FIRM CHARACTERISTICS AND LOW BETA ANOMALY

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First version: September 2015
This version: January 2015

ABSTRACT

Previous studies have shown that expected returns can be explained by risk factors and non-risk firm characteristics. Following this line of research, we propose firm characteristics to explain low beta anomaly, where low beta stocks tend to outperform high beta stocks. Our univariate analysis presents monotonic relations between beta assets and firm characteristics characterized by Qscore, Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, Distress, and Jackpot. Bivariate sort portfolios based on firm characteristics and market beta show insignificant differences in performance between the highest and lowest beta portfolios. Characteristic adjusted returns are higher in high beta stocks than low beta stocks, indicating that adjusting for firm characteristics steepens the security market line. Controlling for aggregate firm characteristics, low beta anomaly and risk-adjusted returns on the betting-against-beta (BAB) factor disappears, suggesting a time-varying pattern associated with firm characteristics to the low beta anomaly. Overall, our results imply that low beta anomaly may be induced by systematic mispricing resulted from firm attributes, and reflect investor preferences for firm characteristics that deviate from the CAPM.

Keywords: Beta, Stock Return Anomalies, Lottery Preference, Distress, Characteristics

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I. Introduction

THE RELATIONSHIP BETWEEN MARKET BETAS AND EXPECTED RETURNS is linear under Capital Asset Pricing Model (CAPM, Sharpe (1964) and Lintner (1965)), suggesting that high-beta stocks should earn higher expected returns than low-beta stocks. However, empirical security market line (SML) is flatter than theoretical security market line, and thus an arbitrage opportunity to generate abnormal profits arises by buying low-beta stocks and selling high-beta stocks. This so-called low beta anomaly is well documented in the literature (e.g. Baker, Bradley, and Wurgler (2011)).

Recent studies have relied on exogenous causes to explain low beta anomaly. Frazzini and Pedersen (2014) propose that leverage and margin constraints lead to overweighting risky securities. Antoniou, Doukas, and Subrahmanyam (2015) hypothesize that increased noise trading during optimistic periods pushes up the stock prices of high-beta stocks, and thus, their subsequent returns are lower. Hong and Sraer (2014) use investor disagreement about the market (market uncertainty) and short-sale constraints to explain why high beta stocks are over-priced. Huang, Lou, and Polk (2014) conclude that high beta-arbitrage activity induces larger abnormal returns from betting on the flatter security market line, but the returns revert in the long run. Bai, Hou, Kung, and Zhang (2015) explain the low beta anomaly by introducing disasters in an investment model with disasters. Bali, Brown, Murray, and Tang (2014) argue that demand for high beta stocks simply reflects demand for the lottery characteristics of stocks.

In this paper, we examine how investor preferences and behavior towards firm characteristics explain low beta anomaly. Our study is motivated by a large amount of research that has been conducted to understand the relationship between firm characteristics and the cross-sectional variation in stock returns, both in theory and empirical work. Berk, Green, and Naik (1999) develop a partial equilibrium model to explain the relation between book-to-market, market value, and return by channeling changes in a firm's assets in place and growth options to changes in a firm's systematic risk in predictable ways. Extending the work of Berk, Green, and Naik, Gomes, Kogan, and Zhang (2003) construct a general equilibrium model in which size and book-to-market are correlated with mismeasurement of true market betas. Lee and Swaminathan (2000) document that trading volume predicts momentum, and firms with high trading volume exhibit glamour characteristics and earn lower future returns. Daniel and Titman (1997) argue that size and value premiums are driven by firm characteristics rather than the comovement of these stocks with common factors. Behavioral finance theories (e.g. Barberis and Shleifer (2003)) suggest that because style investors tilt towards stocks with certain characteristics, stocks with similar characteristics tend to commove together, and thus, firm characteristics might induce another systemic factor. Brennan, Chordia, and Subrahmanyam (1998) and Avramov and Chordia (2006) regress risk-adjusted individual stock returns on firm characteristics and conclude that non-risk firm characteristics have marginal explanatory power for returns relative to chosen benchmarks. Ferson and Harvey (1998) explore this line of research within an international context.

We examine firm characteristics that have been demonstrated to predict future returns in the literature. [1] We find that high beta firms display growth potential in terms of higher intangibles, R&D expenses, and growth options, suggesting that investing in high beta firms possibly generate lottery-like returns. In addition, high beta firms are younger and more distressed, display more extreme bets on systematic factors, and exhibit positively skewed returns. The

[1] The firm characteristics and their classifications are detailed in Appendix A.

level of skewness decreases monotonically from the high beta portfolio to the low beta portfolio. These results are robust to adjusting for industry effect.

We select firm characteristics that predict distress and lottery-like returns to investigate whether high beta firms are more likely to default and generate extreme positive returns. Campbell, Hilscher, and Szilagyi (2008) identify variables that predict default probabilities and show that high distressed stocks earn low subsequent returns. Chen, Hong, and Stein (2001) and Boyer, Mitton, and Vorkink (2010) indicate variables that predict lottery-like returns. Conrad, Kapadia, and Xing (2014) relate these two lines of research and show that firms with a high probability of default also tend to have a high probability of lottery-like returns, and thus, high distressed firms earn low future returns because they exhibit characteristics that predict positive skewness in returns. We find that high beta firms are more likely to be distressed and generate extremely large returns.

Our results on the relationship between beta portfolios and lottery-like returns also provide supporting evidence to Bali, Brown, Murray, and Tang (2014) without resorting to a proxy for lottery preference. They show that high beta stocks covary the most with MAX, defined as the average of the five highest daily returns of the given stock in a given month (Bali et al. (2011)). We find that the stock characteristics that predict future skewness show that high beta firms have higher jackpot probabilities, which predict lower returns, and the probabilities of jackpot returns decrease monotonically from highest to lowest beta firms. Moreover, what differentiates their paper from ours is that in addition to firm characteristics that infer positive skeweness, we link a more extensive list of firm characteristics to low beta anomaly. Therefore, our results indicate that investor preferences towards particular firm characteristics drive up (down) the prices in high (low) beta stocks, leading to the flat security market line, not just limited to preferences for lottery-like returns.

Following Jegadeesh, Kim, Krische, and Lee (2004), we group similar firm characteristics into the following categories: QScore, Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, Distress, Jackpot, and All.[2] This aggregation allows us to reduce the dimension of the firm characteristics and to sort firms based on firm characteristics independent of one another. We use these firm characteristic categories to perform dependent and independent double sorting. For instance, we first sort stocks by QScore and then beta to form portfolios. After controlling for firm characteristics, the return differential between the high and low beta firms turn to either insignificance or positive significance. This result holds for all firm characteristic categories.

Next, we construct aggregate time series for each firm characteristic category, and interact with the constant term in the CAPM regression.[3] These series can be used to signal the state of the economy as they predict future returns. For example, during the periods with relative high aggregate market value, stock returns are relatively lower on average. Conditioning the CAPM alpha on aggregate firm characteristics captures firm characteristics in the economy over time, which yields time variation in returns. We find that controlling for aggregate firm characteristics,

[2] Aggregating firm characteristics does not necessarily suggest that beta-arbitrage trading strategy is anchored (Stein (2009)) or time invariant (Huang, Lou, and Polk (2014)). An anchored trading strategy is one that bases its demand on the estimate of fundamental value. Even if arbitrageurs are able to use intrinsic firm value to predict future returns and allocate arbitrage capital accordingly, because the spread between two extreme portfolios formed based on firm characteristic categories may not have predictive power due to correlated multiple signals in the same category, there might be some periods crowded with beta arbitrage activities destabilizing prices.

[3] One might argue that firm characteristics may be correlated with factor loadings, and therefore, we should condition market beta on aggregate firm characteristics. However, this is debatable since there is no evidence proving that such conditioning would improve the model in a significant way and mispricings from firm characteristics may be completely uncorrelated with risk. Our results show that conditioning the CAPM alpha on aggregate firm characteristics is sufficient to explain low beta anomaly. In addition, we assume that expected return variation can be captured by non-risk firm characteristics and risky factors independently as in Daniel and Titman (1997) and Chordia, Goyal, and Shanken (2013).

the low beta anomaly disappears. The other aggregate firm characteristic measure is attribute spreads, calculated as the difference in firm characteristic categories between the high and low beta portfolios. The results are slightly weaker because only five out of eight categories yield insignificant alpha, but the t-statistics on alpha are all reduced after controlling for attribute spreads. Furthermore, as Frazzini and Pedersen (2014) argue that leverage plays an important role in beta-arbitrage strategies, we find consistent results when examining the returns of the BAB factor adjusted for common factors and our aggregate firm characteristic measures. These findings imply that low beta anomaly could be a result of missing the time-varying systematic mispricing associated with firm attributes.

We also find that low beta anomaly is more prevalent in firms that are harder to arbitrage. Small firms and firms with low institutional ownership and analyst following show significant differentials in returns between high and low beta portfolios. However, since size and institutional ownership or analyst coverage correlate, our novel finding is that forming portfolios based on institutional ownership or analyst following orthogonalized by size do not support the argument of limit to arbitrage. The four and five factor alphas between the high and low beta portfolios are insignificant in these portfolios. This result deserves more research in the future as it challenges arbitrage related arguments to explain low beta anomaly.

The remainder of the paper is organized as follows. Section II explains how we aggregate firm characteristics and construct characteristic adjusted returns. Section III provides data and variable descriptions. Section IV presents empirical results. Section V concludes.

II. Methodology

We examine fifty seven individual firm characteristic variables that have been documented with explanatory power to predict future returns in the literature.[4] Appendix A outlines each firm characteristic variable. The large number of firm characteristic variables reduces the degrees of freedom in estimation, and the results will thus be biased towards firms with data available in all characteristic variables. Therefore, to reduce the dimension of firm characteristic variables, in some tables (Table VI, VII, and VIII), we rely on aggregate firm characteristics.

To combine firm characteristic signals, following Jegadeesh, Kim, Krische, and Lee (2004), we construct 10 summary quantitative measures based on firm level characteristic variables.[5] We first create a binary dummy for each firm characteristic variable. For variables that are expected to be positively (negatively) related with future returns, we assign a value of one if its value is higher (lower) than its median value in a given quarter, and zero otherwise. To determine the sign of each firm characteristic variable, we follow the findings in previous studies. For each stock, we then aggregate binary dummies in each firm characteristic category.

We follow Brennan, Chorida, and Subrahmanyam (1998) and Avramov and Chordia (2006) to consider the following equation to incorporate non-risk firm characteristics into asset pricing models to explain stock returns:[6]

[4] See Jegadeesh, Kim, Krische, and Lee (2004), Gupta-Mukherjee (2012), Aaker and Jacobson (1987), Miller and Bromiley (1990), Rajan (2000), Cao, Simin, and Zhao (2008), Bar, Kempf, and Ruenzi (2011), Hirshleifer and Jiang (2010), Campbell, Hilscher, and Szilagyi (2008), and Conrad, Kapadia, and xing (2014).

[5] Note that some of the variables in QScore overlap with those in Momentum and Contrarian. To avoid multicollinearity issues in regressions, we drop Momentum and Contrarian. ALL also excludes Momentum and Contrarian.

[6] We assume that non-risk firm characteristics have explanatory power relative to benchmark models at the portfolio level.

$$E_t(R_{pt+1}) - RF_{t+1} = a_p + \sum_{k=1}^{K} \beta_{pt} F_{kt+1} + \sum_{m=1}^{M} C_{mt+1} Z_{mpt} \tag{1}$$

where E_t denotes conditional expectation, R_{pt+1} is the return on portfolio *p* at time *t+1*, RF_{t+1} is the risk free rate at time *t+1*, Z_{mpt} is the value of characteristic *m* for portfolio *p* at time *t* , C_{mt+1} is the cross-sectional regression estimator for portfolio *p* at time *t+1*. In the case of CAPM, *K*, the number of factors, is equal to one.

To estimate *Ct*, we follow Brennan, Chorida, and Subrahmanyam and Avramov and Chordia to regress risk-adjusted returns on firm characteristic categories to derive the time-series of cross-sectional regression coefficient estimators. Then we calculate characteristic-adjusted returns (CAR_{pt+1}) at time *t+1* as the following:

$$CAR_{pt+1} = R_{pt+1} - RF_{t+1} - \sum_{m=1}^{M} Z_{mpt} C_{mt+1} \tag{2}$$

where R_{pt+1} is the return on portfolio *p* at time *t+1*, RF_{t+1} is the risk free rate at time *t+1*, Z_{mpt} is the value of characteristic *m* for portfolio *p* at time *t* , C_{mt+1} is the cross-sectional regression estimator for portfolio *p* at time *t+1*.

To examine how aggregate firm characteristics affect low beta anomaly, we extend equation (1) to model the differential returns between the high and low beta portfolios as follows:

$$R_{Ht+1} - R_{Lt+1} = \alpha + \sum_{k=1}^{K} \beta_{HLt} F_{kt+1} + \sum_{m=1}^{M} C_{mt+1} Z_{mHLt} + e_{HLt+1} \tag{3}$$

where R_{Ht+1} (R_{Lt+1}) is the return on the high (low) beta portfolio at time *t+1*, F_{kt+1} is the sum of the factor innovation and its corresponding risk premium, β_{HLt} is the factor loading of the high-minus-low beta portfolio on factor k, Z_{mHLt} is the value of characteristic *m* for the high-minus-low beta portfolio, C_{mt+1} is the premium associated with characteristic *m* or a spread portfolio sorted on attribute m.

