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The information content of the sentiment index

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ABSTRACT

The widely-used Baker and Wurgler (2006) sentiment index is strongly correlated with business cycle variables, especially the short interest rate and Lee (2011) liquidity risk factor. The power of the sentiment index to predict cross-sectional stock returns is mainly driven by its information content related to these business cycle variables. About 63% percent of the total variation in the investor sentiment index can be explained by well-known, contemporaneous risk/business cycle variables. We decompose the widely used investor sentiment index into two components: one related to standard risk/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 risk/business cycle component, while the residual component has little significance in predicting cross-sectional stock returns.

> "One possible definition of investor sentiment is the propensity to speculate … One might also define investor sentiment as optimism or pessimism about stocks in general".
> [Baker and Wurgler (2006)]

Investor sentiment is a rather elusive concept, difficult to define and difficult to measure. Traditional asset pricing models usually leave no role for investor sentiment. One influential paper by Baker and Wurgler (2006, BW hereafter) develops a proxy for investor sentiment, the "sentiment index", which is the first principal component of the following six sentiment proxies suggested by prior research: the closed-end fund discount, market turnover, number of IPOs, average first day return on IPOs, equity share of new issuances, and the log difference in book-to-market ratios between dividend payers and dividend non-payers. Baker and Wurgler (2006) present strong evidence that the BW sentiment index predicts stock returns in the cross-section, possibly through the channel of sentiment-driven mispricing.

Since the creation of the influential BW sentiment index, many papers use it for predicting stock returns.[1] Most of these papers treat the Baker and Wurgler sentiment index as a behavioral variable and interpret their empirical results as consistent with the idea that investors' sentiment, unrelated to systematic risks, drives prices and returns in the market. Based on the definitions of sentiment cited at the beginning of the article, and BW's characterization of sentiment as reflecting "uninformed demand shocks" and "subjective valuations" of "unsophisticated investors", the BW sentiment index is intended to capture investors' less-than-rational behavior.

Alternatively, it is possible that the sentiment index contains significant information about economic fundamentals or state variables, which are important for rational asset pricing models, and this information is the root of its predictive power. In fact, many seemingly irrational phenomena and anecdotal accounts of investor sentiment through history, such as IPO waves and the NASDAQ "bubble", can be explained in rational models such as those presented in Pastor and Veronesi (2003, 2005, 2006). Most of the six proxies used to construct the BW sentiment index are closely related to risk factors, stock market conditions, and the overall business environment. For the close-end fund discount proxy, Cherkes et al. (2009) demonstrate that a liquidity-based model successfully generates the observed closed-end fund discount phenomenon. The market turnover variable is often used as a proxy for liquidity risk, which Pastor and Stambaugh (2003) have shown is a priced risk factor. Related to Pastor and Veronesi (2005), the number of IPOs and average first day return on IPOs are tied to overall economic and market conditions and recent stock market performance.

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[1] Baker et al. (2012) show that global sentiment is a contrarian predictor of country-level returns. Stambaugh et al. (2012) find that the short legs of eleven anomaly-based trading strategies are more profitable following periods of high sentiment. Yu and Yuan (2011) find that the sentiment index in Baker and Wurgler (2006) significantly affects mean–variance tradeoff. Yu (2013) documents the fact that the same sentiment index helps explain the forward premium.

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Note that the above two alternative explanations of sentiment's predictive power, "behavioral" and "rational", are not necessarily mutually exclusive. Investor sentiment does not arise in a vacuum, and it is plausible that fluctuations in economic fundamentals affect investor sentiment, and/or vice versa. In this paper, we take an agnostic view on this issue, and we focus instead on examining the information content of the sentiment index, or the information the sentiment index contains which is related to economic fundamentals and risk factors. First, we explore whether information from economic fundamentals drives the predictive power of sentiment, and if so, which particular economic fundamental variables are important. Next, in parallel to the sentiment index, we create two "economic fundamentals" indices and compare these indices' power to predict future stock returns with that of the sentiment index. The answers to these research questions are important for developing a better understanding of the sentiment index, especially given the strong empirical evidence that the sentiment index can predict cross-sectional and time series stock returns.

Similar to "investor sentiment", "economic fundamentals" sometimes can be difficult to observe or to measure. Following the vast asset pricing literature, we measure "economic fundamentals" using 13 business cycle variables and risk factors, such as the unemployment rate, consumption growth rate, inflation, production growth rate, income growth rate, interest rate, yield spreads, market return, market volatility and market liquidity. We provide a detailed discussion on the choice of each of the 13 variable in a later section. We would like to acknowledge two caveats of this approach upfront. First, although we aim to be comprehensive and include the most important and relevant business cycle variables and risk factors, there is always the risk that we omit other potentially important business cycle variables or risk factors. Second, we recognize that despite the fact that the 13 fundamental variables are heavily used in rational asset pricing literatures either as risk factors or as state variables, it is possible that these variables are influenced by sentiment and thus carry information about sentiment. Our exercise is based on the assumption that the 13 variables are business cycle variables reflecting economy fundamentals, and our results should be interpreted accordingly. To fully disentangle the causal relationship between business cycle variables and investor sentiment, we would need a general equilibrium model, and we leave that to future research.

Our empirical work proceeds in three steps. First, we document the close link between sentiment's predictive power and fundamental economic variables. We extract the information content of the BW sentiment index that is related to economic fundamentals by projecting the (orthorgonalized) sentiment index on the aforementioned 13 variables. The sentiment index is strongly correlated with these economic variables. Approximately 63% of the total variations in the sentiment index can be attributed to the 13 economic variables, especially the T-bill rate and the market liquidity risk factor. To ease the concern that projecting the sentiment index onto 13 variables might over-fit the data, we conduct a robustness check in which we only use two variables, the T-bill rate and the liquidity risk factor, for the projection. These two variables alone can explain around 41% of the total variations in the BW sentiment index. The regression of the sentiment index onto the 13 variables naturally decomposes the sentiment index into two orthogonal components, the fundamental-related component and the residual component. To clarify, the identification of the fundamental-related component and the residual component clearly depends on our choices of the fundamental variables, and should be treated accordingly.

In the second step, 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 et al. (2012). The sentiment index itself significantly predicts the return spread in 19 of 28 cases. We find the fundamental-related component significantly predicts spread portfolio returns in 16 of 28 cases, while the residual component 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 fundamental-related 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. These results imply that the information in the sentiment index related to fundamentals seems to be the main driver of its predictive power. We conduct extensive simulations to confirm that these results are not spuriously driven by the persistence of the regressors, a concern raised in Novy-Marx (2014).

In the third step, to further separate between the "behavioral" and "rational" hypotheses for the sentiment index's predictive power, we construct two "fundamentals" indices in parallel to the sentiment index. That is, we first orthogonlaize the 13 fundamental variables to a sentiment proxy, the Michigan Consumer Confidence index, and then we estimate the principal components of the 13 fundamental variables. In case the first principal component cannot fully capture the common component of 13 variables, we use the first two principal components as "fundamentals" indices. When we use the "fundamentals" indices to predict future stock returns, they can predict 24 long-leg returns, 21 short-leg returns and 3 spread returns. Compared to the sentiment index, the fundamental indices have comparable predictive power for both long- and short-leg returns, which further supports that fundamentals are important for predicting future stock returns.

We conduct a battery of robustness checks. Our main empirical findings remain strong and significant with simulated data, alternative measures of liquidity and interest rates, and alternative risk-adjustment models. To summarize, in this paper we investigate the information content of the BW sentiment index. Our empirical findings suggest that the sentiment index contains rich information about economic fundamentals, particularly the short-term interest rate and market liquidity. After we orthogonalize the sentiment index with respect to the above fundamental variables, the sentiment index's predictive power diminishes. Compared to the original interpretation that the sentiment index is a proxy for investor's irrational beliefs, our paper provides new insights about the nature of the widely used BW sentiment index and the sources of its predictive power.

This article is connected to the large and diverse literature on investor sentiment. For instance, Lemmon and Portniaguina (2006) present evidence that their measure of sentiment based on consumer confidence indices negatively predicts the future size premium. They also show that the residual component of consumer confidence that is orthogonal to business cycle variables still has significant power to predict the future size premium. Qiu and Welch (2006) examine the closed-end fund discount and consumer confidence as alternative measures of sentiment, and find that only the latter plays a significant pricing role. Glushkov (2006) finds that sentiment is not priced using a set of portfolios sorted on their loadings on the sentiment index. Hwang (2011) 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. Barone-Adesi et al. (2014) find that the sentiment index reflects excessive optimism rather than overconfidence. Our paper, however, suggests that one should be cautious about interpreting the information content of investor sentiment measures.

