Characteristics-Based Factors

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Abstract

Recent studies have proposed a large set of new powerful characteristics-based factors in the stock market. This study examines the pricing of these factors using portfolios that are formed by directly sorting stocks based on their exposure to these factors. These beta-sorted portfolios have very large ex post factor beta spreads. However, the return spreads between high- and low-beta firms are typically tiny and insignificant (on average, 0.01% per month). The differences between factor-adjusted returns and characteristics-adjusted returns for these beta-sorted portfolios are both economically and statistically significant at about 0.41% per month. More important, we show that factor-adjusted returns and characteristics-adjusted returns can be significantly different for a large number of anomalies and mutual funds. Our results thus urge cautions regarding the common practice of using factor models such as adjusting for investment style, performance evaluation, and performance attribution.

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1 Introduction

Several recent prominent studies have proposed a new set of factors for the stock market that can parsimoniously account for many asset pricing anomalies simultaneously. In particular, these papers have shown that many asset pricing anomalies have insignificant alphas once exposure to these new factors is adjusted. This data dimension reduction is important since it eliminates the need to deal with this very large list of anomalies. Instead, one only needs to investigate the underlying base factors. More important, factor models have many applications in practice, including the calculation of the cost of capital, event study, measurement of abnormal returns, portfolio performance evaluation, and performance attribution.

This study investigates the pricing of a large set of charateristics-based factors using portfolios that are formed by directly sorting stocks based on their exposure to these factors. These factors include the Fama-French 5 factors (Fama and French (2015)), the Hou-Xue-Zhang 4 q-factors (Hou, Xue, and Zhang (2015)), the gross profitability factor (Novy-Marx (2013)), the quatlity-minus-junk factor (Asness, Frazzini, and Pedersen (2017)), the momentum factor (Carhart (1997)), the two mispricing factors (Stambaugh and Yuan (2017)), and short- and long-run behavioral factors (Daniel, Hirshleifer, and Sun (2017)). We choose beta-sorted portfolios as our testing portfolios because these portfolios produce economically large and statistically highly significant ex post factor beta spreads. However, we find that the return spreads between high- and low-beta firms are typically tiny and insignificant and even reversed in sign. Specifically, for the 13 factors we consider in this paper, the average return spread between high- and low-beta firms is close to zero at 0.01% (t-stat = 0.05). Thus, although these factors are "priced" factors using anomaly-based portfolios as testing assets, most of these factors are not significantly priced when using portfolios sorted directly by individual stock's factor exposure.

Furthermore, we show that firms with high factor loadings do not necessarily have a high value for the corresponding firm-level characteristics underlying these factors. The cross-sectional correlation between the beta and the corresponding characteristics is only 14% on average. Take the momentum factor as an example. Firms with high momentum beta are not necessarily winner stocks, and the correlation between the momentum beta and the past 12-month return is only 0.04. Thus, after the usual factor-based adjustment using the momentum factor as a regressor in regression analysis, the high-minus-low beta portfolio earns a negative alpha of -0.66% per month (t-stat = -2.48). However, if one employs a characteristics-based adjustment for momentum style, the alpha of this long-short portfolio is only -0.31% (t-stat $=-1.52$). The difference in factor-based adjusted returns and characteristics-based adjusted returns for the beta-sorted portfolios is both economically and statistically significant at -0.35% per month (t-stat $= -3.81$). Similar results hold for most of the other prominent factors, with an average difference between factor-adjusted returns and characteristics-adjusted returns for these beta-sorted portfolios of -0.41% per month (t-stat$= -5.70$). This result has important implications for the common practice of using factor models, as we shall discuss in more detail below.

One important reason why factor models are so popular and influential is that they are very convenient to use. For example, in portfolio performance attribution and evaluation analysis, one does not need the fund's holdings data to evaluate its performance. The typical approach is to regress fund returns onto a set of tradeable factors. The intercept is then interpreted as an abnormal return and is regarded as reflecting the ability of the fund manager. On the other hand, characteristics-based adjustment is more complex and requires holdings data that are not always available to investors. However, there are still debates on the underlying economic interpretation for many factors. Indeed, these prominent factors may or may not be risk factors. Thus, the purpose of adjusting for exposure to these factors is not necessarily to account for risk exposure. Instead, one typical argument is that even if these factors may not be risk factors, one still needs to adjust for the investment "style" underlying these factors. For example, it is well known that there are momentum effects in the data. If a fund manager employs a momentum strategy now, the manager should probably not be compensated for the superior performance of the fund, since using momentum does not reflect any special information or abilities on the part of the manager that allow funds to ferret out underpriced stocks. Thus, it is important to properly adjust for exposure to the momentum style to evaluate the manager's true skill level and, in turn, managerial compensation.

As we mentioned earlier, if we sort stocks based on past betas, firms with high betas do not necessarily have high returns, even if the underlying factor itself earns a significant positive return. Thus, if a fund manager uses a strategy that coincides with our high-minus-low (H-L) momentum beta portfolios, and if one adjusts fund performance by a momentum-based factor model, one would get a negative alpha for this manager, suggesting inferior managerial ability. However, in this particular case, since the purpose is to eliminate the part of the return that is due to the well-known momentum effect, the proper adjustment is to use the characteristics-based method, rather than the more user-friendly factor-based method. If one uses the correct adjustment for the momentum style, the evaluation result could be quite different. Indeed, these two methods of adjustment could create a substantial difference of 0.35% per month. Thus, even if a fund manager has genuine stock selection ability, when evaluated against a factor model, the manager could be viewed as having no ability at all. Or the opposite could be true. Thus, our results cast doubt on the wisdom of employing the widely used factor-based approach to evaluate portfolio performance.[1]

We also examine the impact of investor sentiment on the return spreads between high- and low-beta portfolios. Previous studies find that investor sentiment plays a significant role in both the time series and cross-sectional risk-return trade-off. In addition, investor sentiment affects the profitability of many asset pricing anomalies. Thus, by investigating the link between the return spreads between high- and low-beta portfolios and investor sentiment, we can shed light on the underlying mechanism for these factors. For example, for mispricing factors, exposure to these factors could be a proxy for underpricing. For risk factors, on the other hand, the factor betas are proxies for exposure to systematic risk. Thus, as we shall discuss in more detail, one should expect that for factors driven by mispricing, the beta-sorted long-short portfolio spreads are larger following high-sentiment periods than they are following low-sentiment periods, whereas for risk factors, the return spreads are larger following low-sentiment periods than they are following high-sentiment periods. Our purpose is not to classify a factor as either a mispricing factor or a risk factor; it could be the case that a factor can capture both mispricing and risk. However, we do find that the MGMT factor in Stambaugh and Yuan (2017) and the FIN factor in Daniel, Hirshleifer, and Sun (2017) are more likely to be proxies for mispricing than for risk, as the beta-sorted long-short portfolio return spreads for these factors are significantly higher following high-sentiment periods.

We further gauge the difference between the factor-based benchmark and the characteristics-based benchmark in evaluating anomalies. To ensure that the newly discovered anomaly under study is not just a repackaging of existing anomalies, one typically uses regression analysis to control for some common factors such as the Fama-French 5 factors, which can account for many anomalies simultaneously. In light of our previous argument, even if the alpha is zero after controlling for these prominent common factors, it

[1]For performance attribution analysis, the same logic goes through. Even if a fund employs a strategy that holds no or few winner stocks and shorts no or few loser stocks, the portfolio returns could happen to have a high exposure to the momentum factor. Using regression analysis to adjust for the momentum factor could result in wrongly attributing the performance of the fund to the momentum strategy, whereas in reality, this fund does not long winners or short losers.

does not imply that this new anomaly is just a repackaging of existing anomalies or existing factors. It could be the case that the characteristics of the new anomaly variable and the corresponding characteristics underlying these factors are only weakly correlated, and this new anomaly is actually genuine and beyond the existing anomalies. Of course, the reverse could also be true. Indeed, for the 12 prominent anomalies, the average difference between these two adjustment methods is statistically significant at about 0.18% per month for recent multi-factor models. Thus, our findings suggest that the standard way of evaluating a newly discovered anomaly is also sometimes problematic, and the characteristics-based adjustment is more appropriate in many cases.

Lastly, we use mutual fund holdings data to investigate the economic magnitude of the differences between using the characteristics-based benchmark and the factor-based benchmark. We find that the differences can be economically large for many of these recent prominent factors. On average, the difference is about 3.0% per annum. About one-third of funds have differences of over 2.4% per annum. This is a big number considering that the factor-based alpha difference between the 75th percentile fund and the 25th percentile fund is only about 3.7% per annum. The adjustment methods can also significantly influence the relative ranking of the fund's performance. The average percentile rank change between these two methods is about 20. These findings highlight the importance of using fund holdings data to adjust for investment style when evaluating managers' ability.

Regarding related studies, our study is motivated by the recent influx of new factors in the stock market, including Novy-Marx (2013), Fama and French (2015), Hou, Xue, and Zhang (2015), Stambaugh and Yuan (2017), Asness, Frazzini, and Pedersen (2017), and Daniel, Hirshleifer, and Sun (2017), among others. These papers show that many anomalies can be parsimoniously summarized by a few factors, which are in turn formed by sorting on firm-level (sometimes composite) characteristics. Our paper explores potential issues when subsequent studies use these factor models in performance evaluation and the evaluation of anomalies.

Our study is also inspired by the seminal studies emphasizing the importance of characteristics in predicting returns and characteristics-based adjustment for performance evaluation, such as Daniel and Titman (1997), Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW hereafter), and Daniel and Titman (2012).[2] Previous studies tend to focus on

[2]Many subsequent studies also emphasize the importance of characteristics, including Brennan, Chordia, and Subrahmanyam (1998), Avramov and Chordia (2006), Chordia, Goyal, and Shanken (2015), Busse, Jiang, and Tang (2017), and Jegadeesh, Noh, Pukthuanthong, Roll, and Wang (2017), among others.

the horse race between the predictive power of factor betas and the underlying characteristics for a few factors such as the value factor and the momentum factor. Our study covers a much broader set of new factors. More important, our focus is not on the predictive power of beta versus characteristics, as in the seminal work of Daniel and Titman (1997) and its follow-up studies. Instead, we emphasize the importance of using characteristics-based adjustment to account for investment style and show the potential problem associated with the standard factor-based adjustment. Relatedly, DGTW first propose characteristics-based adjustment in performance evaluation as an alternative to factor-based adjustment. We differ by investigating the quantitative differences between these two methods and highlighting the potential issues behind the factor-based adjustment for investment style arising from the inability of factor beta to predict returns. We find that although for some factors, factor-based adjustment for style poses less of an issue, for other factors, it can potentially produce misleading results, especially for many recently proposed factors.

Previous studies have found that beta-sorted portfolios typically generate small return spreads for the market factor (e.g., Black (1972), Jensen, Black, and Scholes (1972), Frazzini and Pedersen (2014), and Antoniou, Doukas, and Subrahmanyam (2016)) and for the value factor (e.g., Daniel and Titman (1997)). We show that this result holds for most tradeable characteristics-based factors. Recently, Shen, Yu, and Zhao (2017) also find that beta-sorted portfolios produce close-to-zero return spreads for 10 macro-related factors and they link these portfolio return spreads to the time variation of investor sentiment. In addition, Daniel, Mota, Rottke, and Santos (2018) and Herskovic, Moreira, and Muir (2018) find that beta-sorted portfolios produce tiny return spreads for the Fama-French 5 factors, the momentum factor, and some macro factors. They use this fact cleverly to propose hedged factor portfolios that yield much higher Sharpe ratios than original factors. We, on the other hand, use the low return spreads for beta-sorted portfolios to shed light on the potential problem of using these factor models in adjusting for investment style and other applications. In particular, our primary purpose is not to show that high-beta stocks earn similar returns with low-beta stocks. Instead, we simply use these beta-sorted portfolios to illustrate that characteristics-based adjustment and factor-based adjustment could lead to very different alphas. More important, we also use anomaly portfolios and actual mutual fund returns to evaluate the differences between these two alternative adjustment methods.

Although we argue that subsequent studies need to be careful in using factor models in applications such as performance evaluation, these factors themselves are still very useful. Even the characteristics-based adjustment favored by our analysis crucially relies on the characteristics underlying these new factors. For example, Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2017) cleverly construct two mispricing/behavioral factors by combining many simple firm-level characteristics into composite ones based on cluster analysis or classifications of under- and over-reaction, respectively. They show that the factors based on their two corresponding characteristics can account for a wide range of anomalies. Their findings are extremely important, since the limited number of stocks in the universe make it almost infeasible to use more than 5 characteristics simultaneously to perform characteristics-based adjustment. Thus, instead of using 100 characteristics to adjust for those 100 corresponding investment styles simultaneously, in practice one could just use their two composite firm-level characteristics to perform characteristics-based adjustment. Similarly, Novy-Marx (2013), Fama and French (2015), Hou, Xue, and Zhang (2015), and Asness, Frazzini, and Pedersen (2017) show that their factors can succinctly account for many portfolio returns in an economically meaningful way; thus, the characteristics underlying these powerful factors could also be the basis for characteristics-based adjustment. Lastly, since these factors can summarize variations in portfolio return behavior very well, these factors can certainly be very useful in other applications such as covariance estimation or improving the estimation of the mean-variance efficiency frontier. For example, building on the original Fama-French 5 factors, Daniel, Mota, Rottke, and Santos (2018) and Herskovic, Moreira, and Muir (2018) propose hedged factor portfolios that yield much higher Sharpe ratios.

Our paper also contributes to the literature that critiques the capital asset pricing model (CAPM) alpha, estimated from the perspective of an uninformed investor, as a measure of skill (see, e.g., Admati and Ross (1985), Dybvig and Ross (1985), Grinblatt and Titman (1989), and Mayers and Rice (1979), among many).[3] Our study is a broader investigation of the general factor model, and shows the potential problem with using factor models to adjust for investment style when it is not certain whether the underlying factor is a priced risk factor. More recently, Gârleanu, Panageas, and Yu (2017) show theoretically that informational frictions can lead to the nonexistence of a stochastic discount factor (SDF). Thus, using factor-based adjustment can also be misleading, and the style analysis of Sharpe (1992) could be more appropriate in capturing the skill level of a manager. Our empirical results also cast doubt on the popular factor-based adjustment in portfolio performance evaluation/attribution analysis and suggest that characteristics-based adjustments might be

[3]These studies identify a different set of problems associated with using the CAPM to measure portfolio performance, such as the difficulty of identifying an appropriate benchmark portfolio, the possibility of overestimating risk because of market-timing ability, and the failure of informed investors to earn positive risk-adjusted returns because of increasing risk aversion, and etc.

more appropriate in many settings such as accounting for investment styles.

2 Data Description and Summary Statistics

This section describes how we construct characteristics-based factors, various factor betas, and the benchmark portfolios based on corresponding characteristics. Summary statistics on beta-sorted portfolios and the relation between factor beta and characteristics are also reported. Our sample includes all NYSE, AMEX, and NASDAQ (CRSP exchange code 1, 2, and 3) listed ordinary common stocks (CRSP share code 10 and 11). We also describe the mutual fund data at the end of this section.

2.1 Characteristics-Based Factors

We explore several sets of factors that have been extensively used in risk adjustment and performance evaluation. We consider a total of 13 characteristics-based tradeable factors including the four factors (i.e., size (SMB),[4] value (HML), operating profitability (RMW) and investment (CMA) factors) from Fama and French (2015)'s 5-factor model (FF5), the two factors (i.e., investment (IA) and profitability (ROE) factors) from Hou, Xue, and Zhang (2015)'s q-factor model (Q4), the profitable-minus-unprofitable (PMU) factor from Novy-Marx (2013), the quality-minus-junk (QMJ) factor from Asness et al. (2017), the momentum (MOM) factor from Carhart (1997)'s 4-factor model (CARHART), the two mispricing factors (i.e., management-related mispricing factor (MGMT) and performance-related mispricing factor (PERF)) from Stambaugh and Yuan (2017)'s mispricing factor model (M4), and the two behavioral factors (i.e., long-run behavioral factor (FIN) and short-run behavior factor (PEAD)) from Daniel, Hirshleifer, and Sun (2017)'s behavioral factor model (BF3).[5]

Following these original studies, the corresponding firm characteristics underlying these factors are: *size* for SMB, the book-to-market ratio (BM) for HML, operating profitability

[4]We do not separately examine the size factor from other factor models including Hou, Xue, and Zhang (2015)'s q-factor model, Fama and French (2015)'s 5-factor model, and Stambaugh and Yuan (2017)'s mispricing factor model since SMB and these other size factors are highly correlated with the correlation being at least 95%.

[5]Although we study a relatively large set of characteristics-based factors, we have to omit many factors due to space limit. For example, Kelly, Pruitt, and Su (2017) and Kozak, Nagel, and Santosh (2017b) use more sophisticated statistical methods to construct factors based on many characteristics simultaneously, and we do not investigate these factors in our current study.

(OP) for RMW, investment-over-assets (Inv) for CMA and IA, return on equity (ROE) for ROE, gross profitability (GP) for PMU, a composite score based on various measures of firm quality ($Z_{Quality}$) for QMJ, stock returns over the previous 11 months with a one-month gap ($R_{-12,-2}$) for MOM, a composite score based on net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment-to-assets ($Score_{MGMT}$) for MGMT, a composite score based on financial distress, O-score, momentum, gross profitability, and return-on-assets ($Score_{PERF}$) for PERF, a composite score based on one-year net share issuance and 5-year composite issuance (Z_{FIN}) for FIN, and the cumulative abnormal returns around earnings announcements (CAR) for PEAD. The construction details of the 13 characteristics-based factors and the corresponding characteristics are provided in the Appendix. The sample period is from 1972:1 to 2016:12 for the IA and ROE factors, 1972:7 to 2016:12 for the FIN and PEAD factors, and 1963:7 to 2016:12 for the other factors.

Panel A of Table 1 reports the pairwise correlation coefficients between these characteristics-based factors. Some of the factors have a high correlation as expected since the underlying characteristics are similar. On the other hand, some factors have a low correlation with other factors. For example, the size factor tends to have a negative correlation with other factors, especially the QMJ factor. For each factor, the average correlation with other factors tend to be low, around 20%. Panel B of Table 1 reports the monthly factor returns and CAPM alphas. The raw return spreads for these factors are all statistically significant. The CAPM alphas are also significant except for the size factor. We shall discuss the results in Panel C in the next section when we discuss the beta-sorted portfolios.

2.2 Characteristics-Based Benchmark Portfolios

In our subsequent analysis, we need to use both the factor-based benchmark and the characteristics-based benchmark to evaluate portfolio performance in the spirit of DGTW. We consider three sets of characteristics-based benchmarks in our analysis. First, for each of the 13 characteristics, we form 10 decile value-weighted benchmark portfolios according to the NYSE breakpoints using all NYSE/AMEX/NASDAQ common stocks.[6] A stock's monthly

[6] The only exclusions are the portfolios related to the two mispricing characteristics, $Score_{MGMT}$ and $Score_{PERF}$, for which NYSE/AMEX/NASDAQ breakpoints are used since relative mispricing is more likely to be a property of extremes, following Stambaugh and Yuan (2017). Specifically, the benchmark portfolios under the $Score_{MGMT}$ and $Score_{PERF}$ adjusted returns use the NYSE/AMEX/NASDAQ breakpoints for $Score_{MGMT}$ and $Score_{PERF}$, respectively. The benchmark portfolios under the size-$Score_{MGMT}$ and size-

characteristics-adjusted excess return is thus the return difference between the raw return and the benchmark portfolio return to which it belongs. For the benchmark portfolios formed by characteristics $size$, BM, OP, Inv, GP, $Z_{Quality}$, and Z_{FIN}, the rebalance frequency is annual at each June; for the benchmark portfolios formed by characteristics ROE, $R_{-12,-2}$, $Score_{MGMT}$, $Score_{PERF}$, and CAR, the rebalance frequency is monthly.

Second, since most characteristics-based return spreads depend on firm size, we sequentially sort all stocks into five size groups and then five characteristics groups, and form 5×5 value-weighted benchmark portfolios according to the NYSE breakpoints. A stock's monthly size-characteristics-adjusted excess return is defined the same way as the single-dimension characteristics-adjusted returns by taking the difference between its raw return and the matched benchmark portfolio return.

Third, we form benchmark portfolios that are associated with six multiple-factor models. The aim here is to adjust for many investment styles simultaneously. The Fama-French three-factor model's corresponding characteristics benchmark portfolios are the sequentially 5×5 $size{-}BM$ sorted value-weighted portfolios. The Carhart's four-factor model's corresponding characteristics benchmark portfolios are the sequentially 2×3×3 $size{-}BM{-}Ret_{-12,-2}$ sorted value-weighted portfolios. The Fama-French five-factor model's corresponding characteristics benchmark portfolios are the sequentially 2×2×2×2 $size - BM - OP - Inv$ sorted value-weighted portfolios. The q-factor model's corresponding characteristics benchmark portfolios are the sequentially 2×3×3 $size - Inv - ROE$ sorted value-weighted portfolios. The Stambaugh and Yuan (2017) mispricing four-factor model's corresponding characteristics benchmark portfolios are the sequentially 2×3×3 $size - Score_{MGMT} - Score_{PERF}$ sorted value-weighted portfolios. The Daniel et al. (2017) behavioral three-factor model's corresponding characteristics benchmark portfolios are the sequentially 5×5 $Z_{FIN} - CAR$ sorted value-weighted portfolios.

2.3 Mutual Fund Data

The mutual fund data come from two sources. The Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12) database includes information on quarterly or semi-annual

$Score_{PERF}$ adjusted returns use the NYSE breakpoints for size and NYSE/AMEX/NASDAQ breakpoints for $Score_{MGMT}$ or $Score_{PERF}$ within each size quintile, respectively. The multi-factor model benchmark portfolios use sequential $size - Score_{MGMT} - Score_{PERF}$ sorts based on NYSE breakpoints for size and the NYSE/AMEX/NASDAQ breakpoints for $Score_{MGMT}$ and $Score_{PERF}$ within each size portfolio. Our results are robust to using NYSE breakpoints for $Score_{MGMT}$ and $Score_{PERF}$.

holdings of all U.S. equity mutual funds. We match each reported stock holding to the CRSP stock database in order to find its price and return. The CRSP Survivor-Bias-Free US Mutual Fund Database contains information on fund assets under management (TNA), net returns (RET), expense ratio (EXP), and investment policy and objectives at the monthly frequency. These two datasets are merged using the MFLinks tables from Wharton Research Data Services (WRDS).