To capture the aggregate firm characteristics for the high-minus-low beta portfolio, we construct two aggregate measures.[7] One measure is the aggregate firm characteristic index, constructed by giving equal weight or value weight to firm characteristic binary dummies across stocks.[8] This is motivated by the predictability of firm characteristics such that at the aggregate level, a high value of firm characteristics represents a state of high future returns in the economy when they are positively correlated. The other measure is the difference in firm characteristics between high and low beta portfolios. Similar to the index, we weight firm characteristics equally or by firm size at the portfolio level. This measure is derived directly from equation (1).

III. Data

We use monthly stock returns from Center for Research in Security Prices (CRSP), balance sheet data from Compustat, and stock analysts' forecasts data from Institutional Broker Estimates System (IBES). Monthly market excess returns and risk factor returns are from Kenneth French's data library.[9] Our sample covers the period from January, 1963 to December, 2013.

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[7] We also employ a third aggregate measure, though less intuitive, which is the attribute-sorted spread. Each month, we use quintile breakpoints to assign each stock to a portfolio based on the specific firm characteristic category. We then create the attribute-sorted spread as the difference of the value-weighted, equal-weighted, or beta-weighted firm characteristic category between the highest firm characteristic portfolio and the lowest firm characteristic portfolio. The results are qualitatively and quantitatively similar to the results based on aggregate firm characteristic indexes.

[8] We also consider the weighting scheme by betas. The results are qualitatively unchanged.

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The first part of our study is to confirm the low-beta anomaly exists in our stock return data. In addition, we present the descriptive statistics of various firm characteristics that display predictive power for the cross-section of stock returns in the literature.

A. The Low Beta Anomaly

For all the stocks in the sample, we estimate betas from running rolling regressions of monthly excess returns on monthly market excess returns using prior 60 monthly returns with a minimum of 12 months. We then assign stocks into quintiles based on pre-ranking betas to form equal-weighted portfolio returns. For each beta portfolio, we regress portfolio excess return on market excess returns and report alpha estimators in Table I. Note that since our sample starts on January, 1963 and we require a minimum of 12 non-missing observations to estimate stock betas, excess returns of five beta portfolios starts on January, 1964.

[Insert Table I here.]

Panel A presents the alphas of five beta portfolios under this screening criterion. The alphas decrease monotonically from the lowest to highest beta quintiles, and the alpha of extreme differences is significant with a t-stat of -2.44. The difference in alpha remains significant at the 1% level across different factor models.

We also estimate alphas across five beta portfolios over a sub-period between August, 1984 and December, 2013 because this is the period that our firm characteristics variables all exist. Our results show that low beta anomaly still exist regardless of which factor models used. While adding factors such as size, value, momentum, and liquidity could reduce the difference in alpha between highest and lowest beta portfolios, they are unable to eliminate it completely. Thus, low beta anomaly is quite robust across different models and time periods.

B. Firm Characteristics

Prior studies have shown that firm characteristics can explain the cross section of stock returns. We include fifty seven firm characteristic variables to examine how their effect on stock returns influences low beta anomaly. Definitions of these variables can be found in Appendix A. Table II shows the average value of these variables across five beta portfolios as well as the difference in means between the high and low beta portfolios.

[Insert Table II here.]

Stocks in the high beta portfolio differ significantly from those in the low beta portfolios for most of the firm characteristic variables. For example, stocks in the high beta portfolio tend to have a smaller size (size), a lower book to price ratio (BP), and a lower earnings to price ratio (EP). We also control for the industry effect by subtracting the industry average weighted by either total assets or sales from each firm characteristic variable because the differences between extreme portfolios may be attributed to possible differences in the industries in which firms are in. The results are qualitatively unchanged. Note that these variables do not predict cross-sectional returns in the same direction. While book to price ratio and earnings to price ratio are positively related to returns (e.g. Basu(1977) and Fama and French (1992)), size is inversely related to returns (e.g. Banz (1981) and Reinganum (1982)). As a result, one could draw opposite conclusions based on the predictive sign of the firm characteristic variable. To control for this, we assess the aggregate effect of these variables on the stock return. We categorize these variables into 10 groups. They are QScore, Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, Distress, Jackpot, and All. Appendix A describes what firm characteristics are included in each category.

IV. Empirical Results

A. Distress Risk and Jackpot Return

Bali, Brown, Murray, and Tang (2014) show that lottery demand explains the low beta anomaly while other measures of firm characteristics and risk fail to explain it. They use MAX, the average of the five highest daily returns of the given stock in a given month, to proxy for lottery demand. Conrad, Kapadia, and Xing (2014) show that firms with a high level of distress risk tend to have a high probability of jackpot returns. Following their results, we should find that stocks in the high beta portfolio are associated with high probabilities of jackpot payoffs and high distress risks. To test this conjecture, we run two logistic regressions to see whether high betas could be explained by variables that predict jackpot return or distress risk. In the first model, following Conrad, Kapadia, and Xing (2014), we regress a dummy variable that equals one if the stock is in the high beta portfolio and zero otherwise on the firm characteristic variables that predict jackpot returns.

[Insert Table III here.]

Panel A of Table III reports the results. All of these variables are statistically significant and their signs are consistent with the prior study, which implies that stocks with high betas tend to have high probabilities of jackpot payoffs. This confirms with Bali, Brown, Murray, and Tang that preference for lottery demand can explain low beta anomaly.

Following Campbell, Hilscher, and Szilagyi (2008), in the second model, we regress the same dummy variable indicating a stock in the high beta portfolio on a set of firm characteristic variables that predict distress. Panel B shows the results from the logistic model. These variables are all significant, indicating that high beta firms share similar characteristics as distressed firms.

Based on our logistic regression results in Table III, we apply estimated coefficients to calculate the implied probability of distress and jackpot returns for each beta portfolio. Every month we calculate both probabilities at the stock level and average them across stocks in each beta portfolio. Table IV reports the time-series averages of the probabilities across five beta portfolios. If a stock is in the low beta portfolio, on average it has 10.98% chance of incurring jackpot returns in the future. In contrast, the probability of jackpot returns increases to 31.43% for a stock in the high beta portfolio. Jackpot probabilities increase monotonically from the low to high beta portfolios, and the difference between extreme portfolios, 20.45%, is statistically significant. These results suggest that high beta stocks are more likely to deliver jackpot returns to investors than low beta stocks. If investors prefer lottery-like returns, their demand for high beta stocks will bid the price up. Our results also support Conrad, Kapadia, and Xing (2014) as high beta stocks tend to have higher distress risks than low beta stocks, and the difference is also statistically significant. In sum, high beta stocks are associated with high probabilities of distress and jackpot returns.

[Insert Table IV here.]

B. Firm Characteristics and Low Beta Anomaly

So far we have established that investor preferences for certain firm characteristics drive the low beta anomaly. Our next step is to examine whether any particular sets of firm characteristic variables, at the aggregate level, can explain the low beta anomaly.

B.1. Bivariate Portfolio Analysis

We first assess the risk-adjusted alphas among five beta portfolios after controlling for each of the 10 firm characteristic categories. Each month, all stocks in the sample are sorted into five groups, based on an ascending sort of one of the firm characteristic categories. For dependent sort, within each control variable group, quintile portfolios based on an ascending sort of beta and a high-minus-low portfolio, which is long the high beta stocks and short the low beta stocks of the same firm characteristic category, are created. For independent sort, quintile portfolios based on an ascending sort of beta and a high-minus-low portfolio, which is long the high beta stocks and short the low beta stocks, are created independent of firm characteristic categories.

[Insert Table V here.]

Table V shows risk-adjusted alphas from high-minus-low beta portfolios after controlling for firm characteristic categories. For the dependent sort, we find risk-adjusted alphas relative to CAPM become insignificant for QScore, Momentum, Contrarian, Extreme, Jackpot, and ALL. After controlling for Distress, alpha becomes significant, but positive. For Operating, Growth, and Misvaluation, the signs of alphas do not alter. However, for Fama and French (1993) and Carhart (1997) four-factor model with or without a liquidity factor by Pastor and Stambaugh

(2003), alphas become either insignificant or significantly positive for all firm characteristic categories. These findings indicate that low beta anomaly would disappear after controlling for seven out 10 firm characteristic categories. When it comes to Fama and French (1993) and Carhart (1997) four-factor model with or without a liquidity factor by Pastor and Stambaugh (2003), all firm characteristic categories explain the low beta anomaly. These results are robust to the independent sort as well.

B.2. Multivariate Analysis

To construct characteristic adjusted returns, we first calculate beta adjusted returns. Every month, we subtract the risk free rate and the multiplication of a stock's beta from the previous month and market excess return, from stock returns. By construction, beta adjusted returns are orthogonal to both risk free rate and risk premium associated with beta. We next run cross-sectional regressions of beta adjusted returns on firm characteristic categories to obtain cross-sectional regression coefficients. Based on these regression estimators, we calculate characteristic adjusted returns by subtracting the characteristic component, which is the sum of each firm characteristic summary measure times its own coefficient, from stock returns.

Panel A of table VI shows that, when we regress characteristic adjusted returns on risk factors, alphas are statistically significant across five beta portfolios. They range from 10.66% to 11.31%. More importantly, alphas in the high-minus-low beta portfolio conditional on risk factors, in particular, Fama French size and value, Carhart momentum, and Pastor-Stambaugh liquidity factors, become positive and significant. For example, the abnormal return in the high-minus-low beta portfolio under Fama and French (1993) and Carhart (1997) four factors plus Pastor and Stambaugh (2003) liquidity factor is 0.55% per month. To further confirm our result, we also conduct the bivariate portfolio analysis based on characteristic adjusted returns. We sort stocks on characteristic adjusted returns to form quintile portfolios, and examine the alpha of the high-minus-low beta portfolio across these portfolios. Panel B reports the average of risk-adjusted alphas. No matter what sorting methods or model specifications we employ, the average alphas in the high-minus-low beta portfolio remain insignificant.

Table VII presents the cross-sectional regression of stock excess returns on betas after controlling firm characteristics. Due to the flat security market line, the loadings on betas should be insignificant. In the cross section, we regress one-month ahead excess returns of all stocks on their betas and firm characteristic categorical measures. Since each firm characteristic category starts with different times, the corresponding baseline model will have different sample sizes. Therefore, we add a baseline model where beta is the only independent variable to see the improvement from controlling firm characteristics. Panel A reports the coefficients on betas with respect to different samples for the baseline model, and Panel B shows the results after controlling for firm characteristic category one at a time. In the baseline model, the coefficients on betas remain insignificant for most cases, except for marginal significance in Extreme. Controlling for firm characteristic categories, our results show that risk premiums associated with betas are significantly positive for Distress, Jackpot, and All, and the coefficients on firm characteristic categories are significant, except for Contrarian and Extreme. A similar test is to use characteristic adjusted returns as the dependent variable while beta is the only independent variable. In Panel C, we show the beta coefficient from the regression of characteristic adjusted returns on betas, whose dependent variable is the return adjusted by firm characteristic categories one at a time. Five out of eight measures show significant loadings on betas.

[Insert Table VII here.]

We next perform analyses to understand the relationship between aggregate time series of firm characteristics and returns on beta-sorted portfolios. We adopt two aggregate firm characteristic categories: aggregate index and attribute spread. To construct aggregate firm characteristic indexes, we compute monthly value-weighted and equal-weighted averages of firm characteristic categories. To construct the spread in attributes, we calculate monthly value-weighted and equal-weighted averages of firm characteristic categories for each beta portfolio, and the difference of the time-series averages between the high and low beta portfolios is used. We then regress the excess returns of each beta portfolio on Fama and French (1993) and Carhart (1997) four factors plus the aggregate firm characteristic index or the attribute spread.

[Insert Table VIII here.]

Table VIII shows the coefficients and t-statistics of alphas across five beta portfolios and the high-minus-low beta portfolio after controlling aggregate firm characteristics, and the last column reports the results without the control. In panel A, we use value-weighted firm characteristic indexes as a control for aggregate firm characteristics. For the high-minus-low beta portfolio, the risk-adjusted alpha estimate based on the four factor model is insignificant from zero. In panel B, the results are qualitatively and quantitatively unchanged when we use equal-weighted firm characteristic indexes as the control variable. The results based on attribute spreads are reported in Panel C and D. Panel C shows the results when attribute spreads are value-weighted and panel D shows the results when attribute spreads are equal-weighted. For seven out of ten control variables, the alphas in the high-minus-low beta portfolio become insignificant from zero.

Frazzini and Pedersen (2014) suggest that since some investors are constrained in the leverage that they can take, a trading strategy that de-levers or overweights high-beta assets and levers up low-beta assets can generate positive risk-adjusted returns. In particular, Frazzini and Pedersen create the BAB factor, which long leveraged low-beta securities and short high-beta securities. In this portfolio, both low-beta securities and high-beta securities have a beta of one through leverage and deleverage, respectively. To maintain market-neutral and self-financing in the BAB factor, risk-free assets are used to offset positions in low-beta and high-beta securities. However, Bali, Brown, Murray, and Tang (2014) show that their lottery demand factor, FMAX, can explain the return of the BAB factor, while the BAB factor fails to explain the return of the FMAX factor. In our test, we analyze whether the return of the BAB factor can be explained by firm characteristics that explain the return of the high-minus-low beta portfolio, including those that predict jackpot payoff probabilities. We thus test whether our aggregate firm characteristic measures can explain the return of the BAB factor.

