, which are the difference between the average asset returns and the expected returns from each model. We only include pricing errors for the conditional and unconditional CAPM in order to save space, and we use bold fonts to indicate statistical significance at 5%. The unconditional CAPM has difficulty in pricing smaller firms and firms with high BM ratios. As a result, 12 of the 25 pricing errors are statistically significant. When we include the sentiment index as a conditioning variable, the pricing errors are greatly reduced, particularly for value firms with high BM ratios. Only 6 assets still have significant pricing errors. Similarly, 6 out of 25 are significant when using SENTHAT as a conditioning variable, while 9 out of 25 are significant when using SENTRES as a conditioning variable.

Combining all of the information above, the sentiment index clearly contains relevant and important information for cross-sectional returns, and is a significant conditioning variable for benchmark asset pricing models. Meanwhile, the underlying source of its significance as a conditioning variable is the common business cycle component of the sentiment index.

VI. Conclusion

There is a long and growing literature investigating the impact of investor sentiment on financial markets. Baker and Wurgler (2006) construct an investor sentiment index, and recent literature show this sentiment index significantly predicts future stock returns. But exactly what is sentiment? Despite the claim from Baker and Wurgler (2006) that $SENTIMENT_{\perp}$ is orthogonal to macroeconomic conditions, we find that the sentiment indices constructed in Baker and Wurgler (2006) have a substantial amount of information related to the business cycle, as it co-varies strongly with commonly used business cycle variables such as the T-bill rate and market liquidity conditions.

We decompose the widely used investor sentiment index into two components. One component is related to business cycle variables and the other orthogonal component is unrelated to the business cycle. We show that the predictive power of the sentiment index for cross-sectional stock returns is mainly driven by the business cycle component, while the component unrelated to the business cycle has essentially no predictive power. Our results also indicate that part of the predictive power of the business cycle component of sentiment on the cross-sectional stock returns is due to its significant correlation with the future size factor in the Fama and French three-factor model. Furthermore, we document that including the sentiment index as a conditioning variable in both the CAPM and the Fama and French 3-factor model drastically improves the models' abilities to price the 25 Fama and French size and book-to-market portfolios. Of the two orthogonal components we construct from the sentiment index, it is the component of sentiment related to commonly used business cycle variables that is more useful as a conditioning variable in these asset pricing tests.

In summary, our empirical results suggest that the widely used investor sentiment index contains rich information about economic fundamentals and might not be a pure behavioral measure of sentiment. It remains a challenge to find a true investor sentiment proxy. Meanwhile, we do not rule out the possibility that sentiment might be a general equilibrium phenomenon, and it could cause business cycle variables such as interest rates and liquidity to fluctuate. Nevertheless, without a full-fledged general equilibrium model, it is empirically difficult to test the direction of causality between sentiment measures and business cycle variables, and we leave this agenda to future research.

Appendix A. Baker Wurgler (2006) Portfolio Descriptions

Firm age: Measured as the number of years since a firm first appears in the CRSP database. Younger firms with a shorter history of cash flows are likely more difficult to value than older firms.

Dividends to book equity: Measured as dividends per share times shares outstanding divided by the book value of equity. Firms that pay substantial dividends are likely more easily valued than firms that pay little to no dividends.

External finance to assets: Measured as the change in assets minus the change in retained earnings divided by assets. This variable might be indicative of growth opportunities, distress, or both. Low values of this variable may indicate distress, while high values may reflect growth opportunities. Therefore, three portfolios are formed on this variable. One takes a long position in the top 30% and a short position in the bottom 30%, while another takes a long position in the top 30% and a short position in the middle 40%, and the last takes a long position in the middle 40% and a short position in the bottom 30%.

Earnings to book equity: Return on equity, measured as earnings divided by the book value of equity, is a profitability measure. Currently unprofitable firms are likely more difficult to value or arbitrage than firms with high levels of profitability.

Growth in sales: Measured as the change in net sales divided sales of the previous year, sales growth is a measure of growth opportunities. Firms with high values of this variable may have numerous growth opportunities, while firms with low values might be in distress. Firms in either of these categories might be difficult to value or hard to arbitrage. Three spread portfolios are formed on this variable in exactly the same way as described above for "External finance to assets."

Property, plant, and equipment to total assets: Constructed as the ratio of property, plant and equipment to total assets, this variable is a measure of asset tangibility. Firms with a high proportion of intangible assets are likely more difficult to value.

Research and development expense to total assets: Another measure of asset tangibility, this characteristic is constructed as the ratio of research and development expense to total assets. Firms with high levels of R&D spending might be more difficult to value.

Sigma: This is measured as the standard deviation of stock returns over the previous 12 months. Stock return volatility is likely a good proxy for difficulty in valuation and/or arbitrage.

Market equity: Constructed as the price per share times the number of shares outstanding, market equity is a proxy for firm size. Small firms might be more difficult to value or arbitrage than large firms.

Book equity to market equity: As a proxy for either growth opportunities or distress, this variable is constructed as the ratio of book equity to market equity. Three different spread portfolios are constructed from this variable in the same manner as “Growth in Sales” and External Finance to Assets” variables.

Appendix B. Stambaugh, Yu, and Yuan (2012a) Portfolio Descriptions

Financial distress (1 and 2): Campbell, Hilscher, and Szilagyi (2007) and Ohlson (1980) find that firms with a high probability of failure have lower, not higher, subsequent returns

Net issues and composite equity issues (3 and 4): Ritter (1991) and Daniel and Titman (2006) document that issuers underperform non-issuers.

Accruals (5): Sloan (1996) finds that a portfolio with a long position in firms with low accruals and a short position in firms with high accruals generates positive abnormal returns.

Net operating assets (6): Hirshleifer, Hou, Teoh, and Zhang (2004) document that a portfolio shorting firms with high net operating assets (NOA) and longing firms with low NOA generates positive abnormal returns.

Momentum (7): First documented in Jegadeesh and Titman (1993), a portfolio longing firms with high 11-month returns from month *t-12* to *t-2* generates positive abnormal returns. Further evidence presented in Antoniou, Doukas, and Subrahmanyam (2012) suggests that momentum is stronger when sentiment is high.

Gross profitability (8): Novy-Marx (2012) finds that a portfolio longing firms with high gross profitability and shorting firms with low gross profitability earns positive abnormal returns.

Asset growth (9): Cooper, Gulen, and Schill (2008) document that a portfolio with a long position in stocks with low total asset growth over the previous year and a short position in stocks with high previous-year total asset growth earns positive abnormal returns.

Return on assets (10): Fama and French (2006) present evidence that a portfolio longing high past ROA firms and shorting low past ROA firms generates positive abnormal returns. Wang and Yu (2010) find that this exists primarily among firms with high arbitrage costs and high information uncertainty.

Investment-to-assets (11): Titman, Wei, and Xie (2004) and Xing (2008) document that positive abnormal returns are earned by a portfolio with a long position in firms with low past investment to assets and a short position in firms with high past investment to assets.

Appendix C. Simulation for "The Long of It"

We conduct the same simulations for our study for robustness as did the original Stambaugh, Yu and Yuan (2012b) study, using only the 11 anomalies and combination portfolio that they included. Using the same simulated series of SENTHAT and SENTRES as described in Section II, we follow Stambaugh, Yu and Yuan (2012b) in determining whether a simulated series predicts returns as strongly as SENTHAT or SENTES. Following the nomenclature of Stambaugh, Yu and Yuan (2012b), let $\bar{t}_i^x$ denote the *i*-th highest t-statistic for the simulated regressors and $\bar{t}_i^S$ denote the *i*-th highest t-statistic for the sentiment component of interest across the 11 anomalies. Similarly, let $\underline{t}_i^x$ ($\underline{t}_i^S$) denote the *i*-th lowest t-statistic for the simulated (actual) component of sentiment. For spread portfolios, a simulated regressor performs better than its respective component of sentiment for *j* anomalies if $\bar{t}_i^x \geq \bar{t}_i^S$ *j* times for $i = 1, \ldots, 11$. A simulated regressor outperforms its sentiment component counterpart for the short leg of *j* anomalies if $\underline{t}_i^x \leq \underline{t}_i^S$ *j* times for $i = 1,\ldots,11$. Finally, for the long leg, a simulated regressor outperforms its respective sentiment component if $\left|\underline{t}_i^x\right| \leq \left|\underline{t}_i^S\right|$.

