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Investor Sentiment and the Pricing of Characteristics-Based Factors

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Previous research has revealed that return spreads between stocks with high and low characteristics-based factor beta remain insignificant. This study investigates the time variation in the pricing of various characteristics-based factors, uncovering a notable two-regime pattern: high-beta portfolios yield higher returns than low-beta portfolios after high-sentiment periods, while the opposite occurs after low-sentiment periods. Remarkably, this two-regime pattern is completely reversed for macro factors. Mutual fund and hedge fund returns corroborate these findings. Our results suggest that exposure to characteristics-based factors likely represents mispricing levels, particularly during high-sentiment periods, whereas exposure to macro factors likely represents risk, particularly during low-sentiment periods. (*JEL* G12)

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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. These models have been widely used in subsequent studies, such as anomaly analysis, event studies, fund performance attribution analysis, and risk management in practice.

However, there are still debates about the underlying interpretation of these prominent factors. On the one hand, recent studies including Kogan and Papanikolaou (2014), Kogan, Li, and Zhang (2023), and Ai, Li, and Tong (2024) have provided rational explanations for the anomalies underlying these factors, suggesting that these factors capture systematic risks. On the other hand, Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2020) label their factors as mispricing factors or behavioral factors, suggesting that their factors capture systematic mispricing. Indeed, both studies 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). Moreover, Chen et al. (2018) and Daniel et al. (2020) 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. (2018) 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.

In this paper, we examine the role of investor sentiment in the pricing of these factors. Theoretically, as shown by earlier studies, such as De Long et al. (1990), Dumas, Kurshev, and Uppal (2009), Kozak, Nagel, and Santosh (2018), and Yu and Yuan (2011), sentiment can both affect the factor risk premiums and create risks for arbitrageurs. We choose to explore empirically how sentiment affects the return spreads of these factor-beta-sorted portfolios and casts light on the underlying forces behind these characteristics-based factors and the weak beta-return relation for beta-sorted portfolios. By shedding light on the underlying mechanisms for these factors, our results also provide several

[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 quality-minus-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 2020).

important implications, especially on the proper applications of these factor models.

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 due to systematic mispricing, and the factor exposure is a proxy for the level of mispricing, 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] Taken together, these two concepts suggest that many assets may be overpriced during high-sentiment periods, as rational investors—being relatively pessimistic—stay out of the market due to short-sale constraints. 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 irrational pessimists tend to stay out of the market because of short-sale impediments. In other words, because of short-sale impediments, market participants are more likely to be irrational during high sentiment than during low sentiment.

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, as argued in Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2020), the factor beta could be a noisy proxy for the level of mispricing with lower beta being more overpriced. Then, the return spread between high- and low-beta portfolios should be larger following high-sentiment periods than

[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), Hwang (2011), Yu and Yuan (2011), Baker, Wurgler, and Yuan (2012), Chung, Hung, and Yeh (2012), Stambaugh, Yu, and Yuan (2012), Antoniou, Doukas, and Subrahmanyam (2013, 2016), Yu (2013), Huang et al. (2015), Sibley et al. (2016), Huang et al. (2018), Guo et al. (2019), Jiang et al. (2019), Livnat and Petrovits (2019), Gao, Ren, and Zhang (2020), and Chen et al. (2022).

[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, Garleanu, 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 (2020).

following low-sentiment periods since during high-sentiment periods, market participants are more irrational and there are more mispriced, especially, overpriced assets. These concepts, taken together, indicate that by investigating the pattern in the return spreads of characteristics-beta-sorted portfolios 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 following low-sentiment periods, these factors are more likely to be mispricing (risk) factors. That is, sentiment should exert an *opposite impact* on the beta-sorted portfolios for mispricing factors and risk-based factors. Thus, by inspecting how sentiment affects the pricing of these long-short beta-sorted portfolios, our setting is uniquely designed to distinguish alternative underlying mechanisms for these prominent 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), and the same set of factors studied in Chen et al. (2018). We then construct a set of beta-sorted portfolios as our testing portfolios, which produce economically large and statistically highly significant ex post factor beta spreads. The large ex post factor beta spreads tend to increase the power of the test (see, e.g., Daniel and Titman 2011). Indeed, confirming the findings in Chen et al. (2018), Daniel et al. (2020), and Herskovic, Moreira, and Muir (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, beta-sorted long-short portfolios have a negative return spread (−0.31% per month on average) following low-sentiment periods, whereas the return spreads are significantly higher (by 0.95% per month) and positive (0.64% per month) following 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 shown 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 substantially 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 rather than for risk, as the return spreads of beta-sorted long-short portfolios 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 1.19% per month, whereas this difference is merely 0.25% 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 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 behind the relatively weak unconditional relation between factor beta and expected returns and the two-regime pattern, we examine the contemporaneous relation between beta-sorted portfolios and sentiment changes. We find that low-beta firms tend to have higher loadings on 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.

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

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, we find that the beta-sorted mutual fund portfolios have an average negative return spread (−0.32% per month on average) following low levels of sentiment, whereas the return spreads are significantly higher (by 0.57% per month) and positive (0.25% per month) following high levels of sentiment. This return difference across the two sentiment regimes is economically significant since Chen et al. (2018) show that the inter-quartile ranges of mutual fund raw returns, factor-adjusted alphas, and characteristics-adjusted returns are only 5.4%, 3.7%, and 2.7% per annum, respectively. When we use hedge fund returns, the pattern is even more salient. The beta-sorted portfolios have an average negative return spread (−0.75% per month on average) following low levels of sentiment, whereas the return spreads are significantly higher (by 1.57% per month) and positive (0.82% 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, the Conference Board Consumer Confidence Index, a sentiment index based on survey data from the American Association of Individual Investors (AAII Sentiment Survey), 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 many other economic forces, such as TED, inflation, or dispersion, and a comprehensive list of equity premium predictors. Third, we also perform a placebo test by replacing our sentiment measure with these variables, and we show that the significant two-regime results do not hold for these variables, highlighting the unique role of investor sentiment in the beta-return relation. Lastly, motivated by the findings in Lou, Polk, and Skouras (2019) and Hendershott, Livdan, and Rösch (2020), which suggest that investors demand a premium for bearing systematic risk overnight, we also explore the pricing of factors 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.

Our findings have several implications. First, our findings provide new trading strategies or anomalies. For example, the average high-minus-low beta-sorted portfolio spread is only about 0.18% per month. However, following high-sentiment periods, this spread is 0.64% per month, a much more profitable strategy. We also find that factor beta and characteristics have low correlations at about 15% on average. In addition, the average percentage overlap of stocks in the characteristics-sorted long-short portfolio and the beta-sorted long-short portfolio is only about 10%. Thus, these beta-sorted long-short portfolios are different from the original anomalies, and they are trading different sets of stocks. As a result, these new strategies can at least increase the capacity of a fund manager, which is a key obstacle faced by practitioners.

Second, our evidence that these characteristics-based factors are likely to be mispricing factors, coupled with the low correlation between factor beta and characteristics, also has important implications for popular applications of these factor models, such as anomaly studies, mutual fund performance evaluation/attribution, and event studies. Take the PERF factor as an example. Notice that even if the PERF is a mispricing factor, for anomaly studies, we still want to make sure that the newly discovered anomaly is not simply a repackaging of existing anomalies, such as the anomaly underlying the PERF factor. Traditionally, people tend to regress anomaly returns on PERF factor returns to adjust for the anomaly underlying the PERF factor. Intuitively, firms with strong performance tend to have high PERF beta. Thus, if one buys firms with strong performance, using the PERF factor to adjust seems to be appropriate since it reduces the alpha due to buying strong performers. However, the reverse is not necessarily true. That is, firms with high PERF beta are not necessarily firms with strong performance. Indeed, the time-series average of the cross-sectional correlation between PERF beta and performance characteristics is about 18%. Thus, if PERF is not a risk factor as our evidence suggests, then in this case, the part of return due to the “exposure” to the PERF factor should not be deducted for anomaly analysis, as long as this firm is not a strong performer. Hence, if these high PERF beta stocks have a higher future return, it would still be a good strategy to buy these firms. Although this strategy has high PERF beta and low PERF-adjusted alpha, it is different from the well-known anomaly underlying PERF factor. Thus, factor-based adjustment for anomaly analysis might be inappropriate. To further highlight this point, we also examine the performance of two other strategies during the quant crisis in August 2007 (i.e., the traditional momentum strategy and the high-minus-low momentum beta strategy). The traditional momentum strategy suffers huge losses, whereas the high-minus-low momentum beta strategy is almost untouched, as shown in Figure 1.

In sum, to make sure that a newly discovered anomaly is not simply a repackaging of existing anomalies, an adjustment similar to the characteristics-based approach as in Daniel et al. (1997) could be more appropriate. However, for a large number of characteristics, the original Daniel et al. (1997) approach is infeasible. Thus, it may be more appropriate to adopt the characteristics-based benchmark adjustment based on Fama-MacBeth regressions, as in Bessembinder, Cooper, and Zhang (2019), to account for multiple existing anomalies simultaneously. In particular, Bessembinder, Cooper, and Zhang (2019) propose that fitted values from market-wide regressions of firm returns on lagged firm characteristics provide useful benchmarks for assessing whether average returns to certain stocks are abnormal. Lastly, similar arguments can

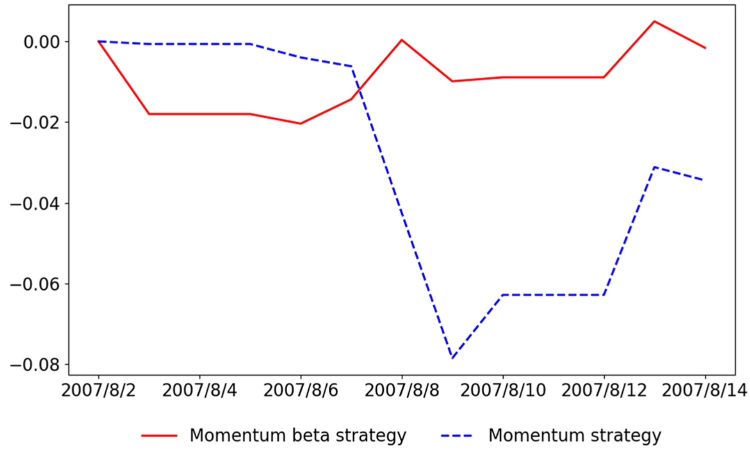

Figure 1
Quant crisis for momentum strategy and momentum beta strategy
This figure presents the cumulative returns for a momentum strategy and a momentum beta strategy during the August 2007 quant crisis. The momentum strategy is a value-weighted portfolio that longs the winner decile of stocks with the highest past 12-month cumulative returns and shorts the loser decile of stocks with the lowest past 12-month cumulative returns, skipping 1 month from the portfolio formation month. The momentum beta strategy is a value-weighted portfolio that longs the top decile of stocks with the largest momentum factor betas and shorts the bottom decile of stocks with the lowest momentum factor betas, where the betas are estimated with respect to the momentum factor using daily returns over the past 3 months with a minimum of 45 days.

be applied to mutual fund performance analysis, attribution analysis, and event studies.

