Investor Sentiment and the Pricing of Characteristics-Based Factors

by*

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Abstract

Using portfolios that are formed by directly sorting stocks based on their exposure to characteristics-based factors, earlier studies find that these beta-sorted portfolios have very large ex post factor beta spreads. However, the return spreads between high- and low-beta firms are typically tiny and insignificant. This study examines the time variation in the pricing of a large set of characteristics-based factors. Our evidence shows a striking two-regime pattern for most of the factor-beta-sorted portfolios: high-beta portfolios earn significantly higher returns than low-beta portfolios following high-sentiment periods, whereas the exact opposite occurs following low-sentiment periods. Remarkably, this two-regime pattern is completely reversed when macro-related factors, such as consumption growth and TFP growth, are used. The evidence based on mutual fund and hedge fund returns also confirms this two-regime pattern. Our findings suggest that the exposure to most of these characteristics-based factors is likely to be a proxy for the level of mispricing, rather than risk, especially during high-sentiment periods.

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1 Introduction

Recent studies have proposed several prominent characteristics-based factors that can parsimoniously account for many asset pricing anomalies simultaneously.[1] Typically, the testing portfolios in these studies are a set of portfolios based on anomalies. The studies show that most asset pricing anomalies have insignificant alphas after adjusting for exposure to these new factors. However, Chen et al. (2020) and Daniel et al. (2019) find that when portfolios formed by directly sorting stocks based on their exposure to these factors are used as testing portfolios, these characteristics-based factors are not priced. In fact, Chen et al. (2020) show that for the 13 prominent factors they consider in their paper, the average monthly return spread between high- and low-beta firms is close to zero at 0.01%.

In this paper, we explore the role of investor sentiment in the pricing of these factors and shed light on the weak pricing results when beta-sorted portfolios are used in testing these factor models. Whether and how investor sentiment affects stock prices has been a question of long-standing interest to economists. Investor sentiment does not play a role in asset prices in standard rational models. However, researchers in behavioral finance suggest that noise trader sentiment can persist in financial markets and affect asset prices because of limits to arbitrage (e.g., Delong et al. 1990 and Shleifer and Vishny (1997)). This paper explores how sentiment affects the return spreads of these factor-beta-sorted portfolios and casts lights on the underlying forces for these characteristics-based factors.

Indeed, there are still debates about the underlying interpretation of these prominent factors. For example, motivated by valuation model and q-theory, Fama and French (2015) and Hou, Xue, and Zhang (2015) argue that these factors might be capturing systematic risks. On the other hand, Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2019) label their factors as mispricing factors or behavioral factors, suggesting that their factors capture systematic mispricing. Indeed, Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2019) argue that the exposure to these factors could be a proxy for the level of mispricing; that is, firms with higher (lower) beta are more underpriced (overpriced). If these factors are indeed genuine risk-based factors, following the argument in Shen, Yu, and Zhao (2017), one should expect the return spread between high- and low-beta portfolios to be larger following low-sentiment periods. On the other hand, if these factors are indeed

[1] A partial list for these factors includes the Fama-French five factors (Fama and French (2015)), the Hou-Xue-Zhang four factors (Hou, Xue, and Zhang (2015)), the gross profitability factor (Novy-Marx (2013)), the quatlity-minu-junk factor (Asness, Frazzini, and Pedersen (2019)), the mispricing factors (Stambaugh and Yuan (2017)), and the short- and long-run behavioral factors (Daniel, Hirshleifer, and Sun (2019)).

due to systematic mispricing, and the factor exposure is a proxy for the level of underpricing, then, following the argument in Stambaugh, Yu, and Yuan (2012), one should expect the return spread between high- and low-beta portfolios to be larger following high-sentiment periods.

To see why the above statement holds, one needs to combine two prominent concepts in the literature. The first concept is that time-varying market-wide investor sentiment could affect prices on many securities in the same direction at the same time.[2] The second concept is that short-sale impediments can limit the ability of rational traders to exploit overpricing.[3] These two concepts, taken together, indicate that there are potentially many overpriced assets during high-sentiment periods since rational investors are relatively pessimistic during this time and stay out of the market because of short-sale impediments. On the other hand, asset prices should be close to their fundamental value during low-sentiment periods since underpricing can be counterveiled by arbitrageurs and pessimists tend to stay out of the market because of short-sale impediments. In other words, when sentiment is high, market participants are more likely to be irrational since rational investors are relatively pessimistic and stay out of the market because of short-sale impediments. On the other hand, when market sentiment is low, market participants are closer to being rational since irrational investors are relatively pessimistic and stay out of the market, again, because of short-sale impediments.

Thus, if these factors are risk factors and factor beta is a proxy for risk exposure, then during low-sentiment periods when investors are relatively more rational and care more about genuine risk, the beta-return relation should be stronger. However, during high-sentiment periods, the beta-return relation could be weaker since the market has relatively more irrational investors. On the other hand, if a factor is due to systematic mispricing,

[2]Studies addressing market-wide sentiment include, among others, De Long et al. (1990), Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Vishny (1998), Brown and Cliff (2004, 2005), Baker and Wurgler (2006, 2007, 2012), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), Frazzini and Lamont (2008), Kaniel, Saar, and Titman (2008), Livnat and Petrovits (2019), Antoniou, Doukas, and Subrahmanyam (2013, 2016), Hwang (2011), Baker, Wurgler, and Yuan (2012), Yu and Yuan (2011), Stambaugh, Yu, and Yuan (2012), Chung, Hung, and Yeh (2012), Yu (2013), Huang et al. (2015), Sibley et al. (2016), Huang et al. (2018), Chen et al. (2019), Gao, Ren, and Zhang (2019), Guo et al. (2019), and Jiang et al. (2019).

[3]Notable papers exploring the role of short-sale constraints in asset prices include Figlewski (1981), Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), Duffie, Gârleanu, and Pedersen (2002), Jones and Lamont (2002), Hong and Stein (2003), Scheinkman and Xiong (2003), Lamont and Stein (2004), Ofek, Richardson, and Whitelaw (2004), Nagel (2005), Grundy, Lim, and Verwijmeren (2012), Boehmer, Jones, and Zhang (2013), Jiao, Massa, and Zhang (2016), Chen, Da, and Huang (2019), and Chu, Hirshleifer, and Ma (2019).

as argued in Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2019), the factor beta could be a noisy proxy for the level of underpricing. In addition, there are more mispriced securities during high sentiment periods than during low sentiment periods. Thus, a strategy that takes advantage of mispricing should yield higher returns following high-sentiment periods than during low-sentiment periods. Thus, the return spread between high- and low-beta portfolios should be larger following high-sentiment periods than following low-sentiment periods. This is because during high-sentiment periods, market participants are more irrational and there are more overpriced assets. These concepts, taken together, indicate that by investigating the pattern in the beta-sorted portfolio return spread across different sentiment regimes, one can identify the underlying mechanism (whether rational or behavioral) for these factors. If this return spread is higher (lower) following high-sentiment periods than low-sentiment periods, these factors are more likely to be mispricing (risk) factors.

To test the role of investor sentiment in the pricing of a large set of characteristics-based factors, we use the market-wide sentiment index constructed by Baker and Wurgler (2006). We follow Chen et al (2020) in constructing a set of beta-sorted portfolios as our testing portfolios. We use this set of portfolios as our testing portfolios because they produce economically large and statistically highly significant ex post factor beta spreads. The large ex post beta spreads tend to increase the power of the test (see, e.g., Daniel and Titman 2012). Indeed, confirming the findings in Chen et al. (2020) and Daniel et al. (2019), despite the large ex post beta spreads, we find that the return spreads between high- and low-beta firms are typically tiny and insignificant and even reversed in sign. In addition to stock returns, we confirm that the same results hold when we use hedge fund and mutual fund returns. Thus, although these factors are "priced" factors using anomaly-based portfolios as testing assets, most of these factors are not significantly priced when beta-sorted portfolios are used.

More important, we find a striking two-regime pattern for most of the characteristics-based factors: high-beta portfolios earn significantly higher returns than low-beta portfolios following high-sentiment periods, whereas the exact opposite occurs following low-sentiment periods. The evidence based on mutual fund and hedge fund returns also confirms this two-regime pattern. In particular, all the beta-sorted long-short portfolios have a negative return spread (-0.38% per month on average) following low-sentiment periods, whereas the return spreads are significantly higher (by 1.02% per month) and positive (0.64% per month) following high-sentiment periods. In addition to the raw return, we also investigate the CAPM alpha and find a significant average CAPM alpha of 0.28% per month for these factor-beta-sorted portfolios, which itself is consistent with either that factor beta is a proxy for mispricing or that factor beta captures some additional risk beyond market risk. However, the average alpha is insignificant at -0.13% per month (t-statistic = -0.70) following low-sentiment periods, whereas the alpha is highly significant and positive at 0.81% per month (t-statistic = 4.54) following high-sentiment periods. Thus, our findings are consistent with the view that the exposure to most of the characteristics-based factors is likely to be proxy for the level of mispricing, rather than the amount of risk, especially during high-sentiment periods. Remarkably, the two-regime results for the characteristics-based factors are *exactly the opposite* of the two-regime results based on macro-related factors, as in Shen, Yu, and Zhao (2017). Compared to the macro-related factors, the characteristics-based factors tend to produce large and highly significant ex post beta spreads, which significantly increase the power of our tests relative to the tests based on macro factors. These large ex post beta spreads are probably a result of the more persistent characteristics-based factor betas or less severe measurement errors in the ex ante beta estimation. Overall, our results indicate that most of the characteristics-based factors are more likely to be proxies for mispricing than for risk, as the beta-sorted long-short portfolio return spreads for these factors are significantly higher following high-sentiment periods than following low-sentiment periods.

Because of short-sale impediments, the effect of market-wide sentiment on overpricing should be more pronounced than that on underpricing. Indeed, we find that the sentiment effect on low-beta firms is much stronger than that on high-beta firms, consistent with the view that low-beta (high-beta) firms are more overpriced (underpriced). More specifically, the return difference for low-beta firms between low- and high-sentiment periods is economically large at 1.09% per month, whereas this difference is merely 0.07% per month for high-beta firms. This asymmetric effect is also consistent with the interpretation that the characteristics-based factor beta is a noisy proxy for the level of underpricing and the presence of short-sale impediments.

In addition to the above two-regime portfolio analysis, further time-series predictive regressions confirm a significant positive relation between investor sentiment and the return spreads between high- and low-beta portfolios. Unlike the two-regime portfolio analysis, the time series analysis allows us to easily control for additional risk factors and other macroeconomic effects. We show that after controlling for these additional effects, investor sentiment can still significantly predict the return spreads between high- and low-beta portfolios. In addition, the predictive power mainly comes from the low-beta portfolios, confirming the results based on the earlier two-regime analysis.

To further investigate the underlying forces for the relatively weak unconditional relation between factor beta and expected returns and the two-regime pattern, we examine the contemporaneous relation between beta-sorted firms and sentiment changes. We find that low-beta firms tend to have higher beta to sentiment changes.[4] That is, firms with low factor exposure are more subject to the sentiment movement. Thus, when sentiment is high (low), many firms are overpriced (underpriced), and low-beta firms are relatively more overpriced (underpriced) than high-beta firms. Following the argument in Baker and Wurgler (2006, 2007), when sentiment is high, these low-beta firms tend to earn lower future returns than high-beta firms. On the other hand, when sentiment is low, these low-beta firms tend to earn higher future return than high-beta firms. Combining these two regimes yields low average return spreads between high- and low-beta firms. Thus, the differential sensitivity to sentiment changes could be one of the underlying reasons for the above two-regime pattern and for the weak unconditional relation between factor beta and expected returns.

In addition to the portfolio analysis using individual stocks, we also perform a similar exercise using hedge fund and mutual fund returns, and we find exactly the same two-regime pattern. That is, using mutual fund returns, we find that the beta-sorted portfolios have an average negative return spread (-0.18% per month on average) following low levels of sentiment, whereas the return spreads are significantly (0.51% per month) higher and positive (0.38% per month) following high levels of sentiment. This return difference across the two sentiment regimes is economically significant since the inter-quantile of mutual fund raw returns, factor-adjusted alphas, and characteristics-adjusted returns are 5.4%, 3.7%, and 2.7% per annum, respectively (see Chen et al. 2020). When we use hedge fund returns, the pattern is even more salient. The beta-sorted portfolios have an average negative return spread (-0.96% per month on average) following low levels of sentiment, whereas the return spreads are significantly (1.28% per month) higher and positive (0.32% per month) following high levels of sentiment.

We perform a few additional robustness checks. First, our results are robust to the use of the survey-based Michigan Consumer Sentiment Index, Conference Board Sentiment Index, a sentiment index based on survey data from the American Association of Individual Investors, and a revised Baker-Wurgler sentiment index proposed by Huang et al. (2015). Second, we show that the sentiment effect on these beta-sorted portfolios still exists after controlling for

[4]This pattern is again exactly the opposite when macro-related factors (such as the market return factor or consumption growth) are used.

many other economic forces such as TED, inflation, dispersion, and a comprehensive list of equity premium predictors. Lastly, we also perform a placebo test by replacing our sentiment measure with these variables, and we show that the two-regime results do not hold for any of these variables, highlighting the unique role of investor sentiment in the beta-return relation. Third, motivated by Hendershott, Livdan, and Rosch (2019) and Lou, Polk, and Skouras (2018) which suggest that investors demand premium for bearing systematic risk overnight, we also explore the factor pricing overnight and intraday separately. We find that on average, firms with high characteristics-based factor beta tend to earn higher intraday returns than firms with low characteristics-based factor beta, whereas high-beta firms earn lower overnight returns than low-beta firms. Again, the opposite pattern holds when macro-related factors are used. This evidence also suggests that characteristics-based factor beta may be a proxy for mispricing, rather than for risk exposure.

In terms of the literature, this study builds on the earlier work of Baker and Wurgler (2006, 2007), who argue that market-wide sentiment should have a greater effect on securities that are hard to arbitrage and difficult to value. Using observable proxies for these two characteristics, such as firm size, age and volatility, Baker and Wurgler (2006, 2007) demonstrate intriguing patterns in the cross section of returns across different sentiment states, which are consistent with the importance of those characteristics.

Our paper is related to studies on the influence of investor sentiment on the risk-return trade-off and anomalies. Yu and Yuan (2011) and Shen, Yu, and Zhao (2017) show that investor sentiment can influence the risk-return relation in time series and the cross section, respectively. Shen, Yu, and Zhao (2017) only consider factors with a strong economic foundation but mostly focus on non-tradable factors such as consumption growth and total factor productivity (TFP) growth. The relation between our beta-sorted portfolios and investor sentiment is consistent with these studies in the sense that for factors that are more likely to be mispricing factors, the beta-sorted portfolio return spread is indeed higher following high-sentiment periods. However, the focus of our paper is on charactirsitics-based factors, which are more powerful in accounting for asset pricing anomalies. Our main contribution is to show that although many of these factors are not priced against the corresponding beta-sorted portfolios, there is significant sentiment-induced variation in this beta-return trade-off. Lastly, it is worthwhile to emphasize that our two-regime results for characteristics-based factors are exactly the opposite of the two-regime pattern for macro-related factors, as in Shen, Yu, and Zhao (2017).

In a related study, Stambaugh, Yu, and Yuan (2012) investigate the effect of investor sentiment on anomalies. They find that anomalous return spreads are much more pronounced following *high-sentiment* periods because of sentiment-induced overpricing. This paper examines the effect of investor sentiment on the pricing of a large set of characteristics-based factors, rather than on anomalies themselves. Unlike anomalies, beta-sorted portfolios produce virtually zero return spreads. Thus, the effect of sentiment on anomalies cannot mechanically carry over to these beta-sorted portfolios. In addition, we also extend the analysis to professionally managed portfolios such as hedge fund and mutual fund portfolios. In this sense, our paper is also related to Bali, Brown and Caglayan (2011, 2014) on hedge fund uncertainty/macroeconomic beta. They find that funds with high uncertaity/macroeconomic beta tend to earn higher average returns, whereas our focus is on hedge fund exposure to characteristics-based factors. Overall, our evidence suggests that sentiment-induced mispricing should at least play a partial role in the inability of characteristics-based factor beta to predict returns.

Finally, this paper is also related to studies on the failure of the traditional one-factor CAPM model. Previous studies have suggested several forces that are responsible for the empirical failure of the CAPM, such as leverage aversion (Black 1972, Asness, Frazzini, and Pedersen 2012, Frazzini and Pedersen 2014, Jylha 2018, and Chen and Lu 2019), benchmarked institutional investors (Brennan 1993, Baker, Bradley, and Wurgler 2011), money illusion (Cohen, Polk, and Vuolteenaho 2005), and disagreement (Hong and Sraer 2016). This paper shows that the sentiment effect on the failure of prominent multi-factor models remains robust after controlling for these important economic forces and that sentiment plays a significant role in the pricing of a broad set of characteristics-related factors.

The rest of the paper is organized as follows. Section 2 describes the data on investor sentiment and the characteristics-based factors and discusses the portfolios based on exposure to those factors. Section 3 reports the main empirical results using stock returns. Section 4 investigates the extension of our results using hedge fund and mutual fund returns. Section 5 performs additional robustness checks by using alternative sentiment measures,controlling for many business cycle variables and equity premium predictors, and by using placebo tests using equity premium predictors. Section 6 concludes.

2 Data Description and Summary Statistics

This section describes the construction of investor sentiment measures, characteristics-based factors and the corresponding factor betas, as well as the mutual fund and hedge fund samples. Summary statistics on beta-sorted portfolios and the relation between factors and investor sentiment are also reported. Our stock sample includes all NYSE, AMEX, and NASDAQ (CRSP exchange codes 1, 2, and 3) listed ordinary common stocks (CRSP share codes 10 and 11) from 1966:7 to 2017:12.

2.1 Investor Sentiment Measures

We use the BW investor sentiment index proposed by Baker and Wugler (2006) for our main analyses. The BW sentiment index is constructed as the first principal component of five sentiment proxies that have first been standardized and orthogonalized with respect to a set of macroeconomic indicators. These five proxies include the average closed-end fund discount, the number of IPOs and their average first-day returns, the dividend premium, and the equity share in new issues. The monthly BW sentiment index is obtained from Jeffrey Wurgler's website.

In addition to the BW index, we also conduct our analyses using alternative sentiment measures. The first one is the survey-based Michigan Consumer Sentiment Index. The second one is the Conference Board Consumer Confidence Index that captures the degree of optimism through consumers' purchasing and saving activities. The third one is the augmented BW index proposed by Huang et al. (2015), which has strong time-series predictive power for the aggregate stock market. The last one is the American Association of Individual Investors sentiment index.

2.2 Portfolios sorted on Characteristics-Based Factor Betas

Following Chen et al. (2020), we form 10 value-weighted decile portfolios according to each of the betas of 13 characteristics-based tradable factors that have been extensively used in the literature. These factors include size (SMB), value (HML), operating profitability (RMW), and investment (CMA) factors from Fama and French (2015)'s five-factor model, investment (IA) and profitability (ROE) factors from Hou, Xue, and Zhang (2015)'s q-factor model, the profitable-minus-unprofitable (PMU) factor from Novy-Marx (2013), the quality-minus-junk (QMJ) factor from Asness, Frazzini, and Pedersen (2019), the momentum (MOM) factor from Carhart (1997)'s four-factor model, the management-related mispricing factor (MGMT) and performance-related mispricing factor (PERF) from Stambaugh and Yuan (2017)'s mispricing factor model, and the long-run behavioral factor (FIN) and short-run behavior factor (PEAD) from Daniel, Hirshleifer, and Sun (2019)'s behavioral factor model. All betas are estimated using a single-factor model for each of the 13 factors. To estimate the betas of individual stocks with respect to MOM, PEAD, and PERF factors, we use daily stock returns over the past 3 months with a minimum of 45 days. To estimate other factor betas, we use monthly stock returns over the past 60 months with a minimum of 36 months. We use a shorter horizon to estimate the ex ante beta for MOM, PEAD, and PERF because earlier studies (e.g., Daniel, Hirshleifer, and Sun, 2019) suggest that these factors are based on short-horizon anomalies. Thus, their factor beta may vary more over longer horizons. As a result, to maximize the ex post beta spread, we use a shorter window to estimate the ex ante beta for these factors. More important, we show in the Appendix that our results are robust if we use a longer window to estimate the ex ante beta for these factors. The sample period is from 1972:1 to 2017:12 for the IA and ROE factors, 1972:7 to 2017:12 for the FIN and PEAD factors, and 1963:7 to 2017:12 for the other factors. The factor construction details can be found in Chen et al. (2020).

Panel A of Table 1 reports the pairwise Pearson correlation coefficients among the 13 characteristics-based factors. Except for those factors with similar underlying characteristics, most factors have small or moderate correlations with others. In Panel B of Table 1, we report the raw returns and CAPM alphas for those factors. The raw returns and CAPM alphas are all statistically significant except for the size factor, consistent with the well-known disappearance of the size effect in the recent sample.

