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Sentiment-scaled CAPM and market mispricing

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Abstract

This study explores the conditional version of the capital asset pricing model on sentiment to provide a behavioural intuition behind the value premium and market mispricing. We find betas (β) and the market risk premium to vary over time across different sentiment indices and portfolios. More importantly, the state β derived from this sentiment-scaled model provides a behavioural explanation of the value premium and a set of anomalies driven by mispricing. Different from the static β–return relation that gives a flat security market line, we document upward security market lines when plotting portfolio returns against their state βs and portfolios with higher state βs earn higher returns.

KEYWORDS

conditional CAPM, market anomalies, security market line, state beta, stochastic discount factor, time-varying risk premium, value premium

JEL CLASSIFICATION

G12

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1 | INTRODUCTION

The static capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) posits a simple linear relationship between a security's systematic risk exposure, defined as beta (β), and the expected rate of return assuming that traders are rational and sophisticated. The seminal study of E. Fama and French (1992), however, shows that β is unrelated to returns, casting doubt on the relevance of the CAPM. Several explanations have been suggested to explain this puzzle such as inefficiency of market proxies (Roll and Ross, 1994), frictions (Baker et al., 2011; Black, 1972) and misspecification of risk (Jagannathan and Wang, 1996). Lettau and Ludvigson (2001b) argue that the risk premium is time-varying, whereas the static CAPM assumes that risk premium is constant. This implies that stocks with higher static market βs do not necessarily yield higher average returns due to the misspecification of risk by the CAPM.

In response to this CAPM failure, in this paper, we present a stochastic discount factor scaled by investor sentiment with respect to the conditional CAPM and provide empirical evidence to show that this scaled version performs far better than the nonconditional specification at explaining the cross-sectional variation of average returns and, especially, for the size and book-to-market (BM) portfolios. Our first motivation to use sentiment as conditional information in the CAPM stems from the theoretical model proposed by Hong and Sraer (2016) in which market-level disagreement is the key determinant of the slope of the security market line (SML). When aggregate disagreement is high, high-β assets that are sensitive to this divergence of opinion are overpriced by optimistic investors due to short-sale constraints, which force pessimistic investors to be sidelined. Accordingly, high-β stocks earn lower returns with the increase of aggregate disagreement, and the SML can even be downward sloping in high enough disagreement states. Similar to aggregate disagreement, sentiment is another well-documented indicator of overpricing, and studies such as Antoniou et al. (2015) and Shen et al. (2017) find that high-β stocks are speculative and susceptible to sentiment-driven overpricing, especially in the presence of short-sale constraints. These observations suggest that market-wide sentiment, like aggregate investor disagreement, is important conditional information that warrants to examine the relation between returns and CAPM βs. In addition, incorporating sentiment into the CAPM contributes to understanding the intuition behind the flat SML. Moreover, as sentiment can trigger uninformed demand shocks and, thus, change the distribution of future returns, it is quite reasonable to expect that sentiment can predict market returns and, therefore, serve as an instrument in cross-sectional asset pricing tests.

Second, it has been well understood that instruments that predict market returns can be natural candidates of conditional information in cross-section tests (Santos and Veronesi, 2005). Ferson and Harvey (1999) find evidence indicating that proxies for time variation in expected returns, based on common lagged instruments such as the spread between a 10-year and a 1-year Treasury bond yield (E. F. Fama and French, 1989), have strong explanatory power for the cross-section of portfolio returns. Thus, if a variable can predict market returns, it is plausible to use it as conditional information on cross-section tests. In this study, it is shown that investor sentiment has strong negative predictability on the value-weighted market excess returns. This finding is consistent with different sentiment indices used and with the findings of Huang et al. (2015) and of Greenwood and Shleifer (2014) who use survey data of investor expectation. Hence, investor sentiment seems to be a suitable instrument to explain the time variation in stock returns.

In accord with a well-established test on the conditional version of CAPM,[1] we conduct a cross-sectional investigation of the sentiment-scaled CAPM using excess returns of 25 size and BM portfolios constructed in E. Fama and French (1993). We use these portfolios in our empirical analysis because they have been of great challenges to asset pricing models. Moreover, Cochrane (2007) highlights that these portfolios represent the testing ground of asset pricing models, and the value premium has long been of interest to asset pricing studies. In sharp contrast to the adjusted R^2 in the static CAPM, which only explains 3% of the variation in the cross-section of average returns, the R^2 in the scaled CAPM using different sentiment indices jumps to a range between 45% and 61%. In addition, the average pricing errors become much smaller in the scaled model than in the static one. To address the concern in Lewellen et al. (2010) that any three-factor model can explain returns on the size and BM portfolios well, we conduct and report results based on a robust measure of model performance (i.e., the generalized least squares [GLS] R^2) determined by the model factor's proximity to the minimum-variance boundary. The highest GLS R^2 of a sentiment-scaled model is 0.35, which is much higher than that of the static CAPM and the Fama–French three-factor models. We also use several portfolios, formed on eight anomaly variables, to test the sentiment-scaled model, and we find a modest performance as well.[2]

Besides its extraordinary performance in the cross-section tests, another important feature of the sentiment-scaled CAPM is its success in providing a behavioural intuition behind the 'value premium'. For many years, the value effect was a well-documented cross-sectional pattern showing that firms with high BM equity ratios realized higher average returns than those with low ratios. One possible explanation, as argued most forcefully by E. Fama and French (1992), is that value stocks are fundamentally riskier. In the spirit of this view, Lettau and Ludvigson (2001b) show that value stocks have greater systematic risk. That is, they have higher correlations with consumption growth than growth stocks in bad times.[3] Lakonishok et al. (1994), however, find no evidence in support of greater fundamental risk in value stocks. An alternative explanation proposed by Lakonishok et al. (1994), however, is that 'glamour' stocks have higher past earnings or growth and are, thus, more likely to be overpriced, whereas value stocks are more likely to be underpriced. This unsettled issue further motivates this study with the aim to provide a behavioural explanation of the intuition behind the value premium.

Using sentiment as an instrument to identify good and bad states,[4] this study confirms the finding of Lakonishok et al. (1994) that in bad states (low sentiment) when the risk premium is high, both value and growth portfolios bear similar systematic risk (their market βs conditioning on sentiment are close to each other). Therefore, the low-sentiment periods present no significant return difference between value and growth portfolios and imply that there is no value effect. In contrast to the findings in low-sentiment periods, growth portfolios in high-sentiment periods have higher market βs but earn more negative returns than value portfolios. Given each size category, the average returns of growth portfolios range from −0.734% to −2.289%, whereas the average returns of value portfolios range from −0.417% to −0.832%.

[1]See Jagannathan and Wang (1996), Lettau and Ludvigson (2001b), Santos and Veronesi (2005) and Eiling (2013)

[2]The cross-section tests on sentiment-scaled CAPM remain robust when testing portfolios formed on β and size. The result is reported in Appendix.

[3]However, Roussanov (2014) finds that when value stocks are more exposed to consumption risk, conditional expected returns of value stocks do not increase more than those of growth stocks.

[4]In our main analysis, we define a good (bad) state as a month in which the augmented sentiment is one standard deviation above (below) its mean value. Our results remain robust when defining good (above the mean value of sentiment) and bad (below the mean value of sentiment) states based on the mean value of sentiment.

This is exactly the 'value premium' in which the value portfolios outperform the growth ones, although the returns here are negative. More importantly, this finding is consistent with the conjecture of Lakonishok et al. (1994) that growth stocks are more likely to be overpriced. It is also consistent with Antoniou et al. (2015) who find that stocks with high βs in high-sentiment periods are more appealing to sentiment traders and, thus, are more overpriced.

Finally, the other important feature of the sentiment-scaled CAPM is that the β derived from this model, namely, 'state β', solves the puzzle of the flat security market line: An insignificant relationship between βs and returns with respect to the static CAPM.[5] When regressing excess returns of 25 size and BM portfolios on their static market βs, this study confirms the insignificant β pricing finding: The slope coefficient is −0.54 with a t statistic of −1.63. Conditional on sentiment, however, our evidence reveals a positive relation between returns and conditional market βs during low-sentiment periods, whereas the exact opposite is documented when sentiment is high. These observations suggest that portfolios with higher (lower) βs in low (high) sentiment should be able to earn much higher average returns than other portfolios. Thus, when combining the two sentiment states, a portfolio's average return is determined by the difference between its conditional β in low- and high-sentiment states, not by its static market β. In this case, one should expect a strong positive relation between this β difference and the portfolio's average return.

In this study, we refer to this β difference as 'state β', because it is state-dependent on investor sentiment. In sharp contrast to the flat security market line in the case of the static market β, an upward slope occurs when plotting portfolio average returns against their state βs. Specifically, our results show a slope coefficient of 1.26 with a t-statistic of 6.00 indicating that a one-unit increase in the state β is associated with 1.26% higher returns. More importantly, the R^2 is 56%, suggesting a relatively strong explanatory power of the state β compared to the static one. The state β also successfully captures the value effect—value portfolios have higher state βs than growth portfolios and, thus, earn higher returns in equilibrium.[6]

To the extent that the state β reflects sentiment effects on the cross-section of returns and, thus, can better specify mispricing-driven asset risk, we also test whether a positive relation between the returns of decile portfolios and their state βs exists in the sentiment-related anomalies, documented in Stambaugh et al. (2012). Such anomalies examined in this study comprise asset growth, net operating asset regression, net stock Issue, total accruals, composite equity issue, investment-to-assets, return on equity, and failure probability.[7] For each anomaly, we run the regression of decile portfolios' returns against their state βs, which are calculated in the same way as the 25 size and BM portfolios. We find positive state β–return relations across these eight cross-section regressions with four of them being significantly positive. Though the other four regressions do not show a strong relation between state βs and returns, we find that short legs have greater βs than long legs during good states (high-sentiment periods). To the extent that high sentiment indicates overpricing (Stambaugh et al., 2012) and that stocks with high βs are more susceptible to sentiment-driven overpricing (Antoniou et al., 2015) and Hong and Sraer, 2016), our finding implies that short legs are more exposed to sentiment-driven

[5] See Black (1972), E. Fama and French (1992), Frazzini and Pedersen (2014), Antoniou et al. (2015), and Hong and Sraer (2016)

[6] We find that portfolios' average BM value and their state βs also exhibit a strong positive correlation of 0.92.

[7] Another three anomalies as documented in Stambaugh et al. (2012) are Oscore, gross profitability and momentum. We exclude Oscore and gross profitability, because the long-short strategies in these two anomalies do not earn statistically significant returns over our sample period. (The insignificant return of Oscore has also been reported in Hou et al., 2015). We exclude the momentum strategy in which the holding period is 6 months, because the conditioning variable, sentiment, in our model is 1-month lagged and, thus, has conflict with the 6-month holding period.

overpricing and, thus, more likely to realize lower returns than long legs. In fact, we find that during good states, returns on long legs are much higher than returns on short legs. Although the return differences between long legs and short legs turn out negative (insignificantly) during bad states, their magnitudes are lower than those of positive differences during good states. Hence, when aggregating two states, returns on long-short strategies become significantly positive. We also find that state βs of short legs for all eight anomalies are smaller than those of long legs. Therefore, the state β successfully reveals the intuition behind sentiment-related anomalies, as it does for the value effect. That is, stocks with lower state βs are expected to earn lower returns in equilibrium, as a result of sentiment-driven overpricing effects.

For many years, investor irrationality or sentiment has been overlooked by the traditional finance paradigm. However, many studies provide both theoretical and empirical evidence demonstrating that sentiment is not noisy information but the perception of the state of the economy and the valuation of stocks; it skews investor expectations about expected returns, reflected in the variation of the risk premium over time and also causes uninformed demand shocks that in the presence of limits to arbitrage have significant effects on cross-section returns. Though investors' information set is unobservable and, thus, a conditional factor model may not be testable (Cochrane, 2006; Lettau and Ludvigson, 2001b) argue that using a conditional variable that summarises investors' expectation of excess returns can largely circumvent this issue. Thus, given that sentiment prominently reflects market-wide investor expectations with the potential to affect asset prices in the same direction at the same time (see empirical evidence from Brown and Cliff, 2005, and Greenwood and Shleifer, 2014, and theoretical evidence from Delong et al., 1990, and Dumas et al., 2009), the choice of sentiment as an instrument to examine the conditional version of CAPM is central to our study.[8]

We add to the growing body of behavioural finance studies that explore how sentiment affects asset prices and conduct empirical research to test the conditional version of the CAPM that provides a sentiment-related explanation for the cross-section of expected returns, especially, for the size and BM portfolios. By examining the role of state β, derived from investor sentiment, this study also contributes to the literature by providing a behavioural insight to both the value premium effect and by solving the flat security market line documented in the previous literature. Therefore, the most strikingly different feature of our study relative to the previous conditional CAPM studies with rational instrument variables such as the consumption–wealth ratio (CAY) is that we shed light on well-established behavioural studies through the use of investor sentiment as conditional information to show the economic intuition behind the value effect and market anomalies driven by mispricing. Therefore, our study demonstrates that market-wide sentiment and macro-related risks can exist simultaneously and affect asset prices simultaneously.

Perhaps the most related studies that examine sentiment effects on the β–return relationship comprise Antoniou et al. (2015) and Shen et al. (2017). However, the limitation of these studies is that they use sentiment as an instrument to test the two-regime pattern of security market line. Unlike this strand of research, the contribution of our approach to this literature is that we draw on this two-regime pattern and derive the state β to solve the puzzle of the flat security market line. In addition, the β in Antoniou et al. (2015) is estimated from the static CAPM.

