Sentiment Sensitivity, Limits of Arbitrage, and Pricing Anomalies

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Abstract

We investigate whether an investor sentiment factor explains the cross-section of stock returns. The average return differential is 1.48% (0.75%) per month between the decile portfolios with the highest positive sentiment beta and that with negative sentiment beta. The sentiment factor, *LMS*, has statistically significant average returns of 1.71% per month, and shows a positive and statistically significant market price. The sentiment-augmented asset-pricing models explain the size effect, and conditional models often capture the size, value and momentum effects.

JEL classification: G12; G14

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1. Introduction

Arbitrage activities in the financial market ensure that deviations in securities prices are detected and eliminated such that the market price moves alongside the 'fair' value of an asset. Behavioral finance theories suggest that investor sentiment is one such candidate that drives security price away from that can be justified by the fundamentals (De Long, Shleifer, Summers and Waldmann (DSSW, 1990), Lee, Shleifer, and Thaler (1991), and Baker and Wurgler (2006)). The limits of arbitrage and short sales constraints, however, weaken the effectiveness of arbitrage pricing (see, excellent discussions in, e.g., Shleifer and Vishny (1997), Ofek, Richardson, and Whitelaw (2004), and Chung, Hung and Yeh (2012)). Consequently, mispricing as measured by models such as the CAPM or empirical factors can be prevalent, and to which, asset pricing literatures has long documented various pricing anomalies such as the size, book-to-market, and momentum effects.

In this paper we contribute to the literature by studying the ability of an investor sentiment factor in explaining the cross-section of stock returns, hence diminishing the cross-sectional effect of asset pricing anomalies. Our study is motivated by the theory and evidence that the unpredictable fluctuations in investor sentiment unrelated to fundamentals deter arbitrage activities. DSSW (1990) argue that arbitrageurs face an extra uncertainty arising from investors' excessive optimism or pessimism. Black (1986) demonstrates that individuals often trade on noise not related to fundamentals, and Kumar and Lee (2006) show that individuals buy or sell stocks in concert. Baker and Wurgler (2007) argue that investor sentiment represents the degree of investors' optimistic/pessimistic beliefs about future cash flows and investment risks that are not justified by the facts at hand. Yu and Yuan (2011) suggest the integration of investor sentiment into models of stock prices.

Our study shows that the investor sentiment factor is associated with the costs and difficulties of arbitrage such as the stock price, price volatility, and institutional ownerships, capturing the component of mispricing not eliminated by arbitrage, and thus helps explain the cross-section of stock returns. Recent research documents that investor sentiment influences the cross-section of the average stock returns. Baker and Wurgler (2006) show that a wave of sentiment impacts the cross-section of stock prices pertaining to firm characteristics. Stambaugh, Yu, and Yuan (2011) show that in months following high sentiment the short-legs of the anomalies strategies are more profitable, supporting the argument that overpricing should be more prevalent than underpricing. Chung, Hung and Yeh (2012) find that only in the economic expansionary state does sentiment perform predictive power for the cross-section of stock returns.

We first present evidence of strong cross-sectional patterns in the relations between sentiment betas, the sensitivities of individual stocks to investor sentiment which we proxy by the monthly orthogonalized sentiment index of Baker and Wurgler (2006), and the attributes of firms, including stock returns, measures of arbitrage costs, and firm characteristics. These patterns suggest that investor sentiment may be an important factor affecting the cross-section of stock returns, and may help capture the asset pricing anomalies.

In order to test our hypothesis that investor sentiment could be an important factor that reduces the impacts of the firm-specific characteristics on stock returns at the firm level, we construct a sentiment-based factor *LMS* (large minus small sentiment sensitivities)–the return differential between the largest sentiment-sensitive and smallest sentiment-sensitive portfolios.

Our approach of constructing the sentiment factor is similar in spirit to the *SMB* and *HML* factors constructed by Fama and French (1993) and the factor mimicking portfolio of the liquidity factor proposed by Pastor and Stambaugh (2003). In essence, the *SMB* and *HML* factors capture the average return differentials between the stocks with high and low values of the particular firm characteristics (namely, market capitalization and book-to-market ratio), and the liquidity factor is constructed based on the sensitivities of individual stock returns to liquidity. In our sample period from August 1967 to December 2010, the average return on the LMS factor is 1.71% per month and is economically and statistically significant at the 5% level.

Prior to assessing the degree to which the *LMS* factor helps explain the anomalies, it is natural to test whether the sentiment factor is priced. We run the Fama-MacBeth (1973) two-pass regressions of the market factor and sentiment factor at the firm level. We find that the sentiment factor *LMS* commands an economically and statistically significant risk premium, and has significant explanatory power for the cross-section of individual stock returns. The risk premium on the LMS factor loading (i.e., the estimated λ on the *LMS* beta) is positive with a value of 1.40% per month and statistically significant at the 10% level. This indicates that stocks more sensitive to the *LMS* factor loading earn expected average returns, suggesting that investors require extra compensation for bearing the noise trader risk. As expected, the Fama-MacBeth estimate of the *LMS* risk premium, 1.40%, is smaller than the time-series average of the monthly LMS returns, 1.71%[1].

Finally, we examine whether incorporating the sentiment factor into different specifications of asset pricing models reduces the impacts of the firm-specific characteristics on the cross-

[1] Even though the measurement error associated with the LMS beta tends to cause a downward bias on the Fama-MacBeth coefficient estimate, our Fama-MacBeth test results complement our findings of the LMS returns and the returns and characteristics of portfolios sorted by the sentiment beta.

section of stock returns. Our evidence shows that sentiment-augmented pricing models often capture the size and value effects, and most importantly, the momentum effect.

Following the two-pass framework put forth by Avramov and Chordia (2006), we form different specifications of the *LMS*-augmented asset pricing models to investigate the explanatory power of the *LMS* for on the size, value, liquidity, and momentum effects. We consider both unconditional version of asset pricing models where the factor loadings are constant over time, and various conditional versions where the factor loadings are time varying with the information variables.

We find that the size effect ceases to be significant in the second-pass cross-sectional test once the LMS factor is present in the first-pass regression. The power of the sentiment factor to explain the size effect does not require the factor loadings of the risk factors to vary over time, although overall the conditional models outperform the unconditional models. Consistent with the extant evidence that investor sentiment predicts the returns on small stocks and the size premium (Swaminathan (1996), Neal and Wheatley (1998), and Lemmon and Portniaguina (2006)), our findings indicate that the high average returns on small stocks are attributable to their high sensitivities to the *LMS* facto. This suggests that the size premium is directly associated with stocks' exposures to the noise trader risk. The underlying reason for this result is also in line with our report early that small firms are disproportionally held by individual investors who are prone to investor sentiment than larger firms with larger institutional ownership[2], and that small stocks are associated with higher transaction costs, and hence are difficult to arbitrage and are more responsive to investor sentiment than large stocks.

[2] Also, Lee, Shleifer and Thaler (1991) and Nagel (2005) give evidence that small size stocks are disproportionally held by individual investors

When allowing the factor loadings in the sentiment-augmented models to vary with size, book-to-market ratio and the default spread over the time, we are able to consistently capture the size effect, which Avramov and Chordia (2006) fail to explain in the same time-varying beta specifications but without considering the sentiment factor when the sample firms are extended to the NASDAQ-listed stocks. This improvement further reinforces the important role of investor sentiment in capturing the size effect.

Another striking finding is, perhaps the most important contribution of our study, that by adding the sentiment factor to the traditional risk factor models, we can successfully capture the short-term momentum effect[3]. This finding provides evidence that supports Avramov and Chordia's (2006) conjecture, when their conditional models fail to capture the momentum effect, that "*there may exist a yet undiscovered risk factor related to the business cycle there may capture the impact of momentum on the cross section of individual stock returns.*" (p. 1005). Also, when conditioning on the firm-specific variables and the default spread, together with the Fama-French three factors, the sentiment factor can explain both the size and value effects.