In Table 2, we present summary statistics for the long-short portfolios sorted by various characteristics-based factor betas. Panel A of Table 2 presents the pairwise correlations of the return spreads of portfolios sorted by the 13 factor betas. The magnitudes of correlation coefficients vary across different pairs of beta-sorted spreads, ranging from -0.87 to 0.89. Consistent with the findings in Chen et al. (2020) and Daniel et al. (2019), while the unconditional ex post beta spreads are economically and statistically significant with an average magnitude of 1.57 and t-statistic of 38.51 (Panel C of Table 2), none of the beta-sorted portfolios delivers significant return spreads (Panel B of Table 2). However, the average CAPM alpha is statistically significant at 0.28% per month for these factor-beta-sorted portfolios. This positive CAPM alpha itself could be consistent with either that factor beta is a proxy for mispricing or that factor beta captures some additional risk beyond market risk.

2.3 Data on Hedge Funds and Mutual Funds

Data from the CRSP Survivor-Bias-Free US Mutual Fund Database are used for our mutual fund exercises. We obtain fund-level information including assets under management, net returns, expense ratio, and investment policy and objectives. We focus on actively managed diversified equity funds in the United States, and several standard filters are applied (e.g., Busse, Jiang, and Tang (2017); Pastor, Stambaugh, and Taylor (2017)). First, we eliminate balanced, bond, index, international, commodity, and sector funds based on various objective codes and detailed asset compositions.[5] Second, duplicated funds are dropped and fund-level variables are aggregated across different share classes for funds with multiple share classes. Third, only fund-month observations with a lagged fund size above $15 million in 2011 US dollars are kept. Lastly, to address concerns about incubation bias concern (Evans (2010)), we drop the first three years of returns for each fund. To estimate betas for MOM, PEAD, and PERF factors, we use daily mutual fund returns over the past 3 months with a minimum of 45 days. Since daily mutual fund return data start from September 1998, the portfolios based on these factor betas start from 1998:12. For other factor betas, we use monthly mutual fund returns over the past 24 months with a minimum of 18 months. Our final mutual fund sample includes 3,710 unique funds and 497,666 fund-month observations from 1980:1 to 2017:12.

Our hedge fund data come from Thomson Reuters Lipper Hedge Fund Database (TASS). This database includes information on fund characteristics, assets under management, net returns, and strategy category. We apply several filters following Bali, Brown, and Caglayan (2011). First, we only include funds with returns net of fees in US dollars at a monthly frequency. Second, we drop the first year of returns of each fund to mitigate concerns about backfill bias. Lastly, we require each fund to have at least 24 months of return history to address the issue of multi-period sampling bias. To estimate factor betas, we use monthly hedge fund returns over the past 24 months with a minimum of 18 months. Our final hedge fund sample includes 6,404 unique funds and 433,769 fund-month observations from 1996:7

[5] A detailed fund code selection process can be found in Busse et al. (2017).

to 2017:12.[6]

3 Main Empirical Analysis

Our empirical design is closely related to Stambaugh, Yu, and Yuan (2012) and Shen, Yu, and Zhao (2017). Thus, the presentation of our empirical results in this section closely follows their structure.

3.1 Average Returns across Two Sentiment Regimes

We use the Baker-Wurgler sentiment index for our main analysis. In the robustness check section, we show that our results hold when alternative sentiment indices are used. First, we use the BW investor sentiment index to classify the entire period into high- and low-sentiment periods: a month is classified as high sentiment (low sentiment) if the sentiment level in the previous month is in the top (bottom) 50% of the entire sentiment series. Average portfolio returns are calculated separately for these two regimes. Incidentally, out of the 83 months of NBER recession during our sample, 40 months are classified as high sentiment, and 43 months are classified as low sentiment.

We now examine the relation between this long-short beta-sorted return spread and investor sentiment. As argued by Stambaugh, Yu, and Yuan (2012) and Shen, Yu, and Zhao (2017), when market-wide sentiment is combined with short-sale impediments, the market participants tend to be more rational during low-sentiment periods since irrational pessimistic agents are out of the market. On the other hand, market participants tend to be more irrational during high sentiment periods since rational agents stay out of the market because of short-sale impediments. Thus, systematic risk should play a larger role during low-sentiment periods, whereas mispricing should be amplified during high-sentiment periods. Indeed, Stambaugh, Yu, and Yuan (2012) find that the 11 anomalies are more pronounced following high-sentiment periods, especially the short legs. On the other hand, Shen, Yu, and Zhao (2017) find that for all 10 macro-related factors, high-beta portfolios earn significantly higher returns than low-beta portfolios following low-sentiment periods, whereas the exact opposite occurs following high-sentiment periods. Thus, for economically grounded macro factors, there is indeed a significant risk-return trade-off following low sentiment when the

[6] Details on hedge fund data cleaning can be found in Chen, Lu, and Zhu (2019).

participants are closer to be rational. In addition, Yu and Yuan (2011) also find evidence that the aggregate mean-variance relation (i.e., the risk-return trade-off) is stronger following low sentiment periods.

Thus, if these factors are systematic risk factors, betas are then proxies for genuine risk exposure. Following the argument in Shen, Yu, and Zhao (2017), one should expect the high-minus-low beta return spreads to be larger following low-sentiment periods than following high-sentiment periods. On the other hand, if these factors are mispricing factors, the factor betas are noisy proxies for the level of underpricing, as argued in Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2019). Then following the argument in Stambaugh, Yu, and Yuan (2012), one should expect the high-minus-low beta return spreads to be larger following high-sentiment periods than following low-sentiment periods. Because of these opposite predictions based on different underlying mechanisms for these factors, the sentiment-dependent beta-sorted return spread could be useful in distinguishing alternative interpretations of these factors. Nonetheless, a factor could be driven by both risk and mispricing. The confounding effects of risk and mispricing could weaken the effect of sentiment on the return spreads between high- and low-beta firms since the two effects tend to cancel out each other. In addition, the factors could also be due to mispricing, but betas are unrelated to mispricing because of the low correlation between factor beta and the underlying firm-level characteristics. Thus, it is possible that sentiment has a very limited effect on the return spreads between high- and low-beta firms.

Panel A of Table 3 reports the return spreads between high-beta firms and low-beta firms following high- and low-sentiment periods. For most of the factors, the return spreads are higher and positive following high-sentiment periods than following low-sentiment periods. For example, the average return spread between high- and low-beta firms across the 13 factors is 0.54% per month following high-sentiment periods and −0.30% per month following low-sentiment periods. The difference of 0.83% per month is economically large and statistically significant (t-statistic = 3.64). Notice that the sentiment effect on the size factor is exactly the opposite of the other 12 characteristics-based factors. Two potential reasons could explain this result. First, the size factor could be a genuine risk factor, just like the macro-related factors in Shen, Yu and Zhao (2017), and thus the return spread would be higher following low-sentiment periods than following high-sentiment periods. Second, firms with high size factor beta are more likely to be smaller firms and are the firms more subject to the influence of investor sentiment. Thus, argued in Bake and Wurgler (2006, 2007), during high-sentiment periods, these high size-beta firms are relatively more overvalued than low size-beta firms.

As a result, the subsequent returns of high size-beta firms are lower than that of low size-beta firms, leading to a negative return spread between high- and low- size-beta firms following high-sentiment periods. On the other hand, during low-sentiment periods, these high size-beta firms are relatively more undervalued than low size-beta firms and thus, the subsequent returns of these high size-beta firms are higher than that of low size-beta firms, leading to a positive return spread between high- and low size-beta firms following high sentiment periods. In this paper, we do not try to distinguish these two interpretations because both forces likely play significant roles. Thus, although the result on the size factor could be consistent with a mispricing interpretation, the pattern is the opposite of the prediction based on the earlier assumption that the betas are noisy proxies for mispricing, with high-beta firms being relatively underpriced. Thus, we also report the average results across all the factors excluding the size factor.

Indeed, if we exclude the size factor, the average return spread between high- and low-beta firms is 0.64% per month following high-sentiment periods and -0.38% per month following low-sentiment periods. The difference of 1.02% per month is economically large and statistically significant (t-statistic = 3.62). These results are in sharp contrast with those in Shen, Yu, and Zhao (2017), who consider 10 macro-related factors such as consumption growth and TFP growth. Shen, Yu, and Zhao (2017) find that the return spread between high- and low-beta firms is much higher and positive following low-sentiment periods than following high-sentiment periods, the exact opposite of our pattern here. These results suggest that those macro-related factors are more likely to be driven by risk, whereas many of the characteristics-based factors are more likely to be driven by mispricing/behavioral effects.

In addition, the sentiment effect on low- and high-beta firms is very different. As we can see from Table 3, the effect of sentiment on low-beta firms is much stronger than that in high-beta firms. Following high-sentiment periods, the firms with low beta underperform by 1.09% per month (t-statistic = 2.06), as compared with that following low-sentiment periods. However, the firms with low beta only underperform by 0.07% per month (t-statistic = 0.19). This differential sentiment effect on low- and high-beta firms is consistent with the notion that beta is a noisy proxy for underpricing, and thus low-beta firms are likely to be overpriced. More specifically, as argued in Stambaugh, Yu, and Yuan (2012), the existence of short-sale impediments implies that overpriced is more prevalent than underpricing, and thus, the effect of market-wide sentiment on overpricing firms (i.e., the short leg of an anomaly) should be higher than that on underpriced firms (i.e., the long leg of an anomaly). Thus, our results are consistent with those in Stambaugh, Yu, and Yuan (2012), who study the effect of sentiment on anomalies.

The previous raw returns in Panel A of Table 3 does not take into account of systematic risk. Next we report benchmark adjusted returns in Panel B of Table 3. We only report CAPM alpha instead of other multi-factor alphas since our evidence suggests that many of these factors are probably mispricing factors, rather than systematic risk factors, and there is no universally accepted multi-factor model. In general, adjusting for market exposure does not affect our conclusions from Panel A of Table 3. For example, the average return spread between high- and low-beta portfolios is 0.81% higher per month (t-statistic = 4.54) following high-sentiment periods than following low-sentiment periods. Moreover, the CAPM-adjusted return on the high-beta portfolios in the combined strategy exhibits a small difference (0.27% per month) between high- and low-sentiment periods. On the other hand, the CAPM-adjusted return on the low-beta firms in the combined strategy exhibits a significant -0.67% difference between high- and low-sentiment periods. Thus, after controlling for market exposure, the evidence is still consistent with the view that investor sentiment induces more mispricing in low-beta firms and less in high-beta firms. In addition, most of the CAPM alpha spreads for the high-minus-low beta portfolios are from the high-sentiment periods, a phenomenon also documented for 11 anomalies by Stambaugh, Yu, and Yuan (2012). Indeed, following high-sentiment periods, the average CAPM alpha spread is 0.81% (t-statistic = 4.54), whereas following low-sentiment periods, the average CAPM alpha spread is only -0.13% (t-statistic = -0.70). This finding is again consistent with the mispricing interpretation where overpricing is more prevalent than underpricing because of short-sale impediments. Further supportive evidence comes from the asymmetric contribution of the alpha from the short leg and the long leg. Specifically, most of the alpha comes from the short leg (i.e., low-beta firms) following high-sentiment periods. The alpha is 0.62% per month for the short leg and only 0.19% per month for the long leg.

Based on the previous findings, it is likely that many of these factors are driven by systematic mispricing, and thus the factor beta is a proxy for the level of underpricing. Following a similar argument in Stambaugh, Yu, and Yuan (2012), because of short-sale impediments, sentiment should exert a stronger effect on low-beta portfolios and a weaker or no effect on high-beta portfolios. Panel A of Table 3 shows that low-beta portfolios earn lower returns following high-sentiment periods than during low-sentiment periods, and 10 out of the 12 factors (excluding the size factor) have a t-statisticistic that rejects the no-difference null across high- and low-sentiment periods. High-beta portfolios also tend to earn lower raw returns following high-sentiment periods than low-sentiment periods, but the magnitude is very small, and none of the 12 factors is significant. For example, the basis points for high-beta portfolios in the average strategy are lower by 7 bps per month following high-sentiment periods and the t-statistic is only -0.19. In addition, any evidence for sentiment effects on high-beta portfolios becomes even weaker after benchmark adjustment. In fact, the CAPM alphas of high-beta portfolios tend to be slightly higher following high-sentiment periods than low-sentiment periods, with a magnitude of 27 bps and a t-statistic of 2.27. This asymmetric effect on high- and low-beta firms is again exactly the opposite of Shen, Yu, and Zhao (2017), where macro-related factors are used.

It is worth noting that most of the high-beta portfolios earn close to zero CAPM benchmark-adjusted returns following both high- and low-sentiment periods, suggesting that underpricing is less prevalent than overpricing, consistent with the findings in Stambaugh, Yu, and Yuan (2012). However, all of the 12 low-beta portfolios earn negative CAPM alpha returns following high-sentiment periods. The average CAPM alphas are significantly negative (-0.62% per month with a t-statistic of 4.91), again suggesting overpricing for low-beta firms during high-sentiment periods. In contrast, none of the 12 low-beta portfolios earn significant CAPM alpha (positive or negative) following low sentiment. The average CAPM alphas are slightly positive and insignificant (0.05% per month with t-statistic of 0.33), suggesting again that very little underpricing exists for low-beta firms during low-sentiment periods.

Since some mispricing, such as the moment effect or the PEAD effect, is short-lived, as argued in Daniel, Hirshleifer, and Sun (2019), it could be the case that estimating beta with 5-year monthly return data is not a good measure for mispricing. So far, to address this point, the pre-ranking betas for MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. In Internet Appendix Table IA1, we repeat our exercise by using monthly return data and changing the estimation window. In general, we find that our main conclusion regarding the effect of sentiment on these beta-sorted portfolios remains similar. Overall, the average effect across all the factors remains similarly significant. For example, the average return spread between high- and low-beta firms is indeed positive following high-sentiment periods with a monthly value of 0.56% (t-statistic = 3.69), 0.54% (t-statistic = 3.81), and 0.44% (t-statistic = 3.24), depending on the data frequency and estimation window choice. Excluding the size factor raises this average spread to 0.66% (t-statistic = 3.50), 0.65% (t-statistic = 3.69), and 0.56% (t-statistic = 3.29), respectively. In addition, the average difference between these long-short beta-sorted return spreads following high-sentiment and low-sentiment periods is 0.70% per month (t-statistic = 3.19), 0.70% per month (t-statistic = 3.22), and 0.61% per month (t-statistic = 3.02). In addition, to maximize the ex post factor beta of our portfolios, we have used a one-factor model to estimate the ex ante beta. One can also estimate the ex ante betas of these factors with a two-factor model that includes the market factor and a characteristics-based factor. The results are reported in Internet Appendix Table IA2. The main two-regime pattern remains the same.

One might argue that the measurement errors in betas could lead to a low average return spread between high- and low-beta firms. Our study certainly does not rule out the potential role of measurement errors in the observed insignificant *average return spread* between high- and low-beta firms. However, since our ex post beta spread has large t-statistics, it is unlikely that the lack of return spread is due to the lack of ex post beta spreads. More important, since measurement errors in betas tend to reduce the true beta spread between high- and low-risk portfolios, it is more difficult to identify a positive return spread between high- and low-beta firms following high-sentiment periods. In addition, taking this measurement error view to the extreme that the measured betas are pure noise, one should observe close to zero return spreads between high- and low-beta firms following both high- and low-sentiment periods. Thus, the noises in beta estimation are likely to *weaken* the two-regime pattern that we have documented above.

Lastly, we would like to link our findings on the two-regime pattern to Shen, Yu, and Zhao (2017), who also find a striking two-regime pattern for 10 macro-related factors: high-risk portfolios earn significantly higher returns than low-risk portfolios following low-sentiment periods, whereas the exact opposite occurs following high-sentiment periods. Their findings are consistent with a setting in which market-wide sentiment is combined with short-sale impediments and sentiment-driven investors undermine the traditional risk-return trade-off, especially during high-sentiment periods. However, our two-regime results for characteristics-based factors are exactly the opposite of the two-regime pattern for macro-related factors, as in Shen, Yu, and Zhao (2017), suggesting that the underlying forces for the characteristics-based factors and macro-related factors might be very different.

Overall, the evidence in Table 3 appears to support the notion that most of these factors are at least partially due to systematic mispricing. Beta is a proxy for the level of underpricing. In addition, high market-wide sentiment creates overpricing, probably because of short-sale impediments, whereas low market-wide sentiment may only produce moderate underpricing. Thus, this asymmetry leads to a stronger positive relation between beta and return following high-sentiment periods. Moreover, the effect of sentiment on relatively undervalued assets such as high-beta stocks is smaller than the effect on relatively overvalued assets such as low-beta stocks.

3.2 Predictive Regressions

The previous subsection reports the average portfolio returns within two sentiment regimes, where the regime classification is simply a dummy variable. This subsection conducts an alternative analysis, using predictive regressions to investigate whether the level of the BW sentiment index predicts returns in ways that are consistent with the previous two-regime results. The regression approach allows us to easily control for other popular risk factors (e.g., the CAPM market factor) and macro variables, which enables us to check that the sentiment effect documented in the previous subsection is not just due to comovement with macroeconomic variables. Table 4 reports the results of regressing excess returns on the lagged sentiment index.

The regime pattern documented earlier suggests a positive relation between the profitability of each high-minus-low beta portfolio spread and lagged investor sentiment. Consistent with this pattern, the slope coefficients for the spreads based on all 12 factors are positive in Panel A of Table 4. Eight of the individual t-statistics are significant at a 0.05 significance level. The last average strategy (excluding the size factor) has a t-statistic of -3.68. Here, returns are measured in percentages per month, and the sentiment index is scaled to have a zero mean and unit standard deviation. Thus, for example, the slope coefficient of 0.53 for the average strategy indicates that a one-standard-deviation increase in sentiment is associated with a 0.51% increase per month in the long-short beta-sorted portfolio strategy.

Our earlier two-regime evidence implies a significant negative relation between the returns on low-beta portfolios and the lagged sentiment level. Consistent with this implication, the slope coefficients for the low-beta portfolios based on all 12 factors are negative. Moreover, 8 out of all 12 individual t-statistics are significant at 0.05, and the remaining 4 are marginally significant as well. The last average strategy has a t-statistic of -2.46. It is seen that a one-standard-deviation increase in sentiment is associated with a 0.73% lower monthly excess return on the low-beta portfolio. Our results also indicate a weaker relation between the returns on high-beta portfolios and lagged sentiment. Consistent with this prediction, the slope coefficients for the high-beta portfolios based on all 12 factors are smaller in magnitude. For example, the average high-beta portfolio in the last row of Panel A of Table 4 has an insignificant slope of -0.22 (t-statistic = -0.97), which is less than one-third of the magnitude for the average low-beta portfolio.

Panel B of Table 4 reports the results of regressing CAPM benchmark-adjusted returns on the lagged sentiment index. Incidentally, after CAPM adjustment, there is also no significant relation between returns on the high-beta (likely to be underpriced) portfolios and lagged sentiment, and the sign is the opposite of the case without CAPM adjustment. Without benchmark adjustment, the coefficients for the high-beta portfolio returns are all negative and insignificant at a 5% significance level. After adjusting for CAPM exposures, however, all the coefficients (again, except for SMB) turn positive and insignificant. Also, the average strategy has a slope of close to zero, thus confirming our conjecture that high-beta firms are much less sensitive to the influence of investor sentiment. On the other hand, the low-beta firms are still highly influenced by sentiment even after CAPM adjustment, with a coefficient of -0.34 (t-statistic = -4.00). Finally, the CAPM-adjusted return for the high-minus-low beta portfolio is also highly influenced by lagged sentiment, reported in the last two columns of Panel B, Table 4.[7]

Next, one might argue that our findings could potentially be consistent with a risk-based explanation without resorting to irrational investor sentiment since sentiment could be correlated with business cycle variables or risk aversion. In constructing their sentiment index, Baker and Wurgler (2006) have removed macro-related fluctuations by regressing raw sentiment measures on six macroeconomic variables: growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and an indicator for NBER recessions. In Table 5, we control for an additional set of five macro-related variables that have been shown to be correlated with risk premia and business conditions: the default premium, the term premium, the real interest rate, the inflation rate, and Lettau and Ludvigson's (2001) wealth-consumption ratio (CAY). This set of macro variables is also used as a control in Stambaugh, Yu, and Yuan (2012).

By regressing excess returns on the lagged sentiment index and the five lagged macro-related variables, one can investigate whether the predictive ability of sentiment for

[7]Although our evidence so far suggests that most of these characteristics-based factors are at least partially driven by mispricing, one might still be curious about our results if we also adjust for the Fama-French three-factor model. Thus, in untabulated analysis, in addition to CAPM adjustment, we also repeat the analysis using the Fama-French three-factor model as a benchmark and obtain very similar patterns.

subsequent returns is robust to including macro-related fluctuations in addition to those already controlled for by Baker and Wurgler (2006). The regression results, reported in Table 5, indicate that the effects of investor sentiment remain largely unchanged after including the additional five variables. In particular, the coefficients and their t-statistics are close to those in Table 4, in which the five additional macro-related variables are not included in the regressions.