Appendix Table 1. Predicting equal-weighted Stambaugh, Yu and Yuan (2012a) portfolio returns with SENTIMENT

This table presents the results of using SENTIMENT to predict returns on equal weighted Stambaugh, Yu and Yuan (2012a) portfolios. Panel A and B present results for the following two regressions, respectively:

$R_{i,t} = a + bSENTIMENT_{t-1} + u_t$,

$R_{i,t} = a + bSENTIMENT_{t-1} + dMKT_t + eSMB_t + fHML_t + gWML_t + u_t$.

Variable Ri,t is the time t monthly return on the long-short portfolio, SENTIMENT is the time t-1 sentiment index. We report coefficient estimates, one-sided empirical p-values, and Novy-Marx (NM) t-statistics (OLS t-statistics scaled by the standard deviation of t-statistics from simulations). The sample period for 8 of the 11 Stambaugh, Yu and Yuan (2012a) portfolios is August 1965 through January 2008. For the O-score and the ROA anomalies, data are available beginning in January 1972, while the failure-probability data begin in December 1974. Details on portfolio construction can be found in section IV.A of the text.

Panel A. predicting short/long leg and spread portfolio returns at *t* using SENTIMENT from *t-1* only

	Short leg			Long leg			Spread		
	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue
Distress	-1.44	-2.81	0.01	-0.39	-1.72	0.08	1.05	3.12	0.01
O-score	-0.53	-0.80	0.23	-0.57	-2.86	0.01	-0.04	-0.07	0.48
ROA	-0.24	-0.36	0.41	-0.10	-0.33	0.40	0.14	0.29	0.43
NSI	-0.57	-2.34	0.04	-0.52	-2.61	0.04	0.06	0.40	0.40
CEI	-0.76	-3.49	0.01	-0.16	-0.91	0.24	0.61	3.29	0.01
Accruals	-0.80	-2.77	0.03	-0.83	-3.66	0.01	-0.04	-0.31	0.41
NOA	-0.77	-3.41	0.01	-0.34	-1.26	0.17	0.44	1.99	0.06
MOM	-0.64	-1.30	0.17	-0.78	-2.62	0.03	-0.14	-0.42	0.40
GP	-0.30	-1.30	0.17	-0.29	-1.21	0.18	0.02	0.15	0.45
AG	-0.92	-3.54	0.01	-0.64	-2.70	0.03	0.28	1.55	0.12
INV	-0.55	-2.35	0.04	-0.66	-2.80	0.02	-0.11	-2.13	0.06
Combination	-0.68	-2.35	0.04	-0.53	-2.49	0.04	0.15	1.35	0.16

Panel B. predicting short/long leg portfolio returns at *t* using SENTIMENT from *t-1* and Fama and French factors from *t*

	Short leg			Long leg			Spread		
	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue
Distress	-0.73	-3.09	0.01	0.03	0.32	0.40	0.75	3.37	0.01
O-score	-0.04	-0.06	0.48	0.20	1.72	0.05	0.25	0.41	0.38
ROA	0.20	0.32	0.42	0.21	1.33	0.14	0.01	0.02	0.50
NSI	-0.04	-0.28	0.43	-0.12	-1.42	0.14	-0.08	-0.62	0.34
CEI	-0.19	-1.43	0.15	0.12	1.75	0.10	0.31	1.73	0.09
Accruals	-0.16	-1.02	0.22	-0.26	-1.95	0.07	-0.11	-1.00	0.22
NOA	-0.20	-1.94	0.08	0.10	0.56	0.37	0.30	1.29	0.17
MOM	-0.04	-0.08	0.48	-0.13	-0.85	0.27	-0.09	-0.27	0.44
GP	0.14	1.02	0.24	0.22	1.78	0.09	0.08	0.68	0.30
AG	-0.24	-2.48	0.04	-0.12	-0.71	0.30	0.13	0.78	0.29
INV	-0.04	-0.31	0.41	-0.11	-0.84	0.27	-0.07	-1.41	0.14
Combination	-0.08	-0.47	0.39	-0.04	-0.42	0.38	0.04	0.40	0.40

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Table 1. Summary Statistics

This table reports summary statistics for key variables used in our analyses. Panel A reports means, standard deviations, and serial autocorrelation coefficients (AR1) for the Fama and French factors (MKT, SMB, and HML), momentum factor WML, and the Baker and Wurgler (2006) raw and orthogonalized sentiment indices (*SENTIMENT* and $SENTIMENT_{\perp}$). The last 6 columns report the correlations between each of these variables. Panel B presents the means, standard deviations, and serial autocorrelation coefficients (AR1) for the 13 macroeconomic variables used in the decomposition procedure as well as their correlations with each of the 2 sentiment measures. These variables are, from top to bottom, the U.S. unemployment rate (Unemp), change in inflation (dCPI), change in consumption (dCons), change in disposable income (dSPI), change in industrial production (dInd), U.S. recession dummy (NBER), T-bill rate (Tbill), default spread (Def), term spread (Term), aggregate CRSP value-weighted dividend yield (Div), the value-weighted market return including dividends (VWRETD), market volatility (MktVol), and percentage of stocks with zero returns (PctZero). Additionally, the last column of Panel B reports the data sources for each of the variables, while the Fama and French factors are from Kenneth French's website. Our sample period is July 1965 to December 2010. All variables are measured at monthly frequency.

Panel A. Summary statistics and correlations of Fama French factors and sentiment indices

				Correlations					
	Mean	Std	AR1	MKT	SMB	HML	WML	SENTIMENT	$SENTIMENT_{\perp}$
MKT	0.43	4.61	0.09	1.00					
SMB	0.28	3.23	0.06	0.31	1.00				
HML	0.39	2.99	0.16	-0.31	-0.24	1.00			
WML	0.72	4.43	0.06	-0.13	-0.01	-0.16	1.00		
SENTIMENT	0.00	1.00	0.99	-0.06	-0.10	0.05	0.01	1.00	
$SENTIMENT_{\perp}$	0.00	1.00	0.99	-0.07	-0.10	0.06	0.01	0.97	1.00

Panel B. Summary statistics of business cycle variables and correlations with sentiment indices

	Mean	Std	AR1	Corr with SENTIMENT	p-value	Corr with $SENTIMENT_{\perp}$	p-value	Source
Unemp	6.03	1.64	0.997	-0.10	0.02	-0.03	0.45	U.S. Dept. of Labor: Bureau of Labor Statistics
dCPI	0.36	0.33	0.617	-0.18	0.00	-0.09	0.03	U.S. Dept. of Labor: Bureau of Labor Statistics
dCons	0.58	0.56	-0.075	-0.12	0.00	-0.10	0.03	U.S. Dept. of Commerce: Bureau of Economic Analysis
dSPI	0.58	0.76	-0.136	-0.07	0.13	-0.04	0.30	U.S. Dept. of Commerce: Bureau of Economic Analysis
dInd	0.20	0.76	0.355	-0.07	0.11	-0.12	0.01	Board of Governors of the Federal Reserve System
NBER	0.15	0.36	0.901	0.08	0.05	0.13	0.00	NBER
Tbill	5.49	2.95	0.989	0.21	0.00	0.28	0.00	Board of Governors of the Federal Reserve System
Def	1.07	0.47	0.963	0.09	0.03	0.18	0.00	Board of Governors of the Federal Reserve System
Term	1.54	1.32	0.957	0.01	0.78	-0.04	0.35	Board of Governors of the Federal Reserve System
Div	2.95	1.09	0.990	-0.18	0.00	-0.11	0.01	CRSP
VWRETD	0.88	4.60	0.089	-0.06	0.15	-0.06	0.18	CRSP
MktVol	13.53	8.24	0.692	0.06	0.13	0.09	0.03	CRSP
PctZero	24.62	14.46	0.995	-0.26	0.00	-0.22	0.00	CRSP

