PAWEL BILINSKI AND DANIELLE LYSSIMACHOU

The Risk Interpretation of the CAPM's Beta: Evidence from a New Research Method

This study tests the validity of using the CAPM beta as a risk control in cross-sectional accounting and finance research. We recognize that high risk stocks should experience either very good or very bad returns more frequently compared to low risk stocks, i.e. high risk stocks should cluster in the tails of the cross-sectional return distribution. Building on this intuition, we test the risk interpretation of the CAPM's beta by examining if high beta stocks are more likely than low beta stocks to experience either very high or very low returns. Our empirical results indicate that beta is a strong predictor of large positive and large negative returns, which confirms that beta is a valid empirical risk measure and that researchers should use beta as a risk control in empirical tests. Further, we show that because the relation between beta and returns is U-shaped, i.e. high betas predict both very high and very low returns, linear cross-sectional regression models, e.g. Fama-MacBeth regressions, will fail on average to reject the null hypothesis that beta does not capture risk. This result explains why previous studies find no significant cross-sectional relation between beta and returns.

Key words: Market beta; New research method; Empirical accounting and finance research.

PAWEL BILINSKI (pawel.bilinski.1@city.ac.uk) and DANIELLE LYSSIMACHOU (danielle.lyssimachou.1@city.ac.uk) are Associate Professors of Accounting at Cass Business School, City University London.
The authors would like to thank Michael Brennan, Paul Griffin, Gilad Livne and Peter Pope for helpful comments.

INTRODUCTION

The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) lies at the heart of empirical accounting and finance research.[1] Early empirical tests by Black *et al.* (1972), Blume and Friend (1973) and Fama and MacBeth (1973) show that beta explains the cross-section of stock returns. However, a plethora of subsequent studies, including Lakonishok and Shapiro (1986) and Ritter and Chopra (1989) find no evidence of a significant cross-sectional relation between beta and returns. Fama and French (1992) provide the most convincing evidence challenging beta's ability to explain the cross-section of stock returns. They show that beta sorts produce no significant return spread, but that two other characteristics, firm size and the book-to-market ratio, capture the cross-section of asset returns. They obtain similar conclusions using Fama-MacBeth regressions.

To date, the accounting and finance literature has not arrived at a satisfactory conclusion on the validity of using the CAPM's beta as a risk control in empirical research.[2] However, without clear-cut resolutions, discarding beta as a risk control can lead to asset pricing model misspecification and, consequently, erroneous conclusions in empirical tests.[3] This paper uses a simple test to examine if market beta captures risk and, consequently, if researchers should use beta as a risk control in empirical tests. The framework we propose also explains why previous studies have failed to reject the null hypothesis that beta does not capture the cross-section of stock returns.

The departure point for our tests is the intuition that risky stocks should experience very good or very bad returns more frequently compared to low risk stocks, i.e. risky stocks should concentrate in the tails of the cross-sectional return distribution. Building on this insight, a test of whether high beta stocks are more risky is equivalent to testing if high beta stocks tend to experience very high and very low returns more often than low beta stocks.[4] We operationalize this test with two logistic regressions, one that predicts large positive returns and the other that predicts large negative returns from beta. If beta risk helps explain the return cross-section, the coefficients on market betas in both regressions should be significant and positive. The two regressions control for common empirical risk factors, such as firm size and the book-to-market ratio, to examine if these risk proxies subsume beta's role in explaining the return cross-section (Fama and French, 1992, 1993).

We start the analysis by replicating previous evidence that beta shows no association with the return cross-section. A simple portfolio analysis that sorts stocks into deciles based on beta shows a flat relation between beta and monthly returns, consistent with previous evidence (Lakonishok and Shapiro, 1986; Ritter and Chopra, 1989; Fama and French, 1992). Further, we find no relation between beta and returns when we use pooled cross-sectional OLS regressions or the Fama-MacBeth method. Together, this confirms previous conclusions that standard research methods produce no evidence of a cross-sectional association between beta and stock returns.

Next, we test if high beta stocks are more likely than low beta stocks to experience large negative and large positive returns. We start by splitting stocks into deciles based on their monthly returns. This allows us to identify the tails of the cross-sectional return distribution. Consistent with our prediction, we find that high beta stocks tend to cluster among stocks with large positive and large negative returns.

In subsequent analysis, we use two logistic regressions to test if high betas predict large negative and large positive returns. As a starting point, we use arbitrary cut-off points to define the dependent variables for the two logistic models. Specifically, the dependent variable in the regression predicting high returns takes the value of one if the stock's monthly returns are higher than 20%, and zero otherwise. For the logistic model testing if high beta stocks are more likely to experience large negative returns, the dependent variable is one if monthly returns are lower than −15%, and zero otherwise.[5] Multivariate logistic regressions show that the coefficients on betas are positive and significant in both models, consistent with high beta stocks being more likely to experience extreme favorable and unfavorable outcomes. This evidence supports the prediction that beta captures risk and that researchers should use beta as a risk control in empirical tests.

Our conclusion that beta reflects risk is robust to a battery of sensitivity tests. First, we show that our conclusion is not sensitive to the specification of the cut-off points we use to define the dependent variables in the two logistic models, and the conclusion remains unchanged when we use past stock returns to construct the dependent variables in the logistic regressions.[6] Second, we show that beta predicts large positive and large negative returns when we use Dimson's (1979) beta to control for stock thin trading and the resultant downward bias in beta coefficients, when we use betas estimated at portfolio-level rather than at firm-level to control for the errors-in-variables problem, and when we estimate betas over a five-year rather than a three-year period. The latter test addresses the problem of beta's instability over time (Bos and Newbold, 1984). Finally, as part of the sensitivity analysis, we also show that our inferences remain the same when we use non-parametric quantile regressions to test for the association between beta and large positive and negative returns. Quantile regressions examine the association between beta and returns for various cut-off points of the return distribution. Standard OLS/Fama-MacBeth methods only estimate if beta explains the conditional mean return. Quantile regressions show that beta is a strong predictor of returns in the top and the bottom decile of the return distribution, which supports our main conclusions.

Our study offers two important contributions to the literature. First, using a simple research framework that focuses on the tails of the cross-sectional return distribution, we provide robust evidence that beta captures risk that drives stock returns. This adds important new evidence to the literature that examines the validity of using beta as a risk control in empirical accounting and finance research. Our testing framework has numerous advantages. It is very simple to implement, it builds on the intuition of 'what a risky stock is', and avoids imposing a linear constraint on the relation between betas and returns that is implicit in pooled OLS regressions or the Fama-MacBeth method. The approach does not increase the likelihood of falsely rejecting the null hypothesis that beta does not reflect risk because for beta to associate with risk, coefficients on betas in both predictive regressions need to be significant and have the same sign.[7]

Second, our study explains why standard portfolio analysis, and cross-sectional OLS/Fama-MacBeth regressions have low power to reject the null hypothesis that beta does not explain the return cross-section. We show that high beta stocks experience large positive and large negative returns more often compared to low beta stocks. Standard cross-sectional sorts that allocate high beta stocks into a single portfolio will combine stocks with positive and negative returns producing only average portfolio returns. In other words, standard sorts on beta impose a linear constraint on the relation between beta and returns, whereas this relation is U-shaped. This produces weak or no evidence on the cross-sectional association between beta and returns using standard sorts on beta. In a similar way, cross-sectional OLS/Fama-MacBeth regressions impose a linear relation between beta and returns, which biases beta coefficients towards zero. We advocate that future research uses either logit models or quantile regressions focused on the tails of the return distribution in asset pricing tests as both models accommodate the U-shaped relation between the risk proxy (such as market beta) and stock returns.

A NEW APPROACH FOR TESTING THE RISK INTERPRETATION OF BETA

This paper uses a new method to examine if cross-sectional differences in market beta reflect differences in risk. We build on the intuition that risky stocks should concentrate in the tails of the cross-sectional return distribution, i.e. risky stocks should be more likely, on average, to experience large positive or large negative returns compared to low risk stocks. Why is it that the case?

Assume that expected excess stock returns are generated according to the CAPM: $E(r_{it}) - r_{ft} = Beta_i[E(R_{mt}) - r_{ft}]$, where r_{it} is the return on stock *i* at time *t*, r_{ft} is the risk free rate,

R_{mt} is the market return, and $Beta_i$ measures the sensitivity of stock's i returns to the expected market risk premium and captures systematic risk. The realized stock return for firm i equals $r_{it} - r_{ft} = Beta_i[R_{mt} - r_{ft}] + \varepsilon_{it}$, where ε_{it} is the stock's idiosyncratic return component that has zero-expectation and is uncorrelated with the market premium.