Overall, if time variation in the risk premium drives our results, it appears that this variation is not strongly related to either the six macro variables controlled by Baker and Wurgler (2006) or the five additional variables included in our analysis. Of course, it could still be possible that the sentiment index itself captures time variation in risk, or risk aversion, which is not captured by the 11 macro variables. At minimum, our results show that sentiment contains information regarding time variation in risk premia that is not captured by standard macro-related variables.

Finally, as argued by Stambaugh, Yu, and Yuan (2015), investor sentiment could be related to macroeconomic conditions. It is quite possible that after favorable (adverse) macroeconomic shocks, some investors become too optimistic (pessimistic) and push stock prices above (below) levels justified by fundamental values. Thus, as long as high (low) sentiment makes overpricing (underpricing) more likely, the extent to which sentiment relates to the macroeconomy or risk aversion does not affect the implications explored in this study. For instance, even if there is a strong link between sentiment and risk aversion, there still remains the challenge of explaining, across all 12 characteristics-based factors, why low-beta firms earn lower returns than high-beta firms following high-sentiment periods, whereas the opposite occurs following low-sentiment periods. If low sentiment coincides with high risk aversion, and if these factors are purely proxies for systematic risks,[8] we should expect high-minus-low beta portfolio spread to be especially large following low-sentiment periods (i.e., high risk aversion). Thus, the time variation in risk aversion cannot account for our results, and it appears that sentiment-induced mispricing, especially overpricing, is at least partially responsible for this empirical fact.

In sum, the predictive regressions in this subsection confirm the results from the simple comparisons of returns following high- and low-sentiment periods in the last subsection. Our evidence supports the view that sentiment-induced overpricing plays an especially large role

[8]For example, Yu and Yuan (2011) show that low-sentiment periods could be endogenously associated with periods of high effective risk aversion because of the limited market participation resulting from short-sale constraints or a convex demand function for stocks.

among firms with low factor beta.[9]

3.3 Relation to Contemporaneous Sentiment Changes

Although the factor beta could be a proxy for the level of underpricing, its correlation with the underlying firm-level characteristics is actually quite low (about 14% on average across all of the 13 factors). This is one reason why the unconditional relation between factor beta and future return is very flat. We now further investigate the relation between these beta-sorted portfolios and contemporaneous sentiment, in addition to the lagged sentiment, to shed further light on the underlying reason for this flat relation.

Shen, Yu, and Zhao (2017) show that firms with high exposure to sentiment changes earn higher returns following low-sentiment periods, whereas the opposite is true following high-sentiment periods. These findings are consistent with Baker and Wurgler (2006), who argue that firms that are more subject to the influence of sentiment (i.e., firms with high exposure to sentiment changes), should be more overpriced (underpriced) during high- (low-) sentiment periods. Baker and Wurgler (2006) use a few firm characteristics as proxies for the degree of sentiment influence. Instead of sorting on firm characteristics as in Baker and Wurgler (2006), however, one can directly study the sensitivity of beta-sorted portfolio returns to changes in sentiment. Thus, we examine the sensitivity of our beta-sorted portfolios to contemporaneous sentiment changes.

In Table 6, beta-sorted portfolio returns are regressed onto contemporaneous sentiment changes. We find that firms with low betas are more subject to the influence of sentiment, and we observe a stronger comovement between returns on low-beta firms and sentiment changes. The regression coefficient is larger for low-beta portfolios than for high-beta portfolios. This is true for all 12 characteristics-based factors except for PMU, MOM, PERF, and PEAD, which are all relatively short-lived anomalies and all likely to be driven by inattention-induced underreaction. This result is consistent with the findings in Duan, Guo, Li, and Tu (2018), who show that sentiment has a weaker effect on underreaction-related (in particular, the inattention-induced) anomalies. Because low-beta firms are more subject to the influence of sentiment, following low-sentiment periods, low-beta firms could earn a higher return than high-beta firms, destroying the expected positive relation between beta and expected returns.

[9]Because of the small correlation between the predictive regression residuals and the innovations in sentiment, the potential small-sample bias in predictive regressions, as studied by Stambaugh (1999), does not appear to be a problem in the results reported here.

This partially explains the flat relation between beta and expected returns, as documented in Table 2 and in Chen et al. (2020).

4 Evidence Based on Mutual Funds and Hedge Funds

In this section, we extend the analysis in the previous section based on stock returns to professionally managed portfolios such as mutual funds and hedge funds. Earlier studies(e.g., Avramov and Wermers (2006)), show that returns of mutual funds depend on risk loadings. More recently, researchers find that mutual fund returns are related to the funds' exposure to tightness in market-wide leverage constraints (Boguth and Simutin (2018)), liquidity risk (Lynch and Yan (2012); Dong, Feng, and Sadka (2019)), and macroeconomic state variables (Banegas et al. (2013)). Several other studies examine how hedge funds' cross-sectional return spreads are affected by their exposure to uncertainty/macroeconomic risk (Bali, Brown and Caglayan (2011, 2014)), liquidity risk (Sadka (2010); Hu, Pan, and Wang (2013); Golez, Jackwerth, and Slavutskaya (2018)), sentiment change (Chen, Han, and Pan (2016)), or rare disaster concerns (Gao, Gao, and Song (2018)). Here, our focus is on the effect of funds' exposure to characteristics-based factors on their performance. Our paper extends previous studies' risk/macro/liquidity/sentiment factors to characteristics-based factors. We think that the extension to characteristics-based factors is important. Although macro factors are theoretically well motivated, they are not very successful in explaining the cross section of stock returns, whereas characteristics-based factors are much more powerful in accounting for many anomalies. More important, we document a two-regime pattern on the beta-return relation, depending on the level of investor sentiment.

First, we find that mutual funds and hedge funds with high factor beta tend to earn returns that are similar to those of funds with low factor beta, a result similar to those based on stock returns. The return spread on beta-sorted long-short portfolios is 0.08% (t-statistic = 0.83) and -0.30% (t-statistic = -1.03) for mutual funds and hedge funds, respectively. Compared with standard macro risk factors, our characteristics-based factors are more powerful in explaining existing asset pricing anomalies in the stock market. Thus, the above insignificant result is in sharp contrast with earlier studies, which typically find that macro/liquidity/sentiment factor risks are priced using mutual fund and hedge fund returns.

Second, we also find a striking, consistent two-regime pattern among both hedge funds and mutual funds. Panel A of Table 7 reports the two-regime returns of beta-sorted portfolios using mutual funds. The beta-sorted long-short portfolios have an average negative return spread of -0.18% per month (t-statistic = -1.57) following low-sentiment periods, whereas this return spread is 0.38% per month (t-statistic = 2.36) following high-sentiment periods. The difference in return spreads across high- and low-sentiment periods is 0.51% per month (t-statistic = 2.87). This return spread difference across two sentiment regimes is also economically large since Chen et al. (2020) show that the inter-quartile of mutual fund raw returns, factor-adjusted alphas, and characteristics-adjusted returns are 5.4%, 3.7%, and 2.7% per annum, respectively.[10]

Panel B of Table 7 reports the CAPM alphas for these beta-sorted mutual fund portfolios across different sentiment periods. The main pattern remains similar. For example, the alpha spread difference across two sentiment regimes is now 0.50% per month (vs. 0.51% per month of raw return spread as in Panel A) with t-statistic = 3.49. In addition, most of the CAPM alpha is derived from the high-sentiment periods rather than the low-sentiment periods. In particular, the beta-sorted long-short mutual fund portfolio has a CAPM alpha of 0.47% per month (t-statistic = 3.93) following high-sentiment periods, and a CAPM alpha of -0.03% per month (t-statistic = -0.38) following low-sentiment periods. In addition, the CAPM alpha of low-beta portfolio is now significantly covarying with lagged investor sentiment, although the low-beta portfolio raw return is not significantly influenced by lagged investor sentiment.

Third, the pattern is even more salient when we use hedge fund returns (Table 8). These beta-sorted long-short portfolios have an average negative return spread of -0.96% per month (t-statistic = -2.18) following low-sentiment periods, whereas the return spreads are significantly (1.28% per month, t-statistic = 2.73) higher and positive at 0.32% per month (t-statistic = 1.20) following high-sentiment periods. We also report the CAPM alphas in Panel B. Again, a majority of the CAPM alpha is derived from the high-sentiment periods rather than the low-sentiment periods. In particular, the beta-sorted long-short hedge fund portfolio has a CAPM alpha of 0.52% per month (t-statistic = 3.40) following high-sentiment periods, and a CAPM alpha of -0.24% per month (t-statistic = -1.01) following low-sentiment periods. This evidence on asymmetry is again consistent with the notion

[10]Similar to the analysis using stock returns, one can also estimate the MF/HF ex ante betas of these factors with a two-factor model that includes the market factor and a characteristics-based factor. The results are reported in the Internet Appendix as Tables IA3 and IA4. The main two-regime pattern remains the same. In addition, focusing on pure equity hedge funds also yields similar results, as shown in Table IA5 in the Internet Appendix.

that overpricing is more prevalent during high-sentiment periods than underpricing during low-sentiment periods.

Relatedly, Chen, Han, and Pan (2016) find that hedge funds with higher exposure to sentiment risk tend to earn higher average returns. Using macro-related factors, Chen, Lu, and Zhu (2019) find that both mutual funds and hedge funds with higher macro-factor beta tend to earn higher (lower) returns than those funds with low macro-factor beta following low- (high-) sentiment periods. Their evidence is consistent with the findings based on stock returns in Shen, Yu, and Zhao (2017), suggesting that these macro-related factors are indeed risk factors and their pricing effects are moderated by investor sentiment. Our opposite results based on mutual/hedge funds and characteristics-based factors corroborate the view that many of the characteristics-based factors are at least partially due to systematic mispricing and the factor beta is a noisy proxy for the level of underpricing. Overall, our evidence suggests that sentiment-induced mispricing should at least play a partial role in the inability of characteristics-based factor beta to predict returns.

5 Robustness Checks

This section provides various robustness checks. First, alternative sentiment indices are used to repeat previous exercises. Second, alternative potential mechanisms for the failure of these multi-factor models are discussed. Lastly, we investigate the factor pricing overnight and intraday separately.

5.1 Alternative Sentiment Indices

This subsection investigates the robustness of our results by using an alternative sentiment index: the University of Michigan Consumer Sentiment Index, the Conference Board Consumer Confidence index, the PLS sentiment index, which is a partial least square-based Baker-Wurgler sentiment index, and the American Association of Individual Investors sentiment index.

While the BW sentiment index is a measure of sentiment based on stock market indicators, the Michigan sentiment index is a survey-based summary measure based on a large number of survey responses to queries about households' current and expected financial conditions. The monthly survey is mailed to 500 random households and asks for their views about both current and expected business conditions. As a result, the Michigan Consumer Sentiment Index might be less tied to the sentiment of stock market participants. Nonetheless, this sentiment index is still very influential, and many previous studies regarding investor sentiment have used the Michigan Consumer Sentiment Index (see, e.g., Ludvigson (2004), Lemmon and Portniaguina (2006), and Bergman and Roychowdhury (2008)). Thus, we use this index as a robustness check.

Panel A of Table 9 reports the two-regime results using the lagged Michigan sentiment index. The results are similar to those based on the BW sentiment index in Table 3. For the average high-minus-low beta portfolio based on the 12 factors, the return spread is significantly lower following low-sentiment periods than following high-sentiment periods. The spread differences across the two sentiment regimes is 0.87% per month (t-statistic = 2.62). In addition, the high-beta firms have very similar returns across the two sentiment regimes, and the difference is only 0.02% per month. That is, the high-beta firms are not very influenced by the market-wide sentiment. The patterns of the results across the 12 characteristics-based factors are thus similar to those obtained using the BW index, as reported in Table 3, although some of the patterns are slightly weaker. The BW index is arguably a better measure of the mood of stock market participants, whereas the Michigan sentiment index captures consumer sentiment more precisely. Thus, the weaker results based on the Michigan sentiment index are somewhat expected.

Panel B of Table 9 shows that our results remain the same when Conference Board Consumer Confidence Index is used as a proxy for investor sentiment. In addition, Huang et al. (2015) propose a new sentiment index based on the BW investor sentiment index that has stronger return predictive power. Thus, the exercise in Panel A of Table 9 is repeated by replacing the Michigan sentiment index with this new sentiment index. Panel C of Table 9 reports the results. The main pattern remains quantitatively similar. Lastly, in light of the concerns about the market-based BW sentiment index raised in Qiu and Welch (2006), Panel D of Table 9 repeats our exercise with the American Association of Individual Investors sentiment index. Panel D shows that, once again, the key pattern on the effect of investor sentiment on the cross-sectional risk-return relation remains largely the same.

5.2 Controlling for Alternative Mechanisms

As mentioned earlier, many studies have suggested possible forces that are responsible for the empirical failure of the CAPM, such as leverage aversion, money illusion, and disagreement. Although a much broader set of factors are considered in this paper, it is still conceivable that the mechanisms proposed by these studies also work for our broad set of characteristics-based factors. Moreover, it is certainly possible that the forces proposed by these studies overlap with our sentiment channel. For example, when aggregate disagreement is high, there might be more overpricing because of short-sale impediments. Indeed, the correlation between sentiment and aggregate disagreement is about 20%. Thus, it is interesting to investigate whether sentiment still has predictive power after controlling for these mechanisms.

To investigate this possibility, Table 10 performs the regression analysis by simultaneously controlling for the funding constraints effect (TED) of Frazzini and Pedersen (2014), the money illusion effect (inflation) of Cohen, Polk, and Vuolteenaho (2005), and the aggregate dispersion effect of Hong and Sraer (2016) and Yu (2011). As shown in Table 10, the predictive power of sentiment for the high-minus-low return spreads remains statistically significant and economically large. Thus, our mispricing channel provides incremental predictive power for the high-minus-low beta-sorted portfolio returns.

Lastly, in Table 11, a placebo test is performed by replacing our sentiment index with a list of variables that can predict the equity premium, as shown by previous studies. The list of variables includes the 14 equity premium predictors as in Goyal and Welch (2008), the surplus ratio, and the aggregate dispersion as in Hong and Sraer (2016). The 14 predictors include log dividend price ratio, log dividend yield, log earnings-price ratio, log dividend-payout ratio, stock excess return volatility, book-to-market ratio, net equity issuance, Treasury bill rate, long-term yield, long-term return, term spread, default yield spread, default return spread, and inflation. This table reports the results of factor-beta-sorted value-weighted decile portfolios following high- and low-state regimes, as classified based on the median level. We report the monthly excess returns of the high-low beta average portfolios after low-state regimes, high-state regimes, and their differences. To make our results comparable across different equity premium predictors, we transform our predictors by taking the inverse if necessary such that the classified high states are the states with lower expected future market returns.

The results indicate that these variables cannot produce the pattern produced by investor sentiment. In particular, none of these variables can produce a significant two-regime pattern.

In particular, the differences between the high-minus-low beta-sorted return spreads of the average portfolio across high- and low-state regimes is 0.17%, 0.17%, -0.05%, -0.05%, 0.23%, -0.09%, -0.17%, 0.54%, -0.06%, 0.18%, -0.07%, 0.23%, 0.15%, 0.13%, 0.22%, and -0.31% per month, respectively. The average difference is a mere 7 basis points per month, as compared with 1.02% per month when sentiment is used to identify regimes. The most significant results are produced by the Treasury bill rate, with a difference of 0.54% (t-statistic= 1.77). Since the market risk premium is higher during low-state regimes, for genuine risk factors, the beta-sorted return spread should be higher following low-state periods than following high-state periods. Thus, the sign for the Treasury bill rate is the opposite of this prediction. In addition, the surplus ratio has been used as a proxy for time variation in effective risk aversion. Thus, if a factor is a genuine risk factor, one should expect that following periods with low surplus ratios (i.e., higher effective risk aversion), the beta-sorted return spread should be higher than that following periods with high surplus ratios. Our results, however, show that there are no significant return spread differences across high and low surplus ratio periods, and the sign is also not consistent with the above argument. Overall, these results provide further support for the unique role of sentiment in the cross-sectional risk-return relation.

In addition to the two-regime placebo analysis, in Table 12, we perform predictive regressions by controlling for these equity premium predictors one by one. As we can see, our results again remain quantitatively similar to previous results. In particular, the sentiment effect on the low-beta firms is very strong, whereas the sentiment effect on the high-beta firms is much weaker. Overall, the effect of sentiment on the high-minus-low beta-sorted portfolio is statistically and economically significant. Controlling for these equity premium predictors does not alter our main conclusion.

5.3 Overnight and Intraday Pricing

As our last robustness check, we investigate the pricing of these characteristics-based factors and macro-related factors overnight and intraday separately. Earlier studies suggest that the stock market might be more rational during overnight than intraday. For example, Hendershott, Livdan, and Rosch (2019) and Lou, Polk, and Skouras (2018) find that CAPM performs much better overnight than intraday, suggesting overnight stock market is more efficient. Indeed, Hendershott, Livdan, and Rosch (2019) argue that when assets are illiquid, investors demand higher returns to hold stocks with high systematic risk. If this is indeed the case, we would also expect different pricing for our factors overnight and intraday. That is, the overnight pricing behavior should be similar to that during low sentiment periods when market participants tend to be more rational, whereas the intraday pricing behavior should be similar to that during high sentiment periods when markets are less rational.

Table 13 reports our results. We find that on average, firms with high characteristics-based factor beta earn 0.45% higher intraday returns per month than firms with low characteristics-based factor beta, whereas firms with high characteristics-based factor beta earn 0.62% lower overnight returns per month than firms with low characteristics-based factor beta.[11] Remarkably, for macro-related factors, the pattern is exactly the opposite, as shown in Panel B of Table 13. More specifically, on average, firms with high macro factor beta earn 0.71% higher overnight returns per month than firms with low macro factor beta, whereas firms with high macro factor beta earn 0.50% lower intraday returns per month than firms with low macro factor beta. Thus, for macro-related factors, which have strong economic foundation, high-beta firms tend to earn higher returns overnight, consistent with the findings in Hendershott, Livdan, and Rosch (2019) which focues on the market factor only.

Overall, the above evidence confirms the general message of our paper. During more rational times (i.e., low sentiment periods or overnights), macro-related factors tend to be priced whereas the characteristics-based factors are not. However, during more irrational times (i.e., high sentiment periods or intraday), firms with high characteristics-based factor beta tend to earn higher returns than firms with low characteristics-based factor beta, and the opposite pattern holds for macro-related factors. These results again suggest that the beta on characteristics-based factors may be a proxy for mispricing rather than risk exposure.

6 Conclusions

Recent studies have proposed many prominent new characteristics-based factors that can account for a large set of asset pricing anomalies. However, the underlying economic forces behind these new factors are still debatable. By investigating the time variation of the pricing of these factors, we shed light on the underlying forces for these factors. In particular, instead of using the traditional anomaly-based portfolios as testing assets, we use portfolios that are

[11]Return-based factors such as MOM and PEAD are exceptions. This might be due to the clientele mechanism proposed in Lou, Polk, and Skouras (2018).

formed by directly sorting stocks based on their exposure to these characteristics-based factors. Earlier studies find that the return spreads between high- and low-beta firms are typically tiny and insignificant. However, we find that high-beta portfolios earn significantly higher returns than low-beta portfolios following high-sentiment periods, whereas the exact opposite occurs following low-sentiment periods. The above two-regime pattern is in sharp contrast with the reversed two-regime pattern when economically motivated factors, such as consumption growth and TFP growth, are used. We provide further consistent evidence based on mutual fund and hedge fund returns. Overall, our findings suggest that mispricing plays at least some role behind these factors, and the exposure to these characteristics-based factors is likely to be a noisy proxy for the level of mispricing, rather than risk, especially during high-sentiment periods.

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Table 1: Summary statistics of the characteristics-based factors

This table reports the summary statistics of characteristics-based tradable factors. Panel A presents the pairwise Pearson correlations of the 13 factors' monthly returns. Panel B presents the factors' monthly mean returns (in percentages) and CAPM alphas (in percentages) with Newey-West (1987) 5-lag adjusted t-statistics in parentheses. Panel C presents the correlations between the Baker-Wurgler (BW) sentiment index and the characteristics-based factors. The sample period is from 1972:1 to 2017:12 for IA and ROE factors, 1972:7 to 2017:12 for FIN and PEAD factors, and 1963:7 to 2017:12 for other factors.