Our paper also contributes to the debates on what explains cross-sectional stock returns and asset pricing anomalies. Asset pricing anomalies could reflect mispricing, as suggested by

Baker and Wurgler (2006) and Stambaugh et al. (2012, 2014), who argue that, because the BW sentiment index predicts anomaly returns, anomaly returns are likely driven by sentiment-driven mispricing. Moreover, according to Hirshleifer and Jiang (2010), mispricing can be correlated across firms and can also affect stock returns in the cross-section. Hirshleifer and Yu (2013) and Barberis et al. (2014) both argue that mispricing can also be correlated with economic fundamentals. On the other hand, anomalies could also result from rational equilibrium models. For instance, in recent years, researchers have shown that asset pricing models based on q-theory can explain many cross-sectional asset pricing anomalies. Zhang (2005), Liu et al. (2009) and Chen et al. (2010) are a few examples of those who illustrate implications from q-theory based models with respect to asset pricing anomalies. Our results suggest that, both rational models and investor behaviors can account for part of sentiment's predictive power. From this perspective, the main contribution of this article is to provide insights into the information content of the BW sentiment index.

The rest of the paper is organized as follows. We introduce data in Section 1. In Section 2, we decompose the sentiment index into two parts, one related to economic fundamental variables and one unrelated. In Section 3, we examine which of the two parts of the sentiment index drives the predictive power of the sentiment index. In Section 4, we construct fundamental indices and compare them with the sentiment index in terms of predicting future stock returns. We conduct thorough robustness check in Section 5. We conclude in Section 6.

1. Data

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

Baker and Wurgler (2006) construct the raw investor sentiment index as the first principal component of 6 different proxies for investor sentiment as suggested by prior literature.[2] 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 performing principal components analysis to construct the orthogonalized sentiment index. The original sentiment and the orthogonalized sentiment are correlated at 97%, and the orthogonalized sentiment is the main sentiment index examined in BW. Therefore, for brevity of the presentation, we only report results using the orthogonalized sentiment index, denoted *SENTIMENT*. Results using the raw sentiment index are quantitatively similar, and are available on request. We obtain the sentiment data from Jeffrey Wurgler's website. Due to sentiment data availability, we restrict our sample to July 1965 to December 2010. Baker and Wurgler (2006) normalize the sentiment index to have a mean of zero and a variance of one.

To determine whether *SENTIMENT* is related to economic fundamentals, we regress it on a variety of macroeconomic variables, business cycle indicators and risk factors. The asset pricing literature has a long history of using business cycle variables as risk factors or conditioning variables. A short and non-exhaustive list includes: Chen et al. (1986), Ferson and Harvey (1991, 1999) and Fama and French (1993). Instead of including all business cycle variables that are available, we only select variables that are relevant as state variables for time-varying risk prices, or directly relevant as risk factors. 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) and Chen et al. (1986); the consumption growth rate (dCons) as in Chen et al. (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 et al. (1986); and the NBER recession dummy (NBER) as in Baker and Wurgler (2006). Additionally, we include four variables from financial markets that have been frequently used as indicators of 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, 1993) and Chen et al. (1986); 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 et al. (1986); the dividend yield (Div) of the value-weighted CRSP market portfolio as in Campbell and Shiller (1988a,b). Finally, we include 3 risk factors: the return (VWRETD) on the value-weighted CRSP all-market index as in the original CAPM in Sharpe (1964) and Campbell (1996); the stock market volatility (MktVol) computed as the annualized standard deviation of market daily return within each month, as in Bollerslev et al. (2009), and the liquidity risk factor used in Lee (2011). Numerous papers, such as Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), establish that liquidity risk is significantly priced in the cross-section of stocks. Our proxy for liquidity risk is the market average of firm level percentage of zero return days (*PctZero*), as introduced in Lesmond et al. (1999). Lee (2011) clearly shows that the *PctZero* is a priced risk factor in global capital markets in the framework of Acharya and Pedersen (2005).[3]

Data sources for each variable are provided alongside the summary statistics in Table 1. The summary statistics include the means, standard deviations, serial autocorrelations, as well as their correlations with the sentiment index. As noted by Novy-Marx (2014), the sentiment indices are highly persistent, with autocorrelations of nearly 0.99. Many of the macro variables are also highly persistent. The orthogonalized sentiment index is constructed by Baker and Wurgler (2006) to be orthogonal to business cycle conditions. However, we see that *SENTIMENT* is significantly correlated with many of the business cycle variables. At the 5% significance level, *SENTIMENT* is correlated with inflation (dCPI), consumption growth rate (dCons), industrial production growth rate (dInd), NBER dummy, T-bill rate (*Tbill*), default spread (Def), dividend yield (Div), market volatility (MktVol) and market liquidity proxy (*PctZero*). In particular, the correlation between *SENTIMENT* 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* and these fundamental-related variables, it is hard to draw the conclusion that it is unrelated to systematic risks.

In Fig. 1 Panel A, we plot the time series of *SENTIMENT* together with the T-bill rate and *PctZero*. For easy comparison, we normalize T-bill and *PctZero* to have means of zero and standard deviations of one. The co-movement between the T-bill rate and the sentiment index is particularly striking. Both the sentiment index and the T-bill rate reach a peak between 1968 and 1969, both are high

[2] The principal component analysis in BW is estimated over the whole sample period. From results not reported, we estimate sentiment index using a rolling window, and results are quite similar.

[3] 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.

Table 1
Summary Statistics. This table reports summary statistics for the orthogonalized sentiment index and 13 macroeconomic variables. We present the means, standard deviations, serial autocorrelation coefficients (AR1), and their correlations with the orthogonalized sentiment index. The 13 macro variables are: 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*). Our sample period is July 1965 to December 2010. All variables are measured at monthly frequency.

	Mean	Std	AR1	Corr with *SENTIMENT*	*p*-value	Source
SENTIMENT	0.00	1.00	0.984	1.00	0.00	Wurgler's website
Unemp	6.03	1.64	0.997	−0.03	0.45	U.S. Dept. of Labor: Bureau of Labor Statistics
dCPI	0.36	0.33	0.617	−0.09	0.03	U.S. Dept. of Labor: Bureau of Labor Statistics
dCons	0.58	0.56	−0.075	−0.10	0.03	U.S. Dept. of Commerce: Bureau of Economic Analysis
dSPI	0.58	0.76	−0.136	−0.04	0.30	U.S. Dept. of Commerce: Bureau of Economic Analysis
dInd	0.20	0.76	0.355	−0.12	0.01	Board of Governors of the Federal Reserve System
NBER	0.15	0.36	0.901	0.13	0.00	NBER
Tbill	5.49	2.95	0.989	0.28	0.00	Board of Governors of the Federal Reserve System
Def	1.07	0.47	0.963	0.18	0.00	Board of Governors of the Federal Reserve System
Term	1.54	1.32	0.957	−0.04	0.35	Board of Governors of the Federal Reserve System
Div	2.95	1.09	0.990	−0.11	0.01	CRSP
VWRETD	0.88	4.60	0.089	−0.06	0.18	CRSP
MktVol	13.53	8.24	0.692	0.09	0.03	CRSP
PctZero	24.62	14.46	0.995	−0.22	0.00	CRSP

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.

2. Decomposition of the Sentiment Index

In this section, we decompose the sentiment index into two parts, one related to our economic fundamental variables, and the other one unrelated. 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 fundamental-related variables,[4] and e_t is the regression residual. Based on the estimated coefficients, $\hat{a}$ *and* $\hat{b}$, 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 our choice of economic fundamentals and *SENTRES* as the residual component orthogonal to the fundamental-related component. As mentioned earlier, the identification of the fundamental-related component and the residual component clearly depends on our choices of the fundamental variables, and should be treated jointly with our selection of fundamental variables.

Novy-Marx (2014) 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 (2014) suggests scaling the standard OLS *t*-statistics by the standard deviation of the empirical distribution of *t*-statistics using simulated regressors with similar autocorrelations.

Although our decomposition procedure is not a predictive regression as discussed in Novy-Marx (2014), both dependent and independent variables are highly persistent. To ensure that the significance of coefficients is not a result of a spurious regression, we conduct the following simulation to address potential bias in both coefficients and *t*-statistics. First, we estimate a vector autoregressive (VAR) model of order 1 to fit the data, as follows:

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

where X_t is the vector of fundamental-related 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.[5] After estimating the parameters of the VAR(1) model, we simulate 100,000 series of artificial macroeconomic variables, matching the variables' means, variances, and autocorrelations. Third, for each simulated series, we estimate the decomposition regression using both original and orthogonal sentiment indices and record coefficient estimates, $\hat{b}$, as in Eq. (1) and OLS *t*-stats.

The results of the decomposition depend on which variables are included in X_t. We consider two alternative sets of variables. In the first set, we include all 13 variables mentioned in the data section. To ease the concern that we use too many variables and over-fit in the projection, in the second set, we only include the two most important fundamental-related variables: the T-bill rate and *PctZero*. The decomposition results are reported in Table 2, Panel A. The top half panel presents the results from the 13-variable system, while the bottom half panel reports the results from the 2-variable system. We present the coefficient estimates, an empirical *p*-value from the simulation procedure and the Novy-Marx (NM) *t*-statistics, which is the OLS *t*-statistics scaled by the standard deviation of OLS *t*-statistics over the 100,000 simulations. Additionally, we report the percentage of variance explained by each individual variable.