Our empirical analysis primarily focuses on actively managed diversified equity funds in the United States, so we apply several filters to screen the sample following the previous literature (e.g., Fama and French (2010), Patton and Weller (2017), Busse, Jiang, and Tang (2017)). First, we apply several filters based on various objective codes and detailed asset compositions to eliminate balanced, bond, index, international, commodity, and sector funds.[7] Further, we eliminate the duplicated funds and compute the fund-level variables by aggregating across the different share classes for funds with multiple share classes. For the TNA, we sum the TNAs of the different classes. For returns, we first add back expense ratio at individual share class level and then take the weighted average raw returns across individual share classes, with the weights being the lagged TNAs of the individual share classes. Finally, we add filters on fund size and number of stock holdings. Specifically, we only keep observations after a fund size reaches \$5 million in 2006 US dollars (Fama and French (2010)) and have at least 10 different stock holdings are identified. Once a fund passes these two requirements, all its subsequent observations are included in the sample to avoid introducing a selection bias.[8] To further address the concern about incubation bias

[7] We exclude funds in Thomson Reuters Mutual Fund Holdings database that have the Investment Objective Codes (variable: ioc) being 1 (International), 5 (Municipal Bonds), 6 (Bond and Preferred), and 7 (Balanced), and funds in CRSP mutual fund database with average stock holdings less than 70%. We select funds with CRSP objective code: ED, EDCI, EDCL, EDCM, EDCS, EDYB, EDYG, EDYH, EDYI, EDYS, M. If CRSP objective code is missing, we select funds with the Lipper objective codes CA, EI, G, GI, MC, MR, and SG. If both CRSP and Lipper objective codes are missing, we keep funds with the Strategic Insight objective codes AGG, GMC, GRI, GRO, ING, and SCG. If all CRSP, Lipper and Strategic Insight objective codes are missing, we then keep funds with Wiesenberger objective codes equal to G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. If none of these objective codes are available, we keep a fund if it has a CS policy. To exclude the index funds, we delete funds whose names contain any of the following strings: *Index,Ind*, *Idx*, *Indx*, *Mkt*, *Market*, *Composite*, *S&P*, *Russel*, *Nasdaq*, *DJ*, *Dow*, *Wilshire*, *NYSE*, *iShares*, *SPDR*, *HOLDRs*, *ETF*, *Exchange-Traded Fund*, *PowerShares*, *StreetTRACKS*, *100*, *400*, *500*, *600*, *1000*, *1500*, *2000*, *3000*, *5000*. We also exclude funds with a CRSP index fund flag equal to "D" (pure index fund) or "E" (enhanced index fund).

[8] According to the CRSP mutual fund database mutual, TNAs being \$100,000 US dollars denote TNAs less than or equal to this value. Therefore, following Patton and Weller (2017), we set TNA values less than or equal to \$100,000 US dollars or over \$1 trillion dollars to be missing. We further follow Patton and Weller (2017) to fill missing TNAs via interpolation in three steps. First, we use the last available TNA and cumulative returns since that date to calculate monthly "predicted" TNA till the next available TNA observation. Second, we use the percentage of deviation of this actual TNA from the predicted TNA to

documented in Evans (2010), we drop observations preceding the first offer date as reported in CRSP. After all of these exclusions, our final sample includes 3,456 unique funds and 548,813 fund-month observations from 1980:1 to 2016:12.

3 Empirical Analysis: Factor versus Characteristics

3.1 Beta-Sorted Portfolios

In this section, we present the key results of our paper. Traditionally, when testing whether a factor is priced, one chooses a set of anomaly-based portfolios as testing assets. Since anomaly-based portfolios have large return spreads, this choice can increase the power of the tests. In this section, we choose an alternative set of testing assets. Instead of focusing on testing assets with average large return spreads, we focus on testing assets with large spreads in ex post factor betas. Indeed, Daniel and Titman (2012) argue that it is also important to have large spreads on factor betas to increase the power of the tests.

Specifically, for each of the 13 characteristics-based factors described in Section 2.1, we estimate the individual stock's factor betas and form single-sorted value-weighted portfolios based on each of these betas. This way, we try to maximize the ex post beta spreads of our testing portfolios. Factor betas are estimated from a single-factor model using the past 60 months' returns with a minimum of 36 months. All NYSE/AMEX/NASDAQ common stocks are sorted into 10 value-weighted portfolios based on their factor loadings on each of the 13 characteristics-based factors using NYSE breakpoints. For decile portfolios sorted by SMB, HML, RMW, CMA, IA, PMU, QMJ, and FIN betas, portfolios are rebalanced at the end of each June so that the beta-sorted portfolio rebalance frequency matches with the characteristics benchmark portfolio rebalance frequency. For decile portfolios sorted by other factor betas, portfolios are rebalanced monthly.[9] Thirteen sets of beta-sorted decile portfolios, an average portfolio, and the spread between the top and the bottom decile portfolios are formed. Since at least 36 months of data are needed to construct beta, the sample period is from 1975:1 to 2016:12 for IA and ROE beta-sorted portfolios, 1975:7 to

back out the fund flows by assuming the fund flows are constant between these two dates with known TNA values. We then adjust the predicted TNA by this flow to fill the missing value of TNA. Third, for months before the first available TNA, we do the first and second steps backward using the nonmissing return data to fill the missing TNA values. Please see Appendix A in Patton and Weller (2017) for the details.

[9]Our results are similar if all portfolios are rebalanced monthly and are presented in Table IA1 in the Internet Appendix.

2016:12 for FIN and PEAD beta-sorted portfolios, and 1966:7 to 2016:12 for other beta-sorted portfolios.

Panel A of Table 2 shows that the ex post beta spreads are economically large and statistically highly significant. For example, the average ex post beta spread for the 13 factors is 1.38 (t-stat = 31.54).[10] For 11 out of the 13 factors, the t-statistics for the ex post beta spread are more than 7. It is well known that the firm-level beta estimation can be very noisy. However, our results indicate that firm-level ex ante beta of these tradable factors is not just pure noise, and it contains meaningful information about ex post beta. On the other hand, it is true that the firm-level beta estimation for non-tradable macro factors such as consumption growth is much more noisy (see, e.g., Shen, Yu, and Zhao (2017)).

Given the large ex post beta spreads between our high- and low-beta portfolios and the significant positive average returns of these factors, one would expect the return spread between high- and low-beta portfolios to be large and significant. On the contrary, Panel B of Table 2 shows that the average return spread is virtually zero at 0.01% per month (t-stat = 0.05). Daniel and Titman (1997) have shown that once *controlling for* the book-to-market characteristics, the HML beta has no significant power in predicting future returns.[11] Here, we find that even without controlling for characteristics, most characteristics-based factor betas do not have predictive power for future stock returns. This is true even though the beta spread for our beta-sorted portfolios is much larger than the beta spread of those conditionally sorted portfolios in Daniel and Titman (1997). More important, this insignificant result is remarkably consistent among all the tradable factors we consider in this study except the HML factor, for which the beta sorted return spread is marginally significant with t-stat=1.78.

In Panel C of Table 2, we use the corresponding factors to perform the standard factor-based regression analysis to adjust for the factor exposure and obtain "abnormal" returns for these long-short strategies. In addition, to account for the market exposure, we always control for the market factor. A majority of these high-minus-low beta-sorted portfolios earn significant negative two-factor alphas. This is expected since these long-short portfolios have

[10]To obtain the average ex post beta, we run a pooled time-series regression of beta-sorted portfolio returns onto the corresponding factors, allowing for different intercepts but a common factor loading coefficient across different factors. This common factor loading coefficient is the average ex post beta. The t-stat is based on standard errors clustered by month.

[11]Using a longer sample period, Davis, Fama, and French (2000) show that the HML beta still has significant predictive power after controlling for the book-to-market characteristics. Other studies find that both the beta and the characteristics have predictive power. More recently, Jegadeesh, Noh, Pukthuanthong, Roll, and Wang (2017) find that only characteristics have predictive power for Fama-French 5 factors.

large ex post factor beta, and these factors have positive average returns. Regressing these high-minus-low portfolio returns onto the corresponding factors thus yields an intercept (i.e., alpha) that is lower than the average long-short portfolio returns. As a result, the factor-adjusted returns are mostly negative for our beta-sorted long-short portfolios. Specifically, the average alpha is -0.50% per month (t-stat $= -5.60$). The effect is especially strong for the momentum factor, the two mispricing factors of Stambaugh and Yuan (2017), the ROE factor, and the PEAD factor. We now discuss the implications of the above results for performance evaluation in more detail.

One of the most prominent applications of factor models is portfolio performance evaluation. Typically, one regresses portfolio returns onto a set of factors, and the intercept is interpreted as the abnormal return of the portfolio, and thus the skill of the portfolio manager. However, notice that many of these newly proposed characteristics-based factors are not necessarily risk factors: the purpose of the standard factor-based regression adjustment may not be to adjust for risk exposure. For example, despite several decades of research, whether the HML factor is a risk factor or a result of mispricing is still being debated.[12] Whether these newly proposed factors are proxies for some risks or mispricing will certainly attract a lot of attention in future research. However, our purpose here is not to investigate whether the underlying characteristics-based factors are risk or behavioral factors. Regardless of the underlying economic reasons for these factor return spreads, the overall consensus is that we need to adjust for investment style underlying these factors when evaluating portfolio strategies, especially after the publication of these factors.

More specifically, let's take the value premium as an example. Although the underlying economic forces are still being debated, it is reasonable to adjust for the value-style investment when evaluating a portfolio strategy. This is because the value-style strategy is now well known and public. Thus, using value-style investing does not reflect the genuine skill of the portfolio manager, and therefore the portfolio manager should not be compensated (much) as a result of the value effect.[13] One might use the HML factor to adjust for the value style, perhaps because of its convenience or due to the belief that HML is a proxy

[12]For earlier studies, see, for example, Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001), among others. More recently, Lin and Zhang (2013), for example, argue that the evidence that characteristics dominate covariances in horse races does not necessarily mean mispricing and that measurement errors in covariances are also likely to be the culprit. On the other hand, Kozak, Nagel, and Santosh (2017a) argue that even in a world with mispricing, expected returns could still line up with common factor covariances.

[13]If one uses the value strategy before it becomes well known, there is probably no need to adjust for the value style since it is still a measure of genuine skill (see, e.g., Berk and van Binsbergen (2015)).

for some risk factor. If the HML factor is indeed a risk factor, this adjustment is fine since it is intended to adjust for risk exposure. On the other hand, if the purpose is simply to adjust for the value style since one is not sure (or does not care) about the underlying economic forces driving the value premium, the factor-based adjustment could introduce bias in skill estimation. As an illustrative example, if one portfolio manager happens to use the high-minus-low HML beta strategy, and assuming that the HML factor is not a risk factor, the proper way to adjust for the value style is to use characteristics-based adjustment. Thus, we could perform characterstics-based adjustment by following the DGTW approach. Specifically, as described in Section 2.2, we can adjust a stock's return by subtracting the return of the characteristics-based benchmark portfolio to which it belongs. Panel D of Table 2 shows that this strategy has an alpha of 0.28% per month (t-stat = 1.42) after characteristics-based adjustment, whereas the alpha of factor-based adjustment is -0.08% per month (t-stat= -0.41). Later on, Table 3 shows that the difference of -0.36% per month is statistically significant (t-stat = -2.69).[14]

The previous example shows that using the factor-based approach could potentially be problematic if the purpose is to adjust for investment style rather than risk. In many practical applications, the purpose is indeed to adjust for investment style since we are not confident that the underlying factor is a risk factor. Indeed, several of these prominent factors have a significant probability of being driven by mispricing, and thus, the purpose of adjustment is probably to account for the underlying investment style rather than exposure to these factors. Panel D of Table 2 reports the results of using characteristics-based adjustment to account for investment styles underlying the 13 factors. It can be seen that the characteristics-adjusted returns are not so negative for most of our high-minus-low (H-L) beta-sorted portfolios, compared to the factor-based adjusted alphas. The average characteristics-adjusted return for these 13 beta-sorted long-short portfolios is only -0.09% per month (t-stat = -0.96). More important, column 5 of Table 3 shows that the differences between the two-factor alphas and characteristics-adjusted excess returns are statistically significant for 11 out of the 13 factors, especially for mispricing/behavioral factors.[15] Specifically, the MGMT and PERF

[14]The purpose of these two adjustment methods (i.e., the factor-based adjustment and the characteristics-based adjustment) is essentially the same: finding a benchmark return for individual stocks. Under the factor-based adjustment, the benchmark is betas multiplying by the corresponding factors. Under the characteristics-based adjustment, the benchmark is the return of the portfolio to which individual stocks are matched.

[15]The monthly difference between these two adjustment methods is computed as difference between the intercept plus the monthly residual from the factor-based regressions and the monthly characteristics-adjusted returns. This is equivalent to the difference between the monthly characteristics-based benchmark and the monthly factor-based benchmark.

factors in Stambaugh and Yuan (2017) have differences of −0.69% and −0.53% per month, respectively. Similarly, for Daniel, Hirshleifer, and Sun (2017), the differences are −0.42% and −0.54% per month for the short-horizon factor PEAD and the long-horizon factor FIN, respectively. On the other hand, the differences are smaller and statistically insignificant for Fama and French's RMW and CMA factors. For the 13 factors considered in this study, the average difference of these two adjustment methods is −0.41% per month (t-stat = −5.70). This difference is economically large for portfolio performance evaluation since many of the portfolio managers have an alpha close to zero. In addition, the differences tend to be positive for low-beta portfolios and negative for high-beta portfolios. This is expected since low-beta firms tend to have positive factor alphas, whereas high-beta firms tend to have negative factor alphas.

So far, we use characteristics-sorted decile portfolios as our characteristics-based benchmarks. If we choose a finer portfolio classification, the characteristics-adjusted return should move closer to zero, and thus, the difference between the two adjustment methods should be closer to the factor alpha, which is −0.50% per month on average. On the other hand, if we choose more coarse classifications such as using the quintile or tercile portfolios as benchmarks, the characteristics-adjusted returns for the long-short beta-sorted portfolios should move closer to the raw returns, which is close to zero as shown in Panel B of Table 2. Thus, the difference between the two adjustment methods should also be closer to the factor alpha. Thus, our current characteristics-based benchmark is likely to provide a conservative estimation on the difference between the two adjustment methods.[16]

In the last column of Table 3, we also control for the size effect. That is, for the characteristics-based adjustment, we match both size and the characteristics underlying each factor, and for factor-based adjustment, we control for the market factor, the size factor, and each one of the 12 factors other than the size factor. The results are similar with slightly smaller magnitude. The average difference between these two adjustment methods for the 13 factors is −0.35% per month (t-stat = −3.80).

The above findings have important implications for performance evaluation or strategy

[16]As a robustness check, Table IA2 in the Internet Appendix uses an alternative definition of characteristics-based adjustment based on finer benchmark portfolios, and reports the characteristics-adjusted returns and the difference between the two adjustments for our single characteristics-factor beta portfolios and two-factor beta portfolios. In particular, the benchmark portfolios are 25 value-weighted characteristics-sorted portfolios for characteristics-adjusted returns, and 10×10 value-weighted size-characteristics sequentially sorted portfolios for size-characteristics-adjusted return. Our results remain quantitatively very similar under these alternative characteristics-based benchmarks.

development in practice. For example, there could be a strategy that genuinely has no relation to the momentum strategy and earns positive abnormal returns after adjusting for theoretically grounded risk factors. That is, the stocks in the long leg are not winners, and the stocks in the short leg are not losers. However, the return on this strategy could have a positive correlation with the momentum factor, and the strategy alpha after controlling for the momentum factor could be close to zero. In this case, we believe that this strategy still reflects the superior skill level of the fund manager since this fund manager does not exploit the standard momentum strategy. In addition, since this strategy is buying and selling a completely different set of stocks with the momentum strategy, one can easily increase the capacity of the overall strategy. Moreover, this new strategy is less subject to contagion risk due to using the same well-known momentum strategy with many other funds.

To further illustrate this potential contagion risk, we consider the following example during the quant crisis of August 2007. It is well known that during the first week of August 2007, traditional quant strategies suffered huge losses, whereas the market index moved very little. As argued in Pedersen (2015), some banks and hedge funds experienced significant losses from the developing subprime credit crisis in July 2017. These losses led hedge funds to reduce their positions. Since many hedge funds had employed similar strategies such as the momentum strategy, the deleveraging led to further losses for these common strategies, and thus more losses for many hedge funds and more subsequent deleveraging of quant funds. Figure 1 plots the daily return of the standard long-short momentum strategy. This strategy indeed suffered substantial losses during the deleveraging process. As argued earlier, although our high-minus-low beta-sorted portfolios have high a exposure to the underlying factor, this strategy is genuinely very different from the momentum strategy since it does not necessarily buy winner firms and short loser firms. Thus, we expect that the high-minus-low beta-sorted strategy should be less affected by the contagion/deleveraging risk in August 2007. Figure 1 indeed shows that the daily return of the high-minus-low momentum beta-sorted portfolio strategy suffered little loss during this quant event.

Given our previous results, fund managers could, in principle, exploit the bias from the factor-based portfolio performance evaluation in the following way. One could buy low momentum-beta stocks and sell high momentum-beta stocks, leading to a negative exposure to the momentum factor. Thus, by betting against momentum beta, this alternative strategy earns a positive alpha after controlling for the momentum factor. By contrast, with characteristics-based adjustment, this strategy tends to show close to zero alpha, thus correctly identifying managers' ability levels. In the next section, we shall use mutual fund holdings data to evaluate the difference between characteristics-based adjustment and factor-based adjustment for our 13 factors.

So far, to increase the ex post beta spreads for our testing portfolios, we do not control for any other factors when calculating the ex ante stock-level beta. In addition, since we do not have a favorite model in mind, we have not controlled for the other factors so far. On the other hand, one might argue that the CAPM has a strong theoretical foundation, and thus one should control for the market factor when calculating ex ante betas. In Table 4, we perform a robustness check by always controlling for the market factor when calculating an individual stock's ex ante exposure to these factors. We then repeat the exercise in Tables 2 and 3. As we can see, our main results remain quantitatively similar. In particular, the average ex post beta spread is 1.21 (t-stat = 22.98), while the average return spreads between high- and low-beta firms are 0.07% per month (t-stat = 0.77). The average difference between factor-based adjustment and characteristics-based adjustment for the high-minus-low portfolio is −0.43% per month (t-stat = −7.35). To downplay the role of small stocks on our results, we have been focusing on value-weighted portfolio returns. To further alleviate the potential concern that our results are driven by stocks with small market capitalization, in Table 5, we repeat the analysis in Table 4 within the subsample of largest 1,000 stocks and obtain similar pattern.[17]

Lastly, Daniel, Hirshleifer, and Sun (2017) show that their long-horizon factor beta is positively related to future returns in Fama-MacBeth (1973) regressions. They use a different method to calculate ex ante beta. Specifically, they estimate firms' loadings on their behavioral factors using daily stock returns over the previous one-month period, whereas we use the standard monthly return over the previous 5-year rolling window to estimate ex ante beta. If mispricing is short lived, beta estimated over shorter horizons in Daniel, Hirshleifer, and Sun (2017) might be a better proxy for mispricing. On the other hand, the ex post beta spread using our approach is still highly significant, although our method is probably not the best way to capture the true expected factor exposure. Nonetheless, in Table IA4 in the Internet Appendix, we conduct robustness checks using daily data to estimate ex ante beta, and our main conclusions, especially those regarding the differences between the two adjustment methods, remain largely the same. In addition, in Table IA5 in the Internet Appendix, we conduct another robustness check using the more powerful method in Frazzini and Pedersen (2014) to estimate ex ante beta, and our main conclusions, again, remain largely

[17]As another robustness test, table IA3 in the Internet Appendix divides the full sample into two subperiods and show similar results in both subsamples.

the same. More important, the purpose of this section is to show that there is a set of testing portfolios for which the characteristics-based adjustment and factor-based adjustment can potentially yield very different adjusted returns. In other words, the primary purpose is not to show that high-beta stocks earn returns similar to low-beta stocks. We simply use these portfolios to illustrate that the differences between these two adjustment methods could be very different. In subsequent analysis, we use anomaly portfolios and actual mutual fund returns to evaluate the differences between these two alternative adjustment methods.

3.2 Beta, Characteristics, and the Role of Investor Sentiment

It seems puzzling that the underlying characteristics for all 13 factors can predict stock returns and the factors themselves, which all have beta of one, also earn significant returns, whereas the high-minus-low beta-sorted portfolios earn close to zero returns. Indeed, in pure risk-based factor models, the beta is a proxy for risk exposure, and it should be able to predict future returns. Thus, the high-minus-low beta-sorted portfolios should earn positive average returns. On the other hand, because of measurement error in beta estimation, it is possible that characteristics are better proxies for risk exposure and thus better determinants for expected returns. As a result, the high-minus-low beta-sorted portfolios could earn close to zero returns while the factors themselves earn significant return spreads. However, we have shown that the ex post beta spreads are quite large and are estimated with large t-statistics. Thus, measurement error in beta estimation cannot fully account for our results, and thus it is possible that some of the factors are not pure risk factors.

In behavioral models, however, factor exposure to behavioral/mispricing factors could be the proxy for mispricing with high-beta firms being relatively underpriced. As argued in Daniel, Hirshleifer, and Sun (2017), when investors make correlated mistakes about related stocks, the commonality in stock mispricing can lead to return comovement among these stocks. For example, investors could become excited about many growth stocks simultaneously, leading to correlated pricing errors among these stocks, even when news about underlying cash flows for these stocks is uncorrelated. As a result, shocks to these characteristics-based factors could lead to comovement among stocks with similar levels of mispricing, as such stocks share similar exposure to the economic factors. Thus, in behavioral models, exposure to these factors could be a proxy for the level of mispricing. Indeed, this line of argument motivates Daniel, Hirshleifer, and Sun (2017) to use behavioral factor models to describe the cross section of expected returns.[18]

In behavioral models with correlated errors, the underlying firm-level attributes are proxies for mispricing, and the factor beta could be a proxy for mispricing as well. Typically, characteristics and beta should be positively correlated, and beta should also be a strong predictor for stock returns in the cross section, contrary to our previous findings. On the other hand, it is also possible that beta is unrelated to either characteristics or mispricing for other types of behavioral factor models. To illustrate this, we contrive the following simplified example in a reduced form, inspired by the classic analysis in Daniel and Titman (1997). If a firm-level characteristic, $c_{i,t}$, captures underpricing, one could write the following one-factor approximate dynamics for firm-level stock returns:

$$r_{i,t+1} = \phi_0 c_{i,t} + \phi_i F_{t+1} + \varepsilon_{i,t+1,}, \tag{1}$$

where F_{t+1}, with $E_t(F_{t+1}) = 0$, is the unpriced common factor as in Daniel et al. (2017). The return on the long-short portfolio (i.e., the characteristics-based factor) is given by

$$r_{LS,t+1} = \phi_0 c_{LS,t} + \phi_{LS} F_{t+1} + \varepsilon_{L,t+1} - \varepsilon_{S,t+1}, \tag{2}$$

where $c_{LS,t} = \sum_{i \in L} c_{i,t}/N - \sum_{i \in S} c_{i,t}/N$, and $\phi_{LS} = \sum_{i \in L} \phi_i/N - \sum_{i \in S} \phi_i/N$, L and S denote the index of firms that are in the long and short leg of the factor, respectively, and N is the number of firms in the short and long legs. For a well-diversified portfolio, the error terms, $\varepsilon_L = \sum_{i \in L} \varepsilon_{i,t+1}/N$ and $\varepsilon_S = \sum_{i \in S} \varepsilon_{i,t+1}/N$, should be close to zero, and the variation is mostly determined by the common factor F_t. It could be the case that ϕ_i and c_i are uncorrelated or even negatively correlated in the cross section. Thus, since the exposure to the factor β_i is mostly determined by ϕ_i, it could be only weakly related to the characteristics $c_{i,t}$ in the cross section.[19]

Thus, although in behavioral models, it is possible that the exposure to factors is a proxy for the level of mispricing, it is also possible that beta is uncorrelated to mispricing. In addition, it is likely that most of these factors are driven by both genuine risk and mispricing simultaneously, and there are measurement errors in beta as well. Thus, the correlation between characteristics and beta could be positive, negative, or close to zero. In

[18]In addition, Kozak, Nagel, and Santosh (2017a) argue that in absence of near-arbitrage opportunity, factor beta could also be a proxy for mispricing in a model with investor sentiment.