Panel A: Pairwise correlations among characteristics-based factors

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	SMB	1.00												
(2)	HML	-0.07	1.00											
(3)	RMW	-0.35	0.06	1.00										
(4)	CMA	-0.10	0.70	-0.04	1.00									
(5)	IA	-0.13	0.67	0.13	0.91	1.00								
(6)	ROE	-0.38	-0.12	0.67	-0.06	0.06	1.00							
(7)	PMU	0.03	-0.36	0.47	-0.36	-0.25	0.37	1.00						
(8)	QMJ	-0.48	-0.05	0.72	0.07	0.11	0.69	0.47	1.00					
(9)	MOM	-0.03	-0.18	0.12	-0.02	0.03	0.50	0.06	0.28	1.00				
(10)	MGMT	-0.33	0.71	0.20	0.79	0.76	0.09	-0.20	0.35	0.01	1.00			
(11)	PERF	-0.11	-0.36	0.41	-0.15	-0.11	0.62	0.43	0.59	0.72	-0.09	1.00		
(12)	FIN	-0.32	0.63	0.57	0.60	0.65	0.33	0.06	0.51	0.07	0.78	0.11	1.00	
(13)	PEAD	-0.03	-0.16	-0.07	-0.03	-0.07	0.25	0.04	0.16	0.47	-0.01	0.37	-0.08	1.00

Panel B: Factor returns and CAPM alphas

Return	0.25	0.35	0.26	0.29	0.38	0.55	0.28	0.38	0.66	0.55	0.62	0.81	0.58
	(2.01)	(2.70)	(2.68)	(3.23)	(4.39)	(5.03)	(2.80)	(3.80)	(3.93)	(4.44)	(4.16)	(4.40)	(7.18)
Alpha^{CAPM}	0.15	0.43	0.32	0.38	0.46	0.61	0.27	0.53	0.73	0.73	0.72	1.03	0.6
	(1.25)	(3.25)	(3.15)	(4.43)	(5.38)	(6.07)	(2.49)	(6.02)	(4.70)	(6.48)	(4.94)	(6.16)	(8.02)

Panel C: Correlations between characteristics-based factors and BW sentiment index

S_{t-1}	-0.12	0.05	0.14	0.07	0.02	0.11	0.12	0.18	0.01	0.14	0.06	0.09	-0.02
ΔS_t	0.38	-0.29	-0.34	-0.29	-0.29	-0.25	0.04	-0.36	0.06	-0.41	-0.01	-0.46	0.12

Table 2: Beta-sorted portfolios

This table reports the results of decile value-weighted portfolios sorted by factor betas. The betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. The betas of other factors are estimated from a single factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Panel A presents the pairwise Pearson correlations of monthly returns for the high-minus-low beta-sorted portfolios. Panel B (C) presents the monthly mean excess returns and CAPM alphas (ex post betas) of high-beta, low-beta, and high-minus-low portfolios with Newey-West (1987) 5-lag adjusted t-statistics in parentheses. Ex post betas are estimated using the corresponding single characteristics-based factor model. Ave refers to the average portfolios across all beta-sorted portfolios. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2017:12 for IA and ROE beta-sorted portfolios, 1975:7 to 2017:12 for FIN and PEAD beta-sorted portfolios, and 1966:7 to 2017:12 for other beta-sorted portfolios. Returns and alphas are in percentages.

Panel A: Pairwise correlations among beta-sorted high-minus-low portfolios

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	SMB	1.00														
(2)	HML	-0.33	1.00													
(3)	RMW	-0.59	0.11	1.00												
(4)	CMA	-0.57	0.81	0.27	1.00											
(5)	IA	-0.53	0.84	0.35	0.95	1.00										
(6)	ROE	-0.69	-0.03	0.81	0.15	0.16	1.00									
(7)	PMU	0.14	-0.34	0.22	-0.32	-0.20	0.23	1.00								
(8)	QMJ	-0.87	0.21	0.70	0.50	0.47	0.74	0.09	1.00							
(9)	MOM	0.00	-0.07	0.12	0.00	-0.07	0.17	-0.01	0.13	1.00						
(10)	MGMT	-0.71	0.73	0.34	0.88	0.89	0.24	-0.18	0.62	-0.11	1.00					
(11)	PERF	-0.11	-0.22	0.29	-0.09	-0.13	0.37	0.12	0.27	0.77	-0.15	1.00				
(12)	FIN	-0.68	0.68	0.57	0.83	0.84	0.37	0.03	0.66	0.01	0.87	0.01	1.00			
(13)	PEAD	0.01	-0.21	0.06	-0.10	-0.15	0.12	0.06	0.14	0.38	-0.15	0.36	-0.04	1.00		
(14)	Ave	-0.62	0.52	0.68	0.69	0.71	0.59	0.12	0.74	0.42	0.69	0.44	0.83	0.24	1.00	
(15)	$\text{Ave}_{w/oSMB}$	-0.73	0.52	0.69	0.71	0.72	0.63	0.07	0.81	0.37	0.74	0.41	0.84	0.21	0.99	1.00

Table 2 (cont.): Beta-sorted portfolios

Panel B: Excess returns and CAPM alphas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Ret^e_H	0.54	0.78	0.50	0.54	0.76	0.67	0.56	0.55	0.52	0.51	0.63	0.76	0.64	0.56	0.57
	(1.44)	(3.16)	(2.46)	(2.60)	(3.15)	(3.15)	(2.01)	(3.32)	(2.04)	(2.63)	(2.70)	(3.68)	(2.31)	(2.73)	(2.91)
Ret^e_L	0.50	0.39	0.55	0.40	0.76	0.95	0.37	0.46	0.35	0.39	0.22	0.52	0.57	0.43	0.43
	(3.37)	(1.35)	(1.91)	(1.28)	(2.28)	(2.78)	(1.37)	(1.29)	(1.16)	(1.15)	(0.74)	(1.56)	(1.99)	(1.63)	(1.52)
Ret^e_{H-L}	0.04	0.39	-0.05	0.14	0.01	-0.29	0.19	0.09	0.17	0.12	0.41	0.23	0.08	0.13	0.14
	(0.14)	(1.49)	(-0.22)	(0.53)	(0.02)	(-0.99)	(0.72)	(0.30)	(0.65)	(0.40)	(1.63)	(0.79)	(0.28)	(1.04)	(0.93)
$\text{Alpha}^{CAPM}_{H-L}$	-0.46	0.59	0.18	0.46	0.4	0.08	0.1	0.55	0.22	0.55	0.51	0.69	0.08	0.28	0.35
	(-1.98)	(2.17)	(0.7)	(1.80)	(1.34)	(0.28)	(0.37)	(2.32)	(0.80)	(2.12)	(2.06)	(2.46)	(0.29)	(2.46)	(2.60)

Panel C: Ex post betas

High Beta	1.66	0.42	0.26	-0.05	0.1	0.11	0.9	-0.32	0.35	-0.11	0.22	-0.01	0.28	0.33	0.19
	(13.86)	(2.38)	(2.21)	(-0.42)	(0.66)	(0.92)	(5.65)	(-3.05)	(2.87)	(-1.07)	(2.08)	(-0.12)	(1.43)	(7.12)	(4.07)
Low Beta	-0.09	-1.19	-1.61	-1.98	-2.11	-1.54	-0.96	-2.6	-0.95	-1.95	-1.11	-1.27	-1.03	-1.26	-1.38
	(-1.04)	(-7.57)	(-9.52)	(-11.26)	(-9.21)	(-8.52)	(-5.84)	(-20.69)	(-9.66)	(-23.6)	(-10.53)	(-14.59)	(-4.11)	(-25.93)	(-26.78)
High - Low	1.74	1.61	1.87	1.93	2.21	1.64	1.86	2.28	1.3	1.85	1.34	1.26	1.32	1.59	1.57
	(21.10)	(14.34)	(19.30)	(10.44)	(9.46)	(13.36)	(19.97)	(23.45)	(19.31)	(17.44)	(19.02)	(19.34)	(6.91)	(40.96)	(38.31)

Table 3: Beta-sorted portfolio returns following high and low sentiment

This table reports the results of factor beta-sorted decile value-weighted portfolios following high- and low-sentiment regimes, as classified based on the median level of the Baker and Wurgler (2006) sentiment index. We report the excess returns (Panel A) and CAPM alphas (Panel B) for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2017:12 for IA and ROE, 1975:7 to 2017:12 for FIN and PEAD, and 1966:7 to 2017:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Excess returns

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.46	0.53	0.07	1.20	-0.10	-1.30	0.74	-0.63	-1.37
	(2.17)	(2.67)	(0.24)	(2.09)	(-0.23)	(-1.85)	(1.63)	(-1.73)	(-2.46)
HML	0.81	-0.02	-0.83	0.85	0.71	-0.14	0.04	0.73	0.69
	(1.94)	(-0.05)	(-1.52)	(1.93)	(2.77)	(-0.28)	(0.11)	(2.10)	(1.31)
RMW	1.19	-0.07	-1.25	0.52	0.47	-0.05	-0.67	0.54	1.21
	(2.73)	(-0.19)	(-2.35)	(1.64)	(1.86)	(-0.11)	(-1.82)	(1.70)	(2.52)
CMA	0.90	-0.09	-0.99	0.45	0.64	0.19	-0.45	0.72	1.18
	(1.94)	(-0.22)	(-1.68)	(1.35)	(2.43)	(0.48)	(-1.21)	(2.08)	(2.38)
IA	1.64	0.01	-1.63	0.85	0.69	-0.16	-0.79	0.68	1.47
	(3.19)	(0.02)	(-2.69)	(2.00)	(2.58)	(-0.34)	(-1.91)	(1.84)	(2.74)
ROE	1.72	0.30	-1.42	0.86	0.50	-0.35	-0.86	0.20	1.06
	(2.93)	(0.80)	(-2.16)	(2.51)	(1.83)	(-0.84)	(-1.84)	(0.57)	(1.83)
PMU	0.94	-0.19	-1.13	0.69	0.43	-0.27	-0.24	0.62	0.87
	(2.23)	(-0.59)	(-2.23)	(1.66)	(1.17)	(-0.49)	(-0.60)	(1.69)	(1.66)
QMJ	1.32	-0.37	-1.69	0.38	0.72	0.34	-0.94	1.09	2.03
	(2.34)	(-0.88)	(-2.49)	(1.60)	(3.19)	(1.05)	(-2.07)	(3.43)	(3.77)
MOM	0.74	-0.04	-0.78	0.71	0.33	-0.38	-0.03	0.37	0.39
	(1.51)	(-0.11)	(-1.35)	(1.85)	(0.96)	(-0.75)	(-0.07)	(1.04)	(0.70)
MGMT	0.96	-0.16	-1.13	0.40	0.61	0.21	-0.56	0.77	1.33
	(1.86)	(-0.39)	(-1.74)	(1.27)	(2.65)	(0.53)	(-1.34)	(2.07)	(2.34)
PERF	0.76	-0.30	-1.06	0.75	0.52	-0.23	-0.01	0.82	0.83
	(1.59)	(-0.82)	(-1.84)	(2.11)	(1.63)	(-0.48)	(-0.02)	(2.64)	(1.58)
FIN	1.30	-0.12	-1.42	0.80	0.72	-0.08	-0.50	0.84	1.34
	(2.49)	(-0.3)	(-2.31)	(2.32)	(2.87)	(-0.20)	(-1.13)	(2.29)	(2.41)
PEAD	1.17	0.07	-1.10	0.90	0.43	-0.47	-0.27	0.36	0.63
	(2.2)	(0.22)	(-1.89)	(2.17)	(1.23)	(-0.96)	(-0.61)	(1.12)	(1.14)
Ave	0.94	-0.06	-1.00	0.65	0.48	-0.17	-0.30	0.54	0.83
	(2.26)	(-0.19)	(-1.99)	(1.99)	(1.88)	(-0.42)	(-1.64)	(3.60)	(3.64)
$\text{Ave}_{w/o\ SMB}$	0.98	-0.11	-1.09	0.60	0.53	-0.07	-0.38	0.64	1.02
	(2.23)	(-0.33)	(-2.06)	(1.95)	(2.19)	(-0.19)	(-1.68)	(3.51)	(3.62)

Table 3 (cont.): Beta-sorted portfolio returns following high and low sentiment

Panel B: CAPM alphas

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	-0.05	0.26	0.31	0.04	-0.72	-0.77	0.09	-0.99	-1.07
	(-0.53)	(2.29)	(2.14)	(0.16)	(-3.62)	(-2.48)	(0.28)	(-3.48)	(-2.61)
HML	-0.04	-0.56	-0.53	0.04	0.44	0.41	0.07	1.00	0.93
	(-0.19)	(-3.19)	(-2.13)	(0.13)	(2.26)	(1.18)	(0.18)	(2.95)	(1.76)
RMW	0.27	-0.56	-0.84	-0.10	0.15	0.25	-0.37	0.71	1.08
	(1.21)	(-2.85)	(-2.81)	(-0.69)	(0.86)	(1.08)	(-1.09)	(2.13)	(2.26)
CMA	-0.03	-0.66	-0.63	-0.20	0.36	0.56	-0.17	1.01	1.18
	(-0.15)	(-3.50)	(-2.33)	(-1.07)	(1.91)	(2.18)	(-0.49)	(3.03)	(2.52)
IA	0.27	-0.66	-0.94	-0.23	0.37	0.59	-0.50	1.03	1.53
	(1.30)	(-3.19)	(-3.27)	(-0.85)	(1.84)	(1.83)	(-1.19)	(2.78)	(2.78)
ROE	0.13	-0.26	-0.39	-0.00	0.09	0.10	-0.13	0.35	0.49
	(0.44)	(-1.08)	(-1.07)	(-0.03)	(0.48)	(0.39)	(-0.35)	(0.89)	(0.90)
PMU	0.22	-0.60	-0.82	-0.15	-0.05	0.09	-0.36	0.55	0.91
	(0.85)	(-2.43)	(-2.41)	(-0.74)	(-0.30)	(0.38)	(-0.9)	(1.47)	(1.77)
QMJ	0.17	-0.96	-1.13	-0.15	0.44	0.59	-0.32	1.40	1.72
	(0.67)	(-4.93)	(-3.58)	(-1.28)	(3.50)	(3.46)	(-0.91)	(5.09)	(3.92)
MOM	-0.19	-0.45	-0.26	-0.04	-0.12	-0.08	0.15	0.33	0.18
	(-0.84)	(-1.89)	(-0.78)	(-0.20)	(-0.64)	(-0.31)	(0.41)	(0.87)	(0.33)
MGMT	-0.05	-0.78	-0.73	-0.18	0.38	0.56	-0.13	1.16	1.29
	(-0.25)	(-4.13)	(-2.63)	(-0.89)	(2.15)	(1.96)	(-0.35)	(3.62)	(2.60)
PERF	-0.15	-0.74	-0.59	0.05	0.10	0.05	0.20	0.84	0.64
	(-0.67)	(-3.40)	(-1.76)	(0.29)	(0.63)	(0.21)	(0.57)	(2.55)	(1.24)
FIN	0.08	-0.82	-0.90	-0.01	0.42	0.42	-0.08	1.24	1.32
	(0.32)	(-4.07)	(-2.89)	(-0.03)	(2.35)	(1.52)	(-0.21)	(3.64)	(2.50)
PEAD	-0.02	-0.39	-0.37	-0.05	-0.13	-0.08	-0.03	0.26	0.29
	(-0.08)	(-1.88)	(-1.15)	(-0.26)	(-0.68)	(-0.29)	(-0.08)	(0.76)	(0.56)
Ave	0.04	-0.55	-0.59	-0.08	0.11	0.19	-0.12	0.66	0.78
	(0.35)	(-4.88)	(-3.61)	(-1.01)	(1.43)	(1.73)	(-0.80)	(4.34)	(3.66)
$\text{Ave}_{w/o\ SMB}$	0.05	-0.62	-0.67	-0.08	0.19	0.27	-0.13	0.81	0.94
	(0.33)	(-4.91)	(-3.61)	(-0.97)	(2.20)	(2.27)	(-0.70)	(4.54)	(3.71)

Table 4: Beta-sorted portfolios: predictive regressions on lagged sentiment

This table reports the point estimates of b ($\hat{b}$), along with Newey-West 5-lag adjusted t-statistics, in the regression specifications: $R_{i,t} = a + bS_{t-1} + e_{i,t}$ (Panel A) and $R_{i,t} = a + bS_{t-1} + cMKT_t + e_{i,t}$ (Panel B).Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile (High beta) portfolio, and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave (Ave$_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2017:12 for IA and ROE, 1975:7 to 2017:12 for FIN and PEAD, and 1966:7 to 2017:12 for others.

Panel A: Lagged BW sentiment

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	-0.06	(-0.32)	-1.1	(-2.77)	-1.04	(-3.56)
HML	-0.5	(-1.55)	-0.3	(-1.18)	0.2	(0.72)
RMW	-0.77	(-2.73)	-0.13	(-0.52)	0.63	(2.57)
CMA	-0.64	(-1.8)	-0.09	(-0.43)	0.55	(1.94)
IA	-1.14	(-2.68)	-0.19	(-0.81)	0.95	(2.59)
ROE	-1.23	(-2.74)	-0.21	(-0.88)	1.02	(2.87)
PMU	-0.66	(-2.84)	-0.45	(-1.28)	0.21	(0.72)
QMJ	-1.15	(-3.16)	0	(0)	1.15	(4.55)
MOM	-0.59	(-1.91)	-0.41	(-1.59)	0.18	(0.8)
MGMT	-0.76	(-2.09)	-0.08	(-0.43)	0.68	(2.36)
PERF	-0.81	(-2.65)	-0.27	(-1.07)	0.54	(2.79)
FIN	-0.86	(-2.27)	-0.07	(-0.37)	0.78	(2.32)
PEAD	-0.56	(-1.91)	-0.49	(-1.49)	0.06	(0.18)
Ave	-0.68	(-2.38)	-0.29	(-1.22)	0.39	(3.4)
Ave$_{w/o\ SMB}$	-0.73	(-2.46)	-0.22	(-0.97)	0.51	(3.68)

Panel B: Lagged BW sentiment, controlling market factor

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	0.16	(1.92)	-0.61	(-4.09)	-0.77	(-3.7)
HML	-0.11	(-0.79)	-0.02	(-0.11)	0.09	(0.35)
RMW	-0.38	(-2.75)	0.13	(0.95)	0.51	(2.07)
CMA	-0.22	(-1.59)	0.15	(1.26)	0.38	(1.61)
IA	-0.46	(-2.66)	0.22	(1.43)	0.69	(2.27)
ROE	-0.57	(-2.89)	0.21	(1.68)	0.79	(2.82)
PMU	-0.35	(-2.28)	-0.09	(-0.6)	0.26	(0.97)
QMJ	-0.68	(-4.57)	0.22	(2.3)	0.9	(4.17)
MOM	-0.23	(-1.66)	-0.07	(-0.67)	0.16	(0.74)
MGMT	-0.31	(-2.45)	0.13	(1.13)	0.44	(2.05)
PERF	-0.44	(-3.58)	0.04	(0.46)	0.48	(2.67)
FIN	-0.38	(-2.45)	0.18	(1.23)	0.56	(2.1)
PEAD	-0.18	(-0.8)	-0.12	(-0.81)	0.06	(0.18)
Ave	-0.29	(-4.00)	0.01	(0.11)	0.3	(2.95)
Ave$_{w/o\ SMB}$	-0.33	(-4.00)	0.06	(1.00)	0.4	(3.37)

Table 5: Beta-sorted portfolios: predictive regressions on lagged sentiment and macro variables

This table reports the point estimates of b ($\hat{b}$), along with Newey-West 5-lag adjusted t-statistics, in the regression specifications: $R_{i,t} = a + b \times S_{t-1} + \sum_{j=1}^{4} m_j \times X_{j,t-1}$. Macro variables $X_{j,t-1}$ include the default premium, the term premium, the real interest rate, and the log wealth-consumption ratio. Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2017:12 for IA and ROE, 1975:7 to 2017:12 for FIN and PEAD, and 1966:7 to 2017:12 for others.

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	-0.06	(-0.35)	-1.01	(-2.72)	-0.95	(-3.37)
HML	-0.46	(-1.45)	-0.28	(-1.13)	0.18	(0.65)
RMW	-0.69	(-2.62)	-0.11	(-0.43)	0.58	(2.4)
CMA	-0.58	(-1.7)	-0.05	(-0.27)	0.52	(1.89)
IA	-1.02	(-2.43)	-0.07	(-0.33)	0.95	(2.63)
ROE	-1.15	(-2.67)	-0.21	(-0.83)	0.94	(2.74)
PMU	-0.65	(-2.83)	-0.41	(-1.18)	0.25	(0.83)
QMJ	-1.11	(-3.25)	0.01	(0.04)	1.12	(4.59)
MOM	-0.58	(-1.95)	-0.36	(-1.4)	0.23	(1)
MGMT	-0.72	(-2.04)	-0.06	(-0.3)	0.66	(2.34)
PERF	-0.81	(-2.75)	-0.19	(-0.74)	0.62	(3.29)
FIN	-0.82	(-2.21)	-0.01	(-0.03)	0.81	(2.41)
PEAD	-0.53	(-2.07)	-0.38	(-1.11)	0.15	(0.43)
Ave	-0.64	(-2.39)	-0.24	(-1.05)	0.4	(3.51)
$\text{Ave}_{w/o\ SMB}$	-0.7	(-2.47)	-0.17	(-0.79)	0.52	(3.81)

Table 6: Beta-sorted portfolios: contemporaneous regressions on change in sentiment

This table reports the point estimates of b ($\hat{b}$), along with Newey-West 5-lag adjusted t-statistics, in the regression specifications: $R_{i,t} = a + b\Delta S_t + cMKT_t + e_{i,t}$. Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave (Ave$_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2010:12 for IA and ROE, 1975:7 to 2010:12 for FIN and PEAD, and 1966:7 to 2010:12 for others.