The fundamental-related variables are able to explain a large part of the total variation of the sentiment index. When we use the 13 variables in the top half panel, the adjusted R-squares for *SENTIMENT* is 62.56%. When we use only 2 variables in the bottom half panel, the adjusted R-squares for *SENTIMENT* is 41.03%. The

[4] In results not reported, we estimate Eq. (1) using X_{t-1}. We find results are qualitatively similar to those reported in the paper, given that most of the independent variables are highly auto-correlated.

[5] 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 optimal for our variables according to both selection criteria.

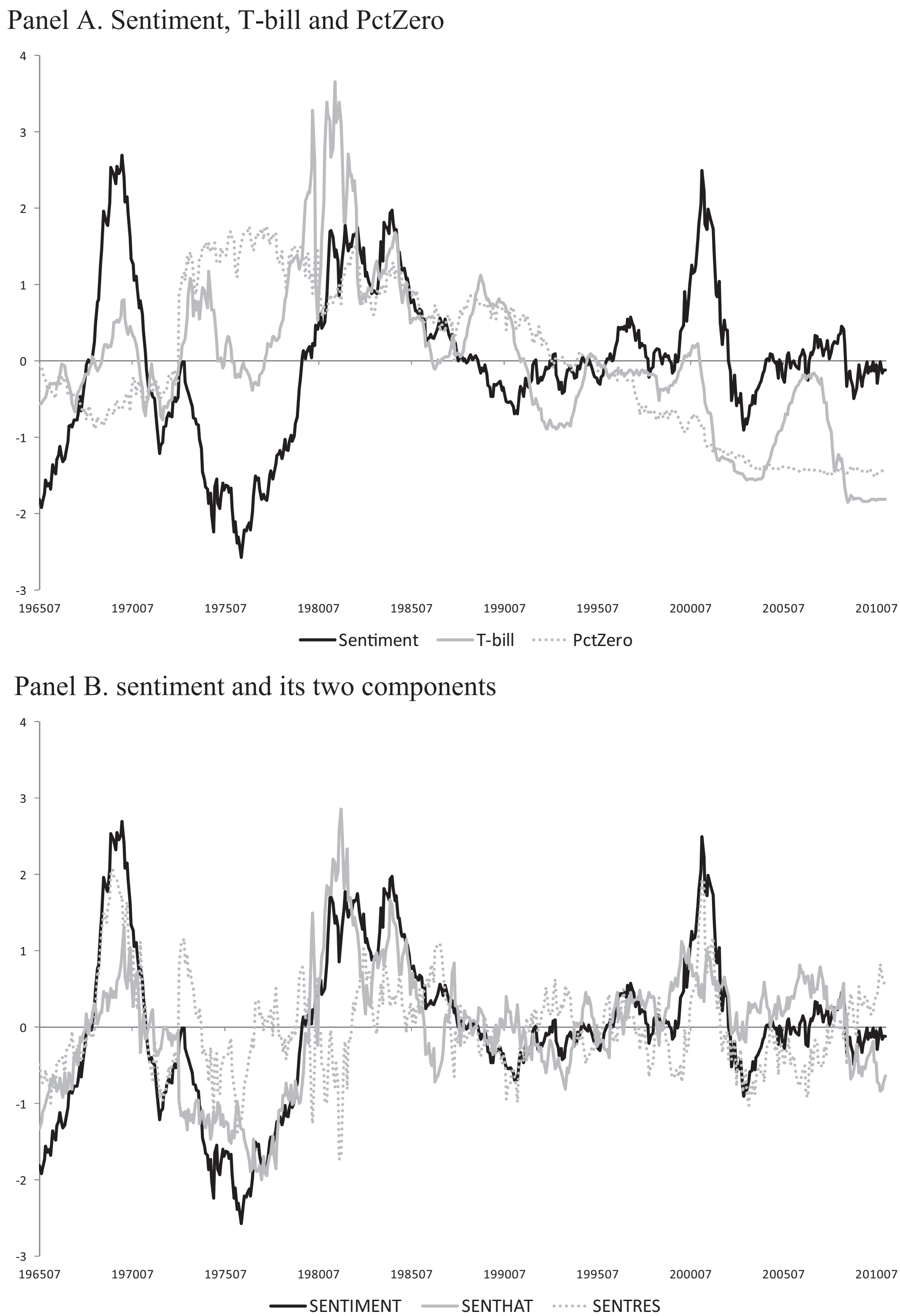

Fig. 1. Time series plot of different components of sentiment. Sample period is July 1965 to December 2010. Panel A plots the sentiment index, *SENTIMENT*, the T-bill rate, and *PctZero* (percentage of zero returns). Panel B plots the *SENTIMENT*, the component of sentiment related to risk/business cycle variables (*SENTHAT*), and the residual component (*SENTRES*). All series are normalized to have zero mean and a standard deviation of one.

additional 11 variables in the top panel help to increase adjusted R-squares by about 21%.

Among the independent variables, *Tbill* and *PctZero* show up with the highest NM *t*-statistics, significant at the 1% level for both specifications. These significant NM *t*-statistics alleviate concerns that our decomposition results might be spuriously driven by the persistence of either the sentiment index or the independent variables. The bulk of the explained variance of both sentiment indices comes from these two fundamental-related variables. For example, in the 13-variable system, around two-thirds of the adjusted R-square (62.56%) is due to the contribution of *Tbill* (39.48%). For the liquidity risk factor, *PctZero*, it contributes 20.13% of the R-square for *SENTIMENT*. The results from the 2-variable system are quite similar. In terms of sign, *SENTIMENT*

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 risk/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 risk/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, a one-sided *p*-value of the coefficient from the simulation procedure, the Novy-Marx (NM) *t*-stats presents OLS *t*-statistics scaled by the standard deviation of OLS *t*-statistics over the 100,000 simulations and the R-square in the decomposition. Panel B presents summary statistics of the sentiment index and *SENTHAT* and *SENTRES*. Panel C reports the correlation between *SENTIMENT*, *SENTHAT*, *SENTRES*, and Fama French factors, contemporaneous or one period ahead. Our sample period is July 1965 to December 2010.

	Coef.	Emp. *p*-value	NM *t*-stat	Var. Explained
Panel A. Regression of Sentiment on risk/business cycle variables				
13 variables				
Intercept	−0.71	0.26	−0.95	0.00%
Unemp	−0.06	0.37	−0.46	0.34%
dCPI	−0.12	0.3	−0.76	0.35%
dCons	0.04	0.23	1.03	−0.23%
dSPI	−0.01	0.38	−0.4	0.04%
dInd	−0.13	0.05	−2.16	1.10%
NBER	0.17	0.3	0.72	0.79%
Tbill	0.48	0	4.99	39.48%
Def	0.11	0.42	0.27	0.89%
Term	0.48	0.03	3.05	−2.55%
Div	−0.27	0.29	−0.95	3.09%
VWRETD	−0.01	0.24	−1.01	0.20%
MktVol	0	0.41	−0.3	−0.23%
PctZero	−0.06	0.04	−2.9	20.13%
R-square				63.52%
adj R-square				62.56%
2 variables				
Intercept	−0.19	−2.64	−0.86	0.00%
Tbill	0.29	18.38	5.12	23.38%
PctZero	−0.06	−17.66	−4.36	17.90%
R-square				41.35%
adj R-square				41.03%

				Correlations		
	Mean	Std	AR1	*SENTIMENT*	*SENTHAT*	*SENTRES*
Panel B. Summary statistics and correlations of sentiment components						
SENTIMENT	0.00	1.00	0.98	1.00		
SENTHAT	0.00	0.80	0.96	0.80	1.00	
SENTRES	0.00	0.60	0.91	0.60	0.00	1.00

	MKT_t	SMB_t	HML_t	WML_t	MKT_{t+1}	SMB_{t+1}	HML_{t+1}	WML_{t+1}
Panel C. Correlations between SENTHAT and SENTRE with contemporaneous and future Fama and French factors								
$SENTHAT_t$	−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
$SENTRES_t$	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

is high when interest rates are high, and when market liquidity conditions (measured by *PctZero*) are good.[6]

Intuitively, the T-bill rate measures investors' time preferences between current consumption and future consumption, and it is one important determinant for investment opportunity set. Therefore, it is included in numerous asset pricing models as one determinant of expected returns. In terms of predictive power for future returns, Ang and Bekaert (2007) show that the short rate is the only robust and significant predictor of future market returns. Similarly, market wide liquidity also defines investment opportunity set, and affects expected returns of all securities. Previous studies, such as Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Korajczyk and Sadka (2008) and Lee (2011), show that liquidity is a systematic risk factor that affects the cross-section of stock returns.

While the literature has largely treated the T-bill rate as a business cycle variable and treated liquidity as a risk factor, it is possible that sentiment might drive interest rates and the level of liquidity in the stock market. Investors subject to optimistic opinions might lever up their positions, pushing up interest rates, or the Federal Reserve Bank might set their federal funds rate target to combat "irrational exuberance". For the purposes of this paper, we interpret the T-bill rate and liquidity factor as economic fundamental variables and acknowledge the possibility that they might be influenced by investor sentiments.