The rest of this paper is organized as follows. The next section provides the motivation of the paper. Section 3 describes the data, estimates the sentiment beta of individual stocks, and examines the characteristics of portfolios sorted by sentiment betas. Section 4 explains the construction of the sentiment factor and conducts tests of the factor risk premium. Section 5 specifies the two-pass test framework for various sentiment-augmented asset pricing models, and discusses the explanatory power of the sentiment-augmented models for the asset pricing anomalies. Section 6 concludes.

[3] The explanatory power for the momentum effect exists when the factor loadings are scaled by the default spread in the models in which both the sentiment factor and the Fama-French factors are present.

2 Motivation

As described earlier, we develop our sentiment factor based on the following arguments and evidence documented in the literature. First, investors are subject to sentiment. Our own evidence (detailed in Section 3.2) shows that the portfolios with high sentiment betas tend to earn much higher returns than low sentiment-beta portfolios. This suggests that stocks respond to the shifts in investor sentiment differently as a result of investors' trading decisions subject to their sentiments.

Second, theory and evidence demonstrate that betting against sentimental investors is costly and risky. Shleifer and Vishny (1997) claim that financial market anomalies are likely to appear because of the limits of arbitrage. Baker and Wurgler (2006) argue that stocks whose valuations are highly subjective and difficult to arbitrage are more sentiment-prone. One of the reasons why arbitrageurs are less likely to bet against sentimental investors, especially by holding positions in stocks which are highly sensitive to investor sentiment, is because more sentiment-prone stocks tend to accompany higher price movement uncertainty and larger transaction costs. Our analysis supports this view. We find that more sentiment-prone stocks are associated with higher volatility and larger measures of transaction costs. This provides evidence that trading sentiment-prone stocks involves higher noise trader risk and is costly.

Furthermore, by examining the average firm characteristics across portfolios formed according to sentiment sensitivities, we find that stocks in the high sentiment sensitivity portfolios display small market values, lower book-to-market ratios, higher turnover, and, in general, superior past performance than those in the low sentiment sensitivity portfolios.

Therefore, it is plausible that sentiment effects associated with the limits of arbitrage could be a reason for the existence of the well-documented size, value, liquidity, and momentum effects.

3 Sentiment beta, stock returns and firm characteristics

3.1 Data and sample

Our firm-level data are from the Center for Research in Security Prices (CRSP) and COMPUSTAT datasets. We retrieve monthly data of all NYSE, AMEX, and NASDAQ common stocks for the period from August 1965 to December 2010. We include firms that meet the following criteria in our analysis. First, the returns in the current month, t, and over the past 60 months must be available[4]. Second, stock prices and shares outstanding have to be available in order to calculate firm size, and trading volume in month $t - 2$ must be available to calculate the turnover. Third, sufficient data has to be available from the COMPUSTAT dataset to calculate the book-to-market ratio as of December of the previous year. Only stocks with positive book-to-market ratios are included in our sample[5].

We control for the COMPUSTAT survival bias by dropping the first two years of COMPUSTAT data for every firm. After the screening process, the total number of different stocks is 10,820 over the period from August 1967 through to December 2010. The value of book-to-market for July of year t to June of year $t + 1$ is computed using accounting data at the end of year t -1. Book-to-market ratio values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. The institutional holdings records are retrieved from CDA/Spectrum Institutional (13f) Holdings.

We use the CRSP value-weighted returns to proxy for the market returns and the one-month Treasury bill rate for the risk-free rate. Other monthly variables for each firm include

[4] As can be seen in Section 2.2.1 that the estimation of the sentiment beta β_j^s at time t in (1) requires monthly observations from months t through t-24. In order to estimate the models in the first-pass regression, we require further 36 monthly observations prior to the current month. Therefore, at least 60 monthly observations are needed for each firm for the tests.

[5] However, we include all stocks regardless of the signs of the book values when constructing the LMS factor.

SIZE (the logarithm of the individual firm market capitalization measured in billions of dollars), B/M (the logarithm of the book-to-market ratio), TURNOVER (the ratio of trading volume to the number of shares outstanding), RET2-3, RET4-6, and RET7-12 (the cumulative returns over the past second through the past third, the past fourth through the past sixth, and the past seventh through the past twelfth months, respectively) and the default spread (z, the return differential between Baa and Aaa bonds rated by Moody's).

Table 1 reports the descriptive statistics of firm characteristics and the Fama-MacBeth coefficients from regressing the excess returns on firm characteristics. The mean excess return of all stocks in our sample is 0.84% per month. The average firm market capitalization is $1.44 billion and the average book-to-market ratio is 1.44. The average monthly turnover is 7.74%. The momentum profits range from 2.53% to 7.54%. Columns 5 and 6 show that the firm-level characteristics are associated with cross-sectional differences in average returns. Smaller firms and firms with lower turnover have higher excess returns. Also, firms with higher book-to-market ratio and firms with better past performance tend to yield higher excess returns. In summary, it provides confirmatory evidence of the existence of the size, value, liquidity, and momentum effect over the sample period.

[Insert Table 1 about here]

3.2 Returns, arbitrage costs, and firm characteristics across portfolios by sentiment sensitivities

We investigate arbitrage costs and firm characteristics and average returns across the portfolios sorted by their sensitivities to the shifts in the market-wide sentiment as proxied by the monthly orthogonalized sentiment index of Baker and Wurgler (2006) [6]. We first estimate the sentiment

[6] Baker and Wurgler (2006) first regress each of their six raw sentiment proxies (including NYSE turnover, closed-end fund discount, the number of IPOs, the first-day return on IPOs, the equity share in new issues and the dividend premium) on

betas of individual stocks on a monthly rolling basis and rank all the sample stocks each month in ascending order according to the sentiment beta estimates. We then sort the stocks into ten sentiment beta deciles, and form equally weighted portfolios. The overall pattern of the results indicates that the sensitivity of a stock to investor sentiment is strongly related to stock returns, arbitrage costs, and firm characteristics, and hence investor sentiment may play an important role in capturing the pricing anomalies.

Similar to Lee, Shleifer, and Thaler (1991), we use a two-factor model, with the monthly excess market return and the changes in the monthly investor sentiment index, to estimate sentiment sensitivities for each individual stocks. Our regression model is:

$$R_{it} - R_{ft} = \alpha_i + \beta_i^s \Delta SENT_t^{\perp} + \beta_i^m (R_{mt} - R_{ft}) + \varepsilon_{it} \tag{1}$$

where R_{it} and R_{ft} are, respectively, the return on stock *i* and the risk-free rate which we proxy by the 1-month treasury bill rate at month *t*, R_{mt} is the return on the CRSP value-weighted index at month *t*, and $\Delta SENT_t^{\perp}$ is the monthly changes in the orthogonalized investor sentiment index of Baker and Wurgler (2006).

We estimate the sentiment beta β_i^s for a stock *i* in (1) at each month *t* using the observations from months *t* through *t*-24, rolling one month forward. The use of estimation windows of 25 months is motivated by the finding of Brown and Cliff (2005) that high levels of sentiment result in lower market returns over the next 2 to 3 years (i.e., 24 to 36 months).

Stocks with negative sentiment betas, form the first portfolio whose sentiment sensitivities are smallest, 'Portfolio S'. We then equally split and order the rest of the stocks by the raw values of

macroeconomic variables (including the growth rate in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions). They then obtain the orthogonalized sentiment index as the first principal component of the regression residuals. The sentiment index data are available from Jeffrey Wurgler's website: http://pages.stern.nyu.edu/~jwurgler/.

the sentiment betas. The stocks with the largest sentiment sensitivities form 'Portfolio L'. Panel A in Table 2 reports the average returns and arbitrage costs across the 10 sentiment-beta portfolios. The average sentiment beta of the portfolios ranges from -2.11 to 10.11, indicating stock returns respond to the shifts in investor sentiment unequally. Some stocks are more responsive to investor sentiment than others. There are even some stocks whose prices move in an opposition to the market sentiment.