[Insert Table IX here.]

Table IX reports the alphas of the monthly U.S. equity BAB factor relative to different model specifications with and without controlling for aggregate firm characteristic measures. When we regress the BAB factor on Fama and French (1993) and Carhart (1997) four factors, alphas are all positive and significant, regardless of the sample periods we examine. With the addition of the Pastor and Stambaugh (2003) liquidity factor, the results are qualitatively unchanged. Interestingly, once we control for the aggregate firm characteristic index, as reported in panel A and panel B, the alphas become either significantly negative for the Growth index, or insignificant from zero relative to other indexes. In panel C and D, when the attribute spread is controlled, the magnitude of the alpha and its significance decrease in eight out of ten attribute spreads, although two categories remain significant. Note that consistent with Bali, Brown, Murray, and Tang (2104), aggregate firm characteristic measures that predict jackpot returns also explain the return of the BAB factor. Overall, these results suggest that the leverage in beta trading strategies does matter and helps generate abnormal performance.

C. Limits to Arbitrage

In this part of analyses, we assess the relation between limits to arbitrage and the low beta anomaly. Prior studies have shown mixed results about the strength of the low beta anomaly among stocks with different level of limits to arbitrage. Bali, Brown, Murray, and Tang (2014) show that low beta anomaly only exists among stocks with a low proportion of institutional shareholders. Huang, Lou, and Polk (2014) show that the cross-sectional spread in betas increases when beta-arbitrage activity is high and beta-arbitrage stocks are more levered. Further, their findings are exclusively in stocks with relatively low limits to arbitrage. Frazzini and Pedersen (2014) find that both mutual funds and individual investors hold high-beta stocks. Christoffersen and Simutin (2015) show that benchmarking leads mutual managers to tilt their portfolios towards high beta stocks and away from low beta stocks, reinforcing low beta anomaly.

We consider five measures of limits to arbitrage: size, institutional ownership orthogonal to size, analyst coverage orthogonal to size, institutional ownership, and analyst coverage. Since institutional ownership and analyst coverage are highly correlated with size, we use the residuals to avoid the size effect when sorting stocks. We still include institutional ownership and analyst coverage to examine the size effect on these two measures. For size, we sort stocks in two groups. Small (big) stocks are smaller (larger) than the 30^{th} (70^{th}) NYSE size percentile. For institutional ownership and analyst coverage, low institutional ownership or analyst coverage stocks are in the smallest tercile, while high stocks are in the largest tercile. For institutional ownership and analyst coverage that are orthogonal to size, we first measure the residuals of each variable in a regression on size and time dummies. Low institutional ownership or analyst coverage stocks are in the smallest tercile, while high stocks are in the largest tercile of their respective residuals. Within each group, we regress the return of the high-minus-low beta portfolio on different risk factors. Table X reports the results.

[Insert Table X here.]

The result after controlling for size shows that the low beta anomaly is prominent among small-cap stocks as three risk-adjusted alphas are all negatively significant. For big-cap stocks, only the alpha relative to CAPM is significant. For institutional ownership and analyst coverage, we find similar results that low beta anomaly is strong among stocks with relatively high limits to arbitrage. However, once we control for the size effect, the high-minus-low beta portfolio in the high institutional ownership group or the high analyst coverage group delivers a negative alpha. In sum, we show that the low beta anomaly is prominent among small-cap, high institutional ownership, and high analyst coverage stocks.

V. Conclusion

The well-documented low beta anomaly persists despite the theoretical relation between beta and expected return and beta-arbitrage activity. In this paper we focus on firm characteristics that have shown ability to predict the cross-sectional returns of stocks in prior studies and study their effects on the low beta anomaly.

We confirm that the low beta anomaly exists over our full sample period after controlling for Fama and French (1993) and Carhart (1997) four factors plus the liquidity factor by Pastor and Stambaugh (2003). The low beta anomaly is still prominent over the sub-sample period where all firm characteristic categories are available.

We find that for the majority of firm characteristic variables, high beta stocks differ significantly from low beta stocks. Our results remain the same after we control for the industry effect. Moreover, we find that high beta stocks are associated with a high probability of jackpot payoffs and distress. After controlling for firm characteristics that have explanatory power for future returns, low beta anomaly disappears. These empirical findings support our argument that investors bid up (down) stock prices with certain characteristics. Moreover, consistent with Bali, Brown, Murray, and Tang (2014), we show that lottery demand explains the low beta anomaly. However, on top of investor preferences for lottery-like returns, we also show that firm characteristics, such as Qscore (analysts' preferences), Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, and Distress, could also explain the low beta anomaly. In the multivariate regression at the aggregate level, though weaker, but most of our aggregate firm characteristic measures could explain the low beta anomaly.

We also find mixed evidence on limits to arbitrage argument. While strong among small-cap stocks, the low beta anomaly is also prominent among stocks with high institutional ownership or high analyst coverage.

Overall, our results imply that there might be a missing factor correlated with firm characteristics or systematic mispricing results from firm characteristics in low beta anomaly. High beta stocks exhibit lower returns as a result of their characteristics. Investor preferences for firm characteristics drive the low beta anomaly.

APPENDIX A

Variable Description

RETXP: cumulative market-adjusted return (adjusted for dividends) for the preceding 6 months following Jegadeesh, Kim, Krische, and Lee (2004).

RETX2P: Cumulative market-adjusted return (adjusted for dividends) for the second preceding 6 months following Jegadeesh, Kim, Krische, and Lee (2004).

TURN2: Average daily volume turnover following Jegadeesh, Kim, Krische, and Lee (2004).

SIZE: Market cap following Jegadeesh, Kim, Krische, and Lee (2004).

FREV: Analyst earnings forecast revisions to price following Jegadeesh, Kim, Krische, and Lee (2004).

LTG: long-term growth forecast following Jegadeesh, Kim, Krische, and Lee (2004).

SUE: Standardized unexpected earnings following Jegadeesh, Kim, Krische, and Lee (2004).

SG: Sales growth following Jegadeesh, Kim, Krische, and Lee (2004).

TA: Total Accruals to Total Assets following Jegadeesh, Kim, Krische, and Lee (2004).

CAPEX2: Capital Expenditure to Total Assets following Jegadeesh, Kim, Krische, and Lee (2004).

BP: Book to Price following Jegadeesh, Kim, Krische, and Lee (2004).

EP: Earnings to price following Jegadeesh, Kim, Krische, and Lee (2004).

ROE: Return on equity.

SKEW: Skewness of ROE.

VAR: Variance of ROE for the preceding 12 months.

IIR_G: Following Gupta-Mukherjee (2012), IIR_G is defined as R&D Expense to PPE Expense (gross) ratio.

PBETA: Profitability beta following Aaker and Jacobson (1987).

CAPIN: Capital intensity following Miller and Bromiley (1990).

RDIN: R&D intensity following Miller and Bromiley (1990).

STDROA: Standard devation of return on asset following Miller and Bromiley (1990).

DIVERSITY: Diversity measure following Rajan (2000).

MABA: Following Cao, Simin, and Zhao (2008), MABA is defined as [Total Assets - Total Common Equity + Price x Common Shares Outstanding]/ Total Assets.

Q: Following Cao, Simin, and Zhao (2008), Q is defined as [Price x Common Shares Outstanding + Preferred Stock + Current Liabilities - Current Assets Total + Long-Term Debt] / Total Assets.

DTE: Following Cao, Simin, and Zhao (2008), DTE is defined as [Debt in Current Liabilities + Total Long-Term Debt + Preferred Stock]/[Common Shares Outstanding x Price].

CAPEX: Following Cao, Simin, and Zhao (2008), CAPEX is defined as Capital Expenditures/ Property, Plant, and Equipment.

MKTSE: Style extremity measure based on market following Bar, Kempf, and Ruenzi (2011).

SMBSE: Style extremity measure based on size following Bar, Kempf, and Ruenzi (2011).

HMLSE: Style extremity measure based on value following Bar, Kempf, and Ruenzi (2011).

UMDSE: Style extremity measure based on momentum factor following Bar, Kempf, and Ruenzi (2011).

PE: Performance extremity measure based on momentum factor following Bar, Kempf, and Ruenzi (2011).

BM: Book to market equity following Hirshleifer and Jiang (2010).

IVA: Investment To Total Asset following Hirshleifer and Jiang (2010).

LEV: Book value of total liabilities over the market value of equity following Hirshleifer and Jiang (2010).

EXFIN: Following Hirshleifer and Jiang (2010), EXFIN is defined as the net amount of cash flow received from external financing activities, including net equity and debt financing, scaled by total assets.

IR: The net composite issuance variable following Hirshleifer and Jiang (2010).

NOA: Following Hirshleifer and Jiang (2010), NOA is defined as the difference of operating assets minus operating liabilities over total assets.

ACC: Operating accruals following Hirshleifer and Jiang (2010).

CI: Following Hirshleifer and Jiang (2010), CI is defined as a firm's capital expenditures scaled by the moving-average of its capital expenditures over the previous three years.

NIMTAAVG: Following Campbell, Hilscher, and Szilagyi (2008), NIMTAAVG is defined as the moving average of Net Income to Market-valued Total Assets.

TLMTA: Following Campbell, Hilscher, and Szilagyi (2008), NIMTAAVG is defined as the Total Liabilities to Market-valued Total Assets.

EXRETAVG: Following Campbell, Hilscher, and Szilagyi (2008), EXRETAVG is defined as monthly log excess return on each firm's equity relative to the S&P 500 index.

SIGMA: Following Campbell, Hilscher, and Szilagyi (2008), SIGMA is the standard deviation of each firm's daily log return over the past 3 months.

RSIZE: Following Campbell, Hilscher, and Szilagyi (2008), RSIZE is the log ratio of a firm's market capitalization to that of the S&P 500.

CASHMTA: Following Campbell, Hilscher, and Szilagyi (2008), CASHMTA is the ratio of a firm's cash and short-term assets to the market value of its assets.

MB: Following Campbell, Hilscher, and Szilagyi (2008), MB is the market-to-book ratio.

PRICE: Following Campbell, Hilscher, and Szilagyi (2008), PRICE is is the firm's log price per share.

SKEW3: The skewness of a stock's daily log return over the past 3 months following Conrad, Kapadia, and xing (2014).

RET: A stock's log return in the past 12 months following Conrad, Kapadia, and xing (2014).

STD3: The standard deviation of a stock's daily log return over the past 3 months following Conrad, Kapadia, and xing (2014).

AGE: Number of years since first appearance on the Center for Research in Security Pricing data set following Conrad, Kapadia, and xing (2014).

TURN: Following Conrad, Kapadia, and xing (2014), TURN is defined as [Six-Month Volume/Shares Outstanding] - [18-Month Volume/Shares Outstanding].

ASSETTANG: Following Conrad, Kapadia, and xing (2014), TURN is defined as [Gross Property Plant and Equipment (PPE)/Total Assets].

SALEG: Sales growth following Conrad, Kapadia, and xing (2014).

MKTCAP: Log market capitalization following Conrad, Kapadia, and xing (2014).

XRDQ: Normalized R&D expense.

INTAN: Normalized intangible asset.

DTER: Debt to equity ratio following Miller and Bromiley (1990).

Description on Firm Characteristic Categories

We combine firm characteristic variables into the following categories: QScore, Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, Distress, and Jackpot. Following Jegadeesh, Kim, Krische, and Lee (2004), we first convert each of the individual firm characteristic variables into a binary signal. Based on previous studies, if a firm characteristic variable is expected to be positively (negatively) correlated with future returns, we assign a value of one when its value is higher (lower) than its median value in a given quarter, and zero otherwise. We then compute the firm characteristic categories for each stock by aggregating their binary signals. We exclude three firm characteristic variables, xrdq (R&D expense), intan (intangible assets), and dter (Debt-to-Equity), in any category because iir_g (R&D-to-PPE expense ratio) is correlated with xrdq and intan and normalized, and dter resembles dte (Debt-to-Equity). To capture the aggregated effect from all categories, we further construct the ALL category, which combine all aforementioned firm characteristic categories, except for Momentum and Contrarian, due to overlapping variables with those in Qscore.

QSCORE: Following Jegadeesh, Kim, Krische, and Lee (2004), we use RETXP, RET2XP, TURN2, SIZE, FREV, LTG, SUE, SG, TA, CAPEX, BP, and EP to create QSCORE.

MOMENTUM: Following Jegadeesh, Kim, Krische, and Lee (2004), we use RETXP, RET2XP, FREV, and SUE to create MOMENTUM.

CONTRARIAN: Following Jegadeesh, Kim, Krische, and Lee (2004), we use TURN2, LTG, SG, TA, CAPEX, BP, and EP to create CONTRARIAN.

OPERATING: We use ROE, SKEW, VAR, IRR_G, PBETA, CAPIN, RDIN, STDROA, and DIVERSITY to create OPERATING.

GROWTH: We use MABA, Q, DET, and CAPEX to create GROWTH.

EXTREME: We use MKTSE, SMBSE, HMLSE, UMDSE, and PE to create EXTREME.

MISVALUATION: We use BM, IVA, LEV, EXFIN, IR, NOA, ACC, and CI to create MISVALUATION.

DISTRESS: We use NIMTAAVG, TLMTA, EXRETAVG, SIGMA, RSIZE, CASHMTA, MB, and PRICE to create DISTRESS.