In terms of the literature, this study builds on the earlier work of Baker and Wurgler (2006, 2007), who show that market-wide sentiment has a greater effect on securities that are hard to arbitrage and difficult to value. Our paper is also 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 the time series and cross section, respectively. Shen, Yu, and Zhao (2017) only consider factors with a strong economic foundation but mostly focus on nontradable factors, such as consumption 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 characteristics-based factors, which are more powerful in accounting for asset pricing anomalies. 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 another related study, Stambaugh, Yu, and Yuan (2012) investigate the effect of investor sentiment on anomalies. They find that return spreads of anomalies are much more pronounced following *high-sentiment* periods because of sentiment-induced overpricing. Our paper examines the effect of investor sentiment on the pricing of a large set of characteristics-based factors, rather than on the anomalies themselves. Unlike anomalies, beta-sorted portfolios produce very low return spreads. In addition, the time-series average of the cross-sectional correlation between firm-level characteristics and firm-level factor beta is only about 15% on average. The average percentage overlap of stocks in anomalies and the beta-sorted portfolios is also only about 10%. Thus, the beta-sorted long-short portfolios and the anomaly portfolios are trading very different stocks. As a result, the effect of sentiment on anomalies cannot mechanically carry over to these beta-sorted portfolios. More important, sentiment should exert an *opposite impact* on the beta-sorted portfolios for mispricing factors and risk-based factors. Thus, by inspecting how sentiment affects the pricing of these long-short beta-sorted portfolios, our setting is uniquely designed to distinguish alternative underlying mechanisms for these prominent factors. In addition, we also extend the analysis to professionally managed portfolios, such as mutual fund and hedge 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 uncertainty/macroeconomic beta tend to earn higher average returns, whereas our focus is on hedge fund exposure to characteristics-based factors.

Finally, this paper is also related to studies on the failure of the traditional capital asset pricing model (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; Jylhä 2018; Chen and Lu 2019), benchmarked institutional investors (Brennan and Li 2008; 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 prominent characteristics-based factors 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.

1. 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 portfolio 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 2023:12. Delisting bias in the stock return is adjusted according to Shumway (1997).

1.1 Investor sentiment measures

We use the BW investor sentiment index proposed by Baker and Wurgler (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, which 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 sentiment index based on AAII Sentiment Survey.

1.2 Portfolios sorted on characteristics-based factor betas

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 (MGMT) factor and performance-related mispricing (PERF) factor from Stambaugh and Yuan (2017)'s mispricing factor model, and the long-run behavioral (FIN) factor and short-run behavior (PEAD) factor from Daniel, Hirshleifer, and Sun (2020)'s behavioral factor model. The sample period is from 1967:1 to 2023:12 for the IA and ROE factors, 1972:7 to 2023:12 for the FIN and PEAD factors, and 1963:7 to 2023:12 for the other factors.[5] For each of the 13 factors, betas are estimated using a single-factor model. 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,

[5] We use the factor datasets directly provided by the original authors whenever possible. The Fama-French factors and the momentum factor are from Kenneth French's data library. The q factors are obtained from Lu Zhang's website. The FIN and PEAD factors come from Lin Sun's website. The QMJ factor is provided by AQR. Since the original authors no longer update the remaining three factors, we obtain the MGMT and PERF factors from PyAnomaly and extend the PMU factor ourselves. For these three factors, the correlation coefficients between the original factors and our constructed versions during the original sample period are .9, .92, and .96, respectively.

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 (2020)), 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 Internet Appendix that our results are robust if we use a longer window to estimate the ex ante beta for these factors.

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 panel C of Table 1, we present the correlations between factor returns and lagged sentiment level, as well as the change in sentiment. Panel C shows that the correlation coefficients of these factors with lagged sentiment are mostly positive, albeit weak, consistent with the findings in Stambaugh, Yu and Yuan (2012) that anomalies tend to be more pronounced following high-sentiment periods.

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 −.87 to .93. Consistent with the findings in Chen et al. (2018) and Daniel, Hirshleifer, and Sun (2020), while the unconditional ex post beta spreads are economically and statistically significant with an average magnitude of 1.89 and t-statistic of 38.64 (panel C of Table 2), only one of the beta-sorted portfolios delivers significant return spreads (panel B of Table 2). However, the average CAPM alpha is statistically significant at 0.37% per month for these factor-beta-sorted portfolios. This positive CAPM alpha itself could be consistent with one of two possibilities: factor beta is a proxy for mispricing, or factor beta captures some additional risk beyond market risk.

In panel D of Table 2, we present the time-series average of the cross-sectional signed correlations between the factor betas of stocks and their respective characteristics where the correlation sign is adjusted so that the value of characteristics predicts cross-sectional returns with a positive sign. The observed correlations are relatively low, with an average value of .15, indicating a lack of a pronounced relationship between a stock's beta and its corresponding characteristics at the individual stock level. Put simply, stocks with higher factor betas do not consistently show elevated characteristics in that particular dimension.

Table 1
Summary statistics of the characteristics-based factors

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	−.01	1.00											
(3)	RMW	−.36	.08	1.00										
(4)	CMA	−.09	.69	−.01	1.00									
(5)	IA	−.13	.68	.09	.92	1.00								
(6)	ROE	−.40	−.12	.66	−.05	.05	1.00							
(7)	PMU	−.02	−.39	.45	−.36	−.32	.39	1.00						
(8)	QMJ	−.49	−.03	.69	.09	.14	.70	.46	1.00					
(9)	MOM	−.07	−.19	.09	−.01	.04	.49	.07	.30	1.00				
(10)	MGMT	−.29	.66	.23	.78	.75	.09	−.18	.38	−.05	1.00			
(11)	PERF	−.27	−.35	.53	−.11	−.07	.72	.48	.69	.64	−.02	1.00		
(12)	FIN	−.38	.61	.59	.59	.63	.37	.02	.55	.09	.74	.22	1.00	
(13)	PEAD	−.06	−.20	−.08	−.05	−.08	.24	.09	.18	.47	−.05	.33	−.04	1.00

B. Factor returns and CAPM alphas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Return	0.21	0.29	0.28	0.27	0.36	0.53	0.33	0.38	0.60	0.51	0.56	0.71	0.57
	(1.80)	(2.18)	(3.13)	(3.10)	(4.10)	(5.28)	(3.39)	(4.03)	(3.80)	(5.13)	(5.03)	(4.26)	(7.37)
Alpha^{CAPM}	0.11	0.37	0.34	0.37	0.45	0.61	0.32	0.53	0.69	0.65	0.64	0.95	0.61
	(0.93)	(2.60)	(3.54)	(4.28)	(5.23)	(6.59)	(3.09)	(6.54)	(4.79)	(6.94)	(6.29)	(6.15)	(8.09)

C. Correlations between characteristics-based factors and BW sentiment index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
S_{t-1}	−.11	.06	.15	.08	.07	.09	.12	.18	.01	.11	.09	.10	−.03
ΔS_t	.09	−.15	−.12	−.10	−.08	−.04	.09	−.06	.03	−.14	.00	−.17	.03

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 and West (1987) five-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 1967:1 to 2023:12 for IA and ROE factors, 1972:7 to 2023:12 for FIN and PEAD factors, and 1963:7 to 2023:12 for other factors. The sample period is 1965:07 to 2023:12 for the BW sentiment index.

Table 2
Beta-sorted portfolios

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
A. Pairwise correlations among beta-sorted high-minus-low portfolios																
(1)	SMB	1.00														
(2)	HML	−.31	1.00													
(3)	RMW	−.64	.32	1.00												
(4)	CMA	−.43	.81	.33	1.00											
(5)	IA	−.45	.83	.40	.93	1.00										
(6)	ROE	−.75	.12	.80	.19	.25	1.00									
(7)	PMU	−.06	−.31	.19	−.36	−.30	.28	1.00								
(8)	QMJ	−.87	.29	.74	.44	.46	.80	.19	1.00							
(9)	MOM	−.02	−.09	.11	.01	.01	.15	.06	.14	1.00						
(10)	MGMT	−.63	.75	.49	.87	.87	.36	−.18	.64	.00	1.00					
(11)	PERF	−.34	−.02	.48	.09	.12	.55	.18	.46	.60	.15	1.00				
(12)	FIN	−.68	.69	.67	.76	.80	.50	.04	.71	.03	.88	.28	1.00			
(13)	PEAD	.04	−.18	−.01	−.09	−.13	.06	.03	.08	.39	−.07	.24	−.08	1.00		
(14)	Ave	−.63	.61	.75	.70	.74	.66	.10	.77	.37	.79	.59	.85	.18	1.00	
(15)	$\text{Ave}_{w/oSMB}$	−.72	.59	.76	.70	.74	.70	.09	.83	.34	.80	.58	.87	.16	.99	1.00
B. Excess returns and CAPM alphas																
Ret^e_H		0.38	0.81	0.54	0.52	0.53	0.56	0.67	0.54	0.49	0.60	0.68	0.70	0.65	0.57	0.59
		(1.02)	(3.23)	(2.62)	(2.45)	(2.24)	(2.85)	(2.44)	(3.60)	(1.94)	(3.34)	(3.07)	(3.75)	(2.21)	(2.92)	(3.19)
Ret^e_L		0.56	0.57	0.23	0.58	0.63	0.64	0.38	0.39	0.47	0.56	−0.15	0.46	0.49	0.42	0.41
		(3.92)	(1.75)	(0.69)	(1.74)	(1.76)	(1.81)	(1.38)	(1.02)	(1.55)	(1.50)	(−0.45)	(1.20)	(1.58)	(1.48)	(1.36)
Ret^e_{H-L}		−0.17	0.24	0.31	−0.06	−0.10	−0.09	0.29	0.15	0.01	0.04	0.83	0.24	0.16	0.15	0.18
		(−0.57)	(0.76)	(1.07)	(−0.19)	(−0.30)	(−0.29)	(1.01)	(0.46)	(0.04)	(0.11)	(3.04)	(0.70)	(0.56)	(0.97)	(0.96)
$\text{Alpha}^{CAPM}_{H-L}$		−0.71	0.48	0.62	0.28	0.26	0.28	0.25	0.73	0.11	0.55	1.06	0.85	0.18	0.37	0.46
		(−2.93)	(1.44)	(2.20)	(0.96)	(0.77)	(0.98)	(0.83)	(2.74)	(0.37)	(1.81)	(3.92)	(2.64)	(0.59)	(2.61)	(2.84)