[Insert Table 2 about here]

The second raw reports the average returns of the portfolios and shows that high sentiment-beta portfolios tend to earn high stock returns. Investors holding the stocks with the largest sentiment-beta portfolio expect to earn higher returns (2.97%), in fact, more than doubled, than holding the smallest sentiment-beta portfolio (1.21%). The average return differential is 1.76% per month and statistically significant with a *t*-statistic of 2.49 between the portfolios with the largest and the smallest sentiment betas.

Motivated by Baker and Wurgler (2006) that stocks in the high sentiment-beta deciles are more difficult to value and harder to arbitrage than low sentiment-beta, we further examine whether stocks highly sensitive to sentiment exhibit larger transaction costs and hence such stocks face larger degree of limits-to-arbitrage. We use three measures of potential transaction costs: the stock price, price volatility, and institutional ownership.

The first measure is the stock price. The literature has documented that stock price is inversely related to transaction costs such as bid-ask spread, relative bid-ask spread and brokerage commission (Bhardwaj and Brooks (1992), Ball, Kothari, and Shanken (1995), and Stoll (2000)). The third raw reports the stock prices across the sentiment-beta portfolios. Figure 1 clearly shows a negative relation between price and sentiment beta: low price stocks are more sensitive to investor sentiment. This confirms the view that trading sentiment-prone stocks are costly.

The second measure is the monthly volatility of stock prices, measured by the difference between the highest daily price and the lowest daily price in each month. Since the magnitude of the price difference could be biased toward high-price stocks, we scale the price difference by the corresponding stock price at the end of each month. We use stock volatility to as a proxy for arbitrage risk: high volatility suggests higher arbitrage risk. The fourth raw in Panel A presents the price volatilities of the portfolios with different sentiment sensitivities. Figure 1 shows that volatility tends to increase as stock return becomes more sensitive to investor sentiment. From the perspective of arbitrageurs, the high sentiment beta stocks are those in which arbitrageurs would rather avoid taking positions to bet against noise traders because they are more risky and are more likely to be subject to the risk caused by the unpredictability of shifts in investor sentiment.

[Insert Figure 1 about here]

Results of price and price volatility in Panel A so far all indicate that high sentiment beta stocks should have lower percentage of outstanding shares held by institutional investors. The last raw in Panel A in Table 2 reports the institutional ownership for each individual sentiment-beta portfolio. Figure 1 clearly demonstrates that the institutional ownership monotonically decreases as the stocks become more sentiment prone. In other words, stock prices would be more sensitive to investor sentiment when stocks are disproportionally held by individual investors. This provides indirect evidence that individual investors are more likely to be the noise traders who trade on noise rather than information as opposed to institutional investors.

Lee, Shleifer, and Thaler (1991) claim that if different noise traders trade randomly across assets, the risk their sentiment creates would be diversifiable; however, if fluctuations in the noise trader sentiment affect many assets and are correlated across noise traders as shown in Kumar and Lee (2006), the risk that these fluctuations create cannot be diversified. Noise trader risk arising from the stochastic investor sentiment will therefore be priced in equilibrium. As a result, assets subject to noise trader risk earn higher expected returns than assets not subject to such risk. These assets will be underpriced relative to their fundamental values. Their findings point to the existence of nonfundamental risks, implying that stock returns may be attributable to movements in investor sentiment.

[Insert Figure 2 about here]

Panel B in Table 2 reports the firm characteristics across the portfolios formed by their sentiment sensitivities. The graphical relation between the firm characteristics and sentiment betas are illustrated in Figure 2. Several patterns are present. First, firm size decreases monotonically and sharply as the sentiment beta increases, indicating that small firms tend to be more responsive to the shifts in investor sentiment. Prior research has provided explanations for why smaller stocks may be more sentiment-prone than larger stocks. For example, Kumar and Lee (2006) show that smaller stocks and lower institutionally-owned firms are most sensitive to changes in retail investor sentiment because retail investors concentrate their holdings in small stocks and their trading activities are systematically correlated. Baker and Wurgler (2006) argue that small stocks are most sentiment-prone since they are difficult to value and hard to arbitrage.

Second, Figure 2 also shows that book-to-market ratio decreases monotonically with sentiment beta, i.e., growth stocks tend to have high sentiment betas and value stocks exhibit negative sentiment beta. This relation implies that investors increase their demand for growth stocks but decrease demand for value stocks when investors become more optimistic. It also explains why growth stocks are more likely to be overpriced and value stocks underpriced (Lakonishok, Shleifer, and Vishny (1994)).

Similar patterns are also present both in turnover, as measured by the ratio of monthly trading volume to number of shares outstanding, and momentum profits with various horizons. Specifically, stocks in the high sentiment-beta portfolios tend to yield higher turnover and earn larger momentum profits. In other words, high turnover stocks and stocks with larger momentum profits are more responsive to the shift in investor sentiment. Prior studies actually provide potential explanations for these observed patterns. Baker and Stein (2004), for example, develop a theoretical model in which both smart and dumb investors are present in the market. Their analysis shows that turnover increases with investor sentiment as more dumb investors dominate the market and smart investors are sitting on the sidelines. Datar, Naik, and Radcliffe (1998) show that high turnover firms earn lower future returns, while low turnover firms earn higher future returns. Lee and Swaminathan (2000) find this turnover effect to be most pronounced among the extreme winner and loser portfolios.

4. The market price of the sentiment factor

Before empirically assessing the capability of investor sentiment to explain the pricing anomalies, in this section we first investigate the role that investor sentiment may play as a prominent factor in determining the cross-section of stock returns. To this end, we construct a sentiment factor, *LMS*, and conduct the Fama-MacBeth test across individual stocks for the risk premium of the sentiment factor.

The *LMS* factor is the return differential between the decile portfolios with the highest and the lowest raw sentiment betas. We subtract the return on the equally weighted decile portfolio with the lowest sentiment beta from the return on the equally-weighted portfolio with the highest sentiment beta. The average returns on the LMS factor is 1.71% (*t*-statistic = 2.66), showing that the decile portfolio with the highest positive sentiment beta significantly outperforms the decile portfolio with lowest sentiment beta.

[Insert Table 3 about here]

We now empirically test whether the investor sentiment risk, i.e., the LMS beta, commands a premium using the widely adopted Fama-MacBeth procedure (see, e.g., Jagannathan and Wang (1996) for testing the conditional CAPM, Petkova (2006) for testing the intertemporal CAPM, and Pastor and Stambaugh (2003) for testing the liquidity risk, among many others). In the first stage, we estimate the LMS factor beta for each firm by running a time-series regression as in (2) of contemporaneous excess stock returns on the factor returns of the LMS and the market factor using estimation windows of 25 months rolling forward one month:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_{it}^{LMS} LMS_t + \beta_{it}^{MKT}(R_{mt} - R_{ft}) + \mu_{it} \quad (2)$$

In the second stage, we run a cross-sectional regression each month of excess stock returns on the estimates of the LMS and the market betas:

$$R_{it} - R_{ft} = \lambda_0 + \lambda_1 \widehat{\beta_{it}^{LMS}} + \lambda_2 \widehat{\beta_{it}^{MKT}} + e_{it} \quad (3)$$

We test whether the slope coefficient estimate of λ_1 on the LMS factor beta is statistically significant. If we cannot reject the null that the estimate of λ_1 is significantly different from zero, the result will indicate that the LMS factor commands a reward. A positive sign of this coefficient estimate indicates that the LMS factor has a positive risk premium, and that investors require higher expected returns as a compensation for bearing the exposure to the LMS factor.

Table 3 also presents the Fama-MacBeth estimates for the *LMS* factor. The coefficient estimate λ_1 is positive and statistically significant, while the market factor is statistically insignificant even at the 10% level. The λ_1 estimate is lower than the average *LMS* factor return reported earlier, consistent with the intuition that measurement errors in the *LMS* beta of individual stocks tend to downwardly bias the Fama-MacBeth estimate for the risk premium of the *LMS* beta.