Table 2. Sentiment Decomposition

This table reports the results of the decomposition of the raw and orthogonalized investor sentiment indices in the following regression: $SENTIMENT_t = a + b'(X_t) + e_t$, where $SENTIMENT_t$ is one of the two sentiment indices, X_t is a vector of monthly business cycle variables described below, and e_t is the regression residual. We then denote *SENTHAT* as the fitted value from the regression and *SENTRES* as the residual. The business cycle variables include the U.S. unemployment rate (Unemp), change in inflation (dCPI), change in consumption (dCons), change in disposable income (dSPI), change in industrial production (dInd), U.S. recession dummy (NBER), T-bill rate (Tbill), default spread (Def), term spread (Term), aggregate CRSP value-weighted dividend yield (Div), the value-weighted market return including dividends (VWRETD), market volatility (MktVol), and percentage of stocks with zero returns (PctZero). Panel A reports the regression coefficient estimates, OLS t-statistics, Newey-West t-statistics (NW t-stat) adjusted for 24 lags, and R-square decomposition. Panel B presents results from simulated macroeconomic variables. We report the 2.5th and 97.5th percentile of coefficient estimates from the simulation procedure, a one-sided p-value of the coefficient estimate, the Novy-Marx (NM) t-stats presents OLS t-statistics scaled by the standard deviation of OLS t-statistics over the 100,000 simulations. Panel C presents summary statistics of the sentiment indices and SENTHAT and SENTRES. Panel D reports the correlation between $SENTIMENT_{\perp}$, SENTHAT, SENTRES, and Fama French factors, contemporaneous or one period ahead. Our sample period is July 1965 to December 2010.

Panel A. Regression of Sentiment on business cycle variables

	SENTIMENT				SENTIMENT$_{\perp}$			
	coef.	OLS t-stat	NW t-stat	var explained	coef.	OLS t-stat	NW t-stat	var explained
Intercept	-0.28	-2.00	-0.68	0.00%	-0.71	-5.02	-1.62	0.00%
Unemp	-0.13	-4.46	-1.56	2.06%	-0.06	-2.22	-0.76	0.34%
dCPI	-0.33	-3.21	-2.14	1.91%	-0.12	-1.15	-0.85	0.35%
dCons	0.01	0.15	0.21	-0.05%	0.04	0.83	1.13	-0.23%
dSPI	-0.03	-0.89	-1.28	0.16%	-0.01	-0.33	-0.53	0.04%
dInd	-0.08	-1.95	-1.71	0.44%	-0.13	-2.89	-2.39	1.10%
NBER	0.21	2.13	1.06	0.62%	0.17	1.70	0.83	0.79%
Tbill	0.48	26.84	7.92	29.46%	0.48	26.71	8.22	39.48%
Def	0.02	0.14	0.07	0.06%	0.11	1.01	0.49	0.89%
Term	0.56	15.82	6.52	0.89%	0.48	13.67	6.10	-2.55%
Div	-0.27	-5.08	-1.51	5.30%	-0.27	-4.99	-1.39	3.09%
VWRETD	-0.01	-1.41	-1.71	0.26%	-0.01	-1.18	-1.21	0.20%
MktVol	-0.01	-1.27	-0.85	-0.29%	0.00	-0.67	-0.41	-0.23%
PctZero	-0.06	-15.13	-3.76	22.67%	-0.06	-15.92	-3.78	20.13%
R-square				63.60%				63.52%
adj R-square				62.64%				62.56%

Panel B. Simulation-based statistics

	SENTIMENT				SENTIMENT$_{\perp}$			
	2.5% CV	97.5% CV	p-value	NM t-stat	2.5% CV	97.5% CV	p-value	NM t-stat
Intercept	-2.70	2.13	0.41	-0.35	-2.57	2.03	0.26	-0.95
Unemp	-0.36	0.36	0.25	-0.90	-0.35	0.35	0.37	-0.46
dCPI	-0.44	0.43	0.07	-2.10	-0.44	0.44	0.30	-0.76
dCons	-0.12	0.12	0.45	0.19	-0.12	0.12	0.23	1.03
dSPI	-0.08	0.08	0.22	-1.09	-0.08	0.08	0.38	-0.40
dInd	-0.15	0.15	0.13	-1.46	-0.15	0.16	0.05	-2.16
NBER	-0.51	0.58	0.24	0.90	-0.51	0.59	0.30	0.72
Tbill	-0.32	0.32	0.00	4.90	-0.32	0.32	0.00	4.99
Def	-1.03	1.03	0.48	0.04	-1.04	1.04	0.42	0.27
Term	-0.49	0.49	0.01	3.46	-0.49	0.49	0.03	3.05
Div	-0.87	0.86	0.28	-0.94	-0.87	0.86	0.29	-0.95
VWRETD	-0.02	0.02	0.19	-1.20	-0.02	0.02	0.24	-1.01
MktVol	-0.02	0.02	0.32	-0.57	-0.02	0.02	0.41	-0.30
PctZero	-0.07	0.07	0.05	-2.66	-0.07	0.07	0.04	-2.90

Panel C. Summary statistics and correlations of sentiment components

	Mean	Std	AR1	Correlation SENTIMENT	SENTHAT	SENTRES	$SENTIMENT_{\perp}$	$SENTHAT_{\perp}$	$SENTRES_{\perp}$
SENTIMENT	0.00	1.00	0.99	1.00					
SENTHAT	0.00	0.80	0.96	0.80	1.00				
SENTRES	0.00	0.61	0.92	0.60	0.00	1.00			
$SENTIMENT_{\perp}$	0.00	1.00	0.98	0.97	0.78	0.57	1.00		
$SENTHAT_{\perp}$	0.00	0.80	0.96	0.78	0.98	0.00	0.80	1.00	
$SENTRES_{\perp}$	0.00	0.60	0.91	0.57	0.00	0.95	0.60	0.00	1.00

Panel D: Correlations between $SENTHAT_{\perp}$ and $SENTRES_{\perp}$ with contemporaneous and future Fama and French factors

	MKT_t	SMB_t	HML_t	WML_t	MKT_{t+1}	SMB_{t+1}	HML_{t+1}	WML_{t+1}
$SENTHAT_{\perp,t}$	-0.09	-0.08	0.04	0.02	-0.08	-0.10	0.05	0.02
p-value	0.04	0.08	0.39	0.73	0.06	0.02	0.26	0.57
$SENTRES_{\perp,t}$	0.00	-0.04	0.07	-0.01	-0.01	-0.03	0.03	-0.02
p-value	0.99	0.34	0.09	0.80	0.78	0.48	0.43	0.63

Table 3. Summary Statistics for Long-Short Portfolios Returns

This table presents the mean monthly returns, CAPM alphas, and momentum-augmented Fama and French alphas for each of the 16 long-short spread portfolios adopted from Baker and Wurgler (2006) and the 12 spread portfolios adopted from Stambaugh, Yu, and Yuan (2012a). Additionally, we present Newey-West t-statistics for the alphas, adjusted for 24 lags. The sample period for the 16 Baker and Wurgler (2006) portfolios is August 1965 through January 2010, while the sample period for 8 of the 11 Stambaugh, Yu and Yuan (2012a) portfolios is August 1965 through January 2008. For the O-score and the ROA anomalies, data are available beginning in January 1972, while the failure-probability data begin in December 1974. Details of the portfolio formation procedure are in section IV.A of the text.