(Continued)

Table 2
(Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
C. Ex post betas															
High beta	1.97	0.56	0.23	0.01	0.13	0.07	0.92	−0.29	0.36	−0.18	0.21	−0.05	0.28	0.37	0.21
	(16.55)	(3.59)	(1.96)	(0.06)	(0.98)	(0.69)	(6.01)	(−3.25)	(2.66)	(−1.72)	(1.77)	(−0.63)	(1.03)	(7.51)	(4.18)
Low beta	−0.01	−1.33	−2.10	−2.09	−2.17	−1.79	−1.13	−2.89	−1.08	−2.51	−1.67	−1.71	−1.09	−1.52	−1.67
	(−0.10)	(−7.68)	(−10.71)	(−11.36)	(−9.25)	(−9.78)	(−6.73)	(−19.84)	(−9.53)	(−14.28)	(−11.51)	(−17.61)	(−4.23)	(−25.53)	(−26.45)
High - Low	1.98	1.88	2.32	2.10	2.30	1.85	2.05	2.60	1.44	2.32	1.88	1.67	1.37	1.89	1.88
	(16.01)	(14.46)	(17.54)	(11.86)	(11.10)	(12.69)	(20.29)	(20.60)	(15.44)	(15.32)	(18.86)	(23.39)	(6.01)	(38.64)	(37.07)
D. Cross-sectional signed correlations: Beta versus characteristics															
Corr	.17	.20	.05	.07	.05	.07	.18	.36	.22	.13	.18	.28	.02	.15	.15
E. Percentage of overlap stocks in top and bottom decile beta and characteristics portfolios															
% of overlap	13.18	10.57	9.52	8.51	8.14	7.48	8.87	11.10	13.61	6.10	10.12	9.09	8.22	9.58	9.28
F. Correlation of high-minus-low return spreads of beta vs. characteristics portfolios															
Corr	.53	.46	.63	.28	.23	.62	.36	.80	.71	.53	.60	.55	.25	.50	.50

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 in percentage (ex post betas) of high-beta, low-beta, and high-minus-low portfolios with Newey-West (1987) five-lag adjusted t-statistics in parentheses. Ex post betas are estimated using the corresponding single characteristics-based factor model. Panel D presents the time-series average of cross-sectional signed correlations between factor beta and respective stock characteristics, where the correlation sign is adjusted so that the value of characteristics predicts cross-sectional returns with a positive sign. Panel E presents the time-series average of the percentage of overlap stocks in the top and bottom decile beta and characteristics portfolios. For top (bottom) decile portfolios, we first calculate the percentage of overlap stocks in the top (bottom) decile beta and characteristics portfolios each month. We take an average of the percentages between the top and bottom decile portfolios and then the time-series average of the percentages. Panel F presents the time-series correlations between the return spreads of high-minus-low portfolios for the factor-beta-sorted portfolio and corresponding stock-characteristics-sorted portfolio. Ave refers to the average portfolios across all beta-sorted portfolios. Ave ($Ave_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). The sample period is from 1970:1 to 2023:12 for IA and ROE beta-sorted portfolios, 1975:7 to 2023:12 for FIN and PEAD beta-sorted portfolios, and 1966:7 to 2023:12 for other beta-sorted portfolios.

In panel E of Table 2, we present the time-series average of the percentage of overlap stocks in the top and bottom decile beta and characteristics portfolios. On average, less than 10% of stocks overlap in the long and short legs of these portfolios, suggesting that these two sets of long-short portfolios are quite different.

In panel F of Table 2, we calculate the correlations between the return spreads of the high-minus-low beta-sorted portfolio and the corresponding high-minus-low characteristics-sorted portfolio. The average correlation is at a moderate level of .5; thus, these two sets of long-short portfolios capture distinct pieces of information.

1.3 Data on hedge funds and mutual funds

Data from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database and Thomson Reuters Mutual Fund Holdings 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., Kacperczyk, Sialm, and Zheng 2008; Busse, Jiang, and Tang 2021; Pástor, Stambaugh, and Taylor 2017). First, we eliminate balanced, bond, index, international, commodity, and sector funds based on various objective codes and detailed asset compositions.[6] We require funds in the CRSP mutual fund database to have average stock holdings of at least 70% and require the number of stocks held in Thomson Reuters Mutual Fund Holdings database to be at least 10 to focus on diversified funds. 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 U.S. dollars are kept. Lastly, to address concerns about incubation bias (Evans 2010), we drop the first 3 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 3,566 unique funds and 531,727 fund-month observations from 1980:1 to 2023:12.

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) and Chen, Lu, and Zhu (2025). First, we include both live and graveyard funds with returns net of fees

[6] A detailed fund code selection process can be found in Busse, Jiang, and Tang (2021).

in U.S. dollars at a monthly frequency. Second, we require funds to have an initial NAV of greater than US$10 million. Third, we require each fund to have at least 24 months of return history to address the issue of multiperiod sampling bias. Lastly, to mitigate concerns about backfill bias, we drop the first year of returns for each fund. 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 8,233 unique funds and 601,956 fund-month observations from 1996:7 to 2023:12.

2. 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 follows their structure.

2.1 Average returns across two sentiment regimes

We use the Baker-Wurgler sentiment index for our main analysis. In the robustness analysis, 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, of the 85 months of NBER recession during our sample, 41 months are classified as high sentiment, and 44 months are classified as low sentiment.

We now examine the relation between the 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, 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, especially the short legs, are more pronounced following high-sentiment periods. 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 participants are closer to being 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 characteristics-based 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 and the factor betas are noisy proxies for the level of underpricing, as argued in Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2020), 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.

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 0.51% per month following high-sentiment periods and −0.23% per month following low-sentiment periods. The difference of 0.75% per month is economically large and statistically significant (t-statistic = 2.54). 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. After all, many rational models, such as Carlson, Giammarino, and Fisher (2004) and Gârleanu, Panageas, and Yu (2012), show that small firms could be riskier than large firms. Second, firms with high size factor beta should be more subject to the influence of investor sentiment. That is, the returns of firms with high size factor beta are more positively correlated with sentiment changes than the returns of firms with low size factor beta, a fact confirmed in Table 6 later on. As argued in Baker and Wurgler (2006, 2007), during high-sentiment periods, firms that are more subject to the influence of sentiment should be relatively more overvalued. Thus, firms with high size beta are relatively more overvalued

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

	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	0.52	−0.08	1.23	−0.44	−1.67	0.63	−0.95	−1.59
	(2.94)	(2.52)	(−0.29)	(2.29)	(−0.89)	(−2.33)	(1.48)	(−2.41)	(−2.80)
HML	1.06	0.09	−0.97	0.80	0.82	0.03	−0.26	0.73	0.99
	(2.48)	(0.20)	(−1.57)	(1.94)	(2.67)	(0.05)	(−0.64)	(1.56)	(1.59)
RMW	1.00	−0.52	−1.53	0.53	0.54	0.01	−0.47	1.06	1.54
	(2.25)	(−1.13)	(−2.41)	(1.83)	(1.87)	(0.02)	(−1.18)	(2.75)	(2.77)
CMA	0.95	0.22	−0.73	0.51	0.53	0.02	−0.44	0.31	0.74
	(2.07)	(0.48)	(−1.14)	(1.69)	(1.76)	(0.04)	(−1.10)	(0.67)	(1.27)
IA	1.17	0.12	−1.05	0.53	0.53	0.00	−0.64	0.41	1.05
	(2.35)	(0.24)	(−1.53)	(1.47)	(1.72)	(0.00)	(−1.50)	(0.83)	(1.65)
ROE	1.25	0.07	−1.18	0.74	0.38	−0.36	−0.51	0.31	0.82
	(2.32)	(0.14)	(−1.67)	(2.67)	(1.37)	(−0.91)	(−1.12)	(0.77)	(1.35)
PMU	0.86	−0.08	−0.94	0.90	0.45	−0.46	0.05	0.53	0.48
	(2.24)	(−0.20)	(−1.71)	(2.29)	(1.19)	(−0.86)	(0.12)	(1.29)	(0.85)
QMJ	1.29	−0.47	−1.76	0.50	0.59	0.09	−0.79	1.06	1.85
	(2.41)	(−0.91)	(−2.39)	(2.31)	(2.75)	(0.31)	(−1.77)	(2.50)	(3.02)
MOM	0.89	0.07	−0.83	0.85	0.13	−0.72	−0.04	0.06	0.10
	(1.99)	(0.16)	(−1.35)	(2.46)	(0.39)	(−1.48)	(−0.11)	(0.14)	(0.18)
MGMT	1.24	−0.09	−1.33	0.47	0.73	0.25	−0.77	0.81	1.58
	(2.42)	(−0.17)	(−1.84)	(1.83)	(2.84)	(0.68)	(−1.72)	(1.70)	(2.46)
PERF	0.54	−0.83	−1.37	1.06	0.31	−0.75	0.52	1.14	0.63
	(1.18)	(−1.66)	(−2.05)	(3.33)	(1.04)	(−1.67)	(1.43)	(2.77)	(1.11)
FIN	1.46	−0.37	−1.83	0.80	0.62	−0.19	−0.65	0.99	1.64
	(2.89)	(−0.69)	(−2.61)	(2.66)	(2.59)	(−0.48)	(−1.46)	(2.06)	(2.63)
PEAD	1.11	−0.03	−1.15	1.16	0.22	−0.94	0.05	0.26	0.20
	(2.33)	(−0.08)	(−1.87)	(2.88)	(0.55)	(−1.74)	(0.12)	(0.62)	(0.35)
Ave	0.98	−0.12	−1.10	0.75	0.39	−0.36	−0.23	0.51	0.75
	(2.43)	(−0.31)	(−2.00)	(2.59)	(1.51)	(−0.93)	(−1.16)	(2.33)	(2.54)
$\text{Ave}_{w/o\ SMB}$	1.02	−0.18	−1.19	0.71	0.46	−0.25	−0.31	0.64	0.95
	(2.38)	(−0.42)	(−2.05)	(2.60)	(1.89)	(−0.68)	(−1.24)	(2.49)	(2.72)
$\text{Ave}^{\alpha CAPM}$	−0.06	−0.69	−0.63	−0.05	0.00	0.05	0.01	0.69	0.68
	(−0.37)	(−4.13)	(−2.82)	(−0.71)	(0.02)	(0.46)	(0.03)	(3.37)	(2.62)
$\text{Ave}^{\alpha CAPM}_{w/o\ SMB}$	−0.06	−0.77	−0.70	−0.05	0.10	0.15	0.01	0.86	0.85
	(−0.37)	(−4.18)	(−2.83)	(−0.66)	(1.10)	(1.24)	(0.08)	(3.74)	(2.81)