Our finding supports the theoretical prediction of the noise trader model of De Long, Shleifer, Summers, and Waldmann (1990) and the empirical evidence of Lee, Shliefer, and Thaler (1991) and Brown and Cliff (2005) that stock prices could be affected not only by fundamental factors but also by the unpredicted movements in investor sentiment. This result also provides complementary evidence for the work of Lemmon and Portniaguina (2006) and Baker and Wurgler (2006) that investor sentiment exhibits cross-sectional effects on stock returns.

5. The conditional framework for testing the sentiment-augmented asset pricing models

In this section we explore whether incorporating the sentiment factor *LMS* into asset pricing models helps explain the asset-pricing anomalies. We assess the extent to which the unconditional and conditional versions of pricing models, without or with the *LMS* factor explain the anomalies.

We test whether adding the *LMS* factor to asset pricing models helps explain asset pricing anomalies using the two-pass framework of Avramov and Chordia (2006). The pricing specification of a *K*-factor model is:

$$E_{t-1}(R_{it}) \equiv R_{ft} + \sum_{k=1}^{K} \lambda_{kt-1}\beta_{ikt-1} \tag{4}$$

where $E_{t\text{-}1}$ is the conditional expectation operator, $\lambda_{kt\text{-}1}$ is the risk premium for factor k at time t – 1, and $\beta_{ikt\text{-}1}$ is the conditional beta of stock i on factor k. In addition to the factors that have been widely considered such as the excess market return and the Fama-French *SMB* and *SML* factors, we include the Pastor-Stambaugh liquidity factor, the momentum factor, and most importantly, the *LMS* factor to the model. The primary purpose in this test is to examine whether such a *K*-factor model can capture the impacts of firm characteristics on stock returns that traditional asset pricing models fail to explain.

In the first-pass, we estimate a time-series regression of an asset pricing model. The sum of the intercept estimate and the residual is the risk-adjusted return on stock i at time t, R^*_{it}:

$$R^*_{it} \equiv R_{it} - \left[R_{ft} + \beta(\theta; z_{t-1}, X_{it-1})' F_t\right] \tag{5}$$

where β is the vector of the conditional beta estimated from the first-pass time-series regression over the entire sample period. θ denotes the parameters that capture the dependence of β on macroeconomic variables z_{t-1}, and firm characteristics X_{it-1}. F_t denotes the vector of factors specified in the asset pricing model.

In the second-pass, we run a cross-sectional regression each month of the risk-adjusted individual stock return R_{it}^{*} on the variables of size, book-to-market ratio, liquidity, and prior returns as:

$$R_{it}^{*} = c_{0t} + c_t Z_{it-1} + e_{it} \tag{6}$$

where Z_{it-1} is the vector of the anomalies variables, and c_t denotes the vector of characteristics rewards. We test the null hypothesis that the slope coefficient c_t of an anomaly variable is zero and statistically insignificant. If the pricing model specified in the first-pass fails to adequately explain stock returns, the unexplained component of the return is then left in the risk-adjusted return. Consequently, the asset-pricing anomalies may show significant impacts on the cross-section of the risk-adjusted returns, leading to statistically significant characteristics rewards in the second-past test. A *low* adjusted *R* squared ($\bar{R}^2$) in the second-pass regression indicates that the anomalies do not explain a substantial part of the cross-section of the risk-adjusted returns. Thus, the *lower* is the $\bar{R}^2$ in the second-pass regression, the higher is the overall pricing performance of the asset pricing model specified in the first-pass regression.

We start with adding the constructed sentiment factor to the common factors to the first-pass regression and explore whether the impacts of the asset-pricing anomalies on the risk-adjusted stock returns in the second-pass regression are eliminated. The pricing models we assess include: (i) the CAPM-S model (the sentiment-augmented CAPM), (ii) the FF-S model (the sentiment-augmented Fama-French (1993) three-factor model), (iii) the FFP-S model (the sentiment-augmented Fama-French model plus the Pastor-Stambaugh's (2003) liquidity factor, (iv) the FFW-S model (the sentiment-augmented Fama-French model plus the momentum factor, and the (v) the FFPW-S model (the sentiment-augmented Fama-French model plus both the liquidity factor and the momentum factor). Finally, we also test its explanatory power for the pricing anomalies when the sentiment stands alone in the first-pass regression.

We first examine the unconditional version of each of the sentiment-augmented models. We then allow the factor loadings in the models to vary with firm-specific market capitalization and the book-to-market ratio as well as the default spread. This is motivated by the theory and empirical evidence that dynamic versions of pricing models provide better descriptions for stock returns than static models (e.g., Hansen and Richard (1987), and Gomes, Kogan, and Zhang (2003)). To illustrate the specification of the time-varying factor loadings, we use the most parsimonious asset pricing model we have considered – the *LMS* model – as an example. The specification of the conditional sentiment beta of security *i*, β_i, is

$$\beta_{it-1} = \beta_{i1} + \beta_{i2} z_{t-1} + (\beta_{i3} + \beta_{i4} z_{t-1}) SIZE_{it-1} + (\beta_{i5} + \beta_{i6} z_{t-1}) B/M_{it-1} \tag{7}$$

where $SIZE_{it-1}$ and B/M_{it-1} denote, respectively, the market capitalization and the book-to-market ratio of firm *i* at time $t-1$. We use the default spread, *def*, as the macroeconomic variable, z_{t-1}. The specifications of the conditional betas depend on the conditioning variables. For example, an unconditional model emerges when all βs in (7) are restricted to be zero except for β_{i1}. One can arrive at three conditional specifications by considering the beta in (7) to be a function of different conditioning variables:

Specification A: function of (SIZE + B/M) (i.e., $\beta_{i2} = \beta_{i4} = \beta_{i6} = 0$)

Specification B: function of *def* (i.e., $\beta_{i3} = \beta_{i4} = \beta_{i5} = \beta_{i6} = 0$)

Specification C: function of (SIZE + B/M)*def* (i.e., all $\beta s \neq 0$) (8)

Using the most comprehensive version, specification C, we can form a conditional *LMS* model in the first-pass time-series regression as:

$$r_{it} = \alpha_i + \beta_{i1} SMN_t + \beta_{i2} z_{t-1} SMN_t + \beta_{i3} SIZE_{it-1} SMN_t$$
$$+\beta_{i4} z_{t-1} SIZE_{it-1} SMN_t + \beta_{i5} B/M_{it-1} SMN_t + \beta_{i6} z_{t-1} B/M_{it-1} SMN_t + u_{it} \quad (9)$$

where $r_{it} = R_{it} - R_{ft}$ and LMS denotes the sentiment factor. The macroeconomic variable, z_{t-1}, and the firm characteristics – SIZE and B/M – are all lagged one period as compared to the individual excess stock return and the sentiment factor. We run the time-series regression of (9) over the entire sample period, and obtain the estimated risk-adjusted return on stock *i* at time *t* in (5), R_{it}^*, by summing the intercept and the residual (i.e., $R_{it}^* = \alpha_i + u_{it}$). We then run the cross-sectional regression of the estimated risk-adjusted returns on the variables of asset-pricing anomalies.

The models specified in the time-series regression are deemed to have better pricing ability than others if the significance of the coefficient estimates in the cross-sectional regressions of risk-adjusted returns on size, book-to-market, turnover, and prior returns drops considerably. The asset pricing anomalies under consideration are deemed to be captured if the corresponding coefficient estimates are statistically insignificant.