	Mean	CAPM		Four-Factor			Mean	CAPM		Four-Factor	
BW Portfolio	return	Alpha	t-stat	Alpha	t-stat	SYY Portfolio	return	Alpha	t-stat	Alpha	t-stat
Age	-0.14	-0.03	-0.19	-0.14	-1.17	Distress	0.95	1.37	2.70	0.71	2.75
D/BE	-0.20	-0.08	-0.70	0.00	0.06	O-score	0.70	0.88	2.96	0.97	5.25
EF/A	-0.64	-0.71	-9.21	-0.51	-8.28	ROA	0.98	1.13	3.82	0.93	3.50
E/BE	-0.17	-0.17	-1.27	-0.09	-0.83	NSI	0.63	0.74	4.21	0.53	3.77
GS	-0.34	-0.40	-4.66	-0.23	-2.91	CEI	0.42	0.60	3.97	0.27	1.98
PPE/A	0.13	0.27	1.71	0.07	0.63	Accruals	0.58	0.68	2.51	0.47	1.63
RD/A	0.43	0.32	1.93	0.53	3.76	NOA	0.65	0.71	3.78	0.66	3.89
Sigma	0.18	-0.09	-0.41	-0.05	-0.32	MOM	1.56	1.65	7.66	0.39	2.67
GS High - Med	-0.24	-0.34	-3.71	-0.18	-2.89	GP	0.40	0.39	1.92	0.52	3.75
GS Med - Low	-0.11	-0.06	-0.67	-0.05	-0.59	AG	0.96	1.06	4.09	0.55	2.70
EF/A High - Med	-0.34	-0.43	-4.82	-0.28	-5.20	INV	0.75	0.81	3.95	0.50	2.61
EF/A Med - Low	-0.30	-0.27	-4.46	-0.23	-5.29	Combination	0.77	0.88	5.84	0.56	6.03
ME	-0.38	-0.30	-1.48	-0.15	-1.72						
B/M	0.95	1.03	6.09	0.99	9.61						
B/M High - Med	0.64	0.63	7.34	0.69	9.26						
B/M Med - Low	0.31	0.40	3.24	0.31	4.45						

Table 4. Predicting Spread Portfolio Returns with SENTHAT and SENTRES

This table presents the results of using SENTHAT and SENTRES to predict long-short spread portfolio returns. Panel A, B, C present results for the following three regressions, respectively:

$R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + u_t$,

$R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + dMKT_{t-1} + eSMB_{t-1} + fHML_{t-1} + gWML_{t-1} + u_t$,

$R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + dMKT_t + eSMB_t + fHML_t + gWML_t + u_t$.

Variable $R_{i,t}$ is the time t monthly return on the long-short portfolio, *SENTHAT* is the time *t-1* component of $SENTIMENT_{\perp}$ related to business cycle variables, and *SENTRES* is the pure sentiment component of $SENTIMENT_{\perp}$ at time t-1. The top 16 portfolios adopted from Baker and Wurgler (2006) include the momentum factor (WML), while the bottom 12 adopted from Stambaugh, Yu and Yuan (2012a) (2012) do not. Furthermore, SMB is omitted in the regression using the Baker and Wurgler (2006) portfolio formed on market value of equity, while HML is omitted in the regressions that include the three Baker and Wurgler (2006) portfolios formed on book-to-market values of equity. For both SENTHAT and SENTRES, we report coefficient estimates, one-sided empirical p-values, and Novy-Marx (NM) t-statistics (OLS t-statistics scaled by the standard deviation of t-statistics from simulations). The sample period for the 16 Baker and Wurgler (2006) portfolios is August 1965 through January 2010, while the sample period for 8 of the 11 Stambaugh, Yu and Yuan (2012a) portfolios is August 1965 through January 2008. For the O-score and the ROA anomalies, data are available beginning in January 1972, while the failure-probability data begin in December 1974. Details on portfolio construction can be found in section IV.A of the text.

Panel A. Predicting spread portfolio returns at *t* using SENTHAT and SENTRES from *t-1* only

	SENTHAT				SENTRES			
	coef.	OLS t-stat	NM t-stat	Emp. p-value	coef.	OLS t-stat	NM t-stat	Emp. p-value
Age	0.62	3.22	2.80	0.01	0.36	1.42	1.21	0.13
D/BE	0.56	4.67	3.60	0.00	0.04	0.24	0.19	0.43
EF/A	-0.10	-1.17	-1.18	0.15	-0.26	-2.17	-2.09	0.02
E/BE	0.48	3.51	2.79	0.01	0.24	1.31	1.08	0.16
GS	-0.01	-0.11	-0.10	0.46	-0.17	-1.31	-1.19	0.13
PPE/A	0.41	2.18	2.08	0.03	0.35	1.41	1.23	0.12
RD/A	-0.21	-1.21	-1.01	0.18	-0.26	-1.14	-0.92	0.19
Sigma	-1.06	-4.14	-3.76	0.00	-0.41	-1.20	-1.02	0.17
GS High - Med	-0.43	-4.16	-3.99	0.00	-0.28	-2.08	-1.80	0.05
GS Med - Low	0.42	4.08	3.37	0.00	0.12	0.85	0.69	0.26
EF/A High - Med	-0.41	-4.06	-3.67	0.00	-0.23	-1.71	-1.52	0.08
EF/A Med - Low	0.30	4.35	4.05	0.00	-0.03	-0.32	-0.27	0.40
ME	0.68	3.41	2.59	0.01	0.14	0.54	0.44	0.34
B/M	0.02	0.12	0.11	0.46	0.31	1.31	1.08	0.15
B/M High - Med	-0.27	-2.43	-2.57	0.01	0.09	0.58	0.57	0.29
B/M Med - Low	0.30	2.62	2.00	0.04	0.22	1.51	1.07	0.16
Distress	1.23	3.12	2.16	0.03	1.26	2.03	1.48	0.06
O-score	0.66	2.43	1.75	0.07	0.94	2.22	1.65	0.04
ROA	0.71	2.37	2.42	0.03	1.21	2.56	2.27	0.01
NSI	0.40	2.71	1.84	0.06	0.65	3.31	2.34	0.02
CEI	0.38	1.92	1.83	0.06	0.49	1.90	1.79	0.05
Accruals	0.32	1.39	0.92	0.22	0.38	1.23	0.91	0.20
NOA	0.73	4.09	2.92	0.00	0.09	0.38	0.31	0.39
MOM	0.28	0.80	1.05	0.17	0.15	0.32	0.38	0.36
GP	0.26	1.31	1.09	0.17	0.52	1.97	1.74	0.05
AG	0.40	1.79	1.15	0.16	0.31	1.05	0.78	0.24
INV	0.13	0.71	0.50	0.33	-0.07	-0.32	-0.24	0.41
Combination	0.46	3.44	2.51	0.02	0.42	2.37	1.84	0.05

Panel B. Predicting spread portfolio returns at *t* using SENTHAT, SENTRES, and Fama and French factors from *t-1*

	SENTHAT coef.	OLS t-stat	NM t-stat	Emp. p-value	SENTRES coef.	OLS t-stat	NM t-stat	Emp. p-value
Age	0.49	2.66	2.43	0.02	0.30	1.24	1.17	0.14
D/BE	0.47	4.13	3.38	0.00	0.04	0.28	0.25	0.41
EF/A	-0.11	-1.28	-1.31	0.12	-0.23	-1.99	-1.99	0.03
E/BE	0.40	3.00	2.32	0.02	0.25	1.40	1.17	0.14
GS	-0.05	-0.54	-0.48	0.33	-0.16	-1.23	-1.08	0.15
PPE/A	0.31	1.69	1.79	0.06	0.28	1.15	1.12	0.15
RD/A	-0.21	-1.23	-1.10	0.16	-0.20	-0.91	-0.80	0.23
Sigma	-0.93	-3.67	-3.57	0.00	-0.35	-1.05	-0.98	0.18
GS High - Med	-0.40	-3.88	-3.98	0.00	-0.25	-1.85	-1.77	0.05
GS Med - Low	0.34	3.49	2.82	0.01	0.09	0.72	0.60	0.29
EF/A High - Med	-0.36	-3.65	-3.41	0.00	-0.20	-1.53	-1.50	0.08
EF/A Med - Low	0.25	3.74	3.54	0.00	-0.03	-0.39	-0.35	0.37
ME	0.55	2.89	1.98	0.04	0.15	0.58	0.45	0.34
B/M	0.09	0.52	0.45	0.34	0.31	1.32	1.05	0.16
B/M High - Med	-0.20	-1.82	-1.79	0.05	0.09	0.63	0.61	0.28
B/M Med - Low	0.29	2.54	1.97	0.04	0.22	1.46	1.06	0.16
Distress	1.09	2.76	1.93	0.05	1.33	2.13	1.60	0.04
O-score	0.60	2.25	1.53	0.10	0.95	2.24	1.63	0.04
ROA	0.69	2.29	2.34	0.03	1.20	2.53	2.28	0.01
NSI	0.40	2.70	1.86	0.06	0.62	3.18	2.34	0.02
CEI	0.33	1.69	1.73	0.07	0.46	1.76	1.77	0.05
Accruals	0.34	1.47	0.98	0.20	0.38	1.23	0.92	0.20
NOA	0.75	4.23	2.96	0.00	0.10	0.44	0.35	0.38
MOM	0.24	0.67	0.83	0.23	0.19	0.41	0.45	0.34
GP	0.29	1.45	1.18	0.15	0.52	1.99	1.72	0.06
AG	0.45	2.04	1.32	0.13	0.31	1.05	0.78	0.24
INV	0.17	0.97	0.74	0.26	-0.10	-0.42	-0.33	0.38
Combination	0.46	3.41	2.48	0.02	0.42	2.35	1.87	0.04