[19]The correlated errors could potentially introduce another stochastic term besides F_t in equation (1), and the coefficients on this term could be positively correlated to characteristics. This could increase the correlation between beta and characteristics, thus raising the predictive power of beta.

any case, the correlation could be far from perfect. Indeed, the time series average of the cross-sectional correlation between characteristics and the corresponding factor beta is very low. On average, it is only 14% for our 13 factors, as shown in Panel C of Table 1. The maximum correlation is only 36%. Thus, although the underlying characteristics have strong predictive power for future stock returns in the cross section, it is not necessarily true that factor beta has predictive power, consistent with the results in Table 2.

We now examine the relation between this long-short return spread and investor sentiment. As argued by Stambaugh, Yu, and Yuan (2012) and Shen, Yu, and Zhao (2017), when market-wide sentiment is combined with short-sale impediments, the market participants tend to be more rational during low-sentiment periods since irrational pessimistic agents are out of the market. On the other hand, market participants tend to be more irrational during high sentiment periods since rational agents stay out of the market because of short-sale impediments. Thus, the traditional risk-return trade-off should hold better following low-sentiment periods, whereas mispricing-driven anomalies should be amplified following high-sentiment periods. Indeed, Stambaugh, Yu, and Yuan (2012) find that the 11 anomalies are more pronounced following high-sentiment periods, especially the short legs. In addition, 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, if the factor are risk factors and betas are noisy proxies for risk exposure, then following the argument in Shen, Yu, and Zhao (2017), one should expect that the high-minus-low beta return spreads are larger following low-sentiment periods than they are following high-sentiment periods. On the other hand, if the factors are mispricing factors, and the betas are noisy proxies for mispricing, then following the argument in Stambaugh, Yu, and Yuan (2012), one should expect that the high-minus-low beta return spreads are larger following high-sentiment periods than they are following low-sentiment periods. Thus, because of these opposite predictions, investor sentiment could be useful in distinguishing alternative interpretations of those factors.[20] Nonetheless, a factor could be driven by both risk and mispricing, and the confounding effects of risk and mispricing could weaken the effect of sentiment on the return spreads between high- and low-beta firms. Even though our main purpose is not to investigate the underlying economic forces for these factors and

[20]As argued in Lin and Zhang (2013) and Kozak, Nagel, and Santosh (2017a), the horse races between "covariance" and "characteristics" cannot discriminate between rational and behavioral models. Our conditional tests using investor sentiment can, on the other hand, be potentially informative about the underlying forces for these factors.

the potential difficulty with interpreting the results, we still perform a simple test using investor sentiment as a conditional variable.[21]

The investor sentiment measure is obtained from Jeffrey Wurgler's website. Table 6 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 they are following low-sentiment periods. For example, the average return spread between high- and low-beta firms is 0.30% per month following high-sentiment periods and −0.30% per month following low-sentiment periods. The difference of 0.60% per month is statistically significant (t-stat = 2.79). These results are in sharp contrast with those of Shen, Yu, and Zhao (2017) who consider 10 macro-related factors such as consumption growth and TFP growth. Shen, Yu, and Zhao (2017) find that the return spread between high-beta firms and low-beta firms is much higher and positive following low-sentiment periods than it is following high-sentiment periods, the exact opposite of our pattern here. These results suggest that those macro-related factors are more likely to be driven by risk, whereas many of the characteristics-based factors are more likely to be driven by mispricing/behavioral effects. In Panel B of Table 6, we report the results on CAPM alphas, and the main pattern remains the same.

In addition, we would also like to point out that for some factors such as size, both its beta and the underlying characteristics could capture the stock price's sensitivity to sentiment movement. Thus, following the argument in Baker and Wurgler (2006, 2007), when sentiment is high, these high-beta firms are relatively more overpriced than firms with low beta and thus future returns are lower. On the other hand, when sentiment is low, high-beta firms are relatively more underpriced than low-beta firms, and thus earn higher future returns. Table 6 shows that for the size factor, the return spread is indeed negative following high sentiment and positive following low sentiment. Although this result is consistent with a mispricing interpretation, the pattern is opposite to the prediction based on the earlier assumption that the betas are noisy proxies for mispricing with high-beta firms being relatively underpriced. Thus, if we exclude the size factor, the average differences between return spreads following high- and low-sentiment periods are larger and statistically more significant at 0.77% per month (t-stat = 2.83). As a result, the evidence provides stronger support for the notion that many of these factors are indeed mispricing factors and betas are noisy proxies for mispricing. In addition, the effect of sentiment on these beta-sorted portfolio are indeed strong for the

[21] After all, it is also possible that the factors are due to mispricing but betas are unrelated to mispricing, as illustrated by the above contrived example. Thus, sentiment has a very limited effect on the return spreads between high- and low-beta firms.

MGMT factor proposed by Stambaugh and Yuan (2017) and the FIN factor proposed by Daniel, Hirshleifer, and Sun (2017), consistent with the mispricing interpretation for these factors. On the other hand, sentiment exhibits insignificant effect on the PERF factor and PEAD factor, lending no additional support for the mispricing interpretation of these factors.

4 Application in Anomaly Studies

For illustrative purposes, we have been focusing on our high-minus-low beta long-short portfolio strategies since these strategies yield large ex post factor beta spreads. However, since previous studies mostly use these factors to account for well-known anomalies, we thus also study the effect of different adjustment methods on anomalies in this section. Moreover, many portfolio managers may indeed use strategies resembling these anomaly-based portfolios, rather than our beta-sorted long-short portfolios. Thus, the differences between factor-based and characteristics-based adjustment for these anomaly-based portfolios might be more relevant in practice. In addition, as discussed earlier in the introduction, when researchers discover a new anomaly, they usually want to make sure that this new anomaly is not just a repackaging of existing anomalies. The dominating approach in the current literature is to use factor-based models to remove the returns arising from factor exposure. However, as argued before, in many cases the true purpose is actually to account for investment styles that may employ a set of known anomalies. Thus, the characteristics-based approach better fits the purpose, and it would be interesting to investigate the potential differences between these two adjustment approaches.

In particular, here we investigate the differences between two adjustment methods using the 11 anomalies used in Stambaugh, Yu, and Yuan (2012, 2014).[22] We also consider the value strategy since it is one of the most popular investment styles in practice. For anomaly-based portfolios, to align with the literature, instead of using only one factor each time, we use multiple factor models such as the Fama-French 5-factor model. As a result, we also adjust for the corresponding multiple characteristics simultaneously, following an approach similar to that in DGTW. Table 7 reports the results. As we can see, for many anomalies, the differences between these two adjustments are still statistically significant, although the magnitude is not as extreme as in our beta-sorted portfolios. For example, for the momentum

[22]The 11 anomalies include financial distress, O-score, net stock issues, composite equity issues, accruals, net operating assets, momentum, gross profitability, asset growth, and return on assets. Construction details of these anomalies can be found in Stambaugh, Yu, and Yuan (2012).

anomaly, the difference between the Hou-Xue-Zhang q-factor model and the corresponding characteristics-based adjustment is -0.24% per month (t-stat = -2.00). The magnitude of this difference is even higher for other factor models, ranging from -0.69% to 0.57% per month. This wide range highlights the need for caution when we use factor models to adjust for investment style. Since we are more interested in the magnitude of the difference rather than the sign of this difference, we could adjust the signs so that all the differences have the same sign and then compute the average difference for these anomalies. After such adjustment, we find that the average magnitude of these differences ranges from 0.13% to 0.22% per month with t-statistics ranging from 4.03 to 7.76 for different factor models. This magnitude is smaller than that for beta-sorted portfolios, probably because the ex post beta spreads for these anomaly-based portfolios are smaller than those for beta-sorted portfolios.

In Table IA6 in the Internet Appendix, we repeat the above analysis using a broader set of 68 anomalies based on firm-level characteristics in Stambaugh and Yuan (2017), and find similar results.[23] We follow Hou, Xue, and Zhang (2017) to construct these 68 anomalies.[24] The average magnitude of the differences between two adjustment methods ranges from 0.12% to 0.19% per month with t-statistics ranging from 4.29 to 6.38 for these multi-factor models. Among these 68 anomalies, 36, 22, 26, 31, 35, and 32 anomalies have (absolute) t-statistics of the differences between two adjustment methods greater than or equal to 1.96 for Fama-French three-factor model, Carhart four-factor model, Fama-French five-factor model, Hou-Xue-Zhang q-factor model, Stambaugh-Yuan mispricing factor model, and Daniel-Hirshleifer-Sun behavioral factor model, respectively. Thus, the two adjustment methods produce significantly different results for about one third of the anomalies.[25]

[23] Among the 73 anomalies studied in Stambaugh and Yuan (2017), we exclude four momentum anomalies using overlapping holding periods since the underlying firm-level signal is the same as the corresponding anomaly with one-month holding period. We also exclude industry momentum anomaly since it is not a firm-level characteristic.

[24] The result for NSI portfolio spread is slightly different in Table 7 and Table IA6 due to the different portfolio construction in Stambaugh and Yuan (2017) and Hou, Xue, and Zhang (2017). In Stambaugh and Yuan (2017), decile NSI portfolios are formed using NYSE breakpoints. In Hou, Xue, and Zhang (2017), stocks with negative NSI are divided into two portfolios using NYSE breakpoints, stocks with zero NSI is treated as one portfolio, and stocks with positive NSI are divided into seven portfolios using NYSE breakpoints.

[25] As another robustness check, Table IA7 in the Internet Appendix repeats the analysis using an alternative definition of characteristics-based adjustment based on finer benchmark portfolios. In particular, for FF3 and DHS models, the corresponding benchmark portfolios are sequentially 10×10 size-BM sorted and FIN-CAR sorted value-weighted portfolios using NYSE breakpoints, respectively. For CARHART and Q4 models, the corresponding benchmark portfolios are sequentially $5\times5\times5$ size-BM-Ret$_{-2,-12}$ sorted and size-Inv-ROE sorted value-weighted portfolios using NYSE breakpoints, respectively. For M4 model, the corresponding benchmark portfolios are sequentially $5\times5\times5$ size-score$_{MGMT}$-score$_{PERF}$ sorted value-weighted portfolios using NYSE breakpoints for size and NYSE/AMEX/NASDAQ breakpoints for score$_{MGMT}$ and score$_{PERF}$. For FF5 model, the corresponding benchmark portfolios are sequentially

Overall, for leading anomaly strategies, the differences between various factor-based adjustment and their corresponding characteristics-based adjustment are still statistically significant and economically important, although the magnitudes are not as extreme as in our beta-sorted portfolios. Thus, our results suggest that in anomaly analysis, one should probably also use the characteristics-based approach to gauge the incremental value of newly discovered anomalies, especially when the underlying purpose is to account for existing investment styles or there is uncertainty about whether the underlying factors are genuine risk factors. In the next section, we apply these two performance evaluation methods to actual mutual fund holdings data and gauge the economic magnitude of the difference between these two methods.

5 Application in Performance Evaluation: Evidence from Mutual Fund Holdings

In this section, we use mutual fund holdings data to evaluate the differences between factor-based adjustment and characteristics-based adjustment in performance evaluation and attribution. The purpose of this section is not to evaluate whether mutual fund managers have ability or whether their performance is persistent, topics that have been studied extensively by the existing literature. Rather, we are simply interested in the difference between using the factor-based benchmark and using the characteristics-based benchmark.

Because the correlation between factor betas and the corresponding characteristics underlying these factors is very low, we have shown that the two adjustment methods tend to generate significant differences in the resulting alphas for both beta-sorted portfolios and many prominent anomaly-based portfolios in the literature. This result is especially relevant for mutual fund performance evaluation in practice. The factor-based approach has been very popular for mutual fund and hedge fund performance evaluation, partly because exact and timely holdings data are rarely available. On the other hand, the true purpose of adjusting for factor exposure for mutual funds is typically to remove well-known investment styles such as the value, momentum, quality, and low-risk styles, rather than fundamental risks. In addition, adjusting for popular investment styles is important since abnormal

$3\times3\times3\times3$ size-BM-OP-Inv sorted value-weighted portfolios using 30th and 70th NYSE percentiles breakpoints. Our results remain quantitatively similar under these alternative characteristics-based benchmarks.

returns arising from those well-known styles may not reflect the stock-selection skills of fund managers. Indeed, industry leaders are starting many smart-beta funds and charge a much lower performance fee for these funds, exactly because these strategies do not necessarily reflect the true stock-selection skills of portfolio managers. Thus, when evaluating active fund performance, one needs to properly account for investment styles that are known to earn high expected returns.

We compute both factor-adjusted alphas and characteristic-adjusted returns of mutual funds as follows. The factor-adjusted alphas are calculated in a way similar to standard factor-based regressions. For each single characteristics factor, the fund-level alpha inferred from the factor model is the intercept (α) from the following factor regression using the full return history of the fund:

$$R_{i,t} = \alpha_i + \beta_{mkt} MKTRF_t + \beta_{smb} SMB_t + \beta_{factor} F_t + \epsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the monthly excess return (i.e., the gross return in excess of the risk free rate) of fund i in month t. We add back the expense ratio to the reported net return to get the gross return for each fund. The variables $MKTRF$, SMB, and F are the market factor, the size factor, and an individual factor, respectively. Besides these single-factor models, we also consider five multi-factor models including the Carhart (1997) 4-factor model (CARHART), the Hou-Xue-Zhang (2015) q-factor model (Q4), the Fama-French (2015) 5-factor model (FF5), the Stambaugh and Yuan (2017) mispricing-factor model (M4), and the Daniel, Hirshleifer and Sun (2017) behavioral-factor model (BF3).[26] We run the same type of regression using all the factors in the corresponding factor model and obtain the factor-adjusted alpha. We require a minimum of 36 months of nonmissing returns to estimate the alpha.

For characteristic-adjusted returns, we construct the holding-based characteristics-adjusted returns, following an approach similar to the characteristic selectivity (CS) measure in DGTW. We populate the holdings from Thomson Reuters Mutual Fund Holdings database to the monthly frequency.[27] For each fund and each month, we then compute the value-

[26]We do not report Fama-French (1993) 3-factor model (FF3) separately since FF3 model is the same as the HML factor controlling for the size factor.

[27]Before 1985 and after July 2004, all funds were required to report their holdings quarterly. Although funds were required to report their holdings only semiannually between 1985 and early 2004, Wermers (1999) points out that the majority of funds choose to continue to report holdings on a quarterly basis. In cases where the gap between the two consecutive reporting dates is longer than 3 months, we use the most recently available holdings. To avoid using stale information, the lag holdings are carried forward for a maximum of 12 months.

weighted average of adjusted returns in its portfolio. The return for each stock is adjusted to the benchmark portfolio that is matched to

$$CS_{i,t} = \sum_{j} w_{i,j,t-1}(R_{j,t} - R_t^{b_{j,t-1}}), \tag{4}$$

where $R_{j,t}$ is the return of stock j in month t, $w_{i,j,t-1}$ is the relative weight of stock j in month $t-1$ in fund i's portfolio holdings, and $R_t^{b_{j,t-1}}$ is the return of the benchmark portfolio in month t. The benchmark portfolio is constructed in the same way as the characteristics-based benchmark portfolio in Section 2.3. For each single characteristic, the benchmark portfolio is matched along the dimension of both size and the characteristic. For multi-factor models, the benchmark portfolio is matched along the dimension of all factors. The fund-level characteristic-adjusted return is the average of its monthly characteristic-adjusted return throughout the fund's life.

To show the differences between the two methods, Table 8 reports the mean, the standard deviation, and the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the differences (in absolute value) between these two adjustment methods for performance evaluation, and Figure 2 plots the corresponding distribution. The difference between the two adjustment methods is about 3.0% per annum. Moreover, one third of the mutual funds have absolute differences above 2.4% per annum. This number is economically significant since the inter-quantile of fund raw returns, factor-adjusted alphas, and characteristics-adjusted returns are 5.4%, 3.7%, and 2.7% per annum, respectively. In addition, Figure 3 plots the same type of distribution based on the multi-factor-adjusted returns, and the characteristic-adjusted returns matching along the corresponding multiple dimensions. The overall quantitative magnitude remains similar.

Using different methods could also yield very different relative performance rankings for mutual funds. For example, Table 9 shows that the percentile ranking could change by at least 12% for a median fund. That is, a fund that ranks in the 50th percentile based on factor models ranks in the 38th percentile or 62th percentile with the characteristics-based adjustment. This is also a large number compared to existing studies. For example, Busse, Jiang, and Tang (2017) show that compared to standard factor-based adjustment, their double-adjustment procedure leads to a median percentile ranking change of about 5%. Lastly, we would like to point out two caveats. First, we focus exclusively on selectivity ability rather than timing ability. Second, we do not have continuous holding data, and thus we do not observe all the actions of fund managers. Sometimes these unobserved actions include important information, as pointed out by Kacperczyk, Sialm, and Zheng (2008). Thus, not all the differences between these two adjustment methods are a result of the beta-sorted return spreads being close to zero. At the very least, our results show the quantitative differences between two popular methods, which, in many cases, have been used to serve the same purpose, that is, to adjust for investment styles.

6 Conclusions

Many prominent characteristics-based factors are proposed by recent studies. These factors are extremely powerful in accounting for many asset pricing anomalies, and thus they provide a parsimonious summary of the cross section of stock returns. In this study, we show that the return spreads between high- and low-beta portfolios are close to zero for most of the 13 factors,even though the ex post beta spreads are large and statistically significant. More important, the factor-based benchmark and the corresponding characteristics-based benchmark yield significantly different return spreads between high- and low-beta portfolios. Similar significant differences are also found for many asset pricing anomalies and actual mutual fund returns. Since in many cases the purpose of the benchmark adjustment is to account for well-known investment styles, our results indicate that the characteristics-based benchmark may be more appropriate and that the factor-based benchmark could introduce potential bias in portfolio performance evaluation. Similar analysis can be applied to event studies such as initial public equity offerings, mergers and acquisitions, dividend initiations, and so forth.

In sum, although it is important to propose a few parsimonious factors to account for many anomalies, as several recent prominent studies do, subsequent researchers need to be careful in using these factor models in applications such as performance evaluation and performance attribution. On the other hand, since the characteristics underlying these factors can summarize the cross section of stock returns parsimoniously, they can be extremely useful in forming a characteristics-based benchmark. This is an important and desirable feature for those factors since controlling for many characteristics simultaneously is infeasible. Thus, one can just use the firm-level, sometimes composite, characteristics underlying those factors to perform a characteristics-based adjustment.

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Figure 1: Quant crisis for momentum strategy and momentum beta strategy The 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 highest past 12-month cumulative returns and shorts the loser decile of stocks with the lowest past 12-month cumulative returns, skipping one 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 the past 60 months' data with a minimum of 36 months.

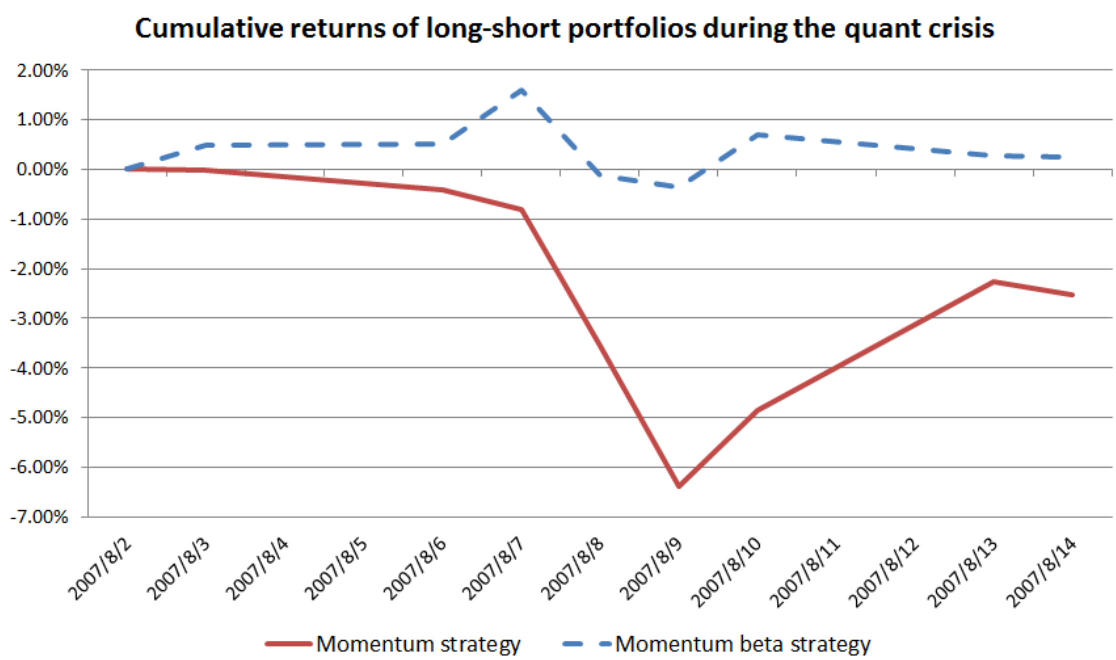

Figure 2: Histogram of the absolute difference between factor-adjusted and characteristic-adjusted returns of mutual funds

This figure plots the distribution of the absolute difference (in percentages) between factor-based alpha and fund-level characteristic-adjusted return of mutual funds. For each factor, its factor-based alpha is the intercept from the monthly factor regression of fund's excess return on the market factor, the size factor SMB, and the factor itself. For the characteristics-adjusted returns, we first compute the weighted average of stock-level size-characteristics adjusted returns. The fund-level characteristic-adjusted return is the average of its monthly characteristic-adjusted return throughout the fund's life. We compute these measures using data from 1980:1 to 2016:12. The reported distribution is based on 3,456 unique funds. To make the plots more compact, we trim the distribution at 2.7%, which is the maximum 99th percentiles of these distributions.