6. Sentiment-augmented models and asset pricing anomalies

6.1 Sentiment-augmented unconditional asset pricing models

We fist examine the pricing abilities of each of the unconditional asset pricing models specified in the first-pass time-series regression. We then add the *LMS* factor to each of the unconditional models to test whether the sentiment-augmented models are able to capture the anomalies. Table 4 reports the Fama-MacBeth coefficient estimates from running cross-sectional regressions of monthly risk-adjusted returns of individual stocks on the anomaly variables. Panel A shows the results for the unconditional versions of the models with the common risk factors. As shown in each of the columns 1 through 5, all standard asset pricing models without the *LMS* factor show statistically significant coefficients on all the anomaly variables, indicating that they fail to capture these anomalies.

[Insert Table 4 about here]

Panel B incorporates the *LMS* factor to the factors discussed in Panel A to explore whether the *LMS* factor can improve the capability of the model to explain the anomalies. Adding *LMS* to the standard asset pricing models makes a difference in terms of capturing the size effect. We find that the significance of the coefficient estimate for SIZE is greatly reduced when *LMS* is present in a model. The *t*-statistic for SIZE under the unconditional CAPM is -2.72 but it notably drops to -1.66 in absolute terms under the sentiment-augmented CAPM. The efficacy of the sentiment-augmented model in explaining the size effect is also profoundly evident in the FF-based models. For example, the *t*-statistics for SIZE under the standard FF, FFP, and FFPW are -3.12, -3.00, and -2.99, respectively. When *LMS* is added to the standard FF, FFP, and FFPW, the *t*-statistics for SIZE drop considerably in absolute terms to -2.06, -1.97, and -1.92, respectively, indicating that the impact of firm size on the risk-adjusted return has been reduced. The most right-hand column in Panel B shows results from using only the *LMS* factor. Strikingly, using the *LMS* as the single factor the SIZE variable shows no statistical significance.

Overall, our findings that the *LMS* factor can capture the size effect provide additional support for the view that smaller stocks exhibit higher noise trader risk because they are more sensitive to changes in investor sentiment and stock returns may be attributable to movements in investor sentiment. In the following sections, we investigate whether time-varying models with *LMS* can also explain the other anomalies in addition to the size effect.

a. Sentiment-augmented conditional CAPM (*Conditional SCAPM*)

We now consider the pricing ability of a two-factor model that consists of the *LMS* and excess market return. Table 5 reports that, similar to the results in the first column in Panel B of Table 4 for the unconditional *LMS*-augmented CAPM, the c*onditional SCAPM* captures the size effect conditional on either (SIZE+B/M) or (SIZE+B/M)def. Allowing betas to vary over time, however, does not help explain the value or momentum effects.

[Insert Table 5 about here]

b. Sentiment-augmented conditional Fama-French three-factor model (*Conditional SFF*)

Table 6 presents the estimates of coefficients on the anomaly variables when in the first–pass regression the risk-adjusted return is estimated based on the conditional *LMS*-augmented Fama-French 3-factor model. Again, the SIZE variable does not exert any significant impact on the cross-section of risk-adjusted returns when using the conditioning information set of either (SIZE+B/M) or (SIZE+B/M)def. Apart from capturing the size effect, the conditional SFF models are able to successfully capture the value effect, and reduce the impact of the short-term momentum effect RET2-3. In terms of capturing the value effect the third row shows that when the factors are scaled by (SIZE+B/M)def, the coefficient estimate on book-to-market ratio is no longer significant.

[Insert Table 7 about here]

c. Sentiment-augmented conditional Fama-French three-factor model plus the Pastor-

Stambaugh liquidity factor (*Conditional SFFP*)

Pastor and Stambaugh (2003) find that the stocks with high sensitivities to liquidity, on average, earn higher returns than those with low sensitivities to liquidity. In this section, we examine whether adding the Pastor-Stambaugh (2003) liquidity factor to the conditional LMS-augmented FF model helps eliminate the liquidity effect[7]. The results in Table 7, however, do not indicate the ability of this model in capturing the impact of turnover on the cross-section of individual stock returns. The overall results presented here are very similar to those in Table 6. Once the conditional forms of the *LMS*-augmented FF model has been considered in the first-pass regression, the Pastor-Stambaugh liquidity factor does not help capture the impact of the anomalies.

[Insert Table 7 about here]

d. Sentiment-augmented conditional Fama-French three-factor model plus a momentum factor (*Conditional SFFW*)

We now ask whether adding a momentum factor to the *LMS*-augmented FF models helps capture the impact of prior returns on the cross-section of stock returns. Following Avramov and Chordia (2006), we use the momentum factor obtained from Ken French's website that reflects the momentum strategy of buying winners and selling losers as depicted by Jegadeesh and Titman (1993). The results in Table 8 show that the conditional SFFW models have the ability to capture the impact of the short-term prior returns when betas are scaled by the default spread. However, the conditional SFFW models have no power to capture the liquidity effect. Also, the coefficient

[7] We thank Lubos Pastor for providing data of this factor.

estimates on *RET4-6* and *RET7-12* are always statistically significant in all the time-varying beta specifications.

[Insert Table 8 about here]

e. The comprehensive sentiment-augmented conditional models (*Conditional SFFPW*)

The results of SFFP and SFFW models indicate that adding either a liquidity factor or a momentum factor does not necessarily enhance the pricing ability of the sentiment-augmented Fama-French conditional models. In this section, we ask whether adding both the liquidity and momentum factors in the *LMS*-augmented FF model would improve the model's explanatory power for the asset-pricing anomalies.

The results in Table 9 for the conditional SFFPW models do not indicate much superior performance in capturing the market anomalies, compared to the results of the more parsimonious conditional SFF models. Overall, these findings clearly indicate that the sentiment-augmented conditional models that contain most of the risk factors do not necessarily enhance the ability in explaining the anomalies. Adding a liquidity factor or a momentum factor to the sentiment-augmented Fama-French models does not increase the number of anomalies captured.

[Insert Table 9 about here]

We find two important observations when comparing the results of our conditional models with those of the models analyzed by Avarmove and Chorida (2006) that do not include the sentiment factor. Our evidence in Tables 6, 7, 8 and 9 suggests that the model incorporating *LMS* and the FF factors exhibits certain degree of explanatory power for the short-term momentum effect (RET2-3) which Avarmov and Chordia (2006) fail to explain using their models. On the other hand, our sentiment-augmented models (Tables 6, 7, 8, and 9) explain the value effect mainly when the factor loadings are conditional on either (SIZE+B/M) or (SIZE+B/M)def. The models of Avramov and Chordia (2006) fail to capture the value effect only when the factor loadings are scaled by the default spread.

f. Conditional LMS-alone models

We test to what extent the *LMS* factor *alone* explains the pricing anomalies. Strikingly, using the *LMS* as the single factor the SIZE variable shows no statistical significance. Table 10 reports the results of the coefficient estimates when there is only one factor – *LMS* – in the pricing model. Interestingly, we find that firm size no longer has impacts on the cross-section of stock returns under the conditional *LMS*-alone model when the factor loading is conditional on any of the three sets of the conditioning variables. In other words, the SIZE variable ceases to exert its cross-sectional impact on risk-adjusted returns when the model in the first-pass regression incorporates the *LMS* factor alone.

[Insert Table 10 about here]

7. Conclusions

We examine whether an investor sentiment factor helps explain the cross-section of stock returns, and hence diminishes the cross-sectional effect of asset-pricing anomalies. We first show evidence of strong cross-sectional patterns in the relations between the sensitivities of individual stocks to investor sentiment, stock returns, costs of arbitrage (proxied by price, volatility and institutional owenership), and firm characteristics including firm size, turnover ratio, short-term past return and book-to-market equity ratio. These patterns suggest that the sensitivity to investor sentiment influences the cross-section of stock returns, and may have the potential in explaining the asset pricing anomalies.