Panel C. Predicting spread portfolio returns at *t* using SENTHAT, SENTRES from *t-1*, and Fama and French factors from *t*

	SENTHAT coef.	OLS t-stat	NM t-stat	Emp. p-value	SENTRES coef.	OLS t-stat	NM t-stat	Emp. p-value
Age	0.24	2.05	1.81	0.05	0.19	1.25	1.17	0.14
D/BE	0.31	4.25	3.01	0.00	-0.04	-0.44	-0.35	0.38
EF/A	0.00	0.05	0.04	0.49	-0.20	-2.38	-2.01	0.03
E/BE	0.35	3.05	2.38	0.02	0.21	1.36	1.08	0.16
GS	0.06	0.75	0.53	0.32	-0.12	-1.19	-0.87	0.20
PPE/A	0.04	0.33	0.27	0.41	0.19	1.25	1.08	0.16
RD/A	0.03	0.27	0.18	0.44	-0.11	-0.66	-0.49	0.33
Sigma	-0.48	-3.51	-2.57	0.01	-0.22	-1.23	-0.90	0.20
GS High - Med	-0.22	-3.74	-2.67	0.01	-0.20	-2.54	-1.89	0.04
GS Med - Low	0.28	3.26	2.31	0.02	0.08	0.67	0.50	0.32
EF/A High - Med	-0.21	-3.32	-2.50	0.01	-0.16	-1.87	-1.70	0.06
EF/A Med - Low	0.21	3.81	3.46	0.00	-0.05	-0.64	-0.58	0.29
ME	0.59	3.05	2.16	0.03	0.15	0.58	0.46	0.34
B/M	-0.01	-0.09	-0.06	0.48	0.23	1.25	0.92	0.19
B/M High - Med	-0.19	-2.12	-1.68	0.06	0.07	0.60	0.53	0.31
B/M Med - Low	0.18	2.00	1.32	0.12	0.16	1.32	0.86	0.21
Distress	0.55	1.71	1.12	0.17	1.53	3.05	2.08	0.01
O-score	0.35	2.07	1.62	0.09	1.12	4.18	3.13	0.00
ROA	0.46	1.82	1.49	0.11	1.32	3.38	2.56	0.00
NSI	0.25	1.90	1.20	0.15	0.56	3.25	2.29	0.02
CEI	0.15	0.98	0.97	0.20	0.35	1.68	1.69	0.06
Accruals	0.20	0.89	0.57	0.31	0.30	1.02	0.75	0.25
NOA	0.63	3.60	2.50	0.01	0.05	0.20	0.16	0.44
MOM	0.21	0.59	0.80	0.24	0.13	0.29	0.35	0.37
GP	0.26	1.36	1.10	0.17	0.56	2.27	1.90	0.04
AG	0.41	2.14	1.49	0.10	0.24	0.96	0.75	0.24
INV	0.11	0.66	0.49	0.33	-0.13	-0.62	-0.48	0.33
Combination	0.29	2.59	1.64	0.08	0.33	2.26	1.64	0.07

Table 5. Predicting Long and Short Leg Portfolio Returns with SENTHAT and SENTRES

This table presents the results of using SENTHAT and SENTRES to predict the long and short leg portfolio returns. Panels A, B, and C present results of the following three regression, respectively:

$R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + u_t$,

$R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + dMKT_{t-1} + eSMB_{t-1} + fHML_{t-1} + gWML_{t-1} + u_t$,

$R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + dMKT_t + eSMB_t + fHML_t + gWML_t + u_t$.

Variable $R_{i,t}$ is the monthly return on either the long or short portfolio, *SENTHAT* is the time *t-1* component of $SENTIMENT_{\perp}$ related to business cycle variables, and *SENTRES* is the pure sentiment component of $SENTIMENT_{\perp}$ at time t-1. The top 16 portfolios adopted from Baker and Wurgler (2006) (2006) include the momentum factor (WML), while the bottom 12 adopted from Stambaugh, Yu and Yuan (2012a) (2012) do not. Furthermore, SMB is omitted in the regression using the Baker and Wurgler (2006) portfolio formed on market value of equity, while HML is omitted in the regressions that include the three Baker and Wurgler (2006) portfolios formed on book-to-market values of equity. For both SENTHAT and SENTRES, we report coefficient estimates, one-sided empirical p-values, and Novy-Marx (NM) t-statistics (OLS t-statistics scaled by the standard deviation of t-statistics from simulations). The sample period for the 16 Baker and Wurgler (2006) portfolios is August 1965 through January 2010, while the sample period for 8 of the 11 Stambaugh, Yu and Yuan (2012a) portfolios is August 1965 through January 2008. For the O-score and the ROA anomalies, data are available beginning in January 1972, while the failure-probability data begin in December 1974. Details on portfolio construction can be found in section IV.A of the text.

Panel A. Predicting short/long leg portfolio returns at *t* using SENTHAT and SENTRES from *t-1* only

	Short leg, SENTHAT			Short leg, SENTRES			Long leg, SENTHAT			Long leg, SENTRES		
	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue
Age	-1.10	-3.11	0.01	-0.25	-0.47	0.33	-0.48	-2.16	0.03	0.11	0.31	0.39
D/BE	-0.78	-2.58	0.01	0.09	0.21	0.42	-0.22	-1.05	0.17	0.13	0.41	0.35
EF/A	-0.88	-2.77	0.01	0.06	0.12	0.45	-0.99	-3.01	0.01	-0.20	-0.40	0.35
E/BE	-1.15	-3.31	0.00	-0.20	-0.38	0.36	-0.68	-2.33	0.02	0.04	0.09	0.47
GS	-0.99	-3.02	0.01	-0.07	-0.13	0.45	-1.00	-3.06	0.01	-0.23	-0.48	0.33
PPE/A	-1.15	-3.11	0.01	-0.30	-0.54	0.30	-0.74	-2.81	0.01	0.05	0.12	0.45
RD/A	-0.99	-3.07	0.01	0.02	0.05	0.48	-1.20	-3.33	0.00	-0.24	-0.44	0.34
Sigma	-0.17	-0.74	0.25	0.11	0.34	0.37	-1.23	-3.24	0.00	-0.30	-0.52	0.31
GS High - Med	-0.57	-2.08	0.03	0.05	0.12	0.45	-1.00	-3.06	0.01	-0.23	-0.48	0.33
GS Med - Low	-0.99	-3.02	0.01	-0.07	-0.13	0.45	-0.57	-2.08	0.03	0.05	0.12	0.45
EF/A High - Med	-0.58	-2.08	0.03	0.03	0.07	0.47	-0.99	-3.01	0.01	-0.20	-0.40	0.35
EF/A Med - Low	-0.88	-2.77	0.01	0.06	0.12	0.45	-0.58	-2.08	0.03	0.03	0.07	0.47
ME	-1.00	-2.98	0.01	-0.16	-0.31	0.38	-0.32	-1.38	0.11	-0.02	-0.05	0.48
B/M	-0.91	-2.80	0.01	-0.27	-0.55	0.30	-0.89	-2.62	0.01	0.04	0.08	0.47
B/M High - Med	-0.61	-2.15	0.03	-0.05	-0.11	0.46	-0.89	-2.62	0.01	0.04	0.08	0.47
B/M Med - Low	-0.91	-2.80	0.01	-0.27	-0.55	0.30	-0.61	-2.15	0.03	-0.05	-0.11	0.46
Distress	-1.98	-3.13	0.01	-1.08	-1.05	0.14	-0.75	-2.39	0.02	0.18	0.38	0.34
O-score	-0.99	-2.10	0.04	-0.82	-1.02	0.14	-0.33	-1.10	0.18	0.13	0.26	0.39
ROA	-0.95	-2.07	0.05	-1.03	-1.25	0.09	-0.24	-0.68	0.29	0.18	0.35	0.36
NSI	-0.81	-2.49	0.02	-0.68	-1.46	0.09	-0.40	-1.79	0.06	-0.03	-0.09	0.47
CEI	-0.77	-2.50	0.02	-0.37	-0.85	0.22	-0.39	-1.94	0.05	0.13	0.44	0.34
Accruals	-1.01	-2.58	0.02	-0.54	-0.93	0.20	-0.69	-1.79	0.06	-0.16	-0.33	0.38
NOA	-0.94	-3.07	0.01	-0.48	-1.08	0.16	-0.20	-0.69	0.28	-0.39	-0.99	0.18
MOM	-1.11	-2.81	0.01	-0.52	-0.89	0.21	-0.82	-2.59	0.02	-0.37	-0.78	0.24
GP	-0.39	-1.35	0.12	-0.72	-1.76	0.05	-0.13	-0.42	0.36	-0.20	-0.51	0.32
AG	-0.97	-2.86	0.01	-0.59	-1.20	0.14	-0.58	-1.85	0.05	-0.29	-0.67	0.27
INV	-0.87	-2.94	0.01	-0.42	-0.98	0.19	-0.74	-2.59	0.02	-0.50	-1.20	0.14
Combination	-0.94	-2.89	0.01	-0.65	-1.33	0.11	-0.48	-1.89	0.05	-0.23	-0.65	0.28