Now consider two stocks, A and B, where stock A has higher systematic risk than stock B, i.e. $Beta_A > Beta_B$. What is the relation between beta and the frequency of realized returns on stocks A and B being (1) higher than a return r_U, and (2) lower than a return r_L, where r_U represents a relatively large positive return and r_L a relatively large negative return? As idiosyncratic shocks are random, at any given date *t*, the absolute return for stock A is likely to be higher than for stock B for any realization of the market premium. Further, the larger the absolute magnitudes of the cut-off points r_U and r_L, the 'more risky' a stock has to be for the realized return to be higher than r_U or lower than r_L, i.e. the idiosyncratic component ε_{it} becomes increasingly less important in determining if returns for stocks A and B will beat benchmarks r_U and r_L. Together, this means that the likelihood of a realized return higher than r_U or lower than r_L is on average higher for the more risky stock A than for stock B, particularly for large magnitudes of r_U and r_L. A corollary of the above discussion is that high beta stocks will tend to cluster in the tails of the cross-sectional return distribution, i.e. among stocks experiencing large negative and large positive returns. If beta is not a proper measure of risk and returns are not generated by the CAPM, there should be no systematic positive relation between beta and the frequency of relatively large and low returns.[8]

An important conclusion that follows from the above discussion is that a test of beta as a risk measure is equivalent to testing whether high beta stocks tend to concentrate in the tails of the cross-sectional return distribution. Consequently, one can implement a simple test of whether returns reflect beta risk by using two logistic regressions, one predicting large positive returns and the other predicting large negative returns from beta. Specifically, the two predictive regressions have the form:

$$P(High\_ret) = \alpha_0 + \beta_0 Beta + \mathrm{B}_0 Controls + u_0 \quad (1)$$

$$P(Low\_ret) = \alpha_1 + \beta_1 Beta + \mathrm{B}_1 Controls + u_1 \quad (2)$$

where the dependent variable, *High_ret* (*Low_ret*) equals one if a firm's return is higher (lower) than a set benchmark, and zero otherwise.[9]

To define the dependent variables in models (1) and (2), we measure returns each month over a one-year period starting at the end of the fourth month after the fiscal year-end.[10] As a starting point, we use arbitrary cut-off points of 20% and −15% to define the dependent variables in the two logit models. Specifically, the dependent variable for model (1) is one if the stock's monthly return is higher than 20%, and zero otherwise. For model (2), the dependent variable is one if the monthly return is below −15%, and zero otherwise. Kothari and Shanken (1997) report that the annual equally-weighted return on the CRSP index is 12.5% over 1941–1991, or 0.99% per month. This means that our breakpoints of 20% and −15% should be successful in identifying stocks in the tails of the cross-sectional return distribution. In robustness tests we also consider other cut-off points to test the sensitivity of our results to the specification of the dependent variables.

Under the assumption that returns and betas are jointly normally distributed, and that betas capture risk, we would expect both β_0 and β_1 from models (1) and (2) to be significant and similar in magnitude. However, since the normality assumption is unlikely to hold (Ané and Geman, 2000; Chung *et al.,* 2006), we impose a weaker condition that beta reflects risk if β_0 and β_1 are non-zero and have the same sign. If the coefficients on beta are varying in sign in the two models or beta is significant in only one regression, we conclude that beta is unlikely to capture risk. If both β_0 and β_1 are insignificant, the test results are inconclusive.[11]

Our main tests for models (1) and (2) use pooled cross-sectional samples and we adjust for the cross-sectional and time-series dependence among observations using dual-clustered standard errors on firm and year-month. For robustness purposes and to ensure comparability with previous studies, we also use the Fama-MacBeth method. The Fama-MacBeth approach controls for the time-series dependence among observations, but ignores the cross-sectional correlation among stocks.[12]

Market beta and control variables

We estimate market beta (*Beta*) for each stock over a 3-year period ending four months after the fiscal year-end using the CAPM. We require a minimum of 30 observations for a stock to be included in the beta computation. For each regression, we also calculate the mean squared error to capture the residual pricing error, *Resid*. This is because large positive or large negative returns can be driven by the stock's idiosyncratic risk component that is captured by the CAPM's error term. A positive correlation between beta and the error term can produce a significant coefficient on beta in our regressions, even if beta does not capture risk.

The control variables in models (1) and (2) include firm characteristics commonly associated with stock returns. Following Fama and French (1992), we include firm market capitalization (*MV*) and the book-to-market ratio (*B/M*).[13] Firm market capitalization equals the number of shares outstanding multiplied by the end-of-month stock price measured four months after the fiscal year-end. We follow Daniel and Titman (2006) and define book equity as the difference between total shareholders' equity and the preferred stock value. The book-to-market ratio equals the ratio of book equity over market capitalization measured at the end of the previous fiscal year.

Other return predictors include stock return momentum (*MOM*), which is the difference between the stock's and the market's six-month buy-and-hold returns ending four months after the fiscal year-end. We use firm age (*Age*), which is the difference between the firm's previous fiscal year-end and the firm's first appearance on CRPS files, to capture the stock's information uncertainty. Zhang (2006) proposes that firms with a long listing history have more information available to investors to help with the stock's valuation.[14] Finally, we use a dummy variable to identify loss making firms (*Loss*). Specifically, *Loss* takes a value of one if the net income for the previous fiscal year is negative, and is zero otherwise. Loss making firms are more difficult to value (Watts and Zimmerman, 1986; Collins *et al.,* 1997) and subject to higher financial distress (Ohlson, 1980).[15] All explanatory variables are winsorized at the 1st and 99th percentiles.

DATA AND DESCRIPTIVE STATISTICS

We obtain returns on ordinary common shares from CRSP and accounting information from the CRSP/Compustat merged database. The risk free rate and the market return required to estimate betas are collected from Kenneth French's website. Our sample includes all firms listed on NYSE/AMEX/Nasdaq from January 1975 till December 2005.[16] Following Fama and French (1992), we retain only stocks with positive book values of equity. To avoid the delisting bias (Shumway, 1997; Shumway and Warther, 1999), we include delisting returns. When a delisting return is missing, we assume a return of −1 for delisting due to liquidation (CRSP codes 400–490), −0.33 for performance related delisting (500 and 520–584), and zero otherwise. Our final sample includes 1,015,320 firm-month observations.

Panel A of Table 1 presents the descriptive statistics. The mean monthly return is 1.6% and it ranges from −6.1% in the lower quartile to 7.4% in the upper quartile. The sample beta is 1.05 with an interquartile range of 0.962. Mean *Resid* is 0.133, the mean book-to-market ratio is 0.947 and the average firm has a market capitalization of over $1,035m. The mean past six-month abnormal return equals 3.7% and is consistent with the average beta being higher than one. The average firm age in the sample is 15.661 years and 24.1% of firms reported a negative net income in the previous fiscal year.

[Insert Table 1 here]

Panel B reports the Pearson correlation coefficients. The magnitudes of the correlations are low on average. Importantly, all pairwise correlations are far below 0.8, which is a rule-of-thumb indicator for potential multicollinearity problems. The strongest correlations are between *Beta* and *Resid* (0.366) and *Resid* and the indicator variable for loss-making firms (0.430).

PORTFOLIO ANALYSIS

As a simple test of the relation between beta and stock returns, Panel A of Table 2 presents the results from portfolio analysis that allocates stocks into beta deciles. Specifically, each month we sort stocks into beta deciles (*High beta* to *Low beta*). Subsequently, we calculate the mean monthly return and the average beta for each decile. Consistent with earlier findings, the relation between portfolio betas and portfolio returns is flat and the difference in mean returns between portfolios of high and low beta stocks is indistinguishable from zero (result untabulated). The latter evidence is particularly striking given the very large difference in mean betas between the portfolios of high and low beta stocks (2.707).

[Insert Table 2 here]

We predict that risky stocks should concentrate in the tails of the cross-sectional return distribution. To test whether stocks with high positive or high negative returns have higher betas, Panel B splits stocks into deciles based on their monthly returns (*High return* to *Low return*). In particular, each month we allocate stocks into decile portfolios based on stock returns. We then calculate the mean return and mean beta for each portfolio. Consistent with our prediction, stocks with the most positive and the most negative monthly returns tend to have higher betas. Specifically, the decile portfolio with the most positive returns has a mean beta of 1.206, the medium deciles 5 and 6 have mean betas of 0.924, and the decile with the most negative returns has a mean beta of 1.284. In unreported results we find that the differences in betas between the high and low return deciles and the medium return deciles 5 and 6 are significant at less than 1% level. This confirms that the relation between returns and market beta is U-shaped, i.e. high beta stocks tend to experience high and low returns more often than low beta stocks.