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	-0.79	(-5.97)	2.02	(6.74)	2.8	(6.82)
HML	1.2	(5.02)	-0.52	(-1.78)	-1.72	(-3.4)
RMW	1.22	(3.93)	-0.56	(-2.2)	-1.78	(-3.29)
CMA	1.41	(6.17)	-0.73	(-2.82)	-2.13	(-4.73)
IA	1.51	(5.91)	-1.02	(-3.46)	-2.52	(-4.87)
ROE	1.27	(3.01)	-0.32	(-1.46)	-1.59	(-2.74)
PMU	0.37	(1.43)	0.98	(4.79)	0.62	(1.72)
QMJ	1.72	(6.91)	-0.68	(-4.2)	-2.4	(-6.26)
MOM	0.09	(0.27)	0.71	(2.31)	0.62	(0.99)
MGMT	1.67	(7.02)	-0.91	(-4.19)	-2.58	(-6.09)
PERF	0.09	(0.27)	0.68	(2.34)	0.58	(0.97)
FIN	1.42	(4.38)	-0.75	(-2.57)	-2.17	(-3.67)
PEAD	-0.26	(-0.99)	1.15	(4.62)	1.41	(2.99)
Ave	0.83	(5.47)	0.06	(0.53)	-0.77	(-3.29)
Ave$_{w/o\ SMB}$	0.98	(5.7)	-0.12	(-0.91)	-1.09	(-4.02)

Table 7: Beta-sorted equity mutual fund portfolio returns following high and low sentiment

This table reports the results of factor-beta-sorted decile portfolios of actively managed equity mutual funds following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. We report the monthly excess returns (Panel A) and CAPM alphas (Panel B) for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily mutual fund returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single factor model using monthly mutual fund returns over the past 24 months with a minimum of 18 months. All portfolios are equally weighted and rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1998:12 to 2017:12 for MOM, PERF, and PEAD beta-sorted portfolios, and 1980:1 to 2017:12 for other beta-sorted portfolios. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Excess returns

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.51	0.54	0.04	1.05	0.12	-0.93	0.54	-0.42	-0.96
	(2.13)	(2.66)	(0.13)	(2.60)	(0.35)	(-1.76)	(2.35)	(-1.84)	(-2.97)
HML	0.94	0.18	-0.76	0.72	0.57	-0.15	-0.21	0.39	0.61
	(2.48)	(0.51)	(-1.51)	(2.51)	(2.87)	(-0.46)	(-0.85)	(1.58)	(1.76)
RMW	0.83	0.23	-0.59	0.80	0.49	-0.31	-0.03	0.26	0.28
	(2.47)	(0.77)	(-1.38)	(2.49)	(1.89)	(-0.77)	(-0.11)	(1.20)	(0.93)
CMA	0.99	0.19	-0.80	0.62	0.56	-0.06	-0.36	0.37	0.74
	(2.55)	(0.53)	(-1.57)	(2.31)	(2.78)	(-0.19)	(-1.49)	(1.48)	(2.18)
IA	1.06	0.28	-0.78	0.77	0.64	-0.13	-0.29	0.36	0.66
	(2.49)	(0.77)	(-1.47)	(2.54)	(3.18)	(-0.37)	(-1.02)	(1.35)	(1.74)
ROE	0.93	0.38	-0.55	0.84	0.70	-0.13	-0.10	0.32	0.42
	(2.60)	(1.29)	(-1.26)	(2.35)	(2.49)	(-0.31)	(-0.42)	(1.32)	(1.25)
PMU	0.74	0.14	-0.60	0.85	0.50	-0.35	0.11	0.36	0.24
	(2.50)	(0.53)	(-1.57)	(2.36)	(1.63)	(-0.77)	(0.49)	(1.58)	(0.82)
QMJ	1.12	0.07	-1.06	0.52	0.51	0.00	-0.61	0.45	1.05
	(2.84)	(0.20)	(-2.07)	(2.24)	(2.61)	(-0.01)	(-2.71)	(2.05)	(3.41)
MOM	1.03	-0.26	-1.29	1.15	0.21	-0.94	0.11	0.47	0.35
	(1.88)	(-0.58)	(-1.98)	(2.13)	(0.45)	(-1.52)	(0.27)	(1.02)	(0.60)
MGMT	1.07	0.16	-0.91	0.63	0.55	-0.08	-0.44	0.39	0.83
	(2.65)	(0.43)	(-1.71)	(2.63)	(2.91)	(-0.28)	(-1.63)	(1.52)	(2.27)
PERF	1.20	-0.25	-1.46	1.01	0.16	-0.84	-0.20	0.42	0.61
	(2.04)	(-0.51)	(-2.06)	(2.07)	(0.38)	(-1.51)	(-0.45)	(0.95)	(1.05)
FIN	1.03	0.29	-0.74	0.79	0.62	-0.17	-0.24	0.33	0.57
	(2.45)	(0.79)	(-1.41)	(2.70)	(3.3)	(-0.52)	(-0.88)	(1.22)	(1.55)
PEAD	1.13	0.01	-1.12	1.08	0.00	-1.08	-0.05	-0.01	0.04
	(1.94)	(0.02)	(-1.63)	(2.21)	(0.00)	(-1.75)	(-0.13)	(-0.02)	(0.06)
Ave	0.87	0.23	-0.64	0.75	0.48	-0.27	-0.11	0.26	0.37
	(2.6)	(0.75)	(-1.48)	(2.69)	(2.11)	(-0.79)	(-1.33)	(2.32)	(2.69)
$\text{Ave}_{w/o\ SMB}$	0.90	0.19	-0.71	0.73	0.52	-0.20	-0.18	0.33	0.51
	(2.60)	(0.61)	(-1.57)	(2.72)	(2.41)	(-0.62)	(-1.57)	(2.36)	(2.87)

Table 7 (cont.): Beta-sorted equity mutual fund portfolio returns following high and low sentiment

Panel B: CAPM alphas

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	-0.04	0.25	0.29	0.19	-0.37	-0.56	0.23	-0.62	-0.86
	(-0.63)	(2.83)	(2.88)	(1.22)	(-2.60)	(-2.72)	(1.23)	(-3.30)	(-3.36)
HML	0.14	-0.32	-0.46	0.12	0.30	0.18	-0.02	0.62	0.64
	(0.95)	(-2.24)	(-2.33)	(0.92)	(2.72)	(1.12)	(-0.09)	(2.98)	(2.18)
RMW	0.13	-0.20	-0.33	0.11	0.15	0.04	-0.02	0.34	0.37
	(0.86)	(-1.37)	(-1.66)	(0.95)	(1.12)	(0.21)	(-0.10)	(1.49)	(1.18)
CMA	0.17	-0.31	-0.48	0.05	0.29	0.23	-0.11	0.60	0.71
	(1.10)	(-2.14)	(-2.37)	(0.45)	(2.44)	(1.46)	(-0.54)	(2.79)	(2.46)
IA	0.19	-0.31	-0.49	0.12	0.34	0.21	-0.06	0.64	0.71
	(1.12)	(-1.99)	(-2.31)	(0.88)	(2.70)	(1.17)	(-0.25)	(2.73)	(2.14)
ROE	0.17	-0.08	-0.25	0.09	0.27	0.18	-0.08	0.35	0.42
	(1.21)	(-0.52)	(-1.22)	(0.75)	(1.66)	(0.87)	(-0.37)	(1.25)	(1.22)
PMU	0.14	-0.22	-0.37	0.07	0.08	0.01	-0.08	0.30	0.38
	(1.11)	(-1.79)	(-2.23)	(0.5)	(0.54)	(0.07)	(-0.35)	(1.25)	(1.28)
QMJ	0.29	-0.4	-0.7	-0.02	0.22	0.24	-0.31	0.62	0.93
	(1.94)	(-2.89)	(-3.48)	(-0.29)	(2.33)	(2.12)	(-1.74)	(3.32)	(3.69)
MOM	-0.09	-0.16	-0.07	0.16	0.31	0.15	0.25	0.48	0.22
	(-0.60)	(-0.68)	(-0.25)	(0.66)	(1.24)	(0.49)	(0.73)	(1.08)	(0.42)
MGMT	0.22	-0.36	-0.58	0.11	0.30	0.19	-0.11	0.66	0.77
	(1.36)	(-2.46)	(-2.76)	(1.05)	(2.94)	(1.31)	(-0.5)	(3.31)	(2.69)
PERF	-0.03	-0.14	-0.11	0.15	0.26	0.11	0.18	0.40	0.22
	(-0.19)	(-0.65)	(-0.41)	(0.68)	(1.05)	(0.38)	(0.53)	(0.96)	(0.44)
FIN	0.14	-0.32	-0.46	0.12	0.33	0.21	-0.02	0.65	0.67
	(0.88)	(-2.07)	(-2.19)	(0.89)	(3.12)	(1.26)	(-0.1)	(2.98)	(2.14)
PEAD	-0.03	0.10	0.13	0.13	0.11	-0.01	0.15	0.02	-0.14
	(-0.13)	(0.47)	(0.42)	(0.74)	(0.36)	(-0.03)	(0.46)	(0.03)	(-0.22)
Ave	0.13	-0.21	-0.34	0.11	0.15	0.03	-0.02	0.36	0.38
	(1.36)	(-2.26)	(-2.67)	(1.65)	(1.93)	(0.32)	(-0.24)	(3.65)	(3.2)
$\text{Ave}_{w/o\ SMB}$	0.14	-0.26	-0.41	0.11	0.20	0.09	-0.03	0.47	0.50
	(1.34)	(-2.49)	(-2.81)	(1.74)	(2.67)	(0.95)	(-0.38)	(3.93)	(3.49)

Table 8: Beta-sorted hedge fund portfolio returns following high and low sentiment

This table reports the results of factor-beta-sorted decile portfolios of hedge funds following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. We report the monthly excess returns (Panel A) and CAPM alphas (Panel B) for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas are estimated from a single factor model using monthly hedge fund returns over the past 24 months with a minimum of 18 months. All portfolios are equally weighted and rebalanced monthly. Ave (Ave$_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). Returns and alphas are in percentages. The sample period is from 1996:7 to 2017:12. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Excess returns

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.25	0.30	0.05	1.33	0.04	-1.28	1.08	-0.26	-1.34
	(1.32)	(1.59)	(0.29)	(2.50)	(0.11)	(-2.11)	(2.47)	(-0.59)	(-2.18)
HML	0.81	-0.01	-0.82	0.90	0.51	-0.39	0.09	0.52	0.43
	(1.73)	(-0.03)	(-1.62)	(2.43)	(2.08)	(-0.92)	(0.18)	(1.13)	(0.68)
RMW	1.51	-0.08	-1.59	0.10	0.41	0.31	-1.41	0.49	1.90
	(2.43)	(-0.21)	(-2.46)	(0.87)	(2.69)	(1.66)	(-2.17)	(1.10)	(2.62)
CMA	1.19	0.08	-1.11	0.51	0.38	-0.13	-0.68	0.30	0.98
	(2.22)	(0.20)	(-1.94)	(2.01)	(1.45)	(-0.37)	(-1.29)	(0.57)	(1.48)
IA	1.23	0.05	-1.19	0.47	0.41	-0.06	-0.76	0.36	1.12
	(2.37)	(0.12)	(-2.19)	(1.90)	(1.61)	(-0.18)	(-1.53)	(0.76)	(1.82)
ROE	1.36	-0.30	-1.66	0.23	0.62	0.39	-1.13	0.92	2.05
	(2.25)	(-0.77)	(-2.6)	(2.30)	(3.72)	(2.04)	(-1.93)	(2.25)	(3.09)
PMU	1.15	0.07	-1.08	0.55	0.46	-0.09	-0.60	0.39	0.99
	(1.97)	(0.20)	(-1.81)	(2.20)	(2.29)	(-0.32)	(-0.96)	(1.1)	(1.52)
QMJ	1.40	-0.12	-1.52	0.13	0.44	0.31	-1.27	0.56	1.83
	(2.19)	(-0.29)	(-2.21)	(1.20)	(3.28)	(1.80)	(-1.92)	(1.20)	(2.44)
MOM	1.43	0.30	-1.13	0.30	0.16	-0.15	-1.12	-0.14	0.98
	(2.84)	(1.14)	(-2.23)	(1.12)	(0.45)	(-0.39)	(-2.79)	(-0.35)	(1.76)
MGMT	1.37	0.06	-1.31	0.24	0.35	0.11	-1.13	0.29	1.42
	(2.4)	(0.15)	(-2.04)	(1.66)	(2.05)	(0.52)	(-2.02)	(0.57)	(2.03)
PERF	1.46	0.10	-1.36	0.09	0.27	0.17	-1.37	0.17	1.54
	(2.85)	(0.31)	(-2.47)	(0.41)	(0.91)	(0.55)	(-3.43)	(0.40)	(2.64)
FIN	1.48	0.04	-1.44	0.09	0.44	0.35	-1.39	0.40	1.79
	(2.44)	(0.09)	(-2.22)	(0.90)	(3.14)	(2.12)	(-2.28)	(0.83)	(2.52)
PEAD	1.26	0.40	-0.86	0.56	-0.01	-0.57	-0.70	-0.41	0.30
	(2.58)	(1.54)	(-1.72)	(1.79)	(-0.02)	(-1.44)	(-1.76)	(-1.18)	(0.55)
Ave	1.22	0.07	-1.16	0.42	0.35	-0.08	-0.80	0.28	1.08
	(2.42)	(0.23)	(-2.29)	(2.61)	(2.26)	(-0.41)	(-2.13)	(1.26)	(2.75)
Ave$_{w/o\ SMB}$	1.30	0.05	-1.26	0.35	0.37	0.02	-0.96	0.32	1.28
	(2.43)	(0.15)	(-2.31)	(2.53)	(2.52)	(0.12)	(-2.18)	(1.20)	(2.73)

Table 8 (cont.): Beta-sorted hedge fund portfolio returns following high and low sentiment

Panel B: CAPM alphas

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.10	0.29	0.20	0.50	-0.23	-0.73	0.40	-0.52	-0.92
	(0.46)	(1.50)	(1.03)	(1.84)	(-0.97)	(-2.14)	(1.16)	(-1.59)	(-2.35)
HML	0.22	-0.27	-0.49	0.47	0.49	0.02	0.25	0.76	0.51
	(0.70)	(-1.15)	(-1.55)	(1.91)	(1.85)	(0.06)	(0.54)	(1.91)	(0.90)
RMW	0.51	-0.37	-0.88	0.13	0.44	0.31	-0.38	0.81	1.19
	(1.64)	(-1.72)	(-2.66)	(1.06)	(2.97)	(1.63)	(-1.06)	(3.29)	(3.05)
CMA	0.40	-0.19	-0.59	0.34	0.37	0.03	-0.07	0.55	0.62
	(1.33)	(-0.7)	(-1.72)	(1.62)	(1.32)	(0.09)	(-0.17)	(1.22)	(1.10)
IA	0.45	-0.22	-0.67	0.28	0.39	0.11	-0.17	0.61	0.78
	(1.55)	(-0.9)	(-2.13)	(1.45)	(1.46)	(0.31)	(-0.46)	(1.49)	(1.50)
ROE	0.41	-0.56	-0.97	0.24	0.59	0.35	-0.17	1.15	1.32
	(1.40)	(-2.44)	(-2.89)	(2.37)	(3.20)	(1.72)	(-0.58)	(4.25)	(3.51)
PMU	0.32	-0.11	-0.43	0.43	0.35	-0.07	0.11	0.47	0.36
	(1.08)	(-0.38)	(-1.11)	(2.12)	(2.00)	(-0.31)	(0.29)	(1.33)	(0.71)
QMJ	0.40	-0.42	-0.82	0.20	0.48	0.28	-0.20	0.90	1.11
	(1.27)	(-1.63)	(-2.3)	(1.90)	(3.84)	(1.76)	(-0.60)	(3.26)	(2.87)
MOM	0.63	0.18	-0.45	0.05	-0.02	-0.07	-0.58	-0.20	0.38
	(2.24)	(0.68)	(-1.28)	(0.22)	(-0.07)	(-0.22)	(-1.63)	(-0.45)	(0.72)
MGMT	0.51	-0.25	-0.76	0.20	0.39	0.20	-0.31	0.65	0.96
	(1.64)	(-0.91)	(-2.1)	(1.55)	(2.21)	(0.93)	(-0.89)	(1.82)	(2.11)
PERF	0.62	-0.08	-0.70	-0.08	0.14	0.22	-0.70	0.22	0.92
	(2.11)	(-0.25)	(-1.73)	(-0.34)	(0.51)	(0.72)	(-1.77)	(0.47)	(1.61)
FIN	0.53	-0.27	-0.80	0.12	0.48	0.36	-0.41	0.75	1.16
	(1.68)	(-1.05)	(-2.24)	(1.16)	(3.46)	(2.18)	(-1.22)	(2.53)	(2.83)
PEAD	0.50	0.28	-0.22	0.29	-0.20	-0.49	-0.21	-0.48	-0.27
	(1.96)	(1.10)	(-0.61)	(1.14)	(-0.71)	(-1.53)	(-0.62)	(-1.28)	(-0.55)
Ave	0.43	-0.15	-0.58	0.24	0.28	0.04	-0.19	0.44	0.62
	(1.71)	(-0.84)	(-2.20)	(2.27)	(1.98)	(0.24)	(-0.92)	(3.42)	(2.86)
$\text{Ave}_{w/o\ SMB}$	0.46	-0.19	-0.65	0.22	0.33	0.10	-0.24	0.52	0.75
	(1.72)	(-1.00)	(-2.30)	(2.14)	(2.25)	(0.64)	(-1.01)	(3.40)	(2.98)

Table 9: Beta-sorted portfolio returns following high and low sentiment: alternative sentiment measures

This table reports the results of factor-beta-sorted decile value-weighted portfolios following high- and low-sentiment regimes, as classified based on the median level of the Michigan Consumer Sentiment Index (Panel A), or Corporate Board Consumer Confidence Index (Panel B), the Huang et al. (2015) PLS sentiment index (Panel C), or American Association of Individual Investors (AAII) sentiment index (Panel D). We report the monthly excess returns for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2017:12 for IA and ROE, 1975:7 to 2017:12 for FIN and PEAD, and 1966:7 to 2017:12 for others. The Conference Board Consumer Confidence index in Panel B starts from 1977:7. The Huang et al. (2015) PLS sentiment index in Panel C ends in 2016:12. The AAII sentiment index in Panel D starts from 1987:7. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Michigan Consumer Sentiment Index

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.41	0.61	0.19	1.25	-0.41	-1.66	0.83	-1.02	-1.85
	(1.98)	(3.08)	(0.68)	(2.42)	(-0.79)	(-2.28)	(2.17)	(-2.20)	(-3.13)
HML	0.61	0.10	-0.51	0.94	0.56	-0.38	0.34	0.46	0.13
	(1.53)	(0.22)	(-0.85)	(2.49)	(1.99)	(-0.79)	(1.06)	(0.99)	(0.22)
RMW	1.05	-0.12	-1.17	0.34	0.71	0.37	-0.71	0.83	1.54
	(2.79)	(-0.26)	(-1.94)	(1.10)	(3.37)	(0.99)	(-2.44)	(1.88)	(2.91)
CMA	0.71	-0.01	-0.72	0.63	0.42	-0.21	-0.08	0.44	0.51
	(1.62)	(-0.03)	(-1.14)	(2.02)	(1.76)	(-0.53)	(-0.24)	(0.92)	(0.90)
IA	1.28	0.05	-1.23	0.82	0.69	-0.13	-0.46	0.64	1.10
	(2.82)	(0.09)	(-1.76)	(2.16)	(2.83)	(-0.29)	(-1.38)	(1.20)	(1.73)
ROE	1.71	-0.07	-1.78	0.52	0.87	0.36	-1.19	0.94	2.13
	(3.64)	(-0.14)	(-2.51)	(1.67)	(3.21)	(0.87)	(-3.21)	(2.16)	(3.62)
PMU	0.75	-0.15	-0.89	0.70	0.37	-0.33	-0.05	0.52	0.57
	(1.98)	(-0.39)	(-1.67)	(1.79)	(0.93)	(-0.59)	(-0.13)	(1.35)	(1.06)
QMJ	1.09	-0.39	-1.48	0.44	0.70	0.26	-0.65	1.09	1.74
	(2.16)	(-0.78)	(-2.12)	(1.85)	(3.31)	(0.83)	(-1.72)	(2.47)	(3.06)
MOM	0.66	-0.08	-0.74	0.58	0.43	-0.16	-0.08	0.51	0.58
	(1.47)	(-0.21)	(-1.25)	(1.62)	(1.21)	(-0.31)	(-0.21)	(1.22)	(1.05)
MGMT	0.74	-0.08	-0.83	0.48	0.54	0.06	-0.26	0.63	0.89
	(1.56)	(-0.17)	(-1.22)	(1.66)	(2.48)	(0.17)	(-0.71)	(1.26)	(1.45)
PERF	0.59	-0.27	-0.86	0.59	0.69	0.09	0.00	0.96	0.95
	(1.28)	(-0.69)	(-1.41)	(1.79)	(2.09)	(0.21)	(0.01)	(2.36)	(1.78)
FIN	0.90	0.02	-0.88	0.78	0.73	-0.05	-0.12	0.71	0.83
	(1.97)	(0.04)	(-1.24)	(2.48)	(3.27)	(-0.14)	(-0.33)	(1.30)	(1.26)
PEAD	0.86	0.17	-0.69	0.89	0.31	-0.57	0.03	0.14	0.11
	(2.15)	(0.41)	(-1.16)	(2.25)	(0.81)	(-1.01)	(0.08)	(0.32)	(0.20)
Ave	0.78	-0.03	-0.81	0.62	0.48	-0.14	-0.16	0.51	0.67
	(2.03)	(-0.08)	(-1.51)	(2.00)	(2.03)	(-0.38)	(-1.13)	(2.18)	(2.44)
$\text{Ave}_{w/o\ SMB}$	0.81	-0.09	-0.89	0.57	0.56	-0.02	-0.23	0.64	0.87
	(2.00)	(-0.22)	(-1.58)	(1.94)	(2.54)	(-0.05)	(-1.33)	(2.27)	(2.62)