Panel B. Predicting short/long leg portfolio returns at *t* using SENTHAT, SENTRES and Fama and French factors from *t-1*

	Short leg, SENTHAT			Short leg, SENTRES			Long leg, SENTHAT			Long leg, SENTRES		
	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue
Age	-0.88	-2.98	0.01	-0.20	-0.46	0.33	-0.39	-2.04	0.04	0.10	0.33	0.38
D/BE	-0.63	-2.45	0.02	0.08	0.22	0.42	-0.16	-0.81	0.23	0.12	0.43	0.34
EF/A	-0.68	-2.58	0.01	0.08	0.21	0.42	-0.80	-2.88	0.01	-0.15	-0.38	0.36
E/BE	-0.93	-3.19	0.00	-0.17	-0.41	0.35	-0.53	-2.15	0.03	0.07	0.20	0.42
GS	-0.77	-2.84	0.01	-0.03	-0.09	0.47	-0.82	-2.97	0.01	-0.19	-0.47	0.33
PPE/A	-0.92	-3.00	0.01	-0.24	-0.52	0.31	-0.61	-2.68	0.01	0.04	0.12	0.46
RD/A	-0.79	-2.88	0.01	0.04	0.10	0.46	-1.00	-3.21	0.00	-0.16	-0.36	0.37
Sigma	-0.08	-0.38	0.37	0.10	0.36	0.37	-1.00	-3.12	0.00	-0.25	-0.52	0.31
GS High - Med	-0.42	-1.85	0.05	0.06	0.18	0.43	-0.82	-2.97	0.01	-0.19	-0.47	0.33
GS Med - Low	-0.77	-2.84	0.01	-0.03	-0.09	0.47	-0.42	-1.85	0.05	0.06	0.18	0.43
EF/A High - Med	-0.44	-1.83	0.05	0.05	0.13	0.45	-0.80	-2.88	0.01	-0.15	-0.38	0.36
EF/A Med - Low	-0.68	-2.58	0.01	0.08	0.21	0.42	-0.44	-1.83	0.05	0.05	0.13	0.45
ME	-0.83	-2.74	0.01	-0.15	-0.33	0.38	-0.28	-1.29	0.12	0.00	0.00	0.50
B/M	-0.75	-2.74	0.01	-0.24	-0.58	0.29	-0.66	-2.33	0.02	0.07	0.17	0.44
B/M High - Med	-0.46	-1.92	0.05	-0.02	-0.06	0.48	-0.66	-2.33	0.02	0.07	0.17	0.44
B/M Med - Low	-0.75	-2.74	0.01	-0.24	-0.58	0.29	-0.46	-1.92	0.05	-0.02	-0.06	0.48
Distress	-1.81	-3.02	0.01	-1.01	-1.05	0.13	-0.72	-2.19	0.03	0.32	0.64	0.25
O-score	-0.91	-2.11	0.04	-0.73	-0.99	0.15	-0.31	-1.01	0.20	0.21	0.45	0.32
ROA	-0.90	-2.11	0.04	-0.91	-1.18	0.11	-0.21	-0.59	0.32	0.29	0.55	0.28
NSI	-0.77	-2.51	0.02	-0.61	-1.41	0.10	-0.37	-1.65	0.08	0.01	0.04	0.48
CEI	-0.68	-2.43	0.02	-0.31	-0.79	0.23	-0.35	-1.81	0.06	0.15	0.54	0.31
Accruals	-0.95	-2.63	0.02	-0.45	-0.85	0.22	-0.61	-1.68	0.07	-0.07	-0.15	0.44
NOA	-0.90	-3.15	0.01	-0.44	-1.07	0.16	-0.14	-0.50	0.34	-0.34	-0.91	0.20
MOM	-1.00	-2.74	0.01	-0.46	-0.86	0.21	-0.77	-2.59	0.02	-0.27	-0.63	0.28
GP	-0.38	-1.33	0.12	-0.66	-1.67	0.06	-0.09	-0.29	0.41	-0.14	-0.38	0.37
AG	-0.91	-2.88	0.01	-0.52	-1.15	0.15	-0.46	-1.63	0.08	-0.22	-0.58	0.30
INV	-0.82	-2.94	0.01	-0.37	-0.92	0.20	-0.65	-2.54	0.02	-0.47	-1.27	0.12
Combination	-0.88	-2.96	0.01	-0.58	-1.32	0.11	-0.42	-1.75	0.06	-0.17	-0.51	0.32

Panel C. Predicting short/long leg portfolio returns at *t* using SENTHAT and SENTRES from *t-1* and Fama and French factors from *t*

	Short leg, SENTHAT			Short leg, SENTRES			Long leg, SENTHAT			Long leg, SENTRES		
	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue	Coef.	NM t-stat	emp. pvalue
Age	-0.22	-1.85	0.05	-0.04	-0.27	0.40	0.02	0.34	0.38	0.15	1.71	0.05
D/BE	-0.13	-1.19	0.14	0.20	1.45	0.08	0.18	2.27	0.02	0.16	1.35	0.10
EF/A	-0.15	-1.12	0.16	0.20	1.31	0.11	-0.15	-1.22	0.14	0.00	-0.03	0.49
E/BE	-0.32	-2.22	0.02	-0.02	-0.10	0.47	0.03	0.32	0.38	0.19	1.55	0.07
GS	-0.22	-1.47	0.10	0.09	0.51	0.32	-0.16	-1.43	0.10	-0.03	-0.27	0.40
PPE/A	-0.21	-1.66	0.07	-0.06	-0.41	0.35	-0.17	-1.25	0.14	0.13	0.81	0.23
RD/A	-0.26	-1.66	0.07	0.15	0.83	0.22	-0.22	-1.11	0.16	0.04	0.17	0.43
Sigma	0.20	1.68	0.07	0.16	1.01	0.17	-0.29	-1.86	0.05	-0.07	-0.37	0.37
GS High - Med	0.06	0.73	0.26	0.16	1.57	0.07	-0.16	-1.43	0.10	-0.03	-0.27	0.40
GS Med - Low	-0.22	-1.47	0.10	0.09	0.51	0.32	0.06	0.73	0.26	0.16	1.57	0.07
EF/A High - Med	0.06	0.57	0.31	0.15	1.26	0.12	-0.15	-1.22	0.14	0.00	-0.03	0.49
EF/A Med - Low	-0.15	-1.12	0.16	0.20	1.31	0.11	0.06	0.57	0.31	0.15	1.26	0.12
ME	-0.44	-1.55	0.08	-0.08	-0.26	0.41	0.15	3.47	0.00	0.06	1.04	0.15
B/M	-0.11	-1.04	0.17	-0.04	-0.29	0.39	-0.12	-0.64	0.28	0.19	0.87	0.21
B/M High - Med	0.07	0.63	0.28	0.12	0.86	0.21	-0.12	-0.64	0.28	0.19	0.87	0.21
B/M Med - Low	-0.11	-1.04	0.17	-0.04	-0.29	0.39	0.07	0.63	0.28	0.12	0.86	0.21
Distress	-0.73	-1.84	0.06	-1.53	-2.41	0.00	-0.18	-0.83	0.25	0.00	0.00	0.50
O-score	-0.42	-1.76	0.07	-1.03	-2.77	0.00	-0.06	-0.63	0.31	0.09	0.67	0.24
ROA	-0.41	-1.37	0.13	-1.15	-2.37	0.01	0.05	0.38	0.38	0.17	1.04	0.14
NSI	-0.40	-2.53	0.02	-0.46	-2.35	0.02	-0.15	-1.56	0.09	0.10	0.89	0.21
CEI	-0.34	-2.17	0.03	-0.15	-0.82	0.23	-0.18	-1.77	0.06	0.20	1.57	0.07
Accruals	-0.38	-1.61	0.08	-0.17	-0.64	0.28	-0.18	-0.74	0.26	0.13	0.46	0.34
NOA	-0.47	-2.36	0.02	-0.24	-1.06	0.17	0.16	1.10	0.18	-0.19	-1.08	0.16
MOM	-0.42	-1.70	0.07	-0.16	-0.53	0.32	-0.22	-1.23	0.14	-0.03	-0.15	0.45
GP	-0.08	-0.50	0.33	-0.56	-2.74	0.01	0.18	1.01	0.19	0.00	0.01	0.49
AG	-0.47	-2.75	0.01	-0.30	-1.52	0.08	-0.06	-0.29	0.40	-0.06	-0.25	0.41
INV	-0.38	-1.79	0.06	-0.16	-0.66	0.27	-0.28	-2.08	0.04	-0.29	-1.58	0.07
Combination	-0.38	-2.48	0.02	-0.35	-1.97	0.04	-0.09	-0.85	0.24	-0.02	-0.16	0.44