JACKPOT: We use SKEW3, RET, AGE, ASSETTANG, SALEG, TURN, STD3, and MKTCAP to create JACKPOT.

ALL: We aggregate QSCORE, OPERATING, GROWTH, EXTREME, MISVALUATION, DISTRESS, and JACKPOT to create ALL.

Description on Aggregate Firm Characteristic Indexes

The aggregate firm characteristic indexes are constructed as either the equal-weighted average or the value-weighted average of firm characteristic categories. Therefore, we have 10 aggregate firm characteristic indexes and they are QScore, Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, Distress, Jackpot, and ALL.

Description on Attribute Spreads

To construct the attribute spreads, we first compute both the equal-weighted average and the value-weighted average of firm characteristic categories within each beta portfolio. Next, we calculate the difference of the average between high and low beta portfolios as the attribute spread. We have 10 attribute spreads and they are QScore, Momentum, Contrarian, Operating, Growth, Extreme, Misvaluation, Distress, Jackpot, and ALL.

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Table I

Summary Statistics

This table presents the alphas of five beta Portfolios across different time periods and models. Each month, we use quintile breakpoints to assign stocks into portfolios according to their betas. Betas are estimated using the prior 60 months (minimum 12 months) of returns. For each beta portfolio, we regress equal-weighted monthly excess portfolio returns on market excess returns, Fama and French (1993) and Carhart (1997) four factors, and Fama and French (1993) and Carhart (1997) four factors plus Pastor and Stambaugh (2003) liquidity factor. Panel A and B report risk-adjusted alphas based on data from January, 1964 to December, 2013, and from August, 1984 to December, 2013, respectively. The column labeled High-Low presents the alpha of the portfolio long beta portfolio five and short beta portfolio one. Newey and West (1987) t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A.1/31/1964 - 2013/12/31

	β 1 (Low)		β 2		β 3		β 4		β 5 (High)		High-Low	
CAPM α	0.69%	***	0.58%	***	0.31%	**	0.11%		-0.05%	**	-0.73%	**
	(5.32)		(4.43)		(2.26)		(0.68)		(-0.20)		(-2.44)	
FFC α	0.60%	***	0.48%	***	0.27%	***	0.12%		-0.03%		-0.62%	***
	(8.21)		(8.09)		(4.15)		(1.47)		(-0.17)		(-2.86)	
FFCPS α	0.59%	***	0.47%	***	0.26%	***	0.12%		-0.03%		-0.62%	***
	(8.25)		(8.21)		(4.21)		(1.45)		(-0.21)		(-2.96)	

Panel B.8/31/1984 - 2013/12/31

	β 1 (Low)		β 2		β 3		β 4		β 5 (High)		High-Low	
CAPM α	0.54%	***	0.31%	*	-0.10%		-0.34%	**	-0.57%	*	-1.10%	**
	(2.86)		(1.79)		(-0.73)		(-2.03)		(-1.94)		(-2.48)	
FFC α	0.54%	***	0.40%	***	0.13%	*	-0.02%		-0.06%		-0.60%	**
	(5.46)		(5.21)		(1.65)		(-0.16)		(-0.35)		(-1.98)	
FFCPS α	0.52%	***	0.38%	***	0.13%		-0.02%		-0.06%		-0.58%	**
	(5.37)		(5.19)		(1.62)		(-0.14)		(-0.34)		(-1.98)	

Table II

Firm Characteristics across Beta Portfolios

This table shows the average firm characteristics, and the average firm characteristics adjusted by industry mean and industry medium of beta portfolios. Panel A reports the unadjusted/adjusted mean of firm characteristics that are components of QSCORE. The row labeled High-Low presents the mean difference between quintile five (highest) and quintile one (lowest). The row labeled t-stat presents t-statistics adjusted following Newey and West (1987). Panel B reports the unadjusted/adjusted mean of characteristics that are components of OPERATING. Panel C reports the unadjusted/adjusted mean of characteristics that are components of GROWTH. Panel D reports the unadjusted/adjusted mean of firm characteristics that are components of EXTREME. Panel E reports the unadjusted/adjusted mean of firm characteristics that are components of MISVALUATION. Panel F reports the unadjusted/adjusted mean of firm characteristics that are components of DISTRESS. Panel G reports the unadjusted/adjusted mean of firm characteristics that are components of JACKPOT. Panel H reports the unadjusted/adjusted mean of the rest firm characteristics. The definition of all the firm characteristic categories is detailed in Appendix A. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A. QSCORE

	RETXP	RETX2P	TURN2	SIZE	FREV	LTG	SUE	SG	TA	CAPEX2	BP	EP
Firm Characteristics Raw												
β 1 (Low)	0.002	0.003	34.266	19.232	-0.010	11.214	0.375	1.090	0.025	0.059	0.882	0.047
β 2	0.016	0.020	46.149	19.021	-0.012	14.084	0.338	1.100	0.033	0.061	0.852	0.012
β 3	0.014	0.029	53.216	18.797	-0.016	16.031	0.347	1.121	0.037	0.061	0.825	-0.016
β 4	0.015	0.042	60.140	18.587	-0.019	18.285	0.315	1.138	0.041	0.062	0.785	-0.054
β 5 (High)	0.019	0.070	68.212	18.321	-0.024	22.176	0.293	1.181	0.047	0.063	0.755	-0.065
High-Low	0.017 **	0.067 ***	33.946 ***	-0.910 ***	-0.014 ***	10.899 ***	-0.082 *	0.090 ***	0.023 **	0.004	-0.127 *	-0.112 **
t-stat	2.36	2.91	36.63	-4.70	-4.64	8.99	-1.71	5.77	2.32	0.76	-1.89	-2.25
Firm Characteristics Adjusted by Asset Weighted Industry Average												
β 1 (Low)	-0.003	-0.006	-12.057	-0.973	0.000	-0.350	-0.030	-0.017	-0.004	0.002	0.094	0.010
β 2	0.002	0.002	-6.924	-1.004	-0.001	0.419	-0.053	-0.013	-0.002	0.002	0.076	-0.023
β 3	-0.001	0.007	-3.464	-1.162	-0.005	1.228	-0.048	-0.004	-0.003	0.001	0.072	-0.044
β 4	0.001	0.018	-0.124	-1.317	-0.006	2.271	-0.058	0.002	-0.001	0.002	0.048	-0.070
β 5 (High)	0.000	0.038	3.916	-1.512	-0.010	4.542	-0.066	0.031	0.004	0.002	0.031	-0.074
High-Low	0.003 **	0.043 **	15.973 ***	-0.539 ***	-0.011 ***	4.892 ***	-0.036	0.048 ***	0.008	-0.001	-0.062 ***	-0.084 **
t-stat	2.34	2.53	18.04	-4.04	-4.45	9.41	-1.55	6.51	1.62	-0.38	-2.85	-2.02

Firm Characteristics Adjusted by Asset Weighted Industry Medium												
β 1 (Low)	0.016	0.0160	-4.808	0.469	-0.007	-0.629	0.121	0.007	0.001	0.013	0.094	-0.017
β 2	0.030	0.0340	-1.657	0.499	-0.008	-0.148	0.105	0.011	0.003	0.014	0.093	-0.046
β 3	0.033	0.0462	0.876	0.375	-0.012	0.466	0.111	0.025	0.002	0.015	0.101	-0.067
β 4	0.040	0.0646	3.558	0.259	-0.014	1.169	0.098	0.037	0.006	0.016	0.082	-0.097
β 5 (High)	0.048	0.0939	7.149	0.105	-0.020	3.057	0.092	0.071	0.009	0.019	0.073	-0.100
High-Low	0.032 ***	0.078 ***	11.957 ***	-0.364 ***	-0.013 ***	3.686 ***	-0.029	0.064 ***	0.007	0.006 ***	-0.021	-0.084 *
t-stat	3.95	4.44	24.60	-5.89	-5.05	9.64	-1.24	6.37	1.41	3.06	-1.12	-1.89
Firm Characteristics Adjusted by Sales Weighted Industry Average												
β 1 (Low)	-0.005	-0.007	-12.399	-1.123	0.000	-0.350	-0.054	-0.021	-0.007	0.001	0.100	0.004
β 2	0.004	0.000	-6.798	-1.151	-0.002	0.419	-0.066	-0.020	-0.006	0.001	0.086	-0.032
β 3	0.006	0.006	-3.425	-1.315	-0.006	1.228	-0.067	-0.010	-0.009	0.000	0.078	-0.055
β 4	0.013	0.016	-0.037	-1.484	-0.007	2.271	-0.085	-0.001	-0.005	0.000	0.057	-0.083
β 5 (High)	0.027	0.035	3.915	-1.666	-0.012	4.542	-0.097	0.030	-0.001	0.000	0.044	-0.090
High-Low	0.032 *	0.042 **	16.314 ***	-0.544 ***	-0.011 ***	4.892 ***	-0.043 *	0.051 ***	0.006	0.000	-0.056 **	-0.094 **
t-stat	1.74	2.26	17.43	-7.06	-4.56	8.84	-1.96	5.79	1.20	-0.25	-2.43	-2.12
Firm Characteristics Adjusted by Sales Weighted Industry Medium												
β 1 (Low)	0.035	0.025	-6.611	-0.123	-0.015	-0.090	-0.021	0.020	-0.001	0.007	0.103	-0.035
β 2	0.040	0.039	-3.572	0.404	-0.014	-0.305	-0.052	0.011	0.001	0.008	0.086	-0.026
β 3	0.047	0.050	-0.070	0.492	-0.017	0.320	0.004	0.013	0.002	0.009	0.087	-0.034
β 4	0.057	0.065	3.023	0.414	-0.024	1.203	-0.041	0.045	0.002	0.014	0.052	-0.059
β 5 (High)	0.095	0.093	6.742	0.218	-0.036	3.134	-0.056	0.105	0.006	0.016	0.026	-0.128
High-Low	0.060 ***	0.068 ***	13.353 ***	0.341 ***	-0.021 ***	3.224 ***	-0.035	0.085 ***	0.007 **	0.009 ***	-0.077 ***	-0.093 ***
t-stat	2.79	3.76	31.63	3.51	-5.57	9.99	-1.32	6.81	2.23	5.25	-2.79	-3.97

Table II Continued

Panel B. OPERATING									
Firm Characteristics Raw									
	ROE	SKEW	VAR	IIR_G	PBETA	CAPIN	RDIN	STDROA	DIVERSITY
β 1 (Low)	0.031	-0.199	0.072	0.039	0.134	11.584	0.079	0.012	0.272
β 2	0.015	-0.297	0.161	0.062	0.163	9.025	0.116	0.016	0.295
β 3	-0.003	-0.346	0.206	0.101	0.209	7.124	0.192	0.023	0.271
β 4	-0.055	-0.364	0.284	0.123	0.239	7.512	0.315	0.030	0.268
β 5 (High)	-0.070	-0.432	0.494	0.161	0.298	7.507	0.436	0.052	0.221
High-Low	-0.101 ***	-0.233 ***	0.422 ***	0.122 ***	0.164 *	-4.077 **	0.357 ***	0.040 ***	-0.051 **
t-stat	-3.33	-4.08	5.39	10.28	1.93	-2.35	11.84	6.01	-2.60
Firm Characteristics Adjusted by Asset Weighted Industry Average									
β 1 (Low)	0.004	0.032	-0.007	0.004	-0.029	-0.884	0.004	0.000	
β 2	-0.010	-0.004	0.082	0.018	-0.016	-0.765	0.012	0.003	
β 3	-0.026	-0.022	0.122	0.045	0.023	-0.383	0.079	0.007	
β 4	-0.076	-0.034	0.189	0.055	0.030	0.310	0.185	0.012	
β 5 (High)	-0.089	-0.059	0.389	0.082	0.059	0.717	0.293	0.031	
High-Low	-0.093 ***	-0.092 ***	0.395 ***	0.078 ***	0.088 ***	1.601 ***	0.289 ***	0.031 ***	
t-stat	-3.14	-2.65	5.37	8.16	4.09	5.64	12.36	5.82	
Firm Characteristics Adjusted by Asset Weighted Industry Medium									
β 1 (Low)	0.006	-0.032	0.039	-0.001	-0.031	0.706	0.015	-0.001	
β 2	-0.009	-0.062	0.124	0.014	-0.012	0.878	0.038	0.001	
β 3	-0.025	-0.094	0.166	0.039	0.019	1.269	0.097	0.005	

β 4	-0.075		-0.090		0.237		0.047		0.028		2.088		0.199		0.009	
β 5 (High)	-0.088		-0.111		0.439		0.072		0.052		2.658		0.299		0.028	
High-Low	-0.094	***	-0.080	**	0.400	***	0.072	***	0.083	***	1.952	***	0.284	***	0.029	***
t-stat	-3.17		-2.47		5.30		8.11		3.75		5.87		11.60		5.52	
Firm Characteristics Adjusted by Sales Weighted Industry Average																
β 1 (Low)	0.002		0.025		-0.004		0.005		-0.023		0.583		0.025		0.000	
β 2	-0.013		-0.012		0.084		0.021		-0.008		0.554		0.052		0.003	
β 3	-0.029		-0.042		0.124		0.049		0.026		0.942		0.119		0.008	
β 4	-0.080		-0.047		0.191		0.059		0.040		1.755		0.229		0.012	
β 5 (High)	-0.094		-0.074		0.391		0.086		0.077		2.386		0.338		0.032	
High-Low	-0.095	***	-0.098	***	0.395	***	0.080	***	0.100	***	1.804	***	0.313	***	0.032	***
t-stat	-3.18		-2.96		5.40		8.49		3.52		5.61		12.04		5.91	
Firm Characteristics Adjusted by Sales weighted Industry Medium																
β 1 (Low)	0.006		-0.030		0.039		-0.001		-0.029		0.713		0.015		-0.001	
β 2	-0.009		-0.053		0.126		0.014		-0.010		0.782		0.038		0.001	
β 3	-0.025		-0.095		0.166		0.039		0.021		1.284		0.097		0.005	
β 4	-0.076		-0.090		0.237		0.047		0.030		2.088		0.199		0.009	
β 5 (High)	-0.089		-0.111		0.439		0.072		0.052		2.658		0.299		0.028	
High-Low	-0.095	***	-0.081	**	0.400	***	0.072	***	0.081	***	1.945	***	0.284	***	0.029	***
t-stat	-3.18		-2.53		5.29		8.11		3.64		5.82		11.60		5.53	