Fama and French (1992) report that beta sorts closely replicate sorts on firm size because of the negative relation between beta and firm market capitalization. This means that our finding in Panel B of Table 2, that high beta stocks tend to have large positive and negative returns more often than low beta stocks, may be simply capturing the size effect. To address this, Panel C repeats the analysis from Panel B where we first split stocks into deciles based on their size. Each size decile is then subdivided into ten portfolios based on stocks' monthly returns. The portfolio formation is repeated each month. For each size decile we find that high beta stocks cluster in the tails of the return distribution. This confirms that clustering of high beta stocks in the tails of the cross-sectional return distribution is independent of the size effect.[17]

In unreported results we find that our conclusion that high beta stocks cluster in the tails of the return distribution remains unchanged when we use betas estimated at portfolio level, instead of individual stock betas.[18] Individual firm betas may be subject to an estimation error (the errors-in-variables problem), which can attenuate the relation between beta and returns (Kim, 1995; Amihud *et al.,* 1993). The evidence that using portfolio betas leads to similar conclusions as when using individual stock betas is consistent with the conclusions in Fama and French (1992, p. 432) that 'post-ranking βs [betas estimated at portfolio level] closely reproduce the ordering of the pre-ranking βs [betas estimated at firm level]. We take this to be evidence that the pre-ranking β sort captures the ordering of true post-ranking βs.'. Fama and French (1992) also conclude that allocating portfolio betas to individual stocks reduces the power of tests to identify a positive correlation between beta and returns. Consequently, we use individual stock betas in the remaining analysis and use portfolio betas in sensitivity tests.[19]

REGRESSION ANALYSIS

Pooled OLS and Fama Macbeth Regressions

Next we examine the relation between beta and returns in a regression framework. Fama and French (1992) conclude that beta shows no association with stock returns over the period 1962–1989. As our sample period ends in 2005, we first examine if using a more recent sample period, beta continues to have an insignificant cross-sectional relation with returns. Consistent with past studies, our cross-sectional regression model takes the form:

$$\begin{aligned} r_{it} &= \gamma_0 + \gamma_1 beta_{it} + \gamma_2 Resid_{it} + \gamma_3 B/M_{it} + \gamma_4 \ln MV_{it} + \gamma_5 MOM_{it} + \gamma_6 \ln Age + \gamma_7 Loss_{it} \\ &+ \sum_{k=0}^{8} \gamma_{8+k} Industry\ effect + \sum_{k=0}^{29} \gamma_{17+k} Year\ effect + \varepsilon_{it} \end{aligned} \tag{3}$$

where ln indicates a logarithmic transformation of a variable and *Industry effect* and *Year effect* are industry and year dummies. Industry dummies are based on the two-digit SIC codes. We estimate model (3) using pooled OLS and we cluster standard errors on firm and year-month to control for the cross-sectional and time-series dependence of observations. For comparability with previous studies, we also use Fama-MacBeth regressions to estimate model (3).[20] We present the regression results in Table 3.[21]

[Insert Table 3 here]

Table 3 shows that using pooled OLS regressions, the coefficient on market beta is indistinguishable from zero when beta is the sole explanatory variable (*Regression* 1), when we control for firm size and the book-to-market ratio (*Regression* 2), and when we include other return predictors as specified in model (3) (*Regression* 3). The coefficient on beta remains insignificant when we use betas estimated at portfolio level in model (3) (*Portfolio betas*), and when we use the Fama-MacBeth approach (*Fama MacBeth*). Finally, our conclusion that beta has no power to explain the cross-section of stock returns remains unchanged when we use Dimson's (1979) beta in model (3) (*Dimson beta*). We calculate Dimson betas as the sum of beta coefficients from regressions of excess stock returns on the lead, current and lagged market premium. Dimson betas adjust for thin trading bias in beta estimates (Dimson, 1979; Dimson and Marsh, 1983).

With respect to the control variables, we document a positive and significant coefficient on the B/M ratio and a negative coefficient on firm size in all specifications of regression (3). This confirms the evidence in Fama and French (1992) that small and high B/M stocks tend to have higher returns than large and low B/M stocks. We also find evidence that stock return momentum and firm age correlate with stock returns. Overall, our analysis in Table 3 confirms that beta shows no significant association with stocks returns.

Logistic Regressions

Table 4 reports regression results for logistic models (1) and (2). Panel A reports results for model (1) and Panel B for model (2). On its own, beta is a strong predictor of large positive and large negative returns (*Regression* 1). Consistent with our prediction, the coefficients on betas in the two logistic regressions are positive and significant, and largely similar in magnitude (0.329 for model (1) and 0.365 for model (2)). A one standard deviation change in beta increases the likelihood of large positive (negative) returns by 26.2% (29.1%), which confirms that beta has an economically significant ability to predict large positive and negative return outcomes. Controlling for the B/M ratio and firm size (*Regression* 2), beta continues to show a significant association with large positive and negative returns. The coefficients on betas remain significant and positive for the full specification of the two logit models (*Regression* 3), and when we use the Fama-MacBeth approach (*Fama MacBeth*). Together, the results in Table 4 confirm our prediction that beta captures risk.

[Insert Table 4 here]

With respect to the control variables, we find that firms with large values of the pricing error *Resid* tend to experience large positive and negative returns more often than firms with smaller pricing errors. This is consistent with Fu (2009), who build on the evidence that investors do not hold well diversified portfolios and argue that under-diversified investors may require a premium for bearing idiosyncratic risk. Further, smaller, younger firms and loss making firms cluster in the tails of the cross-sectional return distribution. This is consistent with the risk interpretation of these variables. The coefficients on return momentum and the B/M ratio are indistinguishable from zero in model (1) that predicts large positive returns and are negative in model (2) that predicts low returns. Together, this shows that high momentum stocks and high B/M stocks do not cluster systematically in the tails of the cross-sectional return distribution, which suggests that they are unlikely to reflect risk factors. This is consistent with the 'anomaly' interpretation of the momentum and value effects.

SENSITIVITY ANALYSIS

Alternative Definitions of the Dependent Variables in the two Logistic Models

Our main tests in Table 4 use arbitrary cut-off points of 20% and −15% to define the dependent variables in models (1) and (2). In sensitivity tests, we first check if our conclusions are robust to two alternative definitions of the two dependent variables. First, we repeat the logit models using a 30% cut-off point to define the dependent variable in model (1) and a −20% cut-off point to define the dependent variable in model (2). Using more extreme cut-off points allocates approximately 3.8% of stocks to the high return portfolio and 5.3% of stocks to the low return portfolio. This compares to 9.5% and 11% of stocks in the high and low return portfolio using the 20% and −15% breakpoints. Second, each month we calculate the mean monthly return over the previous three months for each stock. Then we calculate the mean return for the 5% of stocks with the highest previous three-month returns. The dependent variable for model (1) takes the value of one if the stock's mean monthly return is higher than the mean return of stocks in the top vigintile formed based on the past three-month returns, and is zero otherwise. We follow a similar procedure to define the dependent variable for model (2), but now our cut-off point is based on the mean return for the 5% of stocks with the lowest average returns calculated over the previous three months.[22] The first columns of Table 5 report the regression results for the two logit models when using the two alternative ways to define the dependent variables. The coefficients on betas are positive and significant in both cases, consistent with the results in Table 4. This suggests that the magnitude of the arbitrary cut-off points has no effect on the validity of our inferences.

[Insert Table 5 here]

Other Beta Estimation Methods

Next, we consider the effect that the beta estimation method has on our inferences. Specifically, we use Dimson's (1979) beta to control for the thin trading bias in beta estimates, and portfolio betas to test the sensitivity of our results to the errors-in-variables problem. The regression results for Dimson beta and portfolio beta in Table 5 show positive and significant coefficients on betas in models (1) and (2). This indicates that our inferences that beta reflects risk are not sensitive to the specification of beta.[23]

Quantile Regressions

In our main tests we use two logit models because they offer a simple and robust way to test the risk interpretation for beta and the models build directly on the intuition that high risk stocks should cluster in the tails of the cross-sectional return distribution. Next we show that we reach similar conclusions when we use non-parametric quantile regressions. Quantile models allow us to investigate the relation between beta and returns for the top and bottom decile of the return distribution. If beta reflects risk, beta should be a strong return predictor in the top and the bottom return decile.