Table 6. Robustness

Panels A and B present prediction results of equally weighted Stambaugh, Yu and Yuan (2012a) spread portfolios and long/short leg portfolios, respectively. The predictive variables are SENTHAT and SENTRES only. We report coefficient estimates, one-sided empirical p-values, and Novy-Marx (NM) t-statistics (OLS t-statistics scaled by the standard deviation of t-statistics from simulations). The sample period for 8 of the 11 Stambaugh, Yu and Yuan (2012a) portfolios is August 1965 through January 2008. For the O-score and the ROA anomalies, data are available beginning in January 1972, while the failure-probability data begin in December 1974. Panel C shows the result of replicating the procedure in Stambaugh, Yu, and Yuan (2012b) using the returns of the 11 Stambaugh, Yu and Yuan (2012a) anomalies and the combination strategy. The numbers in the table represent the reciprocal of the frequency with which a randomly simulated SENTHAT/SENTRES has similar t-statistics as the real SENTHAT/SENTRES DO; in other words, the numbers represent the number of simulations one would have to perform before obtaining a simulated regressor that performs as well as its actual counterpart. Columns labeled "1&2" refer to instances in which a simulated regressor jointly satisfies the conditions for the spread and short legs, while the columns labeled “1, 2, & 3” refer to instances in which a simulated regressor jointly satisfies the conditions for the spread, short leg, and long leg.

Panel A. Predicting equally weighted Stambaugh, Yu and Yuan (2012a) spread portfolio returns at *t* using SENTHAT and SENTRES from *t-1* only

	SENTHAT			SENTRES		
	Coef.	NM t-stat	Emp. p-value	Coef.	NM t-stat	Emp. p-value
Distress	1.11	2.90	0.01	0.88	1.48	0.06
O-score	0.15	0.25	0.41	-0.47	-0.79	0.19
ROA	-0.04	-0.08	0.47	0.63	1.12	0.12
NSI	-0.06	-0.41	0.37	0.27	1.38	0.10
CEI	0.64	2.70	0.01	0.54	1.70	0.06
Accruals	-0.05	-0.33	0.39	-0.01	-0.06	0.48
NOA	0.73	2.99	0.00	-0.08	-0.28	0.40
MOM	-0.14	-0.39	0.38	-0.15	-0.39	0.36
GP	-0.18	-1.10	0.17	0.35	1.52	0.08
AG	0.26	1.12	0.17	0.31	1.09	0.16
INV	-0.10	-1.33	0.12	-0.14	-1.31	0.11
Combination	0.13	1.14	0.16	0.18	1.28	0.12

Panel B. Predicting equally weighted Stambaugh, Yu and Yuan (2012a) long/short leg portfolio returns at *t* using SENTHAT and SENTRES from *t-1* only

	Short leg, SENTHAT			Short leg, SENTRES			Long leg, SENTHAT			Long leg, SENTRES		
	Coef.	NM t-stat	Emp. p-value	Coef.	NM t-stat	Emp. p-value	Coef.	NM t-stat	Emp. p-value	Coef.	NM t-stat	Emp. p-value
Distress	-1.83	-3.24	0.00	-0.39	-0.45	0.32	-0.71	-2.84	0.01	0.49	1.16	0.11
O-score	-1.10	-1.71	0.03	0.72	0.96	0.14	-0.95	-3.32	0.00	0.25	0.51	0.28
ROA	-0.30	-0.48	0.35	-0.08	-0.09	0.47	-0.34	-0.98	0.21	0.55	0.99	0.15
NSI	-0.71	-2.21	0.03	-0.35	-0.78	0.24	-0.77	-2.72	0.01	-0.08	-0.20	0.43
CEI	-0.95	-2.92	0.01	-0.44	-0.91	0.20	-0.31	-1.29	0.13	0.10	0.30	0.39
Accruals	-0.99	-2.52	0.02	-0.46	-0.84	0.22	-1.04	-3.25	0.00	-0.47	-1.01	0.18
NOA	-1.02	-3.08	0.01	-0.35	-0.71	0.26	-0.29	-0.90	0.22	-0.42	-1.00	0.18
MOM	-0.72	-1.35	0.12	-0.50	-0.81	0.23	-0.86	-2.12	0.04	-0.65	-1.17	0.14
GP	-0.28	-0.96	0.20	-0.34	-0.85	0.22	-0.46	-1.44	0.10	0.00	0.01	0.49
AG	-1.12	-2.95	0.01	-0.58	-1.03	0.17	-0.86	-2.69	0.01	-0.27	-0.60	0.29
INV	-0.73	-2.34	0.02	-0.25	-0.58	0.30	-0.82	-2.55	0.02	-0.38	-0.84	0.22
Combination	-0.80	-2.19	0.03	-0.46	-0.93	0.20	-0.67	-2.29	0.03	-0.29	-0.70	0.26

Panel C. Replicating "The Long of It" simulations

	Spread SENTHAT	Spread SENTRES	Short SENTHAT	Short SENTRES	Long SENTHAT	Long SENTRES	1&2 SENTHAT	1&2 SENTRES	1, 2, & 3 SENTHAT	1, 2, & 3 SENTRES
1 anomaly	27	7	110	6	1	1				
2 anomaly	48	12	209	7	1	2				
3 anomaly	73	17	275	7	1	2				
4 anomaly	110	26	343	8	1	2				
5 anomaly	162	36	416	9	1	3				
6 anomaly	237	50	496	10	1	3				
7 anomaly	352	66	611	10	1	3				
8 anomaly	525	91	810	11	1	4				
9 anomaly	858	131	1,104	13	1	5				
10 anomaly	1,634	214	1,475	15	1	6				
11 anomaly	5,682	443	6,329	21	1	10	166,667	563	>500,000	62,500
combination	242	31	580	11	1	2	2,155	45	6,944	341
11 & combination	5,682	443	6,329	22	1	10	166,667	563	>500,000	62500

Table 7. Sentiment for Asset Pricing

This table presents the results of asset pricing tests using the sentiment index, (*SENTIMENT*$_\perp$), *SENTHAT* (the part of the sentiment index related to business cycle variables) and *SENTRES* (the part of the sentiment index unrelated to business cycle variables) as a conditioning variable in both the CAPM and the Fama French 3-factor model. For both the conditional CAPM and conditional Fama and French 3-factor (FF3) model, we scale individual factors by the sentiment variables from the prior period. Panel A presents the risk prices and associated t-statistics, Panel B presents specification test statistics, namely the J-test (J) and the Hansen-Jagganathan distance (HJ dist) along with the associated p-values and Panel C presents the pricing errors in the unconditional CAPM model and the CAPM conditioning on sentiment variables. Pricing errors significant at the 5% level are in bold. Our sample period is July 1965 to December 2010.