Table II Continued

Panel C. GROWTH

	MABA		Q		DTE		CAPEX	
Firm Characteristics Raw								
β 1 (Low)	1.403		0.921		0.792		0.127	
β 2	1.517		0.991		0.875		0.141	
β 3	1.698		1.123		0.870		0.152	
β 4	1.789		1.213		0.897		0.169	
β 5 (High)	1.988		1.405		0.949		0.200	
High-Low	0.585	***	0.484	***	0.156		0.072	***
t-stat	5.30		4.03		1.52		9.80	
Firm Characteristics Adjusted by Asset Weighted Industry Average								
β 1 (Low)	-0.033		-0.078		-0.244		0.003	
β 2	0.003		-0.039		-0.035		0.005	
β 3	0.101		0.051		0.018		0.005	
β 4	0.089		0.044		0.061		0.012	
β 5 (High)	0.183		0.147		0.052		0.029	
High-Low	0.216	***	0.225	***	0.296	***	0.026	***
t-stat	4.00		3.87		5.73		8.43	
Firm Characteristics Adjusted by Asset Weighted Industry Medium								
β 1 (Low)	0.120		0.115		0.182		0.023	
β 2	0.166		0.162		0.387		0.025	
β 3	0.286		0.268		0.431		0.026	

Panel D. EXTREME

	MKTSE		SMBSE		HMLSE		UMDSE		PE	
Firm Characteristics Raw										
β 1 (Low)	0.790		0.807		0.793		0.792		0.823	
β 2	0.841		0.879		0.869		0.867		0.879	
β 3	0.907		0.935		0.926		0.923		0.933	
β 4	0.972		0.977		0.986		0.986		0.975	
β 5 (High)	1.116		1.065		1.075		1.088		1.066	
High-Low	0.325	***	0.258	***	0.282	***	0.296	***	0.243	***
t-stat	21.59		16.49		19.22		18.20		17.29	
Firm Characteristics Adjusted by Asset Weighted Industry Average										
β 1 (Low)										
β 2										
β 3										
β 4										
β 5 (High)										
High-Low										
t-stat										
Firm Characteristics Adjusted by Asset Weighted Industry Medium										
β 1 (Low)										
β 2										
β 3										

β 4	0.319		0.310		0.475		0.034		β 4
β 5 (High)	0.452		0.444		0.525		0.054		β 5 (High)
High-Low	0.332	***	0.329	***	0.342	***	0.031	***	High-Low
t-stat	5.87		5.49		5.80		9.14		t-stat
Firm Characteristics Adjusted by Sales Weighted Industry Average									Firm Characteristics Adjusted by Sales Weighted Industry Average
β 1 (Low)	-0.065		-0.102		-0.184		0.001		β 1 (Low)
β 2	-0.034		-0.061		0.028		0.002		β 2
β 3	0.059		0.023		0.077		0.003		β 3
β 4	0.040		0.012		0.119		0.010		β 4
β 5 (High)	0.124		0.106		0.136		0.027		β 5 (High)
High-Low	0.190	***	0.207	***	0.320	***	0.026	***	High-Low
t-stat	3.39		3.43		6.15		8.99		t-stat
Firm Characteristics Adjusted by Sales Weighted Industry Medium									Firm Characteristics Adjusted by Sales Weighted Industry Medium
β 1 (Low)	0.123		0.115		0.183		0.023		β 1 (Low)
β 2	0.172		0.162		0.389		0.025		β 2
β 3	0.288		0.268		0.432		0.026		β 3
β 4	0.320		0.310		0.475		0.034		β 4
β 5 (High)	0.454		0.444		0.528		0.054		β 5 (High)
High-Low	0.331	***	0.329	***	0.345	***	0.031	***	High-Low
t-stat	5.84		5.49		5.84		9.14		t-stat

Table II Continued

Panel E. MISVALUATION

Firm Characteristics Raw

	BM	IVA	LEV	EXFIN	IR	NOA	ACC	CI
β 1 (Low)	1.000	0.070	1.644	-0.015	0.135	0.680	-0.024	1.272
β 2	0.943	0.073	1.431	-0.007	0.015	0.689	-0.025	1.299
β 3	0.903	0.082	1.429	0.008	-0.079	0.682	-0.020	1.340
β 4	0.852	0.096	1.436	0.023	-0.178	0.681	-0.013	1.401
β 5 (High)	0.800	0.107	1.445	0.047	-0.329	0.656	-0.001	1.524
High-Low	-0.200 **	0.037 ***	-0.199	0.062 ***	-0.464 ***	-0.024	0.023 ***	0.252 ***
t-stat	-2.22	3.62	-1.21	10.24	-6.06	-0.92	3.07	4.23

Firm Characteristics Adjusted by Asset Weighted Industry Average

	BM	IVA	LEV	EXFIN	IR	NOA	ACC	CI
β 1 (Low)	0.097	-0.011	-0.508	-0.012	-0.047	-0.018	-0.001	-0.016
β 2	0.062	-0.008	-0.419	-0.007	-0.123	-0.011	-0.001	-0.011
β 3	0.051	-0.004	-0.286	0.003	-0.215	-0.013	-0.001	0.000
β 4	0.024	0.007	-0.253	0.015	-0.309	-0.015	0.007	0.037
β 5 (High)	-0.003	0.016	-0.273	0.034	-0.438	-0.026	0.013	0.120
High-Low	-0.099 ***	0.027 ***	0.235 **	0.046 ***	-0.390 ***	-0.008	0.014 **	0.137 ***
t-stat	-3.01	4.93	2.20	10.97	-6.62	-0.89	2.57	3.84

Firm Characteristics Adjusted by Asset Weighted Industry Medium

	BM	IVA	LEV	EXFIN	IR	NOA	ACC	CI
β 1 (Low)	0.124	0.006	0.178	-0.009	0.012	0.011	0.006	0.173
β 2	0.111	0.008	0.267	-0.005	-0.063	0.018	0.005	0.190
β 3	0.108	0.015	0.412	0.005	-0.142	0.022	0.008	0.224

β 4	0.080		0.027		0.474		0.017		-0.225		0.030		0.018		0.294	
β 5 (High)	0.069		0.037		0.499		0.034		-0.348		0.025		0.027		0.403	
High-Low	-0.056	**	0.032	***	0.321	***	0.043	***	-0.361	***	0.014	**	0.021	***	0.230	***
t-stat	-2.24		5.36		4.29		9.95		-5.66		2.01		3.23		5.62	
Firm Characteristics Adjusted by Sales Weighted Industry Average																
β 1 (Low)	0.133		-0.011		-0.411		-0.008		-0.057		-0.010		0.000		-0.003	
β 2	0.087		-0.009		-0.328		-0.002		-0.146		-0.001		-0.001		-0.001	
β 3	0.070		-0.007		-0.180		0.008		-0.246		-0.006		0.000		-0.002	
β 4	0.033		0.003		-0.147		0.021		-0.340		-0.009		0.009		0.049	
β 5 (High)	0.009		0.016		-0.135		0.041		-0.470		-0.015		0.014		0.150	
High-Low	-0.124	***	0.027	***	0.276	***	0.049	***	-0.412	***	-0.006		0.013	**	0.153	***
t-stat	-3.57		4.64		2.85		11.47		-6.58		-0.62		2.35		4.29	
Firm Characteristics Adjusted by Sales Weighted Industry Medium																
β 1 (Low)	0.133		0.006		0.195		-0.009		0.012		0.012		0.006		0.183	
β 2	0.117		0.008		0.288		-0.005		-0.072		0.022		0.005		0.194	
β 3	0.110		0.011		0.430		0.005		-0.158		0.021		0.008		0.221	
β 4	0.079		0.022		0.491		0.017		-0.246		0.025		0.018		0.288	
β 5 (High)	0.068		0.037		0.513		0.034		-0.364		0.026		0.027		0.414	
High-Low	-0.064	**	0.031	***	0.318	***	0.043	***	-0.375	***	0.014	*	0.021	***	0.231	***
t-stat	-2.54		4.93		4.06		9.95		-5.50		1.86		3.22		5.72	

Table II Continued

Panel F. DISTRESS

Firm Characteristics Raw

	NIMTAAVG		TLMTA		EXRETAVG		SIGMA		RSIZE		CASHMTA		MB		PRICE	
β 1 (Low)	0.006		0.485		-0.002		0.020		-2.269		0.085		1.781		3.422	
β 2	0.005		0.448		-0.002		0.025		-2.479		0.084		1.940		3.440	
β 3	0.003		0.430		-0.004		0.030		-2.703		0.086		2.092		3.412	
β 4	-0.001		0.409		-0.006		0.034		-2.914		0.096		2.279		3.342	
β 5 (High)	-0.008		0.390		-0.009		0.040		-3.179		0.108		2.539		3.277	
High-Low	-0.014	***	-0.095	***	-0.007	**	0.020	***	-0.910	***	0.024	***	0.758	***	-0.145	***
t-stat	-4.41		-3.87		-2.00		10.70		-5.76		2.79		4.22		-5.31	

Firm Characteristics Adjusted by Asset Weighted Industry Average

	NIMTAAVG		TLMTA		EXRETAVG		SIGMA		RSIZE		CASHMTA		MB		PRICE	
β 1 (Low)	0.000		-0.042		0.000		0.000		-0.922		0.018		-0.172		-0.054	
β 2	-0.001		-0.037		0.000		0.003		-0.961		0.014		-0.119		-0.080	
β 3	-0.003		-0.027		-0.002		0.005		-1.122		0.014		-0.030		-0.094	
β 4	-0.005		-0.031		-0.003		0.008		-1.295		0.020		0.072		-0.143	
β 5 (High)	-0.012		-0.032		-0.005		0.012		-1.503		0.025		0.200		-0.195	
High-Low	-0.012	***	0.009		-0.006	**	0.012	***	-0.582	***	0.007		0.372	***	-0.142	***
t-stat	-5.20		1.17		-2.43		11.72		-4.15		1.46		4.20		-10.06	

Firm Characteristics Adjusted by Asset Weighted Industry Medium

	NIMTAAVG		TLMTA		EXRETAVG		SIGMA		RSIZE		CASHMTA		MB		PRICE	
β 1 (Low)	0.000		-0.016		0.001		-0.002		0.499		0.030		0.385		0.078	
β 2	-0.001		-0.005		0.001		0.000		0.527		0.027		0.421		0.067	
β 3	-0.003		0.010		0.000		0.002		0.406		0.028		0.506		0.051	

β 4	-0.005		0.009		-0.001		0.004		0.285		0.033		0.641		0.005	
β 5 (High)	-0.011		0.015		-0.003		0.008		0.122		0.038		0.816		-0.035	
High-Low	-0.011	***	0.031	***	-0.004		0.009	***	-0.377	***	0.008	*	0.431	***	-0.113	***
t-stat	-5.01		4.56		-1.59		12.64		-6.60		1.82		4.37		-12.62	
Firm Characteristics Adjusted by Sales Weighted Industry Average																
β 1 (Low)	0.000		-0.035		0.000		0.000		-1.071		0.021		-0.226		-0.072	
β 2	-0.001		-0.029		-0.001		0.003		-1.105		0.017		-0.170		-0.098	
β 3	-0.004		-0.020		-0.003		0.006		-1.276		0.018		-0.096		-0.114	
β 4	-0.006		-0.025		-0.005		0.009		-1.462		0.024		-0.022		-0.169	
β 5 (High)	-0.013		-0.026		-0.008		0.014		-1.661		0.030		0.084		-0.218	
High-Low	-0.013	***	0.009		-0.007	***	0.014	***	-0.590	***	0.009	*	0.310	***	-0.146	***
t-stat	-5.20		1.16		-2.88		13.24		-7.03		1.94		3.29		-15.62	
Firm Characteristics Adjusted by Sales Weighted Industry Medium																
β 1 (Low)	0.000		-0.016		0.001		-0.002		0.496		0.030		0.385		0.080	
β 2	-0.001		-0.005		0.001		0.000		0.543		0.027		0.421		0.069	
β 3	-0.003		0.010		0.000		0.002		0.417		0.028		0.506		0.053	
β 4	-0.005		0.009		-0.001		0.004		0.291		0.033		0.641		0.003	
β 5 (High)	-0.011		0.015		-0.004		0.008		0.145		0.038		0.816		-0.033	
High-Low	-0.011	***	0.031	***	-0.004	*	0.010	***	-0.351	***	0.008	*	0.431	***	-0.113	***
t-stat	-5.01		4.60		-1.87		12.52		-5.79		1.70		4.37		-12.10	