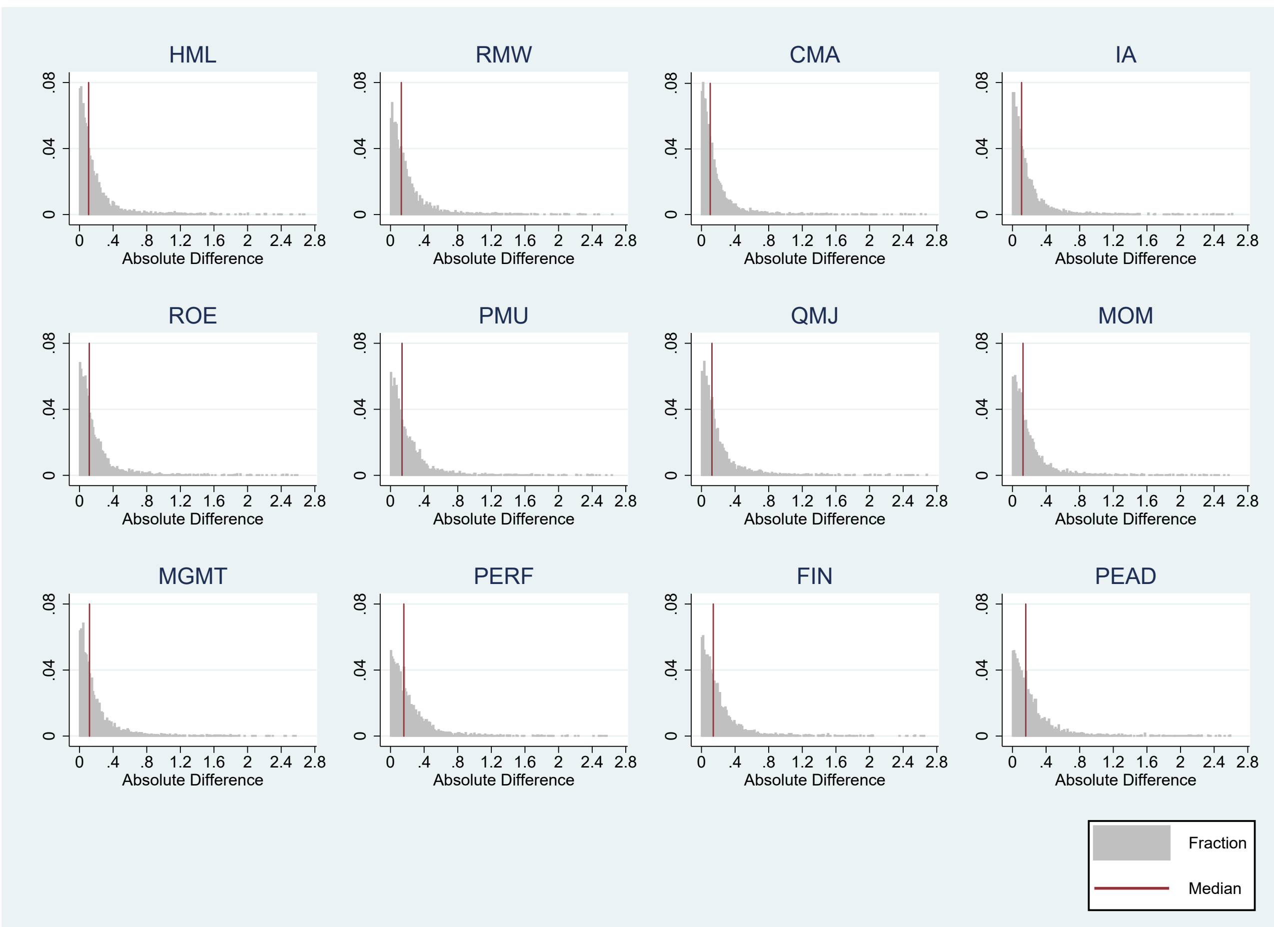

Figure 3: Histogram of the absolute difference between factor-adjusted and characteristic-adjusted returns of mutual funds: Multi-factor models

This figure plots the distribution of the absolute difference (in percentages) between factor-based alpha and fund-level characteristic-adjusted return of mutual funds. We consider five multi-factor models: Carhart (1997) 4-factor model (CARHART), Hou-Xue-Zhang (2015) 4-factor model (Q4), Fama-French (2015) 5-factor model (FF5), Stambaugh and Yuan (2017) mispricing factor model (M4), and Daniel, Hirshleifer, and Sun (2017) behavioral factor model (BF3). For each one of these factor models, its factor-adjusted alpha is the intercept from the monthly factor regression of fund's excess return on the underlying factors. The characteristics-adjusted return inferred from the factor model is the weighted average of adjusted returns in a fund's portfolio with the adjusted return of each stock being the difference between its return and the return of the benchmark portfolio to which it is matched along the dimension of the underlying factors. The fund-level characteristic-adjusted return is the average of its monthly characteristic-adjusted return throughout the fund's life. We compute these measures using data from 1980:1 to 2016:12. The reported distribution is based on 3,456 unique funds. To make the plots more compact, we trim the distribution at 2.6%, which is the maximum 99th percentiles of these distributions.

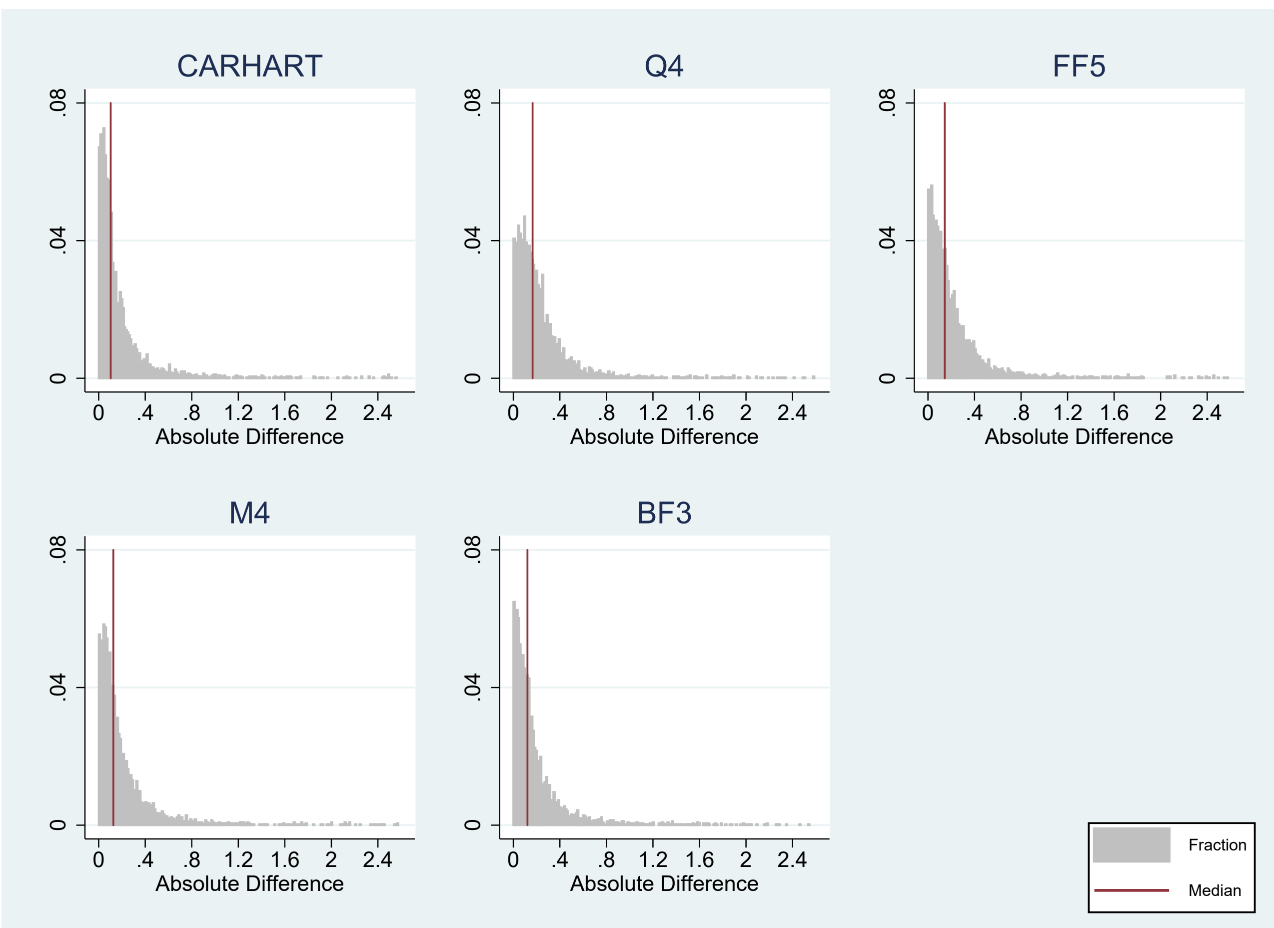

Table 1: Summary statistics

This table reports the summary statistics of characteristics-based tradable factors. Panel A presents the pairwise Pearson correlations of factors' monthly returns. Panel B presents factors' monthly mean returns (in percentages) and CAPM alphas (in percentages) with Newey-West (1987) 5-lag adjusted t-statistics in parentheses. Panel C presents the time series average of cross-sectional Pearson correlations and rank correlations between factor beta and respective stock characteristics, where the correlation sign is adjusted so that beta value and characteristics value have the same direction. Ave refers to the average pairwise correlation (Panel A), average returns (Panel B), and the average correlation (Panel C) across all 13 factors. The sample period is from 1972:1 to 2016:12 for IA and ROE factors, 1972:7 to 2016:12 for FIN and PEAD factors, and 1963:7 to 2016:12 for other factors.

Panel A: Pairwise correlation

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	SMB	1.00													
(2)	HML	-0.21	1.00												
(3)	RMW	-0.44	0.14	1.00											
(4)	CMA	-0.15	0.65	-0.11	1.00										
(5)	IA	-0.21	0.69	0.13	0.90	1.00									
(6)	ROE	-0.40	-0.06	0.66	-0.14	0.06	1.00								
(7)	PMU	0.06	-0.33	0.46	-0.37	-0.25	0.35	1.00							
(8)	QMJ	-0.58	0.08	0.74	0.10	0.18	0.68	0.37	1.00						
(9)	MOM	-0.02	-0.17	0.09	-0.03	0.03	0.49	0.06	0.22	1.00					
(10)	MGMT	-0.40	0.68	0.24	0.76	0.76	0.12	-0.20	0.43	0.03	1.00				
(11)	PERF	-0.10	-0.31	0.38	-0.18	-0.10	0.61	0.43	0.51	0.72	-0.08	1.00			
(12)	FIN	-0.45	0.68	0.61	0.55	0.65	0.34	0.06	0.60	0.05	0.79	0.11	1.00		
(!3)	PEAD	0.00	-0.16	-0.11	0.00	-0.03	0.26	0.02	0.11	0.48	0.01	0.37	-0.07	1.00	
(14)	Ave	-0.24	0.14	0.23	0.17	0.24	0.25	0.05	0.29	0.16	0.26	0.20	0.33	0.07	1.00

Panel B: Factor returns and CAPM alphas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Return	0.22	0.37	0.27	0.25	0.39	0.54	0.28	0.36	0.65	0.58	0.62	0.78	0.61	0.45
	(1.84)	(2.78)	(2.79)	(3.02)	(4.53)	(4.87)	(2.72)	(3.12)	(3.81)	(4.70)	(4.10)	(4.16)	(7.31)	(7.85)
Alpha^{CAPM}	0.12	0.45	0.34	0.33	0.47	0.60	0.26	0.53	0.72	0.75	0.72	1.00	0.63	0.52
	(1.04)	(3.34)	(3.34)	(4.21)	(5.40)	(5.88)	(2.43)	(5.62)	(4.56)	(6.72)	(4.88)	(5.96)	(7.96)	(10.05)

Panel C: Cross-sectional correlations: beta vs. characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Corr	0.17	0.17	0.08	0.07	0.05	0.05	0.18	0.36	0.04	0.23	0.17	0.26	-0.01	0.14

Table 2: Beta-sorted portfolios

This table reports the results of decile value-weighted portfolios sorted by factor betas, which are estimated from a single characteristics-based factor model using returns over the past 60 months with a minimum of 36 months. We report the ex post betas (Panel A), monthly excess returns (Panel B), monthly factor-based alphas (Panel C), and monthly characteristics-adjusted returns (Panel D) of these factor beta-sorted portfolios. Ex post betas are estimated using the corresponding single characteristics-based factor model. Factor-based alpha is the intercept from a two-factor model including the market factor and the corresponding characteristics factor. The characteristics-adjusted return is the difference between the individual stock return and the return of a benchmark portfolio to which it matches along with the dimension of the characteristic. The benchmark portfolios are 10 value-weighted portfolios sorted by the characteristics. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. Ave refers to the average betas, average excess returns, and average alphas across all beta-sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE beta sorted portfolios, 1975:7 to 2016:12 for FIN and PEAD beta sorted portfolios, and 1966:7 to 2016:12 for other beta sorted portfolios. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Ex-post betas

	Low	2	3	4	5	6	7	8	9	High	H-L
SMB	-0.07	0.12	0.31	0.42	0.63	0.73	0.91	0.99	1.28	1.74	1.80
	(-0.7)	(1.03)	(2.29)	(3.11)	(4.95)	(4.51)	(6.63)	(6.25)	(7.71)	(12.60)	(25.10)
HML	-1.21	-0.61	-0.42	-0.29	-0.13	-0.08	-0.03	0.07	0.20	0.38	1.59
	(-8.26)	(-4.97)	(-3.63)	(-2.63)	(-1.10)	(-0.61)	(-0.29)	(0.59)	(1.58)	(2.27)	(14.58)
RMW	-1.65	-1.01	-0.79	-0.67	-0.45	-0.32	-0.18	-0.08	0.02	0.14	1.79
	(-9.33)	(-5.95)	(-3.79)	(-3.69)	(-2.51)	(-1.75)	(-1.12)	(-0.50)	(0.16)	(1.25)	(16.77)
CMA	-2.04	-1.38	-1.13	-0.89	-0.78	-0.62	-0.45	-0.39	-0.30	-0.17	1.87
	(-9.40)	(-9.15)	(-7.99)	(-6.83)	(-6.01)	(-5.24)	(-3.75)	(-3.36)	(-2.67)	(-1.36)	(8.47)
IA	-2.10	-1.24	-0.88	-0.68	-0.56	-0.44	-0.28	-0.21	-0.10	0.06	2.16
	(-9.48)	(-7.32)	(-5.95)	(-4.78)	(-3.74)	(-3.05)	(-1.84)	(-1.44)	(-0.70)	(0.37)	(8.95)
ROE	-1.53	-1.05	-0.86	-0.59	-0.50	-0.27	-0.20	-0.07	0.07	0.12	1.65
	(-8.51)	(-6.15)	(-5.11)	(-4.34)	(-3.38)	(-2.04)	(-1.59)	(-0.60)	(0.59)	(1.03)	(13.35)
PMU	-0.95	-0.56	-0.22	-0.03	0.13	0.32	0.44	0.52	0.58	0.89	1.84
	(-5.74)	(-4.53)	(-1.70)	(-0.22)	(1.00)	(2.43)	(3.53)	(3.87)	(4.02)	(5.58)	(19.48)
QMJ	-2.51	-1.88	-1.63	-1.39	-1.18	-1.02	-0.86	-0.70	-0.49	-0.28	2.23
	(-20.45)	(-11.95)	(-12.87)	(-7.91)	(-7.30)	(-6.38)	(-5.59)	(-4.98)	(-3.52)	(-2.30)	(24.26)
MOM	-0.52	-0.48	-0.31	-0.28	-0.22	-0.16	-0.13	-0.09	-0.07	-0.05	0.48
	(-3.62)	(-4.71)	(-3.65)	(-3.50)	(-2.87)	(-2.22)	(-1.86)	(-1.20)	(-0.92)	(-0.37)	(3.41)
MGMT	-2.00	-1.38	-1.09	-0.90	-0.73	-0.64	-0.54	-0.42	-0.28	-0.12	1.88
	(-22.53)	(-16.26)	(-11.28)	(-9.10)	(-7.16)	(-6.60)	(-4.93)	(-4.28)	(-3.24)	(-1.12)	(17.73)
PERF	-0.99	-0.73	-0.56	-0.40	-0.36	-0.26	-0.22	-0.18	-0.08	0.00	0.99
	(-6.74)	(-7.65)	(-6.08)	(-5.11)	(-4.80)	(-3.76)	(-3.11)	(-2.44)	(-1.00)	(0.03)	(7.32)
FIN	-1.31	-0.79	-0.60	-0.48	-0.31	-0.26	-0.22	-0.14	-0.13	-0.04	1.28
	(-14.53)	(-6.65)	(-5.62)	(-3.88)	(-2.79)	(-2.17)	(-1.96)	(-1.31)	(-1.55)	(-0.41)	(22.66)
PEAD	-0.55	-0.44	-0.36	-0.36	-0.42	-0.32	-0.29	-0.21	-0.07	0.05	0.61
	(-2.17)	(-1.98)	(-1.97)	(-2.33)	(-2.74)	(-2.27)	(-2.32)	(-1.59)	(-0.46)	(0.25)	(3.01)
Ave	-1.17	-0.78	-0.57	-0.44	-0.31	-0.21	-0.12	-0.05	0.06	0.21	1.38
	(-22.46)	(-17.74)	(-14.27)	(-10.82)	(-7.49)	(-5.28)	(-3.19)	(-1.26)	(1.45)	(4.17)	(31.54)

Table 2 (cont.): Beta-sorted portfolios

Panel B: Excess returns

	Low	2	3	4	5	6	7	8	9	High	H-L
SMB	0.48	0.51	0.58	0.68	0.67	0.68	0.75	0.57	0.67	0.53	0.06
	(3.19)	(2.90)	(2.99)	(3.31)	(3.03)	(2.77)	(2.80)	(2.03)	(2.00)	(1.40)	(0.18)
HML	0.35	0.38	0.45	0.54	0.46	0.73	0.61	0.73	0.85	0.84	0.49
	(1.26)	(1.73)	(2.31)	(2.72)	(2.29)	(3.81)	(3.18)	(3.56)	(4.28)	(3.18)	(1.78)
RMW	0.48	0.62	0.70	0.47	0.66	0.61	0.52	0.63	0.66	0.50	0.02
	(1.58)	(2.72)	(3.02)	(2.14)	(3.29)	(3.26)	(2.74)	(3.53)	(3.53)	(2.56)	(0.07)
CMA	0.37	0.49	0.63	0.58	0.71	0.63	0.59	0.56	0.56	0.62	0.25
	(1.16)	(2.06)	(2.96)	(2.83)	(3.72)	(3.51)	(3.29)	(3.14)	(3.17)	(2.95)	(0.98)
IA	0.65	0.71	0.65	0.76	0.73	0.81	0.83	0.76	0.77	0.78	0.13
	(1.98)	(2.82)	(2.99)	(3.79)	(3.74)	(4.16)	(4.27)	(3.78)	(3.86)	(3.08)	(0.47)
ROE	0.99	0.78	0.86	0.80	0.79	0.76	0.77	0.79	0.79	0.61	-0.38
	(2.82)	(2.64)	(3.33)	(3.47)	(3.54)	(3.64)	(3.82)	(4.15)	(4.22)	(2.84)	(-1.30)
PMU	0.38	0.47	0.66	0.70	0.72	0.55	0.46	0.54	0.46	0.53	0.15
	(1.40)	(2.34)	(3.29)	(3.49)	(3.66)	(2.66)	(2.38)	(2.67)	(2.11)	(1.87)	(0.55)
QMJ	0.47	0.55	0.77	0.61	0.54	0.65	0.64	0.67	0.60	0.50	0.03
	(1.25)	(1.82)	(2.71)	(2.38)	(2.45)	(3.09)	(3.29)	(3.76)	(3.82)	(3.16)	(0.08)
MOM	0.81	0.68	0.63	0.72	0.63	0.62	0.59	0.58	0.50	0.41	-0.40
	(2.64)	(2.76)	(2.90)	(3.44)	(3.21)	(3.20)	(3.11)	(2.88)	(2.50)	(1.55)	(-1.53)
MGMT	0.38	0.46	0.51	0.58	0.67	0.64	0.59	0.66	0.55	0.49	0.11
	(1.09)	(1.70)	(2.15)	(2.67)	(3.51)	(3.46)	(3.32)	(3.81)	(3.29)	(2.47)	(0.37)
PERF	0.74	0.58	0.71	0.64	0.68	0.63	0.58	0.56	0.55	0.35	-0.40
	(2.40)	(2.47)	(3.33)	(3.27)	(3.52)	(3.63)	(3.10)	(2.78)	(2.75)	(1.31)	(-1.53)
FIN	0.49	0.55	0.57	0.71	0.80	0.81	0.69	0.71	0.74	0.71	0.22
	(1.44)	(1.98)	(2.44)	(3.23)	(4.09)	(3.97)	(3.98)	(4.05)	(4.18)	(3.58)	(0.71)
PEAD	0.91	0.87	0.73	0.69	0.69	0.64	0.69	0.62	0.75	0.54	-0.37
	(3.12)	(3.60)	(3.37)	(3.45)	(3.41)	(3.13)	(3.60)	(2.94)	(3.39)	(1.91)	(-1.39)
Ave	0.51	0.54	0.60	0.61	0.63	0.63	0.60	0.61	0.60	0.52	0.01
	(1.89)	(2.44)	(2.92)	(3.04)	(3.30)	(3.38)	(3.25)	(3.26)	(3.29)	(2.46)	(0.05)