[8]Studies that investigated market-wide effects of sentiment include Antoniou et al. (2013, 2015), Baker and Wurgler (2006, 2007, 2012), Baker et al. (2012), Brown and Cliff (2005), Chung et al. (2012), Delong et al. (1990), Huang et al. (2015), Kumar and Lee (2006), Lee et al. (1991), Lemmon and Portniaquina (2006), Neal and Wheatley (1998), Shen et al. (2017), Stambaugh and Yuan (2017), Stambaugh et al. (2012, 2014, 2015), and Yu and Yuan (2011).

Thus, the β–return relation cannot be measured precisely as the static β itself might represent the misspecification of risk. By using the sentiment-scaled CAPM to estimate the conditional market β, our approach largely circumvents this limitation. Though Shen et al. (2017) use rolling-window regressions to estimate β loadings on macro-related risks and, thus, bypass this static issue, their analysis only focuses on the bottom and top decile of β-sorted portfolios, thereby failing to (i) detail how sentiment affects the entire cross-section and (ii) examine whether sentiment effects also work for other deciles. Using the 25 size and BM portfolios as well as a set of portfolios formed on anomaly variables, our study avoids the limitations in Shen et al. (2017) and presents more detailed two-regime sentiment effects on the cross-section of returns. More importantly, we extend prior sentiment studies by using state β, derived from the sentiment-scaled CAPM, to test a set of anomalies, and find that long legs of anomaly strategies have greater state βs than short legs. As state βs reflect sentiment-driven overpricing effects, our evidence contributes to the explanations for anomalies by providing behavioural intuition.

Another related study is Ho and Hung (2009) who apply the two-pass framework of Avramov and Chordia (2006) and study the ability of sentiment-scaled CAPM to explain anomalies including size, value, liquidity, and momentum effects. However, their study is limited to examining whether anomaly variables remain significantly priced in the second-stage cross-sectional return regressions in which returns are adjusted by the first-stage time-series conditional model, and therefore, overlooks the time-varying property of sentiment effects. Unlike their study, we account for the time-varying sentiment effects on stock prices and show that the conditional β on sentiment is superior in explaining the cross-section of expected returns than the static β. Moreover, different from the static β–return relation that gives a flat security market line, the state-β derived from our sentiment-scaled CAPM yields an upward security market line and, thus, resolves the β anomaly.

The rest of this study is organized as follows. Section 2 briefly reviews the literature of the conditional linear factor model and outlines the motivation behind the stochastic discount factor scaled by sentiment. Section 3 presents the data and the econometric specifications. Using excess returns of 25 size and BM portfolios, Section 4 first investigates the power of sentiment-scaled CAPM at explaining the cross-section of return variations and then discusses the intuition behind value premium and the flat security market line. Section 5 checks the robustness of the main results by using the mean value of sentiment to define good and bad states. Section 6 concludes.

2 | THE STOCHASTIC DISCOUNT FACTOR WITH SENTIMENT

In this section, we briefly review the literature on linear factor models with scaled stochastic discount factor (SDF). Sections 2.1 and 2.2 discuss the static and conditional CAPM, respectively. Section 2.2 further introduces investor sentiment as an instrument in the conditional CAPM.

2.1 | The static CAPM

In a simple linear factor model:

$$R_t^i = a_i + \beta_i f_t + \epsilon_t^i. \quad (1)$$

Taking the expectation we have:

$$E(R^i) = \beta_i E(f). \quad (2)$$

In the case of CAPM, the factor f_i should be the market excess return: $R^{em} = R^m - R^f$, and $E(f)$ is also known as the factor risk premium. As the model is linear, the SDF can be expressed as:

$$M_{t+1} = a - bR_{t+1}^{em}, \quad (3)$$

where M_{t+1} is the SDF, and coefficients a and b are constant.

This model is also known as the static CAPM, which was first proposed by Sharpe (1964), and perhaps is the most famous and widely used model in asset pricing. However, many studies point out that the static CAPM performs poorly in practice. For instance, E. Fama and French (1992) discover that the CAPM β is not significantly priced in the cross-section asset returns. Other studies, such as Jagannathan and Wang (1996) and Lettau and Ludvigson (2001b), show that the static CAPM can hardly fit the portfolio data, as implied by low R^2s.

2.2 | The conditional CAPM scaled by sentiment

Why does the static CAPM fail in asset pricing tests? One possible explanation, as pointed out by Lettau and Ludvigson (2001b), is that its static specifications fail to take time-varying expected returns into account as the model presumes that the risk premium is constant. Numerous studies, therefore, have come up with some relevant conditional variables and specify their relation with the SDF coefficients a_t and b_t, namely, scaled factors, to explore the time-varying SDF. In this time-varying version, the parameters a and b condition on z_t, an instrument that contains information set, so the SDF is:

$$M_{t+1} = a(z_t) - b(z_t)R_{t+1}^{em}. \quad (4)$$

According to Cochrane (2006), Equation (4) can be further written as:

$$M_{t+1} = a_0 + a_1 z_t - \left(b_0 R_{t+1}^{em} + b_1\left(z_t R_{t+1}^{em}\right)\right), \quad (5)$$

where $a_t = a' z_t$ and $b_t = b' z_t$. Thus, the one factor and one instrument model with time-varying coefficients (Equation (4) can be expressed as a three-factor model $(z_t, R_{t+1}^{em}, z_t R_{t+1}^{em})$ with fixed coefficients; Equation (5)).[9]

Given that sentiment (s_t) is the instrument z_t, Equation (5) becomes:

$$M_{t+1} = a_0 + a_1 s_t - \left(b_0 R_{t+1}^{em} + b_1\left(s_t R_{t+1}^{em}\right)\right), \quad (6)$$

using the basic pricing equation for returns,

[9] See also Cochrane (2006, Chapter 8) or Lettau and Ludvigson (2001a) Section 2 for a more detailed discussion.

$$1 = E_t[M_{t+1}(1 + R_{i,t+1})]. \tag{7}$$

Plug Equation (6) into this basic pricing equation and taking unconditional expectations, we have the unconditional model:

$$1 = E\left[\left[a_0 + a_1 s_t - \left(b_0 R^{em}_{t+1} + b_1\left(s_t R^{em}_{t+1}\right)\right)\right](1 + R_{i,t+1})\right]. \tag{8}$$

Thus, the conditional CAPM scaled by sentiment can be estimated by using an unconditional three-factor model[10]:

$$E(R_{i,t+1}) = r_f + \beta_{i,s}\lambda_s + \beta_{i,m}\lambda_m + \beta^s_{i,m}\lambda^s_m. \tag{9}$$

The factors in this model are, the lagged sentiment, the current-period market return and lagged sentiment times the current-period market return.

3 | DATA AND ECONOMETRIC SPECIFICATION

3.1 | Investor sentiment

In this study, we use the following three well-cited sentiment indices.

Baker and Wurgler (BW) sentiment: Baker and Wurgler (2006) construct an investor sentiment index as the first principal component of a number of these proxies: The closed-end fund discount, the number and average first-day returns on initial public offerings, the equity share in new issues, the dividend premium and the New York Stock Exchange (NYSE) share turnover volume. Because these proxies are likely to include idiosyncratic or business cycle-related information, they are first orthogonalized to seven macroeconomic variables before the principal component analysis is performed. These variables are the industrial production index, nominal durables, nondurables and services consumption, and the NBER recession indicator. This study uses the monthly investor sentiment index as measured by them (BW sentiment hereafter).[11] The sample period spans from July 1965 to September 2015.

University of Michigan Consumer Sentiment Index: According to Lemmon and Portniaquina (2006), the University of Michigan Consumer Sentiment Index (MCSI hereafter) can be a potential measure of investor optimism. This index is based on the survey of a large number of households' views about current and expected business conditions, and many empirical studies have used this index as a proxy for sentiment.[12] MCSI is measured quarterly between 1952 and 1977 and monthly after 1977. For those quarterly figures, we use linear interpolation to transform them into monthly frequency. As the index might contain information of business

[10]The derivation of Equation (9) is presented in the Appendix. Though deriving a continuous function of sentiment is of interest for exploring sentiment effects theoretically across all states, the main issue of our future theoretical work, the focus in this study is to empirically examine the effect of sentiment-scaled CAPM on the 'value premium' and the puzzle of the flat security market line in good and bad states. Another reason is that the availability of monthly market-wide sentiment index data limits the empirical investigation on good and bad states.

[11]We thank Jeffrey Wurgler for providing the updated sentiment index on his website

[12]See Stambaugh et al. (2012), Shen et al. (2017)

TABLE 1 Descriptive statistics and correlation coefficients

Panel A reports the descriptive statistics of four sentiment indices: BW sentiment measured in Baker and Wurgler (2006), the University of Michigan Consumer Sentiment Index (MCSI), Conference Board Consumer Confidence Index (CBCCI), and the Augmented Sentiment Index (AS) from the first principal component of the BW, MCSI and CBCCI. Panel B reports their time-series correlations. BW and MSCI span from July 1965 to September 2015; MCSI and CBCCI spans from February 1967 to September 2015. AR(1) and ADF report the first-order autocorrelation and the Augmented Dicky-Fuller (ADF) test statistics respectively. The critical value for the ADF test without constant are −2.58, −1.95, and −1.62 at 1%, 5%, and 10% level of significance respectively. The null hypothesis here is that the sentiment index has a unit root. *Significance level at 1%.

Panel A: Descriptive statistics						
	Mean	Std	Min	Max	AR(1)	ADF
BW	0.00	1.00	−2.32	3.07	0.98	−3.92*
MSCI	0.00	1.00	−2.89	2.16	0.86	−3.95*
CBCCI	0.00	1.00	−3.14	2.19	0.92	−2.95*
AS	0.00	1.00	−2.70	2.15	0.93	−2.90*

Panel B: Correlation coefficients				
	BW	MCI	CBCCI	AS
BW	1.00			
MSCI	0.24*	1.00		
CBCCI	0.37*	0.74*	1.00	
AS	0.63*	0.88*	0.90*	1.00

cycles, we follow Shen et al. (2017) and regress it on the macro variables used by Baker and Wurgler (2006). Residuals are saved and standardised as the proxy for investor sentiment. The sample period spans from July 1965 to September 2015.

Conference Board Consumer Confidence Index (CBCCI): CBCCI is another survey-based sentiment index that has been well cited in previous behavioural studies.[13] CBCCI starts from February 1967 and is measured every 2 months before 1977 and monthly after 1977. Thus, for the period between February 1967 and February 1977, we use linear interpolation to get the monthly index. To remove its information on business cycles, we repeat the same procedure as that for MSCI. Residuals are saved and standardised as the proxy for investor sentiment. The sample period spans from February 1967 to September 2015.

Augmented sentiment index: To the extent that the above three indices contain the same information of market-wide sentiment, we preform the first principal component analysis to pick up the common component from BW, MSCI and CBCCI, as an augmented sentiment index (AS hereafter). The resulting index is:

$$AS_t = 0.318BW_t + 0.443MCI_t + 0.452CB_t, \tag{10}$$

[13]See Lemmon and Portniaquina (2006) and Antoniou et al. (2013)

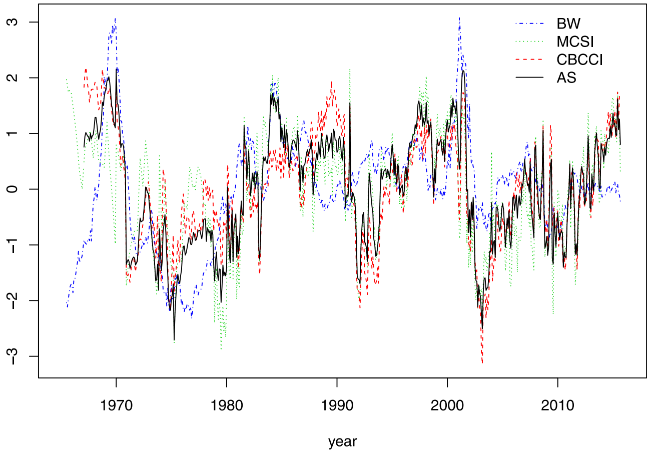

FIGURE 1 Sentiment indices. This graph plots four sentiment indices: BW sentiment measured as in Baker and Wurgler (2006), the University of Michigan Consumer Sentiment Index (MCSI), Conference Board Consumer Confidence Index (CBCCI), and the Augmented Sentiment Index (AS) from the first principal component of the BW, MCSI and CBCCI. BW and MSCI spans from July 1965 to September 2015; MCSI and CBCCI spans from February 1967 to September 2015

where the first principal component explains 66.31% of the sample variance and only the first eigenvalue is more than 1.00 (1.989 in this case). The two statistics indicate that the first principal component captures most of the common variation.

Table 1 reports the summary statistics of the sentiment indices. As they are standardized, the means are zero and standard deviations are one. Consistent with the behavioural studies that deem sentiment as persistent,[14] all these indices exhibit high first-order autocorrelations, ranging from 0.86 to 0.98. Moreover, results of the Augmented Dicky-Fuller tests suggest that the sentiment indices have no unit root, so using them as regressors will not result in material issues such as spurious regressions.

Panel B of Table 1 presents the time-series correlations among these sentiment indices. Though being measured differently, their correlations are positively high, especially for those among MSCI, CBCCI and AS. Such strong correlations strengthen the robustness of different sentiment measurements. Further supporting the high correlations, Figure 1 shows similar trends among these indices.