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). Preranking 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 preranking 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). We report CAPM alphas for the two average portfolios ($\text{Ave}^{\alpha CAPM}$ and $\text{Ave}^{\alpha CAPM}_{w/o\ SMB}$) in the last four rows. The sample period is from 1970:1 to 2023:12 for IA and ROE, 1975:7 to 2023:12 for FIN and PEAD, and 1966:7 to 2023:12 for others. Returns and alphas are in percentages. Newey-West (1987) five-lag adjusted t-statistics are reported in parentheses.

than firms with low size beta during high-sentiment periods. 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 those of low-size-beta firms, leading to a positive return spread between high- and low-size-beta firms following low-sentiment periods. Consequently, the size-beta-sorted long-short portfolio return spread should be larger following low sentiment than following high sentiment. That is, the effect of sentiment on SMB could be different with the effect of sentiment on other characteristics-based factors. In this paper, we do not try to distinguish these two interpretations because both forces likely play significant roles. In sum, 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 the level of underpricing, as suggested in Stambaugh and Yuan (2017). 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 −0.31% per month following low-sentiment periods. The difference of 0.95% per month is economically large and statistically significant (t-statistic = 2.72). 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 total factor productivity (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 almost all 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 1.19% per month (t-statistic = 2.05), as compared with that following low-sentiment periods. However, the firms with high beta only underperform by 0.25% per month (t-statistic = 0.68). 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 overpricing 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 do not take systematic risk into account. We also report benchmark-adjusted returns in the last four rows of Table 3. To save space, we only report the results for the two average portfolios in Table 3 and leave the full results for the individual factor-beta sorted portfolios in Table IA1 in the Internet Appendix. We estimate CAPM-adjusted alphas separately for both subsamples following low and high sentiment. We only report CAPM alpha instead of other multifactor 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 multifactor model. In general, adjusting for market exposure does not affect our conclusions. For example, after excluding the SMB factor beta-sorted portfolios, the average return spread between high- and low-beta portfolios is 0.85% higher per month (t-statistic = 2.81) following high-sentiment periods than following low-sentiment periods. This two-regime alpha spread is still 0.68% per month (t-statistic = 2.62) even when we include the SMB beta-sorted portfolios. Moreover, the CAPM-adjusted return on the high-beta portfolios in the combined strategy exhibits a small difference (0.15% 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 difference of –0.70% per month 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 following high-sentiment periods, a phenomenon also documented for the eleven anomalies by Stambaugh, Yu, and Yuan (2012). Indeed, following high-sentiment periods, the average CAPM alpha spread is 0.86% (t-statistic = 3.74), whereas following low-sentiment periods, the average CAPM alpha spread is only 0.01% (t-statistic = 0.08). 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 −0.77% per month for the short leg and only 0.10% 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. Table 3 shows that low-beta portfolios earn lower returns following high-sentiment periods than following low-sentiment periods: 8 of the 12 factors (excluding the size factor) have a t-statistic that rejects the no-difference null across high- and low-sentiment periods at 10% significance level. 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 only 2 of the 12 factors is significant. For example, the basis points for high-beta portfolios in the average strategy are lower by 25 bps per month following high-sentiment periods, and the t-statistic is only −0.68. In addition, any evidence of 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 following low-sentiment periods, with a magnitude of 15 bps and a t-statistic of 1.24. 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 small 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 (−0.77% per month with a t-statistic of −4.18), again suggesting overpricing for low-beta firms during high-sentiment periods. In contrast, only 1 of the 12 low-beta portfolios earns significant CAPM alpha (positive or negative) following low sentiment. The average CAPM alphas are slightly negative and insignificant (−0.06% per month with t-statistic of −0.37), 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 (2020), 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 preranking 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 Table IA2 in the Internet Appendix, we repeat our exercise by 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 0.55% (t-statistic = 2.21), 0.60% (t-statistic = 2.48), and 0.51% (t-statistic = 2.17), depending on the data frequency and estimation window choice. Excluding the size factor raises this average spread to 0.67% (t-statistic = 2.29), 0.72% (t-statistic = 2.51), and 0.63% (t-statistic = 2.34), respectively. In addition, the average difference between these long-short beta-sorted return spreads following high-sentiment and low-sentiment periods is 0.74% per month (t-statistic = 2.44), 0.82% per month (t-statistic = 2.79), and 0.56% per month (t-statistic = 1.99). 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 Table IA3 in the Internet Appendix. 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.

In addition, Stambaugh, Yu, and Yuan (2012) show that anomalies tend to be more pronounced following high-sentiment periods, while Fama and French (2020) argue that firm characteristics could be proxy for time-varying factor betas. Thus, one might argue that our two-regime pattern is expected based on these two studies. However, by estimating time-varying factor betas using rolling-window methods, we find that the time-series average of the cross-sectional correlation between factor beta and characteristics is low, only about 15% on average. More important, we regress our factor betas onto characteristics and obtain residual factor betas. We find a similarly strong two-regime pattern based on residual factor betas, as shown in Table IA4 in the Internet Appendix. Thus, our two-regime pattern is not a direct consequence of Stambaugh, Yu, and Yuan (2012) and Fama and French (2020).

We also repeat our main analysis using a more extreme tercile cutoff to define high and low sentiments. The results are reported in Table IA5 in the Internet Appendix. The two-regime pattern is stronger when we compare the top and bottom tercile sentiment periods. In particular, the difference-in-differences spreads have increased from 0.75% (0.95%) to 1.24% (1.52%) for Ave ($\text{Ave}_{w/o\ SMB}$) portfolios. To make sure that our results are not mainly driven by small firms, we repeat our main analysis using NYSE breakpoints in Table IA6 in the Internet Appendix. The results remain similar. In addition, we also repeat our main two-regime analysis by excluding micro stocks in Table IA7 and excluding penny stocks in Table IA8 in the Internet Appendix. Our two-regime pattern again remains untouched. Therefore, our results are not mainly driven by small stocks.

Lastly, we would like to link our findings 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 are likely to 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, and thus 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.

2.2 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 of characteristics-based factor beta-sorted portfolios 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 almost all 12 factors are positive in panel A of Table 4. Seven of the individual t-statistics are significant at a significance level of 5%. The last average strategy (excluding the size factor) has a t-statistic of 3.67. 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 0.64 for the average strategy indicates that a one-standard-deviation increase in sentiment is associated with a 0.64% 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 of all 12 individual t-statistics are significant at 5%, and the remaining 4 are marginally significant as well. The last average strategy has a t-statistic of -2.59. It is seen that a

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

A. Lagged BW sentiment

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	−0.04	(−0.23)	−1.02	(−2.48)	−0.98	(−3.22)
HML	−0.61	(−1.65)	−0.21	(−0.79)	0.40	(1.17)
RMW	−0.96	(−2.87)	−0.07	(−0.26)	0.89	(3.18)
CMA	−0.60	(−1.58)	−0.09	(−0.41)	0.52	(1.69)
IA	−0.82	(−1.79)	0.09	(0.44)	0.91	(2.40)
ROE	−0.81	(−1.96)	−0.11	(−0.41)	0.71	(2.21)
PMU	−0.54	(−2.04)	−0.48	(−1.37)	0.06	(0.19)
QMJ	−1.25	(−3.14)	0.06	(0.32)	1.31	(4.53)
MOM	−0.64	(−1.96)	−0.50	(−1.92)	0.14	(0.53)
MGMT	−1.05	(−2.53)	−0.01	(−0.07)	1.04	(3.02)
PERF	−1.24	(−3.26)	−0.22	(−0.87)	1.03	(3.88)
FIN	−1.39	(−3.00)	−0.07	(−0.37)	1.32	(3.21)
PEAD	−0.65	(−1.95)	−0.87	(−2.29)	−0.23	(−0.54)
Ave	−0.79	(−2.50)	−0.28	(−1.21)	0.51	(3.46)
$\text{Ave}_{w/o\ SMB}$	−0.85	(−2.59)	−0.21	(−0.98)	0.64	(3.67)

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	0.15	(2.56)	−0.59	(−2.96)	−0.74	(−3.15)
HML	−0.24	(−1.29)	0.06	(0.35)	0.30	(0.94)
RMW	−0.59	(−3.01)	0.17	(1.30)	0.75	(2.75)
CMA	−0.22	(−1.41)	0.14	(1.09)	0.36	(1.47)
IA	−0.53	(−2.89)	0.27	(1.81)	0.80	(2.69)
ROE	−0.53	(−2.43)	0.06	(0.51)	0.59	(2.05)
PMU	−0.24	(−1.16)	−0.16	(−1.08)	0.08	(0.26)
QMJ	−0.81	(−4.18)	0.25	(3.00)	1.06	(4.40)
MOM	−0.30	(−1.73)	−0.21	(−1.61)	0.09	(0.38)
MGMT	−0.63	(−3.62)	0.18	(1.60)	0.81	(3.13)
PERF	−0.88	(−4.47)	0.05	(0.48)	0.93	(3.89)
FIN	−0.92	(−3.85)	0.14	(1.11)	1.07	(3.33)
PEAD	−0.29	(−1.14)	−0.52	(−2.53)	−0.23	(−0.57)
Ave	−0.42	(−4.06)	−0.01	(−0.24)	0.41	(3.36)
$\text{Ave}_{w/o\ SMB}$	−0.48	(−4.10)	0.04	(0.68)	0.51	(3.70)

This table reports the point estimates of b ($\hat{b}$), along with Newey-West (1987) five-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). Excess returns ($R_{i,t}$) are in percentages, and the sentiment index is scaled to have a zero mean and unit standard deviation. Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile (High beta) portfolio, and their differences (H-L). Preranking 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 preranking 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 1970:1 to 2023:12 for IA and ROE, 1975:7 to 2023:12 for FIN and PEAD, and 1966:7 to 2023:12 for others.

one-standard-deviation increase in sentiment is associated with a 0.85% 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 11 of 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 −0.21 (t-statistic = −0.98), 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 mostly negative and insignificant at a 5% significance level. After adjusting for CAPM exposures, however, most coefficients 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 −0.48 (t-statistic = −4.10). 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 four macro-related variables that have been shown to be correlated with risk premiums and business conditions: the default premium, the term premium, the real interest rate, and the Lettau and Ludvigson (2001) wealth-consumption ratio (CAY).[8] This set of macro variables is also used as controls in Stambaugh, Yu, and Yuan (2012).