We construct a sentiment factor *LMS*. The average returns on these four *LMS* factor measures is 1.7% per month, both economically and statistically significant. We further test the market price of the *LMS* factor beta is statistically significant and positive. Finally, we extend the framework of Avramov and Chordia (2006) to test whether incorporating a sentiment factor into different specifications of asset pricing models captures the expected stock return, and hence reducing the impacts of asset pricing anomalies upon the cross-section of stock returns. Our evidence shows that the impact of firm size on the cross-section of individual stock returns is no longer significant when the sentiment factor *LMS* is present in the asset pricing models. The models incorporating the *LMS* factor always capture the size effect for the NYSE, AMEX and NASDAQ stocks even when the model is unconditional. Furthermore, the conditional versions of the *LMS*-augmented Fama-French based models often capture the value effects. The momentum effect is sharply reduced when the factor loadings are conditional on the default spread in the sentiment-augmented models that contain the momentum factor. This paper shows that an investor sentiment factor is important in the cross-section of expected stock return, and the incorporation of this sentiment factor helps capture the impacts of asset pricing anomalies.

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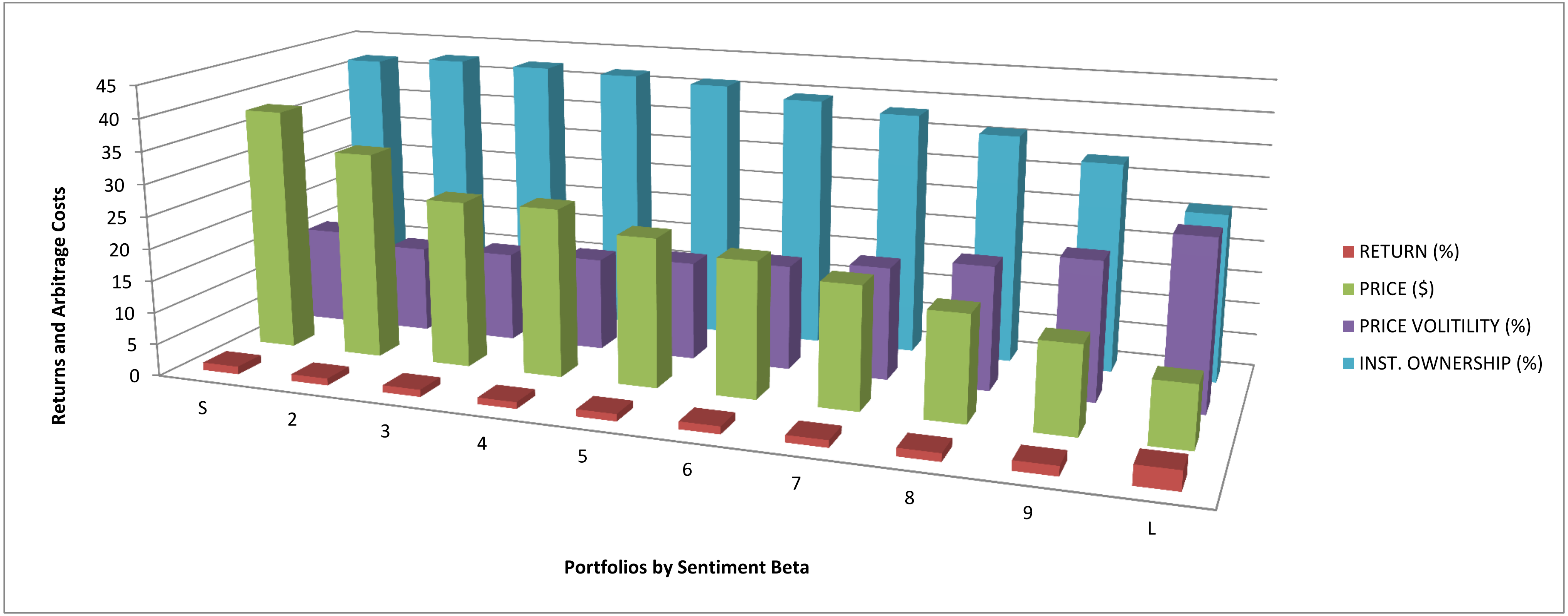

Figure 1: Firm characteristics of decile portfolios sorted by the *raw value* of sentiment beta

The figures depict the firm characteristics of each sentiment beta stock portfolio. Each month stocks are grouped into 10 deciles on the basis of the raw value of the investor sentiment beta coefficient. 'L' denotes the lowest sentiment beta decile. 'H' denotes the highest sentiment beta decile. The value of the sentiment beta for each stock group is depicted in the upper-left graph, followed by firm characteristics such as return, size, B/M, turnover, and various measures of the past performance of stock. Specifically, 'Return' represents the monthly average portfolio return; 'Size' represents the market capitalization in billions of dollars; 'B/M' is the book-to-market ratio of equity; 'Turnover' is the monthly trading volume of shares divided by shares outstanding. Ret2-3, Ret4-6, and Ret7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively.

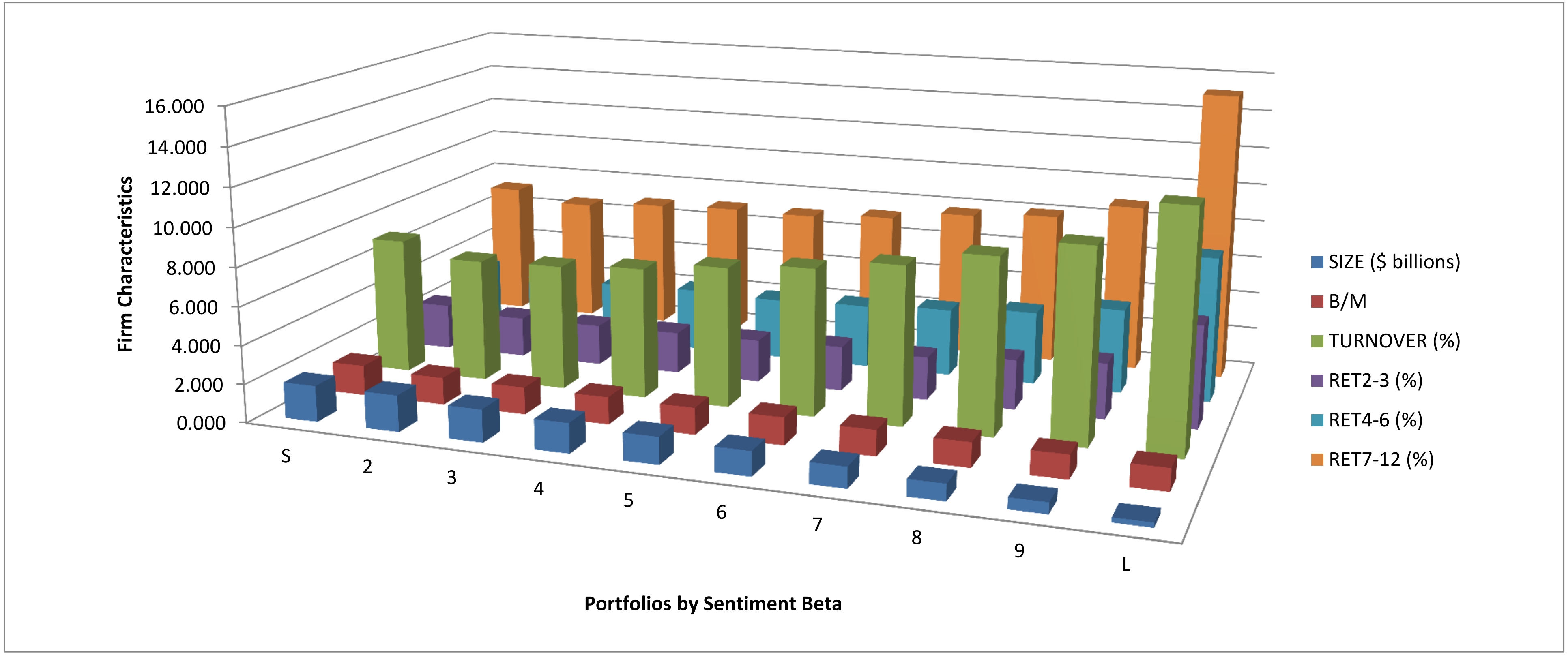

Figure 2: Firm characteristics of quintile portfolios sorted by the *absolute value* of sentiment beta

The figures depict the firm characteristics of each sentiment beta stock portfolio. Each month stocks are grouped into 5 quintiles on the basis of the absolute value of the investor sentiment beta coefficient. 'Lowest' denotes the quintile that are least affected by the shift in investor sentiment. 'Highest' denotes the quintile that is most investor sentiment-prone. The value of the sentiment beta for each stock group is depicted in the upper-left graph, followed by firm characteristics such as return, size, B/M, turnover, and various measures of the past performance of stock. Specifically, 'Return' represents the monthly average portfolio return; 'Size' represents the market capitalization in billions of dollars; 'B/M' is the book-to-market ratio of equity; 'Turnover' is the monthly trading volume of shares divided by shares outstanding. Ret2-3, Ret4-6, and Ret7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively.