3.2 | Portfolio data

Next, we estimate the asset pricing model based on Equation (9) by using two sets of portfolio data. The first one consists of the 25 size and BM sorted portfolios, which are regarded as the testing ground for asset pricing models (Cochrane, 2007). We consider portfolios formed on size and β as robustness tests, as several studies (Jagannathan and Wang, 1996; Eiling, 2013) have tested them in asset pricing models.[15] We also consider decile portfolios formed on a set of

[14]See Brown and Cliff (2005) and Huang et al. (2015)

[15]Portfolios data are available at Kenneth French's website.

anomaly variables documented in Stambaugh et al. (2012) and test whether the sentiment scaled-CAPM can provide behavioural explanation for these anomalies.

3.3 | Econometric tests

In line with a large number of studies on asset pricing tests, the model in Equation (9) is estimated using the Fama-Macbeth approach, which comprises three steps.

In the first stage, we run the full-sample time-series regression of portfolio excess returns on three factors: Lagged sentiment, current-period market return and lagged sentiment times the market return. The coefficients on these factors or βs are saved and used as regressors in the second-stage of cross-sectional regression of portfolio returns at each month t. Finally, we take the time-series average of slope coefficients on these βs as the measure for risk premiums.[16] In the last step, we report two t-statistics. The first is the classical Fama-MacBeth t-statistic. We also report the t-statistic using the Shanken correction (Shanken, 1992) to adjust the sampling error when estimating βs in the first-stage time-series regression.

Evaluating how well the asset pricing models fit, we report both the average pricing errors across all 25 portfolios and the ordinary least squares (OLS) R^2 in the cross-sectional regressions.[17] Furthermore, we report the cross-sectional GLS R^2 to address the test concerns raised by Lewellen et al. (2010) that any three-factor model can explain returns on the size and BM portfolios well. Finally, we test whether the average pricing errors across the 25 portfolios jointly equal zero.[18]

4 | EMPIRICAL ANALYSIS

4.1 | Sentiment as predictor of market returns

One important reason for the failure of the CAPM is that its static specification cannot take into account time-varying expected returns. Many asset pricing studies address this issue and propose different conditional variables, such as the CAY (Lettau and Ludvigson, 2001b) and the labour income to consumption ratio (Santos and Veronesi, 2005) as instruments in the CAPM. These variables show strong forecasting power for stock market returns and incorporating them into the static CAPM for asset pricing tests can perhaps overcome the issue where the model presumes that the risk premium is constant. Indeed, Santos and Veronesi (2005, p. 6) further state that ‘Since Merton (1973), it has been understood that variables that predict market returns are natural conditioning variables for tests of the cross-section’.

Given the fact that sentiment can cause uninformed demand shocks and, thus, change the distribution of future returns, it is plausible to assume that sentiment can predict market returns and, thus, can serve as an instrument in cross-sectional asset pricing tests. One can understand this predictability from the cash flow channel. Specifically, sentiment reflects

[16]For example, if $\widehat{\lambda}$ is the estimated cross-sectional slope coefficients, its average slope is $\bar{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\lambda_t}$, and the standard error is $\sigma^2(\lambda) = \frac{1}{T}var(\widehat{\lambda_t}) = \frac{1}{T^2}\sum_{t=1}^{T}(\widehat{\lambda_t} - \bar{\lambda})$ if $\widehat{\lambda_t}$ are not correlated.

[17]Following Jagannathan and Wang (1996) the cross-sectional R^2 is calculated as $[\mathrm{Var}_c(\bar{R}_i) - \mathrm{Var}_c(\bar{\epsilon}_i)]/\mathrm{Var}_c(\bar{R}_i)$, where ϵ_i and R_i are the residual and excess return for portfolio respectively. Var_c denotes a cross-sectional variance, and bars denote time-series average.

[18]The test statistic here is $\hat{a}'\mathrm{cov}(\hat{a})^{-1}\hat{a} \sim \chi^2_{N-K}$, where $\hat{a}$ is vector of OLS pricing errors and $\mathrm{cov}(\hat{a})^{-1}$ is the estimated covariance matrix (Cochrane, 2006).

TABLE 2 Predicative regressions of market returns on investor sentiment

This table reports the results of return forecasts on four sentiment indices: BW sentiment measured in Baker and Wurgler (2006), the University of Michigan Consumer Sentiment Index (MCSI), Conference Board Consumer Confidence Index (CBCCI), and the Augmented Sentiment Index (AS) from the first principal component of the BW, MCSI and CBCCI. BW and MSCI spans from July 1965 to September 2015; MCSI and CBCCI spans from February 1967 to September 2015. R_{t+1} is the monthly value-weighted excess return of all CRSP stocks that listed on the NYSE, AMEX, or NASDAQ. The control variables that we use are the real interest rate, the inflation rate, the term and default premium, and the consumption-wealth ratio. t-Statistics, reported in the parentheses, are adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors.

$R_{t+1} = a + \beta \text{Sentiment}_t + \epsilon_t$

$R_{t+1} = a + \beta \text{Sentiment}_t + \Sigma_{i=1}^{4} \alpha_i \text{ControlVariables} + \epsilon_t$

	BW	MSCI	CBCCI	AS
Panel A: Univariate predictive regression				
β	−0.27	−0.32	−0.44	−0.43
	(−1.34)	(−1.85)	(−2.51)	(−2.33)
R^2 (%)	0.37	0.49	0.96	0.92
Panel B: Predictive regression with control variables				
β	−0.29	−0.31	−0.43	−0.45
	(−1.41)	(−1.71)	(−2.27)	(−2.28)
R^2 (%)	1.62	1.64	1.88	1.91

investor's biased beliefs about future cash flows not justified by fundamentals (Baker and Wurgler, 2006; Huang et al., 2015). When sentiment traders are excessively optimistic (pessimistic), their erroneous beliefs associated with high (low) demands will force asset prices to be above (below) their intrinsic values. As a result, the subsequent returns will be lower (higher) with assets reversing to their fundamental values, and investor sentiment can be a negative predictor of future returns.

To provide direct evidence of sentiment as a predictor of future market returns, we perform the following standard predictive regression:

$$R_{t+1} = a + \beta \text{Sentiment}_t + \epsilon_t, \tag{11}$$

where R_{t+1} is the monthly value-weighted excess return of all CRSP stocks listed on the NYSE, AMEX, or NASDAQ.[19] Table 2 reports the regression results. Consistent with the behavioural theory, we find that these sentiment indices are negative return predictors. In particular, slope coefficients on three of them are significant at 5%, with t-statistics ranging from −1.85 to −2.51. The average coefficient of −0.37 implies that a one standard deviation increase in sentiment (sentiment is standardized) is associated with a −0.37% lower subsequent monthly return. Finally, the average R^2 reaches 0.69%, confirming that sentiment has explanatory power for future market excess returns.[20]

[19] The monthly market excess return is available at Kenneth French's website. The risk-free rate used here is the 1-month bill rate.

[20] Huang et al. (2015) find no significant predictability of MCI and CBCI on market excess returns. The discrepancy caused here is because of the different market excess returns that we use: This study uses the monthly value-weighted excess return of all CRSP stocks listed on the NYSE, AMEX, or NASDAQ, whereas Huang et al. (2015) use the log return on the S&P 500 index in excess of the risk-free rate.

To the extent that some omitted macro-related variables carry information that coincides with that in investor sentiment, and may partially explain its predictive power, we assess the robustness of our results regarding sentiment predictability by controlling for additional macroeconomic variables that are related to time-varying risk premiums. As in Stambaugh et al. (2012), the control variables that we use are the real interest rate, the inflation rate (E. Fama, 1981), the term and default premium (Chen et al., 1986) and the CAY as defined in Lettau and Ludvigson (2001a).[21] Overall, the results are consistent with the univariate sentiment predicative regressions.

One might be inclined to argue that the sentiment predictability on stock returns might come from the persistent nature of sentiment and, thus, the regression results are likely to be spurious. However, Stambaugh et al. (2014) simulate 200 million regressors that have the same degree of persistence as that of sentiment, but they find none to have the same predicative power as sentiment has. Thus, it is plausible that sentiment is not a spurious return predictor.

4.2 | Cross-sectional tests: 25 size and BM portfolios

4.2.1 | Model tests

We next examine the power of the CAPM and Fama-French three-factor model (FF3 hereafter) in explaining the average returns of 25 size and BM portfolios. The only factor in the CAPM is the CRSP value-weighted return:

$$E(R_{i,t+1}) = r_f + \beta_{i,m}\lambda_m,$$

while FF3 adds another two mimicking portfolios, namely, the 'small minus big size' (SMB) and 'high minus low book-to-market equity ratio' (HML) portfolios, to the CAPM (E. Fama and French, 1993).

$$E(R_{i,t+1}) = r_f + \beta_{i,m}\lambda_m + \beta_{i,\mathrm{SMB}}\lambda_{\mathrm{SMB}} + \beta_{i,\mathrm{HML}}\lambda_{\mathrm{HML}}.$$

Rows 1 and 2 of Table 3 report the results for the CAPM and FF3 model, respectively. Consistent with a large number of asset pricing studies, we find that the CAPM does not work in the cross-section tests. The market risk premium λ_m has a low t-statistic (−0.90), implying that the β is not significantly priced. Moreover, the adjusted R^2 is 3%, so the CAPM can explain only 3% of the cross-sectional variation in stock returns. However, the FF3 model preforms far better than the CAPM with the ability to explain almost 63% of the variation in the cross-section of stock returns. In particular, the coefficient on the HML factor has a significant statistic (3.02), and the Shanken-correction is negligible here.

Using four sentiment indices as described in Section 3.1, we now estimate the scaled CAPM with three factors:

$$E(R_{i,t+1}) = r_f + \beta_{i,s}\lambda_s + \beta_{i,m}\lambda_m + \beta_{i,m}^s\lambda_m^s,$$

[21] The real interest rate is the difference between return on the 30-day T-bill and inflation rates. The term premium is defined as the spread between the 20-year T-bill and the 1-year T-bill. The default premium is the difference between the yields on BAA and AAA bonds. The inflation rate and T-bill return are obtained from CRSP. The default premium comes from the St.louis Federal Reserve and cay is obtained from Martin Lettau's website.

TABLE 3 Fama-MacBeth regressions on returns of 25 size and book-to-market portfolios

This table reports the λ estimates from cross-sectional Fama-MacBeth regressions using returns of 25 portfolios formed on size and the book-to-market equity ratio. The βs are estimated in the first-stage time-series regressions on different factors. In the capital asset pricing model (CAPM), the factor is the monthly value-weighted excess return of all CRSP stocks. In the FF3 model, the factors are the market excess return and mimicking portfolios with respect to size and book-market equity ratios. In the scaled CAPM with sentiment, the factors are lagged sentiment, the current-period market return and lagged sentiment times the market excess return. Four sentiment indices here are used as conditional variables. The sample period is from July 1965 to September 2015 for all models but for the scaled CAPM with CBCCI and AS, whose data begin from February 1967. t-Statistics for each λ estimate are reported in the parentheses. The top statistic uses uncorrected Fama-MacBeth standard errors; the bottom statistic uses the Shanken correction. For each model, the first R^2 term denotes the unadjusted cross-sectional R^2; the second one denotes the adjusted cross-sectional R^2; the third one denotes the generalized least squares R^2.

$E_t(R_{i,t+1}) = r_f + \beta_{i,m}\lambda_m$ (CAPM),

$E_t(R_{i,t+1}) = r_f + \beta_{i,m}\lambda_m + \beta_{i,\mathrm{SMB}}\lambda_{\mathrm{SMB}} + \beta_{i,\mathrm{HML}}\lambda_{\mathrm{HML}}$ (FF3),

$E_t(R_{i,t+1}) = r_f + \beta_{i,s}\lambda_s + \beta_{i,m}\lambda_m + \beta_{i,m}^s\lambda_m^s$ (Scaled CAPM with sentiment).

	Constant	λ_s	λ_m	λ_m^s	λ_{SMB}	λ_{HML}	R^2
CAPM	1.54		−0.39				0.07
	(3.88)		(−0.90)				0.03
	(3.87)		(−0.89)				0.10
FF3	1.71		−0.77		0.17	0.36	0.68
	(6.31)		(−2.36)		(1.31)	(3.02)	0.64
	(6.13)		(−2.31)		(1.31)	(2.99)	0.28
BW	0.33	0.41	0.62	−4.09			0.67
	(1.02)	(1.73)	(1.68)	(−4.83)			0.62
	(0.72)	(1.08)	(1.36)	(−3.47)			0.35
MSCI	1.04	−0.02	−0.09	−3.67			0.52
	(2.95)	(−0.07)	(−0.23)	(−3.55)			0.45
	(2.30)	(−0.05)	(−0.20)	(−2.79)			0.13
CBCCI	1.68	−0.88	−0.74	−2.68			0.60
	(4.85)	(−3.09)	(−1.91)	(−2.41)			0.54
	(3.51)	(−2.26)	(−1.47)	(−1.87)			0.21
AS	1.24	−0.18	−0.29	−3.20			0.57
	(3.90)	(−0.60)	(−0.80)	(−3.53)			0.51
	(3.22)	(−0.45)	(−0.76)	(−2.95)			0.17

Abbreviations: AS, augmented sentiment; BW, Baker and Wurgler index; CBCCI, Conference Board Consumer Confidence Index; FF3, Fama-French three-factor model; MSCI, University of Michigan Consumer Sentiment Index.