To implement quantile regressions, we set up two models, one explaining the top decile of monthly stock returns (the high return portfolio) and the other explaining the bottom decile of monthly stock returns (the low return portfolio). The specifications of the two models are:

$$Q_{90}(return) = \psi_0 + \theta_0 Beta + \Phi_0 Controls + u_0 \quad (4)$$

$$Q_{10}(return) = \psi_1 + \theta_1 Beta + \Phi_1 Controls + u_1 \quad (5)$$

where the set of controls is the same as in models (1) and (2). For models (4) and (5), it is critical to recognize that if beta reflects risk, beta coefficients in the two regressions should have opposite signs. To clarify, if high betas indicate more risky stocks, then the coefficient on beta should be positive in the regression explaining the top returns decile, $\theta_0>0$, i.e. high beta stocks should associate with more positive returns in the right tail of the return distribution. However, for stocks in the bottom return decile, the coefficient on beta should be negative, $\theta_1<0$, i.e. returns should be decreasing in beta in the left tail of the return distribution.

Columns *Quantile regressions (F-M)* in Table 5 report the results for the two quantile regressions (4) and (5). Because quantile regressions do not allow for clustering of standard errors, we use the Fama-MacBeth method to control (at minimum) for the time-series dependence of observations. Consistent with our prediction, the coefficient on beta is positive in the regression explaining the top return decile, i.e. high beta stocks tend to have large positive returns in the right tail of the return distribution. The coefficient on beta is negative in the regression for the bottom return decile. This is in line with the prediction that high beta stocks should have more negative returns in the left tail of the return distribution. Together, the quantile regression results support our conclusion that beta captures risk.

Unreported additional results

In unreported results, we perform four further tests. First, we find that our conclusions from Table 4 are unchanged when we use 12-month buy-and-hold returns and cut-off points of 75% to define the dependent variable for model (1) and −50% for model (2).[24] Second, our conclusions from Table 4 are unchanged when we use a simultaneous regression model to jointly estimate models (1) and (2), which allows for potential correlation in error terms between the two models.[25] Third, we document positive and significant coefficients on betas in both logit models when we repeat logit regressions (1) and (2) for each decade over our sample period. This shows that our conclusion that beta predicts large positive and large negative returns are not driven by a specific sample period. Fourth, we find that betas predict returns for other parts of the return distribution than the tails. Specifically, each month we split stocks into quintiles based on their returns and use a multinomial logistic regression to predict returns for each quintile portfolio. We find that beta coefficients are significant in all regressions. Further, we confirm our earlier conclusion that the relation between beta and returns is U-shaped. Specifically, the coefficients on betas reduce in magnitude when moving from portfolios located in the left and right tail of the return distribution to portfolios in the center of the return distribution. This is consistent with the intuition that stock risk reduces moving from the tails to the center of the return distribution and corroborates our conclusion that beta captures risk.

CONCLUSIONS

Previous studies find no evidence of a significant cross-sectional relation between beta and returns, which questions whether market risk helps explain the return cross-section. This study builds on the intuition that risky stocks should concentrate in the tails of the cross-sectional return distribution to test if stock returns reflect beta risk. Using two logistic regressions, one predicting large positive returns and the other predicting large negative returns, we show that high beta stocks cluster in the tails of the cross-sectional return distribution. This supports the prediction that high beta stocks are more risky. Our results validate the use of market beta as a risk control in empirical accounting and finance research.

REFERENCES

Abarbanell J., and V. Bernard, 'Is the U.S. Stock Market Myopic?', *Journal of Accounting Research,* Vol. 38, 2000.

Amihud Y., B.J. Christensen and H. Mendelson, '*Further Evidence on the Risk-Return Relationship*', Working paper, New York University, 1993.

Anderson J.A., and R.W. Faff, 'Point and Figure Charting: A Computational Methodology and Trading Rule Performance in the S&P 500 Futures Market', *International Review of Financial Analysis*, Vol. 17, 2006.

Ané T., and H. Geman, 'Order Flow, Transaction Clock, and Normality of Asset Returns', *Journal of Finance,* Vol. 55, 2000.

Ball R., and P. Brown, 'An Empirical Evaluation of Accounting Income Numbers', *Journal of Accounting Research,* Vol. 6, 1968.

Benson, K., and R.W. Faff, 'β', *Abacus*, Vol. 49, 2013.

Berkman, H., 'The Capital Asset Pricing Model: A Revolutionary Idea in Finance!', *Abacus*, Vol. 49, 2013.

Bilinski P., and J. Ohlson, '*Risk vs. Anomaly: A New Methodology Applied to 'Accruals*'', Working paper, NYU Stern School of Business, 2012.

Black F., M. Jensen and M. Scholes, 'The Capital Asset Pricing Model: Some Empirical Tests', in M. Jensen (ed.), *Studies in the Theory of Capital Markets*, Praeger, 1972.

Blume, M.E., and I. Friend, 'A New Look at the Capital Asset Pricing Model', *Journal of Finance,* Vol. 28, 1973.

Bornholt, G., 'The Failure of the Capital Asset Pricing Model (CAPM): An Update and Discussion', *Abacus*, Vol. 49, 2013.

Bos, T., and P. Newbold, 'An Empirical Investigation of the Possibility of Stochastic Systematic Risk in the Market Model', *Journal of Business*, Vol. 57, 1984.

Brav, A., R. Lehavy and R. Michaely, 'Using Expectations to Test Asset Pricing Models', *Financial Management*, Vol. 34, 2005.

Cai, Ch.X., I. Clacher, and K. Keasey, 'Consequences of the Capital Asset Pricing Model (CAPM)—a Critical and Broad Perspective', *Abacus*, Vol. 49, 2013.

Campbell, J., J. Hilscher and J. Szilagyi, 'In Search of Distress Risk', *Journal of Finance*, Vol. 63, 2008.

Chan, K.C., and N. Chen, 'Structural and Return Characteristics of Small and Large Firms', *Journal of Finance,* Vol. 46, 1991.

Chan, K.C., and J. Lakonishok, 'Are the Reports of Beta's Death Premature?', *Journal of Portfolio Management*, Vol. 19, 1993.

Christensen, H., E. Lee and M. Walker, 'Do IFRS Reconciliations Convey Information?, The effect of debt contracting. *Journal of Accounting Research,* Vol. 47, 2009.

Chung, Y.P., H. Johnson and M.J. Schill, 'Asset Pricing when Returns are Nonnormal: Fama-French Factors versus Higher-Order Systematic Comoments', *Journal of Business*, Vol. 79, 2006.

Coles, J., and U. Loewenstein, 'Equilibrium pricing and portfolio composition in the presence of uncertain parameters', *Journal of Financial Economics,* Vol. 22, 1988.

Collins, D.W., 'SEC Product-Line Reporting and Market Efficiency', *Journal of Financial Economics,* 2, 1975.

Collins, D.W., E.L. Maydew and I.S. Weiss, 'Changes in the Value Relevance of Earnings and Book Values over the Past Forty Years', *Journal of Accounting and Economics,* Vol. 24, 1997.

Connolly, RA., 'An Examination of the Robustness of the Weekend Effect', *Journal of Financial and Quantitative Analysis*, Vol. 24, 1989.

Daniel, K., and S. Titman, 'Market Reactions to Tangible and Intangible Information', *Journal of Finance,* Vol. 61, 2006.

Dechow, P., and I. Dichev, 'The Quality Of Accruals and Earnings: The Role of Accrual Estimation Errors', *The Accounting Review*, Vol. 77, 2002.

Dechow, P., and W. Ge, 'The Persistence of Earnings and Cash Flows and the Role of Special Items: Implications for the Accrual Anomaly', *Review of Accounting Studies,* Vol. 11, 2006.

Dempsey, M., 'The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance? ', *Abacus*, Vol. 49, 2013a.

Dempsey, M., 'The CAPM: A Case of Elegance is for Tailors? ', *Abacus*, Vol. 49, 2013b.

Diamond, D.W., and R.E. Verrecchia, 'Disclosure, Liquidity, and the Cost of Capital', *Journal of Finance,* Vol. 66, 1991.

Dichev, I., 'Is the Risk of Bankruptcy a Systematic Risk?', *Journal of Finance,* Vol. 53, 1998.

Dimson, E., 'Risk Measurement when Shares are Subject to Infrequent Trading', *Journal of Financial Economics,* Vol. 7, 1979.

Dimson, E., and P.R. Marsh, 'The Stability of UK Risk Measures and the Problem of Thin Trading', *Journal of Finance,* Vol. 38, 1983.

Faff, R.W., 'A Multivariate Test of a Dual-Beta CAPM: Australian Evidence', *Financial Review*, Vol. 36, 2001.