Table 2 (cont.): Beta-sorted portfolios

Panel C: Two-factor model-adjusted alphas

	Low	2	3	4	5	6	7	8	9	High	H-L
SMB	0.15	0.11	0.11	0.18	0.09	0.07	0.08	-0.14	-0.14	-0.42	-0.57
	(2.08)	(1.72)	(1.59)	(2.45)	(1.50)	(0.89)	(0.81)	(-1.77)	(-1.07)	(-3.26)	(-3.29)
HML	0.02	-0.08	-0.05	0.00	-0.14	0.11	-0.03	0.01	0.09	-0.06	-0.08
	(0.20)	(-0.81)	(-0.83)	(-0.06)	(-1.62)	(1.45)	(-0.34)	(0.10)	(1.06)	(-0.41)	(-0.41)
RMW	0.12	0.18	0.21	0.00	0.14	0.09	-0.06	0.06	0.05	-0.14	-0.26
	(0.96)	(1.73)	(2.21)	(-0.04)	(1.70)	(1.08)	(-0.86)	(1.04)	(0.87)	(-1.61)	(-1.56)
CMA	-0.07	0.05	0.15	0.06	0.19	0.10	0.03	-0.01	-0.02	-0.07	-0.01
	(-0.46)	(0.62)	(2.34)	(0.80)	(2.91)	(1.38)	(0.36)	(-0.16)	(-0.22)	(-0.59)	(-0.02)
IA	0.14	0.06	-0.03	0.05	-0.02	0.07	0.03	-0.06	-0.08	-0.23	-0.37
	(0.95)	(0.64)	(-0.31)	(0.68)	(-0.35)	(0.82)	(0.33)	(-0.55)	(-0.70)	(-1.44)	(-1.44)
ROE	0.68	0.33	0.36	0.23	0.16	0.05	0.03	0.01	-0.06	-0.30	-0.98
	(3.76)	(2.20)	(3.06)	(2.38)	(1.45)	(0.69)	(0.38)	(0.13)	(-0.70)	(-2.51)	(-3.89)
PMU	0.11	0.18	0.26	0.23	0.22	-0.01	-0.11	-0.05	-0.16	-0.29	-0.40
	(0.83)	(2.12)	(3.25)	(3.04)	(2.81)	(-0.13)	(-1.83)	(-0.83)	(-2.13)	(-2.54)	(-2.05)
QMJ	0.34	0.20	0.38	0.12	0.04	0.09	0.05	0.07	-0.03	-0.19	-0.53
	(2.17)	(1.62)	(3.31)	(1.00)	(0.50)	(1.02)	(0.63)	(1.11)	(-0.42)	(-2.47)	(-2.55)
MOM	0.40	0.34	0.22	0.30	0.20	0.14	0.11	0.07	-0.04	-0.26	-0.66
	(2.22)	(2.58)	(2.16)	(3.14)	(2.31)	(1.62)	(1.56)	(0.81)	(-0.41)	(-2.08)	(-2.48)
MGMT	0.32	0.16	0.06	0.06	0.09	0.02	-0.06	-0.03	-0.18	-0.40	-0.72
	(2.23)	(1.61)	(0.72)	(0.75)	(1.15)	(0.34)	(-0.90)	(-0.40)	(-2.20)	(-2.85)	(-3.04)
PERF	0.57	0.36	0.40	0.24	0.26	0.19	0.09	0.04	-0.06	-0.46	-1.03
	(3.78)	(3.87)	(4.47)	(3.27)	(3.94)	(2.67)	(1.26)	(0.52)	(-0.73)	(-4.10)	(-4.69)
FIN	0.23	-0.06	-0.07	-0.02	0.02	-0.05	-0.10	-0.12	-0.03	-0.21	-0.43
	(1.64)	(-0.57)	(-0.67)	(-0.23)	(0.20)	(-0.63)	(-1.23)	(-1.59)	(-0.41)	(-1.89)	(-1.99)
PEAD	0.37	0.38	0.22	0.21	0.25	0.15	0.19	0.05	0.07	-0.36	-0.73
	(1.99)	(2.57)	(2.05)	(2.35)	(2.80)	(1.33)	(2.31)	(0.64)	(0.90)	(-2.71)	(-2.56)
Ave	0.24	0.16	0.17	0.13	0.12	0.08	0.02	0.00	-0.05	-0.26	-0.50
	(2.99)	(3.35)	(4.35)	(3.16)	(3.00)	(2.04)	(0.53)	(-0.12)	(-1.37)	(-5.39)	(-5.60)

Table 2 (cont.): Beta-sorted portfolios

Panel D: Characteristics-adjusted returns

	Low	2	3	4	5	6	7	8	9	High	H-L
SMB	0.00	0.02	0.07	0.15	0.10	0.11	0.14	-0.01	0.08	-0.09	-0.09
	(0.02)	(0.25)	(1.24)	(2.37)	(1.58)	(1.38)	(1.38)	(-0.14)	(0.54)	(-0.54)	(-0.40)
HML	-0.07	-0.14	-0.05	0.02	-0.08	0.19	0.06	0.14	0.19	0.21	0.28
	(-0.57)	(-1.73)	(-0.98)	(0.34)	(-1.06)	(2.53)	(0.72)	(1.94)	(2.35)	(1.68)	(1.42)
RMW	0.03	0.14	0.22	-0.07	0.12	0.07	-0.01	0.09	0.12	-0.04	-0.07
	(0.20)	(1.52)	(2.50)	(-0.90)	(2.08)	(1.15)	(-0.15)	(1.63)	(1.80)	(-0.41)	(-0.31)
CMA	-0.08	-0.04	0.10	0.04	0.17	0.11	0.04	-0.01	0.00	0.05	0.12
	(-0.55)	(-0.56)	(1.76)	(0.59)	(2.89)	(1.51)	(0.52)	(-0.19)	(0.03)	(0.46)	(0.60)
IA	0.01	0.02	-0.05	0.05	0.02	0.10	0.12	0.03	0.03	0.05	0.05
	(0.04)	(0.24)	(-0.72)	(0.70)	(0.36)	(1.43)	(1.49)	(0.33)	(0.30)	(0.42)	(0.21)
ROE	0.36	0.13	0.19	0.11	0.06	0.06	0.05	0.08	0.06	-0.10	-0.46
	(2.10)	(1.00)	(2.05)	(1.37)	(0.72)	(0.97)	(0.88)	(0.99)	(0.90)	(-0.97)	(-1.94)
PMU	-0.10	0.00	0.15	0.17	0.19	0.03	-0.04	0.00	-0.07	-0.03	0.07
	(-0.68)	(-0.01)	(2.10)	(2.71)	(2.86)	(0.48)	(-0.70)	(-0.06)	(-1.01)	(-0.27)	(0.30)
QMJ	0.05	0.09	0.28	0.10	0.01	0.14	0.10	0.09	0.07	-0.07	-0.12
	(0.30)	(0.76)	(2.45)	(1.14)	(0.25)	(2.16)	(1.80)	(1.58)	(0.93)	(-0.71)	(-0.46)
MOM	0.19	0.14	0.09	0.14	0.10	0.11	0.07	0.07	-0.04	-0.12	-0.31
	(1.30)	(1.37)	(1.17)	(1.97)	(1.73)	(1.81)	(1.37)	(1.23)	(-0.57)	(-1.15)	(-1.52)
MGMT	-0.02	-0.03	0.05	0.04	0.13	0.10	0.03	0.10	-0.01	-0.05	-0.03
	(-0.15)	(-0.30)	(0.62)	(0.68)	(2.32)	(1.84)	(0.51)	(1.47)	(-0.16)	(-0.45)	(-0.11)
PERF	0.29	0.12	0.20	0.15	0.15	0.08	0.02	0.01	-0.04	-0.21	-0.50
	(2.38)	(1.73)	(2.94)	(2.40)	(2.72)	(1.30)	(0.32)	(0.15)	(-0.51)	(-1.88)	(-2.69)
FIN	-0.04	-0.07	-0.03	0.08	0.14	0.12	0.03	0.08	0.07	0.06	0.10
	(-0.25)	(-0.69)	(-0.38)	(1.17)	(2.01)	(1.76)	(0.40)	(0.92)	(0.83)	(0.58)	(0.42)
PEAD	0.28	0.22	0.10	0.04	0.06	0.00	0.05	0.00	0.13	-0.03	-0.32
	(1.72)	(1.90)	(1.20)	(0.54)	(0.83)	(-0.01)	(0.71)	(-0.06)	(1.71)	(-0.28)	(-1.31)
Ave	0.05	0.04	0.10	0.08	0.09	0.10	0.05	0.05	0.04	-0.04	-0.09
	(0.55)	(0.91)	(2.94)	(2.50)	(2.72)	(2.60)	(1.43)	(1.46)	(1.21)	(-0.93)	(-0.96)

Table 3: Differences between factor- and characteristics-adjusted returns

This table reports the monthly differences (in percentages) between factor-adjusted returns and characteristics-adjusted returns of decile value-weighted portfolios sorted by factor betas, which are estimated from a single characteristics-based factor model using returns over the past 60 months with a minimum of 36 months. Diff_1 is the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted alphas and characteristics-adjusted returns. Diff_2 is the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted alphas and size-characteristics-adjusted returns. The characteristics-adjusted return is the return difference between individual stock and a benchmark portfolio to which it matches. The benchmark portfolios are 10 value-weighted characteristics-sorted portfolios for Diff_1, and 5×5 value-weighted size-characteristics sequentially sorted portfolios for Diff_2. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. We report the results for the bottom decile (Low beta), the top decile (High beta), and their difference (H-L), to save space. Ave refers to the average spread between factor-based alpha and characteristics-adjusted return across all beta sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	Low beta		High beta		H-L	
	Diff_1	Diff_2	Diff_1	Diff_2	Diff_1	Diff_2
SMB	0.15		-0.32		-0.47	
	(2.85)		(-2.70)		(-2.76)	
HML	0.09	0.04	-0.27	-0.26	-0.36	-0.29
	(1.04)	(0.41)	(-4.31)	(-3.31)	(-2.69)	(-2.01)
RMW	0.09	0.01	-0.10	-0.10	-0.19	-0.11
	(0.84)	(0.15)	(-1.90)	(-1.87)	(-1.24)	(-0.79)
CMA	0.01	-0.03	-0.12	-0.05	-0.13	-0.02
	(0.14)	(-0.34)	(-2.27)	(-0.90)	(-1.02)	(-0.16)
IA	0.13	0.07	-0.29	-0.22	-0.42	-0.29
	(1.45)	(0.74)	(-4.60)	(-3.24)	(-2.92)	(-1.98)
ROE	0.32	0.31	-0.20	-0.21	-0.52	-0.51
	(2.95)	(2.75)	(-4.17)	(-4.52)	(-3.46)	(-3.41)
PMU	0.20	0.21	-0.26	-0.26	-0.47	-0.47
	(2.28)	(2.31)	(-3.30)	(-3.07)	(-3.11)	(-3.06)
QMJ	0.29	0.11	-0.12	-0.07	-0.41	-0.18
	(2.12)	(0.89)	(-1.65)	(-1.07)	(-1.98)	(-0.97)
MOM	0.21	0.18	-0.14	-0.15	-0.35	-0.32
	(2.76)	(2.27)	(-3.11)	(-3.09)	(-3.81)	(-3.19)
MGMT	0.35	0.20	-0.35	-0.32	-0.69	-0.52
	(2.74)	(1.60)	(-4.77)	(-4.23)	(-3.57)	(-2.69)
PERF	0.28	0.31	-0.25	-0.30	-0.53	-0.61
	(3.89)	(4.11)	(-5.73)	(-6.22)	(-6.33)	(-6.32)
FIN	0.27	0.19	-0.27	-0.23	-0.54	-0.42
	(2.00)	(1.50)	(-3.82)	(-3.03)	(-2.69)	(-2.12)
PEAD	0.09	0.17	-0.33	-0.33	-0.42	-0.49
	(1.74)	(2.95)	(-6.63)	(-6.17)	(-6.58)	(-6.14)
Ave	0.19	0.15	-0.22	-0.20	-0.41	-0.35
	(3.13)	(2.02)	(-9.23)	(-7.17)	(-5.70)	(-3.80)

Table 4: Beta-sorted portfolios: Estimation with two-factor models

This table reports the results for Decile 10-minus-Decile 1 (H-L) portfolios sorted by factor betas, which are estimated from a two-factor model (including the market factor and the corresponding characteristics-based factor) using returns over the past 60 months with a minimum of 36 months. $\beta^{ex\ post}$ refers to the H-L portfolios' ex post betas w.r.t. a two-factor model including the market factor and the corresponding characteristics-based factor. R^{ex} refers to monthly excess returns. $\alpha^{two-factor}$ refers to monthly two-factor model (including the market factor and a characteristics-based factor) adjusted alphas. R^{char} refers to monthly characteristics-adjusted returns. Diff_1 is the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics-adjusted returns. Diff_2 is the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics-adjusted returns. The details for benchmark portfolios are defined in Table 3. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. Ave refers to the average across all beta-sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	1.52	0.04	-0.48	-0.11	-0.37	
	(22.13)	(0.15)	(-2.92)	(-0.55)	(-2.74)	
HML	1.53	0.48	-0.15	0.27	-0.42	-0.34
	(13.62)	(1.94)	(-0.83)	(1.60)	(-3.25)	(-2.42)
RMW	1.53	0.09	-0.25	0.01	-0.26	-0.17
	(17.86)	(0.40)	(-1.46)	(0.04)	(-2.04)	(-1.46)
CMA	1.63	0.32	-0.12	0.17	-0.29	-0.14
	(8.48)	(1.39)	(-0.60)	(0.91)	(-2.82)	(-1.20)
IA	1.97	0.30	-0.34	0.19	-0.53	-0.34
	(8.20)	(1.13)	(-1.39)	(0.87)	(-3.84)	(-2.42)
ROE	1.31	-0.19	-0.65	-0.32	-0.33	-0.34
	(9.47)	(-0.69)	(-2.53)	(-1.42)	(-2.42)	(-2.44)
PMU	1.71	0.08	-0.43	-0.01	-0.42	-0.43
	(19.59)	(0.33)	(-2.61)	(-0.04)	(-3.09)	(-3.15)
QMJ	1.84	0.09	-0.60	-0.04	-0.56	-0.38
	(19.03)	(0.36)	(-3.53)	(-0.20)	(-3.56)	(-2.77)
MOM	0.40	-0.29	-0.52	-0.28	-0.25	-0.25
	(3.44)	(-1.23)	(-2.06)	(-1.47)	(-2.91)	(-2.63)
MGMT	1.59	0.19	-0.77	0.01	-0.78	-0.60
	(9.90)	(0.70)	(-3.29)	(0.04)	(-5.24)	(-3.81)
PERF	0.83	-0.22	-0.81	-0.36	-0.45	-0.55
	(7.03)	(-0.99)	(-4.17)	(-2.15)	(-6.35)	(-6.83)
FIN	1.12	0.35	-0.49	0.26	-0.75	-0.62
	(13.38)	(1.28)	(-1.95)	(1.08)	(-4.25)	(-3.41)
PEAD	0.49	-0.33	-0.65	-0.28	-0.38	-0.46
	(3.19)	(-1.39)	(-2.49)	(-1.26)	(-6.52)	(-5.99)
Ave	1.21	0.07	-0.47	-0.04	-0.43	-0.37
	(22.98)	(0.77)	(-6.24)	(-0.53)	(-7.35)	(-5.21)

Table 5: Beta-sorted portfolios, largest 1,000 stocks

This table reports the results for Decile 10-minus-Decile 1 (H-L) portfolios sorted by factor betas, which are estimated from a two-factor model (including the market factor and the corresponding characteristics-based factor) using returns over the past 60 months with a minimum of 36 months. The sample only includes the largest 1,000 stocks at the portfolio formation date. $\beta^{ex\ post}$ refers to the H-L portfolios' ex post betas w.r.t. a two-factor model including the market factor and the corresponding characteristics-based factor. R^{ex} refers to monthly excess returns. $\alpha^{two-factor}$ refers to monthly two-factor model (including the market factor and a characteristics-based factor) adjusted alphas. R^{char} refers to monthly characteristics-adjusted returns. Diff_1 is the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics-adjusted returns. Diff_2 is the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics-adjusted returns. The details for benchmark portfolios are defined in Table 3. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. Ave refers to the average across all beta-sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	1.16	0.08	-0.39	-0.05	-0.35	
	(15.31)	(0.29)	(-2.12)	(-0.21)	(-2.52)	
HML	1.45	0.38	-0.18	0.19	-0.37	-0.35
	(13.55)	(1.64)	(-1.12)	(1.17)	(-3.08)	(-2.79)
RMW	1.38	0.11	-0.21	0.05	-0.26	-0.24
	(13.27)	(0.49)	(-1.26)	(0.27)	(-2.25)	(-2.13)
CMA	1.59	0.28	-0.13	0.14	-0.27	-0.20
	(8.50)	(1.20)	(-0.64)	(0.77)	(-2.70)	(-1.85)
IA	1.89	0.20	-0.38	0.11	-0.49	-0.36
	(8.17)	(0.76)	(-1.66)	(0.49)	(-3.65)	(-2.66)
ROE	1.11	-0.10	-0.53	-0.22	-0.31	-0.30
	(9.59)	(-0.41)	(-2.13)	(-1.08)	(-2.70)	(-2.51)
PMU	1.69	0.07	-0.44	0.01	-0.45	-0.48
	(17.16)	(0.30)	(-2.49)	(0.03)	(-3.37)	(-3.53)
QMJ	1.55	0.16	-0.41	0.04	-0.46	-0.37
	(18.30)	(0.70)	(-2.72)	(0.25)	(-3.27)	(-2.74)
MOM	0.41	-0.22	-0.49	-0.25	-0.24	-0.24
	(3.57)	(-0.98)	(-1.99)	(-1.40)	(-2.87)	(-2.68)
MGMT	1.57	0.19	-0.76	0.03	-0.79	-0.65
	(9.96)	(0.71)	(-3.24)	(0.13)	(-5.28)	(-4.23)
PERF	0.80	-0.17	-0.78	-0.31	-0.47	-0.56
	(6.51)	(-0.76)	(-4.07)	(-1.92)	(-6.49)	(-6.71)
FIN	1.01	0.28	-0.45	0.19	-0.63	-0.60
	(13.47)	(1.07)	(-2.00)	(0.82)	(-3.85)	(-3.59)
PEAD	0.48	-0.29	-0.64	-0.24	-0.40	-0.42
	(2.98)	(-1.20)	(-2.38)	(-1.11)	(-6.78)	(-6.36)
Ave	1.12	0.07	-0.44	-0.03	-0.41	-0.39
	(21.92)	(0.91)	(-6.48)	(-0.45)	(-7.36)	(-5.85)

Table 6: Beta-sorted portfolio returns following high and low sentiment

This table reports the results of factor beta-sorted decile portfolios following high- and low-sentiment regimes, as classified based on the median level of the Baker and Wurlger (2006) sentiment index. We report the excess returns (Panel A) and CAPM alphas (Panel B) for the bottom decile (Low beta), the top decile (High beta), and their difference (H-L) portfolios. Pre-ranking betas are estimated from a single characteristics-based factor model using returns over the past 60 months with a minimum of 36 months. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. Ave (Ave$_{w/o\ SMB}$) refers to the average portfolio of all beta-sorted portfolios (excluding SMB). Due to the availability of sentiment data, the sample period is from 1972:7 to 2015:10 for IA and ROE, 1975:7 to 2015:10 for FIN and PEAD, and 1966:7 to 2015:10 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

Panel A: Excess returns

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	0.39	0.54	0.15	1.20	-0.10	-1.30	0.81	-0.64	-1.45
	(1.77)	(2.76)	(0.50)	(2.07)	(-0.21)	(-1.77)	(1.77)	(-1.62)	(-2.48)
HML	0.76	-0.03	-0.80	0.95	0.72	-0.23	0.19	0.76	0.57
	(1.85)	(-0.09)	(-1.43)	(2.03)	(2.71)	(-0.43)	(0.45)	(2.07)	(1.05)
RMW	1.19	-0.23	-1.42	0.48	0.50	0.03	-0.71	0.73	1.44
	(2.65)	(-0.59)	(-2.47)	(1.59)	(2.04)	(0.07)	(-2.00)	(2.26)	(3.06)
CMA	0.83	-0.10	-0.93	0.61	0.61	0.00	-0.22	0.71	0.93
	(1.74)	(-0.25)	(-1.49)	(1.83)	(2.33)	(0.01)	(-0.62)	(1.98)	(1.85)
IA	1.41	0.00	-1.41	0.92	0.65	-0.27	-0.50	0.64	1.14
	(2.80)	(0.00)	(-2.25)	(1.98)	(2.33)	(-0.53)	(-1.19)	(1.67)	(2.02)
ROE	1.88	0.26	-1.63	0.83	0.44	-0.39	-1.05	0.18	1.23
	(3.19)	(0.67)	(-2.42)	(2.35)	(1.55)	(-0.87)	(-2.24)	(0.49)	(2.08)
PMU	0.96	-0.22	-1.18	0.65	0.40	-0.24	-0.31	0.63	0.94
	(2.40)	(-0.67)	(-2.33)	(1.48)	(1.06)	(-0.42)	(-0.77)	(1.67)	(1.75)
QMJ	1.31	-0.34	-1.65	0.27	0.71	0.45	-1.04	1.05	2.10
	(2.24)	(-0.74)	(-2.24)	(1.13)	(3.50)	(1.43)	(-2.15)	(2.82)	(3.45)
MOM	0.89	0.73	-0.16	0.89	-0.05	-0.95	0.00	-0.78	-0.78
	(1.63)	(2.33)	(-0.26)	(2.46)	(-0.15)	(-1.82)	(0.00)	(-2.34)	(-1.38)
MGMT	0.98	-0.21	-1.19	0.35	0.59	0.24	-0.63	0.80	1.43
	(1.83)	(-0.47)	(-1.74)	(1.08)	(2.55)	(0.59)	(-1.47)	(2.05)	(2.42)
PERF	0.86	0.59	-0.27	0.59	0.09	-0.50	-0.27	-0.49	-0.23
	(1.62)	(1.76)	(-0.44)	(1.58)	(0.26)	(-0.96)	(-0.68)	(-1.43)	(-0.41)
FIN	1.33	-0.19	-1.52	0.67	0.73	0.06	-0.66	0.92	1.59
	(2.46)	(-0.44)	(-2.30)	(1.92)	(3.12)	(0.15)	(-1.49)	(2.40)	(2.79)
PEAD	1.34	0.56	-0.78	0.96	0.21	-0.76	-0.38	-0.35	0.02
	(2.57)	(1.76)	(-1.30)	(2.30)	(0.54)	(-1.37)	(-0.91)	(-1.07)	(0.04)
Ave	0.94	0.08	-0.86	0.64	0.38	-0.26	-0.30	0.30	0.60
	(2.20)	(0.25)	(-1.64)	(1.95)	(1.46)	(-0.62)	(-1.73)	(2.23)	(2.79)
Ave$_{w/o\ SMB}$	0.98	0.04	-0.94	0.60	0.43	-0.18	-0.38	0.39	0.77
	(2.19)	(0.12)	(-1.71)	(1.92)	(1.72)	(-0.45)	(-1.73)	(2.28)	(2.83)