Table 1: Summary statistics of firm characteristics and test of anomalies

	Mean	Median	Std	Coeff. (%)	t -statistic
EXCESS RETS (%)	0.844	1.077	5.739		
SIZE ($ billions)	1.442	0.803	1.262	-0.121	-2.84
B/M	1.443	1.383	0.431	0.201	4.28
TURNOVER (%)	7.738	5.830	5.642	-0.088	-1.58
RET2-3 (%)	2.528	2.709	8.846	0.629	2.38
RET4-6 (%)	3.661	3.497	11.196	0.615	2.59
RET7-12 (%)	7.544	7.246	16.603	0.710	4.98
$\overline{R}^2$ (%)	4.686				

This table presents the time-series averages of the cross-sectional means and standard deviations for 10,820 NYSE-AMEX-NASDAQ stocks from August 1965 through December 2010. The column labeled with "Coefficient" represents the time-series averages of the slop coefficients from the cross-sectional OLS regressions of excess return on the firm characteristics. The t-values for the slop coefficients of the characteristics are in the last column. $\overline{R}^2$ denotes the adjusted R squared. SIZE represents the market capitalization in billions of dollars. B/M is the book-to-market ratio of equity. TURNOVER is the monthly trading volume of shares divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. A common stock must meet the following criteria in order to be included in the analysis: (i) the returns of the stock must be available in the current month, t, and over the past 36 months in the CRSP, (ii) stock prices and shares outstanding for calculating the size of a firm and the month t – 2 trading volume for calculating turnover must be available, (iii) the B/M as of December of the previous calendar year has to be available from the COMPUSTAT dataset, (iv) the B/M must be positive, and (v) the B/M values greater than the 0.995 fractile or less than the 0.005 fractile are set to be the 0.995 and 0.005 fractile values, respectively.

Table 2: Arbitrage costs and firm characteristics across sentiment portfolios

Panel A: Returns and Arbitrage Costs										
Sentiment Beta Deciles	S	2	3	4	5	6	7	8	9	L
SENTIMENT BETA (%)	-2.110	0.215	0.649	1.116	1.638	2.256	3.020	4.049	5.642	10.105
RETURN (%)	1.212	1.070	1.115	1.037	1.107	1.184	1.117	1.248	1.498	2.972
PRICE ($)	38.135	32.434	26.111	26.323	23.212	21.148	19.063	16.407	13.623	9.647
PRICE VOLITILITY (%)	15.194	13.609	14.045	14.585	15.435	16.370	17.578	19.260	21.593	26.421
INST. OWNERSHIP (%)	41.660	42.477	42.144	41.682	40.953	39.414	38.105	35.890	32.668	26.147

Panel B: Firm Characteristics										
Sentiment Beta Deciles	S	2	3	4	5	6	7	8	9	L
SIZE ($ billions)	1.874	1.894	1.696	1.548	1.403	1.262	1.073	0.847	0.571	0.248
B/M	1.585	1.430	1.419	1.418	1.392	1.428	1.338	1.282	1.235	1.157
TURNOVER (%)	7.171	6.455	6.580	6.862	7.333	7.703	8.274	9.130	10.044	12.310
RET2-3 (%)	2.424	2.137	2.154	2.209	2.249	2.365	2.276	2.625	2.926	5.354
RET4-6 (%)	3.487	3.243	3.250	3.343	3.244	3.362	3.579	3.875	4.465	7.637
RET7-12 (%)	7.178	6.595	6.901	7.047	7.009	7.260	7.764	8.047	8.910	15.171

This table presents the monthly averages of the firm characteristics of stock portfolios by the raw value of the sentiment beta in Panel A and by the absolute value of the sentiment beta in Panel B. For each firm, using 25-month rolling windows, we regress the excess return on the monthly changes in investor sentiment controlled for the excess market return. Firms are then grouped into 10 stock portfolios by the coefficient on the changes in investor sentiment (i.e., the sentiment beta) in each month. RETS denotes the average return on the sentiment beta portfolio. The rest of the variables reported are the same as those reported in Table 1.

Table 3: Fama-MacBeth regression

	Coefficient	t-statistic	p -value
α_i	0.004	3.19	0.002
β_i^s	0.014*	1.70	0.089
β_i^m	0.003	1.42	0.156
$\overline{R}^2$ (%)	12.90		

This table presents the monthly average of the LMS factor and the Fama-MacBeth (1973) estimated coefficients of the cross-sectional regression of firm-specific excess returns on the estimated beta for the LMS factor controlled for the market beta. Specifically, we run the following regression.

$$R_{it} - R_{ft} = \lambda_0 + \lambda_1 \widehat{\beta_{it}^{LMS}} + \lambda_2 \widehat{\beta_{it}^{MKT}} + e_{it}$$

The regression model is estimated using 25-month rolling windows. ***, **, * indicate significant at the level of 1%, 5%, and 10%, respectively. *LMSPlus* denotes the investor sentiment factor constructed using the returns differential between the stock portfolio of the highest *positive* sentiment beta (decile 10) and the stock portfolio of the lowest *positive* sentiment beta (decile 6). *LMSMinus* denotes the investor sentiment factor constructed using the returns differential between the stock portfolio of the most *negative* sentiment beta (decile 1) and the stock portfolio of the least *negative* sentiment beta (decile 5). *LMSMinus* denotes the investor sentiment factor is constructed by taking the average of *LMSPlus* and *LMSMinus* (i.e., 0.5(*LMSPlus* + *LMSMinus*)). *LMSAbs* denotes the investor sentiment factor constructed using the returns differential between the stock portfolio with the largest *absolute value* in sentiment beta (quintile 5) and the stock portfolio the smallest *absolute value* in sentiment beta (quintile 1). The LMS factors reported in Tables 3 – 9 adopt the same definitions.

Table 4: Fama-MacBeth regression estimates for unconditional models

Panel A: Traditional Models

Coefficients	CAPM	FF	FFP	FFW	FFPW
Intercept	0.447	0.180	0.176	0.282	0.276
	(3.66)	(2.68)	(2.61)	(4.60)	(4.52)
SIZE	-0.113	-0.086	-0.082	0.085	-0.081
	(-2.72)	(-3.12)	(-3.00)	(-3.12)	(-2.99)
B/M	0.207	0.134	0.134	0.134	0.135
	(4.72)	(4.22)	(4.24)	(4.25)	(4.30)
TURNOVER	-0.139	-0.108	-0.112	-0.079	-0.083
	(-3.48)	(-3.48)	(-3.62)	(-2.58)	(-2.72)
RET2-3	0.670	0.540	0.545	0.534)	0.536
	(2.84)	(2.52)	(2.55)	2.65)	(2.67)
RET4-6	0.636	0.624	0.609	0.626	0.612
	(3.09)	(3.45)	(3.34)	(3.77)	(3.65)
RET7-12	0.756	0.627	0.639	0.630	0.643
	(6.13)	(5.49)	(5.64)	(5.89)	(6.04)
$\bar{R}^2$ (%)	3.74	2.19	2.20	2.12	2.12