Fama, E.F., and K.R. French, 'The Cross-Section of Expected Stock Returns', *Journal of Finance,* Vol. 47, 1992.

Fama, E.F., and K.R. French, 'Common Risk Factors in the Returns on Stocks and Bonds', *Journal of Financial Economics,* Vol. 33, 1993.

Fama, E.F., and K.R. French, 'Dissecting Anomalies', *Journal of Finance,* Vol. 63, 2008.

Fama, E.F., and J. MacBeth, 'Risk, Return and Equilibrium: Empirical Tests', *Journal of Political Economy,* Vol. 81, 1973.

Ferson, W.E., and R.A. Korajczyk, 'Do Arbitrage Pricing Models Explain the Predictability of Stock Returns?', *Journal of Business,* Vol. 68, 1995.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 'The Market Pricing of Accruals Quality', *Journal of Accounting and Economics,* Vol. 39, 2005.

Fu, F., 'Idiosyncratic risk and the cross-section of expected stock returns', *Journal of Financial Economics*, Vol. 91, 2009.

George, T., and C.H. Hwang, 'A Resolution of the Distress Risk and Leverage Puzzles in the Cross Section of Stock Returns', *Journal of Financial Journal of Political Economy,* Vol. 96, 2010.

Gertler, M., and S. Gilchrist, 'Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms', *Quarterly Journal of Political Economics,* Vol. 109, 1994.

Gomes, J., L. Kogan and L. Zhang, 'Equilibrium Cross-Section of Returns', *Journal of Political Economy*, Vol. 111, 2003.

Gow, I., G. Ormazabal, and D. Taylor, 'Correcting for Cross-Sectional and Time-Series Dependence in Accounting Research', *The Accounting Review,* Vol. 85, 2010.

Howton, S.W., and D.R.. Peterson, 'An Examination of Cross-Sectional Realized Stock Returns using a Varying-Risk Beta Model', *Financial Review*, Vol. 33, 1998.

Jagannathan, R., and Z. Wang, 'The Conditional CAPM and Cross-Section of Expected Returns', *Journal of Finance,* Vol. 51, 1996.

Johnstone, D.J., 'The CAPM Debate and the Logic and Philosophy of Finance', Abacus, Vol. 49, 2013.

Kim, D., 'The errors in the Variables Problem in the Cross-Section of Expected Stock Returns', *Journal of Finance,* Vol. 50, 1995.

Kothari, S.P., and J. Shanken, 'Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis', *Journal of Financial Economics,* Vol. 44, 1997.

Kothari, S.P., J. Shanken and R.G. Sloan, 'Another Look at the Cross-Section of Expected Stock Returns', *Journal of Finance,* Vol. 50, 1995.

Lakonishok, J., and A. Shapiro, 'Systematic Risk, Total Risk and Size as Determinants of Stock Market Returns', *Journal of Banking and Finance,* Vol. 10, 1986.

Lindley, D., 'A Statistical Paradox', *Biometrica*, Vol. 44, 1957.

Lintner, J., 'The Valuation of Risk Assets and Selection of Risky Investments in Stock Portfolios and Capital Budgets', *Review of Economics and Statistics*, Vol. 47, 1965.

Lo, A., and C. MacKinlay, 'Data-snooping Biases in Tests of Financial Asset Pricing Models', *Review of Financial Studies,* Vol. 3, 1990.

McNichols, M., 'Discussion of "The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors"', *The Accounting Review,* Vol. 77, 2002.

Mech, T., 'Portfolio Return Autocorrelation', *Journal of Financial Economics,* Vol. 34, 1993.

Modigliani, F., and M. Miller, 'The Cost of Capital, Corporation Finance, and the Theory of Investment', *American Economic Review,* Vol. 48, 1958.

Moosa, I.A., 'The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance?' Comments and Extensions', *Abacus*, Vol. 49, 2013.

Ohlson, J., 'Financial Ratios and the Probabilistic Prediction of Bankruptcy', *Journal of Accounting Research,* Vol. 19, 1980.

Partington, G., 'Death Where is Thy Sting? A Response to Dempsey's Despatching of the CAPM', *Abacus*, Vol. 49, 2013.

Pastor, L., and R. Stambaugh, 'Mutual Fund Performance and Seemingly Unrelated Assets', *Journal of Financial Economics*, Vol. 63, 2002.

Penman, S.H., 'An Empirical Investigation of the Voluntary Disclosure of Corporate Earnings Forecasts', *Journal of Accounting Research,* Vol. 18, 1980.

Penman, S.H., 'Financial Forecasting, Risk, and Valuation: Accounting for the Future', *Abacus,* Vol. 46, 2010.

Penman, S.H., 'Accounting for Risk and Return in Equity Valuation', *Journal of Applied Corporate Finance,* Vol. 23, 2011.

Penman, S.H., and T. Sougiannis, 'A Comparison of Dividend, Cash Flow, and Earnings Approaches to Equity Valuation', *Contemporary Accounting Research,* Vol. 15, 1998.

Perez-Quiros, G., and A. Timmermann, 'Firm Size and Cyclical Variations in Stock Returns', *Journal of Finance,* Vol. 55, 2000.

Pettengill *G.N., S.* Sundaram, and I. Mathur, 'The Conditional Relation between Beta and Returns', *The Journal of Financial and Quantitative Analysis*, Vol. 30, 1995.

Ritter, J.R., and N. Chopra, 'Portfolio Rebalancing and the Turn-Of-The-Year-Effect'*, Journal of Finance,* Vol. 44, 1989.

Roll, R., 'A Critique of the Asset Pricing Theory's Tests; Part I: On Past and Potential Testability of the Theory', *Journal of Financial Economics,* Vol. 4, 1977.

Sharpe, W.F., 'Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk', *Journal of Finance,* Vol. 19, 1964.

Shumway, T., 'The Delisting Bias in CRSP Data', *Journal of Finance,* Vol. 52, 1997.

Shumway, T., and V. Warther, 'The Delisting Bias in CRSP's Nasdaq Data and its Implications for the Size Effect', *Journal of Finance,* Vol. 54, 1999.

Sloan, R., 'Do stock prices fully reflect information in accruals and cash flows about future earnings?', *The Accounting Review*, Vol.71, 1996.

Smith, T., and K. Walsh, 'Why the CAPM is Half-Right and Everything Else is Wrong', *Abacus*, Vol. 49, 2013.

Stambaugh, R.F., 'On the Exclusion of Assets from Tests of the Two-Parameter Model: A Sensitivity Analysis', *Journal of Financial Economics,* Vol. 10, 1982.

Subrahmanyam, A., 'Comments and Perspectives on 'The Capital Asset Pricing Model'', *Abacus*, Vol. 49, 2013.

Verrecchia, R., 'Essays on Disclosure', *Journal of Accounting and Economics,* Vol. 22, 97–180, 2001.

Watts, R.L., and J.L. Zimmerman, '*Positive Accounting Theory'*, Prentice Hall, 1986.

Zhang, X.F., 'Information Uncertainty And Stock Return', *Journal of Finance,* Vol. 61, 2006.

TABLE 1
DESCRIPTIVE STATISTICS

Panel A: Descriptive Statistics (N=1,015,320)

	Mean	Median	STD	Lower Quartile	Upper Quartile
Return	1.6%	0.0%	17.1%	−6.1%	7.4%
Beta	1.050	0.961	0.796	0.511	1.473
Resid	0.133	0.112	0.078	0.077	0.166
B/M	0.947	0.732	0.808	0.413	1.215
MV	1035.690	104.142	3206.760	24.185	523.552
Mom	3.7%	−0.5%	36.4%	−17.4%	18.1%
Age	15.661	10.756	14.186	5.918	19.923
Loss	24.1%	0.0%	42.8%	0.0%	0.0%

Panel B: Pearson Correlation Coefficients (N =1,015,320)

	Return	*Beta*	*Resid*	*B/M*	*MV*	*Mom*	*Age*
Beta	0.003						
p	0.011						
Resid	0.011	0.366					
p	0.000	0.000					
B/M	0.031	−0.120	−0.060				
p	0.000	0.000	0.000				
MV	−0.011	−0.022	−0.191	−0.162			
p	0.000	0.000	0.000	0.000			
Mom	−0.001	0.094	0.114	−0.015	0.021		
p	0.459	0.000	0.000	0.000	0.000		
Age	−0.007	−0.127	−0.322	0.014	0.360	−0.010	
p	0.000	0.000	0.000	0.000	0.000	0.000	
Loss	0.008	0.129	0.430	0.053	−0.117	−0.076	−0.144
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Panel A presents descriptive statistics and Panel B the Pearson correlation coefficients. *Return* represents monthly stock returns, *Beta* is the market beta estimated from the CAPM over a three-year period ending four months after the fiscal year-end and *Resid* is the mean squared error from the beta estimates. *B/M* is the book-to-market ratio for the previous fiscal year, *MV* is the firm market capitalization measured four months after the fiscal year-end, and *Mom* is the 6-month market-adjusted abnormal return ending four months after the fiscal year-end. *Age* is the number of years since the firm first appeared on the CRSP files. *Loss* is an indicator that takes the value of one if the net income for the previous fiscal year is negative, and is zero otherwise.

