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The beta anomaly and the quality effect in international stock markets

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A B S T R A C T

We investigate the beta anomaly and its relationship with stock quality in international stock markets. The beta anomaly exists in three aggregates (Europe, Pacific, and Global) and fourteen of the twenty-two country portfolios. We further demonstrate that stock quality explains the beta anomaly in international markets. The beta anomaly is statistically significant among junk (low-quality) stocks, and it does not exist among quality (high-quality) stocks. The results are robust in portfolio and regression analyses, both before and after controls. Finally, we show that the alphas of the beta anomaly estimated using the Fama–French–Carhart factor as well as Fama–French five-factor models disappear when augmented by the quality-minus-junk (QMJ) factor.

1. Introduction

The Sharpe–Lintner Capital Asset Pricing Model (CAPM) (Lintner, 1965; Sharpe, 1964) provides a framework where investors assess the investment risks related to the market portfolio, and beta measures the systematic risk of an investment associated with the market. Early studies find that a higher beta is associated with a higher expected return and that this relationship is linear (Black et al., 1972; Fama and MacBeth, 1973; Gibbons, 1982; Stambaugh, 1982). However, Black (1972), Black et al. (1972), and Haugen and Heins (1975) find that the returns of low beta stocks are higher than expected according to CAPM, which implies that betas cannot explain expected returns. Indeed, compelling empirical evidence suggests that lower-risk assets earn higher returns on average.[1]

Recent research confirms the low-beta anomalies and provides several explanations for this phenomenon, such as leverage constraints (Frazzini and Pedersen, 2014; Boguth and Simutin, 2018; Jylha, 2018), benchmarking (Baker et al., 2011; Iwasawa and Uchiyama, 2014), profitability (Novy-Marx, 2014; Fama and French, 2016), seasonality (Fiore and Saha, 2015), sentiment (Antoniou et al., 2016), aggregate disagreement (Hong and Sraer, 2016), gambling (Bali et al., 2017), arbitrage (Huang et al., 2018), coskewness (Schneider et al., 2020), and herding (Hwang et al., 2021). While the outperformance of low-risk stocks has been widely explored in the US market,[2] and the evidence suggests a form of market inefficiency, very few studies have examined this anomaly and its potential explanations in non-US markets. The concentration of research in the US equity market leads to the risk of generalizing the US evidence.

In this study, we examine the prevalence of the beta anomaly in international stock markets using an extensive global database across twenty-two countries and three aggregate markets. This is important as research in different equity markets is essential to identify the beta anomaly's fundamental drivers in different settings. Also, the outperformance of strategies based on the beta anomaly can be large and there has always been interest in low beta approaches in equity investing among academics and practitioners around the world.

The aggregate portfolios are Europe, Pacific, and Global. The Europe aggregate portfolio contains all stocks of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. We do not include Eastern European markets due to availability of data. The Pacific aggregate portfolio

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[1] See, for example, Haugen and Heins (1975); Haugen and Baker (1991); Ang et al. (2009); Clarke et al. (2006, 2011); Blitz and van Vliet (2007); Baker et al. (2011); Baker and Haugen (2012); and Blitz et al. (2013).

[2] See, for example, Asness et al. (2020); Fiore and Saha (2015); Bali et al. (2017); Baker et al. (2020); Blitz and Vidojevic (2017); Boloorforoosh et al. (2020); Cederburg and O'Doherty (2016); Cohen et al. (2005); Hong and Sraer (2016); Huang et al. (2018); Jylha (2018); Liu et al. (2018); and Schneider et al. (2020).

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contains the stocks of Australia, Hong Kong, Japan, New Zealand, and Singapore. Finally, the Global aggregate comprises all stocks, including the Europe and Pacific aggregates, plus stocks from Canada. We also explore the beta anomaly at the country level in each of those twenty-two country portfolios.

We show that portfolios of low-beta stocks have significantly higher average returns than those of high-beta stocks for the aggregate portfolios. Furthermore, the beta anomaly is economically and statistically significant in the country stock portfolios except for those of Austria, Belgium, Finland, Greece, Ireland, Italy, Japan, and New Zealand. For example, for the Global (Pacific) aggregate portfolio, a strategy that takes a long position in low-beta stocks and a short position in high-beta stocks, i.e. the low–high beta portfolio, generates monthly excess returns, CAPM, Fama–French, and Fama–French–Carhart alphas of 0.57% (0.36%), 0.93% (0.63%), 0.99% (0.73%), and 0.64% (0.43%), respectively. A dollar invested in January 1993 in a low–high beta portfolio increases to 358.04 (107.24) US dollars by March 2021. Our analysis provides evidence of the beta anomaly across many developed countries and regions using the most recent data.

We further investigate whether the quality of stocks can explain the beta anomaly across the international markets. Asness et al. (2019) define quality stocks as those of firms that are profitable, growing, safe, and well managed, whereas junk stocks are those of firms that are unprofitable, stagnant, risky, and poorly managed. They show that quality (junk) stocks are underpriced (overpriced). Consequently, quality (junk) stocks have positive (negative) risk-adjusted returns, known as the stock quality effect. Asness et al. (2019) show that a quality-minus-junk (QMJ) factor that is long in quality stocks and short in junk stocks earns significant risk-adjusted returns.

We test the hypothesis that the beta anomaly is concentrated among junk stocks. The intuition is that since high-beta stocks are riskier, they are more likely to be junk stocks and therefore overpriced (Asness et al., 2019). On the other hand, since low-beta stocks are less risky, they are more likely to be quality stocks, and hence underpriced (Asness et al., 2019). As the beta anomaly is restricted to overpriced stocks (Liu et al., 2018), the outperformance of low-beta stocks, or beta anomaly, should exist among junk stocks (Geppert and Zhao, 2018).