Table 9 (cont.): Beta-sorted portfolio returns following high and low sentiment: alternative sentiment measures

Panel B: Conference Board Consumer Confidence Index

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.56	0.7	0.14	1.57	-0.14	-1.71	1	-0.84	-1.85
	(2.5)	(3.17)	(0.43)	(2.79)	(-0.26)	(-2.19)	(2.34)	(-1.74)	(-2.89)
HML	1	0.15	-0.86	0.88	0.93	0.05	-0.12	0.78	0.91
	(2.38)	(0.3)	(-1.31)	(1.83)	(3.38)	(0.09)	(-0.31)	(1.62)	(1.45)
RMW	1.15	0.13	-1.03	0.58	0.67	0.09	-0.57	0.55	1.11
	(2.56)	(0.24)	(-1.48)	(1.85)	(2.86)	(0.22)	(-1.56)	(1.14)	(1.82)
CMA	1.15	0.17	-0.97	0.74	0.59	-0.15	-0.41	0.41	0.82
	(2.5)	(0.35)	(-1.42)	(1.89)	(2.3)	(-0.32)	(-1.13)	(0.81)	(1.32)
IA	1.17	0.18	-0.99	0.77	0.64	-0.13	-0.4	0.46	0.86
	(2.51)	(0.36)	(-1.44)	(1.76)	(2.69)	(-0.26)	(-1.16)	(0.93)	(1.44)
ROE	1.43	0.21	-1.22	0.53	0.81	0.28	-0.89	0.61	1.5
	(2.89)	(0.42)	(-1.73)	(1.59)	(3.1)	(0.65)	(-2.19)	(1.45)	(2.55)
PMU	0.86	-0.03	-0.89	1.08	0.45	-0.64	0.22	0.48	0.25
	(1.69)	(-0.07)	(-1.36)	(3.14)	(1.06)	(-1.15)	(0.52)	(1.16)	(0.43)
QMJ	1.28	-0.08	-1.36	0.72	0.71	-0.01	-0.56	0.79	1.35
	(2.21)	(-0.15)	(-1.74)	(2.99)	(3.06)	(-0.03)	(-1.18)	(1.72)	(2.06)
MOM	0.89	0.02	-0.87	0.66	0.69	0.03	-0.23	0.67	0.9
	(1.65)	(0.04)	(-1.3)	(1.54)	(1.88)	(0.05)	(-0.47)	(1.63)	(1.37)
MGMT	1.09	0.12	-0.97	0.59	0.61	0.02	-0.5	0.49	0.99
	(2.09)	(0.23)	(-1.32)	(1.6)	(2.65)	(0.03)	(-1.17)	(0.92)	(1.47)
PERF	0.91	-0.25	-1.16	0.74	0.77	0.02	-0.17	1.02	1.18
	(1.71)	(-0.62)	(-1.7)	(2.02)	(2.26)	(0.04)	(-0.38)	(2.58)	(1.96)
FIN	0.93	0.15	-0.79	0.84	0.68	-0.16	-0.09	0.53	0.63
	(1.88)	(0.3)	(-1.1)	(2.36)	(3.06)	(-0.38)	(-0.24)	(1.07)	(0.98)
PEAD	0.87	0.27	-0.6	0.9	0.4	-0.5	0.03	0.13	0.1
	(1.87)	(0.74)	(-1)	(2.09)	(1.09)	(-0.87)	(0.08)	(0.35)	(0.17)
Ave	1.02	0.13	-0.89	0.82	0.6	-0.22	-0.21	0.47	0.67
	(2.35)	(0.33)	(-1.47)	(2.36)	(2.49)	(-0.51)	(-1.12)	(1.89)	(2.15)
$Ave_{w/o\ SMB}$	1.06	0.09	-0.98	0.75	0.66	-0.09	-0.31	0.58	0.88
	(2.32)	(0.2)	(-1.54)	(2.27)	(2.91)	(-0.22)	(-1.37)	(1.92)	(2.33)

Table 9 (cont.): Beta-sorted portfolio returns following high and low sentiment: alternative sentiment measures

Panel C: Huang et al. (2015) PLS sentiment index

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.67	0.28	-0.39	1.35	-0.28	-1.63	0.68	-0.56	-1.24
	(4.27)	(1.15)	(-1.32)	(3.33)	(-0.45)	(-2.16)	(2.02)	(-1.12)	(-2.04)
HML	0.98	-0.25	-1.23	1.05	0.52	-0.54	0.07	0.76	0.69
	(3.22)	(-0.51)	(-2.16)	(3.88)	(1.26)	(-1.1)	(0.22)	(1.81)	(1.35)
RMW	0.97	0.10	-0.87	0.79	0.17	-0.62	-0.18	0.07	0.25
	(2.92)	(0.2)	(-1.48)	(3.37)	(0.53)	(-1.54)	(-0.58)	(0.18)	(0.48)
CMA	1.05	-0.30	-1.36	0.66	0.45	-0.22	-0.39	0.75	1.14
	(3.17)	(-0.58)	(-2.18)	(2.8)	(1.30)	(-0.52)	(-1.26)	(1.80)	(2.24)
IA	1.32	0.00	-1.32	0.78	0.74	-0.04	-0.54	0.73	1.28
	(3.89)	(0.01)	(-1.84)	(3.45)	(1.56)	(-0.08)	(-1.68)	(1.48)	(2.19)
ROE	1.31	0.56	-0.75	0.86	0.39	-0.47	-0.45	-0.17	0.28
	(3.47)	(0.86)	(-1)	(4.12)	(0.98)	(-1.03)	(-1.30)	(-0.33)	(0.47)
PMU	0.85	-0.09	-0.94	1.04	0.05	-0.99	0.18	0.14	-0.04
	(3.00)	(-0.2)	(-1.74)	(3.26)	(0.12)	(-1.83)	(0.54)	(0.34)	(-0.08)
QMJ	1.23	-0.30	-1.53	0.65	0.43	-0.23	-0.58	0.72	1.30
	(3.16)	(-0.49)	(-2.09)	(3.55)	(1.55)	(-0.69)	(-1.69)	(1.52)	(2.20)
MOM	0.84	-0.19	-1.02	0.84	0.17	-0.67	0.00	0.36	0.36
	(2.27)	(-0.39)	(-1.67)	(3.15)	(0.40)	(-1.32)	(0.00)	(0.83)	(0.64)
MGMT	1.11	-0.37	-1.48	0.68	0.29	-0.39	-0.42	0.66	1.08
	(3.06)	(-0.65)	(-2.19)	(3.40)	(0.90)	(-1.03)	(-1.29)	(1.36)	(1.86)
PERF	0.86	-0.40	-1.26	0.89	0.33	-0.56	0.03	0.73	0.70
	(2.25)	(-0.84)	(-2.06)	(3.42)	(0.85)	(-1.18)	(0.07)	(1.95)	(1.34)
FIN	0.93	-0.01	-0.94	0.69	0.82	0.12	-0.24	0.83	1.06
	(2.76)	(-0.02)	(-1.31)	(3.87)	(1.97)	(0.27)	(-0.75)	(1.55)	(1.73)
PEAD	0.77	0.28	-0.49	0.94	0.23	-0.71	0.17	-0.05	-0.22
	(2.44)	(0.54)	(-0.78)	(3.14)	(0.47)	(-1.21)	(0.52)	(-0.12)	(-0.4)
Ave	0.99	-0.14	-1.12	0.86	0.24	-0.62	-0.12	0.38	0.50
	(3.39)	(-0.31)	(-2.08)	(4.00)	(0.71)	(-1.53)	(-0.84)	(1.88)	(1.99)
$\text{Ave}_{w/o\ SMB}$	1.01	-0.18	-1.19	0.82	0.30	-0.52	-0.20	0.47	0.67
	(3.30)	(-0.38)	(-2.10)	(4.01)	(0.91)	(-1.35)	(-1.11)	(1.89)	(2.16)

Table 9 (cont.): Beta-sorted portfolio returns following high and low sentiment: alternative sentiment measures

Panel D: AAII sentiment index

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.74	0.52	-0.22	1.73	-0.43	-2.15	0.98	-0.95	-1.93
	(2.63)	(1.94)	(-0.57)	(2.60)	(-0.62)	(-2.27)	(1.82)	(-1.47)	(-2.31)
HML	1.59	-0.22	-1.80	0.82	0.70	-0.12	-0.77	0.92	1.68
	(3.09)	(-0.33)	(-2.15)	(1.36)	(2.14)	(-0.18)	(-1.42)	(1.31)	(1.87)
RMW	1.51	-0.34	-1.86	0.75	0.72	-0.03	-0.77	1.06	1.83
	(2.61)	(-0.52)	(-2.13)	(2.18)	(2.49)	(-0.06)	(-1.52)	(1.59)	(2.15)
CMA	1.84	-0.22	-2.06	0.43	0.53	0.10	-1.41	0.75	2.16
	(3.17)	(-0.35)	(-2.29)	(0.98)	(1.57)	(0.18)	(-3.04)	(1.05)	(2.43)
IA	1.73	-0.19	-1.92	0.65	0.51	-0.15	-1.08	0.70	1.78
	(2.99)	(-0.3)	(-2.14)	(1.22)	(1.58)	(-0.24)	(-2.21)	(0.99)	(1.98)
ROE	1.47	-0.10	-1.57	0.82	0.65	-0.18	-0.65	0.75	1.40
	(2.37)	(-0.15)	(-1.75)	(2.2)	(2.06)	(-0.35)	(-1.35)	(1.24)	(1.74)
PMU	0.89	-0.13	-1.02	1.42	0.07	-1.35	0.52	0.19	-0.33
	(1.45)	(-0.26)	(-1.29)	(3.18)	(0.12)	(-1.91)	(1.09)	(0.43)	(-0.49)
QMJ	1.57	-0.3	-1.88	0.76	0.64	-0.12	-0.82	0.94	1.76
	(2.29)	(-0.46)	(-1.98)	(2.43)	(2.36)	(-0.29)	(-1.37)	(1.54)	(2.06)
MOM	1.07	-0.09	-1.16	0.86	0.35	-0.51	-0.21	0.44	0.65
	(1.65)	(-0.18)	(-1.37)	(1.77)	(0.72)	(-0.71)	(-0.37)	(0.78)	(0.76)
MGMT	1.63	-0.28	-1.90	0.55	0.51	-0.04	-1.08	0.78	1.87
	(2.64)	(-0.41)	(-2.01)	(1.21)	(1.48)	(-0.07)	(-2.08)	(1.02)	(1.92)
PERF	0.81	-0.12	-0.94	1.00	0.40	-0.6	0.18	0.52	0.34
	(1.23)	(-0.24)	(-1.12)	(2.41)	(0.85)	(-0.91)	(0.32)	(0.97)	(0.41)
FIN	1.68	-0.35	-2.03	0.45	0.69	0.25	-1.24	1.04	2.28
	(2.76)	(-0.54)	(-2.25)	(1.20)	(2.41)	(0.52)	(-2.39)	(1.49)	(2.55)
PEAD	1.33	0.00	-1.33	1.00	0.18	-0.82	-0.33	0.18	0.51
	(2.25)	(0.00)	(-1.78)	(1.84)	(0.39)	(-1.11)	(-0.61)	(0.38)	(0.66)
Ave	1.38	-0.14	-1.52	0.86	0.42	-0.44	-0.51	0.56	1.08
	(2.55)	(-0.27)	(-2.00)	(2.14)	(1.48)	(-0.89)	(-1.89)	(1.66)	(2.36)
$\text{Ave}_{w/o\ SMB}$	1.43	-0.19	-1.62	0.79	0.50	-0.3	-0.64	0.69	1.33
	(2.52)	(-0.35)	(-2.02)	(2.03)	(1.83)	(-0.63)	(-1.94)	(1.67)	(2.41)

Table 10: Beta-sorted portfolios: predictive regressions on lagged sentiment and macro variables

This table reports the point estimates of b ($\hat{b}$), along with Newey-West 5-lag adjusted t-statistics, in the regression specifications: $R_{i,t} = a + b \times S_{t-1} + \sum_{j=1}^{4} m_j \times X_{j,t-1} + c \times TED_{t-1} + d \times Inf_{t-1} + e \times Disp_{t-1} + e_{i,t}$. Macro variables $X_{j,t-1}$ include the default premium, the term premium, the real interest rate, and the log wealth-consumption ratio. Additional control variables include the difference between the three-month LIBOR and Treasury bill rate (TED), the inflation rate, and the beta-weighted aggregate dispersion (Disp) as in Hong and Sraer (2016). Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave (Ave$_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1986:2 to 2017:12.

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	-0.2	(-1.09)	-1.21	(-2.2)	-1	(-2.02)
HML	-0.95	(-2.01)	-0.13	(-0.49)	0.82	(1.63)
RMW	-1.01	(-1.9)	-0.2	(-0.83)	0.81	(1.57)
CMA	-0.94	(-1.97)	0	(0.01)	0.95	(1.83)
IA	-0.88	(-1.84)	-0.1	(-0.41)	0.78	(1.59)
ROE	-1.05	(-1.99)	-0.41	(-1.61)	0.63	(1.45)
PMU	-0.75	(-2.16)	-0.61	(-1.5)	0.14	(0.42)
QMJ	-1.06	(-2.06)	-0.26	(-1.21)	0.79	(1.68)
MOM	-0.76	(-1.87)	-0.18	(-0.47)	0.58	(1.29)
MGMT	-1.04	(-2.03)	-0.13	(-0.53)	0.91	(1.66)
PERF	-0.93	(-2.25)	-0.19	(-0.56)	0.74	(1.77)
FIN	-1	(-1.95)	-0.12	(-0.49)	0.88	(1.68)
PEAD	-0.55	(-1.47)	-0.66	(-1.65)	-0.1	(-0.21)
Ave	-0.86	(-2.15)	-0.32	(-1.32)	0.53	(2.14)
Ave$_{w/o\ SMB}$	-0.91	(-2.16)	-0.25	(-1.08)	0.66	(2.17)

Table 11: Beta-sorted portfolios: after high and low state

This table reports the results of factor beta-sorted value-weighted decile portfolios following high- and low-state regimes, as classified based on the median level of the 14 equity premium predictors as in Goyal and Welch (2008), the surplus ratio, and the aggregate dispersion as in Hong and Sraer (2016). The 14 predictors include the log dividend price ratio (dp), log dividend yield (dy), log earnings-price ratio (ep), log dividend-payout ratio (dpay), stock excess return volatility (rvol), book-to-market ratio (bm), net equity issuance (ntis), Treasury bill rate (tbl), long-term yield (lty), long-term return (ltr), term spread (tms), default yield spread (dfy), default return spread (dfr), and inflation (infl). We take the negative of dp, dy, ep, dpay, rvol, bm, ltr, tms, dfy, and dfr, to be consistent with other predictors that a high value predicts a lower return. We report the monthly excess returns of the high-low beta average portfolios after low-state periods (Panel A), high-state periods (Panel B), and their differences (Panel C). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1982:1 to 2017:12 for the specification with aggregate dispersion as the control variable and 1966:7 to 2017:12 for other specifications. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	dp	dy	ep	dpay	rvol	bm	ntis	tbl	lty	ltr	tms	dfy	dfr	infl	surp	disp
Panel A: After low-state period																
Ave	0.08	0.09	0.17	0.13	0.05	0.18	0.21	-0.06	0.14	0.06	0.18	0.06	0.07	0.08	0.04	0.27
	(0.58)	(0.65)	(1.51)	(0.68)	(0.24)	(1.53)	(1.16)	(-0.32)	(0.67)	(0.4)	(1.01)	(0.31)	(0.4)	(0.44)	(0.22)	(2.07)
$\text{Ave}_{w/o\ SMB}$	0.05	0.05	0.17	0.16	0.03	0.19	0.22	-0.13	0.17	0.05	0.18	0.03	0.06	0.08	0.03	0.31
	(0.32)	(0.31)	(1.21)	(0.7)	(0.11)	(1.25)	(0.99)	(-0.54)	(0.67)	(0.28)	(0.81)	(0.12)	(0.32)	(0.35)	(0.14)	(1.87)
Panel B: After high-state period																
Ave	0.17	0.17	0.09	0.13	0.2	0.08	0.04	0.32	0.11	0.19	0.07	0.2	0.19	0.18	0.22	-0.00
	(0.86)	(0.83)	(0.4)	(0.81)	(1.98)	(0.37)	(0.26)	(1.98)	(0.89)	(1.21)	(0.41)	(1.31)	(1.06)	(1.41)	(1.33)	(-0.01)
$\text{Ave}_{w/o\ SMB}$	0.22	0.23	0.11	0.12	0.26	0.09	0.06	0.41	0.11	0.23	0.1	0.26	0.21	0.2	0.25	-0.00
	(0.91)	(0.91)	(0.42)	(0.6)	(1.96)	(0.37)	(0.29)	(2.04)	(0.66)	(1.17)	(0.47)	(1.32)	(0.98)	(1.28)	(1.2)	(-0.01)
Panel C: High-low																
Ave	0.09	0.08	-0.08	-0.00	0.15	-0.1	-0.17	0.38	-0.03	0.13	-0.11	0.14	0.12	0.1	0.18	-0.27
	(0.39)	(0.32)	(-0.33)	(-0.01)	(0.65)	(-0.42)	(-0.73)	(1.54)	(-0.11)	(0.7)	(-0.44)	(0.58)	(0.53)	(0.49)	(0.73)	(-0.81)
$\text{Ave}_{w/o\ SMB}$	0.17	0.17	-0.05	-0.05	0.23	-0.09	-0.17	0.54	-0.06	0.18	-0.07	0.23	0.15	0.13	0.22	-0.31
	(0.57)	(0.57)	(-0.18)	(-0.16)	(0.77)	(-0.31)	(-0.57)	(1.77)	(-0.2)	(0.76)	(-0.24)	(0.76)	(0.55)	(0.52)	(0.74)	(-0.76)

Table 12: Beta-sorted portfolios: predictive regressions on lagged sentiment controlling for additional state variables

This table reports the point estimates of b ($\hat{b}$), along with Newey-West 5-lag adjusted t-statistics, in the regression specifications: $R_{i,t} = a + bS_{t-1} + cSV_{j,t-1} + e_{i,t}$, for each state variable j. State variables include the log dividend price ratio (dp), log dividend yield (dy), log earnings-price ratio (ep), log dividend-payout ratio (dpay), stock excess return volatility (rvol), book-to-market ratio (bm), net equity issuance (ntis), Treasury bill rate (tbl), long-term yield (lty), long-term return (ltr), term spread (tms), default yield spread (dfy), default return spread (dfr), inflation (infl), surplus ratio (surp), and the aggregate dispersion (disp). Point estimates of b are presented for the bottom decile average portfolio (Low beta), the top decile average portfolio (High beta), and their differences (H-L). Ave (Panel A) and Ave$_{w/o\ SMB}$ (Panel B) refer to the average portfolios of all beta-sorted portfolios and the one excluding SMB. Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. The sample period is from 1982:1 to 2017:12 for the specification with aggregate dispersion as the control variable and 1966:7 to 2017:12 for other specifications.