Table II Continued

Panel G. JACKPOT

Firm Characteristics Raw								
	SKEW3	RET	STD3	AGE	TURN	ASSETTANG	SALEG	MKTCAP
β 1 (Low)	0.219	-0.005	0.020	21.015	0.610	0.765	0.068	12.324
β 2	0.252	-0.006	0.025	18.830	0.561	0.635	0.078	12.113
β 3	0.260	-0.024	0.030	17.151	0.515	0.577	0.090	11.889
β 4	0.276	-0.043	0.034	14.374	0.476	0.526	0.100	11.679
β 5 (High)	0.283	-0.067	0.040	10.471	0.427	0.475	0.126	11.414
High-Low	0.064 **	-0.062	0.020 ***	-10.544 ***	-0.184	-0.290 ***	0.058 ***	-0.910 ***
t-stat	2.24	-1.45	10.78	-16.46	-1.39	-12.12	3.74	-4.70
Firm Characteristics Adjusted by Asset Weighted Industry Average								
β 1 (Low)	0.009	0.003	0.000	-0.771	0.023	0.014	-0.024	-0.973
β 2	0.030	0.005	0.003	-1.496	0.008	0.000	-0.019	-1.004
β 3	0.041	-0.007	0.005	-2.681	-0.002	-0.013	-0.015	-1.162
β 4	0.061	-0.019	0.008	-4.228	-0.022	-0.039	-0.011	-1.317
β 5 (High)	0.065	-0.036	0.012	-6.456	-0.045	-0.070	0.006	-1.512
High-Low	0.056 ***	-0.040 *	0.012 ***	-5.685 ***	-0.067	-0.084 ***	0.029 ***	-0.539 ***
t-stat	3.36	-1.94	11.90	-7.40	-0.60	-6.85	3.05	-4.04
Firm Characteristics Adjusted by Asset Weighted Industry Medium								
β 1 (Low)	-0.009	-0.011	-0.002	6.533	0.053	0.042	-0.013	0.469
β 2	0.004	-0.002	0.000	6.509	0.047	0.048	-0.010	0.499
β 3	0.009	-0.009	0.002	5.469	0.043	0.041	-0.004	0.375

Panel H. OTHER

Firm Characteristics Raw			
	XRDQ	INTAN	DTER
β 1 (Low)	0.011	0.056	0.469
β 2	0.018	0.077	0.443
β 3	0.021	0.082	0.464
β 4	0.025	0.085	0.476
β 5 (High)	0.032	0.092	0.477
High-Low	0.020 ***	0.036 *	0.008
t-stat	12.10	1.88	0.17
Firm Characteristics Adjusted by Asset Weighted Industry Average			
β 1 (Low)	0.001	-0.016	-0.149
β 2	0.005	-0.027	-0.109
β 3	0.006	-0.029	-0.065
β 4	0.008	-0.034	-0.052
β 5 (High)	0.013	-0.035	-0.039
High-Low	0.012 ***	-0.019 **	0.111 ***
t-stat	11.25	-2.41	5.44
Firm Characteristics Adjusted by Asset Weighted Industry Medium			
β 1 (Low)	-0.001	0.024	0.119
β 2	0.003	0.031	0.157
β 3	0.004	0.035	0.203

β 4	0.021	-0.014	0.004	3.737	0.029	0.025	0.002	0.259
β 5 (High)	0.021	-0.029	0.007	1.268	0.013	0.007	0.018	0.105
High-Low	0.030 **	-0.018	0.009 ***	-5.265 ***	-0.039	-0.034 ***	0.031 ***	-0.364 ***
t-stat	2.01	-0.89	12.86	-12.78	-0.42	-4.06	3.15	-5.89
Firm Characteristics Adjusted by Sales Weighted Industry Average								
β 1 (Low)	0.016	0.002	0.005	-1.576	0.009	0.011	-0.029	-1.123
β 2	0.038	0.000	-0.001	-2.368	-0.007	-0.003	-0.024	-1.151
β 3	0.048	-0.014	-0.014	-3.567	-0.012	-0.016	-0.022	-1.315
β 4	0.064	-0.029	-0.027	-5.293	-0.038	-0.043	-0.016	-1.484
β 5 (High)	0.069	-0.051	-0.041	-7.569	-0.061	-0.075	0.000	-1.666
High-Low	0.053 ***	-0.054 **	-0.046 ***	-5.993 ***	-0.070	-0.087 ***	0.029 ***	-0.544 ***
t-stat	3.46	-2.42	13.46	-8.66	-0.89	-6.55	2.79	-7.06
Firm Characteristics Adjusted by Sales Weighted Industry Medium								
β 1 (Low)	-0.003	-0.008	-0.006	6.708	0.054	0.042	-0.013	0.473
β 2	0.008	-0.001	-0.001	6.755	0.049	0.048	-0.011	0.521
β 3	0.011	-0.008	-0.009	5.794	0.049	0.041	-0.007	0.395
β 4	0.022	-0.016	-0.014	3.855	0.030	0.025	-0.001	0.271
β 5 (High)	0.023	-0.033	-0.023	1.359	0.018	0.007	0.017	0.130
High-Low	0.026 *	-0.025	-0.018 ***	-5.348 ***	-0.035	-0.034 ***	0.030 ***	-0.343 ***
t-stat	1.73	-1.20	12.74	-12.42	-0.67	-3.59	2.92	-5.23

β 4	0.005	0.038	0.221
β 5 (High)	0.008	0.044	0.238
High-Low	0.009 ***	0.020 **	0.120 ***
t-stat	9.83	2.18	4.81
Firm Characteristics Adjusted by Sales Weighted Industry Average			
β 1 (Low)	0.000	-0.014	-0.118
β 2	0.005	-0.024	-0.077
β 3	0.006	-0.023	-0.030
β 4	0.008	-0.027	-0.018
β 5 (High)	0.012	-0.026	-0.007
High-Low	0.012 ***	-0.012 *	0.112 ***
t-stat	10.98	-1.79	5.59
Firm Characteristics Adjusted by Sales Weighted Industry Medium			
β 1 (Low)	-0.001	0.024	0.119
β 2	0.003	0.031	0.157
β 3	0.004	0.035	0.203
β 4	0.005	0.038	0.221
β 5 (High)	0.008	0.044	0.240
High-Low	0.009 ***	0.020 **	0.121 ***
t-stat	9.83	2.18	4.86

Table III

Logistic Regressions

This table presents logistic regression results. The dependent variable is a dummy that equals one if the stock is in the beta portfolio five (highest) and zero if the stock is in other beta portfolios. In Panel A, we run the regression of the dummy variable on firm characteristics that predict jackpot returns following Chen, Hong, and Stein (2001), Boyer, Mitton, and Vorkink (2010), and Conrad, Kapadia, and Xing (2014) and report coefficient estimators and pseudo r-squared. In Panel B, we run the regression of the dummy variable on firm characteristics that predict distress following Campbell, Hilscher, and Szilagyi (2008) and report coefficient estimators and pseudo r-squared. We detail the construction of firm characteristic variables in Appendix A. The data cover the period between January, 1964 and December, 2013. P-values are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A. Jackpot			Panel B. Distress		
INTERCEPT	-0.288	***	INTERCEPT	7.289	***
	(0.001)			(0.001)	
SKEW3	0.007	***	NIMTAAVG	-7.286	***
	(0.001)			(0.001)	
RET	0.176	***	TLMTA	-0.983	***
	(0.001)			(0.001)	
AGE	-0.037	***	EXRETAVG	4.114	***
	(0.001)			(0.001)	
ASSETTANG	-0.506	***	SIGMA	1.759	***
	(0.001)			(0.001)	
SALEG	0.228	***	RSIZE	0.151	***
	(0.001)			(0.001)	

TURN	-0.124	***	CASHMTA	1.908	***
	(0.001)			(0.001)	
STD3	1.313	***	MB	0.000	**
	(0.001)			(0.047)	
MKTCAP	-0.047	***	PRICE	-0.610	***
	(0.001)			(0.001)	
Pseudo r-squared	12.22%		Pseudo r-squared	10.94%	

Table IV

Expected Probability of Jackpot Returns and Distress

This table shows the time-series average of the expected probability of jackpot returns and the time-series average of the expected probability of distress across beta portfolios. Each month, we use quintile breakpoints to assign stocks into portfolios based on their betas. We calculate monthly expected probability of jackpot returns and monthly expected probability of distress for each stock based on coefficients from the logistic regressions reported in Table III. For each beta portfolio, we first calculate the average of both probabilities across all stocks in the portfolio, and report their time-series averages. The column labeled High-Low presents the difference between quintile five and quintile one. The column labeled t-stat presents t-statistics adjusted following Newey and West (1987). The data cover the period between January, 1964 and December, 2013. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	β 1 (Low)	β 2	β 3	β 4	β 5 (High)	High-Low	t-stat
JACKPOT	10.98%	16.48%	20.25%	24.84%	31.43%	20.45%***	214.18
DISTRESS	7.83%	11.41%	14.13%	18.50%	25.30%	17.47%***	103.44

Table V

Bivariate Portfolio Analyses of Relation Between Beta and Returns

This table presents the results of bivariate dependent and independent sort portfolio analyses of the relation between beta and future returns after controlling for firm characteristic summary measures. Each month, all stocks in the sample are sorted into five groups, based on the ascending sort of one of the firm characteristic summary measures. For dependent sort, within each control variable group, quintile portfolios based on an ascending sort of beta and a High-Low portfolio long beta portfolio five and short beta portfolio one are created. For independent sort, quintile portfolios based on an ascending sort of beta and a High-Low portfolio long beta portfolio five and short beta portfolio one are created. Panel A, based on the dependent sort groups, reports the mean of risk-adjusted alphas relative to CAPM, Fama and French (1993) and Carhart (1997) four factors, and Fama and French (1993) and Carhart (1997) four factors plus Pastor and Stambaugh (2003) liquidity factor across five High-Low portfolios for each firm characteristic summary measure. Panel B, based on the independent sort groups, reports the mean of risk-adjusted alphas relative to CAPM, Fama and French (1993) and Carhart (1997) four factors, and Fama and French (1993) and Carhart (1997) four factors plus Pastor and Stambaugh (2003) liquidity factor across five High-Low portfolios for each firm characteristic summary measure. We detail the construction of firm characteristic summary measures in Appendix A. Data of QSCORE start at August, 1984. Data of MOMENTUM start at January, 1978. Data of CONTRARIAN start at July, 1984. Data of OPERATING start at October, 1988. Data of GROWTH start at January, 1983. Data of EXTREME start at January, 1964. Data of MISVALUATION start at January, 1972. Data of DISTRESS and JACKPOT start at April, 1975. Data of ALL start at January, 1991. Data of all firm characteristic summary measures end at December, 2013. The mean of Newey and West (1987) t-statistics is shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	Panel A. Dependent Sort				Panel B. Independent Sort			
	CAPM α		FFC α	FFCPS α	CAPM α		FFC α	FFCPS α
QSCORE	-0.31%		0.25%	0.27%	-0.42%		0.11%	0.10%
	(-0.72)		(0.42)	(0.44)	(-0.88)		(0.12)	(0.10)
MOMENTUM	-0.43%		0.12%	0.18%	-0.36%		0.25%	0.30%
	(-1.42)		(0.52)	(0.76)	(-1.19)		(1.04)	(1.24)
CONTRARIAN	-0.51%		0.09%	0.11%	-0.46%		0.06%	0.06%
	(-1.22)		(0.17)	(0.23)	(-1.01)		(-0.02)	(-0.02)
OPERATING	-1.10%	***	-0.39%	-0.36%	-1.17%	***	-0.55%	-0.52%
	(-2.86)		(-1.01)	(-0.92)	(-2.70)		(-1.39)	(-1.32)
GROWTH	-0.88%	***	-0.34%	-0.30%	-0.95%	***	-0.37%	-0.33%

	(-2.68)		(-1.34)		(-1.17)		(-2.78)		(-1.48)		(-1.30)	
EXTREME	-0.34%		-0.09%		-0.07%		-0.34%		-0.10%		-0.07%	
	(-1.20)		(-0.38)		(-0.27)		(-1.22)		(-0.41)		(-0.27)	
MISVALUATION	-0.51%	*	-0.20%		-0.16%		-0.59%	*	-0.26%		-0.24%	
	(-1.80)		(-0.74)		(-0.62)		(-1.94)		(-0.87)		(-0.83)	
DISTRESS	1.27%	***	1.63%	***	1.65%	***	1.33%	***	1.79%	***	1.84%	***
	(4.49)		(5.60)		(5.61)		(4.53)		(5.41)		(5.46)	
JACKPOT	0.03%		0.27%		0.29%		0.00%		0.23%		0.25%	
	(0.14)		(1.20)		(1.28)		(0.03)		(0.97)		(1.06)	
ALL	0.55%		0.90%		0.90%		0.47%		1.05%		1.10%	
	(0.56)		(0.93)		(0.93)		(0.40)		(1.09)		(1.11)	