There is the additional concern that the inclusion of market turnover in the original construction of the sentiment index leads to a mechanical relationship between the liquidity risk factor (*PctZero*) and the sentiment index. We compute the correlation between market turnover and the *PctZero* variable, and it is merely −0.08 with a *p*-value of 6%, which suggests that the relationship between *PctZero* and the sentiment index is not driven by the market turnover proxy.

Comparing the 13-variable system and the 2-variable system, it is evident that the sentiment index contains information primarily related to the T-bill rate and the liquidity factor, while other macroeconomic variables contribute a nontrivial amount of

[6] Because we use 13 variables, there is concern about data mining. Because we select T-bill and *PctZero* from the complete set of 13 variables, there is concern about data snooping. To alleviate these concerns, we conduct extensive simulation exercises. We find that the significant relationship between the sentiment index and the 13 or 2 economic variables is not results of data mining or data snooping. The methodology of these simulation exercises is discussed in Internet Appendix 1, and the results are presented in Internet Appendix Table 1.

explanatory power. Given that the *SENTHAT* (*SENTRES*) from the 13-variable and 2-variable systems are 97% (95%) correlated, we report our future results using the estimates from the 13-variable system. The results using the 2-variable system are qualitatively similar, and we discuss main results using the 2-variable system in Section 5.

In Panel B of Table 2 we report the summary statistics of the two orthogonal components, *SENTHAT* and *SENTRES*. Note that the sentiment index is 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 autocorrelations above 90% for both *SENTHAT* and *SENTRES*. Interestingly, we observe that *SENTHAT* is more strongly related to the sentiment index with a correlation coefficient of 0.80 when compared to the 0.60 correlation between the sentiment index and *SENTRES*.

We obtain four widely used pricing factors from Kenneth French's website: the market excess return (MKT), the size factor (SMB), the value factor (HML) and the momentum factor (WML). To examine how the two sentiment components are related to Fama and French factors, we report correlations between *SENTHAT*, *SENTRES*, and contemporaneous and future Fama and French factors in Panel C of Table 2. *SENTHAT* is significantly negatively correlated with the contemporaneous and future excess market return with a correlation coefficient of -0.09 (with *p*-value of 0.04) and -0.08 (with *p*-value of 0.06), while *SENTRES* is not significantly correlated with either the contemporaneous or future market return. Previous studies document that the sentiment index is a contrarian predictor of future market returns. Our results indicate that it is *SENTHAT* that is largely responsible for the sentiment index's ability to predict future market returns. In addition, *SENTHAT* is also significantly correlated with the future Fama and French size factor, SMB. 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 $t + 1$. From results not shown, the sentiment index itself is significantly correlated with SMB; the decomposition shows us that this correlation is solely coming from the common fundamental-related component of the sentiment index.

We plot the time-series of *SENTHAT*, *SENTRES* and *SENTIMENT* in Fig. 1 Panel B. 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 noted earlier, *SENTHAT* has a higher correlation with the sentiment index than *SENTRES* does.

3. Predictive power of the sentiment index

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 et al. (2012). Baker and Wurgler (2006) challenge the traditional view in finance theory that investor sentiment plays no role in the cross-section of stock returns by showing that investor sentiment index has significant power to predict future cross-sectional stock returns. Stambaugh et al. (2012) find that anomalous long-short strategies are more profitable following periods of high sentiment, and further, that sentiment is related to the returns of the short leg of the long-short strategy but not the long-leg returns.

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 the *SENTHAT* and *SENTRES* variables generated through our decomposition procedure. We begin by describing the anomalies in Section 3.1. We discuss the empirical design in Section 3.2. In Section 3.3, we discuss the results of predictive regressions for the spread portfolios, and in Section 3.4, we present the results for the long and short legs.

3.1. The anomalies

In order that our results are comparable to original results in the literature, we adopt the exact 16 spread portfolios from Baker and Wurgler (2006) as well as 12 anomalies from Stambaugh et al. (2012). We denote them "the 16 Baker and Wurgler (2006) portfolios" and "the 12 Stambaugh et al. (2012) anomalies".

Baker and Wurgler (2006) suggest that the stocks most likely to be sensitive to investor sentiment are 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 long-short spread portfolios formed 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 the exact procedures documented in Baker and Wurgler (2006), and we refer readers to Internet Appendix 2 for more details.

Stambaugh et al. (2012) 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 et al. (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 et al. (2012), we also study the returns on a "combination" portfolio, the 12th anomaly, formed as an equally weighted portfolio of all 11 anomaly portfolios. We refer readers to Internet Appendix 3 for more precise 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 et al. (2012) 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. The summary statistics of these 28 trading strategies are reported in Table 3.

We would like to point out that the returns on the Baker and Wurgler (2006) 16 spread portfolios are constructed as equally weighted average returns. The Stambaugh et al. (2012) portfolio returns, however, are value-weighted. To facilitate easy comparison of our results to those of the previous papers, we report results using equally weighted Baker and Wurgler (2006) portfolio returns and value-weighted Stambaugh et al. (2012) portfolio returns.

3.2. Empirical approach

Following Baker and Wurgler (2006) and Stambaugh et al. (2012), the benchmark predictive regression takes the following form:

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 (2012). 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 et al. (2012) 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.

	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						

$$R_t = a + bSENTMENT_{t-1} + u_t. \quad (2)$$

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. $SENTMENT_{t-1}$ 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:

$$R_t = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + u_t, \quad (3)$$

where *SENTHAT* is the fundamental-related component in sentiment, and *SENTRES* is the residual component. 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 in the presence of other asset pricing factors, we specify the following predictive regressions:

$$R_t = a + bSENTIMENT_{t-1} + c'FACTOR_t + u_t, \quad (4)$$

$$R_t = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + d'FACTOR_t + u_t. \quad (5)$$

Following Baker and Wurgler (2006) and Stambaugh et al. (2012), our *FACTOR* vector includes the market factor (MKT), size factor (SMB), value factor (HML) and momentum factor (WML). Regressions (1) and (3) are exactly the same regressions as in Baker and Wurgler (2006) and Stambaugh et al. (2012), which facilitates easy comparison of results. Notice that in Eqs. (3) and (4), the factors are observed at time t, rather than time $t-1$, so Eqs. (3) and (4) are not "strictly predictive". To be "strictly" predictive, we also consider using factors from $t-1$,

$$R_t = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + d'FACTOR_{t-1} + u_t. \quad (6)$$

The results we obtain from Eq. (5) are quite similar to those from Eq. (2), so we don't report them in this paper.

As discussed earlier, Novy-Marx (2014) 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 power of the original sentiment index, as in Stambaugh et al. (2012), 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 (2014) in order to ease this concern. We first estimate an AR(1) model for both *SENTHAT* and *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 autocorrelation 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 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 et al. (2012) 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, we follow the same procedures as used in the original studies and do not adjust for this look-ahead bias.

3.3. Predictive regression results on spread portfolios

Table 4 reports the results of using the two components of sentiment as predictors of long-short spread portfolio returns. Panel A reports results on predicting the spread portfolios, using different sets of controls. The left side reports results without the Fama and French factors as controls, as in Eq. (2), and the right side reports results when contemporaneous Fama and French factors are used as controls, as in Eq. (4).

As a benchmark, in the first two columns in Table 4, the orthogonal sentiment index in Baker and Wurgler (2006) is statistically significant in predicting 19 of the 28 spread returns, when no Fama and French factors are included. In the next two columns, we find that *SENTHAT* demonstrates significant predictive ability in 16 out

Table 4
Predicting Portfolio Returns with *SENTHAT* and *SENTRES*. This table presents the results of using *SENTHAT* and *SENTRES* to predict spread, long or short portfolio returns. Each panel presents results for the following two regressions, respectively: $R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + u_t$, $R_{i,t} = a + bSENTHAT_{t-1} + cSENTRES_{t-1} + dMKT_t + eSMB_t + fHML_t + gWML_t + u_t$. Variable $R_{i,t}$ is the time t monthly return on the spread, long or short portfolio, *SENTHAT* is the time $t-1$ component of $SENTIMENT_{\perp}$ related to risk/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 et al. (2012) do not. For both *SENTHAT* and *SENTRES*, we report coefficient estimates and one-sided empirical p-values (Emp. p.). Panel A reports results using spread portfolios. Panel B reports results using short portfolios, and Panel C reports results using long portfolios.