Panel A: Ave

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
dp	-0.67	(-2.37)	-0.27	(-1.12)	0.4	(3.61)
dy	-0.66	(-2.3)	-0.26	(-1.06)	0.39	(3.59)
ep	-0.73	(-2.49)	-0.28	(-1.11)	0.45	(3.78)
dpay	-0.67	(-2.41)	-0.29	(-1.22)	0.38	(3.67)
rvol	-0.61	(-2.13)	-0.25	(-1.07)	0.36	(3.04)
bm	-0.77	(-2.68)	-0.31	(-1.25)	0.45	(3.73)
ntis	-0.68	(-2.41)	-0.29	(-1.25)	0.39	(3.4)
tbl	-0.53	(-1.89)	-0.15	(-0.66)	0.37	(3.36)
lty	-0.65	(-2.27)	-0.28	(-1.17)	0.37	(3.28)
ltr	-0.69	(-2.45)	-0.3	(-1.27)	0.39	(3.4)
tms	-0.66	(-2.4)	-0.27	(-1.19)	0.39	(3.43)
dfy	-0.65	(-2.34)	-0.27	(-1.16)	0.38	(3.42)
dfr	-0.67	(-2.33)	-0.28	(-1.18)	0.39	(3.36)
infl	-0.7	(-2.53)	-0.3	(-1.24)	0.4	(3.45)
surp	-0.71	(-2.7)	-0.32	(-1.42)	0.4	(3.48)
disp	-0.93	(-3.07)	-0.28	(-1.3)	0.65	(3.66)

Table 12 (cont.): Beta-sorted portfolios: predictive regressions on lagged sentiment controlling for additional state variables

Panel B: $\text{Ave}_{w/oSMB}$

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
dp	-0.73	(-2.44)	-0.2	(-0.88)	0.52	(3.87)
dy	-0.71	(-2.38)	-0.19	(-0.83)	0.52	(3.83)
ep	-0.79	(-2.58)	-0.2	(-0.85)	0.59	(4.02)
dpay	-0.73	(-2.49)	-0.22	(-0.97)	0.51	(3.95)
rvol	-0.66	(-2.2)	-0.19	(-0.83)	0.48	(3.29)
bm	-0.83	(-2.75)	-0.24	(-0.99)	0.59	(4.02)
ntis	-0.73	(-2.48)	-0.22	(-1)	0.51	(3.67)
tbl	-0.57	(-1.97)	-0.09	(-0.4)	0.48	(3.58)
lty	-0.7	(-2.35)	-0.21	(-0.92)	0.49	(3.55)
ltr	-0.74	(-2.52)	-0.22	(-1.01)	0.52	(3.68)
tms	-0.71	(-2.47)	-0.2	(-0.93)	0.51	(3.7)
dfy	-0.7	(-2.42)	-0.2	(-0.91)	0.5	(3.69)
dfr	-0.72	(-2.41)	-0.21	(-0.92)	0.51	(3.62)
infl	-0.76	(-2.61)	-0.22	(-0.97)	0.54	(3.78)
surp	-0.77	(-2.77)	-0.24	(-1.14)	0.53	(3.8)
disp	-1	(-3.12)	-0.2	(-0.95)	0.8	(3.77)

Table 13: Beta-sorted portfolio overnight and intraday returns

This table reports the overnight returns (ON), intraday returns (Intra), and their differences (Intra-ON) of characteristics-factor beta-sorted (Panel A) and macro-factor beta-sorted (Panel B) decile value-weighted portfolios. We report the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Following Lou, Polk, and Skouras (2018), intraday return is the price appreciation between market open and close of each day, and the overnight return is imputed based on daily return and this intraday return. Beta-sorted portfolios in Panel A are constructed in the same way as Table 3. In Panel B, we consider ten macro factors including consumption growth (CON), industrial production growth (IPG), term premium (TERM), default premium (DEF), unexpected inflation (UI), changes in expected inflation (DEI), aggregate market volatility (VOL), market excess returns (MKT), labor income growth (LAB), TFP growth (TFP). Following Shen et al. (2017), we take the inverse of the betas based on DEF, TERM, and VOL to be consistent with other macro-factor betas that high beta portfolio have high return. Ave1 refers to the average portfolios of beta-sorted portfolios including CON, TFP, IPG, VOL, LAB and MKT, Ave2 adds TERM and DEF beta-sorted portfolios, Ave3 includes all beta-sorted portfolios. Pre-ranking betas of TFP are estimated from a single-factor model using quarterly data over the past 24 quarters with a minimum of 12 quarters, and other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. The sample period is from 1992:7 to 2017:12. Returns are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Characteristics-based factor beta-sorted portfolios

	Low beta			High beta			H-L		
	ON	Intra	Intra-ON	ON	Intra	Intra-ON	ON	Intra	Intra-ON
SMB	0.37	0.58	0.21	1.95	-0.41	-2.36	1.58	-0.99	-2.57
	(3.13)	(3.53)	(0.99)	(6.44)	(-0.99)	(-4.66)	(6.28)	(-2.49)	(-5.24)
HML	1.31	-0.11	-1.42	1.18	0.09	-1.09	-0.13	0.2	0.33
	(4.7)	(-0.35)	(-3.32)	(5.5)	(0.25)	(-2.49)	(-0.38)	(0.47)	(0.52)
RMW	1.77	-0.36	-2.13	0.36	0.72	0.36	-1.41	1.08	2.49
	(5.35)	(-0.94)	(-4.04)	(2.74)	(3.81)	(1.46)	(-4.69)	(2.64)	(4.44)
CMA	1.66	-0.27	-1.94	0.5	0.43	-0.08	-1.16	0.7	1.86
	(6.07)	(-0.83)	(-4.56)	(3.37)	(1.51)	(-0.24)	(-4.6)	(1.8)	(3.69)
IA	1.64	-0.26	-1.9	0.6	0.44	-0.17	-1.03	0.7	1.73
	(6.07)	(-0.79)	(-4.46)	(3.35)	(1.45)	(-0.48)	(-3.52)	(1.83)	(3.15)
ROE	1.69	-0.24	-1.93	0.6	0.51	-0.09	-1.09	0.75	1.84
	(5.12)	(-0.56)	(-3.26)	(3.24)	(2.59)	(-0.32)	(-3.34)	(1.84)	(3.02)
PMU	1.66	-0.68	-2.34	1	0.26	-0.74	-0.66	0.95	1.6
	(6.78)	(-1.71)	(-4.83)	(4.02)	(1.19)	(-2.21)	(-2.42)	(2.73)	(3.23)
QMJ	2.16	-0.68	-2.84	0.24	0.78	0.54	-1.92	1.46	3.38
	(5.4)	(-1.57)	(-4.51)	(1.79)	(4.32)	(2.24)	(-5.04)	(3.38)	(5.3)
MOM	0.79	0.25	-0.55	1.9	-0.77	-2.67	1.11	-1.02	-2.13
	(2.99)	(0.63)	(-1.11)	(7.6)	(-2.66)	(-6.45)	(3.39)	(-2.52)	(-3.58)
MGMT	1.74	-0.43	-2.17	0.49	0.44	-0.05	-1.25	0.87	2.12
	(5.53)	(-1.16)	(-4.42)	(3.24)	(1.51)	(-0.13)	(-4.09)	(2.12)	(3.78)
PERF	1.03	-0.08	-1.11	1.6	-0.35	-1.95	0.57	-0.27	-0.84
	(4.34)	(-0.21)	(-2.43)	(6.7)	(-1.34)	(-4.92)	(1.98)	(-0.7)	(-1.56)
FIN	1.76	-0.44	-2.21	0.38	0.56	0.18	-1.38	1.01	2.39
	(5.67)	(-1.22)	(-4.56)	(3.14)	(2.36)	(0.62)	(-4.67)	(2.56)	(4.4)
PEAD	0.98	0.32	-0.67	1.95	-0.64	-2.59	0.96	-0.96	-1.92
	(3.84)	(0.96)	(-1.59)	(7.76)	(-1.97)	(-5.75)	(3.26)	(-2.79)	(-3.98)
Ave	1.43	-0.19	-1.61	0.98	0.16	-0.82	-0.45	0.34	0.79
	(5.94)	(-0.6)	(-4.16)	(6.73)	(0.76)	(-3.42)	(-3.27)	(1.74)	(3.05)
$\text{Ave}_{w/o\ SMB}$	1.52	-0.25	-1.77	0.9	0.2	-0.7	-0.62	0.45	1.07
	(5.97)	(-0.76)	(-4.29)	(6.55)	(1.01)	(-2.93)	(-3.71)	(1.88)	(3.4)

Table 13 (cont.): Beta-sorted portfolio overnight and intraday returns

Panel B: Macro-factor beta-sorted portfolios

	Low beta			High beta			H-L		
	ON	Intra	Intra-ON	ON	Intra	Intra-ON	ON	Intra	Intra-ON
CON	1.06	0.28	-0.78	1.39	-0.25	-1.65	0.33	-0.54	-0.87
	(4.91)	(1.02)	(-2.15)	(6.28)	(-0.81)	(-4.3)	(1.88)	(-1.98)	(-2.37)
IPG	0.75	0.38	-0.37	1.86	-0.27	-2.13	1.11	-0.65	-1.76
	(5.13)	(1.74)	(-1.42)	(6.63)	(-0.84)	(-5.06)	(5.12)	(-2.77)	(-5.38)
TERM	1.01	0.14	-0.87	1.22	0.02	-1.2	0.21	-0.12	-0.33
	(3.82)	(0.5)	(-2.18)	(6.26)	(0.05)	(-3.53)	(1.11)	(-0.49)	(-1.02)
DEF	1.07	0.22	-0.85	1.61	-0.38	-1.98	0.53	-0.6	-1.13
	(4.06)	(0.97)	(-2.14)	(7.56)	(-0.98)	(-4.48)	(2.18)	(-1.91)	(-2.38)
UI	1.01	0.04	-0.97	1.43	-0.01	-1.44	0.42	-0.05	-0.46
	(4.43)	(0.13)	(-2.52)	(5.03)	(-0.02)	(-3.07)	(2.38)	(-0.15)	(-1.19)
DEI	0.95	0.12	-0.83	1.42	-0.12	-1.54	0.47	-0.24	-0.71
	(4.61)	(0.43)	(-2.29)	(5.5)	(-0.34)	(-3.5)	(2.81)	(-0.81)	(-1.9)
VOL	0.6	0.41	-0.19	1.68	-0.13	-1.82	1.08	-0.55	-1.63
	(3.46)	(2.22)	(-0.75)	(6.38)	(-0.36)	(-4.01)	(6.56)	(-1.6)	(-3.74)
MKT	0.07	0.84	0.77	1.92	-0.45	-2.38	1.86	-1.29	-3.15
	(0.75)	(4.13)	(3.38)	(5.68)	(-1.19)	(-4.92)	(5.75)	(-3.41)	(-6.49)
LAB	0.9	0.39	-0.51	1.48	-0.21	-1.69	0.58	-0.6	-1.18
	(4.71)	(1.77)	(-1.61)	(6.51)	(-0.54)	(-3.84)	(3.39)	(-1.84)	(-3)
TFP	1.04	0.31	-0.73	1.53	-0.06	-1.59	0.49	-0.37	-0.86
	(4.12)	(1.24)	(-1.84)	(6.44)	(-0.18)	(-4.06)	(2.83)	(-1.22)	(-2.34)
Ave1	0.74	0.43	-0.3	1.65	-0.23	-1.88	0.91	-0.66	-1.57
	(4.72)	(2.32)	(-1.23)	(6.67)	(-0.68)	(-4.71)	(6.73)	(-2.75)	(-5.64)
Ave2	0.81	0.37	-0.44	1.59	-0.22	-1.8	0.77	-0.59	-1.36
	(4.55)	(1.95)	(-1.65)	(7)	(-0.66)	(-4.77)	(6.98)	(-2.73)	(-5.61)
Ave3	0.85	0.31	-0.53	1.55	-0.19	-1.74	0.71	-0.5	-1.21
	(4.63)	(1.54)	(-1.9)	(6.72)	(-0.57)	(-4.55)	(6.5)	(-2.39)	(-5.03)

Internet Appendix to "Investor Sentiment and the Pricing of Characteristics-Based Factors"

This Internet Appendix presents additional results.

Table IA1: Beta-sorted portfolio returns following high and low sentiment: alternative estimation windows

This table reports the results of factor-beta-sorted decile value-weighted portfolios following high- and low-sentiment regimes, as classified based on the median level of the Baker and Wurgler (2006) sentiment index. We report the monthly excess returns for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a single characteristics-based factor model using daily returns over the past 1 month with a minimum of 15 days (Panel A), daily returns over the past 6 months with a minimum of 90 days (Panel B) or monthly returns over the past 12 months with a minimum of 8 months (Panel C). Other pre-ranking betas are estimated from a single-factor model using monthly returns over the past 36 months with a minimum of 24 months (Panel A), monthly returns over the past 24 months with a minimum of 18 month (Panel B), or monthly returns over the past 12 months with a minimum of 8 months (Panel C). All portfolios are rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1965:8 to 2017:12 except for 1974:1 to 2017:12 for IA and ROE and 1974:7 to 2017:12 for FIN and PEAD in Panel A, 1973:7 to 2017:12 for IA and ROE and 1974:1 to 2017:12 for FIN and PEAD in Panel B, and 1972:9 to 2017:12 for IA and ROE and 1973:3 to 2017:12 for FIN and PEAD in Panel C. Returns are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: 36-month monthly or 1-month daily estimation window

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.40	0.51	0.11	1.31	-0.01	-1.32	0.91	-0.52	-1.43
	(1.84)	(2.41)	(0.37)	(2.28)	(-0.03)	(-1.88)	(2.01)	(-1.41)	(-2.54)
HML	0.69	-0.05	-0.74	0.81	0.67	-0.14	0.12	0.72	0.60
	(1.66)	(-0.14)	(-1.36)	(1.89)	(2.64)	(-0.28)	(0.31)	(2.01)	(1.14)
RMW	1.09	-0.21	-1.30	0.45	0.53	0.08	-0.64	0.74	1.38
	(2.43)	(-0.55)	(-2.36)	(1.41)	(1.96)	(0.19)	(-1.7)	(2.24)	(2.81)
CMA	0.83	0.02	-0.81	0.64	0.53	-0.10	-0.19	0.52	0.71
	(1.90)	(0.04)	(-1.42)	(1.82)	(2.04)	(-0.25)	(-0.56)	(1.48)	(1.46)
IA	1.09	0.05	-1.03	0.88	0.62	-0.26	-0.21	0.56	0.77
	(2.19)	(0.13)	(-1.71)	(2.02)	(2.45)	(-0.54)	(-0.55)	(1.51)	(1.48)
ROE	1.32	0.03	-1.30	0.61	0.56	-0.05	-0.72	0.53	1.25
	(2.21)	(0.07)	(-1.95)	(1.53)	(1.9)	(-0.11)	(-1.57)	(1.35)	(2.05)
PMU	0.98	-0.22	-1.20	0.61	0.57	-0.04	-0.38	0.79	1.16
	(2.35)	(-0.64)	(-2.35)	(1.47)	(1.74)	(-0.07)	(-1.01)	(2.22)	(2.38)
QMJ	1.40	-0.37	-1.77	0.27	0.75	0.48	-1.13	1.12	2.25
	(2.47)	(-0.9)	(-2.61)	(1.15)	(3.33)	(1.50)	(-2.46)	(3.48)	(4.11)
MOM	0.62	-0.15	-0.77	0.89	0.28	-0.61	0.27	0.43	0.16
	(1.31)	(-0.46)	(-1.39)	(2.41)	(0.82)	(-1.26)	(0.76)	(1.51)	(0.35)
MGMT	0.87	-0.12	-0.99	0.46	0.6	0.14	-0.41	0.72	1.13
	(1.72)	(-0.27)	(-1.55)	(1.42)	(2.65)	(0.35)	(-1.04)	(1.95)	(2.08)
PERF	0.65	-0.34	-0.99	0.81	0.37	-0.44	0.16	0.71	0.55
	(1.36)	(-0.90)	(-1.68)	(2.23)	(1.14)	(-0.91)	(0.48)	(2.41)	(1.17)
FIN	1.20	-0.17	-1.37	0.82	0.75	-0.07	-0.39	0.92	1.31
	(2.34)	(-0.41)	(-2.24)	(2.16)	(3.17)	(-0.15)	(-1.01)	(2.51)	(2.48)
PEAD	1.00	0.07	-0.93	0.99	0.24	-0.75	-0.01	0.17	0.18
	(1.86)	(0.21)	(-1.54)	(2.25)	(0.72)	(-1.49)	(-0.03)	(0.60)	(0.38)
Ave	0.84	-0.09	-0.93	0.70	0.47	-0.23	-0.14	0.56	0.70
	(2.02)	(-0.28)	(-1.84)	(2.08)	(1.87)	(-0.57)	(-0.84)	(3.69)	(3.19)
$\text{Ave}_{w/o\ SMB}$	0.87	-0.15	-1.02	0.65	0.51	-0.14	-0.23	0.66	0.88
	(2.00)	(-0.42)	(-1.91)	(2.04)	(2.16)	(-0.36)	(-1.10)	(3.50)	(3.28)

Table IA1 (cont.): Beta-sorted returns following high and low sentiment alternative estimation windows

Panel B: 24-month monthly or 6-month daily estimation window

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.36	0.5	0.13	1.30	-0.2	-1.49	0.93	-0.69	-1.63
	(1.58)	(2.27)	(0.45)	(2.23)	(-0.44)	(-2.09)	(2.06)	(-2.00)	(-2.87)
HML	0.85	-0.05	-0.90	0.69	0.53	-0.16	-0.17	0.58	0.75
	(2.14)	(-0.12)	(-1.67)	(1.55)	(1.88)	(-0.31)	(-0.47)	(1.57)	(1.44)
RMW	1.02	-0.12	-1.14	0.54	0.46	-0.07	-0.48	0.58	1.07
	(2.27)	(-0.31)	(-2.04)	(1.71)	(1.71)	(-0.19)	(-1.34)	(1.75)	(2.19)
CMA	1.00	-0.05	-1.06	0.60	0.58	-0.03	-0.40	0.63	1.03
	(2.35)	(-0.13)	(-1.88)	(1.64)	(2.17)	(-0.06)	(-1.19)	(1.77)	(2.10)
IA	1.15	0.09	-1.07	0.86	0.67	-0.19	-0.29	0.59	0.88
	(2.33)	(0.21)	(-1.77)	(1.92)	(2.55)	(-0.37)	(-0.78)	(1.56)	(1.68)
ROE	1.20	0.11	-1.09	0.63	0.55	-0.08	-0.57	0.45	1.01
	(2.02)	(0.27)	(-1.65)	(1.62)	(1.83)	(-0.16)	(-1.23)	(1.19)	(1.69)
PMU	0.91	-0.31	-1.22	0.69	0.48	-0.21	-0.22	0.79	1.01
	(2.20)	(-0.92)	(-2.39)	(1.72)	(1.41)	(-0.4)	(-0.62)	(2.28)	(2.10)
QMJ	1.39	-0.42	-1.81	0.28	0.67	0.39	-1.11	1.09	2.20
	(2.49)	(-0.96)	(-2.67)	(1.14)	(2.9)	(1.22)	(-2.5)	(3.28)	(4.06)
MOM	0.62	-0.12	-0.75	1.09	0.38	-0.71	0.46	0.50	0.04
	(1.29)	(-0.37)	(-1.31)	(2.86)	(1.11)	(-1.39)	(1.12)	(1.37)	(0.07)
MGMT	1.09	-0.22	-1.31	0.44	0.61	0.17	-0.65	0.83	1.48
	(2.22)	(-0.53)	(-2.08)	(1.29)	(2.62)	(0.42)	(-1.76)	(2.26)	(2.78)
PERF	0.73	-0.16	-0.89	0.91	0.45	-0.46	0.18	0.62	0.44
	(1.6)	(-0.44)	(-1.58)	(2.55)	(1.4)	(-0.95)	(0.44)	(1.76)	(0.78)
FIN	1.21	-0.18	-1.39	0.74	0.72	-0.02	-0.47	0.90	1.37
	(2.26)	(-0.41)	(-2.15)	(1.88)	(3.02)	(-0.03)	(-1.24)	(2.35)	(2.54)
PEAD	0.96	0.06	-0.91	1.06	0.33	-0.73	0.10	0.28	0.18
	(1.75)	(0.19)	(-1.53)	(2.62)	(0.91)	(-1.46)	(0.24)	(0.93)	(0.35)
Ave	0.89	-0.09	-0.99	0.74	0.45	-0.29	-0.15	0.54	0.70
	(2.19)	(-0.28)	(-1.98)	(2.21)	(1.77)	(-0.71)	(-0.92)	(3.81)	(3.22)
$\text{Ave}_{w/o\ SMB}$	0.94	-0.14	-1.08	0.70	0.51	-0.19	-0.24	0.65	0.89
	(2.20)	(-0.42)	(-2.07)	(2.19)	(2.1)	(-0.49)	(-1.20)	(3.69)	(3.40)

Table IA1 (cont.): Beta-sorted returns following high and low sentiment alternative estimation windows