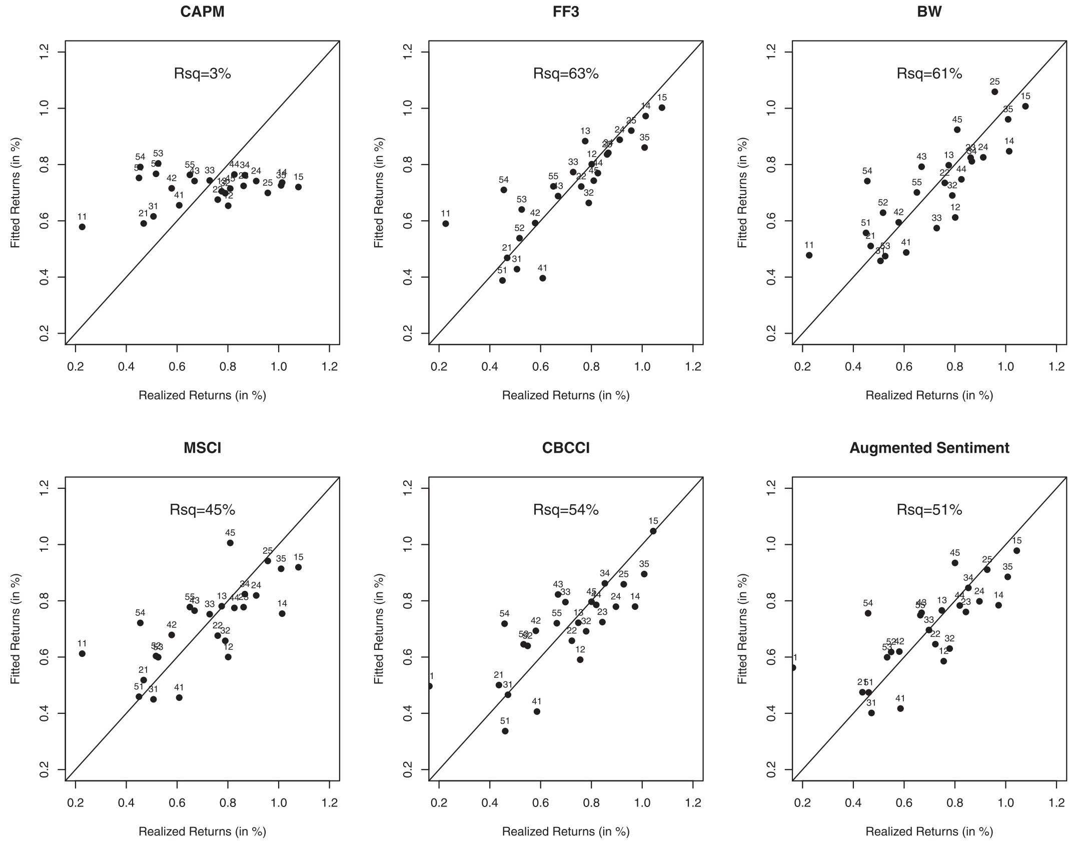

FIGURE 2 Realized versus fitted returns: 25 Fama-French size and book-to-market (BM) portfolios. This graph plots realized and fitted returns of 25 size and BM portfolios with respect to different models: CAPM, Fama-French three-factor model and the scaled CAPM with sentiment (four sentiment indices here are used as conditional variables). The pricing errors are generated from the Fama-MacBeth regressions reported in Table 3. Each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), and the second digit refers to the book-to-market quintiles (1 indicating the portfolio with the lowest book-to-market ratio, 5 with the highest). 'Rsq' here denotes the adjusted cross-sectional R^2

where the factors are lagged sentiment, the current-period market return and lagged sentiment times the current-period market return. Rows 3–6 in Table 3 report the regression results for the sentiment conditional CAPM. In sharp contrast to the static CAPM, the sentiment-scaled model performs relatively well in testing the cross-section average returns. The adjusted R^2 jump from 3% to a range between 45% and 61% with different sentiment indices used. Moreover, the GLS R^2 ranges from 0.13 to 0.42, confirming the strong ability of the sentiment-scaled CAPM to explain the cross-sectional variations in stock returns.

Consistent with the negative sentiment predictability in the market returns, we find that the coefficient on the scaled factor, λ_m^s, is significantly negative. This finding is also robust when using different sentiment index: λ_m^s ranges from −2.68 to −4.09 and its t-statistic ranges from −2.41 to −4.83. In addition, though these t-statistics become small, they remain significant after using Shanken correction.

The estimated slope coefficients λ_s are not significantly different from zero for the majority of scaled models, indicating that the time-varying component of the intercept is not an important determinant for the cross-section of average returns. In sum, our finding of significant coefficients on the interactive variable—lagged sentiment times the current period return—suggests that only the sentiment-scaled market factor is priced and, thus, the market risk premium is significantly time-variant. Accordingly, sentiment is an important instrument to estimate this time-varying pattern.

4.2.2 | Average pricing errors

How well does the scaled CAPM with investor sentiment work for the cross-section average returns? We address this question by plotting fitted returns of each 25 size and BM portfolios against their realized returns in Figure 2. In this graph, each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), and the second digit refers to BM quintiles (1 indicating the portfolio with the lowest BM equity ratio, 5 with the highest).

Consistent with the evidence in Table 3, the static CAPM explains none of the variations on average stocks returns on these portfolios. In addition, the fitted values generated by the static CAPM almost stay almost at the same level, so the model also fails to account for 'value premium'—portfolios with the highest BM equity ratio ('value portfolios') should earn higher returns than those with the lowest ('growth portfolios'). In sharp contrast, the FF3 model performs far better than the CAPM, in that the portfolios lie near to the 45-degree line. This suggests that the FF3 model can capture most variation in the cross-sectional average returns. Moreover, the fitted expected returns of 'value portfolios' (the second digit labelled with 5) cluster in the top-right of the graph, whereas those of the 'growth portfolios' (the second digit labelled with 1) show at the bottom-left area, implying a strong 'value effect'.

In Figure 2, the last four graphs titled with BW, MSCI, CBCCI, and Argumentd Sentiment show that the scaled CAPM with investor sentiment performs as well as the FF3 model does. All the two-digit numbers that represent different portfolios are close to the 45-degree line, demonstrating a good explanatory power of the cross-section of average returns. More importantly, most 'value portfolios', including ones labelled with 15, 25, 35 and 45 sit in the top-right of these graphs, whereas the exact opposite pattern occurs on 'growth portfolios'. Therefore, the fitted expected returns generated by the scaled CAPM do about as well as those generated by the FF3 model in explaining this value effect.

Table 4 reports the average pricing errors for each of the 25 size and BM portfolios and their joint significance across the five different asset pricing models. As indicated in the bottom of Table 4, the square root of the average squared pricing errors across all portfolios displays the same pattern as the R^2 statistics in Table 3—its value is much lower in the FF3 model and the scaled CAPMs with sentiment in comparison to the static CAPM. However, one unappealing result here is that the χ^2 statistics for all tested models reject the null hypothesis that all pricing errors are jointly zero. This might be because the first-stage time series regression gives a small estimate of $\text{cov}(\varepsilon_t \varepsilon_t')$ (ε_t is the residual) as this regression involves monthly returns. Accordingly, $\text{cov}(\hat{\alpha})^{-1}$ becomes large, resulting a high χ^2 statistic.[22] Nevertheless, the cross-sectional residual α itself is much lower in the scaled models than that in the static CAPM.

[22] See Cochrane (2006) Chapter 12: $\text{cov}(\hat{\alpha}) = \frac{1}{T}[I - \beta(\beta'\beta)^{-1}\beta']\Sigma[I - \beta(\beta'\beta)^{-1}\beta']'$, where $\Sigma = \text{cov}(\varepsilon_t \varepsilon_t')$.

TABLE 4 Pricing errors of 25 size and book-to-market portfolios

This table reports the average pricing errors (in percentage) from the cross-sectional Fama-MacBeth regressions with respect to different models reported in Table 3, for each of the 25 size and book-to-market portfolios. S1 (5) denotes portfolios with the smallest (biggest) size, and B1(5) denotes portfolios with the lowest (highest) book-to-market equity ratio. For example, S1BI refers to the smallest size and lowest book-to-market portfolio. S1B5 refers to the smallest size and highest book-to-market portfolio. The last two rows report the square root of average squared pricing error across all portfolios, the χ^2 statistic for the test that all asset pricing errors are jointly zero. *Significance level at 1%.

Portfolio	CAPM	FF3	BW	MSCI	CICCI	AS
SlBl	−0.3524	−0.3638	−0.2515	−0.3860	−0.3349	−0.4005
SIB2	0.1474	−0.0002	0.1891	0.2009	0.1650	0.1703
SIB3	0.0705	−0.1079	−0.0222	−0.0054	0.0264	−0.0174
SIB4	0.2774	0.0411	0.1662	0.2591	0.1923	0.1875
SIB5	0.3576	0.0753	0.0704	0.1584	−0.0043	0.0654
S2B1	−0.1223	−0.0002	−0.0423	−0.0501	−0.0647	−0.0393
S2B2	0.0845	0.0379	0.0251	0.0837	0.0649	0.0770
S2B3	0.1375	0.0256	0.0371	0.0842	0.1187	0.0827
S2B4	0.1700	0.0232	0.0857	0.0923	0.1173	0.0983
S2B5	0.2578	0.0363	−0.1019	0.0153	0.0684	0.0164
S3B1	−0.1089	0.0786	0.0493	0.0570	0.0054	0.0701
S3B2	0.0914	0.1259	0.0994	0.1316	0.0874	0.1491
S3B3	−0.0153	−0.0451	0.1540	−0.0242	−0.0979	0.0013
S3B4	0.1044	0.0250	0.0550	0.0428	−0.0091	0.0068
S3B5	0.2835	0.1488	0.0486	0.0955	0.1127	0.1227
S4B1	−0.0470	0.2121	0.1209	0.1524	0.1793	0.1685
S4B2	−0.1371	−0.0136	−0.0163	−0.1002	−0.1124	−0.0386
S4B3	−0.0730	−0.0194	−0.1237	−0.0964	−0.1540	−0.0889
S4B4	0.0606	0.0559	0.0779	0.0506	0.0333	0.0356
S4B5	0.0945	0.0664	−0.1149	−0.1966	0.0036	−0.1345
S5B1	−0.3028	0.0618	−0.1073	−0.0094	0.1236	−0.0138
S5B2	−0.2502	−0.0215	−0.1120	−0.0871	−0.0911	−0.0695
S5B3	−0.2784	−0.1150	0.0508	−0.0742	−0.1126	−0.0664
S5B4	−0.3364	−0.2550	−0.2864	−0.2665	−0.2607	−0.2978
S5B5	−0.1132	−0.0724	−0.0508	−0.1277	−0.0566	−0.0851
Mean squared error	0.2001	0.1171	0.1193	0.1447	0.1304	0.1354
χ^2	76.48*	60.19*	53.68*	74.70*	65.51*	69.02*

Abbreviations: AS, augmented sentiment; BW, Baker and Wurgler index; CBCCI, Conference Board Consumer Confidence Index; FF3, Fama-French three-factor model; MSCI, University of Michigan Consumer Sentiment Index.

To sum up, given the evidence of the high cross-sectional R^2 and the low average asset pricing errors, the scaled CAPM with sentiment appears to have a strong explanatory power for the cross-section of average returns of the 25 size and BM portfolios. Compared to the static CAPM, this scaled CAPM also performs relatively well at explaining why value stocks earn higher returns than growth stocks.

4.3 | Intuition

Next, we examine the conditional market β derived from sentiment in different states to show why the sentiment-scaled CAPM performs much better than the static CAPM at explaining the cross-section expected returns. We then introduce a measure of asset pricing risk, namely, 'state β', to explain the intuition behind the value premium effect and to solve the flat security market line puzzle.

4.3.1 | The conditional market β

As described earlier, one important reason for the better performance of the sentiment-scaled CAPM is that it overcomes the failure of the static CAPM to take into account the time-varying market risk premium. This is because asset risk is not determined by the correlation of its return with market return but by the correlation of its return conditioned on some information that reflects time-varying risk premium (Lettau and Ludvigson, 2001b). In fact, the risk premium does vary over time with business cycles and expected returns are typically high (low) in bad (good) states (Cochrane, 2006). Therefore, investor sentiment qualifies to serve as a conditional variable in the CAPM by its ability to reflect the state of the economy and predict the market returns.

If this conditional information is important empirically, one perhaps will expect that portfolios such as value ones should be more likely to be correlated with market risk in bad states (low sentiment) where risk premium is high, but to have a lower correlation with market risk in a good state (high sentiment) where risk premium is low. In other words, portfolios that earn higher returns in equilibrium may have high conditional market βs in bad states, but low conditional market βs in good states. Lettau and Ludvigson (2001b) illustrate this intuition by dividing the sample period into good times (when CAY is one standard deviation higher above its mean) and bad times (when CAY is one standard deviation higher below its mean) and discover that value portfolios have higher consumption βs in bad times but lower βs in good times than growth ones (low BM ratio). Accordingly, value stocks can earn particularly higher returns in bad times than growth stocks as they are too risky to hold.