TABLE 2

PORTFOLIO ANALYSIS

Panel A: Mean Returns for Sorts on Beta

	High beta	*Beta 2*	*Beta 3*	*Beta 4*	*Beta 5*	*Beta 6*	*Beta 7*	*Beta 8*	*Beta 9*	*Low beta*	*High−Low*
Beta	2.631	1.850	1.478	1.223	1.027	0.852	0.685	0.517	0.316	−0.076	2.707
Return	1.57%	1.53%	1.63%	1.60%	1.52%	1.59%	1.54%	1.57%	1.55%	1.59%	−0.02%

Panel B: Mean Betas for Sorts on Returns

	High return	*Return 2*	*Return 3*	*Return 4*	*Return 5*	*Return 6*	*Return 7*	*Return 8*	*Return 9*	*Low return*	*High−Low*
Return	30.96%	12.28%	7.19%	4.05%	1.53%	−0.71%	−3.13%	−6.00%	−10.17%	−20.83%	51.79%
Beta	1.206	1.086	0.999	0.948	0.924	0.924	0.962	1.033	1.138	1.284	−0.078

Panel C: Mean Betas for Portfolios Created on Double Sorts on Firm Size and Returns

	High return	*Return 2*	*Return 3*	*Return 4*	*Return 5*	*Return 6*	*Return 7*	*Return 8*	*Return 9*	*Low return*	*High−Low*
Small	1.217	1.077	1.009	0.967	0.946	0.940	0.968	1.013	1.097	1.310	0.093
MV 2	1.317	1.137	1.036	0.980	0.958	0.965	0.989	1.060	1.207	1.415	0.098
MV 3	1.381	1.167	1.051	0.987	0.963	0.963	1.014	1.080	1.235	1.486	0.105
MV 4	1.390	1.154	1.068	1.004	0.989	0.980	1.038	1.124	1.261	1.482	0.092
MV 5	1.360	1.172	1.082	1.024	1.009	1.002	1.035	1.124	1.253	1.491	0.130
MV 6	1.339	1.159	1.064	1.006	0.988	0.975	1.009	1.104	1.226	1.432	0.093
MV 7	1.260	1.075	0.992	0.952	0.911	0.925	0.965	1.054	1.163	1.335	0.075
MV 8	1.186	1.044	0.931	0.881	0.857	0.867	0.919	0.996	1.102	1.269	0.084
MV 9	1.095	0.976	0.884	0.833	0.823	0.848	0.877	0.932	1.024	1.170	0.076
Large	0.912	0.821	0.743	0.733	0.690	0.695	0.738	0.796	0.837	0.950	0.038

Note: Panel A reports mean returns for monthly decile sorts based on market beta (*High beta* to *Low beta*). Column *High−Low* reports the difference in mean values between the extreme decile portfolios. Panel B reports mean betas for monthly decile sorts based on monthly stock returns (*High return* to *Low return*). Panel C reports mean betas for 100 portfolios formed from sorts on firm size and monthly stock returns.

TABLE 3

POOLED OLS AND FAMA-MACBETH REGRESSIONS OF MONTHLY STOCKS RETURNS ON MARKET BETA AND OTHER RISK CONTROLS

	Regression 1			*Regression 2*			*Regression 3*			*Portfolio betas*			*Fama MacBeth*			*Dimson beta*		
	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig
Intercept	0.017	1.85		0.023	2.15		0.020	1.96		0.024	1.86		0.005	1.27		0.020	1.93	
Beta	0.000	−0.15		0.001	0.53		0.001	0.62					0.000	0.10				
Resid				0.003	0.12		0.004	0.17					0.023	1.72				
Beta portfolio										0.005	0.93							
Resid portfolio										−0.251	−1.34							
Beta dimson																0.000	0.46	
Resid dimson																0.006	0.31	
B/M				0.004	5.53	**	0.004	5.42	**	0.004	4.78	**	0.003	4.73	**	0.004	5.43	**
ln *MV*				−0.002	−3.89	**	−0.002	−4.17	**	−0.002	−4.17	**	−0.002	−4.75	**	−0.002	−3.75	**
Mom							0.001	0.45		0.004	1.06		0.003	2.18	**	0.001	0.45	
ln *Age*							0.001	2.25		0.000	0.59		0.001	3.34	**	0.001	2.10	
Loss							0.000	0.08		0.002	0.68		−0.001	−0.54		0.000	0.07	
Industry effect	Yes			Yes			Yes			Yes			Yes			Yes		
Year effect	Yes			Yes			Yes			Yes			No			Yes		
N	1015320			1015320			1015320			621024			382			1015320		
F-test	144.52			150.95			141.95			146.57						142.21		
p(F)	0.000			0.000			0.000			0.000						0.000		
R^2	0.47%			0.58%			0.58%			0.90%						0.58%		

Note: See Table 1 for variable definitions in *Regression 1* to *Regression 3*. *Beta portfolio* is beta estimated at portfolio level. *Resid portfolio* is the mean squared error from the estimation of portfolio betas. *Dimson beta* is beta calculated as the sum of coefficients from regressions of excess stocks returns on the lead, current and lagged market premium. *Resid Dimson* is the mean squared error from the estimation of Dimson betas. *Industry effect* and *Year effect* are industry and year dummies. For the *Fama MacBeth* regressions, *t*-statistics are based on the time-series standard errors. For all other regressions, *t*-statistics are based on dual-clustered standard errors. 5% sig equals ** to indicate significance at the 5% level using sample size-adjusted critical values calculated as $[(N-1)(N^{1/N}-1)]^{0.5}$, where N is the number of observations.

TABLE 4

LOGISTIC REGRESSIONS PREDICTING HIGH AND LOW FUTURE RETURNS

Panel A: Predicting High Future Returns

	Regression 1				*Regression 2*				*Regression 3*				*Fama MacBeth*		
	Estimate	ME (%)	t-stat	5% sig	Estimate	ME (%)	t-stat	5% sig	Estimate	ME (%)	t-stat	5% sig	Estimate	t-stat	5% sig
Intercept	−2.830		−40.43	**	−2.659		−21.70	**	−2.377		−19.42	**	−4.832	−16.60	**
Beta	0.329	0.262	8.33	**	0.173	0.138	8.24	**	0.154	0.123	8.47	**	0.128	6.78	**
Resid					3.604	0.283	27.68	**	2.932	0.230	21.71	**	3.122	8.83	**
B/M					0.014	0.012	0.76		0.022	0.018	1.29		−0.118	−1.55	
ln *MV*					−0.173	−0.370	−9.38	**	−0.143	−0.306	−7.89	**	−0.256	−21.06	**
Mom									0.004	0.002	0.15		0.014	0.31	
ln *Age*									−0.168	−0.124	−11.61	**	−0.158	−3.29	**
Loss									0.301	0.129	14.16	**	0.236	3.87	**
Industry effect	No				Yes				Yes				Yes		
Year effect	No				Yes				Yes				No		
N	1015320				1015320				1015320				382		
χ^2*-test*	3739				31672				35123						
$p(\chi^2)$	0.000				0.000				0.000						
Pseudo R^2	1.00%				6.87%				7.22%						

(continued on next page)

TABLE 4 (continued)

Panel B: Predicting Low Future Returns															
	Regression 1				*Regression 2*				*Regression 3*				*Fama MacBeth*		
	Estimate	ME (%)	t-stat	5% sig	Estimate	ME (%)	t-stat	5% sig	Estimate	ME (%)	t-stat	5% sig	Estimate	t-stat	5% sig
Intercept	−2.719		−25.13	**	−3.156		−28.25	**	−2.874		−23.08	**	−3.997	−13.92	**
Beta	0.365	29.1%	7.98	**	0.150	12.0%	8.29	**	0.125	9.9%	7.70	**	0.109	4.75	**
Resid					5.243	41.1%	24.92	**	4.407	34.6%	24.91	**	5.083	22.82	**
B/M					−0.088	−7.2%	−3.77	**	−0.076	−6.2%	−3.75	**	−0.117	−2.79	**
ln *MV*					−0.108	−23.0%	−6.02	**	−0.062	−13.2%	−4.06	**	−0.174	−15.20	**
Mom									−0.095	−3.5%	−2.29		−0.248	−4.57	**
ln *Age*									−0.214	−15.9%	−10.45	**	−0.276	−12.87	**
Loss									0.434	18.6%	17.20	**	0.507	11.62	**
Industry effect		No				Yes				Yes				Yes	
Year effect		No				Yes				Yes				No	
N		1015320				1015320				1015320				382	
χ^2*-test*		3542				35479				41853					
$p(\chi^2)$		0.000				0.000				0.000					
Pseudo R^2		1.28%				9.51%				10.23%					