	No FF controls						FF(t) as controls					
	SENTIMENT		*SENTHAT*		*SENTRES*		*SENTIMENT*		*SENTHAT*		*SENTRES*	
	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p
Panel A. Predicting spread portfolio returns at t												
Age	0.52	0.01	0.62	0.01	0.36	0.13	0.23	0.06	0.24	0.05	0.19	0.14
D/BE	0.37	0.01	0.56	0.00	0.04	0.43	0.20	0.06	0.31	0.00	−0.04	0.38
EF/A	−0.16	0.04	−0.10	0.15	−0.26	0.02	−0.10	0.23	0.00	0.49	−0.20	0.03
E/BE	0.39	0.02	0.48	0.01	0.24	0.16	0.25	0.03	0.35	0.02	0.21	0.16
GS	−0.07	0.24	−0.01	0.46	−0.17	0.13	−0.06	0.30	0.06	0.32	−0.12	0.20
PPE/A	0.39	0.03	0.41	0.03	0.35	0.12	0.14	0.16	0.04	0.41	0.19	0.16
RD/A	−0.23	0.13	−0.21	0.18	−0.26	0.19	−0.03	0.44	0.03	0.44	−0.11	0.33
Sigma	−0.83	0.00	−1.06	0.00	−0.41	0.17	−0.36	0.02	−0.48	0.01	−0.22	0.20
GS High–Med	−0.38	0.00	−0.43	0.00	−0.28	0.05	−0.24	0.01	−0.22	0.01	−0.20	0.04
GS Med–Low	0.31	0.01	0.42	0.00	0.12	0.26	0.18	0.06	0.28	0.02	0.08	0.32
EF/A High–Med	−0.34	0.00	−0.41	0.00	−0.23	0.08	−0.20	0.03	−0.21	0.01	−0.16	0.06
EF/A Med–Low	0.18	0.01	0.30	0.00	−0.03	0.40	0.10	0.12	0.21	0.00	−0.05	0.29
ME	0.48	0.04	0.68	0.01	0.14	0.34	0.36	0.15	0.59	0.03	0.15	0.34
B/M	0.13	0.21	0.02	0.46	0.31	0.15	0.11	0.29	−0.01	0.48	0.23	0.19
B/M High–Med	−0.14	0.08	−0.27	0.01	0.09	0.29	−0.08	0.28	−0.19	0.06	0.07	0.31
B/M Med–Low	0.27	0.03	0.30	0.04	0.22	0.16	0.19	0.10	0.18	0.12	0.16	0.21
Distress	1.24	0.03	1.23	0.03	1.26	0.06	0.95	0.06	0.55	0.17	1.53	0.01
O-score	0.73	0.04	0.66	0.07	0.94	0.04	0.56	0.02	0.35	0.09	1.12	0.00
ROA	0.84	0.01	0.71	0.03	1.21	0.01	0.71	0.03	0.46	0.11	1.32	0.00
NSI	0.50	0.02	0.40	0.06	0.65	0.02	0.42	0.04	0.25	0.15	0.56	0.02
CEI	0.42	0.03	0.38	0.06	0.49	0.05	0.26	0.08	0.15	0.20	0.35	0.06
Accruals	0.34	0.20	0.32	0.22	0.38	0.20	0.23	0.34	0.20	0.31	0.30	0.25
NOA	0.50	0.03	0.73	0.00	0.09	0.39	0.46	0.06	0.63	0.01	0.05	0.44
MOM	0.23	0.16	0.28	0.17	0.15	0.36	0.19	0.23	0.21	0.24	0.13	0.37
GP	0.36	0.07	0.26	0.17	0.52	0.05	0.45	0.05	0.26	0.17	0.56	0.04
AG	0.36	0.17	0.40	0.16	0.31	0.24	0.34	0.18	0.41	0.10	0.24	0.24
INV	0.05	0.42	0.13	0.33	−0.07	0.41	−0.04	0.43	0.11	0.33	−0.13	0.33
Combination	0.45	0.01	0.46	0.02	0.42	0.05	0.33	0.07	0.29	0.08	0.33	0.07

	No FF controls						FF(t) as controls					
	SENTIMENT		*SENTHAT*		*SENTRES*		*SENTIMENT*		*SENTHAT*		*SENTRES*	
	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p
Panel B. Predicting short portfolio returns at t												
Age	−0.86	0.01	−1.10	0.01	−0.25	0.33	−0.20	0.05	−0.22	0.05	−0.04	0.40
D/BE	−0.53	0.03	−0.78	0.01	0.09	0.42	−0.06	0.29	−0.13	0.14	0.20	0.08
EF/A	−0.61	0.03	−0.88	0.01	0.06	0.45	−0.03	0.40	−0.15	0.16	0.20	0.11
E/BE	−0.87	0.01	−1.15	0.00	−0.20	0.36	−0.22	0.05	−0.32	0.02	−0.02	0.47
GS	−0.71	0.02	−0.99	0.01	−0.07	0.45	−0.11	0.20	−0.22	0.10	0.09	0.32
PPE/A	−0.90	0.01	−1.15	0.01	−0.30	0.30	−0.21	0.05	−0.21	0.07	−0.06	0.35
RD/A	−0.68	0.02	−0.99	0.01	0.02	0.48	−0.14	0.24	−0.26	0.07	0.15	0.22
Sigma	−0.13	0.26	−0.17	0.25	0.11	0.37	0.13	0.15	0.20	0.07	0.16	0.17
GS High–Med	−0.41	0.06	−0.57	0.03	0.05	0.45	0.07	0.23	0.06	0.26	0.16	0.07
GS Med–Low	−0.71	0.02	−0.99	0.01	−0.07	0.45	−0.11	0.20	−0.22	0.10	0.09	0.32
EF/A High–Med	−0.42	0.07	−0.58	0.03	0.03	0.47	0.07	0.30	0.06	0.31	0.15	0.12
EF/A Med–Low	−0.61	0.03	−0.88	0.01	0.06	0.45	−0.03	0.40	−0.15	0.16	0.20	0.11
ME	−0.75	0.01	−1.00	0.01	−0.16	0.38	−0.32	0.18	−0.44	0.08	−0.08	0.41
B/M	−0.74	0.01	−0.91	0.01	−0.27	0.30	−0.14	0.10	−0.11	0.17	−0.04	0.39
B/M High–Med	−0.47	0.05	−0.61	0.03	−0.05	0.46	0.05	0.33	0.07	0.28	0.12	0.21
B/M Med–Low	−0.74	0.01	−0.91	0.01	−0.27	0.30	−0.14	0.10	−0.11	0.17	−0.04	0.39
Distress	−1.73	0.01	−1.98	0.01	−1.08	0.14	−0.97	0.03	−0.73	0.06	−1.53	0.00
O-score	−0.95	0.03	−0.99	0.04	−0.82	0.14	−0.52	0.02	−0.42	0.07	−1.03	0.00
ROA	−0.97	0.02	−0.95	0.05	−1.03	0.09	−0.56	0.05	−0.41	0.13	−1.15	0.01
NSI	−0.76	0.01	−0.81	0.02	−0.68	0.09	−0.42	0.01	−0.40	0.02	−0.46	0.02
CEI	−0.62	0.03	−0.77	0.02	−0.37	0.22	−0.23	0.07	−0.34	0.03	−0.15	0.23
Accruals	−0.84	0.02	−1.01	0.02	−0.54	0.20	−0.27	0.19	−0.38	0.08	−0.17	0.28
NOA	−0.77	0.01	−0.94	0.01	−0.48	0.16	−0.37	0.05	−0.47	0.02	−0.24	0.17
MOM	−0.89	0.01	−1.11	0.01	−0.52	0.21	−0.24	0.14	−0.42	0.07	−0.16	0.32
GP	−0.51	0.04	−0.39	0.12	−0.72	0.05	−0.25	0.07	−0.08	0.33	−0.56	0.01
AG	−0.83	0.01	−0.97	0.01	−0.59	0.14	−0.40	0.02	−0.47	0.01	−0.30	0.08
INV	−0.70	0.01	−0.87	0.01	−0.42	0.19	−0.25	0.13	−0.38	0.06	−0.16	0.27
Combination	−0.83	0.01	−0.94	0.01	−0.65	0.11	−0.34	0.02	−0.38	0.02	−0.35	0.04

(*continued on next page*)

Table 4 (*continued*)