To investigate whether the sentiment-scaled CAPM fits the same intuition as that of conditional consumption CAPM with CAY, we calculate the conditional market β in good and bad states based on investor sentiment. Following Lettau and Ludvigson (2001b), we define a good (bad) state as a month in which AS in the previous month is one standard deviation above (below) it's mean value.[23] For each portfolio i, the conditional β is calculated as $B_i = \beta_{i,m} + \beta^s_{i,m}\bar{s}_t$, where $\beta_{i,m}$ and $\beta^s_{i,m}$ are factor loadings in the market returns and the lagged sentiment times the market excess return respectively, see Equation (9). $\bar{s}_t$ is the average value

[23] Because sentiment serves as conditional information, we use sentiment in the previous month to define the current state.

TABLE 5 Conditional market βs: 25 size and book-to-market (BM) portfolios

This table reports the average market βs in good and bad states, conditional on the instrument z_t, the augmented sentiment. For each portfolio i, the conditional β is calculated as $B_i = \beta_{i,m} + \beta^s_{i,m}\bar{s}_t$, where $\beta_{i,m}$ and $\beta^s_{i,m}$ are factor loadings in the market returns and the lagged sentiment times the market excess return respectively. $\bar{s}_t$ is the average value of sentiment in state t. Following Lettau and Ludvigson (2001b), we define a good (bad) state as a month in which the augmented sentiment is at least one standard deviation above (below) it's mean value. As the mean value of sentiment is zero, the β in all states is equivalent to the static market β. The state β here is calculated as the difference between the β in bad state and the one in good state. 'Returns' here denotes the are average returns of each 25 Size-BM portfolio in different states.

	All states		Bad states		Good states		
	Market β	Returns	Good β	Returns	Bad β	Returns	State β (good–bad)
SlBl	1.409	0.568	1.417	3.126	1.401	−1.817	0.016
SIB2	1.216	1.162	1.229	3.151	1.204	−0.854	0.024
SIB3	1.087	1.155	1.176	2.792	1.004	−0.431	0.172
SIB4	1.005	1.378	1.091	3.053	0.923	−0.101	0.168
SIB5	1.045	1.450	1.210	3.415	0.888	−0.360	0.322
S2B1	1.381	0.842	1.354	3.021	1.406	−1.526	−0.053
S2B2	1.166	1.129	1.209	2.841	1.126	−0.674	0.083
S2B3	1.041	1.250	1.124	2.596	0.961	−0.405	0.163
S2B4	0.994	1.303	1.096	2.523	0.898	−0.139	0.198
S2B5	1.102	1.334	1.263	3.126	0.950	−0.259	0.313
S3B1	1.321	0.878	1.267	2.615	1.371	−1.274	−0.104
S3B2	1.109	1.186	1.143	2.528	1.078	−0.401	0.065
S3B3	0.994	1.104	1.043	2.312	0.949	−0.472	0.094
S3B4	0.942	1.259	1.058	2.512	0.832	0.029	0.226
S3B5	1.037	1.414	1.179	3.227	0.903	0.120	0.276
S4B1	1.228	0.992	1.187	2.380	1.268	−0.778	−0.080
S4B2	1.072	0.987	1.099	2.343	1.048	−0.520	0.051
S4B3	1.002	1.075	1.082	2.383	0.925	−0.126	0.157
S4B4	0.942	1.225	1.035	2.298	0.854	−0.023	0.180
S4B5	1.069	1.207	1.245	2.839	0.902	−0.307	0.344
S5B1	0.984	0.867	0.964	1.327	1.002	−0.262	−0.038
S5B2	0.941	0.955	0.964	1.875	0.920	−0.223	0.044
S5B3	0.849	0.939	0.856	1.558	0.843	−0.101	0.013
S5B4	0.879	0.864	0.956	1.839	0.805	−0.268	0.151
S5B5	0.945	1.070	1.030	2.472	0.865	0.055	0.166

TABLE 6 Returns, good states and bad states

This table reports regressions of portfolio returns on their conditional market βs in good and bad states defined in Table 5. t-Statistics are adjusted by White's heteroscedasticity consistent standard errors.
$R_i = a + b\beta_i + \epsilon_i$

	Panel A: Bad states (good β)			Panel B: Good states (bad β)		
	$\hat{b}$	t-Statistic	R^2	$\hat{b}$	t-Statistic	R^2
25 size and book-to-market Port	3.25	6.47	0.66	−2.50	−9.40	0.88

of sentiment in state t, and the main sentiment index applied here is the AS index, which picks up the common information from the other three sentiment indices.

The first column of Table 5 reports the conditional market βs for each of the 25 size and BM portfolios in all states. As the mean value of sentiment is zero over the whole sample period, the β estimated here is equivalent to the static market β. Consistent with the poor performance of static CAPM in the cross-section return tests, the static market βs obviously cannot explain the value effect. That is, portfolios with high BM equity ratios have lower βs but earn higher returns, as shown in the second column of Table 5.

4.3.2 | Bad states

The fourth and fifth columns in Table 5 show the β and returns in bad (low-sentiment) states. If the story of CAY accommodates the conditional CAPM with sentiment, value portfolios should have higher conditional market βs in bad states. However, given the sorting of size categories, most portfolios with the highest BM equity ratios have lower βs in bad states. That is, $B^{15}_{\text{bad}} < B^{11}_{\text{bad}}$, $B^{25}_{\text{bad}} < B^{21}_{\text{bad}}$, $B^{25}_{\text{bad}} < B^{21}_{\text{bad}}$, $B^{35}_{\text{bad}} < B^{31}_{\text{bad}}$ and $B^{45}_{\text{bad}} < B^{41}_{\text{bad}}$. This suggests that the value portfolios are no more risky than growth ones in bad states and, thus, should not be associated with higher expected returns. Indeed, as the fourth column of Table 5 shows, the value portfolios (labelled 15, 25, 35, 45, 55) earn almost the same returns (around 2.5%) as those of growth portfolios (labelled 11, 21, 31, 41 and 51)

Interestingly, βs and returns show a strong positive relation in bad states. Panel A of Table 6 reports the regression results. The slope coefficient of 3.25 (t-statistic is 6.47) indicates that a one-unit increase in the conditional market β is associated with 3.25% higher returns. Furthermore, this positive correlation between return and conditional market β in bad states, as the first graph in Figure 3 shows, demonstrates an upward security market line.

In a nutshell, value portfolios do not realize a premium in bad states as growth portfolios also earn good returns. This is perhaps because growth stocks are as risky as value stocks to hold in bad times, so higher returns should be compensated for holding both types of stock.

4.3.3 | Good states

Columns six and seven in Table 5 present β and returns in good states when sentiment is high. In contrast to the findings during bad states, the average return of each portfolio during good states is strongly negative. One possible explanation for this difference of returns between the

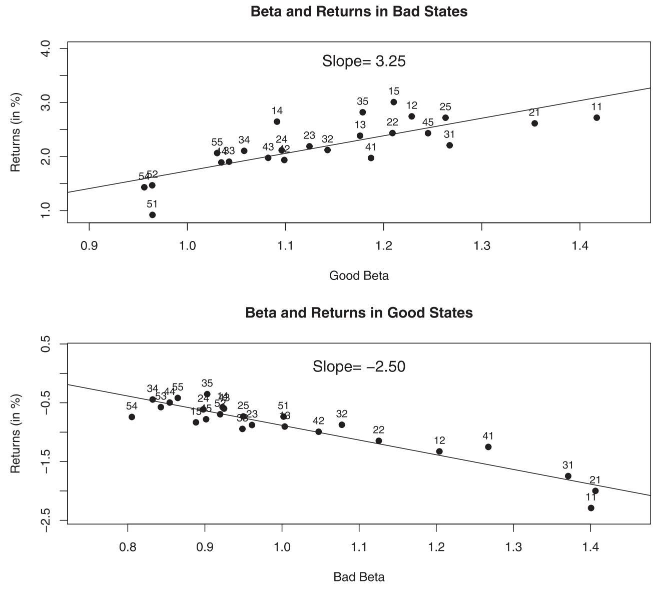

FIGURE 3 Security market line: Bad states versus good states. The two graphs plot the realized return of each size and book-to-market portfolio against its conditional market β in the good and bad state separately (See Table 5 for details of conditional market βs). Following Lettau and Ludvigson (2001b), we define a good (bad) state as a month in which the augmented sentiment is one standard deviation above (below) it's mean value. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), and the second digit refers to book-to-market equity ratio quintiles (1 indicating the portfolio with the lowest book-to-market equity ratio, 5 with the highest). The slope is the coefficient estimate in the regression of portfolio returns on their βs

two states is that assets are more likely to be overpriced when sentiment is high and, thus, earn lower returns. Especially, high-β stocks are more speculative and exposed to sentiment-driven overpricing than low-β stocks. As a result, the security market line plotted in the second graph of Figure 3 shows a strong negative downward slope—a negative β premium. The regression of portfolio returns on their conditional market β presented in Panel B of Table 6, provides additional support for this finding. The slope coefficient on the β is significantly negative, −2.50 with a t-statistic of −9.40. In addition, the R^2 reaches 0.88, implying an impressive power of the sentiment-scaled CAPM at explaining the variation of cross-sectional average returns in good states.

As conventional finance literature states that high risk should be compensated with high return, the interesting question that comes out of this result is why the β premium becomes negative in good states. In this study, we conjecture that high-β stocks are more subject to sentiment-driven overpricing and, therefore, are expected to earn lower returns than those with lower βs. Specifically, irrational investors during high-sentiment periods are typically over-optimistic and in favour of high-β stocks.[24] That is, they hold high expectations about future cash flows of high-β stocks, driving up their prices, especially at the presence of limits to arbitrage (Shleifer and Vishny, 1997) and short-sale constraints (Stambaugh et al., 2012;

[24] In the model of Hong and Sraer (2016), high-β stocks are more speculative and are more likely to be held only by optimists than low-β stocks.

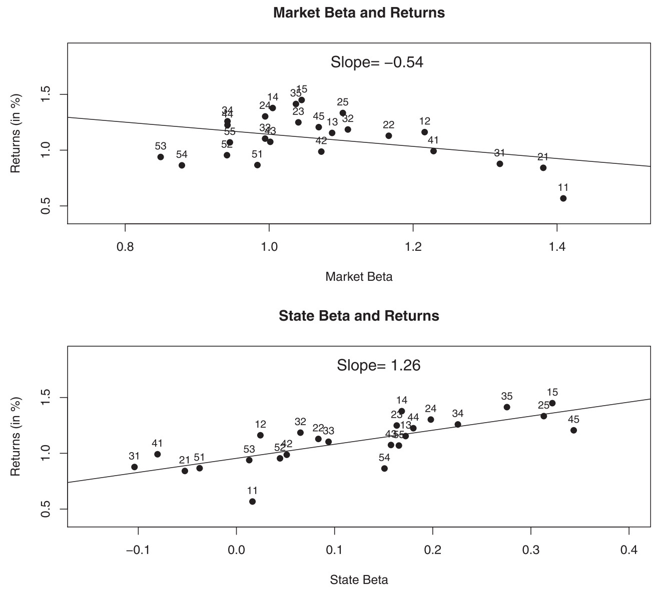

FIGURE 4 Security market line: Market β versus state β. This graph plots the realized return of each size and book-to-market portfolio against its static market β as well as against its state β conditioned on sentiment (See Table 5 for details of market and state βs). Each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), and the second digit refers to book-to-market equity ratio quintiles (1 indicating the portfolio with the lowest book-to-market equity ratio, 5 with the highest). The slope is the coefficient estimate in the regression of portfolio returns on their βs. The sample period is from February 1967 to September 2015

Antoniou et al., 2015). As a result, the subsequent returns of high-β stocks decline and become even negative as their prices revert to their fundamental values.

Our conjecture has been confirmed by Antoniou et al. (2015), who discover a negative β–return relation during high-sentiment periods, due to the heavy presence of sentiment traders associated with excessive investor optimism. Consistent with Antoniou et al. (2015), the second graph of Figure 3 shows that growth portfolios (labelled 11, 21, 31, 41 and 51) have much higher βs than value portfolios (labelled 15, 25, 35, 45, and 55) but earn significantly lower average returns. The average monthly returns for growth portfolios range from −0.734% to −2.289%, whereas the average returns for value portfolios ranges between −0.417% and −0.832%. This is consistent with the 'value premium' anomaly where the value portfolios outperform the growth ones, associated with negative returns although returns here are negative. This finding is also consistent with Lakonishok et al. (1994) who suggest that 'glamour' stocks have higher past earnings or growth and are, thus, more likely to be overpriced.

One might be inclined to argue that the negative returns cannot explain the value effects. Note that in bad states, all these portfolios yield positive returns, whose magnitudes are much higher than those of negative returns in bad states. Thus, when aggregating the two states, the higher returns from bad states dominate and the average portfolio returns in the whole sample period are still positive. However, the value effect is not observed in good states, but in bad states when growth portfolios generate much lower returns.

Another noticeable feature in the second graph of Figure 3, is that among growth portfolios, the conditional market β rises monotonically with firm-size decreases. In particular, both the

TABLE 7 Returns, market β and state β

This table reports regressions of portfolio returns on their market βs as well as on their state βs defined in Table 5. *t*-statistics are adjusted by White's heteroscedasticity consistent standard errors.
$R_i = a + b\beta_i + \epsilon_i$

	Panel A: Market β			Panel B: State β		
	$\hat{b}$	*t*-Statistic	R^2	$\hat{b}$	*t*-Statistic	R^2
25 size and book-to-market port	−0.54	−1.63	0.14	1.26	6.00	0.56

portfolio with the smallest size (labelled 11) and the one with the second smallest size (labelled 12) have high βs but earn significantly negative returns. Such findings are consistent with studies indicating that small-cap firms are susceptible to sentiment effects and, thus, are more likely to be overpriced during high-sentiment periods.