Table 6 (cont.): Beta-sorted portfolio returns following high and low sentiment

Panel B: CAPM alphas

	Low beta			High beta			H-L		
	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low	Low Sent.	High Sent.	High - Low
SMB	-0.10	0.30	0.40	0.12	-0.68	-0.80	0.22	-0.98	-1.19
	(-1.07)	(2.45)	(2.54)	(0.45)	(-3.30)	(-2.46)	(0.66)	(-3.35)	(-2.76)
HML	-0.02	-0.53	-0.51	0.17	0.46	0.28	0.19	0.99	0.80
	(-0.10)	(-2.89)	(-2.07)	(0.60)	(2.21)	(0.81)	(0.46)	(2.78)	(1.49)
RMW	0.31	-0.72	-1.03	-0.09	0.22	0.31	-0.40	0.94	1.34
	(1.37)	(-3.83)	(-3.51)	(-0.68)	(1.34)	(1.44)	(-1.22)	(3.04)	(2.94)
CMA	-0.05	-0.64	-0.59	-0.02	0.35	0.37	0.03	0.99	0.96
	(-0.24)	(-3.30)	(-2.08)	(-0.13)	(1.91)	(1.49)	(0.08)	(2.93)	(2.05)
IA	0.13	-0.63	-0.76	-0.16	0.34	0.50	-0.29	0.96	1.25
	(0.59)	(-3.03)	(-2.55)	(-0.56)	(1.60)	(1.41)	(-0.66)	(2.56)	(2.15)
ROE	0.36	-0.27	-0.63	-0.03	0.05	0.08	-0.39	0.32	0.72
	(1.21)	(-1.15)	(-1.67)	(-0.22)	(0.27)	(0.32)	(-1.01)	(0.83)	(1.27)
PMU	0.30	-0.61	-0.90	-0.16	-0.05	0.11	-0.46	0.56	1.02
	(1.23)	(-2.43)	(-2.66)	(-0.78)	(-0.26)	(0.44)	(-1.14)	(1.49)	(1.94)
QMJ	0.21	-0.91	-1.12	-0.20	0.49	0.69	-0.41	1.40	1.81
	(0.79)	(-4.72)	(-3.41)	(-1.68)	(3.85)	(3.84)	(-1.14)	(5.01)	(3.94)
MOM	-0.08	0.36	0.44	0.23	-0.51	-0.74	0.30	-0.87	-1.18
	(-0.26)	(1.71)	(1.19)	(1.47)	(-2.93)	(-3.14)	(0.82)	(-2.52)	(-2.19)
MGMT	0.01	-0.79	-0.79	-0.20	0.38	0.58	-0.21	1.16	1.37
	(0.04)	(-4.13)	(-2.75)	(-1.00)	(2.12)	(1.99)	(-0.57)	(3.60)	(2.71)
PERF	-0.07	0.20	0.27	-0.09	-0.35	-0.26	-0.02	-0.55	-0.53
	(-0.25)	(0.89)	(0.74)	(-0.54)	(-2.00)	(-1.14)	(-0.05)	(-1.53)	(-1.01)
FIN	0.16	-0.86	-1.02	-0.11	0.46	0.56	-0.27	1.31	1.58
	(0.63)	(-4.28)	(-3.21)	(-0.53)	(2.72)	(2.10)	(-0.65)	(3.95)	(3.02)
PEAD	0.16	0.14	-0.01	0.07	-0.34	-0.41	-0.09	-0.49	-0.40
	(0.55)	(0.63)	(-0.03)	(0.39)	(-2.13)	(-1.77)	(-0.22)	(-1.42)	(-0.73)
Ave	0.08	-0.37	-0.45	-0.04	0.04	0.08	-0.12	0.41	0.53
	(0.62)	(-3.37)	(-2.69)	(-0.52)	(0.54)	(0.76)	(-0.82)	(3.11)	(2.70)
$Ave_{w/o\ SMB}$	0.09	-0.43	-0.52	-0.04	0.10	0.14	-0.13	0.53	0.67
	(0.62)	(-3.5)	(-2.76)	(-0.51)	(1.41)	(1.34)	(-0.74)	(3.45)	(2.82)

Table 7: Difference between multi-factor model-adjusted returns and the corresponding characteristics-adjusted returns, 12 anomalies

This table reports the monthly return differences (in percentages) between factor-adjusted returns and characteristics-adjusted returns of the anomaly spreads, which are the long-short spreads between the top and the bottom decile portfolios sorted by each underlying anomaly measure using NYSE breakpoints with share price greater than \$5. We consider 12 anomalies including the 11 anomalies underlying the mispricing score of Stambaugh and Yuan (2017), as well as the book-to-market equity. We adjust the sign of the underlying anomaly variables so that the long-short portfolio is predicted to have positive spread. FF3 refers to the Fama-French (1993) three-factor model where the corresponding benchmark portfolios are sequentially 5×5 size-BM sorted value-weighted portfolios. CARHART refers to the Fama-French three-factor plus the Carhart (1997) momentum factor model where the corresponding benchmark portfolios are sequentially 2×3×3 size-BM-Ret$_{-2,-12}$ sorted value-weighted portfolios. FF5 refers to the Fama-French five-factor model where the corresponding benchmark portfolios are sequentially 2×2×2×2 size-BM-OP-Inv sorted value-weighted portfolios. Q4 refers to the Hou, Xue, and Zhang (2015) q-factor model where the corresponding benchmark portfolios are sequentially 2×3×3 size-Inv-ROE sorted value-weighted portfolios. M4 refers to the Stambaugh and Yuan (2017) four-factor model where the corresponding benchmark portfolios are sequentially 2×3×3 size-score$_{MGMT}$-score$_{PERF}$ sorted value-weighted portfolios. BF3 refers to the Daniel, Hirshleifer, and Sun (2017) three-factor model where the corresponding benchmark portfolios are sequentially 5×5 FIN-CAR sorted value-weighted portfolios. Average magnitude refers to the average absolute return difference between the factor model adjustment and characteristics adjustment. The sample period is from 1972:1 to 2016:12 for Q4 model, 1972:7 to 2016:12 for BF3 model, and 1963:7 to 2016:12 for other models. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	FF3	CARHART	FF5	Q4	M4	BF3
Distress	0.53	0.11	0.04	-0.08	-0.34	-0.37
	(3.36)	(0.66)	(0.23)	(-0.50)	(-2.29)	(-2.65)
O-score	0.14	0.20	0.04	0.25	0.28	-0.04
	(2.58)	(3.25)	(0.61)	(3.88)	(4.58)	(-0.67)
Net Stock issues	0.16	0.03	-0.12	-0.05	-0.14	-0.05
	(2.92)	(0.55)	(-2.54)	(-0.95)	(-2.87)	(-0.61)
Composite equity issues	0.18	0.11	0.03	0.13	0.04	0.04
	(2.77)	(1.76)	(0.65)	(2.60)	(0.82)	(0.72)
Accruals	0.13	0.10	0.23	0.23	-0.01	0.09
	(2.37)	(1.81)	(3.81)	(5.14)	(-0.18)	(1.81)
Net operating assets	0.03	0.00	0.09	0.18	0.01	0.01
	(0.66)	(-0.02)	(1.78)	(2.65)	(0.23)	(0.16)
Momentum	0.57	-0.24	0.40	-0.24	-0.66	-0.69
	(6.01)	(-2.34)	(4.64)	(-2.00)	(-5.55)	(-5.84)
Gross Profitability	0.34	0.20	0.19	0.23	0.10	0.07
	(4.83)	(2.86)	(2.63)	(3.79)	(2.15)	(1.11)
Asset growth	0.07	-0.05	-0.14	-0.09	-0.23	-0.13
	(1.26)	(-0.74)	(-2.71)	(-1.57)	(-4.82)	(-2.60)
Return on assets	0.19	0.07	-0.10	-0.09	-0.09	-0.32
	(2.22)	(0.74)	(-1.05)	(-1.11)	(-1.25)	(-4.27)
Investment to assets	0.05	-0.06	0.00	-0.04	-0.19	-0.13
	(1.00)	(-1.01)	(0.09)	(-0.62)	(-4.34)	(-2.48)
Book to market	-0.21	-0.29	-0.34	-0.51	-0.52	-0.25
	(-3.31)	(-4.59)	(-4.53)	(-5.35)	(-6.74)	(-2.90)
Average magnitude	0.21	0.13	0.15	0.18	0.22	0.18
	(5.66)	(4.03)	(5.19)	(6.39)	(7.76)	(6.44)

Table 8: Difference between factor-adjusted returns and characteristic-adjusted returns of mutual funds

This table reports the mean, the standard deviation (Std) and the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the absolute difference (in percentages) between factor-adjusted monthly alpha and fund-level characteristics-adjusted monthly return of mutual funds. The factor-adjusted alpha is the intercept from the time series factor regression of fund's excess return on a set of factors, using all returns from the fund's full history. For each factor except for the CARHART, Q4, FF5, M4, and BF3, its, the set of factors include the market factor, the size factor SMB, and the factor itself. For multi-factor models, Carhart (1997) 4-factor model (CARHART), Hou, Xue, and Zhang (2015) q-factor model (Q4), Fama and French (2015) 5-factor model (FF5), Stambaugh and Yuan (2017) mispricing factor model (M4), and Daniel, Hirshleifer, and Sun (2017) behavioral factor model (BF3), the set of factors are the factors in the corresponding factor models. For characteristics-adjusted returns, we first compute the weighted average of adjusted returns in a fund's portfolio with the adjusted return of each stock being the difference between its return and the return of the benchmark portfolio to which it is matched. For each factor except for the CARHART, Q4, FF5, M4, and BF3, the benchmark portfolio is matched along the dimensions of the characteristics factor and the size factor. For multi-factor models, CARHART, Q4, FF5, M4, and BF3, the benchmark portfolio is matched along the dimension of the characteristics underlying all the factors in the corresponding model. The fund-level characteristic-adjusted return is the average of its monthly characteristics-adjusted return throughout the fund's life. Ave is the average across all factor models. We compute these measures using data from 1980:1 to 2016:12. The reported distribution is based on 3,456 unique actively managed equity funds in the United States.

Factors	Mean	Std	P5	P10	P25	P50	P75	P90	P95
HML	0.23	0.49	0.01	0.02	0.05	0.11	0.23	0.46	0.81
RMW	0.25	0.49	0.01	0.02	0.06	0.13	0.26	0.49	0.84
CMA	0.22	0.51	0.01	0.02	0.05	0.10	0.22	0.42	0.71
IA	0.23	0.51	0.01	0.02	0.05	0.11	0.22	0.43	0.69
ROE	0.24	0.48	0.01	0.02	0.05	0.12	0.24	0.47	0.77
PMU	0.26	0.50	0.01	0.02	0.06	0.14	0.28	0.50	0.77
QMJ	0.25	0.50	0.01	0.02	0.05	0.12	0.25	0.50	0.78
MOM	0.25	0.49	0.01	0.02	0.06	0.13	0.25	0.47	0.75
MGMT	0.25	0.52	0.01	0.02	0.05	0.12	0.24	0.50	0.81
PERF	0.27	0.52	0.01	0.03	0.07	0.16	0.30	0.51	0.81
FIN	0.26	0.52	0.01	0.02	0.06	0.14	0.27	0.48	0.79
PEAD	0.29	0.51	0.01	0.03	0.07	0.16	0.30	0.56	0.90
CARHART	0.23	0.48	0.01	0.02	0.05	0.10	0.22	0.45	0.79
Q4	0.28	0.55	0.02	0.03	0.08	0.17	0.29	0.51	0.79
FF5	0.27	0.54	0.01	0.02	0.06	0.14	0.28	0.52	0.82
M4	0.25	0.50	0.01	0.02	0.06	0.13	0.26	0.51	0.81
BF3	0.25	0.54	0.01	0.02	0.05	0.12	0.24	0.49	0.82
Ave	0.25	0.51	0.01	0.02	0.06	0.13	0.26	0.49	0.79

Table 9: Difference between relative performance ranking based on between factor-adjusted returns and characteristics-adjusted returns of mutual funds

This table reports the mean, the standard deviation (Std), and the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the absolute difference (in percentiles) between the rank based on factor-based alphas and the rank based on fund-level characteristics-adjusted return of mutual funds. The factor-based alphas and the fund-level characteristics-adjusted returns are defined the same way as in Table 8. We rank all funds into 100 groups based on either the factor-alpha or fund-level characteristics-adjusted return, and compute their difference. Ave is the average across all factor models. We compute these measures using data from 1980:1 to 2016:12. The reported distribution is based on 3,456 unique actively managed equity funds in the United States.

Factors	Mean	Std	P5	P10	P25	P50	P75	P90	P95
HML	20.41	21.02	1	2	5	13	28	51	67
RMW	21.70	21.36	1	2	5	15	32	53	68
CMA	19.27	19.99	1	2	5	13	27	48	63
IA	19.64	20.08	1	2	5	13	28	49	63
ROE	19.19	19.92	1	2	5	12	27	47	63
PMU	19.89	19.83	1	2	5	13	28	48	62
QMJ	19.94	20.41	1	2	5	13	28	48	66
MOM	19.32	19.81	1	2	5	13	26	46	63
MGMT	19.56	20.41	1	2	5	12	27	49	65
PERF	20.64	20.18	1	2	5	14	29	50	64
FIN	22.15	21.06	1	2	6	16	32	53	67
PEAD	21.75	21.42	1	2	6	15	31	53	69
CARHART	19.90	20.69	1	2	5	13	28	49	67
Q4	21.10	20.54	1	2	6	14	30	50	65
FF5	22.51	21.69	1	2	6	15	32	55	70
M4	21.27	21.22	1	2	6	14	29	53	69
BF3	18.72	20.04	1	2	5	12	25	45	65
Ave	20.41	20.57	1.00	2.00	5.29	13.53	28.65	49.82	65.65

A Appendix

This Appendix provides details about our construction of characteristics-based factors and the corresponding characteristics.[28]

1. Small minus Big (SMB): Historically, the fact that small stocks earn higher returns than large stocks has been denoted as the size premium (Banz (1981), Basu (1983), Fama and French (1993)). To construct the SMB factor, all stocks are independently divided into six value-weighted size/book-to-market portfolios using NYSE breakpoints at the end of each June. Specifically, the size breakpoint is the median of the end of June NYSE market equity, while the BE/ME breakpoints are the 30th and 70th percentiles of the NYSE BE/ME ratio. The BE/ME ratio for June of year t is the book equity for the fiscal year ending in t-1 divided by the market equity as of December of year t-1. The definition of book equity follows Fama and French (1993, 2015). The high 70th percentile BE/ME group is denoted as the value group, the low 30th percentile BE/ME group is denoted as the growth group, and the median 40% group is denoted as the neutral group. The SMB factor is thus defined as

$$\begin{aligned} SMB = & \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) \\ & -\frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth) \end{aligned} \tag{A.1}$$

2. High minus Low (HML): Value stocks with a high book-to-market (BM) ratio earn higher returns than those growth stocks with a low BM ratio (Rosenburg, Reid, and Lanstein (1985), Fama and French (1993)). The HML factor is constructed using four of the above six portfolios by longing two value portfolios and short selling two growth portfolios:

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Value + Big\ Growth) \tag{A.2}$$

3. Robust minus Weak (RMW): Stocks with robust profitability deliver higher returns than stocks with weak profitability (Fama and French (2015)).[29] To construct the

[28] We construct all factors by ourselves to better keep our sample and analysis updated. The correlation of our self-constructed factors with the original factors are all above 0.95, and in untabulated results, we confirm that our results are very similar if we use available factors posted by the original authors.

[29] Other related studies include Haugen and Baker (1996), Fama and French (2006), Chen, Novy-Marx, and Zhang (2011), Wang and Yu (2013), and Ball, Gerakos, Linnainmaa, and Nikolaev (2016).

RMW factor, all stocks are independently divided into six value-weighted size/operating profitability (OP) portfolios using NYSE breakpoints at the end of each June. The size breakpoint is the median of the end of June NYSE market equity, while the OP breakpoints are the 30th and 70th percentiles of NYSE OP values. The OP for June of year t is defined as the annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the fiscal year end in t-1. The high 70th percentile OP group is denoted as the robust group, the low 30th percentile OP group is denoted as the weak group, and the median 40% group is denoted as the neutral group. The RMW factor is thus defined as

$$RMW = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}(Small\ Weak + Big\ Weak) \tag{A.3}$$

4. Conservative minus Aggressive (CMA): High investment firms earn lower returns than low investment firms (Titman, Wei, and Xie (2004) and Xing (2008)). Fama and French (2015) call stocks with low investment conservative and stocks with high investment aggressive. The CMA factor is constructed by longing two conservative portfolios and short selling two aggressive portfolios:

$$\begin{aligned} CMA = &\frac{1}{2}(Small\ Conservative + Big\ Conservative) \\ &-\frac{1}{2}(Small\ Aggressive + Big\ Aggressive) \end{aligned} \tag{A.4}$$

5&6. Investment-to-assets (IA) & Return on Equity (ROE) : Hou, Xue, and Zhang (2015) propose a four-factor model that is based on neoclassical q-theory of investment. They find that the market factor, the return spread of small stocks and large stocks (r_{ME}), the return spread of low investment stocks and high investment stocks ($r_{I/A}$), along with the return spread of high profitable stocks and low profitable stocks measured by ROE (r_{ROE}), can explain stock return variation in the cross section. To construct q-factors, all stocks are independently divided into 2×3×3 value-weighted size/investment-to-assets (I/A)/return-on-equity (ROE) portfolios using NYSE breakpoints at the end of each month. The size breakpoint is the median of the end of June NYSE market equity, the I/A breakpoints are the 30th and 70th percentile of NYSE annual I/A ratio, and the ROE breakpoints are the 30th and 70th percentiles of NYSE quarterly ROE ratio. The I/A for June of year t is defined as the annual change in total assets with fiscal year end in t-1 divided by 1-year-lagged t-2 total assets. The ROE for each month is defined as the income before extraordinary items divied by 1-quarter-lagged book equity where quarterly Compustat earnings data are used after the quarterly earnings announcement dates. The IA factor is thus defined as the return difference between the simple average of 6 low I/A portfolios' returns and the simple average of 6 high I/A portfolios' returns.

The ROE factor is defined as the return difference between the simple average of 6 high ROE portfolios' returns and the simple average of 6 low ROE portfolios' returns.[30]

7. Profitable minus Unprofitable (PMU): Novy-Marx (2013) finds that sorting on the ratio of gross profitability to total assets delivers higher returns for more profitable firms. To construct the PMU factor, all stocks are independently divided into six value-weighted size/gross profitability (GP) portfolios using NYSE breakpoints at the end of each June. The size breakpoint is the median of the end of June NYSE market equity, while the GP breakpoints are the 30th and 70th percentiles of the NYSE GP values. The GP for June of year t is defined as the annual revenues minus cost of goods sold divided by total assets for the fiscal year end in t-1. The PMU factor is defined as

$$\begin{aligned} PMU = &\frac{1}{2}(Small\ Profitable + Big\ Profitable) \\ &-\frac{1}{2}(Small\ Unprofitable + Big\ Unprofitable) \end{aligned} \tag{A.5}$$

8. Quality minus Junk (QMJ): Asness, Frazzini, and Pedersen (2014) explore 21 firm-level characteristics that measure stocks' quality in four dimensions: profitability, growth, safety, and payout. They convert all measures into ranks and standardize to obtain a z-score for quality. They find that high-quality stocks earn higher returns than low-quality stocks. To construct the QMJ factor, all stocks are sequentially sorted into six value-weighted size/quality portfolios using NYSE breakpoints each month. The size breakpoint is the median of the NYSE market equity, while the quality breakpoints are the 30th and 70th

[30]Detailed factor construction of the IA factor and ROE factor is in Section 2.1 of Hou, Xue, and Zhang (2015).

percentiles of NYSE quality z-scores.[31] The QMJ factor is thus defined as

$$QMJ = \frac{1}{2}(Small\ Quality + Big\ Quality) - \frac{1}{2}(Small\ Junk + Big\ Junk) \tag{A.6}$$

9. Momentum (MOM): Jegadeesh and Titman (1993) document that stocks with good past performance outperform stocks with poor past performance. To construct the MOM factor, all stocks are independently divided into six value-weighted size/prior $t-12$ to month $t-2$ return portfolios using NYSE breakpoints each month. The size breakpoint is the median of the NYSE market equity, and the past return breakpoints are the 30th and 70th percentiles of the NYSE past (2,12) month cumulative returns with a one-month skip before the holding month. The MOM factor is defined as

$$MOM = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low) \tag{A.7}$$

10. MGMT: From the set of 11 well-documented mispricing anomalies examined by Stambaugh, Yu, and Yuan (2012, 2014, 2015), Stambaugh and Yuan (2017) propose two mispricing factors: MGMT and PERF. The MGMT factor comes from the first cluster of six anomalies (net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment-to-assets) that can be directly affected by firms' managements. The PERF factor comes from the second cluster of five anomalies (financial distress, O-score, momentum, gross profitability, and return-on-assets) that are related to performance and less likely to be affected by managers. An average mispricing score is assigned to each of these two clusters of mispricing measures at the end of each month. To construct the MGMT factor, all stocks excluding those with prices less than \$5 are independently divided into six value-weighted size/MGMT mispricing score portfolios. The size breakpoint is the median of the NYSE market equity, and the MGMT breakpoints are the 20th and 80th percentiles

[31] Profitability measures include gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin, and the fraction of earnings composed of cash (minus accruals); growth measures include the five-year growth of each of the profitability measures; safety measures include Frazzini and Pedersen (2014)'s beta, idiosyncratic volatility, leverage measured as the total debt over total assets, Ohlson's O-score, Altman's Z-score, and standard deviation of quarterly ROE over the past 60 quarters; payout measures include net equity issuance, net debt issuance, and total net payout over profits. Construction details of quality z-score are in Appendix A.1 of Asness et al. (2014).

of the NYSE/AMEX/NASDAQ MGMT score. The MGMT factor is defined as

$$\begin{aligned} MGMT = & \frac{1}{2}(Small\ Undervalue^{MGMT} + Big\ Undervalue^{MGMT}) \\ & -\frac{1}{2}(Small\ Overvalue^{MGMT} + Big\ Overvalue^{MGMT}) \end{aligned} \tag{A.8}$$

11. PERF: To construct the PERF factor, all stocks excluding those with prices less than \$5 are independently divided into six value-weighted size/PERF mispricing score portfolios. The size breakpoint is the median of the NYSE market equity, and the PERF breakpoints are the 20th and 80th percentiles of the NYSE/AMEX/NASDAQ PERF score. The PERF factor is defined as

$$\begin{aligned} PERF = & \frac{1}{2}(Small\ Undervalue^{PERF} + Big\ Undervalue^{PERF}) \\ & -\frac{1}{2}(Small\ Overvalue^{PERF} + Big\ Overvalue^{PERF}) \end{aligned} \tag{A.9}$$

Construction details of MGMT and PERF factors are in Section 2.1 of Stambaugh and Yu (2017), and the paper's Appendix provides detailed procedures for constructing those 11 anomaly measures.