	No FF controls						FF(t) as controls					
	SENTIMENT		*SENTHAT*		*SENTRES*		*SENTIMENT*		*SENTHAT*		*SENTRES*	
	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p	Coef.	Emp. p
Panel C. Predicting long portfolio returns at t												
Age	−0.33	0.06	−0.48	0.03	0.11	0.39	0.03	0.36	0.02	0.38	0.15	0.05
D/BE	−0.16	0.23	−0.22	0.17	0.13	0.35	0.13	0.06	0.18	0.02	0.16	0.10
EF/A	−0.77	0.01	−0.99	0.01	−0.20	0.35	−0.13	0.13	−0.15	0.14	0.00	0.49
E/BE	−0.48	0.04	−0.68	0.02	0.04	0.47	0.03	0.35	0.03	0.38	0.19	0.07
GS	−0.78	0.01	−1.00	0.01	−0.23	0.33	−0.17	0.05	−0.16	0.10	−0.03	0.40
PPE/A	−0.52	0.04	−0.74	0.01	0.05	0.45	−0.07	0.28	−0.17	0.14	0.13	0.23
RD/A	−0.91	0.01	−1.20	0.00	−0.24	0.34	−0.17	0.19	−0.22	0.16	0.04	0.43
Sigma	−0.96	0.01	−1.23	0.00	−0.30	0.31	−0.23	0.05	−0.29	0.05	−0.07	0.37
GS High–Med	−0.78	0.01	−1.00	0.01	−0.23	0.33	−0.17	0.05	−0.16	0.10	−0.03	0.40
GS Med–Low	−0.41	0.06	−0.57	0.03	0.05	0.45	0.07	0.23	0.06	0.26	0.16	0.07
EF/A High–Med	−0.77	0.01	−0.99	0.01	−0.20	0.35	−0.13	0.13	−0.15	0.14	0.00	0.49
EF/A Med–Low	−0.42	0.07	−0.58	0.03	0.03	0.47	0.07	0.30	0.06	0.31	0.15	0.12
ME	−0.27	0.12	−0.32	0.11	−0.02	0.48	0.05	0.16	0.15	0.00	0.06	0.15
B/M	−0.61	0.03	−0.89	0.01	0.04	0.47	−0.03	0.43	−0.12	0.28	0.19	0.21
B/M High–Med	−0.61	0.03	−0.89	0.01	0.04	0.47	−0.03	0.43	−0.12	0.28	0.19	0.21
B/M Med–Low	−0.47	0.05	−0.61	0.03	−0.05	0.46	0.05	0.33	0.07	0.28	0.12	0.21
Distress	−0.50	0.07	−0.75	0.02	0.18	0.34	−0.02	0.45	−0.18	0.25	0.00	0.50
O-score	−0.21	0.28	−0.33	0.18	0.13	0.39	0.04	0.26	−0.06	0.31	0.09	0.24
ROA	−0.13	0.39	−0.24	0.29	0.18	0.36	0.15	0.14	0.05	0.38	0.17	0.14
NSI	−0.27	0.14	−0.40	0.06	−0.03	0.47	0.00	0.48	−0.15	0.09	0.10	0.21
CEI	−0.20	0.17	−0.39	0.05	0.13	0.34	0.03	0.38	−0.18	0.06	0.20	0.07
Accruals	−0.50	0.11	−0.69	0.06	−0.16	0.38	−0.04	0.45	−0.18	0.26	0.13	0.34
NOA	−0.27	0.21	−0.20	0.28	−0.39	0.18	0.09	0.27	0.16	0.18	−0.19	0.16
MOM	−0.66	0.02	−0.82	0.02	−0.37	0.24	−0.05	0.35	−0.22	0.14	−0.03	0.45
GP	−0.16	0.35	−0.13	0.36	−0.20	0.32	0.20	0.13	0.18	0.19	0.00	0.49
AG	−0.47	0.07	−0.58	0.05	−0.29	0.27	−0.06	0.41	−0.06	0.40	−0.06	0.41
INV	−0.65	0.02	−0.74	0.02	−0.50	0.14	−0.29	0.03	−0.28	0.04	−0.29	0.07
Combination	−0.39	0.08	−0.48	0.05	−0.23	0.28	−0.01	0.46	−0.09	0.24	−0.02	0.44

of the 28 spread-portfolios considered, with empirical *p*-values less than 5%. In stark contrast, *SENTRES* is significant in predicting only 3 spread returns.

Baker and Wurgler (2006) find that when sentiment is high, returns on small, young, and high volatility firms are relatively low over the following year. The signs of the coefficients on age, volatility (Sigma), and size (BE) 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 fundamental-related component of the sentiment index significantly predicts spread portfolio returns on age, volatility (Sigma) and size (ME) suggests that, it is when interest rates are high and liquidity is high (or transaction costs are low) that the returns on small, young, and high volatility firms are relatively 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 fundamental-related component of sentiment, *SENTHAT*, but cannot be predicted by *SENTRES*. 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) consider, only one spread portfolio formed on external finance can be significantly predicted by *SENTRES*, the residual 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]

We now turn to the 12 Stambaugh et al. (2012) long-short spread 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 et al. (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 covarying with fundamental-related variables, the significance of *SENTHAT* for future long-short strategy returns could simply reflect the fact that *SENTHAT* is related to the future investment opportunity set or underlying economic conditions.

On the right side of Table 4 Panel A, we report the predictive regression equation (4) for spread portfolios, 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, the sentiment index significantly predicts 8, *SENTHAT* significantly predicts 9, while *SENTRES* significantly predicts 5. Baker and Wurgler (2006) similarly 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

[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. 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.

with size. Recall from Panel C of Table 2 that *SENTHAT* is significantly correlated with the MKT and SMB from the next period, while *SENTRES* is not significantly correlated with any future asset pricing factors. The decrease in significance of *SENTHAT* as a predictor of returns is primarily driven by the fact that *SENTHAT* predicts the next period MKT and 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 MKT and SMB. This finding sheds some light on the source of the predictive power of the fundamental-related component in the sentiment index.

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

3.4. Predictive regression results on long and short portfolios

Stambaugh et al. (2012) 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 periods with high levels of sentiment, because high sentiment leads to overpricing, 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 periods of 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 short-leg anomaly returns, while the long-leg returns are unrelated to the sentiment index.

Table 4 Panel B and Panel C report results of predictive regressions involving the short and long legs of the spread portfolios, respectively. Again, note there is a difference between Baker and Wurgler (2006) and Stambaugh et al. (2012) 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 et al. (2012) portfolios, the most profitable (least profitable) value-weighted decile portfolio is the long (short) leg.

We first examine the results for short legs in Table 4 Panel B. On the left, when no Fama and French factors are included, the coefficient on the sentiment index is always negative, which is consistent with Stambaugh et al. (2012), indicating that the return on the short leg is lower after high investor sentiment. The coefficient on *SENTHAT* is also always negative for the short leg. The coefficient on *SENTRES* is negative in all but 7 cases. For the 28 trading strategies, the coefficient on sentiment index is significant for 25 of them, and *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*. From the right side of Panel B, where Fama and French factors from time t are included in the regression, the sentiment index is significant in 10 out of 28 cases, *SENTHAT* is significant in 6 cases, and *SENTRES* is significant in 6 cases as well. Clearly, including Fama and French factors from time t reduces the predictive power of *SENTHAT*, because it is significantly correlated with these factors.

Next we turn to the long legs in Table 4 Panel C. When no Fama and French factors are included, the sentiment index can predict 13 long-leg returns significantly, *SENTHAT* can predict 20 cases, and *SENTRES* can predict none. To be specific, for the 16 Baker and Wurgler (2006) strategies, *SENTHAT* is equally important in predicting returns on the long legs. It carries a significant negative sign for all 16 long legs with two exceptions: D/BE and size portfolios. In contrast, Stambaugh et al. (2012) 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 returns of those two strategies, and in addition, it also significantly predicts the long return of the Campbell et al. (2008) distress strategy, the momentum strategy and the investments-to-assets 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 long- or short-leg returns comes largely from information in the sentiment index related to risk factors and economic fundamentals, and this is overwhelmingly the case. We do not see a single case of significance from *SENTRES*, the residual sentiment component of the sentiment index, in predicting either the long- or short-leg returns of the 28 strategies considered in total.

Second, we find that *SENTHAT* much more strongly predicts the returns of the short legs than those of the long legs for each of the Stambaugh et al. (2012) portfolios. However, this result is very different for the Baker and Wurgler (2006) strategies. For the 16 Baker and Wurgler portfolios, *SENTHAT* strongly predicts 14 of the long legs, while *SENTRES* predicts none. Judging from the 16 Baker and Wurgler (2006) strategies, we see that *SENTHAT* is significant in predicting both the long- and short-leg returns, which is inconsistent with the Stambaugh et al. (2012) prediction that, if sentiment-driven mispricing and short-sales constraints are the driving force behind the anomaly returns, there should be an asymmetrical effect of sentiment on the long- and short-leg returns. From our perspective, the fact that much of the sentiment index's predictive power for both long and short legs comes from the component related to economic fundamentals offers an alternative view to the assertion that it is necessarily irrational investor sentiment that leads to mispricing which causes anomaly returns.

To summarize, we find that the power of sentiment to predict short- and long-leg returns is predominantly driven by the fundamental-related information in sentiment, *SENTHAT*, while the residual component, *SENTRES*, has little ability to predict either the short- or long-leg returns. Furthermore, the asymmetric effect of *SENTHAT* on the short and long legs of anomalies applies only to the Stambaugh et al. (2012) value-weighted strategies and not the portfolios studied in Baker and Wurgler (2006).

4. The fundamentals index[8]

In previous sections, we show that much of the sentiment index's predictive power is driven by its correlation with economy fundamentals and business cycle variables. A natural follow-up question to ask is: can we construct an index from our fundamentals variables, after purging out possible impact from investor sentiment? In addition, can this fundamental index predict future stock returns, and how does it compare to the predictive power of the sentiment index? The answers to these questions help to further understand the usefulness of fundamental-related information for predicting future stock returns. We detail the construction of such a "fundamentals index" in Section 4.1, and in Section 4.2, we present the results of using this index to predict cross-sectional stock returns.

[8] We thank our referee for suggesting this exercise.

Table 5
The Fundamentals Indices. To compute the fundamentals index, we first orthogonalize all 13 economic fundamental variables to the Michigan Consumer Sentiment index. After orthogonalization, we conduct principal component analysis using our whole sample on the 13 economic fundamental related variables' residuals. We include both the first and the second principal components as our "fundamentals indices". Panel A presents the summary statistics for the two PCs. We report the predictive regression results for the fundamentals indices in Panel B and C.