4.3.4 | State β, value effect and the security market line

The flat security market line has long been recognised as a puzzle in asset pricing studies. For instance, Black (1972) documents a flat security market line of U.S. stocks with respect to the CAPM. In a well-cited study, E. Fama and French (1992) discover that the relationship between market β and average return is insignificant. Recent studies such as Antoniou et al. (2015) point out that the security market line is upward sloping in pessimistic sentiment periods, but downward sloping during optimistic periods. However, during the entire sample these effects offset each other, and a flat security market line is observed.

Consistent with the flat security line evidence in the previous literature, the first graph of Figure 4 shows a nearly flat security market line when plotting the realised returns of the 25 size and BM portfolios against their static market βs.[25] Panel A of Table 7 reports the corresponding regression. The slope coefficient of −0.54% is insignificant and confirms the flat slope of the security market line. In addition, the cross-sectional R^2 is only 0.14, implying a poor explanation of the static market β of average portfolio returns. Apparently, the flat slope of security market line fails to account for the value effect as growth portfolios have higher βs but lower average returns during the whole sample period, and one important reason for this failure is that the static market β does not account the time-varying risk premium.

The failure of the static market β at explaining the cross-section of asset returns has been further confirmed in the sections that examine conditional market βs in bad and good states. Specifically, the positive β-pricing only works in bad states when the price of risk is high, whereas the exact opposite occurs in good states. Accordingly, the security market line is upward slopping in bad (low-sentiment) states but is downward slopping in good (high-sentiment) states. When aggregating the two states, these effects offset each other and give rise to a flat security market line.

As β pricing only prevails in bad states, we refer to the β in bad states as good β, whereas the β in good states as bad β. If a portfolio has both high good and bad βs, then perhaps its average returns will not be prominent. However, a portfolio that has high good βs, but low bad βs perhaps should earn higher average returns, as it earns higher returns in bad states but realizes

[25]The data here is presented in the first and second columns in Table 5.

lower negative returns in good states. In this case, the difference between good β and bad β should reflect the degree to which returns will be compensated for bearing market risk. In other words, what determines the portfolio returns in equilibrium is not its static market β, but the difference between good β and bad β. Accordingly, one should expect a strong positive relation between this β difference and average returns.

In this study, we call such a β difference (good β–bad β) as 'state β', because it is state-dependent on investor sentiment. The first graph of Figure 4 plots portfolio average returns against their state βs. In sharp contrast to the flat security market line of the static CAPM market β, the second graph of Figure 4 shows that the security market line is upward slopping when we use state βs, and value portfolios have much higher state βs than growth portfolios ($B^{15}_{\text{StateBeta}} > B^{11}_{\text{StateBeta}}$, $B^{25}_{\text{StateBeta}} > B^{21}_{\text{StateBeta}}$, $B^{35}_{\text{StateBeta}} > B^{31}_{\text{StateBeta}}$, $B^{45}_{\text{StateBeta}} > B^{41}_{\text{StateBeta}}$ and $B^{55}_{\text{StateBeta}} > B^{51}_{\text{StateBeta}}$). More importantly, portfolios' average BM value and their state βs also exhibit a strong positive correlation of 0.92. Therefore, these patterns show that the state β successfully captures the value effect.

Panel B of Table 7 reports the regression of portfolio returns on their state βs. The slope coefficient of 1.26 with a t-statistic of 6.00 indicates that a one-unit increase in the state β is associated with 1.26% higher returns per month. The market β, however, has an insignificant slope coefficient of −0.54 with a t-statistic of −1.63. More impressively, the R^2 is 0.56 suggesting that the scaled CAPM on sentiment has a relatively strong explanatory power of the state β compared to the static one of 0.14.

4.4 | State β and sentiment-related anomalies

As long as the state β reflects sentiment effects on the cross-section of returns and, thus, can better specify mispricing-driven asset risk, one would expect a positive relation between decile portfolio returns and their state βs in sentiment-related anomalies or at least, the state βs of long legs of anomaly strategies to be greater than those of short legs. In this study, we examine the asset growth, net operating asset regression, net stock issue, total accruals, composite equity issue, investment-to-assets, return on equity, and failure probability anomalies as documented in Stambaugh et al. (2012) who find that the long-short strategies of these anomalies are more profitable following high sentiment than following low-sentiment periods and that these profits mainly come from the low returns in short legs that are subject to sentiment-driven overpricing.

For each anomaly, we calculate the state βs of decile portfolios using the same method described in Section 4.3.4. We then run the cross-section regressions of decile portfolio returns on their state βs and we find that their relations are positive for all eight anomalies and that four of them are significant, with t-statistics ranging from 2.09 to 4.39, as reported in Panel B of Table 8. In particular, the cross-sectional R^2s for the anomalies of asset growth, net operating asset and investment-to-asset are more than 45%, implying that the state β has strong explanatory power of the cross-section returns. Though the other four regressions do not show a significantly positive relation between state βs and returns, for all eight long-short strategies, as reported in Panel B of Table 9, we find that the state βs of long legs of anomaly strategies are greater than the βs of short legs. These findings confirm our conjecture that stocks with lower state βs are expected to earn lower returns in equilibrium, as a result of the sentiment-driven overpricing effect. To dissect this overpricing effect further, we study returns on long and short legs during good and bad states. Panel A of Table 9 reports the analysis. These results show that

TABLE 8 Anomalies and sentiment-scaled capital asset pricing model (CAPM)

Panel A reports the descriptive statistics of sentiment-related anomalies, including asset growth, net operating asset regression, net stock Issue, total accruals, composite equity issue, investment-to-assets, return on equity, and failure probability. 'SR' denotes the Sharpe ratio. Panel B reports the regressions of decile portfolio returns against their state βs and against their conditional market βs in good and bad states defined by sentiment. t-Statistics are adjusted by White's heteroscedasticity consistent standard errors. The subscripts i and n denote anomalies and deciles respectively. As Table 3 does, Panel C presents the λ estimates from cross-sectional Fama-MacBeth regressions of sentiment-scaled CAPM using returns of 80 decile portfolios formed on the eight anomaly variables. The top statistic uses uncorrected Fama-MacBeth standard errors; the bottom statistic uses the Shanken correction. For each model, the first R^2 term denotes the unadjusted cross-sectional R^2; the second one denotes the adjusted cross-sectional R^2; the third one denotes the generalized least squares R^2.
$R_{i,n} = a_i + b_i\beta_{i,n} + \in_{i,n}$

Panel A: Descriptive statistics of anomalies

	Mean	t-Statistic	SD	SR	Sample period
Asset growth	0.52	3.88	3.21	0.16	March 1967–October 2015
Net operating asset	0.56	4.88	2.78	0.20	March 1967–October 2015
Net stock issues	0.65	5.97	2.62	0.25	March 1967–October 2015
Total accruals	0.29	2.91	2.38	0.12	March 1967–October 2015
Composite equity issue	0.22	2.02	2.64	0.08	March 1967–October 2015
Investment-to-assets	0.48	3.97	2.95	0.16	March 1967–October 2015
Return on equity	0.72	3.27	5.06	0.14	March 1972–October 2015
Failure profitability	0.89	2.92	6.66	0.13	March 1976–October 2015

Panel B: Regressions of decile portfolio returns on βs

	State β			Bad states (good β)			Good states (bad β)		
	$\hat{b}$	t-Statistic	R^2	$\hat{b}$	t-Statistic	R^2	$\hat{b}$	t-Statistic	R^2
Asset growth	0.83	2.37	0.57	3.55	5.06	0.67	−2.19	−4.92	0.73
Net operating asset	1.41	2.45	0.48	0.79	0.73	0.07	−2.40	−1.64	0.41
Net stock issues	0.63	1.06	0.12	1.57	2.25	0.26	−2.99	−4.33	0.72
Total accruals	0.80	2.09	0.28	4.15	6.27	0.88	−1.48	−2.87	0.33
Composite equity issue	0.38	1.19	0.07	1.40	2.48	0.43	−2.10	−4.40	0.72
Investment-to-assets	0.95	4.39	0.55	3.12	4.62	0.82	−2.74	−5.92	0.80
Return on equity	0.68	0.75	0.12	2.71	4.35	0.72	−3.27	−4.57	0.57
Failure profitability	0.15	0.20	0.00	2.18	8.98	0.91	−3.07	−4.10	0.84

Panel C: Fama-MacBeth regressions on returns of 80 anomaly portfolios

	Constant	λ_s	λ_m	λ_m^s	R^2
AS	1.69	0.05	−0.52	−1.55	0.32
	(3.54)	(0.81)	(−1.69)	(−2.19)	0.29
	(3.15)	(0.18)	(−1.74)	(−2.04)	0.19

TABLE 9 Returns and βs of long and short legs of anomaly strategies during good and bad states

Panel A reports the returns on long legs, short legs and long–short strategies during good and bad states. t-Statistics are reported in the parentheses. Panel B reports the conditional βs of long and short legs in good and bad states as well as their state βs. For the portfolio i, the conditional β is calculated as $B_i = \beta_{i,m} + \beta^s_{i,m}\bar{s}_t$, where $\beta_{i,m}$ and $\beta^s_{i,m}$ are factor loadings in the market returns and the lagged sentiment times the market excess return respectively. $\bar{s}_t$ is the average value of sentiment in state t. Following Lettau and Ludvigson (2001b), we define a good (bad) state as a month in which the augmented sentiment is at least one standard deviation above (below) its mean value. The state β here is calculated as the difference between the β in bad state and the one in good state.

Panel A: Returns on long legs, short legs and long–short strategies

	Long leg		Short leg		Long–short	
	Good states	Bad states	Good states	Bad states	Good states	Bad states
Asset growth	−0.61	2.82	−1.47	2.37	0.86	0.44
	(−1.13)	(4.76)	(−2.01)	(4.01)	(2.20)	(1.56)
Net operating asset	−0.31	2.02	−1.51	2.09	1.21	−0.07
	(−0.47)	(3.80)	(−2.27)	(3.96)	(4.22)	(−0.27)
Net stock issues	−0.04	2.27	−1.41	2.12	1.37	0.15
	(−0.06)	(4.63)	(−2.17)	(3.83)	(4.38)	(0.65)
Total accruals	−0.40	2.47	−0.38	1.42	−0.02	1.04
	(−0.79)	(4.60)	(−0.78)	(3.38)	(0.09)	(4.07)
Composite equity issue	−0.53	2.11	−1.20	2.43	0.67	−0.32
	(−0.93)	(4.72)	(−1.67)	(4.38)	(2.14)	(−1.29)
Investment-to-assets	−0.40	2.79	−1.23	2.40	0.83	0.39
	(−0.71)	(4.83)	(−1.80)	(3.86)	(2.730	(1.32)
Return on equity	0.27	1.81	−1.98	2.51	2.25	−0.69
	(0.42)	(3.25)	(−1.72)	(3.41)	(2.46)	(−1.25)
Failure profitability	−0.11	1.85	−2.86	3.41	2.75	−1.56
	(−0.19)	(3.86)	(−2.09)	(3.63)	(2.35)	(−2.17)

Panel B: βs of long and short legs

	Long leg			Short leg		
	Good states (bad β)	Bad states (good β)	State β	Good states (bad β)	Bad states (good β)	State β
Asset growth	0.88	1.06	0.18	1.34	1.20	−0.14
Net operating asset	1.13	1.08	−0.05	1.22	1.05	−0.17
Net stock issues	1.03	1.00	−0.03	1.21	1.15	−0.06
Total accruals	0.87	1.07	0.19	0.94	0.90	−0.03
Composite equity issue	0.96	0.92	−0.04	1.28	1.18	−0.09
Investment-to-assets	1.00	1.17	0.17	1.23	1.22	−0.01
Return on equity	0.99	1.02	0.33	1.40	1.28	0.12
Failure profitability	0.86	0.94	0.08	1.64	1.67	0.03

short legs earn more negative returns than long legs during good states (high-sentiment periods) in which asset prices are overpriced. As a result, the return differences between long and short legs during good states are significantly positive for seven of eight long-short strategies. The opposite pattern, however, emerges during bad states. Returns on short legs are higher than those of long legs for four of eight long-short strategies, but most of such differences are insignificant.

Why short legs are more overpriced and earn more negative returns during good states than long legs? We address this question by examining their conditional βs and find that for all eight anomalies, short legs have much higher βs than long legs during good states, as reported in Panel B of Table 9. As stocks with high βs are more susceptible to this overpricing, as indicated in the model of Hong and Sraer (2016), it is not surprising to find that short legs are more exposed to sentiment-driven overpricing, especially under the presence of short-sale impediments, and, thus, earn lower returns in equilibrium. The regression analysis reported in Panel B of Table 8, provides additional support to this finding. Specifically, the results demonstrate a significantly negative relation between decile portfolio returns and their conditional βs in good states for seven of eight anomalies. In contrast, this relation becomes significantly positive in bad states, indicating that stocks with higher βs in bad states are likely to earn higher returns. Therefore, using state β, the difference between conditional βs in bad states and those in good states captures the sentiment-driven overpricing and provides an explanation for the behavioural intuition behind anomalies.