Note: Panel A presents the results for logit model (1) where the dependent variable, *High_ret*, is a dummy variable that takes the value of one if the stock's monthly returns are higher than 20%, and is zero otherwise. Panel B reports results for logit model (2) where the dependent variable, *Low_ret*, is a dummy variable that takes the value of one if the stock's monthly returns are lower than −15%, and is zero otherwise. Other variable definitions are in Table 1. *Industry effect* and *Year effect* are industry and year dummies. ME (%) shows the marginal effects in percentages. For the *Fama MacBeth* regressions, *t*-statistics are based on the time-series standard errors. For all other regressions, *t*- statistics are based on dual-clustered standard errors. 5% sig equals ** to indicate significance at the 5% level using sample size-adjusted critical values calculated as $[(N-1)(N^{1/N}-1)]^{0.5}$, where N is the number of observations.

TABLE 5

LOGIT MODELS PREDICTING HIGH AND LOW FUTURE RETURNS: SENSITIVITY ANALYSIS

Panel A: Predicting High Future Returns

	30%/−20% cut-offs			*Top/bottom 5% of stocks*			*Dimson beta*			*Portfolio betas*			*Quantile regressions (F-M)*		
	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig
Intercept	−2.966	−17.93	**	−1.760	−7.37	**	−2.363	−12.72	**	−2.048	−9.70	**	0.118	17.32	**
Beta	0.144	6.58	**	0.118	10.84	**							0.006	4.14	**
Beta Dimson							0.065	9.66	**						
Resid Dimson							3.163	26.00	**						
Beta portfolio										0.504	7.49	**			
Resid portfolio										−1.243	−0.62				
Resid	3.559	21.74	**	2.191	19.43	**							0.585	23.85	**
B/M	0.013	0.60		0.030	3.17		0.021	1.88		−0.013	−0.54		0.002	3.05	**
ln *MV*	−0.224	−7.85	**	−0.036	−3.48		−0.127	−10.14	**	−0.196	−7.90	**	−0.007	−13.56	**
Mom	−0.042	−1.18		0.042	1.92		0.000	0.01		0.127	2.91		−0.004	−1.91	
ln *Age*	−0.203	−12.99	**	−0.088	−9.58	**	−0.176	−14.58	**	−0.231	−13.11	**	−0.004	−5.30	**
Loss	0.477	16.28	**	0.143	9.14	**	0.304	16.69	**	0.443	20.70	**	0.030	14.49	**
Industry effect	Yes			Yes			Yes			Yes			Yes		
Year effect	Yes			Yes			Yes			Yes			No		
N	1015320			1015320			1015320			621024			382		
χ^2*-test*	31782			29602			46035			23729					
$p(\chi^2)$	0.000			0.000			0.000			0.000					
Pseudo R^2	10.70%			3.01%			7.11%			8.13%					

(continued on next page)

TABLE 5 (continued)

Panel B: Predicting Low Future Returns

	30%/−20% cut-offs			*Top/bottom 5% of stocks*			*Dimson beta*			*Portfolio betas*			*Quantile regressions (F-M)*		
	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig	Estimate	t-stat	5% sig
Intercept	−3.499	−22.92	**	−1.931	−7.91	**	−2.845	−14.95	**	−2.200	−11.68	**	−0.099	−23.65	**
Beta	0.120	7.26	**	0.105	8.91	**							−0.006	−6.85	**
Beta Dimson							0.056	8.24	**						
Resid Dimson							4.522	32.79	**						
Beta portfolio										0.435	7.67	**			
Resid portfolio										4.563	2.97				
Resid	4.650	24.56	**	3.768	31.88	**							−0.445	−46.00	**
B/M	−0.084	−3.75	**	−0.050	−5.28	**	−0.078	−6.26	**	−0.154	−4.99	**	0.003	6.72	**
ln *MV*	−0.071			−0.020	−2.68		−0.049	−4.35	**	−0.145	−6.33	**	0.004	11.78	**
Mom	−0.118	−2.28		−0.096	−4.34	**	−0.097	−3.53		0.006	0.08		0.013	10.41	**
ln *Age*	−0.267	−11.65	**	−0.120	−13.11	**	−0.222	−15.61	**	−0.273	−10.78	**	0.006	11.78	**
Loss	0.529	15.81	**	0.308	19.30	**	0.437	21.04	**	0.594	15.58	**	−0.028	−23.82	**
Industry effect	Yes			Yes			Yes			Yes			Yes		
Year effect	Yes			Yes			Yes			Yes			No		
N	1015320			1015320			1015320			621024			382		
χ^2*-test*	35545			50956			68005			27513					
$p(\chi^2)$	0.000			0.000			0.000			0.000					
Pseudo R^2	12.13%			5.07%			10.13%			11.27%					

Note: Columns *30%/−20% cut-offs* report results for the two logit models when using a 30% cut-off point to define the dependent variable in model (1) and −20% cut-off point to define the dependent variable in model (2). Columns *Top/bottom 5% of stocks* present results where the dependent variable for model (1) takes the value of one if the stock's monthly return is higher than the mean return of stocks in the top vigintile formed on the past three-month returns, and is zero otherwise. We follow a similar procedure to define the dependent variable for model (2), but now our cut-off point is based on mean returns for the 5% of stocks with the lowest average returns calculated over the previous three months. Columns *Dimson beta* report results when we use Dimson's (1979) beta in models (1) and (2). Columns *Portfolio betas* present results when using portfolio betas. Columns *Quantile regressions (F-M)* report Fama-MacBeth quantile regressions for the top and bottom return deciles. See Table 1 for other variable definitions. *Industry effect* and *Year effect* are industry and year dummies. For *Quantile regressions (F-M)*, the *t*-statistics are based on time-clustered standard errors. For all other regressions, the *t*- statistics are based on dual-clustered standard errors. 5% sig equals ** to indicate significance at the 5% level using sample size-adjusted critical values calculated as $[(N-1)(N^{1/N}-1)]^{0.5}$, where N is the number of observations.

[1] The CAPM's beta is commonly used to compute the cost of capital, which is applied to capital budgeting problems or in valuation (Penman and Sougiannis, 1998; Abarbanell and Bernard, 2000). The CAPM is also used to evaluate the information content of public disclosure (Ball and Brown, 1968; Penman, 1980), fund managers performance (Pastor and Stambaugh, 2002), and of new regulation (Collins, 1975, Christensen *et al.,* 2009). The importance of market beta in accounting and finance research is emphasized in Benson and Faff (2013), Berkman (2013), Bornholt *et al.* (2013), Cai *et al.* (2013), Johnstone (2013), Dempsey (2013a, 2013b), Moosa (2013), Partington (2013), Smith and Walsh (2013) and Subrahmanyam (2013).

[2] To explain beta's failure to describe the return cross-section, studies identified shortcomings in empirical CAPM tests that could explain its poor performance. Roll (1977) argues that the market portfolio in the CAPM is unobserved and that empirical tests that use the stock market index to approximate the market portfolio do not provide valid CAPM tests. However, Stambaugh (1982) shows that tests of the CAPM are insensitive to the specification of the market benchmark. Chan and Lakonishok (1993) argue that noise in the return data limits the ability of empirical tests to conclude on the positive relation between beta and returns. Later studies focused on the empirical issues related to using realized rather than expected returns in CAPM tests (Brav *et al.,* 2005), the errors-in-variables problem (Kim, 1995), and the time-variation in asset risk premia (Jagannathan and Wang, 1996; Ferson and Korajczyk, 1995).

[3] Misspecification of the asset pricing model leads to incorrect discount rate estimates and consequently stock misvaluation. In event studies, it can lead to erroneous conclusions on the existence of abnormal stock returns and market inefficiencies where none exist. Finally, a strong correlation between beta and various accounting measures, e.g. between beta and accruals (Francis *et al.,* 2005), can produce significant coefficients on the accounting measures in pricing tests when beta is omitted from the return regression (omitted variable bias).