By regressing excess returns on the lagged sentiment index and the four lagged macro-related variables, one can investigate whether the predictive ability of sentiment for 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 four variables. In particular, the coefficients and their t-statistics are close to those

[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.

[8] As a result of the economic disruptions caused by the COVID-19 pandemic, the CAY series may not align well with theoretical expectations as noted by Dauber and Lawrenz (2023). Therefore, we have also repeated the analysis using data up to December 2019, and the results are consistent.

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

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	−0.02	(−0.11)	−0.84	(−2.12)	−0.82	(−2.78)
HML	−0.56	(−1.52)	−0.13	(−0.51)	0.43	(1.24)
RMW	−0.89	(−2.71)	0.00	(0.00)	0.89	(3.22)
CMA	−0.52	(−1.34)	−0.03	(−0.15)	0.49	(1.52)
IA	−0.75	(−1.65)	0.17	(0.84)	0.92	(2.29)
ROE	−0.66	(−1.67)	−0.10	(−0.38)	0.56	(1.87)
PMU	−0.44	(−1.68)	−0.39	(−1.13)	0.05	(0.16)
QMJ	−1.07	(−2.77)	0.08	(0.44)	1.15	(4.04)
MOM	−0.54	(−1.64)	−0.46	(−1.78)	0.09	(0.33)
MGMT	−0.96	(−2.30)	0.03	(0.17)	1.00	(2.85)
PERF	−1.15	(−2.99)	−0.17	(−0.69)	0.98	(3.62)
FIN	−1.40	(−2.97)	−0.02	(−0.09)	1.39	(3.29)
PEAD	−0.55	(−1.66)	−0.85	(−2.20)	−0.29	(−0.72)
Ave	−0.70	(−2.25)	−0.21	(−0.95)	0.49	(3.19)
$\text{Ave}_{w/o\ SMB}$	−0.76	(−2.33)	−0.16	(−0.74)	0.61	(3.38)

This table reports the point estimates of b ($\hat{b}$), along with Newey-West (1987) five-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. Excess returns ($R_{i,t}$) are in percentages, and the sentiment index is scaled to have a zero mean and unit standard deviation. Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Preranking 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 preranking 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 1970:1 to 2023:12 for IA and ROE, 1975:7 to 2023:12 for FIN and PEAD, and 1966:7 to 2023:12 for others.

in Table 4, in which the four 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 four 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 premiums that is not captured by standard macro-related variables.

Moreover, 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,[9] we should expect the 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 among firms with low factor beta.[10]

2.3 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 15% on average across all of the 13 factors). This is one reason the unconditional relation between factor beta and future returns is very flat. We now further investigate the relation between these beta-sorted portfolios and contemporaneous sentiment changes, 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), we directly study the sensitivity of beta-sorted portfolio returns to changes in sentiment.

In Table 6, beta-sorted portfolio returns are regressed on contemporaneous sentiment changes, controlling for the market factor. 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 magnitude of the regression coefficient is on average

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[9] 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.

[10] 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.

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

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	−0.18	(−2.32)	0.45	(1.63)	0.63	(1.88)
HML	0.45	(2.06)	−0.51	(−1.95)	−0.96	(−2.22)
RMW	0.47	(1.86)	−0.23	(−1.64)	−0.70	(−2.03)
CMA	0.52	(2.67)	−0.44	(−1.46)	−0.97	(−2.27)
IA	0.49	(2.27)	−0.47	(−1.53)	−0.96	(−2.21)
ROE	0.23	(0.82)	−0.16	(−1.22)	−0.39	(−1.04)
PMU	−0.25	(−0.80)	0.28	(1.79)	0.53	(1.38)
QMJ	0.42	(1.51)	−0.19	(−1.92)	−0.61	(−1.76)
MOM	−0.12	(−0.40)	0.27	(1.35)	0.39	(0.91)
MGMT	0.54	(2.40)	−0.46	(−2.68)	−0.99	(−2.82)
PERF	0.40	(1.41)	−0.10	(−0.63)	−0.50	(−1.32)
FIN	0.71	(2.80)	−0.32	(−2.26)	−1.04	(−3.00)
PEAD	0.05	(0.23)	0.34	(1.54)	0.29	(0.87)
Ave	0.28	(1.81)	−0.11	(−1.20)	−0.39	(−2.45)
$\text{Ave}_{w/o\ SMB}$	0.32	(1.86)	−0.16	(−1.78)	−0.48	(−2.53)

This table reports the point estimates of b ($\hat{b}$), along with Newey-West (1987) five-lag adjusted t-statistics, in the regression specifications: $R_{i,t} = a + b\Delta S_t + cMKT_t + e_{i,t}$. Excess returns ($R_{i,t}$) are in percentages, and change in sentiment is scaled to have a zero mean and unit standard deviation. Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Preranking 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 preranking 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 1970:1 to 2023:12 for IA and ROE, 1975:7 to 2023:12 for FIN and PEAD, and 1966:7 to 2023:12 for others.

larger for low-beta portfolios than for high-beta portfolios. This is true for all 12 characteristics-based factors except for PMU, MOM, PEAD, and HML, most of which are relatively short-lived anomalies and likely to be driven by inattention-induced underreaction. This result is consistent with the findings in Duan et al. (2020), 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. This partially explains the flat relation between beta and expected returns, as documented in Table 2 and in Chen et al. (2018).

3. 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 showed that returns of mutual funds depend on risk loadings (Avramov and Wermers 2006). More recently, researchers have found that mutual fund returns are related to the funds' exposure to tightness in market-wide leverage constraints (Boguth and Simutin 2018), liquidity risk (Lynch 2011; Dong, Feng, and Sadka 2019), and macroeconomic state variables (Banegas et al. 2013). Several other studies examine how hedge funds' returns 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 2021), 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 since these factors are very powerful in accounting for many anomaly portfolios. 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, similar patterns to those using stock returns. The return spread on beta-sorted long-short portfolios is 0.03% (t-statistic = 0.21) and 0.08% (t-statistic = 0.23) 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 mutual funds and hedge funds. Table 7 reports the two-regime returns of beta-sorted portfolios using mutual funds. Excluding the SMB factor, the beta-sorted long-short portfolios have an average negative return spread of −0.32% per month (t-statistic = −2.43) following low-sentiment periods, whereas this return spread is 0.25% per month (t-statistic = 1.48) following high-sentiment periods. The difference in return spreads across high- and low-sentiment periods is 0.57% per month (t-statistic = 2.70). This return spread difference across two sentiment regimes is also economically large since Chen et al. (2018) show that the inter-quartile ranges of mutual fund raw returns, factor-adjusted alphas, and characteristics-adjusted returns are 5.4%, 3.7%, and 2.7% per annum, respectively.[11]

The last four rows of Table 7 reports the average CAPM alphas for these beta-sorted mutual fund portfolios across different sentiment periods.[12] The main pattern remains similar. For example, the alpha spread difference across

[11] Similar to the analysis using stock returns, one can also estimate the mutual fund ex ante betas to these factors with a two-factor model that includes the market factor and a characteristics-based factor. The results are reported as Table IA9 in the Internet Appendix. The main two-regime pattern remains the same.

[12] To save space, we only report the CAPM alphas for the two average portfolios in Table 7 and leave the results for the individual factor-beta sorted portfolios in Table IA10 in the Internet Appendix.