VI

Characteristic Adjusted Returns across Beta Portfolios

This table presents the alphas of beta-sorted portfolios using characteristic adjusted returns. Panel A reports the alphas from regressing characteristic adjusted portfolio returns on market excess returns, Fama and French (1993) and Carhart (1997) four factors, and Fama and French (1993) and Carhart (1997) four factors plus Pastor and Stambaugh (2003) liquidity factor. The column labeled High-Low represents the difference in alpha between high and low beta portfolios. High (low) beta portfolio is portfolio 5 (1). Panel B reports the averages of risk-adjusted alphas in the High-Low portfolios based on different factor models after controlling for characteristic adjusted returns. Each month, all stocks in the sample are first sorted on characteristic adjusted returns into five groups, and then on betas to form High-Low portfolios. For dependent sort, within each control variable group, quintile portfolios based on an ascending sort of beta and a High-Low portfolio are created. For independent sort, quintile portfolios based on an ascending sort of beta, and a High-Low portfolio are created. For each High-Low portfolio, we run time-series regressions of portfolio excess returns on different risk factors, and report the averages of alphas in five High-Low portfolios. Data are from January, 1991 to December, 2013. Newey and West (1987) t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A.Alpha

	β 1 (Low)		β 2		β 3		β 4		β 5 (High)		High-Low	
CAPM α	10.74%	***	10.66%	***	10.76%	***	10.85%	***	10.97%	***	0.23%	
	(14.03)		(14.22)		(14.35)		(14.90)		(14.73)		(1.25)	
FFC α	10.80%	***	10.78%	***	10.87%	***	11.03%	***	11.31%	***	0.51%	***
	(14.21)		(14.33)		(14.92)		(14.79)		(14.77)		(2.76)	
FFCPS α	10.79%	***	10.79%	***	10.88%	***	11.04%	***	11.34%	***	0.55%	***
	(14.35)		(14.53)		(15.15)		(14.99)		(15.15)		(3.09)	

Panel B. Bivariate Portfolio Analyses of Relation Between Characteristics Adjusted Return and Alpha

	Dependent sort	Independent sort
CAPM α	0.18%	0.30%
	(0.43)	(0.54)
FFC α	0.27%	0.42%

	(0.40)	(0.64)
FFCPS α	0.28%	0.44%
	(0.44)	(0.79)

VII

Fama and MacBeth Regressions

This table presents the results of Fama and MacBeth (1973) regression analysis after controlling for firm characteristic categories. We detail the construction of firm characteristic variables and how we group them into categories in Appendix A. We regress one month ahead excess return of all stocks on their betas and each of the firm characteristic categories. The coefficients are shown in the table for each model specification. Panel A shows the coefficients and t-statistics of beta when we regress excess returns on betas alone. Panel B shows the coefficients and t-statistics of beta and firm characteristic categories. In Panel C, we regress one month ahead characteristic adjusted returns on beta and report the coefficients and t-statistics of beta. Data of QSCORE start at August, 1984. Data of MOMENTUM start at January, 1978. Data of CONTRARIAN start at July, 1984. Data of OPERATING start at October, 1988. Data of GROWTH start at January, 1983. Data of EXTREME start at January, 1964. Data of MISVALUATION start at January, 1972. Data of DISTRESS and JACKPOT start at April, 1975. Data of ALL start at January, 1991. Data of all firm characteristic categories end at December, 2013. Newey and West (1987) t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A. Beta alone										
BETA	0.001	0.002	0.002	0.002	0.002	0.017 *	0.002	0.002	0.003	0.002
	(0.82)	(0.79)	(1.05)	(0.85)	(0.64)	(1.89)	(0.98)	(0.77)	(1.27)	(1.27)
Panel B. Beta and firm characteristic measure										
BETA	0.002	0.003	0.001	0.002	-0.018	0.002	0.002	0.014 ***	0.005 ***	0.012 ***
	(0.96)	(1.30)	(0.46)	(0.79)	(-0.96)	(0.98)	(0.75)	(4.43)	(3.13)	(3.55)
QSCORE	0.002 *									
	(1.71)									
MOMENTUM		0.005 ***								
		(10.38)								
CONTRARIAN			0.000							
			(-0.51)							
OPERATING				0.001 *						
				(1.73)						

GROWTH			-0.006 *					
			(-1.86)					
EXTREME				0.000				
				(1.26)				
MISVALUATION					0.001 ***			
					(5.47)			
DISTRESS						-0.017 ***		
						(-7.55)		
JACKPOT							-0.003 ***	
							(-8.49)	
ALL								-0.001 ***
								(-6.13)

Panel C. Cross-sectional regression of Characteristic Adjusted Return on Beta

	QSCORE	OPERATING	GROWTH	EXTREME
BETA	-0.009 ***	-0.005 *	-0.002	0.003 **
	(-3.37)	(-1.75)	(-0.82)	(-2.09)
	MISVALUATION	DISTRESS	JACKPOT	ALL
BETA	-0.003	0.013 ***	-0.006 **	0.003
	(-1.07)	(3.48)	(-2.10)	(1.05)

Table VIII

Relation Between Beta and Returns Controlled For Aggregate Firm Characteristics

This table shows the time-series regression results after controlling for aggregate firm characteristic indexes and attribute spreads. We regress excess returns of each beta portfolio on Fama and French (1993) and Carhart (1997) four factors and each aggregate firm characteristic index. The index is created by giving either value weight or equal weight to firm characteristic categories across all stocks. Panel A reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors and value-weighted firm characteristic indexes. Panel B reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors and equal-weighted firm characteristic indexes. Panel C reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors and value-weighted attribute spreads. Panel D reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors and equal-weighted attribute spreads. The High-Low FFC column presents the difference in four factor alphas between beta five (highest) and beta one (lowest) groups after controlling for aggregate firm characteristic measures. The FFC column presents the difference in four factor alphas between the beta five (highest) and beta one (lowest) groups without controlling for aggregate firm characteristic measures. We detail the construction of firm characteristic variables and aggregate firm characteristic measures in Appendix A. Data of QSCORE start at August, 1984. Data of MOMENTUM start at January, 1978. Data of CONTRARIAN start at July, 1984. Data of OPERATING start at October, 1988. Data of GROWTH start at January, 1983. Data of EXTREME start at January, 1964. Data of MISVALUATION start at January, 1972. Data of DISTRESS and JACKPOT start at April, 1975. Data of ALL start at January, 1991. Data of all firm characteristic measures end at December, 2013. Newey and West (1987) t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A. Value-Weighted Aggregate firm characteristic indexes

	β 1 (Low)		β 2		β 3		β 4		β 5 (High)	High-Low FFC	FFC	
QSCORE	1.38%		-0.20%		-1.47%		-2.74%		-4.44%	-5.82%	-0.60%	**
	(0.93)		(-0.13)		(-0.93)		(-1.31)		(-1.20)	(-1.06)	(-1.98)	
MOMENTUM	0.38%		0.49%		0.22%		0.79%		1.62%	1.24%	-0.55%	***
	(0.31)		(0.45)		(0.20)		(0.54)		(0.64)	(0.83)	(-2.64)	
CONTRARIAN	1.00%		-0.55%		-1.79%	*	-2.18%	*	-3.82%	-4.82%	-0.47%	**
	(0.73)		(-0.48)		(-1.85)		(-1.67)		(-1.62)	(-1.24)	(-2.01)	
OPERATING	-0.46%		-1.36%		-0.34%		1.75%		5.02%	5.48%	-0.54%	**
	(-0.23)		(-0.91)		(-0.21)		(0.64)		(1.31)	(1.08)	(-2.05)	
GROWTH	-2.26%	*	-2.99%	***	-1.93%		-1.74%		0.13%	2.40%	-0.53%	**
	(-1.79)		(-2.75)		(-1.37)		(-0.91)		(0.06)	(0.49)	(-2.30)	
EXTREME	-1.85%		0.14%		3.34%	*	4.10%	**	3.98%	5.83%	-0.54%	***

	(-0.85)		(0.08)		(1.96)		(2.04)		(1.20)		(0.72)	(-2.86)	
MISVALUATION	5.36%	***	3.20%	**	3.83%	**	4.23%	*	4.24%		-1.12%	-0.56%	***
	(3.12)		(2.02)		(2.15)		(1.89)		(1.44)		(-0.20)	(-2.71)	
DISTRESS	0.61%		-1.67%		-0.89%		-2.40%		-4.16%		-4.77%	-0.60%	***
	(0.36)		(-1.58)		(-0.94)		(-1.50)		(-1.37)		(-1.25)	(-2.86)	
JACKPOT	1.17%		1.56%	*	2.77%	***	3.10%	***	1.81%		0.64%	-0.54%	***
	(1.08)		(1.67)		(3.29)		(2.64)		(0.71)		(0.23)	(-2.86)	
ALL	2.65%		-0.05%		2.25%		5.04%	**	5.62%		2.96%	-0.54%	**
	(1.59)		(-0.03)		(1.26)		(2.24)		(1.30)		(0.38)	(-2.05)	

Panel B. Equal-Weighted Aggregate firm characteristic indexes

	β 1 (Low)		β 2		β 3		β 4		β 5 (High)		High-Low FFC	FFC	
QSCORE	0.41%		-0.35%		-1.57%		-2.04%		-4.63%		-5.04%	-0.60%	**
	(0.26)		(-0.19)		(-0.93)		(-0.92)		(-1.37)		(-1.00)	(-1.98)	
MOMENTUM	-0.67%		-0.08%		-0.48%		0.38%		3.17%		3.84%	-0.55%	***
	(-0.37)		(-0.05)		(-0.29)		(0.19)		(1.16)		(1.60)	(-2.64)	
CONTRARIAN	0.38%		-0.65%		-2.04%	*	-1.86%		-4.07%	*	-4.45%	-0.47%	**
	(0.28)		(-0.50)		(-1.76)		(-1.19)		(-1.72)		(-1.20)	(-2.01)	
OPERATING	0.70%		0.37%		0.82%		1.78%		4.24%		3.54%	-0.54%	**
	(0.30)		(0.21)		(0.39)		(0.54)		(1.00)		(0.54)	(-2.05)	
GROWTH	-1.95%		-3.57%	***	-3.14%		-3.62%		-0.26%		1.68%	-0.53%	**
	(-1.26)		(-2.60)		(-1.59)		(-1.60)		(-0.13)		(0.74)	(-2.30)	
EXTREME	-2.82%		-1.31%		-3.36%		5.43%		1.20%		4.02%	-0.54%	***

	(-0.53)		(-0.27)		(-0.65)		(0.73)		(0.10)		(0.18)		(-2.86)	
MISVALUATION	6.06%	***	4.37%	**	3.27%		0.73%		-2.83%		-8.89%		-0.56%	***
	(2.64)		(2.16)		(1.25)		(0.21)		(-0.53)		(-1.43)		(-2.71)	
DISTRESS	0.44%		-1.73%		-1.46%		-3.11%	*	-4.46%		-4.90%		-0.60%	***
	(0.25)		(-1.59)		(-1.30)		(-1.76)		(-1.44)		(-1.20)		(-2.86)	
JACKPOT	2.19%	*	2.14%	**	3.24%	***	3.71%	***	1.10%		-1.09%		-0.54%	***
	(1.86)		(2.03)		(3.55)		(3.08)		(0.43)		(-0.78)		(-2.86)	
ALL	2.61%		-0.10%		2.11%		4.97%	**	5.58%		2.97%		-0.54%	**
	(1.56)		(-0.05)		(1.22)		(2.26)		(1.29)		(0.39)		(-2.05)	

Panel C. Value-Weighted Attribute Spreads

	β 1 (Low)		β 2		β 3		β 4		β 5 (High)		High-Low FFC		FFC	
QSCORE	0.27%		0.25%	*	0.22%		0.15%		0.27%		0.00%		-0.60%	**
	(1.65)		(1.91)		(1.23)		(0.79)		(0.83)		(0.33)		(-1.98)	
MOMENTUM	0.61%	***	0.48%	***	0.27%	***	0.17%	*	0.10%		-0.52%	**	-0.55%	***
	(7.38)		(5.97)		(3.60)		(1.72)		(0.55)		(-2.17)		(-2.64)	
CONTRARIAN	0.28%		0.19%		0.08%		0.00%		0.10%		-0.18%		-0.47%	**
	(1.48)		(1.48)		(0.51)		(-0.00)		(0.31)		(-0.03)		(-2.01)	
OPERATING	0.48%	**	0.24%		-0.11%		-0.04%		-0.08%		-0.56%		-0.54%	**
	(2.46)		(1.53)		(-0.57)		(-0.18)		(-0.23)		(-1.13)		(-2.05)	
GROWTH	0.36%	***	0.22%	***	0.02%		0.00%		0.10%		-0.25%		-0.53%	**
	(3.25)		(3.08)		(0.22)		(-0.02)		(0.41)		(-0.36)		(-2.30)	
EXTREME	0.80%	***	0.69%	***	0.50%	***	0.28%		-0.46%		-1.26%	**	-0.54%	***

	(3.95)	(4.04)	(2.65)	(1.24)	(-1.10)	(-2.30)	(-2.86)
MISVALUATION	0.63% ***	0.48% ***	0.23% **	0.07%	-0.03%	-0.66% **	-0.56% ***
	(6.49)	(5.18)	(2.39)	(0.61)	(-0.19)	(-2.44)	(-2.71)
DISTRESS	0.49% ***	0.48% ***	0.43% ***	0.39% **	0.43%	-0.06%	-0.60% ***
	(4.34)	(5.55)	(3.97)	(2.21)	(1.57)	(-0.12)	(-2.86)
JACKPOT	0.63% **	0.19%	0.11%	0.13%	-0.20%	-0.83%	-0.54% ***
	(2.50)	(1.02)	(0.55)	(0.53)	(-0.43)	(-1.21)	(-2.86)
ALL	0.53% ***	0.44% ***	0.17%	0.05%	-0.04%	-0.47%	-0.54% **
	(4.79)	(4.99)	(1.50)	(0.34)	(-0.18)	(-1.54)	(-2.05)