Panel B: Sentiment-Augumented Models

Coefficients	CAPM-S	FF-S	FFP-S	FFW-S	FFPW-S	S
Intercept	0.332	0.134	0.128	0.241	0.234	0.628
	(3.07)	(2.10)	(2.01)	(4.09)	(3.99)	(2.70)
SIZE	**-0.054**	-0.051	**-0.049**	-0.051	**-0.047**	**-0.051**
	(-1.66)	(-2.06)	(-1.97)	(-2.05)	(-1.92)	(-1.55)
B/M	0.229	0.154	0.154	0.155	0.156	0.230
	(5.70)	(4.97)	(4.96)	(5.04)	(5.09)	(5.40)
TURNOVER	-0.170	-0.132	-0.136	-0.104	-0.108	-0.140
	(-4.95)	(-4.38)	(-4.53)	(-3.52)	(-3.68)	(-2.90)
RET2-3	0.734	0.592	0.553	0.556	0.549	0.670
	(3.28)	(2.65)	(2.62)	(2.78)	(2.76)	(2.72)
RET4-6	0.703	0.639	0.629	0.630	0.621	0.694
	(3.73)	(3.69)	(3.60)	(3.91)	(3.81)	(3.30)
RET7-12	0.760	0.654	0.662	0.651	0.659	0.729
	(6.27)	(5.92)	(6.03)	(6.20)	(6.31)	(5.35)
$\bar{R}^2$ (%)	3.10	2.10	2.11	2.02	2.03	3.84

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The sentiment-augmented models specified in the first-pass regressions are constructed by adding the LMS factor to the various traditional pricing models, for example, SCAPM denotes the sentiment-augmented CAPM. The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.

Table 5: Conditional CAPM-S in the first-pass

Conditioning variables	Intercept	SIZE	B/M	TURNOVER	RET2-3	RET4-6	RET7-12	$\bar{R}^2$ (%)
Size+B/M	0.303	**-0.038**	0.184	-0.169	0.942	0.809	0.853	2.88
	(3.04)	(-1.23)	(4.97)	(-5.42)	(4.61)	(4.81)	(7.48)	
Def	0.364	**-0.061**	0.223	-0.161	0.724	0.737	0.759	3.04
	(3.48)	(-1.92)	(5.70)	(-4.87)	(3.28)	(4.20)	(6.46)	
(Size+B/M)Def	0.337	**-0.043**	0.159	-0.162	1.054	0.851	0.858	2.82
	(3.58)	(-1.50)	(4.58)	(-5.53)	(5.22)	(5.24)	(8.17)	

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The betas in the first-pass regression with a single LMS factor are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (Def). The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.

Table 6: Conditional FF-S in the first-pass

Conditioning variables	Intercept	SIZE	B/M	TURNOVER	RET2-3	RET4-6	RET7-12	$\overline{R}^2$ (%)
Size+B/M	0.122	**-0.030**	0.064	-0.122	0.742	0.861	0.765	1.90
	(2.35)	(-1.36)	(2.50)	(-4.57)	(3.73)	(5.55)	(7.57)	
Def	0.135	**-0.048**	0.134	-0.124	**0.396**	0.680	0.631	2.05
	(2.24)	(-2.00)	(4.53)	(-4.25)	(1.90)	(4.21)	(6.04)	
(Size+B/M)Def	0.125	**-0.030**	**0.002**	-0.106	0.680	0.859	0.746	1.89
	(2.57)	(-1.52)	(0.08)	(-4.50)	(3.46)	(5.84)	(8.27)	

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The betas of the sentiment-augmented CAPM model in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (Def). The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.

Table 7: Conditional FFP-S in the first-pass

Conditioning variables	Intercept	SIZE	B/M	TURNOVER	RET2-3	RET4-6	RET7-12	$\overline{R}^2$ (%)
Size+B/M	0.105	**-0.022**	0.057	-0.122	0.774	0.87	0.788	1.92
	(2.03)	(-1.02)	(2.26)	(-4.67)	(3.96)	(5.56)	(7.91)	
Def	0.126	**-0.043**	0.133	-0.126	**0.399**	0.675	0.625	2.06
	(2.12)	(-1.79)	(4.54)	(-4.39)	(1.91)	(4.22)	(6.02)	
(Size+B/M)Def	0.102	**-0.021**	**-0.015**	-0.091	0.733	0.871	0.737	1.82
	(2.12)	(-1.09)	(-0.65)	(-4.03)	(3.82)	(6.03)	(8.24)	

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The betas of the sentiment-augmented Fama-French model in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (Def). The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.

Table 8: Conditional FFW-S in the first-pass

Conditioning variables	Intercept	SIZE	B/M	TURNOVER	RET2-3	RET4-6	RET7-12	$\overline{R}^2$ (%)
Size+B/M	0.157	**-0.020**	0.089	-0.105	0.742	0.831	0.739	1.79
	(3.66)	(-0.90)	(3.55)	(-4.08)	(3.94)	(5.80)	(7.96)	
Def	0.23	**-0.046**	0.131	-0.102	**0.364**	0.611	0.624	1.96
	(4.10)	(-1.96)	(4.46)	(-3.59)	(1.86)	(4.09)	(6.37)	
(Size+B/M)Def	0.182	**-0.009**	**0.033**	-0.089	0.615	0.752	0.688	1.77
	(3.83)	(-0.46)	(1.44)	(-4.02)	(3.24)	(5.47)	(8.30)	

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The betas of the sentiment-augmented Fama-French-liquidity model in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (Def). The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.

Table 9: Conditional FFPW-S in the first-pass

Conditioning variables	Intercept	SIZE	B/M	TURNOVER	RET2-3	RET4-6	RET7-12	$\overline{R}^2$ (%)
Size+B/M	0.165	**-0.013**	0.091	-0.108	0.781	0.853	0.788	1.78
	(3.22)	(-0.60)	(3.69)	(-4.32)	(4.22)	(5.90)	(8.61)	
Def	0.220	**-0.041**	0.128	-0.102	**0.379**	0.598	0.617	1.97
	(3.96)	(-1.76)	(4.41)	(-3.67)	(1.93)	(4.02)	(6.32)	
(Size+B/M)Def	0.153	**-0.024**	**-0.010**	-0.124	0.769	0.824	0.741	1.40
	(3.17)	(-1.27)	(-0.44)	(-5.38)	(3.83)	(5.31)	(8.18)	

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The betas of the sentiment-augmented Fama-French-momentum model in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (Def). The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.

Table 10: Conditional S in the first-pass

Conditioning variables	Intercept	SIZE	B/M	TURNOVER	RET2-3	RET4-6	RET7-12	$\bar{R}^2$ (%)
Size+B/M	0.596	**-0.139**	0.198	-0.138	0.789	0.772	0.794	3.75
	(2.61)	(-1.21)	(4.86)	(-2.95)	(3.30)	(4.01)	(5.94)	
Def	0.607	**-0.050**	0.218	-0.140	0.659	0.723	0.721	3.89
	(2.65)	(-1.52)	(5.22)	(-2.94)	(2.61)	(3.66)	(5.39)	
(Size+B/M)Def	0.599	**-0.039**	0.181	-0.134	0.844	0.835	0.766	3.79
	(2.71)	(-1.27)	(4.61)	(-2.92)	(3.54)	(4.51)	(6.06)	

This table presents the averages of the coefficient estimates from the second-pass OLS cross-sectional regressions for the NYSE-AMEX-NASDAQ individual stocks for the period of 1965-2010. The risk-adjusted excess return is cross-sectionally regressed on the anomalies. The betas of the sentiment-augmented Fama-French-liquidity-momentum model in the first-pass regression are time-varying with the market capitalization of equity (Size), book-to-market ratio (B/M), and the default spread (Def). The *t*-statistics are reported in parenthesis. All coefficient estimates are multiplied by 100.