[4] This intuition links directly with the CAPM theory that high beta stocks earn higher expected returns as a compensation for high systematic risk, i.e. higher likelihood that ex-post outcomes will strongly deviate from expected outcomes.

[5] We use asymmetric cut-off points to define the dependent variables for the logit regressions to adjust for the fact that the distribution of returns is right-skewed.

[6] Our main tests are implemented ex-post as we need to know future returns to identify stocks with large positive and negative returns. We do not see this as a disadvantage as (1) we do not claim to test viable trading strategies, (2) ex-post tests are common in empirical accounting research (e.g. estimates of earnings persistence in Dechow and Ge, 2006 and current accruals in Dechow and Dichev, 2002 and McNichols, 2002) and (3) robustness tests show that our conclusions are unaffected when we specify the dependent variables in the two logit models based on past returns.

[7] A concern with multiple testing on related samples is that it can increase the type 1 errors. This means we are more likely to find a significant coefficient on beta in at least one of the two logit models.

[8] Our argument extends to a setting where returns are generated by a multifactor asset pricing model.

[9] This framework is similar in spirit to Bilinski and Ohlson (2012), who examine the relation between accounting accruals and large and small long-run abnormal returns to dissect if Sloan's (1996) accrual anomaly reflects stock mispricing or risk. However, whereas Bilinski and Ohlson (2012) focus their tests on the mispricing explanation for the negative relation between accruals and returns, our tests emphasize the risk explanation for market beta. Further, our study explains why linear regression models, e.g. Fama MacBeth regressions, will fail on average to reject the null hypothesis that beta does not capture risk. This study also relates to the "dual-beta" literature, which advocates conditional tests of market beta (Pettengill *et al.,* 1995; Howton and Peterson, 1998; Faff, 2001). This literature argues that though the CAPM specifies an unconditional relation between beta and returns, using sample periods characterized by a high proportion of months with negative excess returns or regressions that assume time-invariant betas reduces the power of tests to reject the null hypothesis of no relation between beta and returns. Our framework is different from the "dual-beta" approach as it provides unconditional tests of beta as risk measure, which is more consistent with the unconditional relationship between beta and returns in Sharpe (1964) and Lintner (1965). Further, the intuition for the beta tests in this study is to look at the tails of the cross-sectional return distribution to identify if high beta stocks behave like risky stocks. This is different from the setup of "dual beta" studies that examine a linear relation between beta and returns conditional on the market performance.

[10] The four-month gap between the start of the return measurement and the fiscal year-end ensures that the most recent accounting information is available to investors. Because we do not use a fixed starting date for measuring returns, e.g. July of each year as in Fama and French (1992), we are able to include firms in the analysis immediately after the four-month gap after the fiscal year-end. Fama and French (1992) acknowledge that in their study the gap between the fiscal year-end and the start date for measuring returns varies among stocks. Consequently, their sample includes stocks with as little as a one day gap between the fiscal year-end and the start of the holding period (this introduces a hindsight bias to their research), and stocks with close to a 12-month gap (this means using relatively stale accounting information in the analysis). As a robustness test, we also consider a fixed starting date for measuring returns and find that our conclusions are unchanged.

[11] A similar interpretation applies to the coefficients on other risk controls in models (1) and (2). Specifically, if the two coefficients on a risk proxying variable are significant and have the same sign in models (1) and (2), then the variable is more likely to capture risk. If only one coefficient on a risk proxying variable is significant or the coefficients have opposing signs, then the variable is unlikely to capture risk. If both coefficients are zero, then we cannot conclude whether a variable reflects risk.

[12] Gow *et al.* (2010) criticize the use of the Fama-MacBeth method in accounting research pointing out that the method fails to adjust for both the time-series and cross-sectional dependence of observations.

[13] The risk interpretation for firm size relates to distress risk (Chan and Chen, 1991; Perez-Quiros and Timmermann, 2000) and information quality that leads to information asymmetries (Gertler and Gilchrist, 1994). However, the association between the B/M ratio and returns is tenuous. Fama and French (1992) consider high B/M stocks as more risky, however, intuitively one would expect growth stocks, i.e. low B/M stocks, to be more risky. This is because growth options are more risky than assets in place and the success in exercising growth options depends on (unpredictable) economic conditions (Gomes *et al.,* 2003; Penman, 2010; Penman, 2011). Fama and French (1992) do not identify a specific hedge risk that the B/M ratio proxies for and conclude that the cross-sectional variation in the B/M ratio can be driven by either a varying sensitivity to an underlying, yet unknown risk factor, or reflect 'the unraveling (regression toward the mean) of irrational market whims about the prospects of firms.' (Fama and French, 1992, p. 429).

[14] Information uncertainty delays the speed with which prices incorporate information, increasing information asymmetries and mispricing risk (Diamond and Verrecchia, 1991; Verrecchia, 2001), and estimation risk (Coles and Loewenstein, 1988).

[15] We do not use leverage or more sophisticated financial distress measures, such as Ohlson's (1980) O-score, because previous studies find a negative association between distress measures and returns (Dichev, 1998; Campbell *et al.,* 2008). This empirical evidence is inconsistent with the predictions of the Modigliani and Miller (1958) model that the equity premium increases with the firm's distress risk. George and Hwang (2010) propose that firms may actively lower their leverage in anticipation of high distress costs, which explains why empirically high leverage firms tend to have low future returns.

[16] Prior to 1962, Compustat data is subject to strong survivorship bias (Kothari *et al.,* 1995). Nasdaq and AMEX data are available from 1973. Our sample period ends in December 2005 to avoid speculation that our results are due to the recent financial crisis. Extending the sample period to include the financial crisis period leaves our conclusions unchanged.

[17] We reach similar conclusions when we first sort stocks into deciles based on the B/M ratio and then subdivide each B/M decile into ten return portfolios.

[18] To estimate portfolio betas, each April of year t we allocate stocks into decile portfolios based on their betas. For each decile portfolio we calculate equally-weighted monthly returns for the next 12 months. We then calculate portfolio betas for each decile portfolio by regressing the 12-month portfolio returns, less the risk free rate, on the market premium. In April of year $t+1$, we allocate the portfolio beta to each stock in the corresponding decile. For

this analysis we retain only stocks with December fiscal year-ends to ensure a fixed start date for measuring portfolio returns.

[19] An additional reason why we favor beta tests at firm level is that estimating portfolio betas, e.g. for a portfolio of stocks with the highest firm-level betas, means pooling stocks with high and low returns, which can produce portfolio returns that are unrepresentative of the average risk profile of stocks in that portfolio. Thus, tests that use betas estimated at portfolio level need to be evaluated with care.

[20] We implement the Fama MacBeth approach by regressing stock returns on our explanatory variables in model (3) for each month using weighted least squares, where weights reflect the precision of beta estimates. Then we calculate the time-series means of monthly coefficients and the corresponding *t*-statistics based on the time-series standard errors. *t*-statistics are adjusted for the time-series dependence of observations.

[21] Following Connolly (1989) and Anderson and Faff (2006), we calculate sample size-adjusted 5% critical values for the *t*-statistics (in response to Lindley's 1957 paradox). The critical value at the 5% is defined as $[(N-1)(N^{1/N}-1)]^{0.5}$, where N is the number of observations. To illustrate, for N=1,015,320, the size-adjusted 5% critical value is ±3.72.

[22] Our conclusions remain qualitatively similar when (1) we measure past returns over a 12-month period, (2) we use the 1% of stocks with the highest and lowest average returns calculated over the previous three months, and (3) the dependent variable for model (1) equals one if the mean three-month past stock return is higher than 20%, and zero otherwise; the dependent variable for model (2) equals one if the mean three-month past stock return is lower than −15%, and is zero otherwise.

[23] In unreported results we also find that our conclusions from Table 4 are unchanged when we use market beta estimated over a five-year period ending four months after the fiscal year-end. We require a minimum 52 months of returns to estimate betas. We consider beta estimated over a five-year period because the literature is not unanimous on the length of the period for beta estimation.

[24] We consider annual returns because (1) the CAPM does not specify the length of the return horizon to use in tests of beta's ability to explain the cross-section of stock returns and (2) trading frictions, non-synchronous trading and short-interval return autocorrelation (Lo and MacKinlay, 1990; Mech, 1993) can negatively bias tests of the relation between beta and cross-sectional returns when using short-horizon returns.

[25] We consider simultaneous regressions because inferences based on the two logit regressions may be inefficient if there are strong cross-correlations in error terms between models.