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

	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	0.89	0.57	−0.32	1.39	0.39	−1.00	0.49	−0.18	−0.67
	(3.28)	(2.49)	(−0.98)	(3.30)	(1.09)	(−1.85)	(2.21)	(−0.77)	(−2.05)
HML	1.41	0.31	−1.10	0.96	0.89	−0.07	−0.45	0.58	1.03
	(3.41)	(0.83)	(−2.10)	(2.82)	(3.02)	(−0.16)	(−1.52)	(1.63)	(2.33)
RMW	1.31	0.29	−1.02	0.96	0.64	−0.33	−0.34	0.35	0.69
	(3.41)	(0.86)	(−2.09)	(2.86)	(2.41)	(−0.80)	(−1.37)	(1.50)	(2.10)
CMA	1.47	0.37	−1.10	0.86	0.85	−0.01	−0.61	0.48	1.09
	(3.53)	(0.99)	(−2.06)	(2.80)	(3.03)	(−0.02)	(−2.16)	(1.37)	(2.52)
IA	1.43	0.38	−1.05	0.90	0.62	−0.29	−0.52	0.24	0.76
	(3.49)	(1.01)	(−2.00)	(2.83)	(2.72)	(−0.77)	(−1.83)	(0.86)	(2.01)
ROE	1.08	0.64	−0.44	1.17	0.63	−0.53	0.09	−0.01	−0.09
	(2.97)	(1.77)	(−0.88)	(3.48)	(2.41)	(−1.30)	(0.37)	(−0.02)	(−0.24)
PMU	1.02	0.24	−0.79	1.30	0.71	−0.59	0.27	0.47	0.20
	(2.83)	(0.80)	(−1.76)	(3.62)	(2.32)	(−1.31)	(1.07)	(1.98)	(0.60)
QMJ	1.35	0.54	−0.81	0.86	0.59	−0.27	−0.49	0.05	0.54
	(3.22)	(1.36)	(−1.44)	(3.28)	(2.69)	(−0.84)	(−2.25)	(0.16)	(1.41)
MOM	1.13	0.51	−0.62	1.17	0.40	−0.76	0.04	−0.11	−0.15
	(2.55)	(0.80)	(−0.82)	(2.66)	(0.91)	(−1.37)	(0.12)	(−0.17)	(−0.21)
MGMT	1.52	0.36	−1.16	0.78	0.61	−0.16	−0.75	0.25	1.00
	(3.55)	(0.96)	(−2.11)	(2.69)	(2.65)	(−0.45)	(−2.59)	(0.88)	(2.54)
PERF	1.18	0.13	−1.05	1.09	0.57	−0.52	−0.09	0.44	0.54
	(2.59)	(0.19)	(−1.29)	(2.85)	(1.63)	(−1.12)	(−0.35)	(0.72)	(0.82)
FIN	1.44	0.32	−1.12	0.87	0.64	−0.23	−0.57	0.33	0.90
	(3.39)	(0.83)	(−2.07)	(3.03)	(2.95)	(−0.65)	(−2.00)	(1.15)	(2.35)
PEAD	1.32	0.59	−0.72	1.01	0.30	−0.72	−0.30	−0.30	0.01
	(2.89)	(0.99)	(−0.98)	(2.49)	(0.62)	(−1.27)	(−0.97)	(−0.46)	(0.01)
Ave	1.28	0.43	−0.85	1.03	0.65	−0.38	−0.25	0.22	0.47
	(3.46)	(1.33)	(−1.80)	(3.32)	(2.77)	(−1.03)	(−2.34)	(1.51)	(2.66)
$\text{Ave}_{w/o\ SMB}$	1.31	0.42	−0.90	0.99	0.67	−0.32	−0.32	0.25	0.57
	(3.45)	(1.24)	(−1.83)	(3.31)	(2.97)	(−0.91)	(−2.43)	(1.48)	(2.70)
$\text{Ave}^{\alpha CAPM}$	0.08	−0.10	−0.18	0.01	0.24	0.23	−0.07	0.34	0.41
	(0.79)	(−0.72)	(−1.06)	(0.16)	(2.69)	(2.27)	(−0.82)	(2.47)	(2.54)
$\text{Ave}^{\alpha CAPM}_{w/o\ SMB}$	0.09	−0.13	−0.22	0.00	0.27	0.27	−0.09	0.40	0.49
	(0.80)	(−0.84)	(−1.16)	(0.04)	(3.04)	(2.70)	(−0.81)	(2.53)	(2.58)

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). Preranking 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 preranking 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). We report CAPM alphas for the two average portfolios ($\text{Ave}^{\alpha CAPM}$ and $\text{Ave}^{\alpha CAPM}_{w/o\ SMB}$) in the last four rows. The sample period is from 1998:12 to 2023:12 for MOM, PERF, and PEAD beta-sorted portfolios, and 1980:1 to 2023:12 for other beta-sorted portfolios. Returns and alphas are in percentages. Newey-West (1987) five-lag adjusted t-statistics are reported in parentheses.

two sentiment regimes is now 0.49% per month (vs. 0.57% per month raw return spread) with a t-statistic of 2.58. 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 0.40% per month (t-statistic = 2.53) following high-sentiment periods and a CAPM alpha of −0.09% per month (t-statistic = −0.81) following low-sentiment periods. Our results are also related to the findings of DeVault, Sias, and Starks (2019), who show that institutional investors' demand for speculative stocks increases as market-wide sentiment rises, implying that sentiment-driven behavior among these investors can affect the risk-return relation.

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 −0.75% per month (t-statistic = −2.23) following low-sentiment periods, whereas the return spreads are significantly higher (by 1.57% per month, t-statistic = 2.50) and positive at 0.82% per month (t-statistic = 1.64) following high-sentiment periods.[13] We also report the CAPM alphas in the last four rows of Table 8.[14] 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 1.00% per month (t-statistic = 2.16) following high-sentiment periods and a CAPM alpha of −0.08% per month (t-statistic = −0.41) following low-sentiment periods. This evidence on asymmetry is again consistent with the notion that overpricing is more prevalent during high-sentiment periods than underpricing during low-sentiment periods.

Relatedly, Chen, Han, and Pan (2021) find that hedge funds with higher exposure to sentiment risk tend to earn higher average returns. Using macro-related factors, Chen, Lu, and Zhu (2025) 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.

[13] Similar to the analysis using stock returns, one can also estimate the hedge fund ex ante betas to these factors with a two-factor model that includes the market factor and a characteristics-based factor. The results are reported as Table IA11 in the Internet Appendix. The main two-regime pattern remains the same. In addition, focusing on pure equity hedge funds following Agarwal, Ruenzi, and Weigert (2017) classification also yields similar results, as shown in Table IA12 in the Internet Appendix.

[14] To save space, we only report the CAPM alphas for the two average portfolios in Table 8 and leave the results for the individual factor-beta sorted portfolios in Table IA13 in the Internet Appendix.

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

	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	0.09	0.22	0.13	1.17	0.23	−0.94	1.08	0.01	−1.07
	(0.50)	(1.70)	(0.74)	(2.91)	(0.57)	(−1.75)	(3.42)	(0.02)	(−2.09)
HML	0.52	−0.08	−0.60	0.80	2.29	1.49	0.28	2.37	2.09
	(1.37)	(−0.24)	(−1.40)	(2.71)	(1.38)	(0.86)	(0.72)	(1.57)	(1.25)
RMW	1.12	−0.15	−1.27	0.11	0.59	0.48	−1.01	0.74	1.75
	(2.33)	(−0.41)	(−2.38)	(0.99)	(2.53)	(1.90)	(−2.13)	(1.82)	(3.05)
CMA	0.96	0.15	−0.80	0.39	2.04	1.65	−0.57	1.88	2.46
	(2.17)	(0.40)	(−1.52)	(2.03)	(1.23)	(0.96)	(−1.35)	(1.22)	(1.45)
IA	0.97	0.14	−0.82	0.39	2.11	1.72	−0.58	1.96	2.55
	(2.29)	(0.35)	(−1.57)	(2.06)	(1.26)	(0.99)	(−1.52)	(1.27)	(1.50)
ROE	1.17	−0.01	−1.18	0.19	0.44	0.24	−0.97	0.45	1.42
	(2.49)	(−0.02)	(−2.05)	(1.65)	(3.36)	(1.43)	(−2.14)	(1.06)	(2.48)
PMU	0.94	1.98	1.04	0.39	0.30	−0.09	−0.55	−1.68	−1.13
	(2.03)	(1.11)	(0.57)	(1.96)	(1.36)	(−0.38)	(−1.14)	(−1.02)	(−0.64)
QMJ	1.14	0.09	−1.05	0.12	0.43	0.31	−1.02	0.34	1.36
	(2.28)	(0.21)	(−1.70)	(1.36)	(3.75)	(2.19)	(−2.00)	(0.69)	(2.08)
MOM	1.18	0.40	−0.78	0.15	0.08	−0.07	−1.03	−0.32	0.71
	(3.05)	(1.16)	(−1.60)	(0.64)	(0.30)	(−0.22)	(−3.17)	(−0.83)	(1.44)
MGMT	0.94	0.14	−0.80	0.32	2.08	1.76	−0.62	1.94	2.56
	(1.95)	(0.32)	(−1.39)	(2.26)	(1.27)	(1.04)	(−1.32)	(1.28)	(1.52)
PERF	1.22	−0.05	−1.27	-0.01	0.37	0.38	−1.23	0.42	1.65
	(3.07)	(−0.12)	(−2.38)	(-0.06)	(1.92)	(1.65)	(−3.66)	(1.12)	(3.30)
FIN	1.14	0.04	−1.09	0.10	2.27	2.17	−1.04	2.22	3.26
	(2.31)	(0.10)	(−1.88)	(1.11)	(1.38)	(1.28)	(−2.12)	(1.47)	(1.93)
PEAD	1.05	0.53	−0.52	0.36	0.00	−0.36	−0.69	−0.53	0.16
	(2.94)	(1.74)	(−1.17)	(1.26)	(0.00)	(−1.05)	(−2.23)	(−1.50)	(0.36)
Ave	0.96	0.26	−0.69	0.34	1.02	0.67	−0.61	0.75	1.37
	(2.38)	(0.66)	(−1.37)	(2.43)	(1.50)	(0.97)	(−2.10)	(1.65)	(2.42)
$\text{Ave}_{w/o\ SMB}$	1.03	0.27	−0.76	0.28	1.08	0.81	−0.75	0.82	1.57
	(2.42)	(0.62)	(−1.40)	(2.18)	(1.50)	(1.09)	(−2.23)	(1.64)	(2.50)
$\text{Ave}^{\alpha CAPM}$	0.16	0.00	−0.16	0.13	0.90	0.77	−0.04	0.90	0.94
	(0.75)	(0.01)	(−0.58)	(1.15)	(1.46)	(1.24)	(−0.22)	(2.10)	(1.84)
$\text{Ave}^{\alpha CAPM}_{w/o\ SMB}$	0.19	−0.01	−0.20	0.11	0.98	0.87	−0.08	1.00	1.07
	(0.82)	(−0.05)	(−0.67)	(1.01)	(1.48)	(1.29)	(−0.41)	(2.16)	(1.93)

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 for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Preranking 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 ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). We report CAPM alphas for the two average portfolios ($\text{Ave}^{\alpha CAPM}$ and $\text{Ave}^{\alpha CAPM}_{w/o\ SMB}$) in the last four rows. Returns and alphas are in percentages. The sample period is from 1996:7 to 2023:12. Newey-West (1987) five-lag adjusted t-statistics are reported in parentheses.

4. 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 multifactor models are discussed. Third, we investigate the pricing of factors overnight and intraday separately. Lastly, we repeat our main tests using four additional average portfolios by excluding behavioral-related factors.

4.1 Alternative sentiment indices

This subsection investigates the robustness of our results by using alternative sentiment indices: the University of Michigan Consumer Sentiment Index, the Conference Board Consumer Confidence index, the PLS sentiment index, which is a Baker-Wurgler sentiment index based on partial least squares, and the index based on AAII Sentiment Survey.

The BW index is arguably the most popular investor sentiment index used in the literature. However, this measure may be less useful in more recent years relative to earlier years during our sample period. For example, closed-end funds were much more popular decades ago. Thus, we perform a 20-year rolling-window subsample analysis. As shown in Figure IA1 in the Internet Appendix, the effect of sentiment remains consistent and important in most of these rolling windows, and it is particularly strong after the Internet bubble in 2000. However, there is a declining trend in recent years, probably because of the less informative BW sentiment index in recent years. Thus, it is important to make sure that our results are robust using alternative sentiment measures.