	PC1	PC1	PC2	PC2
	PC loading	Variance Explained	PC loading	Variance Explained
Panel A. Summary statistics for the fundamentals indices				
Variance explained		25.62%		17.47%
Unemp	0.06	0.01%	0.60	3.26%
dCPI	0.35	0.01%	−0.26	0.03%
dCons	0.26	0.03%	0.01	0.00%
dSPI	0.20	0.03%	−0.02	0.00%
dInd	0.13	0.01%	0.05	0.01%
NBER	−0.11	0.00%	−0.05	0.00%
T-bill	0.45	0.04%	−0.04	0.00%
Def	−0.01	0.00%	0.47	1.70%
Term	−0.19	0.04%	0.51	1.00%
Div	0.45	5.01%	0.18	3.13%
VWRETD	0.04	0.15%	0.15	6.01%
MktVol	−0.28	18.16%	0.04	1.19%
PctZero	0.46	2.14%	0.17	1.14%
Correlations with	Correlation	*p*-value	Correlation	*p*-value
Orthogonalized *SENTIMENT* index	−0.07	0.12	0.04	0.39
Original *SENTIMENT* index	−0.11	0.01	0.05	0.21

	28 spread portfolios		28 short-leg portfolios		28 long-leg portfolios	
	PC1	PC2	PC1	PC2	PC1	PC2
Panel B. Predictive power of the fundamentals indices for future stock returns						
No FF	0	3	0	21	1	23
FF(t) as controls	0	4	0	1	7	3

	28 spread portfolios			28 short-leg portfolios			28 long-leg portfolios		
	Sentiment	PC1	PC2	Sentiment	PC1	PC2	Sentiment	PC1	PC2
Panel C. Horse race between the fundamentals indices and the sentiment index									
No FF	20	0	5	25	0	26	16	3	26
FF(t) as controls	13	0	3	11	9	1	3	20	2

4.1. Constructing the fundamentals index

Our approach of constructing the fundamentals index is parallel to how Baker and Wurgler (2006) construct their sentiment index. First, we collect a set of variables representing economic fundamentals information, which are the 13 variables we use in previous sections. Second, to minimize the "sentiment" component in the 13 variables, we orthogonalize all 13 variables to a proxy for sentiment. Since we are concerned that the BW sentiment index might contain important information related to fundamentals, here we choose the Michigan Consumer Sentiment index as the proxy for sentiment. After orthogonalization, we conduct principal component analysis using our whole sample for the 13 economic fundamental related variables. Baker and Wurgler (2006) choose the first principal component from 6 orthogonalized sentiment proxies as the sentiment index. We have 13 economic fundamental variables, and to capture the common components of the 13 variables, we include both the first and the second principal component as our "fundamentals" indices.

Summary statistics of the two fundamentals indices are reported in Table 5 Panel A. The first principal component (PC1) explains about 26% of the total variations among the 13 economic fundamental variables, and the second principal component (PC2) explains about 17% of the total variation. To better interpret the principal components, we report the loadings on each of the 13 variables. Since the 13 variables are not normalized to have the same variance, only the sign of the loadings (not the magnitude of the loadings) are informative. We also report the decomposition of variance explained by the principal components due to loadings on each of the 13 variables. Most of the explanatory power of the PC1 comes from its negative loading on market volatility, which explains 18.16% of the covariance among the 13 variables. The PC2's explanatory power mostly comes from its positive loading on the market return, unemployment rate and the dividend yield.

Would the PC1 and PC2 be highly correlated with the sentiment index? There is no clear answer to this question. The sentiment index is the principle component reflecting common variation among the 6 proxies after being orthogonalized to a couple of macroeconomic variables. In our case, the PCs reflect common variation among 13 variables after being orthognalized to the Michigan Consumer Sentiment index. The correlation between PC1, PC2 and the sentiment index should be related to the correlation between the 6 proxies and the 13 variables used to construct them. But after the complicated transformation using orthogonalization and principal component analysis, it is hard to make further inference based on high or low correlation between PC1, PC2 and the sentiment index for the correlation between the 6 proxies and the 13 variables.

At the bottom of Panel A, we report the correlations between the fundamentals indices and the original sentiment index and the orthogonalized sentiment index. The correlation coefficient between the first fundamentals index PC1 and the original (orthogonalized) sentiment index is −0.11 (−0.07), with a *p*-value of 0.01 (0.12). The second fundamentals index is positively correlated with both sentiment indices, yet insignificantly. Given the magnitude and significance of the correlation coefficients, it seems that information content of the sentiment indices overlap with that of the fundamentals indices, but not to a substantial degree. In another word, the information we extract directly out of fundamental variables might be different from that of the six proxies for the sentiment index, after orthogonalization and principal component analysis.

4.2. Predicting future stock returns

In this section, we examine the predictive power of the fundamental indices by re-estimating Eqs. (1) and (3), while replacing the sentiment index by the fundamentals indices. Given that the fundamentals indices and the sentiment index don't have high correlations, our purpose is to investigate whether information from fundamentals can have any predictive power for future stock returns.

Results are presented in Panel B of Table 5. When no contemporaneous factors are included as controls, the first principal component (PC1) is only able to predict 1 long-leg portfolio's future return significantly. In contrast, the second principal component (PC2) is able to significantly predict 3 out of the 28 spread portfolios, 21 out of the 28 short-leg portfolios, and 23 out of 28 long-leg portfolios. This finding suggests that the second fundamentals index has strong predictive power for future stocks returns. In comparison, the sentiment index can significantly predict 13 long-leg portfolios, 25 short-leg portfolios and 19 spread portfolios. The second fundamentals index has similar predictive power for the long and short portfolios, but lacks the ability to predict spread portfolio returns. When we include contemporaneous Fama and French factors in the predictive regressions, the predictive power of the fundamentals indices substantially decreases, which is similar to the pattern we find earlier with the sentiment index.

In Panel C of Table 5, we estimate a horse race between the fundamentals indices and the sentiment index for predicting future stock returns. That is, we include both sentiment index and the two fundamentals indices in the same regression to examine whether one dominates the other in terms of ability to predict stock returns.

When no Fama and French factors are included, the sentiment index can significantly predict 20 spread returns, while PC1 predicts none, and PC2 predicts 5. This confirms our earlier observation: the fundamental indices cannot predict spread portfolio returns well. The results are quite different when we focus on the long and short legs of the spread portfolios. For the 28 short-leg portfolios, the sentiment index can significantly predict 25 out of 28, PC1 can't predict any, while PC2 can significantly predict 26 out of 28. For the 28 long-leg portfolios, the sentiment index can significantly predict 16 out of 28, PC1 can significantly predict 3 out of 28, and while PC2 can significantly predict 26. These results suggest that the second fundamental index (PC2) has significant predictive power for future long and short portfolio returns. Interestingly, the predictive power of the sentiment index is not diminished by including the fundamentals indices or vice versa, which is consistent with the earlier finding of the low correlations between the sentiment index and fundamentals indices.

When we include the Fama and French factors (presented in the bottom row), the predictive power of the sentiment index and the fundamental index PC2 both significantly decreases, which suggests that both the sentiment index and the PC2 contain important information about future factor realizations. Interestingly, the predictive power of PC1 significantly increases: it can significantly predict 9 out of 28 short-leg portfolio returns and 20 out of 28 long leg portfolio returns.

Combining Panel B and Panel C, we have three observations. First, PC1 and PC2 are both capable of predicting future stock returns, especially for the long and short-leg portfolio returns. Second, the fundamental indices and the sentiment index don't subsume each other's predictive power for future stock returns. Third, we have mixed evidence on which index dominates in terms of predictive power: sometimes the sentiment index dominates the fundamentals indices, and sometimes the opposite happens.

5. Robustness checks and further discussion[9]

5.1. The 2-variable System vs. the 13-variable System[10]

In Section 3, our main discussion of the decomposition exercise is focused on the 13-variable system, which includes information from macroeconomic variables, risk factors and business cycle indicators. In the 2-variable system, we only include the T-bill rate and the liquidity risk factor, *PctZero*. We present summary results for the 2-variable system in Panel A of Table 6.

As discussed in Section 2.1, the 2-variable system's explanatory power is about 20% less than that of the 13-variable system. When Fama and French factors are not included as control variables, the 13-variable system *SENTHAT* significantly predicts 16 out of 28 spread portfolios, and 26 out of 28 short-leg portfolios. In comparison, the 2-variable *SENTHAT* significantly predicts 13 out of 28 spread portfolios, and 26 out of 28 short-leg portfolios, while the 2-variable *SENTRES* significantly predicts 7 spread portfolios, and 1 short-leg portfolio. Evidently, the predictive power of *SENTHAT* dominates that of *SENTRES*, even when only two variables are included in the decomposition regression. Since the sentiment index from $t-1$ contains information about time t Fama–French factors, after time t Fama–French factors are included, the significance of all *SENTHAT* variables decreases substantially.