Panel C: 12-month monthly estimation window

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.41	0.53	0.12	1.39	-0.34	-1.73	0.99	-0.87	-1.86
	(1.64)	(1.95)	(0.36)	(2.58)	(-0.8)	(-2.55)	(2.39)	(-2.47)	(-3.42)
HML	0.83	-0.13	-0.97	0.79	0.38	-0.4	-0.05	0.52	0.56
	(2.18)	(-0.34)	(-1.81)	(1.66)	(1.36)	(-0.75)	(-0.14)	(1.46)	(1.13)
RMW	0.97	-0.2	-1.17	0.73	0.46	-0.27	-0.23	0.66	0.90
	(2.07)	(-0.52)	(-1.99)	(2.19)	(1.61)	(-0.66)	(-0.77)	(2.00)	(1.98)
CMA	1.06	-0.01	-1.07	0.61	0.41	-0.2	-0.45	0.42	0.87
	(2.55)	(-0.03)	(-1.97)	(1.57)	(1.46)	(-0.42)	(-1.40)	(1.29)	(1.9)
IA	0.99	0.00	-0.99	0.59	0.48	-0.11	-0.39	0.48	0.87
	(2.09)	(0.00)	(-1.71)	(1.26)	(1.66)	(-0.21)	(-1.09)	(1.35)	(1.72)
ROE	0.86	-0.05	-0.91	0.57	0.64	0.07	-0.29	0.69	0.98
	(1.53)	(-0.13)	(-1.37)	(1.48)	(1.94)	(0.14)	(-0.71)	(1.85)	(1.69)
PMU	0.92	-0.44	-1.36	0.68	0.51	-0.18	-0.24	0.95	1.18
	(2.2)	(-1.17)	(-2.52)	(1.73)	(1.53)	(-0.35)	(-0.71)	(2.94)	(2.6)
QMJ	1.31	-0.43	-1.74	0.28	0.58	0.3	-1.03	1.01	2.04
	(2.51)	(-1.04)	(-2.65)	(1.12)	(2.22)	(0.86)	(-2.76)	(3.16)	(4.11)
MOM	0.88	-0.01	-0.89	0.87	0.20	-0.67	-0.01	0.21	0.22
	(1.78)	(-0.02)	(-1.51)	(2.33)	(0.53)	(-1.31)	(-0.03)	(0.59)	(0.40)
MGMT	1.02	-0.19	-1.21	0.52	0.59	0.07	-0.50	0.78	1.28
	(2.2)	(-0.45)	(-1.99)	(1.43)	(2.23)	(0.15)	(-1.62)	(2.21)	(2.62)
PERF	0.75	0.03	-0.72	0.78	0.28	-0.50	0.03	0.25	0.21
	(1.50)	(0.09)	(-1.18)	(2.14)	(0.80)	(-1.02)	(0.08)	(0.72)	(0.40)
FIN	0.85	-0.16	-1.01	0.60	0.69	0.10	-0.25	0.86	1.11
	(1.63)	(-0.37)	(-1.57)	(1.48)	(2.62)	(0.2)	(-0.72)	(2.22)	(2.10)
PEAD	0.91	0.26	-0.65	0.65	0.11	-0.54	-0.26	-0.15	0.11
	(1.58)	(0.77)	(-1.01)	(1.52)	(0.30)	(-1.00)	(-0.66)	(-0.45)	(0.21)
Ave	0.89	-0.09	-0.98	0.72	0.35	-0.36	-0.17	0.44	0.61
	(2.14)	(-0.26)	(-1.90)	(2.05)	(1.30)	(-0.85)	(-1.17)	(3.24)	(3.02)
$Ave_{w/o\ SMB}$	0.94	-0.14	-1.08	0.66	0.42	-0.24	-0.28	0.56	0.84
	(2.16)	(-0.40)	(-2.00)	(1.94)	(1.58)	(-0.58)	(-1.56)	(3.29)	(3.38)

Table IA2: Beta-sorted portfolio returns following high and low sentiment: two-factor beta

This table reports the results of factor-beta-sorted decile value-weighted portfolios following high- and low-sentiment regimes, as classified based on the median level of the Baker and Wurgler (2006) sentiment index. We report the excess returns for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a two-factor model (including market factor and characteristics-based factor) using daily returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a two-factor model (including market factor and characteristics-based factor) using monthly returns over the past 60 months with a minimum of 36 months. All portfolios are rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1975:1 to 2017:12 for IA and ROE, 1975:7 to 2017:12 for FIN and PEAD, and 1966:7 to 2017:12 for others. Returns are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.53	0.41	-0.12	1.15	-0.12	-1.27	0.61	-0.53	-1.15
	(2.26)	(1.88)	(-0.39)	(2.16)	(-0.28)	(-1.92)	(1.60)	(-1.53)	(-2.32)
HML	0.96	-0.02	-0.98	0.91	0.73	-0.18	-0.05	0.74	0.80
	(2.39)	(-0.05)	(-1.86)	(2.05)	(2.49)	(-0.35)	(-0.15)	(2.35)	(1.68)
RMW	1.12	-0.14	-1.26	0.74	0.49	-0.25	-0.39	0.62	1.01
	(2.83)	(-0.36)	(-2.41)	(2.01)	(1.84)	(-0.58)	(-1.28)	(2.03)	(2.36)
CMA	0.89	0.00	-0.88	0.80	0.63	-0.17	-0.09	0.63	0.72
	(2.09)	(0.00)	(-1.68)	(2.19)	(2.15)	(-0.38)	(-0.26)	(2.04)	(1.63)
IA	1.41	-0.01	-1.42	1.10	0.72	-0.39	-0.30	0.73	1.03
	(2.86)	(-0.03)	(-2.46)	(2.42)	(2.41)	(-0.75)	(-0.82)	(2.07)	(2.07)
ROE	1.59	0.16	-1.44	0.95	0.57	-0.39	-0.64	0.41	1.05
	(2.59)	(0.39)	(-2.04)	(2.69)	(2.16)	(-0.92)	(-1.57)	(1.15)	(1.92)
PMU	0.99	-0.18	-1.17	0.63	0.40	-0.22	-0.36	0.58	0.95
	(2.46)	(-0.54)	(-2.31)	(1.49)	(1.16)	(-0.42)	(-1.01)	(1.72)	(1.97)
QMJ	1.22	-0.20	-1.42	0.54	0.65	0.11	-0.68	0.85	1.53
	(2.32)	(-0.47)	(-2.16)	(1.9)	(2.65)	(0.30)	(-1.95)	(2.74)	(3.28)
MOM	0.74	0.02	-0.72	0.89	0.21	-0.67	0.15	0.20	0.05
	(1.50)	(0.06)	(-1.25)	(2.32)	(0.62)	(-1.31)	(0.40)	(0.56)	(0.09)
MGMT	1.00	-0.11	-1.11	0.76	0.62	-0.15	-0.24	0.73	0.97
	(2.13)	(-0.27)	(-1.85)	(2.05)	(2.32)	(-0.32)	(-0.67)	(2.06)	(1.91)
PERF	0.63	-0.24	-0.87	0.94	0.36	-0.58	0.31	0.59	0.28
	(1.31)	(-0.68)	(-1.53)	(2.55)	(1.06)	(-1.19)	(0.98)	(1.93)	(0.61)
FIN	1.28	-0.12	-1.40	1.07	0.74	-0.33	-0.21	0.87	1.07
	(2.52)	(-0.29)	(-2.31)	(2.23)	(2.7)	(-0.61)	(-0.51)	(2.44)	(1.95)
PEAD	1.32	0.04	-1.28	1.01	0.14	-0.87	-0.31	0.10	0.41
	(2.39)	(0.12)	(-2.09)	(2.46)	(0.37)	(-1.74)	(-0.8)	(0.37)	(0.87)
Ave	0.94	-0.05	-0.99	0.80	0.44	-0.37	-0.14	0.48	0.62
	(2.32)	(-0.14)	(-1.99)	(2.27)	(1.59)	(-0.86)	(-1.02)	(3.27)	(3.17)
$\text{Ave}_{w/o\ SMB}$	0.97	-0.09	-1.06	0.78	0.49	-0.29	-0.19	0.57	0.77
	(2.30)	(-0.26)	(-2.05)	(2.28)	(1.86)	(-0.71)	(-1.19)	(3.31)	(3.33)

Table IA3: Beta-sorted equity mutual fund portfolio returns following high and low sentiment: two-factor beta

This table reports the results of factor-beta-sorted decile portfolios of actively managed equity mutual funds following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. We report the monthly excess returns for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas of MOM, PEAD, and PERF are estimated from a two-factor model (including market factor and characteristics-based factor) using daily mutual fund returns over the past 3 months with a minimum of 45 days. Other pre-ranking betas are estimated from a two-factor model (including market factor and characteristics-based factor) using monthly mutual fund returns over the past 24 months with a minimum of 18 months. All portfolios are equally weighted and rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1998:12 to 2017:12 for MOM, PERF and PEAD beta-sorted portfolios, 1973:7 to 2017:12 for IA and ROE beta-sorted portfolios, 1974:1 to 2017:12 for FIN beta-sorted portfolios, and 1966:7 to 2017:12 for other beta-sorted portfolios. Returns are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.60	0.50	-0.10	1.00	0.19	-0.82	0.40	-0.32	-0.71
	(2.26)	(2.30)	(-0.32)	(2.59)	(0.55)	(-1.62)	(1.94)	(-1.42)	(-2.39)
HML	0.91	0.24	-0.66	0.79	0.57	-0.22	-0.11	0.33	0.44
	(2.42)	(0.70)	(-1.35)	(2.56)	(2.65)	(-0.62)	(-0.48)	(1.47)	(1.42)
RMW	0.83	0.28	-0.54	0.81	0.54	-0.27	-0.02	0.26	0.27
	(2.55)	(0.96)	(-1.29)	(2.34)	(2.02)	(-0.65)	(-0.08)	(1.32)	(1.02)
CMA	0.92	0.24	-0.68	0.73	0.56	-0.17	-0.19	0.33	0.51
	(2.46)	(0.71)	(-1.41)	(2.42)	(2.50)	(-0.46)	(-0.85)	(1.53)	(1.72)
IA	1.00	0.32	-0.68	0.87	0.64	-0.23	-0.13	0.32	0.45
	(2.42)	(0.94)	(-1.34)	(2.60)	(2.78)	(-0.60)	(-0.53)	(1.40)	(1.41)
ROE	0.96	0.37	-0.59	0.83	0.66	-0.17	-0.12	0.29	0.41
	(2.60)	(1.26)	(-1.31)	(2.29)	(2.38)	(-0.40)	(-0.62)	(1.29)	(1.36)
PMU	0.68	0.14	-0.53	0.86	0.52	-0.34	0.18	0.38	0.19
	(2.32)	(0.55)	(-1.42)	(2.34)	(1.71)	(-0.73)	(0.88)	(1.79)	(0.71)
QMJ	0.92	0.21	-0.71	0.67	0.56	-0.11	-0.25	0.35	0.60
	(2.55)	(0.72)	(-1.56)	(2.24)	(2.25)	(-0.29)	(-1.42)	(1.87)	(2.46)
MOM	1.10	-0.12	-1.22	1.17	0.01	-1.16	0.06	0.13	0.06
	(1.99)	(-0.27)	(-1.9)	(2.02)	(0.01)	(-1.74)	(0.15)	(0.29)	(0.11)
MGMT	1.00	0.22	-0.77	0.73	0.59	-0.14	-0.27	0.36	0.63
	(2.53)	(0.64)	(-1.52)	(2.64)	(2.79)	(-0.43)	(-1.11)	(1.62)	(1.99)
PERF	1.06	-0.17	-1.23	1.23	0.08	-1.15	0.17	0.25	0.08
	(1.92)	(-0.37)	(-1.87)	(2.25)	(0.17)	(-1.86)	(0.49)	(0.63)	(0.17)
FIN	1.09	0.28	-0.81	0.89	0.63	-0.26	-0.20	0.35	0.55
	(2.56)	(0.78)	(-1.55)	(2.81)	(2.96)	(-0.72)	(-0.79)	(1.49)	(1.68)
PEAD	1.27	0.01	-1.26	1.12	-0.16	-1.28	-0.14	-0.17	-0.02
	(2.16)	(0.02)	(-1.87)	(2.20)	(-0.32)	(-2.04)	(-0.42)	(-0.52)	(-0.05)
Ave	0.84	0.27	-0.57	0.80	0.49	-0.31	-0.04	0.22	0.26
	(2.53)	(0.95)	(-1.34)	(2.62)	(2.01)	(-0.82)	(-0.57)	(2.53)	(2.42)
$\text{Ave}_{w/o\ SMB}$	0.86	0.25	-0.62	0.78	0.53	-0.25	-0.08	0.28	0.36
	(2.53)	(0.84)	(-1.41)	(2.62)	(2.22)	(-0.69)	(-0.97)	(2.51)	(2.65)

Table IA4: Beta-sorted hedge fund portfolio returns following high and low sentiment: two-factor beta

This table reports the results of factor-beta-sorted decile portfolios of actively managed hedge funds following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. We report the monthly excess returns for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas are estimated from a two-factor model (including market factor and characteristics-based factor) using monthly hedge fund returns over the past 24 months with a minimum of 18 months. All portfolios are equally weighted and rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolio of all beta-sorted portfolios (excluding SMB). The sample period for the hedge fund sample is from 1996:7 to 2017:12. Returns are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.80	0.37	-0.42	0.88	-0.01	-0.89	0.09	-0.38	-0.47
	(2.51)	(1.73)	(-1.43)	(2.17)	(-0.03)	(-1.79)	(0.29)	(-1.08)	(-1.02)
HML	1.04	-0.09	-1.14	0.70	0.59	-0.11	-0.34	0.68	1.03
	(2.26)	(-0.27)	(-2.31)	(2.26)	(2.29)	(-0.31)	(-0.85)	(1.67)	(2.01)
RMW	1.27	-0.04	-1.31	0.64	0.52	-0.13	-0.62	0.56	1.18
	(2.52)	(-0.12)	(-2.43)	(2.64)	(2.33)	(-0.44)	(-1.66)	(1.69)	(2.45)
CMA	1.07	0.19	-0.89	0.82	0.27	-0.55	-0.25	0.09	0.34
	(2.31)	(0.50)	(-1.71)	(2.69)	(1.28)	(-1.66)	(-0.8)	(0.25)	(0.77)
IA	1.20	0.07	-1.14	0.76	0.44	-0.32	-0.44	0.38	0.81
	(2.69)	(0.18)	(-2.29)	(2.54)	(1.97)	(-0.95)	(-1.55)	(1.04)	(1.85)
ROE	1.14	-0.23	-1.37	0.54	0.65	0.11	-0.6	0.88	1.48
	(2.51)	(-0.70)	(-2.7)	(1.95)	(2.96)	(0.37)	(-1.81)	(2.68)	(3.4)
PMU	0.85	0.07	-0.78	0.90	0.41	-0.49	0.05	0.34	0.29
	(1.83)	(0.19)	(-1.59)	(3.25)	(2.08)	(-1.66)	(0.13)	(1.17)	(0.70)
QMJ	1.12	-0.03	-1.15	0.58	0.42	-0.16	-0.54	0.45	0.99
	(2.27)	(-0.08)	(-2.05)	(2.89)	(2.41)	(-0.7)	(-1.41)	(1.35)	(1.94)
MOM	1.13	0.31	-0.82	0.66	0.19	-0.47	-0.48	-0.12	0.35
	(2.92)	(1.22)	(-1.97)	(1.88)	(0.55)	(-1.16)	(-1.83)	(-0.34)	(0.87)
MGMT	1.19	0.12	-1.08	0.44	0.50	0.06	-0.75	0.38	1.13
	(2.35)	(0.29)	(-1.88)	(1.91)	(2.44)	(0.21)	(-1.82)	(0.82)	(1.96)
PERF	1.06	0.21	-0.86	0.76	0.24	-0.52	-0.31	0.03	0.34
	(2.77)	(0.75)	(-2.04)	(2.00)	(0.74)	(-1.27)	(-1.02)	(0.09)	(0.78)
FIN	1.12	0.07	-1.05	0.61	0.50	-0.11	-0.51	0.43	0.94
	(2.24)	(0.18)	(-1.93)	(2.52)	(2.46)	(-0.38)	(-1.47)	(1.11)	(1.89)
PEAD	0.89	0.38	-0.51	0.90	-0.03	-0.93	0.01	-0.41	-0.42
	(2.51)	(1.74)	(-1.4)	(2.21)	(-0.09)	(-2.11)	(0.03)	(-1.48)	(-1.16)
Ave	1.07	0.11	-0.96	0.71	0.36	-0.35	-0.36	0.25	0.62
	(2.54)	(0.38)	(-2.2)	(2.58)	(1.83)	(-1.23)	(-1.87)	(1.78)	(2.63)
$\text{Ave}_{w/o\ SMB}$	1.09	0.08	-1.01	0.69	0.39	-0.30	-0.4	0.31	0.71
	(2.51)	(0.29)	(-2.20)	(2.62)	(2.02)	(-1.11)	(-1.85)	(1.73)	(2.57)

Table IA5: Beta-sorted hedge fund portfolio returns following high and low sentiment: equity hedge funds only

This table reports the results of factor-beta-sorted decile portfolios of actively managed hedge funds following high- and low-sentiment regimes, as classified based on the median level of the BW sentiment index. We report the monthly excess returns for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Pre-ranking betas are estimated from a single characteristics-based factor model using monthly hedge fund returns over the past 24 months with a minimum of 18 months. All portfolios are equally weighted and rebalanced monthly. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample only includes equity hedge funds. The sample period for the hedge fund sample is from 1996:7 to 2017:12. Returns are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.24	0.28	0.04	1.33	0.05	-1.27	1.08	-0.23	-1.31
	(1.25)	(1.45)	(0.2)	(2.46)	(0.14)	(-2.06)	(2.43)	(-0.52)	(-2.11)
HML	0.8	-0.03	-0.82	0.86	0.53	-0.33	0.07	0.56	0.49
	(1.68)	(-0.07)	(-1.6)	(2.29)	(2.12)	(-0.78)	(0.13)	(1.18)	(0.76)
RMW	1.53	-0.13	-1.66	0.08	0.43	0.35	-1.45	0.56	2.01
	(2.46)	(-0.33)	(-2.56)	(0.63)	(2.68)	(1.78)	(-2.22)	(1.25)	(2.75)
CMA	1.22	0.06	-1.16	0.51	0.4	-0.11	-0.71	0.34	1.05
	(2.23)	(0.14)	(-1.99)	(1.98)	(1.55)	(-0.3)	(-1.33)	(0.67)	(1.58)
IA	1.21	0.05	-1.16	0.42	0.43	0.01	-0.79	0.38	1.17
	(2.29)	(0.13)	(-2.09)	(1.61)	(1.68)	(0.04)	(-1.52)	(0.79)	(1.84)
ROE	1.36	-0.29	-1.64	0.23	0.64	0.41	-1.13	0.92	2.05
	(2.21)	(-0.74)	(-2.54)	(2.1)	(3.72)	(2.04)	(-1.9)	(2.24)	(3.06)
PMU	1.15	0.07	-1.08	0.54	0.46	-0.08	-0.61	0.39	1
	(1.95)	(0.18)	(-1.79)	(2.09)	(2.13)	(-0.28)	(-0.97)	(1.08)	(1.53)
QMJ	1.39	-0.13	-1.52	0.12	0.44	0.32	-1.27	0.57	1.84
	(2.16)	(-0.31)	(-2.19)	(1.02)	(3.16)	(1.77)	(-1.9)	(1.19)	(2.41)
MOM	1.42	0.32	-1.11	0.3	0.18	-0.12	-1.12	-0.13	0.99
	(2.82)	(1.17)	(-2.18)	(1.06)	(0.53)	(-0.3)	(-2.8)	(-0.33)	(1.78)
MGMT	1.39	0.06	-1.33	0.22	0.36	0.14	-1.16	0.3	1.47
	(2.39)	(0.13)	(-2.04)	(1.4)	(2.02)	(0.62)	(-2.05)	(0.58)	(2.07)
PERF	1.48	0.12	-1.36	0.07	0.25	0.18	-1.4	0.13	1.53
	(2.84)	(0.36)	(-2.43)	(0.31)	(0.85)	(0.55)	(-3.46)	(0.31)	(2.63)
FIN	1.49	0.01	-1.48	0.06	0.48	0.41	-1.43	0.46	1.89
	(2.43)	(0.03)	(-2.24)	(0.58)	(3.36)	(2.38)	(-2.3)	(0.96)	(2.62)
PEAD	1.27	0.4	-0.87	0.55	0.01	-0.54	-0.72	-0.39	0.33
	(2.57)	(1.49)	(-1.72)	(1.69)	(0.02)	(-1.36)	(-1.77)	(-1.12)	(0.61)
Ave	1.23	0.06	-1.17	0.41	0.36	-0.05	-0.82	0.3	1.12
	(2.4)	(0.2)	(-2.27)	(2.43)	(2.29)	(-0.25)	(-2.15)	(1.33)	(2.81)
$\text{Ave}_{w/o\ SMB}$	1.31	0.04	-1.27	0.33	0.38	0.05	-0.98	0.34	1.32
	(2.41)	(0.13)	(-2.3)	(2.3)	(2.53)	(0.29)	(-2.2)	(1.26)	(2.78)