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 it Ludvigson (2004); Lemmon and Portniaguina (2006); Bergman and Roychowdhury (2008). Thus, we use this index as a robustness check.

To save space, we present the average portfolio returns using alternative sentiment indices in Table 9, with the full set of results provided in Table IA14 in the Internet Appendix. 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 difference across the two sentiment regimes is 0.99% per month (t-statistic = 2.03). In addition, the high-beta firms have very similar returns across the two sentiment regimes, and the difference is only −0.25% 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

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

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
A. Michigan Consumer Sentiment Index									
Ave	1.26	0.12	−1.14	0.95	0.55	−0.40	−0.31	0.43	0.74
	(2.27)	(0.28)	(−1.61)	(2.46)	(2.51)	(−0.89)	(−0.99)	(1.55)	(1.78)
$\text{Ave}_{w/o\ SMB}$	1.31	0.07	−1.24	0.87	0.63	−0.25	−0.43	0.56	0.99
	(2.24)	(0.14)	(−1.66)	(2.37)	(3.08)	(−0.58)	(−1.20)	(1.69)	(2.03)
B. Conference Board Consumer Confidence Index									
Ave	1.14	0.10	−1.04	0.85	0.57	−0.29	−0.29	0.47	0.75
	(2.51)	(0.22)	(−1.65)	(2.50)	(2.50)	(−0.70)	(−1.34)	(1.54)	(2.05)
$\text{Ave}_{w/o\ SMB}$	1.18	0.04	−1.14	0.80	0.63	−0.17	−0.38	0.59	0.97
	(2.48)	(0.09)	(−1.71)	(2.45)	(2.98)	(−0.43)	(−1.49)	(1.66)	(2.24)
C. PLS sentiment index									
Ave	1.31	−0.44	−1.75	0.98	0.17	−0.80	−0.34	0.61	0.95
	(3.70)	(−0.96)	(−3.15)	(4.24)	(0.59)	(−2.21)	(−1.60)	(2.51)	(3.07)
$\text{Ave}_{w/o\ SMB}$	1.36	−0.50	−1.86	0.95	0.23	−0.72	−0.41	0.74	1.14
	(3.62)	(−1.04)	(−3.16)	(4.36)	(0.84)	(−2.10)	(−1.62)	(2.53)	(3.12)
D. AAII Sentiment Survey Index									
Ave	1.40	−0.14	−1.54	0.82	0.46	−0.36	−0.58	0.60	1.18
	(2.47)	(−0.25)	(−1.93)	(2.28)	(1.76)	(−0.80)	(−1.78)	(1.59)	(2.37)
$\text{Ave}_{w/o\ SMB}$	1.46	−0.20	−1.66	0.76	0.54	−0.22	−0.70	0.74	1.44
	(2.43)	(−0.34)	(−1.96)	(2.20)	(2.25)	(−0.51)	(−1.83)	(1.64)	(2.43)

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), the Conference Board Consumer Confidence Index (panel B), the Huang et al. (2015) PLS sentiment index (panel C), or the American Association of Individual Investors (AAII) Sentiment Survey 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). Preranking 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 preranking 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 1970:1 to 2023:12 for IA and ROE, 1975:7 to 2023:12 for FIN and PEAD, and 1966:7 to 2023:12 for others. Ave ($\text{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). We only report these two average portfolios in each panel to save space. The Michigan Consumer Sentiment Index starts from 1978:1, the Conference Board Consumer Confidence Index starts from 1977:6, the PLS sentiment index starts from 1965:7, and the AAII Sentiment Survey Index starts from 1987:7. Returns are in percentages. Newey-West (1987) five-lag adjusted t-statistics are reported in parentheses.

factors are thus similar to those obtained using the BW index, as reported in Table 3.

Panel B of Table 9 shows that our results remain the same when the 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. Panel C of Table 9 reports the results using this new index. 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 index based on AAII Sentiment Survey. Once again, the key pattern on the effect of investor sentiment on the cross-sectional risk-return relation remains largely the same.

4.2 Controlling for alternative mechanisms

Although we find persuasive evidence of sentiment on a broad set of factors, potentially other forces, such as money illusion, financial constraints, and even some more specific behavioral forces, such as disagreement or extrapolation, could be in play. Indeed, 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 14%. Thus, it is interesting to investigate whether sentiment still has predictive power after controlling for these mechanisms.[15]

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 Welch and Goyal (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 variance, book-to-market ratio, net equity issuance, detrended Treasury bill rate, long-term yield, long-term return, term spread, default yield spread, default return spread, and inflation.[16] 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 average

[15] In fact, disagreement, coupled with short-sale constraints, can be one of many specific ways to affect sentiment. When disagreement is high, short-sale impediments imply that the average participants are more optimistic, implying a high sentiment. There are, however, many other ways to affect sentiment. For example, extrapolative belief can produce sentiment. More specifically, after a series of favorable news about aggregate productivity growth, investors tend to extrapolate and be too optimistic about future aggregate productivity growth, leading to high sentiment for the aggregate economy. Thus, we view sentiment as a more general and broad concept, whereas disagreement and extrapolation are more specific behavioral forces, all of which could be related to sentiment.

[16] Following Welch and Goyal (2008), we insert 1 month of waiting before using inflation as a predictor to account for the delayed release of inflation data in the subsequent month.

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

	Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
SMB	−0.35	(−2.09)	−1.20	(−2.78)	−0.84	(−2.14)
HML	−1.43	(−3.27)	−0.10	(−0.36)	1.33	(2.76)
RMW	−1.63	(−3.29)	−0.30	(−1.42)	1.33	(2.89)
CMA	−1.27	(−3.05)	0.01	(0.04)	1.28	(2.93)
IA	−1.38	(−3.15)	−0.03	(−0.10)	1.36	(2.82)
ROE	−1.30	(−2.72)	−0.37	(−1.87)	0.93	(2.26)
PMU	−0.58	(−1.60)	−0.81	(−2.55)	−0.24	(−0.59)
QMJ	−1.33	(−2.87)	−0.23	(−1.36)	1.09	(2.58)
MOM	−0.94	(−2.49)	−0.48	(−1.55)	0.46	(1.17)
MGMT	−1.57	(−3.24)	−0.10	(−0.44)	1.47	(3.08)
PERF	−1.68	(−3.71)	−0.41	(−1.72)	1.27	(3.21)
FIN	−1.65	(−3.43)	−0.25	(−1.35)	1.39	(3.01)
PEAD	−0.78	(−1.99)	−1.08	(−2.77)	−0.29	(−0.55)
Ave	−1.22	(−3.41)	−0.41	(−2.01)	0.81	(3.39)
$\text{Ave}_{w/o\ SMB}$	−1.29	(−3.41)	−0.35	(−1.76)	0.95	(3.40)

This table reports the point estimates of b ($\hat{b}$), along with Newey-West (1987) five-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 3-month LIBOR and Treasury-bill rate (TED), the inflation rate, and the beta-weighted aggregate dispersion (Disp) as in Hong and Sraer (2016). Excess returns ($R_{i,t}$) are in percentages. Point estimates of b are presented for the bottom decile portfolio (Low beta), the top decile portfolio (High beta), and their differences (H-L). Preranking 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 preranking 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 1986:2 to 2023:12.

monthly excess returns of the high-low beta 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 are unable to replicate the pattern driven 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 return spreads of the average portfolio (excluding SMB) across high- and low-state regimes are −0.10%, −0.06%, −0.18%, −0.03%, 0.36%, −0.12%, 0.10%, 0.56%, 0.22%, 0.26%, −0.17%, 0.29%, 0.42%, 0.53%, 0.54%, and −0.16% per month, respectively. The average difference is a mere 15 bps per month, as compared with 0.95% per month when sentiment is used to identify regimes. The most significant results are produced by inflation, with a difference of 0.53% (t-statistic= 1.81). 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 inflation is the opposite of this prediction. In addition, the surplus ratio has been used as a proxy for time variation in

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

	dp	dy	ep	de	svar	bm	ntis	tbl	lty	ltr	tms	dfy	dfr	infl	surp	disp
A. After low-state period																
Ave	0.21	0.20	0.24	0.16	0.04	0.22	0.11	−0.04	0.06	0.03	0.24	0.02	−0.03	−0.06	−0.10	0.17
	(1.58)	(1.46)	(2.16)	(0.72)	(0.13)	(1.54)	(0.52)	(−0.16)	(0.22)	(0.15)	(1.14)	(0.06)	(−0.12)	(−0.30)	(−0.48)	(1.01)
$\text{Ave}_{w/o\ SMB}$	0.22	0.21	0.27	0.19	0.00	0.24	0.13	−0.10	0.07	0.04	0.26	−0.04	−0.03	−0.08	−0.09	0.23
	(1.35)	(1.22)	(1.85)	(0.71)	(0.00)	(1.32)	(0.50)	(−0.34)	(0.23)	(0.19)	(1.06)	(−0.10)	(−0.11)	(−0.32)	(−0.38)	(1.16)
B. After high-state period																
Ave	0.09	0.10	0.05	0.14	0.26	0.08	0.18	0.34	0.24	0.26	0.06	0.19	0.33	0.37	0.40	0.07
	(0.33)	(0.37)	(0.19)	(0.67)	(2.20)	(0.30)	(0.81)	(1.77)	(1.51)	(1.40)	(0.27)	(1.15)	(1.54)	(2.09)	(1.79)	(0.19)
$\text{Ave}_{w/o\ SMB}$	0.13	0.15	0.09	0.16	0.36	0.12	0.23	0.45	0.28	0.30	0.09	0.24	0.39	0.45	0.45	0.07
	(0.41)	(0.46)	(0.27)	(0.67)	(2.41)	(0.37)	(0.82)	(1.99)	(1.43)	(1.36)	(0.34)	(1.25)	(1.51)	(2.12)	(1.65)	(0.17)
C. High-low																
Ave	−0.12	−0.10	−0.19	−0.02	0.22	−0.14	0.07	0.38	0.18	0.23	−0.18	0.17	0.35	0.43	0.49	−0.10
	(−0.41)	(−0.33)	(−0.64)	(−0.06)	(0.74)	(−0.46)	(0.23)	(1.19)	(0.63)	(1.03)	(−0.61)	(0.40)	(1.31)	(1.78)	(1.69)	(−0.26)
$\text{Ave}_{w/o\ SMB}$	−0.10	−0.06	−0.18	−0.03	0.36	−0.12	0.10	0.56	0.22	0.26	−0.17	0.29	0.42	0.53	0.54	−0.16
	(−0.27)	(−0.17)	(−0.50)	(−0.08)	(1.00)	(−0.34)	(0.27)	(1.48)	(0.63)	(0.94)	(−0.49)	(0.58)	(1.29)	(1.81)	(1.52)	(−0.35)

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 Welch and Goyal (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 (de), stock variance (svar), 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, de, svar, 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). Preranking 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 preranking 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 2023:12 for the specification with aggregate dispersion as the control variable and 1966:7 to 2023:12 for other specifications. Returns are in percentages. Newey-West (1987) five-lag adjusted t-statistics are reported in parentheses.