12: Financing (FIN): Daniel, Hirshleifer, and Sun (2017) propose a pair of behavioral factors, including an overconfidence-based financing factor (FIN) and a limited-attention-based post-earnings announcement drift factor (PEAD). Stocks with low financing earn higher returns than those with high financing, and such a return spread (FIN) is able to explain long-horizon anomalies. To construct the FIN factor, all stocks excluding financial firms are independently divided into six value-weighted size/financing portfolios at the end of each June. The size breakpoint is the median of the NYSE market equity, and the financing breakpoints are based on a financing index of one-year net share issuance and the corresponding 5-year composite issuance rankings. The FIN factor is defined as

$$\begin{aligned} FIN = & \frac{1}{2}(Small\ Low^{Financing} + Big\ Low^{Financing}) \\ & -\frac{1}{2}(Small\ High^{Financing} + Big\ High^{Financing}) \end{aligned} \tag{A.10}$$

13: Post-Earnings Announcement Drift (PEAD): Stocks with large four-day cumulative abnormal returns (CAR) after quarterly earnings announcement dates earn higher returns than those with low CAR, and such a return spread (PEAD) explains short-horizon anomalies. To construct the PEAD factor, all stocks excluding financial firms are independently divided into six value-weighted size/CAR portfolios each month. The size breakpoint is the median of the NYSE market equity, and the CAR breakpoints are the 20th and 80th percentiles of the NYSE CAR values. The PEAD factor is defined as

$$PEAD = \frac{1}{2}(Small\ High^{CAR} + Big\ High^{CAR}) - \frac{1}{2}(Small\ Low^{CAR} + Big\ Low^{CAR}) \tag{A.11}$$

We closely follow Section 1.1 of Daniel, Hirshleifer, and Sun (2017) to construct the FIN and PEAD factors.

Internet Appendix to "Characteristics-Based Factors"

This Internet Appendix presents additional results.

Table IA1: Beta-sorted portfolios: Monthly rebalancing

This table reports results for the spread portfolio (H-L) between the top and bottom value-weighted decile portfolios sorted by factor betas, which are estimated from a single factor model using returns over the past 60 months with a minimum of 36 months. $\beta^{ex\ post}$ refers to H-L portfolios' ex post betas with respect to a two-factor model including the market factor and a characteristics-based factor. R^{ex} refers to monthly excess returns. $\alpha^{two-factor}$ refers to two-factor model (including the market factor and a characteristics-based factor) adjusted monthly alphas. R^{char} refers to monthly characteristics adjusted returns. Diff_1 refers to the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics adjusted returns. Diff_2 refers to the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics adjusted returns. The characteristics-adjusted return is the difference between the individual stock return and the return of a benchmark portfolio to which it matches. The benchmark portfolios are defined the same way as in Table 3. All portfolios are rebalanced monthly. Ave refers to the average across all beta-sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted *t*-statistics are reported in parentheses.

	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	2.00	-0.21	-0.96	-0.39	-0.56	
	(14.80)	(-0.63)	(-4.63)	(-1.58)	(-3.13)	
HML	1.88	0.37	-0.17	0.14	-0.31	-0.24
	(11.98)	(1.14)	(-0.72)	(0.56)	(-1.83)	(-1.33)
RMW	2.42	0.04	-0.41	-0.03	-0.38	-0.31
	(18.93)	(0.11)	(-1.96)	(-0.12)	(-1.82)	(-1.51)
CMA	2.02	0.11	-0.29	-0.05	-0.24	-0.13
	(10.08)	(0.37)	(-1.11)	(-0.20)	(-1.68)	(-0.85)
IA	2.38	0.05	-0.61	-0.08	-0.53	-0.43
	(8.32)	(0.13)	(-1.90)	(-0.28)	(-3.05)	(-2.41)
ROE	1.89	-0.12	-0.87	-0.31	-0.56	-0.51
	(12.11)	(-0.35)	(-2.86)	(-1.19)	(-3.39)	(-3.15)
PMU	1.99	0.37	-0.34	0.27	-0.61	-0.60
	(18.14)	(1.24)	(-1.55)	(1.11)	(-3.73)	(-3.54)
QMJ	2.62	0.16	-0.55	0.11	-0.66	-0.43
	(22.10)	(0.45)	(-2.38)	(0.37)	(-2.71)	(-1.97)
MOM	0.51	-0.51	-0.83	-0.41	-0.42	-0.36
	(3.53)	(-1.73)	(-2.75)	(-1.74)	(-4.21)	(-3.32)
MGMT	2.02	0.09	-0.85	-0.08	-0.77	-0.66
	(16.24)	(0.29)	(-3.27)	(-0.28)	(-3.75)	(-3.27)
PERF	0.86	-0.31	-0.97	-0.46	-0.50	-0.59
	(5.61)	(-1.18)	(-4.18)	(-2.24)	(-6.24)	(-6.48)
FIN	1.81	0.28	-0.74	0.10	-0.85	-0.79
	(18.84)	(0.72)	(-2.61)	(0.33)	(-3.28)	(-3.10)
PEAD	0.63	-0.46	-0.92	-0.31	-0.61	-0.64
	(2.35)	(-1.52)	(-2.69)	(-1.13)	(-9.07)	(-7.43)
Ave	1.56	0.00	-0.64	-0.11	-0.53	-0.46
	(20.42)	(-0.02)	(-6.03)	(-0.96)	(-5.92)	(-4.33)

Table IA2: Beta-sorted portfolios, alternative characteristics-adjusted returns definitions

This table reports the results for Decile 10-minus-Decile 1 (H-L) portfolios sorted by factor betas, which are estimated using returns over the past 60 months with a minimum of 36 months. Panel A uses a single characteristics-based factor model and Panel B uses a two-factor model (including the market factor and the corresponding characteristics-based factor) to estimate betas. R^{char} and $R^{size-char}$ refer to monthly characteristics-adjusted and size-characteristics-adjusted returns, respectively. The characteristics-adjusted or size-characteristics-adjusted return is the return difference between individual stock and a benchmark portfolio to which it matches. The benchmark portfolios are 25 value-weighted characteristics-sorted portfolios for R^{char}, and 10×10 value-weighted size-characteristics sequentially sorted portfolios for $R^{size-char}$. Diff_1 is the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics-adjusted returns R^{char}. Diff_2 is the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics-adjusted returns $R^{size-char}$. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. Ave refers to the average across all beta-sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	Panel A: Single-factor beta-sorted portfolios				Panel B: two-factor beta-sorted portfolios			
	R^{Char}	Diff_1	$R^{size-Char}$	Diff_2	R^{Char}	Diff_1	$R^{size-Char}$	Diff_2
SMB	-0.08	-0.48			-0.10	-0.38		
	(-0.36)	(-2.88)			(-0.50)	(-2.87)		
HML	0.27	-0.36	0.17	-0.26	0.26	-0.41	0.14	-0.30
	(1.48)	(-2.82)	(0.96)	(-1.78)	(1.65)	(-3.31)	(0.91)	(-2.17)
RMW	-0.09	-0.17	-0.04	-0.12	-0.01	-0.24	0.04	-0.19
	(-0.44)	(-1.22)	(-0.19)	(-0.90)	(-0.08)	(-2.01)	(0.22)	(-1.73)
CMA	0.13	-0.13	0.04	0.00	0.19	-0.31	0.02	-0.13
	(0.67)	(-1.07)	(0.22)	(-0.02)	(1.10)	(-3.02)	(0.14)	(-1.15)
IA	0.06	-0.43	-0.03	-0.28	0.20	-0.53	0.05	-0.34
	(0.26)	(-3.05)	(-0.14)	(-1.92)	(0.96)	(-4.05)	(0.24)	(-2.45)
ROE	-0.41	-0.57	-0.22	-0.53	-0.26	-0.39	-0.05	-0.34
	(-1.82)	(-3.87)	(-1.04)	(-3.54)	(-1.23)	(-2.90)	(-0.27)	(-2.47)
PMU	0.05	-0.45	0.06	-0.47	-0.01	-0.41	0.03	-0.46
	(0.22)	(-3.09)	(0.29)	(-3.21)	(-0.07)	(-3.14)	(0.20)	(-3.49)
QMJ	-0.11	-0.42	-0.01	-0.15	-0.06	-0.55	0.04	-0.33
	(-0.43)	(-2.15)	(-0.06)	(-0.84)	(-0.29)	(-3.63)	(0.24)	(-2.50)
MOM	-0.29	-0.37	-0.26	-0.37	-0.27	-0.25	-0.20	-0.29
	(-1.54)	(-3.72)	(-1.53)	(-3.26)	(-1.52)	(-2.80)	(-1.25)	(-2.69)
MGMT	-0.04	-0.68	-0.02	-0.53	0.01	-0.78	-0.07	-0.61
	(-0.18)	(-3.55)	(-0.08)	(-2.96)	(0.04)	(-5.31)	(-0.34)	(-4.17)
PERF	-0.49	-0.54	-0.41	-0.61	-0.35	-0.46	-0.25	-0.55
	(-2.84)	(-6.18)	(-2.54)	(-6.39)	(-2.25)	(-6.09)	(-1.82)	(-6.47)
FIN	0.10	-0.53	0.04	-0.39	0.25	-0.74	0.13	-0.60
	(0.40)	(-2.72)	(0.20)	(-2.06)	(1.13)	(-4.40)	(0.61)	(-3.43)
PEAD	-0.31	-0.42	-0.19	-0.54	-0.28	-0.37	-0.14	-0.51
	(-1.37)	(-6.01)	(-0.87)	(-5.83)	(-1.39)	(-5.74)	(-0.71)	(-5.78)
Ave	-0.09	-0.42	-0.06	-0.34	-0.04	-0.44	-0.03	-0.38
	(-0.98)	(-5.94)	(-0.62)	(-3.97)	(-0.51)	(-7.69)	(-0.31)	(-5.51)

Table IA3: Beta-sorted portfolios, subperiod analysis

This table reports the subperiod results for Decile 10-minus-Decile 1 (H-L) portfolios sorted by factor betas, which are estimated from a two-factor model (including the market factor and the corresponding characteristics-based factor) using returns over the past 60 months with a minimum of 36 months. $\beta^{ex\ post}$ refers to the H-L portfolios' ex post betas w.r.t. a two-factor model including the market factor and the corresponding characteristics-based factor. R^{ex} refers to monthly excess returns. $\alpha^{two-factor}$ refers to monthly two-factor model (including the market factor and a characteristics-based factor) adjusted alphas. R^{char} refers to monthly characteristics-adjusted returns. Diff_1 is the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics-adjusted returns. Diff_2 is the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics-adjusted returns. The details for benchmark portfolios are defined in Table 3. Portfolios sorted by SMB, HML, RMW, CMA, IA, QMJ, and FIN betas are rebalanced at the end of each June, and portfolios sorted by ROE, MOM, MGMT, PERF, and PEAD betas are rebalanced each month. Ave refers to the average across all beta-sorted portfolios. The sample period is from 1975:1 to 1996:12 for IA and ROE, 1975:7 to 1996:12 for FIN and PEAD, and 1966:7 to 1991:12 for others in Panel A, and is from 1997:1 to 2016:12 for IA, ROE, FIN and PEAD, and 1992:1 to 2016:12 for others in Panel B. Returns and alphas are in percentages. Newey-West 4-lag adjusted t-statistics are reported in parentheses.

Panel A: early subsample						
	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	1.73	0.09	-0.40	-0.11	-0.29	
	(22.14)	(0.23)	(-2.66)	(-0.49)	(-1.57)	
HML	1.07	0.68	0.20	0.45	-0.25	-0.11
	(8.33)	(2.74)	(0.86)	(2.58)	(-2.29)	(-0.84)
RMW	1.37	-0.11	-0.32	-0.23	-0.09	-0.11
	(9.53)	(-0.45)	(-1.64)	(-1.17)	(-1.07)	(-1.28)
CMA	1.40	0.55	0.12	0.40	-0.27	-0.12
	(8.81)	(2.05)	(0.53)	(1.86)	(-2.21)	(-0.89)
IA	1.45	0.55	-0.05	0.43	-0.48	-0.32
	(5.52)	(1.92)	(-0.15)	(1.75)	(-3.89)	(-2.39)
ROE	1.22	-0.57	-1.22	-0.63	-0.59	-0.65
	(4.51)	(-1.83)	(-3.42)	(-2.34)	(-4.63)	(-4.90)
PMU	1.70	-0.13	-0.52	-0.27	-0.25	-0.29
	(15.04)	(-0.35)	(-2.48)	(-1.02)	(-1.33)	(-1.50)
QMJ	2.11	0.04	-0.84	-0.07	-0.77	-0.49
	(14.06)	(0.14)	(-3.71)	(-0.29)	(-4.71)	(-3.74)
MOM	0.55	0.00	-0.42	-0.10	-0.32	-0.27
	(2.77)	(0.00)	(-1.12)	(-0.41)	(-2.58)	(-1.90)
MGMT	1.18	0.49	-0.20	0.30	-0.50	-0.37
	(10.03)	(1.63)	(-0.92)	(1.28)	(-3.44)	(-2.32)
PERF	0.78	-0.32	-0.90	-0.50	-0.40	-0.48
	(5.50)	(-1.16)	(-3.60)	(-2.48)	(-4.14)	(-4.54)
FIN	0.86	0.59	-0.17	0.47	-0.64	-0.47
	(7.25)	(1.99)	(-0.55)	(1.79)	(-4.53)	(-2.85)
PEAD	0.33	-0.26	-0.48	-0.25	-0.24	-0.34
	(1.45)	(-0.97)	(-1.49)	(-0.98)	(-4.33)	(-3.10)
Ave	1.1517**	0.07	-0.45	-0.05	-0.39	-0.35
	(18.67)	(0.77)	(-4.95)	(-0.66)	(-8.71)	(-5.90)

Table IA3 (cont.): Beta-sorted portfolios, subperiod analysis

	Panel B: late subsample					
	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	1.38	-0.01	-0.66	-0.12	-0.54	
	(11.92)	(-0.01)	(-2.39)	(-0.34)	(-2.45)	
HML	1.81	0.26	-0.38	0.09	-0.46	-0.45
	(17.73)	(0.61)	(-1.56)	(0.29)	(-1.79)	(-1.74)
RMW	1.59	0.30	-0.18	0.25	-0.43	-0.20
	(16.14)	(0.78)	(-0.58)	(0.75)	(-1.78)	(-0.89)
CMA	1.94	0.08	-0.32	-0.06	-0.26	-0.16
	(6.46)	(0.22)	(-1.06)	(-0.20)	(-1.64)	(-0.92)
IA	2.23	0.02	-0.46	-0.07	-0.39	-0.24
	(7.74)	(0.05)	(-1.31)	(-0.19)	(-1.53)	(-0.97)
ROE	1.41	0.23	-0.01	0.03	-0.03	0.03
	(7.71)	(0.51)	(-0.02)	(0.07)	(-0.14)	(0.11)
PMU	1.72	0.29	-0.34	0.26	-0.60	-0.59
	(11.37)	(0.91)	(-1.25)	(0.98)	(-3.09)	(-3.12)
QMJ	1.71	0.14	-0.42	-0.01	-0.41	-0.20
	(14.12)	(0.34)	(-1.58)	(-0.03)	(-1.55)	(-0.78)
MOM	0.32	-0.59	-0.69	-0.46	-0.24	-0.22
	(2.47)	(-1.76)	(-1.75)	(-1.62)	(-2.03)	(-1.77)
MGMT	1.88	-0.12	-1.24	-0.29	-0.96	-0.75
	(8.59)	(-0.28)	(-3.33)	(-0.78)	(-3.58)	(-2.78)
PERF	0.92	-0.12	-0.77	-0.21	-0.55	-0.66
	(5.50)	(-0.33)	(-2.37)	(-0.79)	(-5.19)	(-5.49)
FIN	1.24	0.10	-0.63	0.03	-0.66	-0.62
	(11.87)	(0.21)	(-1.61)	(0.07)	(-2.03)	(-1.91)
PEAD	0.58	-0.41	-0.74	-0.31	-0.44	-0.44
	(3.09)	(-1.01)	(-1.68)	(-0.84)	(-3.78)	(-3.55)
Ave	1.2486**	0.01	-0.55	-0.08	-0.47	-0.39
	(16.36)	(0.05)	(-4.70)	(-0.56)	(-4.22)	(-2.94)

Table IA4: Beta-sorted portfolios: Estimation with daily returns

This table reports results for the spread portfolio (H-L) between the top and bottom value-weighted decile portfolios sorted by factor betas, which are estimated from a single factor model using daily returns over the previous month with a minimum of 15 days. $\beta^{ex\ post}$ refers to H-L portfolios' ex post betas with respect to a two-factor model including the market factor and a characteristics-based factor. R^{ex} refers to monthly excess returns. $\alpha^{two-factor}$ refers to two-factor model (including the market factor and a characteristics-based factor) adjusted monthly alphas. R^{char} refers to monthly characteristics-adjusted returns. Diff_1 refers to the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics adjusted returns. Diff_2 refers to the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics adjusted returns. The characteristics-adjusted return is the difference between individual stock return and the return of a benchmark portfolio to which it matches. The benchmark portfolios are defined the same way as in Table 3. All portfolios are rebalanced monthly. Ave refers to the average across all beta-sorted portfolios. The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	1.34	-0.59	-0.92	-0.72	-0.20	
	(10.18)	(-2.66)	(-5.23)	(-4.29)	(-2.40)	
HML	1.46	0.07	-0.39	-0.05	-0.34	-0.41
	(12.44)	(0.27)	(-1.80)	(-0.21)	(-2.39)	(-2.57)
RMW	2.00	0.54	0.19	0.47	-0.28	-0.29
	(13.45)	(1.98)	(0.92)	(1.94)	(-1.52)	(-1.62)
CMA	2.05	0.23	-0.38	0.07	-0.45	-0.44
	(13.96)	(0.90)	(-1.86)	(0.33)	(-3.02)	(-2.89)
IA	2.30	0.11	-0.77	-0.06	-0.71	-0.70
	(11.42)	(0.42)	(-3.46)	(-0.26)	(-4.35)	(-4.13)
ROE	1.74	0.89	0.03	0.69	-0.66	-0.65
	(11.39)	(2.93)	(0.14)	(2.81)	(-4.16)	(-3.94)
PMU	1.33	0.43	0.05	0.44	-0.39	-0.32
	(12.43)	(1.67)	(0.20)	(1.98)	(-3.31)	(-2.68)
QMJ	1.83	0.45	-0.13	0.38	-0.51	-0.36
	(10.83)	(1.69)	(-0.60)	(1.64)	(-2.94)	(-2.11)
MOM	1.15	0.44	-0.31	0.26	-0.56	-0.55
	(13.65)	(1.78)	(-1.25)	(1.46)	(-5.20)	(-4.13)
MGMT	1.57	0.37	-0.49	0.19	-0.68	-0.69
	(13.69)	(1.47)	(-2.22)	(0.89)	(-4.10)	(-4.03)
PERF	1.11	0.50	-0.27	0.35	-0.62	-0.70
	(12.86)	(2.21)	(-1.44)	(2.22)	(-5.35)	(-5.39)
FIN	1.31	0.03	-0.48	-0.13	-0.35	-0.37
	(13.19)	(0.10)	(-1.77)	(-0.46)	(-1.69)	(-1.76)
PEAD	1.84	0.30	-0.79	0.24	-1.03	-1.02
	(10.50)	(1.04)	(-2.59)	(0.92)	(-7.26)	(-6.78)
Ave	1.45	0.29	-0.35	0.16	-0.51	-0.53
	(33.02)	(2.26)	(-4.12)	(1.53)	(-6.16)	(-5.63)

Table IA5: Beta-sorted portfolios: Alternative beta estimation

This table reports results for the spread portfolio (H-L) between the top and bottom value-weighted decile portfolios sorted by betas estimated following Frazzini and Pedersen (2014): $\beta_i = \rho \frac{\sigma_i}{\sigma_m}$ where the correlation ρ between the market return and individual stock return is estimated based on overlapping three-day rolling windows over five years, and the standard deviation of individual stock (σ_i) and the market (σ_m) are estimated based on daily return in the one-year rolling window. $\beta^{ex\ post}$ is H-L portfolios' ex post betas with respect to a two-factor model including the market factor and the corresponding characteristics-based factor. R^{ex} refers to monthly excess returns. $\alpha^{two-factor}$ refers to two-factor model (including the market factor and a characteristics-based factor) adjusted monthly alphas. R^{char} refers to monthly characteristics-adjusted returns. Diff_1 is the difference between the two-factor-model (the market factor and a characteristics-based factor) adjusted returns and characteristics-adjusted returns. Diff_2 is the difference between the three-factor-model (the market factor, SMB, and a characteristics-based factor) adjusted returns and size-characteristics adjusted returns. The benchmark portfolios are defined the same way as in Table 3. All portfolios are rebalanced monthly. Ave refers to the average across all beta-sorted portfolios.The sample period is from 1975:1 to 2016:12 for IA and ROE, 1975:7 to 2016:12 for FIN and PEAD, and 1966:7 to 2016:12 for others. Returns and alphas are in percentages. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	$\beta^{ex\ post}$	R^{ex}	$\alpha^{two-factor}$	R^{char}	Diff_1	Diff_2
SMB	1.85	-0.04	-0.70	-0.19	-0.51	
	(20.85)	(-0.12)	(-3.13)	(-0.83)	(-3.52)	
HML	1.65	0.47	0.07	0.28	-0.20	-0.13
	(12.73)	(1.48)	(0.3)	(1.14)	(-1.36)	(-0.87)
RMW	2.15	0.00	-0.39	-0.10	-0.29	-0.29
	(12.93)	(-0.01)	(-1.84)	(-0.40)	(-1.59)	(-1.56)
CMA	1.75	0.23	0.03	0.17	-0.14	-0.01
	(7.95)	(0.81)	(0.14)	(0.75)	(-0.95)	(-0.07)
IA	2.11	0.36	-0.05	0.24	-0.29	-0.20
	(8.53)	(1.13)	(-0.18)	(0.91)	(-1.79)	(-1.13)
ROE	2.27	0.23	-0.80	0.01	-0.81	-0.69
	(14.39)	(0.63)	(-2.38)	(0.03)	(-4.30)	(-3.78)
PMU	1.77	0.05	-0.66	-0.04	-0.62	-0.71
	(14.08)	(0.18)	(-3.19)	(-0.22)	(-4.38)	(-4.79)
QMJ	2.42	0.28	-0.27	0.24	-0.52	-0.35
	(18.39)	(0.83)	(-1.25)	(0.85)	(-2.30)	(-1.68)
MOM	0.69	-0.15	-0.65	-0.15	-0.51	-0.42
	(4.35)	(-0.49)	(-2.28)	(-0.64)	(-5.20)	(-3.93)
MGMT	1.97	0.16	-0.63	0.00	-0.63	-0.55
	(20.11)	(0.50)	(-2.27)	(0.00)	(-2.90)	(-2.53)
PERF	0.89	-0.22	-0.95	-0.39	-0.57	-0.66
	(4.27)	(-0.84)	(-4.51)	(-2.20)	(-6.66)	(-7.03)
FIN	1.60	0.36	-0.16	0.18	-0.34	-0.27
	(18.39)	(0.99)	(-0.65)	(0.64)	(-1.48)	(-1.10)
PEAD	1.03	-0.19	-0.93	-0.08	-0.86	-0.82
	(3.76)	(-0.56)	(-2.62)	(-0.24)	(-10.22)	(-8.34)
Ave	1.52	0.11	-0.47	0.01	-0.48	-0.42
	(20.61)	(0.86)	(-4.33)	(0.07)	(-5.57)	(-4.09)

Our next Table IA6 reports the results based on a broad set of the listed 68 anomalies below. We construct these anomalies and form the portfolios following Hou, Xue, and Zhang (2017).[32] See those studies for details.