We also test the performance of sentiment-scaled CAPM in explaining the cross-section of stock returns using 80 decile portfolios formed on the eight anomaly variables. Panel C of Table 8 reports the results. Consistent with the test of 25 BM and size portfolios, we find that the risk premium on the interaction term of lagged sentiment and current market excess return is significantly negative, indicating a negative premium associated with sentiment-driven mispricing. Moreover, the adjusted R^2 of sentiment-scaled CAPM in the Fama-Macbeth regressions is around 0.30 and the GRS R^2 is 0.19, both indicating a modest performance of sentiment-scaled CAPM at explaining the anomalies.

4.5 | The time-varying size premium

In this subsection, we extend our analysis to the sentiment-scaled Fama-French three-factor model to examine whether the size premium is time-varying. Banz (1981) proposes the size effect, where small-cap stocks earn higher returns than that of big-cap stocks, and E. Fama and French (1993) show that the size premium is an important pricing factor in explaining the cross-section of stock returns. Subsequently, the size factor has been widely used in many leading factor models.

However, Baker and Wurgler (2006) find that the size effect only exists during low-sentiment periods, casting doubt on the persistence of the size effect. Antoniou et al. (2015) further support this finding. In the cross-sectional Fama-MacBeth regressions, the coefficient on size is significantly negative when sentiment is low, implying a strong size effect where small-cap stocks yield higher returns than big-cap stocks. However, this coefficient becomes positive and statistically insignificant when sentiment is high. One possible explanation for this result is that small-cap stocks are overpriced during high-sentiment periods and, thus, earn lower returns than big-cap stocks. Accordingly, the size premium disappears in high-sentiment periods.

TABLE 10 Predicative regressions of size premium on investor sentiment

This table reports the results of return forecasts on four sentiment indices: BW and MSCI span from July 1965 to September 2015; MCSI and CBCCI span from February 1967 to September 2015. R_{t+1} is the size premium (small minus big size) obtained from Kenneth French's website. t-statistics, reported in the parentheses, are adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors.

$R_{t+1} = a + \beta \text{Sentiment}_t + \epsilon_t$

	BW	MSCI	CBCCI	AS
β	−0.37	−0.29	−0.36	−0.43
	(−2.87)	(−2.12)	(−2.67)	(−3.25)
R^2 (%)	1.38	0.85	1.38	1.86

To the extent that small-cap stocks earn higher returns during low-sentiment periods but lower returns during high-sentiment periods than large-cap stocks, it is reasonable to expect that sentiment has a negative predictability on size premium. Table 10 reports the results of the forecasting power of the four sentiment indices on the size premium. Consistent with our conjecture, all four sentiment indices are negative return predictors for the size premium: All slope coefficients are significant at 5% (t-statistics range from −2.12 to −3.25); the average coefficient of −0.36 implies that a one standard deviation increase in sentiment (sentiment is standardized) is associated with −0.36% lower subsequent monthly return; the average R^2 is 1.37%, confirming a strong forecasting power of sentiment for the size premium.

To further demonstrate this time-varying size effect in explaining the cross-section returns, we conduct the cross-section test of 25 size and BM portfolios, using the sentiment-scaled FF3 model. Table 11 reports the results. The coefficients on all the scaled-size factor βs, λ^{s}_{smb} are significantly negative across the four different sentiment measures, confirming the negative conditional risk premium of the size effect. More importantly, the adjusted R^2s here are 50%, implying the model has strong explanatory power of the cross-section returns.

An interesting question that emerges from these results is why the size effect is associated with a negative conditional risk premium when sentiment is used as the instrument. Recall, from Table 10, that sentiment is a negative predictor on size premium implying that small-cap stocks yield higher returns when sentiment is low than large-cap stocks, whereas the exact opposite pattern occurs during high-sentiment periods. Such a pattern indicates that small-cap stocks are more likely to be overpriced than large-cap stocks and, thus, the negative risk premium can be regarded as for holding high (unrealistic) expectations about the future returns of small-cap stocks.

5 | ROBUSTNESS CHECK

5.1 | Using mean value of sentiment to define good and bad states

Following the sentiment literature, we check the robustness of our results by regressing portfolio returns on their conditional market β in different states, using the mean value of

TABLE 11 Scaled Fama and French 3-factor model and 25 size and book-to-market portfolios

This table reports the λ estimates from cross-sectional Fama-MacBeth regressions using returns of 25 portfolios formed on size and β equity ratio. βs are estimated in the first-stage time-series regressions on different factors. In this sentiment-scaled Fama and French 3-factor model, the factors are the lagged sentiment times the market excess return, the lagged sentiment times SMB and the lagged sentiment times HML. Four sentiment indices here are used as conditional variables. The sample period is from July 1965 to September 2015 for all models but for the scaled FF3 model with CBCCI and AS, whose data begin from February 1967. The parentheses report t-statistic: the top statistic uses uncorrected Fama-MacBeth standard errors; the bottom statistic uses the Shanken correction. For each model, the first term in R^2 denotes the unadjusted cross-sectional R^2; the second one denotes the adjusted cross-sectional R^2 and the third one denotes the generalized least squares R^2.
$E_t(R_{i,t+1}) = r_f + \beta^s_{i,m}\lambda^s_m + \beta^s_{i,\text{smb}}\lambda^s_{\text{smb}} + \beta^s_{i,\text{hml}}\lambda^s_{\text{hml}}$

	Constant	λ^s_m	λ^s_{smb}	λ^s_{hml}	R^2
BW	0.87	−2.69	−1.12	0.24	0.65
	(5.04)	(−3.09)	(−2.24)	(0.54)	0.61
	(4.37)	(−2.70)	(−1.96)	(0.47)	0.18
MSCI	0.57	−2.03	−1.32	−0.35	0.45
	(2.57)	(−1.63)	(−2.70)	(−0.62)	0.37
	(2.29)	(−1.42)	(−2.37)	(−0.55)	0.13
CBCCI	0.58	0.02	−1.84	−1.35	0.60
	(2.69)	(0.02)	(−3.63)	(−3.50)	0.54
	(2.13)	(0.02)	(−2.92)	(−2.82)	0.21
AS	0.84	−2.90	−1.09	0.12	0.56
	(4.20)	(−2.40)	(−2.47)	(0.27)	0.50
	(2.47)	(−1.43)	(−1.54)	(0.16)	0.13

Abbreviations: AS, augmented sentiment; BW, Baker and Wurgler index; CBCCI, Conference Board Consumer Confidence Index; FF3, Fama-French three-factor model; HML, high minus low book-to-market equity ratio; MSCI, University of Michigan Consumer Sentiment Index; SMB, small minus big size.

sentiment to define high (above the mean value of sentiment) and low (below the mean value of sentiment) sentiment periods and, thus, good and bad states. We also regress portfolio returns on state βs, which are calculated as the difference of the conditional βs in bad and good states.

Table 12 reports the regression results. Consistent with the findings in Section 4.3, we find a positive relation between returns and state β: The coefficient of 2.08 indicates that a one-unit increase of state β is associated with 2.08% higher monthly returns. This positive relation is illustrated in the first graph of Figure 4, with value portfolios (labelled 15, 25, 35 and 45) associated with the highest state βs realizing higher returns than growth portfolios (labelled 11, 12, 13, 14 and 15). Panels B and C of Table 12, show a positive relation between returns (0.84; t-statistic 1.98) and conditional βs in bad states but a strong negative relation in good states (−1.36; t-statistic −4.84), respectively.

TABLE 12 Robustness Check: Returns and state β based on the mean value of sentiment

This table reports the regression results of portfolio returns on their conditional market βs. Good (bad) states are defined as a month when sentiment in previous month is higher (lower) than its mean value. Panel A reports regression results of portfolio returns on state βs, which are calculated as the difference between conditional βs in bad and good states. Panel B and C report regression results of portfolio returns on βs in bad and good states, respectively. t-Statistics are adjusted by White's heteroscedasticity consistent standard errors.

$R_i = a + b\beta_i + \epsilon_i$

	Panel A: State β			Panel B: Bad states (good β)			Panel C: Good states (bad β)		
	$\hat{b}$	t-Statistic	R^2	$\hat{b}$	t-Statistic	R^2	$\hat{b}$	t-Statistic	R^2
25 size and book-to-market port	2.08	6.00	0.56	0.84	1.98	0.18	−1.36	−4.84	0.68

5.2 | Alternative sentiment index

For the alternative sentiment index, we consider the index of Huang et al. (2015). Its construction uses the same sentiment proxies but extracts the common component through partial least squares (PLS) instead of principal components and that, according to the analysis in that paper, results in an index that is better aligned at forecasting returns.[26] Table 13 presents the results of robustness checks of our main empirical findings. Consistent with the negative sentiment predictability on market returns, we find that PLS sentiment can negatively predict the market returns. The coefficient estimate is −0.68 with a t-statistic of −3.99. We also find that the conditional CAPM works well in cross-section test when PLS sentiment is used as conditioning information. Specifically, the adjusted OLS and GLS R^2 are 0.44 and 0.22, respectively. The estimate of risk premium on the interaction term of lagged sentiment and current market return, λ_m^s, is significantly negative, consistent with our findings in Table 3.

6 | DISCUSSION

Merton's intertemporal capital asset pricing model (ICAPM) (Merton, 1973) states that investors who hold assets will be compensated by returns for bearing market (systematic) risk and for bearing any risk of shocks to the state variable that can change the investment opportunity set. As ICAPM, many asset pricing models associated with different candidate state variables have been proposed to describe asset returns. Because they are driven by economic risks and related to expected returns in equilibrium, these candidate variables, such as labour income and CAY, are also known as 'rational variables'.

Indeed, the standard asset pricing models have long been associated with risk-based explanations, and it seems that the asset pricing paradigm fails to account for investor irrationality. However, recent studies provide tremendous evidence to show that the irrational proxy, namely, investor sentiment, also plays an important role in setting the market moves. Borrowing from Nagel (2013), the sentiment- and risk-based explanations as a dichotomy may

[26] We thank Dashan Huang for providing the updated sentiment index on his website.

TABLE 13 Robustness check: The conditional capital asset pricing model (CAPM) model scaled by partial least squares (PLS) sentiment

This table reports the regression results of robustness checks of our main empirical findings by using the PLS sentiment index as constructed in Huang et al. (2015). Panel A reports the predictive regression results of market excess returns on the PLS sentiment index controlling for macroeconomic variables including the real interest rate, the inflation rate, the term and default premium, and the consumption-wealth ratio. Panel B presents the results from cross-sectional Fama-MacBeth regressions of the conditional CAPM model scaled by PLS sentiment, using returns of 25 portfolios formed on size and the book-to-market equity ratio. The top statistic uses uncorrected Fama-MacBeth standard errors; the bottom statistic uses the Shanken correction. For each model, the first R^2 term denotes the unadjusted cross-sectional R^2; the second one denotes the adjusted cross-sectional R^2; the third one denotes the generalized least squares R^2.

$$R_{t+1} = a + \beta \text{Sentiment}_t + \Sigma_{i=1}^{4} \alpha_i \text{ControlVariables} + \epsilon_t \quad \text{(Sentiment predictive regression)}$$
$$E_t(R_{i,t+1}) = r_f + \beta_{i,s}\lambda_s + \beta_{i,m}\lambda_m + \beta_{i,m}^s \lambda_m^s \quad \text{(Scaled CAPM with sentiment)}$$

Panel A	**Panel B: Conditional CAPM**				
β	**Constant**	λ_s	λ_m	λ_m^s	R^2
−0.88	0.19	0.79	0.79	−2.46	0.51
(−5.34)	(0.40)	(3.51)	(1.49)	(−2.41)	0.44
	(0.28)	(2.20)	(1.13)	(−1.75)	0.22

be false, to begin with. That is, both macro-related risks and market-wide sentiment can affect asset prices and exist simultaneously.

In this study, we provide empirical evidence that sentiment can serve as conditional information in the static CAPM to explain the cross-section of expected returns. The evidence remains robust with different sentiment indices used and different portfolios tested. More importantly, our sentiment-scaled model provides the economic intuition behind the value effect and solves the puzzle of the flat security market line. Perhaps given the fact that investor sentiment drives both market returns and the cross-section of stock returns, future studies need to construct a macrofinance model to show how aggregate sentiment affects both the risk premium and the cross-section of asset prices.

REFERENCES

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, *48*, 245–275.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2015). Investor sentiment, beta, and the cost of equity capital. *Management Science*, *62*, 347–367.

Avramov, D., & Chordia, T. (2006). Asset pricing models and financial market anomalies. *The Review of Financial Studies*, *19*(3), 1001–1040.

Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal*, *67*, 40–54.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*, 1645–1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*, 129–152.

Baker, M., & Wurgler, J. (2012). Comovement and predictability relationships between bonds and the cross-section of stocks. *The Review of Asset Pricing Studies*, *2*, 57–87.

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, *104*, 272–287.

Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*, 3–18.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of Business*, *45*, 444–455.

Brown, G., & Cliff, M. (2005). Investor sentiment and asset valuation. *Journal of Business*, *78*, 405–440.

Chen, N., Roll, R., & Ross, S. (1986). Economic forces and the stock market. *Journal of Business*, *59*, 383–403.

Chung, S., Hung, C., & Yeh, C. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance*, *19*, 217–240.

Cochrane, J. H. (2006). *Asset pricing*. Princeton University Press.

Cochrane, J. H. (2007). Financial markets and the real economy. *Foundations and Trends® in Finance*, *1*, 1–101.

Delong, J., Shleifer, A., Summers, L., & Waldmann, R.(1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*, 703–738.