Panel D. Equal-Weighted Attribute Spreads

	β 1 (Low)	β 2	β 3	β 4	β 5 (High)	High-Low FFC	FFC
QSCORE	0.27%	0.25% *	0.22%	0.16%	0.27%	0.00%	-0.60% **
	(1.65)	(1.96)	(1.25)	(0.81)	(0.85)	(0.33)	(-1.98)
MOMENTUM	0.61% ***	0.48% ***	0.27% ***	0.17% *	0.10%	-0.51% **	-0.55% ***
	(7.37)	(5.94)	(3.60)	(1.75)	(0.57)	(-2.14)	(-2.64)
CONTRARIAN	0.28%	0.19%	0.09%	0.01%	0.11%	-0.17%	-0.47% **
	(1.49)	(1.56)	(0.56)	(0.03)	(0.33)	(-0.03)	(-2.01)
OPERATING	0.49% **	0.24%	-0.11%	-0.06%	-0.11%	-0.60%	-0.54% **
	(2.53)	(1.53)	(-0.59)	(-0.23)	(-0.30)	(-1.24)	(-2.05)
GROWTH	0.35% ***	0.22% ***	0.01%	-0.01%	0.10%	-0.25%	-0.53% **
	(3.15)	(2.97)	(0.15)	(-0.06)	(0.39)	(-0.35)	(-2.30)
EXTREME	0.82% ***	0.70% ***	0.50% **	0.27%	-0.49%	-1.30% **	-0.54% ***

	(3.98)	(4.05)	(2.60)	(1.22)	(-1.17)	(-2.37)	(-2.86)
MISVALUATION	0.63% ***	0.48% ***	0.23% **	0.07%	-0.02%	-0.66% **	-0.56% ***
	(6.47)	(5.11)	(2.40)	(0.66)	(-0.15)	(-2.41)	(-2.71)
DISTRESS	0.48% ***	0.48% ***	0.44% ***	0.41% **	0.44%	-0.04%	-0.60% ***
	(4.24)	(5.46)	(3.89)	(2.19)	(1.58)	(-0.13)	(-2.86)
JACKPOT	0.63% **	0.20%	0.11%	0.13%	-0.20%	-0.84%	-0.54% ***
	(2.55)	(1.08)	(0.56)	(0.52)	(-0.44)	(-1.15)	(-2.86)
ALL	0.53% ***	0.44% ***	0.17%	0.05%	-0.04%	-0.57%	-0.54% **
	(4.76)	(4.97)	(1.50)	(0.34)	(-0.17)	(-1.51)	(-2.05)

Table IX

Relation Between BAB and Aggregate Firm Characteristics

This table compares the alphas of the BAB factor across various models and its alphas after adding aggregate firm characteristic indexes and attribute spreads. We regress Frazzini and Pedersen (2014)'s monthly BAB factor on Fama and French (1993) and Carhart (1997) four factors (FFC), plus Pastor and Stambaugh (2003) liquidity factor (FFCPS), and each aggregate firm characteristic measure. The index is created by giving either value weight or equal weight to firm characteristic categories across all stocks. Panel A reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors, Pastor and Stambaugh (2003) liquidity factor, and value-weighted firm characteristic indexes. Panel B reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors, Pastor and Stambaugh (2003) liquidity factor, and equal-weighted firm characteristic indexes. Panel C reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors, Pastor and Stambaugh (2003) liquidity factor, and value-weighted attribute spreads. Panel D reports the alphas adjusted for returns on Fama and French (1993) and Carhart (1997) four factors, Pastor and Stambaugh (2003) liquidity factor, and equal-weighted attribute spreads. The FFC+Index (FFC+Spread) column presents the four factor alphas after controlling for the aggregate firm characteristic index (attribute spread). The FFC column presents the four factor alphas without controlling for aggregate firm characteristic measures. The FFCPS+Index (FFCPS+Spread) column presents the five factor alphas after controlling for the aggregate firm characteristic index (attribute spread). The FFCPS column presents the five factor alphas without controlling for aggregate firm characteristic measures. We detail the construction of firm characteristic variables and aggregate firm characteristic measures in Appendix A. Data of QSCORE start at August, 1984. Data of MOMENTUM start at January, 1978. Data of CONTRARIAN start at July, 1984. Data of OPERATING start at October, 1988. Data of GROWTH start at January, 1983. Data of EXTREME start at January, 1964. Data of MISVALUATION start at January, 1972. Data of DISTRESS and JACKPOT start at April, 1975. Data of ALL start at January, 1991. Data of all firm characteristic measures end at December, 2013. Newey and West (1987) t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A. Value-Weighted Aggregate Firm Characteristic Indexes

	FFC+Index		FFC		FFCPS+Index	FFCPS	
QSCORE	-0.19%		0.68%	***	-0.23%	0.59%	**
	(-0.06)		(2.79)		(-0.07)	(2.47)	
MOMENTUM	-3.65%		0.67%	***	-3.46%	0.58%	***
	(-1.39)		(3.27)		(-1.33)	(2.93)	
CONTRARIAN	-0.16%		0.68%	***	-0.52%	0.59%	**
	(-0.06)		(2.79)		(-0.19)	(2.47)	
OPERATING	8.25%		0.89%	***	7.81%	0.81%	***
	(1.55)		(3.03)		(1.50)	(2.76)	
GROWTH	-6.82%	***	0.66%	***	0.42%	0.56%	**
	(-3.07)		(2.75)		(1.40)	(2.39)	
EXTREME	-1.47%		0.61%	***	-1.72%	0.57%	***
	(-0.34)		(3.83)		(-0.41)	(3.69)	
MISVALUATION	0.32%		0.65%	***	0.14%	0.58%	***
	(0.07)		(3.38)		(0.03)	(3.15)	
DISTRESS	1.67%		0.73%	***	1.23%	0.65%	***
	(0.55)		(3.80)		(0.42)	(3.49)	

JACKPOT	-0.20%		0.61%	***	0.14%		0.57%	***
	(-0.09)		(3.83)		(0.06)		(3.69)	
ALL	2.94%		0.88%	***	3.39%		0.81%	***
	(0.57)		(3.06)		(0.71)		(2.76)	

Panel B. Equal-Weighted Aggregate Firm Characteristic Indexes

	FFC+Index		FFC		FFCPS+Index		FFCPS	
QSCORE	-0.01%		0.68%	***	-0.05%		0.59%	**
	(-0.00)		(2.79)		(-0.01)		(2.47)	
MOMENTUM	-4.32%		0.67%	***	-4.13%		0.58%	***
	(-1.51)		(3.27)		(-1.46)		(2.93)	
CONTRARIAN	0.13%		0.68%	***	-0.29%		0.59%	**
	(0.05)		(2.79)		(-0.10)		(2.47)	
OPERATING	7.50%		0.89%	***	7.10%		0.81%	***
	(1.48)		(3.03)		(1.42)		(2.76)	
GROWTH	-6.95%	***	0.66%	***	0.42%		0.56%	**
	(-3.37)		(2.75)		(1.40)		(2.39)	
EXTREME	-1.82%		0.61%	***	-1.92%		0.57%	***
	(-0.43)		(3.83)		(-0.47)		(3.69)	
MISVALUATION	1.19%		0.65%	***	0.84%		0.58%	***
	(0.27)		(3.38)		(0.21)		(3.15)	
DISTRESS	1.96%		0.73%	***	1.49%		0.65%	***
	(0.64)		(3.80)		(0.50)		(3.49)	
JACKPOT	-0.02%		0.61%	***	0.31%		0.57%	***
	(-0.01)		(3.83)		(0.13)		(3.69)	
ALL	2.73%		0.88%	***	3.14%		0.81%	***
	(0.52)		(3.06)		(0.65)		(2.76)	

Panel C. Value-Weighted Attribute Spreads

	FFC+Spread		FFC		FFCPS+Spread		FFCPS	
QSCORE	0.57%	**	0.68%	***	0.46%		0.59%	**
	(1.97)		(2.79)		(1.58)		(2.47)	
MOMENTUM	0.66%	***	0.67%	***	0.58%	***	0.58%	***

	(3.29)		(3.27)		(3.05)		(2.93)	
CONTRARIAN	0.53%		0.68%	***	0.41%		0.59%	**
	(1.24)		(2.79)		(0.98)		(2.47)	
OPERATING	1.34%	**	0.89%	***	1.16%	**	0.81%	***
	(2.56)		(3.03)		(2.17)		(2.76)	
GROWTH	0.54%	*	0.66%	***	0.41%		0.56%	**
	(1.85)		(2.75)		(1.38)		(2.39)	
EXTREME	0.34%		0.61%	***	0.39%		0.57%	***
	(0.81)		(3.83)		(0.95)		(3.69)	
MISVALUATION	0.54%	***	0.65%	***	0.48%	**	0.58%	***
	(2.62)		(3.38)		(2.46)		(3.15)	
DISTRESS	0.82%	***	0.73%	***	0.77%	***	0.65%	***
	(3.80)		(3.80)		(3.72)		(3.49)	
JACKPOT	0.45%		0.61%	***	0.32%		0.57%	***
	(0.91)		(3.83)		(0.64)		(3.69)	
ALL	0.72%	**	0.88%	***	0.63%	**	0.81%	***
	(2.31)		(3.06)		(2.02)		(2.76)	

Panel D. Equal-Weighted Attribute Spreads

	FFC+Spread		FFC		FFCPS+Spread		FFCPS	
QSCORE	0.58%	**	0.68%	***	0.46%		0.59%	**
	(1.99)		(2.79)		(1.58)		(2.47)	
MOMENTUM	0.66%	***	0.67%	***	0.58%	***	0.58%	***
	(3.30)		(3.27)		(3.06)		(2.93)	
CONTRARIAN	0.54%		0.68%	***	0.41%		0.59%	**
	(1.29)		(2.79)		(0.98)		(2.47)	
OPERATING	1.37%	***	0.89%	***	1.18%	***	0.81%	***
	(2.62)		(3.03)		(2.23)		(2.76)	
GROWTH	0.55%	*	0.66%	***	0.42%		0.56%	**
	(1.88)		(2.75)		(1.40)		(2.39)	
EXTREME	0.37%		0.61%	***	0.42%		0.57%	***
	(0.87)		(3.83)		(1.03)		(3.69)	

MISVALUATION	0.53%	***	0.65%	***	0.48%	**	0.58%	***
	(2.60)		(3.38)		(2.45)		(3.15)	
DISTRESS	0.82%	***	0.73%	***	0.78%	***	0.65%	***
	(3.80)		(3.80)		(3.73)		(3.49)	
JACKPOT	0.48%		0.61%	***	0.34%		0.57%	***
	(0.98)		(3.83)		(0.70)		(3.69)	
ALL	0.71%	**	0.88%	***	0.64%	**	0.81%	***
	(2.30)		(3.06)		(2.03)		(2.76)	

Table X

Limits to Arbitrage

This table presents the effect of limits to arbitrage on low beta anomaly. We consider five measures of limits to arbitrage: size, institutional ownership orthogonal to size, analyst coverage orthogonal to size, institutional ownership, and analyst coverage. We first classify stocks into two groups, based on the limits to arbitrage variables, and then regress the difference in returns between the quintile five (highest) and quintile one (lowest) portfolios within each group on market excess return (CAPM), Fama and French (1993) and Carhart (1997) four factors, and Fama and French (1993) and Carhart (1997) four factors factors plus Pastor and Stambaugh (2003) liquidity factor. Small (big) stocks are smaller (larger) than the 30th (70th) NYSE size percentile. For institutional ownership and analyst coverage orthogonalized to size, we use the residuals of each variable from their regressions on size and time dummies. Low institutional ownership or analyst coverage stocks are in the smallest tercile, while High stocks are in the largest tercile. The data cover the period between January, 1964 and December, 2013. T-statistics adjusted following Newey and West (1987) are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	Size				Institutional Ownership, Orthogonal to Size				Analyst Coverage, Orthogonal to Size				Institutional Ownership				Analyst Coverage			
	Small		Big		Low		High		Low		High		Low		High		Low		High	
CAPM α	-1.63%	***	-0.49%	**	-1.14%	***	-1.51%	***	-0.64%		-1.14%	**	-1.53%	***	-0.73%	*	-1.25%	***	-0.94%	**
	(-5.50)		(-2.16)		(-2.93)		(-4.11)		(-1.52)		(-2.10)		(-3.26)		(-1.88)		(-3.51)		(-2.44)	
FFC α	-1.44%	***	-0.21%		-0.56%		-1.07%	***	-0.21%		-0.79%	*	-1.04%	**	-0.38%		-0.77%	**	-0.51%	
	(-6.47)		(-1.11)		(-1.49)		(-3.28)		(-0.50)		(-1.69)		(-2.44)		(-1.13)		(-2.13)		(-1.43)	
FFCPS α	-1.39%	***	-0.19%		-0.52%		-0.98%	***	-0.21%		-0.72%		-0.98%	**	-0.38%		-0.68%	*	-0.49%	
	(-6.92)		(-1.05)		(-1.40)		(-3.04)		(-0.49)		(-1.52)		(-2.30)		(-1.14)		(-1.96)		(-1.37)	