Panel A. Factor risk prices

Unconditional model

		MKT	SMB	HML
CAPM	coef.	-2.26		
	tstat	-2.37		
FF	coef.	-3.44	-2.40	-6.36
	tstat	-3.10	-1.75	-3.61

Conditional model on SENTIMENT

		MKT	SMB	HML	SENTIMENT	SENTIMENT* MKT	SENTIMENT* SMB	SENTIMENT* HML
CAPM	coef.	-1.81			-0.78	5.89		
	tstat	-1.49			-3.90	1.90		
FF	coef.	-1.82	-3.17	-2.30	-0.89	-1.45	14.30	1.04
	tstat	-1.25	-1.11	-0.71	-3.98	-0.28	1.55	0.13

Conditional model on SENTHAT and SENTRES

		MKT	SMB	HML	SENTHAT	SENTHAT *MKT	SENTHAT *SMB	SENTHAT *HML	SENTRES	SENTRES *MKT	SENTRES *SMB	SENTRES *HML
CAPM	coef.	-2.43			-0.80	10.24			-0.19	6.84		
	tstat	-1.73			-3.34	2.70			-0.50	1.18		
FF	coef.	-1.86	-2.45	-1.91	-0.73	1.13	10.50	0.78	-0.98	-5.42	18.49	-5.25
	tstat	-1.17	-0.77	-0.50	-1.89	0.18	0.94	0.07	-1.91	-0.46	1.59	-0.35

Panel B. Specification tests

	J	p(J)	HJ dist	p(d=0)
CAPM	58.47	0.01%	0.4458	0.00%
CAPM*SENTIMENT	36.49	2.69%	0.3311	6.17%
CAPM*SENTHAT	38.37	1.67%	0.3328	3.89%
CAPM*SENTRES	47.87	0.11%	0.4156	0.03%
FF	51.36	0.04%	0.4026	0.00%
FF*SENTIMENT	24.21	14.84%	0.2827	18.25%
FF*SENTHAT	22.95	19.25%	0.2945	8.39%
FF*SENTRES	27.01	7.87%	0.3368	14.16%

Panel C. Pricing errors

	CAPM					CAPM*SENTIMENT					
	low	2	3	4	high		low	2	3	4	high
small	-0.42	0.25	**0.33**	**0.55**	**0.62**	small	0.20	**0.49**	0.33	**0.50**	**0.57**
2	-0.21	0.18	**0.43**	**0.46**	**0.48**	2	0.19	0.19	**0.35**	0.31	0.29
3	-0.16	**0.22**	**0.29**	**0.40**	**0.58**	3	0.14	0.21	**0.31**	0.27	0.35
4	0.00	0.03	0.19	**0.35**	**0.32**	4	0.14	0.07	0.07	**0.30**	0.11
big	-0.07	0.04	0.03	0.11	0.16	big	-0.16	-0.06	0.04	-0.04	-0.01
	CAPM*SENTHAT					CAPM*SENTRES					
	low	2	3	4	high		low	2	3	4	high
small	0.11	0.42	0.31	**0.48**	**0.55**	small	-0.17	0.38	0.35	**0.54**	**0.61**
2	0.13	0.21	**0.36**	0.32	0.27	2	-0.07	0.13	**0.39**	**0.43**	**0.44**
3	0.04	0.19	**0.30**	**0.32**	0.37	3	-0.03	0.18	**0.29**	**0.34**	**0.49**
4	0.07	0.13	0.18	**0.26**	0.08	4	0.08	-0.02	0.06	**0.39**	0.27
big	-0.18	0.04	0.15	-0.06	0.02	big	-0.08	-0.06	-0.07	0.09	0.09

Figure 1. Time Series Plot of Sentiment, T-Bill and Zero Returns.

This figure plots *SENTIMENT*$_{\perp}$,, the T-bill rate, and PctZero (percentage of zero returns) from July 1965 to December 2010. All series are normalized to have a mean of zero and a standard deviation of one.

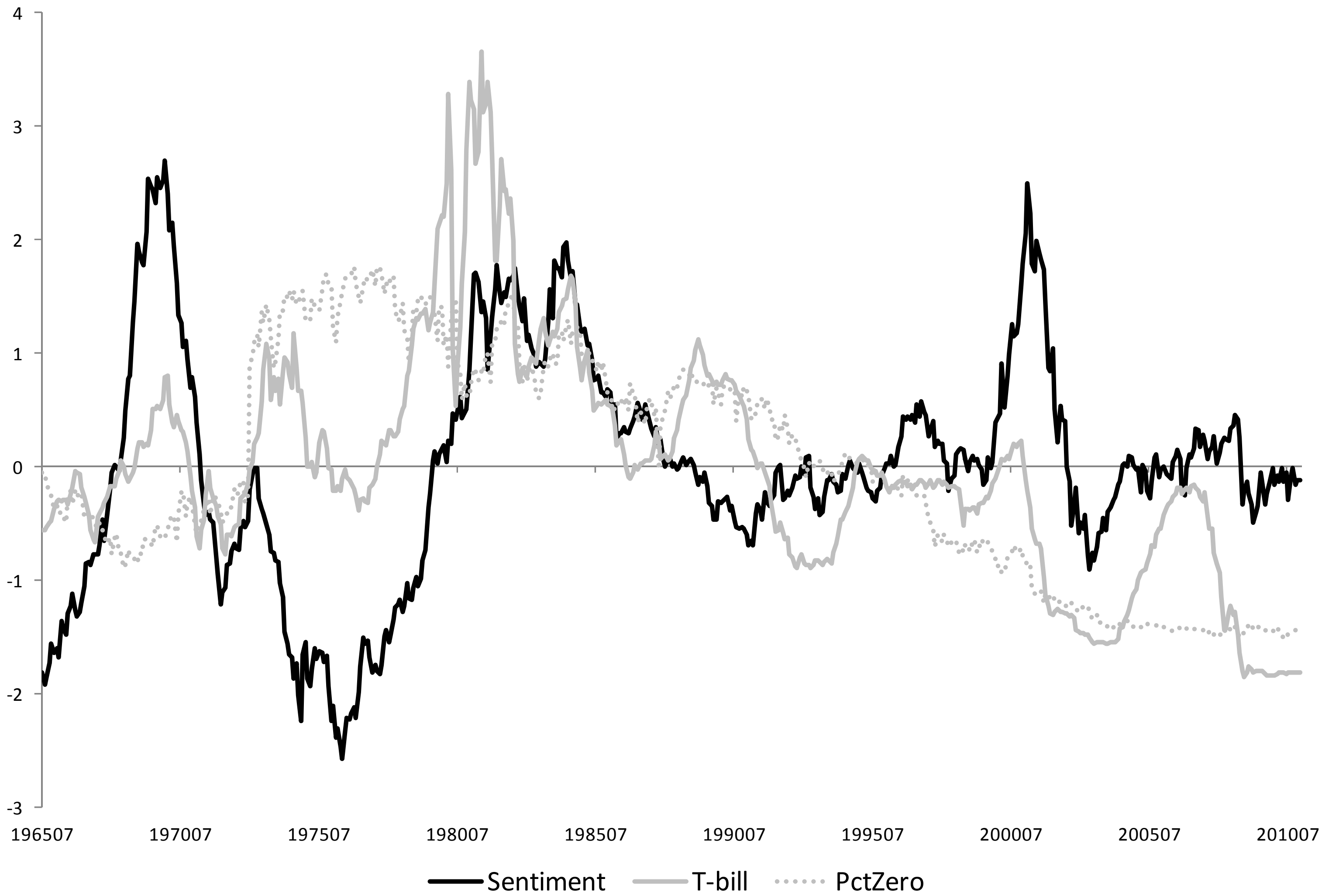

Figure 2. Sentiment and its Two Components

This figure plots the time-series of the sentiment index (*SENTIMENT*$_{\perp}$), the component of sentiment related to business cycle variables (*SENTHAT*), and the component of sentiment orthogonal to business cycle variables (*SENTRES*) from 1965 to 2010.