Dumas, B., Kurshev, A., & Uppal, R. (2009). Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility. *The Journal of Finance*, *64*(2), 579–629.

Eiling, E. (2013). Industry-specific human capital, idiosyncratic risk, and the cross-section of expected stock returns. *The Journal of Finance*, *68*(1), 43–84.

Fama, E. (1981). Stock returns, real activity, inflation, and money. *American Economic Review*, *71*, 545–565.

Fama, E., & French, K. (1992). The cross-section of expected stock return. *Journal of Finance*, *47*, 427–465.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*, 23–49.

Ferson, W. E., & Harvey, C. R. (1999). Conditioning variables and the cross-section of stock returns. *The Journal of Finance*, *54*(4), 1325–1360.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*, 1–25.

Greenwood, R., & Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, *27*(3), 714–746.

Ho, C., & Hung, C.-H. (2009). Investor sentiment as conditioning information in asset pricing. *Journal of Banking & Finance*, *33*(5), 892–903.

Hong, H., & Sraer, D. (2016). Speculative betas. *Journal of Finance*, *71*, 2095–2144.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, *28*, 650–705.

Huang, D., Jiang, F., Tu, J., & Zhou, G.(2015). Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, *28*, 791–837.

Jagannathan, R., & Wang, Z. (1996). The conditional CAPM and the cross-section of expected returns. *The Journal of Finance*, *51*(1), 3–53.

Kumar, A., & Lee, C. (2006). Retail investor sentiment and return comovements. *Journal of Finance*, *64*, 2451–2486.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, *49*(5), 1541–1578.

Lee, C., Shleifer, A., & Thaler, R. (1991). Investor sentiment and the closed-end fund puzzle. *Journal of Finance*, *46*, 75–110.

Lemmon, M., & Portniaquina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies*, *19*, 1499–1530.

Lettau, M., & Ludvigson, S. (2001a). Consumption, aggregate wealth, and expected stock returns. *Journal of Finance*, *56*, 815–849.

Lettau, M., & Ludvigson, S. (2001b). Resurrecting the (c) CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy*, *109*, 1238–1287.

Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, *96*, 175–194.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, *20*(4), 587–615.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, 867–887.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the Econometric Society*, 768–783.

Nagel, S. (2013). Empirical cross-sectional asset pricing. *Annual Reviews of Financial Economics 5*(1), 167–199.

Neal, R., & Wheatley, S. (1998). Do measures of investor sentiment predict returns? *Journal of Financial and Quantitative Analysis*, *33*, 523–547.

Roll, R., & Ross, S. A. (1994). On the cross-sectional relation between expected returns and betas. *The Journal of Finance*, *49*(1), 101–121.

Roussanov, N. (2014). Composition of wealth, conditioning information, and the cross-section of stock returns. *Journal of Financial Economics*, *111*(2), 352–380.

Santos, T., & Veronesi, P. (2005). Labor income and predictable stock returns. *The Review of Financial Studies*, *19*(1), 1–44.

Shanken, J. (1992). On the estimation of beta-pricing models. *The Review of Financial Studies*, *5*(1), 1–33.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, *19*, 425–442.

Shen, J., Yu, J., & Zhao, S. (2017). Investor sentiment and economic forces. *Journal of Monetary Economics*, *86*, 1–21.

Shleifer, A., & Vishny, R. (1997). The limits of arbitrage. *Journal of Finance*, *52*, 35–55.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*, 288–302.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2014). The long of it: Odds that investor sentiment spuriously predicts anomaly returns. *Journal of Financial Economics*, *114*, 613–619.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, *75*, 1903–1948.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *Review of Financial Studies*, *30*, 1270–1315.

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean-variance relation. *Journal of Financial Economics*, *100*, 367–38.

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APPENDIX A

Derivation of Equation (9)

Start with Equation (6),

$$M_{t+1} = a_0 + a_1 s_t - \left(b_0 R^{em}_{t+1} + b_1\left(s_t R^{em}_{t+1}\right)\right). \tag{6}$$

Using the basic pricing equation for returns,

$$1 = E_t[M_{t+1}(1 + R_{i,t+1})] \tag{A1}$$

plugging the Equation (6) into this basic pricing equation and taking unconditional expectations, we have the unconditional model

$$1 = E\left[\left[a_0 + a_1 s_t - \left(b_0 R^{em}_{t+1} + b_1\left(s_t R^{em}_{t+1}\right)\right)\right](1 + R_{i,t+1})\right]. \tag{A2}$$

Using the property $E(mx) = E(m)E(x) + \mathrm{Cov}(m, x)$,

$$1 = E(M_{t+1})E(1 + R_{i,t+1}) + Cov[M_{t+1}, (1 + R_{i,t+1})] \tag{A3}$$

and using $R_f = 1/E(m)$ (Cochrane, 2006), where $R_f = 1 + r_f$ and r_f is risk-free rate,

$$E(R_{i,t+1}) - r_f = -\frac{\mathrm{Cov}[M_{t+1}, (1 + R_{i,t+1})]}{E(M_{t+1})}. \tag{A4}$$

Thus, the expected return on the asset i can be expressed as the risk-free rate plus the right-hand-side variable, namely, risk adjustment. Substituting the Equation (6) into the Equation (A4) gives

$$\begin{aligned} E(R_{i,t+1}) - r_f &= -\frac{\mathrm{Cov}\left[a_0 + a_1 s_t - \left(b_0 R^{em}_{t+1} + b_1\left(s_t R^{em}_{t+1}\right)\right), (1 + R_{i,t+1})\right]}{E(M_{t+1})} \\ &= -\frac{a_1 \mathrm{Cov}[s_t, (R_{i,t+1})]}{E(M_{t+1})} + \frac{\mathrm{Cov}[b_t, (R_{i,t+1})]}{E(M_{t+1})} \\ &= \left(\frac{\mathrm{Cov}[s_t, (R_{i,t+1})]}{\mathrm{Var}(s_t)}\right)\left(-a_1 \frac{\mathrm{Var}(s_t)}{E(M_{t+1})}\right) + \left(\frac{\mathrm{Cov}[b_t, (R_{i,t+1})]}{\mathrm{Var}(b_t)}\right)\left(\frac{\mathrm{Var}_t(b_t)}{E(M_{t+1})}\right) \\ &= \beta_{i,s}\lambda_s + \beta_{i,b}\lambda_b. \end{aligned} \tag{A5}$$

As $b_t = b_0 R^{em}_{t+1} + (b_1 s_t) R^{em}_{t+1}$, the second term in Equation (A5), $\mathrm{Cov}[b_t, (R_{i,t+1})]/E(M_{t+1})$, can be rewritten as

$$\left(\frac{\mathrm{Cov}[b_t,(R_{i,t+1})]}{\mathrm{Var}\left(R^{em}_{t+1}\right)}\right)\left(b_0\frac{\mathrm{Var}\left(R^{em}_{t+1}\right)}{E(M_{t+1})}\right)+\left(\frac{\mathrm{Cov}\left[s_tR^{em}_{t+1},(R_{i,t+1})\right]}{\mathrm{Var}\left(s_tR^{em}_{t+1}\right)}\right)\left(b_1s_t\frac{\mathrm{Var}\left(R^{em}_{t+1}\right)}{E(M_{t+1})}\right)$$
$$=\beta_{i,m}\lambda_m+\beta^s_{i,m}\lambda^s_m, \tag{A6}$$

where $\beta_{i,m}$ is the market β for static CAPM, and $\beta^s_{i,m}$ is the conditional market β formed on the sentiment information set.

Substituting Equation (A6) into Equation (A5) gives Equation (9),

$$E_t(R_{i,t+1})=r_f+\beta_{i,s}\lambda_s+\beta_{i,m}\lambda_m+\beta^s_{i,m}\lambda^s_m. \tag{9}$$

Thus, the factors in this model are lagged sentiment, current-period market return and lagged sentiment times current-period market return.

At a minimum, λ_m is likely to be insignificant, as the average market risk premium is not prominent. Indeed, many studies have found a flat or downward security market line.[27] In contrast, the conditional market premium λ^s_m is perhaps strongly significant; recall from Equation (A6) where $\lambda^s_m=b_1s_t\left(\mathrm{Var}\left(R^{em}_{t+1}\right)/E(M_{t+1})\right)$ and the static market risk premium $\lambda_m=b_0\left(Var\left(R^{em}_{t+1}\right)/E(M_{t+1})\right)$. The specification b_1s_t indicates that the fluctuations in s_t are driven by the time-varying market risk premium.[28] In other words, the conditional information s_t, here, forecasts the future market returns and, thus, the sign and the magnitude of λ^s_m may also vary over time with respect to s_t.

Thus far, the interesting question is what is the sign of λ^s_m in equilibrium. In this study, we conjecture that it has a negative sign because of the negative predictability of sentiment on future market returns. For example, when investors are pessimistic during bad times, they are so risk-averse that expected returns must be high enough to compensate for bearing any extra risk. Accordingly, the price of market risk will also be high. However, the exact opposite should occur during good times when investors are typically optimistic. One potential explanation is that irrational investors fixated by overoptimism drive market prices up but depress subsequent returns. This pattern has been documented in previous empirical studies. Specifically, Huang et al. (2015) relying on investor sentiment and Greenwood and Shleifer (2014) on survey data of investor expectations show that investor sentiment is inversely related to future market returns. Therefore, we conjecture negative (positive) sentiment to be associated with high (low) market premium and the market premium conditioned on sentiment λ^s_m to emerge with a strong negative sign in equilibrium.

One might be inclined to argue for a negative sign of conditional market risk premium, as the risk premium should not be negative on average. Borrowing from Lettau and Ludvigson (2001b), it is important to note that the individual coefficients in Equation (7) do not have a straightforward interpretation as risk prices. In our case, the negative sign of λ^s_m here purely

[27] See Black (1972), Fama and French (1992) and Frazzini and Pedersen (2014) and Antoniou et al. (2015)

[28] See Lettau and Ludvigson (2001b) for a discussion. In their linear factor models with time-varying coefficients, $\lambda_t=-E[R_{0,t}]\mathrm{Cov}(\vec{f},\vec{f}\,')b$, where $E[R_{0,t}]$ is the average return on a zero-β portfolio. One can regard it as $R^f=1+r_f=1/E_t(M_{t+1})$ in the context of this study. The f here denotes the factor: Value-weighted market returns. The extra minus sign comes from their initial specification where $M_{t+1}=a(z_t)+b(z_t)R^{em}_{t+1}$, whereas we assume that $M_{t+1}=a(z_t)-b(z_t)R^{em}_{t+1}$. Nevertheless, the intuition here is identical to that of Lettau and Ludvigson (2001b).

results from the negative predictive power of sentiment for future returns. It can also be viewed as a penalty (negative risk premium) for holding high (unrealistic) expectations about future returns.

Test of 25 size-β portfolios

Table A1

TABLE A1 Fama-MacBeth regressions on returns of 25 size-β portfolios

This table reports the λ estimates from cross-sectional Fama-MacBeth regressions using excess returns of 25 portfolios formed on size and β equity ratio. βs are estimated in the first-stage time-series regressions on different factors. In the capital asset pricing model (CAPM), the factor is the monthly value-weighted excess return of all CRSP stocks. In the FF3 model, the factors are the market excess return and mimicking portfolios with respect to size and book-market equity ratios. In the scaled CAPM with sentiment, the factors are lagged sentiment, the current-period market return and lagged sentiment times the market excess return. Four sentiment indices here are used as conditional variables. The sample period is from July 1965 to September 2015 for all models but for the scaled CAPM with CBCCI and AS, whose data begin from February 1967. The parentheses report t-statistics. For each model, the first term in R^2 denotes the unadjusted cross-sectional R^2 and the one under it denotes the adjusted cross-sectional R^2.

$E_t(R_{i,t+1}) - r_{f,t} = \beta_{i,m}\lambda_m$ (CAPM)

$E_t(R_{i,t+1}) - r_{f,t} = \beta_{i,m}\lambda_m + \beta_{i,\mathrm{SMB}}\lambda_{\mathrm{SMB}} + \beta_{i,\mathrm{HML}}\lambda_{\mathrm{HML}}$ (FF3)

$E_t(R_{i,t+1}) - r_{f,t} = \beta_{i,s}\lambda_s + \beta_{i,m}\lambda_m + \beta_{i,m}^{s}\lambda_m^{s}$ (Scaled CAPM with sentiment)

	Constant	λ_s	λ_m	λ_m^s	λ_{SMB}	λ_{HML}	R^2
CAPM	0.74		−0.02				0.00
	(4.12)		(−0.69)				−0.04
FF3	0.09		0.36		0.10	0.85	0.77
	(0.37)		(1.18)		(0.68)	(2.78)	0.80
BW	0.64	−0.41	−0.08	−2.26			0.53
	(3.55)	(−1.42)	(−0.35)	(−2.61)			0.46
MSCI	1.36	−1.29	−0.75	−1.08			0.75
	(4.85)	(−1.86)	(−2.35)	(−1.40)			0.72
CBCCI	1.15	−1.00	−0.62	−1.54			0.75
	(5.15)	(−2.67)	(−2.09)	(−1.44)			0.72
AS	1.17	−0.74	−0.63	1.74			0.71
	(4.85)	(−2.17)	(−2.09)	(−2.01)			0.67

Abbreviations: AS, augmented sentiment; BW, Baker and Wurgler index; CBCCI, Conference Board Consumer Confidence Index; FF3, Fama-French three-factor model; MSCI, University of Michigan Consumer Sentiment Index.