1. *Momentum*

   SUE: Earnings surprise (1-month holding period)

   ABR: Cumulative abnormal returns around earnings announcements (1-month holding period)

   RE: Revisions in analysts' earnings forecasts (1-month holding period)

   R6: Price momentum (6-month prior returns, 1-month holding period)

   R11: Price momentum (11-month prior returns, 1-month holding period)

   TES: Tax expense surprise (1-month holding period)

   RS: Revenue surprise (1-month holding period)

   NEI: Number of consecutive quarters with earnings increases (1-month holding period)

2. *Value-versus-growth*

   BM: Book to market equity

   AME: Assets to market

   REV: Reversal (1-month holding period)

   EP: Earnings to price

   EFP: Analysts' earnings forecast to price (1-month holding period)

   CFP: Cash flow to price

   DP: Dividend yield

   OP: Payout yield

   NOP: Net payout yield

   SG: Annual sales growth

   LTG: Long-term growth forecasts of analysts (1-month holding period)

   DUR: Equity duration

3. *Investment*

   ACI: Abnormal corporate investment

   IA: Investment to assets

   NOA: Net operating assets

   Δ PIA: Changes in property, plant and equipment plus changes in inventory scaled by assets

   IG: Investment growth

   NSI: Net stock issues

   CEI: Composite equity issuance

   NXF: Net external finance

   IVG: Inventory growth

   IVC: Inventory changes

   OA: Operating accruals

[32] We categorize these anomalies following Hou, Xue, and Zhang (2017). The classification is slightly different from Stambaugh and Yuan (2017) which follows Hou, Xue, and Zhang (2015). For example, TES, RS, and NEI are in the category of momentum related anomalies in Hou, Xue, and Zhang (2017), while they are in the category of profitability related anomalies in Hou, Xue, and Zhang (2015). DISP is in the category of intangibles related anomalies in Hou, Xue, and Zhang (2017), while it is in the category of trading frictions related anomalies in Hou, Xue, and Zhang (2015).

TA: Total accruals
POA: Percent operating accruals
PTA: Percent total accruals

4. *Profitability*
ROE: Return on equity
ROA: Return on assets
RNA: Return on net operating assets
PM: Profit margin
ATO: Asset turnover
CTO: Capital turnover
GPA: Gross profits-to-assets
FSCORE: Fundamental (F) score
TBI: Taxable income-to-book income
FP: Failure probability
OSCORE: O-score

5. *Intangibles*
IOCA: Industry-adjusted organizational capital-to-assets
BCA: Brand capital-to-assets
ADM: Advertisement expense to market
RDS: R&D-to-sales
RDM: R&D-to-market
RCA: R&D capital-to-assets
HN: Hiring rate
OL: Operating leverage
GIND: Corporate governance
ACCQ: Accrual quality
DISP: Dispersion of analysts'earnings forecast (1-month holding period)

6. *Trading frictions*
ME: Market equity
IVOL: Idiosyncratic volatility per the FF3-factor model (1-month holding period)
RETVOL: Total volatility (1-month holding period)
SVOL: Systematic volatility risk (1-month holding period)
MAXRET: Maximum daily return
β^{FP}: The Frazzini-Pedersen (2014) beta (1-month holding period)
β^{D}: The Dimson (1979) beta (1-month holding period)
SREV: Short-term reversal
TURN: Share turnover (1-month holding period)
PPS: Share price (1-month holding period)
DVOL: Dollar trading volume (1-month holding period)
AMIHUD: Absolute return-to-volume (1-month holding period)

Table IA6: Difference between multi-factor model-adjusted returns and the corresponding characteristics-adjusted returns, 68 anomalies

This table reports the monthly return differences (in percentages) between factor-adjusted returns and characteristics-adjusted returns of the anomaly spreads, which are the long-short spreads from the anomaly portfolios formed within the sample of stocks with price greater than $5. We follow Hou, Xue, and Zhang (2017) to construct the 68 anomalies and form portfolios. We adjust the sign of the underlying anomaly variables so that the long-short portfolio is predicted to have positive spread. FF3 refers to the Fama-French (1993) three-factor model where the corresponding benchmark portfolios are sequentially 5×5 size-BM sorted value-weighted portfolios. CARHART refers to the Fama-French three-factor plus the Carhart (1997) momentum factor model where the corresponding benchmark portfolios are sequentially 2×3×3 size-BM-Ret$_{-2,-12}$ sorted value-weighted portfolios. FF5 refers to the Fama-French five-factor model where the corresponding benchmark portfolios are sequentially 2×2×2×2 size-BM-OP-Inv sorted value-weighted portfolios. Q4 refers to the Hou, Xue, and Zhang (2015) q-factor model where the corresponding benchmark portfolios are sequentially 2×3×3 size-Inv-ROE sorted value-weighted portfolios. M4 refers to the Stambaugh and Yuan (2017) four-factor model where the corresponding benchmark portfolios are sequentially 2×3×3 size-score$_{MGMT}$-score$_{PERF}$ sorted value-weighted portfolios. BF3 refers to the Daniel, Hirshleifer, and Sun (2017) three-factor model where the corresponding benchmark portfolios are sequentially 5×5 FIN-CAR sorted value-weighted portfolios. Average magnitude refers to the average absolute return difference between the factor model adjustment and characteristics adjustment. The sample period is from 1972:1 to 2016:12 for Q4 model, 1972:7 to 2016:12 for BF3 model, and 1963:7 to 2016:12 for other models. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	FF3	CARHART	FF5	Q4	M4	BF3
			Panel A: Momentum			
SUE	0.25	0.06	0.09	-0.09	-0.11	-0.25
	(5.35)	(1.11)	(1.86)	(-1.62)	(-2.40)	(-3.83)
ABR	0.17	-0.01	0.20	0.07	0.01	-0.32
	(3.80)	(-0.14)	(4.37)	(1.53)	(0.24)	(-4.69)
RE	0.34	0.00	0.06	-0.31	-0.24	-0.37
	(4.58)	(0.00)	(0.79)	(-3.45)	(-2.49)	(-4.10)
R6	0.45	-0.33	0.33	-0.21	-0.65	-0.84
	(5.11)	(-3.32)	(4.15)	(-1.91)	(-5.76)	(-6.63)
R11	0.57	-0.24	0.40	-0.24	-0.66	-0.69
	(6.01)	(-2.34)	(4.64)	(-2.00)	(-5.55)	(-5.84)
TES	0.10	0.10	0.05	-0.12	-0.01	-0.12
	(1.39)	(1.43)	(0.58)	(-1.34)	(-0.09)	(-1.06)
RS	0.32	0.28	0.22	0.11	0.20	-0.17
	(5.65)	(4.44)	(3.4)	(1.81)	(3.89)	(-2.81)
NEI	0.16	0.13	0.05	-0.06	0.01	-0.23
	(3.32)	(2.88)	(0.91)	(-1.16)	(0.21)	(-4.39)
			Panel B: Value-versus-growth			
BM	-0.20	-0.29	-0.34	-0.51	-0.52	-0.25
	(-3.31)	(-4.58)	(-4.55)	(-5.36)	(-6.74)	(-2.90)
AME	-0.37	-0.33	-0.41	-0.48	-0.44	-0.30
	(-4.62)	(-4.16)	(-4.24)	(-5.31)	(-6.48)	(-3.17)
REV	-0.15	-0.17	-0.24	-0.22	-0.50	0.08
	(-2.21)	(-2.29)	(-3.52)	(-2.82)	(-7.06)	(1.34)
EP	0.02	0.00	-0.18	-0.08	-0.33	-0.27
	(0.26)	(0.01)	(-1.86)	(-0.87)	(-4.01)	(-2.46)

	FF3	CARHART	FF5	Q4	M4	BF3
			Panel B: Value-versus-growth			
EFP	0.09	0.21	-0.18	-0.06	0.12	0.04
	(0.93)	(2.13)	(-1.66)	(-0.76)	(1.32)	(0.40)
CFP	-0.17	-0.19	-0.23	-0.22	-0.32	-0.11
	(-2.57)	(-3.00)	(-3.13)	(-2.74)	(-5.09)	(-1.51)
DP	-0.03	-0.02	-0.09	0.12	-0.15	0.10
	(-0.28)	(-0.16)	(-0.89)	(0.93)	(-1.38)	(0.79)
OP	0.07	0.01	-0.05	0.04	-0.21	0.05
	(0.81)	(0.09)	(-0.66)	(0.49)	(-2.51)	(0.72)
NOP	0.02	0.00	-0.44	-0.15	-0.39	-0.29
	(0.24)	(0.03)	(-5.24)	(-1.67)	(-4.57)	(-3.58)
SG	-0.09	-0.14	-0.22	-0.17	-0.25	-0.04
	(-1.50)	(-2.10)	(-3.56)	(-2.82)	(-5.26)	(-0.77)
LTG	0.19	0.19	-0.10	-0.08	-0.18	-0.05
	(1.15)	(1.20)	(-0.58)	(-0.44)	(-0.96)	(-0.24)
DUR	-0.21	-0.25	-0.26	-0.31	-0.43	-0.16
	(-2.90)	(-3.52)	(-3.03)	(-3.74)	(-6.12)	(-2.13)
			Panel C: Investment			
ACI	0.12	0.01	0.16	0.04	0.00	0.00
	(2.52)	(0.12)	(3.32)	(0.78)	(-0.07)	(-0.01)
IA	0.07	-0.05	-0.14	-0.09	-0.23	-0.13
	(1.26)	(-0.74)	(-2.71)	(-1.57)	(-4.82)	(-2.60)
NOA	0.03	0.00	0.09	0.18	0.01	0.01
	(0.66)	(-0.02)	(1.78)	(2.65)	(0.23)	(0.16)
Δ PIA	0.05	-0.06	0.00	-0.04	-0.19	-0.13
	(1.00)	(-1.01)	(0.09)	(-0.62)	(-4.34)	(-2.48)
IG	0.08	-0.05	-0.04	-0.16	-0.14	-0.15
	(2.15)	(-1.11)	(-1.20)	(-3.63)	(-4.55)	(-3.32)
NSI	0.15	0.03	-0.09	0.00	-0.17	-0.03
	(2.66)	(0.47)	(-1.76)	(0.02)	(-3.7)	(-0.42)
CEI	0.18	0.11	0.03	0.13	0.04	0.04
	(2.77)	(1.76)	(0.65)	(2.60)	(0.82)	(0.72)
NXF	0.15	0.09	-0.06	0.10	-0.11	-0.11
	(1.61)	(0.96)	(-0.89)	(1.71)	(-1.65)	(-1.28)
IVG	0.00	-0.06	-0.14	-0.13	-0.27	-0.13
	(0.08)	(-0.89)	(-3.16)	(-2.71)	(-6.49)	(-2.90)
IVC	0.07	0.02	0.11	0.08	-0.09	0.06
	(1.32)	(0.33)	(2.31)	(1.72)	(-1.91)	(1.24)
OA	0.16	0.15	0.34	0.38	0.19	0.17
	(3.03)	(2.81)	(5.83)	(7.73)	(4.14)	(2.94)
TA	0.00	-0.08	-0.10	-0.15	-0.28	-0.12
	(-0.05)	(-1.36)	(-1.84)	(-2.47)	(-5.62)	(-2.48)
POA	0.12	0.01	0.00	-0.01	-0.10	-0.09
	(2.42)	(0.17)	(0.01)	(-0.19)	(-2.02)	(-1.4)
PTA	0.05	0.06	-0.09	0.04	-0.06	-0.08
	(0.71)	(0.85)	(-1.40)	(0.54)	(-1.18)	(-1.37)

	FF3	CARHART	FF5	Q4	M4	BF3
			Panel D: Profitability			
ROE	0.23	0.10	-0.15	-0.21	-0.16	-0.37
	(2.39)	(0.94)	(-1.60)	(-2.45)	(-2.12)	(-4.11)
ROA	0.19	0.07	-0.10	-0.09	-0.09	-0.32
	(2.22)	(0.74)	(-1.05)	(-1.11)	(-1.25)	(-4.27)
RNA	0.16	0.13	0.03	0.26	0.19	-0.16
	(2.13)	(1.68)	(0.44)	(3.54)	(2.74)	(-2.55)
PM	0.11	0.17	0.01	0.16	0.15	-0.14
	(1.32)	(1.90)	(0.10)	(1.72)	(1.53)	(-1.67)
ATO	0.05	0.06	0.05	0.17	0.12	-0.03
	(0.69)	(0.82)	(0.59)	(2.08)	(1.56)	(-0.32)
CTO	0.18	0.11	0.09	0.14	0.06	0.12
	(3.30)	(1.75)	(1.37)	(2.08)	(1.02)	(1.62)
GPA	0.34	0.20	0.19	0.23	0.10	0.07
	(4.83)	(2.86)	(2.63)	(3.79)	(2.15)	(1.11)
FSCORE	0.06	0.07	-0.09	-0.01	-0.04	-0.02
	(0.56)	(0.60)	(-0.73)	(-0.13)	(-0.40)	(-0.16)
TBI	0.15	0.11	0.02	0.05	0.02	0.07
	(2.75)	(1.84)	(0.32)	(1.28)	(0.49)	(1.38)
FP	0.53	0.11	0.04	-0.08	-0.34	-0.37
	(3.36)	(0.66)	(0.23)	(-0.50)	(-2.29)	(-2.65)
OSCORE	0.14	0.20	0.04	0.25	0.28	-0.04
	(2.58)	(3.25)	(0.61)	(3.88)	(4.58)	(-0.67)
			Panel E: Intangibles			
IOCA	0.13	-0.03	-0.04	-0.17	-0.07	-0.20
	(1.88)	(-0.50)	(-0.74)	(-2.53)	(-1.51)	(-3.18)
BCA	0.29	0.19	0.04	0.20	0.05	0.09
	(2.81)	(2.05)	(0.47)	(3.02)	(0.72)	(1.53)
ADM	-0.07	-0.09	-0.42	-0.41	-0.37	-0.13
	(-0.79)	(-0.86)	(-4.60)	(-4.55)	(-4.45)	(-1.31)
RDS	0.02	0.12	0.49	0.46	0.28	0.25
	(0.22)	(1.06)	(3.58)	(4.03)	(2.78)	(1.94)
RDM	-0.13	-0.18	0.06	0.02	-0.46	0.14
	(-1.17)	(-1.62)	(0.47)	(0.16)	(-4.89)	(1.34)
RCA	0.15	0.16	0.38	0.22	0.10	0.19
	(1.76)	(1.59)	(3.13)	(2.22)	(1.10)	(1.46)
HN	0.01	-0.13	-0.18	-0.20	-0.26	-0.09
	(0.30)	(-2.07)	(-3.31)	(-3.55)	(-5.98)	(-1.70)
OL	0.17	0.14	0.02	0.06	-0.02	0.05
	(3.05)	(2.52)	(0.36)	(0.95)	(-0.36)	(0.68)
GIND	-0.06	-0.12	-0.17	-0.19	0.00	0.06
	(-0.57)	(-1.23)	(-1.64)	(-2.12)	(0.00)	(0.46)
ACCQ	0.20	0.10	0.05	-0.22	-0.09	-0.30
	(2.21)	(1.10)	(0.40)	(-1.95)	(-0.84)	(-2.61)
DISP	0.44	0.32	-0.06	-0.07	0.11	-0.14
	(3.41)	(2.44)	(-0.44)	(-0.61)	(0.89)	(-1.37)

	FF3	CARHART	FF5	Q4	M4	BF3
			Panel F: Trading frictions			
ME	-0.14	-0.17	-0.17	-0.12	-0.18	0.18
	(-2.35)	(-3.89)	(-4.21)	(-2.24)	(-4.48)	(3.58)
IVOL	0.27	0.09	-0.10	-0.18	-0.28	-0.51
	(2.00)	(0.66)	(-0.71)	(-1.14)	(-1.93)	(-3.08)
RETVOL	0.30	0.10	-0.10	-0.12	-0.26	-0.44
	(1.80)	(0.62)	(-0.59)	(-0.63)	(-1.57)	(-2.15)
SVOL	0.07	0.12	-0.21	-0.18	0.04	-0.14
	(0.87)	(1.48)	(-2.48)	(-2.17)	(0.44)	(-1.73)
MAXRET	0.18	0.05	-0.18	-0.14	-0.24	-0.33
	(1.39)	(0.35)	(-1.25)	(-0.93)	(-1.72)	(-2.09)
β^{FP}	0.49	0.29	0.24	0.11	-0.03	-0.15
	(2.57)	(1.70)	(1.27)	(0.52)	(-0.18)	(-0.75)
β^{D}	0.34	0.16	0.08	0.13	-0.09	-0.14
	(2.65)	(1.35)	(0.67)	(1.04)	(-0.68)	(-1.02)
SREV	-0.50	-0.23	-0.51	-0.28	-0.04	0.34
	(-6.27)	(-2.16)	(-6.83)	(-3.38)	(-0.48)	(3.24)
TURN	-0.24	-0.25	0.16	0.02	0.07	0.09
	(-1.45)	(-1.65)	(0.95)	(0.11)	(0.44)	(0.54)
PPS	-0.49	-0.28	-0.38	-0.28	-0.23	0.34
	(-6.33)	(-3.02)	(-4.00)	(-2.86)	(-2.53)	(3.42)
DVOL	0.03	-0.02	-0.09	-0.02	-0.14	0.16
	(0.30)	(-0.32)	(-1.41)	(-0.24)	(-2.24)	(2.64)
AMIHUD	-0.07	-0.13	-0.11	-0.08	-0.24	0.10
	(-1.22)	(-2.93)	(-2.69)	(-1.37)	(-4.96)	(2.30)
Average magnitude	0.18	0.12	0.16	0.16	0.19	0.19
	(4.96)	(4.29)	(5.31)	(5.95)	(6.38)	(4.93)

Table IA7: Difference between multi-factor model-adjusted returns and the corresponding characteristics-adjusted returns, 12 anomalies, alternative characteristics-adjusted returns definitions

This table reports the monthly return differences (in percentages) between factor-adjusted returns and characteristics-adjusted returns of the anomaly spreads, which are the long-short spreads between the top and the bottom decile portfolios sorted by each underlying anomaly measure using NYSE breakpoints with share price greater than \$5. We consider 12 anomalies including the 11 anomalies underlying the mispricing score of Stambaugh and Yuan (2017), as well as the book-to-market equity. We adjust the sign of the underlying anomaly variables so that the long-short portfolio is predicted to have positive spread. FF3 refers to the Fama-French (1993) three-factor model where the corresponding benchmark portfolios are sequentially 10×10 size-BM sorted value-weighted portfolios. CARHART refers to the Fama-French three-factor plus the Carhart (1997) momentum factor model where the corresponding benchmark portfolios are sequentially 5×5×5 size-BM-Ret$_{-2,-12}$ sorted value-weighted portfolios. FF5 refers to the Fama-French five-factor model where the corresponding benchmark portfolios are sequentially 3×3×3×3 size-BM-OP-Inv sorted value-weighted portfolios. Q4 refers to the Hou, Xue, and Zhang (2015) q-factor model where the corresponding benchmark portfolios are sequentially 5×5×5 size-Inv-ROE sorted value-weighted portfolios. M4 refers to the Stambaugh and Yuan (2017) four-factor model where the corresponding benchmark portfolios are sequentially 5×5×5 size-score$_{MGMT}$-score$_{PERF}$ sorted value-weighted portfolios. BF3 refers to the Daniel, Hirshleifer, and Sun (2017) three-factor model where the corresponding benchmark portfolios are sequentially 10×10 FIN-CAR sorted value-weighted portfolios. Average magnitude refers to the average absolute return difference between the factor model adjustment and characteristics adjustment. The sample period is from 1972:1 to 2016:12 for Q4 model, 1972:7 to 2016:12 for BF3 model, and 1963:7 to 2016:12 for other models. Newey-West 5-lag adjusted t-statistics are reported in parentheses.

	FF3	CARHART	FF5	Q4	M4	BF3
Distress	0.59	0.16	0.11	-0.06	-0.22	-0.37
	(3.81)	(1.14)	(0.68)	(-0.47)	(-1.81)	(-2.69)
O-score	0.17	0.17	0.07	0.20	0.32	-0.04
	(2.84)	(2.58)	(1.37)	(3.38)	(4.81)	(-0.54)
Net Stock issues	0.19	0.15	-0.02	0.04	0.04	0.19
	(3.07)	(2.24)	(-0.33)	(0.64)	(0.60)	(2.06)
Composite equity issues	0.21	0.15	0.11	0.19	0.08	0.12
	(3.19)	(2.22)	(1.91)	(3.44)	(1.44)	(1.64)
Accruals	0.19	0.16	0.33	0.24	0.03	0.13
	(2.98)	(2.40)	(4.52)	(4.12)	(0.42)	(1.70)
Net operating assets	0.07	0.11	0.16	0.21	0.12	0.12
	(1.56)	(1.70)	(2.40)	(2.62)	(1.53)	(1.63)
Momentum	0.67	0.00	0.55	-0.11	-0.51	-0.53
	(6.72)	(0.04)	(5.25)	(-0.83)	(-4.39)	(-4.44)
Gross Profitability	0.41	0.20	0.20	0.25	0.17	0.14
	(5.35)	(2.68)	(2.84)	(3.45)	(2.92)	(1.82)
Asset growth	0.11	0.02	-0.05	0.00	-0.12	-0.02
	(1.79)	(0.35)	(-0.98)	(-0.07)	(-2.22)	(-0.36)
Return on assets	0.23	0.08	-0.07	-0.01	0.00	-0.25
	(2.46)	(0.86)	(-0.8)	(-0.08)	(0.01)	(-2.61)
Investment to assets	0.09	-0.01	0.05	0.04	-0.04	-0.04
	(1.60)	(-0.21)	(0.94)	(0.60)	(-0.86)	(-0.53)
Book to market	-0.18	-0.21	-0.27	-0.38	-0.43	-0.15
	(-2.52)	(-3.08)	(-3.84)	(-3.98)	(-5.33)	(-1.50)
Average magnitude	0.26	0.12	0.18	0.15	0.18	0.17
	(6.88)	(3.46)	(5.95)	(4.78)	(5.90)	(5.58)