Overall, the *SENTHAT* and *SENTRES* series constructed from the 2-variable system perform similarly to their counterparts from the 13-variable system. But it is also clear that using the additional 11 variables help the stand-alone predictive power of *SENTHAT* by a small but noticeable amount.

5.2. Revisit BW principal component analysis[11]

One alternative approach to our decomposition exercise and predictive regressions is to redo the orthogonalization and principal components procedures used in Baker and Wurgler (2006). Instead of using the five macroeconomic variables as in the original paper, we orthogonalize the 6 sentiment proxies with respect to either 13 variables or 2 variables, and then we construct a modified sentiment index, which is now orthogonal to all of our macroeconomic variables, risk factors and business cycle indicators. With this modified sentiment index, we re-estimate the predictive regressions as in Section 2.2.

The results are reported in Panel B of Table 6. The original BW sentiment index, which is orthogonal to three macroeconomic variables, predicts 19 out of 28 spread portfolios and 25 out of 28 short-leg portfolios. When we orthogonalize all sentiment proxies to 13 and 2 variables, the modified sentiment indices have significant predictive for only 3 and 6 spread portfolios, and 0 short-leg portfolio, respectively. That is to say, after being orthogonalized to a different set of risk/business cycle variables, the sentiment index loses its predictive power, which is consistent with our results in Section 3.

5.3. Alternative sentiment index: the Michigan consumer sentiment index

An alternative sentiment measure is the Michigan Consumer Sentiment Index. Lemmon and Portniaguina (2006) show that the

[9] To save space, we put additional further discussions in the Internet Appendix.

[10] We thank our CICF discussant, Egor Matveyev, and Jianfeng Yu for this suggestion.

[11] We thank our WFA discussant, Joey Engelberg, for this suggestion.

Table 6
Robustness Checks. Panels A and B report number of significant *t*-statistics for *SENTHAT* and *SENTRES* when predicting spread, short and long portfolio returns using the 2-variable system and with alternative orthogonalization variables prior to performing principal components analysis, respectively. The 2 variables are T-bill and *PctZero*. Panel C and D report predictive regression results using alternative interest rate, liquidity measures and risk factors.

		28 spread portfolios		28 short-leg portfolios		28 long-leg portfolios	
		SENTHAT	*SENTRES*	*SENTHAT*	*SENTRES*	*SENTHAT*	*SENTRES*
Panel A. Number of significant t-statistics for predicting spread and long/short-leg portfolios, using 13-variable system vs. 2-variable system for decomposition							
No FF	13 variables	16	3	26	0	17	0
	2 variables	13	7	26	1	20	0
FF(t) as control	13 variables	9	5	6	6	3	0
	2 variables	8	7	3	10	3	1

	28 spread portfolios	28 short-leg portfolios	28 long-leg portfolios
Panel B. Number of significant t-statistics for predicting spread and long/short-leg portfolios, using different orthogonalization variables			
BW sentiment index orthogonal to 13 variables	3	0	0
BW sentiment index orthogonal to 2 variables	6	0	0

	28 spread portfolios		28 short-leg portfolios		28 long-leg portfolios	
	SENTHAT	*SENTRES*	*SENTHAT*	*SENTRES*	*SENTHAT*	*SENTRES*
Panel C. Number of portfolio returns SENTHAT and SENTRES can predict, using alternative interest rate or liquidity measure						
Replace 3-month T-bill rate with 1-yr T-bill rate	13	12	25	0	24	0
Replace 3-month T-bill rate with 10-yr T-bill rate	16	3	26	0	17	0
Replace 3-month T-bill rate with 20-yr T-bill rate	13	7	21	0	13	0
Replace *PctZero* with Amihud	16	13	27	1	26	0

	28 spread portfolios			28 short-leg portfolios			28 long-leg portfolios		
	SENTIMENT	*SENTHAT*	*SENTRES*	*SENTIMENT*	*SENTHAT*	*SENTRES*	*SENTIMENT*	*SENTHAT*	*SENTRES*
Panel D. Number of portfolio returns SENTHAT and SENTRES can predict, using Hou et al. (2015) factors									
FF(t) as controls	8	9	5	10	6	6	4	3	0
HXZ(t) as controls	5	8	2	1	7	2	0	1	0

component 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 attributed to fundamental-related variables, with disposable personal income growth and unemployment rate explaining the largest portion of its total variations. On the other hand, the Michigan Consumer Sentiment Index is not as powerful a predictor of cross-sectional stock returns as the BW sentiment index. After decomposing the Michigan Consumer Sentiment Index into a risk/business cycle component and a pure sentiment component, we find the risk/business cycle component can predict 5 of the 28 spread portfolios used in our paper, and the residual 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.

5.4. Alternative interest rate and liquidity measures

As alternatives to the 3-month interest rate and the *PctZero* liquidity measure we use thus far, in this section, we examine whether we obtain similar results with alternative interest rate and market liquidity measures.

For a short-term interest rate such as 3-month interest rate, there is a concern that the Federal Reserve could change target federal funds rates, which is more correlated to short-term interest rate, to combat excessive optimism or pessimism. Therefore, the long-term interest rate might be less directly influenced by Federal Reserve policy and less correlated with the sentiment. For alternative interest rates, we consider 1-year, 10-year and 20-year Treasury rates.

For alternative liquidity risk measures, we consider the aggregate Amihud (2002) liquidity measure. The aggregate Amihud measure is constructed as follows. For each stock in NYSE, AMEX and NASDAQ, we compute the daily Amihud price impact measure. Then we compute the monthly average Amihud measure for each stock in every month. Lastly, we average across all stocks to get an aggregate monthly Amihud measure for the stock market. This aggregate liquidity measure is shown to be priced in Acharya and Pedersen (2005).

We report decomposition results when replacing 3-month T-bill rate and *PctZero* with alternative measures in Panel C of Table 6. Regardless of the interest rate or liquidity measure we include in the decomposition, *SENTHAT* can predict the returns of many more portfolios than *SENTRES*, indicating that the predictive power of sentiment arises from its information content that is related to interest rate or liquidity measures. This robustness check assuages the concern that our findings may rely upon our choice of interest rate or liquidity measures.

5.5. Alternative risk factors

Throughout the paper, we use Fama and French factors as risk controls. Hou et al. (2015) recently propose a q-factor model with 4 factors: a market factor, a size factor, an investment factor and a profitability factor. Can our results extend to this new set of risk factors? We provide results in Panel D of Table 6.

When we use the Fama and French factors as controls, the sentiment index can significantly predict 8 out of 28 spread portfolios, 10 out of 28 short portfolios, and 4 out of 28 long portfolios. When the Hou et al. (2015) factors are included in the regression as controls, the sentiment index itself is able to significantly predict 5 out of 28 spread portfolios, 1 out of 28 short portfolios, and 0 out of 28 long portfolios. Succinctly put, the sentiment index's predictive power largely vanishes in the presence of the Hou et al. (2015) factors, more than it does in the presence of the Fama and French factors.

Not surprisingly, the predictive power of *SENTHAT* and *SENTRES* also decreases substantially when the Hou et al. (2015) factors are included in the predictive regressions, which indicates that a significant part of their predictive power comes from their information content related to the risk factors used in Hou et al. (2015).

To summarize, when Hou et al. (2015) factors are included, the predictive power of the sentiment index, *SENTHAT* and *SENTRES*, largely disappear, possibly because the sentiment index, *SENTHAT* and *SENTRES* contain information about future realization of the factors in Hou et al. (2015). Compared to Fama–French factors, the Hou et al. (2015) factors seem to contain more overlapping information with the sentiment index, *SENTHAT* and *SENTRES*.

6. Conclusion

There is a large and growing literature investigating the impact of investor sentiment on financial markets. To this end, Baker and Wurgler (2006) construct an investor sentiment index to proxy for excessive optimism or pessimism about stocks in general and show that this sentiment index significantly predicts future stock returns in the cross-section.

We conduct a series of tests to deepen our understanding of the investor sentiment index and the nature of its informational content. Our first finding is that both the raw and orthogonalized BW sentiment indices contain a substantial amount of information related to economic fundamentals, as it co-varies strongly with the T-bill rate and market liquidity conditions. We decompose the widely used BW investor sentiment index into two components: one related to fundamental variables, and one unrelated. The power of the sentiment index to predict cross-sectional stock returns is mainly driven by the component constructed from variables related to market conditions and economic fundamentals, while the residual component essentially has little predictive power.

These findings suggest that maybe it is not necessarily investor sentiment or irrational exuberance about stocks, per se, that predicts cross-sectional stock returns. Instead, it may be the economic fundamental variables to which sentiment is related that have predictive power. Under this paradigm, the sentiment index likely captures state variables that drive pricing in a rational expectations model, and our findings point to important links between cross-sectional returns patterns and several macroeconomic variables, most notably market liquidity and the short-term interest rate.

Our study does have two caveats. First, we identify economic fundamental variables based on previous literature, and it is always possible we omit some of the important variables. Second, it is possible that our economic fundamental variables are influenced by sentiment itself. To fully disentangle the causal relationship between business cycle variables and sentiment index, we would need a general equilibrium model, and we leave that to future research.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2015.10.001.

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