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 the sign is inconsistent 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. 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.

4.3 Overnight and intraday pricing

As our next robustness check, we investigate the pricing of these characteristics-based factors and macro-related factors overnight and intraday separately. Earlier studies suggest that the overnight stock market might be more rational than it is intraday. For example, Hendershott, Livdan, and Rösch (2020) and Lou, Polk, and Skouras (2019) find that CAPM performs much better overnight than intraday, suggesting that the overnight stock market is more efficient. Indeed, Hendershott, Livdan, and Rösch (2020) 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 behavior 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. To save space, we present the average portfolios in Table 13 and leave the results for individual factor-beta-sorted portfolios in Table IA15 in the Internet Appendix. We find that on average, firms with high characteristics-based factor beta earn 0.68% higher intraday returns per month than firms with low characteristics-based factor beta, whereas firms with high characteristics-based factor beta earn 0.95% lower overnight returns per month than firms with low characteristics-based factor beta (panel A).[17] Remarkably, for macro-related factors, the pattern is exactly the opposite, as shown in

[17] Return-based factors, such as MOM and PEAD, are exceptions. This might be due to the clientele mechanism proposed in Lou, Polk, and Skouras (2019).

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

	A. Ave						B. $\text{Ave}_{w/oSMB}$					
	Low beta		High beta		H-L		Low beta		High beta		H-L	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
dp	−0.80	(−2.57)	−0.26	(−1.10)	0.54	(3.75)	−0.86	(−2.66)	−0.20	(−0.87)	0.67	(3.93)
dy	−0.79	(−2.52)	−0.25	(−1.05)	0.53	(3.73)	−0.85	(−2.60)	−0.19	(−0.84)	0.66	(3.89)
ep	−0.88	(−2.78)	−0.28	(−1.17)	0.60	(4.02)	−0.95	(−2.88)	−0.21	(−0.92)	0.74	(4.21)
de	−0.78	(−2.52)	−0.27	(−1.20)	0.50	(3.63)	−0.84	(−2.61)	−0.21	(−0.97)	0.63	(3.84)
svar	−0.78	(−2.50)	−0.28	(−1.21)	0.51	(3.45)	−0.85	(−2.59)	−0.21	(−0.98)	0.64	(3.65)
bm	−0.90	(−2.86)	−0.29	(−1.17)	0.61	(4.01)	−0.97	(−2.95)	−0.22	(−0.94)	0.75	(4.20)
ntis	−0.79	(−2.54)	−0.28	(−1.23)	0.51	(3.46)	−0.85	(−2.62)	−0.21	(−1.00)	0.64	(3.67)
tbl	−0.68	(−2.24)	−0.18	(−0.82)	0.50	(3.40)	−0.74	(−2.32)	−0.12	(−0.58)	0.62	(3.58)
lty	−0.77	(−2.48)	−0.27	(−1.19)	0.50	(3.39)	−0.84	(−2.56)	−0.21	(−0.96)	0.63	(3.62)
ltr	−0.79	(−2.55)	−0.28	(−1.24)	0.51	(3.47)	−0.86	(−2.63)	−0.21	(−1.00)	0.64	(3.68)
tms	−0.77	(−2.49)	−0.26	(−1.16)	0.51	(3.48)	−0.84	(−2.58)	−0.19	(−0.93)	0.65	(3.68)
dfy	−0.75	(−2.44)	−0.25	(−1.12)	0.50	(3.42)	−0.81	(−2.53)	−0.19	(−0.90)	0.62	(3.63)
dfr	−0.78	(−2.47)	−0.27	(−1.18)	0.51	(3.44)	−0.85	(−2.56)	−0.20	(−0.95)	0.64	(3.64)
infl	−0.83	(−2.76)	−0.29	(−1.27)	0.54	(3.71)	−0.90	(−2.85)	−0.22	(−1.02)	0.68	(3.95)
supl	−0.85	(−2.94)	−0.31	(−1.51)	0.53	(3.64)	−0.91	(−3.03)	−0.24	(−1.25)	0.67	(3.88)
disp	−1.19	(−3.83)	−0.33	(−1.66)	0.86	(4.58)	−1.28	(−3.88)	−0.25	(−1.34)	1.02	(4.64)

This table reports the point estimates of b ($\hat{b}$), along with Newey-West (1987) five-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 (de), stock variance (svar), book-to-market ratio (bm), net equity issuance (ntis), detrended 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). Excess returns ($R_{i,t}$) are in percentages, and the sentiment index is scaled to have a zero mean and unit standard deviation. 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 $\text{Ave}_{w/o\ SMB}$ (panel B) refer to the average portfolios of all beta-sorted portfolios and the one excluding SMB. Preranking 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 preranking 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 2023:12 for the specification with aggregate dispersion as the control variable and 1966:7 to 2023:12 for other specifications.

Table 13
Beta-sorted portfolio overnight and intraday returns

	Low beta			High beta			H-L		
	ON	Intra	Intra-ON	ON	Intra	Intra-ON	ON	Intra	Intra-ON
A. Characteristics-based factor beta-sorted portfolios									
Ave	1.84	−0.48	−2.33	1.12	0.04	−1.08	−0.72	0.52	1.24
	(7.20)	(−1.45)	(−5.46)	(7.29)	(0.20)	(−4.61)	(−4.51)	(2.18)	(3.85)
$\mathrm{Ave}_{w/o\ SMB}$	1.96	−0.57	−2.53	1.01	0.11	−0.90	−0.95	0.68	1.63
	(7.24)	(−1.60)	(−5.56)	(6.89)	(0.65)	(−3.92)	(−4.97)	(2.41)	(4.25)
B. Macro-factor beta-sorted portfolios									
Ave1	0.91	0.28	−0.63	2.00	−0.41	−2.41	1.09	−0.69	−1.78
	(5.52)	(1.59)	(−2.52)	(7.32)	(−1.19)	(−5.49)	(6.77)	(−2.66)	(−5.41)
Ave2	1.02	0.22	−0.80	1.94	−0.37	−2.31	0.92	−0.60	−1.52
	(5.44)	(1.25)	(−2.94)	(7.43)	(−1.09)	(−5.35)	(6.85)	(−2.46)	(−5.02)
Ave3	1.06	0.17	−0.89	1.90	−0.35	−2.25	0.84	−0.52	−1.36
	(5.47)	(0.91)	(−3.12)	(7.12)	(−1.04)	(−5.12)	(6.47)	(−2.27)	(−4.62)

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 (2019), the 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 in Table 3. In panel A, preranking 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, and other preranking betas are estimated from a single-factor model using monthly returns over the past 60 months with a minimum of 36 months. Ave ($\mathrm{Ave}_{w/o\ SMB}$) refers to the average portfolios of all beta-sorted portfolios (excluding SMB). In panel B, we consider 10 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), and TFP growth (TFP). Following Shen, Yu, and Zhao (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 portfolios have high returns. 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; and Ave3 includes all beta-sorted portfolios. Preranking 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 preranking 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. We only report the average portfolios in each panel to save space. The sample period is from 1992:7 to 2023:12. Returns are in percentages. Newey-West (1987) five-lag adjusted t-statistics are reported in parentheses.

panel B of Table 13.[18] More specifically, on average, firms with high macro factor beta earn 0.84% higher overnight returns per month than firms with low macro factor beta, whereas firms with high macro factor beta earn 0.52% lower intraday returns per month than firms with low macro factor beta. Thus, for macro-related factors, which have a strong economic foundation, high-beta firms tend to earn higher returns overnight, consistent with the findings in Hendershott, Livdan, and Rösch (2020), which focus 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 overnight), macro-related factors tend to be priced, whereas the characteristics-based factors are

[18] Following Shen, Yu, and Zhao (2017), we construct 10 macro factors. For the aggregate volatility factor (VOL), we calculate the variance of daily market returns for March 2020 rather than using the original formula of the sum of squared daily returns plus twice the sum of products of adjacent returns, since the latter yields a negative value in that month, reflecting the extreme market turmoil induced by COVID-19.

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.

4.4 Excluding behavioral factors

Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2020) have already suggested that their behavioral factors might be due to mispricing. Thus, it is important to make sure that our results are not completely driven by their factors. To address this concern, we repeat our main tests using four additional average portfolios: (1) the average portfolios of all beta-sorted portfolios excluding the four behavioral factors (MGMT, PERF, FIN, and PEAD); (2) the average portfolios of all beta-sorted portfolios excluding the four behavioral factors (MGMT, PERF, FIN, and PEAD) and QMJ; (3) the average portfolios of all beta-sorted portfolios excluding the four behavioral factors (MGMT, PERF, FIN, and PEAD) and SMB; and (4) the average portfolios of all beta-sorted portfolios excluding the four behavioral factors (MGMT, PERF, FIN, and PEAD), QMJ, and SMB. Table IA16 in the Internet Appendix reports the results. Panel A repeats the tests in Table 3; panel B repeats the tests in Table 4; panel C repeats the tests in Table 7; and panel D repeats the tests in Table 8. Our findings remain similar after excluding these behavioral-related factors, suggesting that our findings are not mainly driven by the more obvious mispricing factors and that other characteristics-based factors are also likely to represent mispricing.

5. 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 in the pricing of these factors, we shed light on the underlying forces behind these factors. In particular, instead of using the traditional anomaly-based portfolios as testing assets, we use portfolios that are 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.

Code Availability: The replication code is available in the Harvard Dataverse at https://doi.org/10.7910/DVN/PTRE3D.

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