We examine the relationship between stock quality and beta across countries and in aggregate portfolios using portfolio and cross-sectional regression analyses. We use each stock's sensitivity to the QMJ factor in each market as a proxy for stock quality.[3] The results show that high-beta (low-beta) stocks have lower (higher) quality values which is consistent with our intuition that high-beta (low-beta) stocks are more likely to be junk (quality) stocks. Furthermore, the beta anomaly is both economically and statistically significant among junk stocks, while it disappears among quality stocks. The performance of the zero-cost portfolio that is long in low-beta stocks and short in high-beta stocks significantly improves once we focus only on junk stocks in our portfolio analysis. In fact, it almost doubles if it is constructed using only junk stocks. The monthly excess returns of the low–high beta portfolios within junk (all) stocks are 1.30% (0.57%), 0.48% (0.14%), and 0.70% (0.36%) for Global, Europe, and Pacific aggregates, respectively. The risk-adjusted returns follow the same patterns. For example, the Fama–French–Carhart alphas of the low–high beta portfolios within junk (all) stocks are 1.25% (0.64%), 0.34% (0.11%), and 0.58% (0.43%) for Global, Europe, and Pacific aggregates, respectively.

Similarly, we find beta predicts future stock returns only in quality stocks in our Fama and MacBeth (1973) regression analysis. In contrast, the beta coefficient is small and statistically insignificant among junk stocks. The regression analysis shows that the market risk is priced among quality stocks, whereas a flat Security Market Line is observed among junk stocks. We also assess the significance of the beta anomaly in the presence of the QMJ factor developed by Asness et al. (2019).[4] We find that the CAPM, FF3 and FFC4 alphas of the zero-cost portfolio that is long low-beta stocks and short high-beta stocks become insignificant once we include the QMJ factor in the portfolio analysis. The results are robust when we consider Fama and French (2015) five-factor model that includes investment and profitability factors to calculate alphas. Our findings suggest that the beta anomaly is more common across low-quality stocks.

This study contributes to the growing literature that investigates asset pricing anomalies in international markets. Only a few studies explore the beta anomaly in non-US stock markets. For instance, Iwasawa and Uchiyama (2014) attribute the beta anomaly in the Japanese stock market to foreign institutional investors. Bradrania and Veron (2022) relate the beta anomaly to lottery demand in the Australian market. Pyo and Lee (2018) use machine learning to exploit the beta anomaly in South Korea. Walkshausl (2014) studies low-risk investing in aggregate equity markets, including developed, emerging, European, US and Japanese markets. Our paper extends this literature by providing evidence for the underperformance of high-risk stocks in three aggregate and fourteen country portfolios. We also show that the beta anomaly remains economically strong and statistically significant among junk stocks, while it disappears among quality stocks. Geppert and Zhao (2018) provide evidence of the relationship between the beta anomaly and stock quality in the US market. However, like any asset pricing study, those findings can be sample-specific, so they must be tested in different stock markets. In this paper, we provide evidence from three aggregates and twenty-two individual countries for quality as an explanation for the beta anomaly. We show that there is a negative relationship between beta and stock quality and that stock quality is a fundamental component of the profitability of the investment strategies based on the beta anomaly. In addition, in the context of the research in linear multi-factor models, we provide evidence that QMJ is an important factor that should be included in asset pricing models. We show that beta anomaly disappears when we incorporate QMJ into the traditional factor models such as FF3 and FFC4 as well as recent models such as Fama–French five-factor (FF5) and FF5 augmented by the momentum factor.

Our findings offer guidance for academics as well as practitioners interested in pricing models and, specifically, low-risk trading strategies in the global market. We show that the significant premium for the beta anomaly disappears when quality and particularly QMJ factor is incorporated in the traditional factor pricing models. This provides evidence that practitioners and academics should treat QMJ as a factor in their pricing models and cross-sectional analysis. In addition, our findings have important investment implications for traders and portfolio managers as considering the quality of stocks may affect mispricing opportunities and portfolio choice due to the well-known beta anomaly. Also, we shed light on beta-based investment strategies within twenty-two different equity markets as well as three important aggregate portfolios. This provides better understating on potential opportunities among junk stocks, and also variation of

[3] Previous studies (Fama and French, 1992; Daniel and Titman, 1997; Davis et al., 2000; Daniel et al., 2001) document that firm characteristics and factor loading are highly correlated (Geppert and Zhao, 2018). For example, Fama and French (1993) find that returns of value stocks covary strongly with the HML returns, and small stock returns covary with SMB portfolio returns. They demonstrate that firm characteristics are a proxy for future return patterns.

[4] Recent studies argue that the QMJ factor contains unique information and explanatory power of future stock returns (Ali and Ülkü, 2021; González-Urteaga and Rubio, 2021; Harvey, 2021).

the existence and the degree of profitability of low-risk trading strategies across countries.

The rest of the paper is organized as follows. Section 2 describes data and variable construction. Section 3 examines the beta anomaly in international stock markets. Section 4 investigates the link between stock quality and the beta anomaly, and Section 5 explores the ability of the quality factor to explain the returns associated with the beta anomaly. Finally, Section 6 concludes.

2. Data and variable construction

2.1. Data

The daily and monthly transaction data are collected from Refinitiv[5] DataStream from January 1, 1990, to March 31, 2021. The data includes closing prices, prices adjusted for splits and dividends,[6] price-to-book ratios, number of shares, and volume for all stocks from twenty-two developed markets (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom). The twenty-two markets cover all countries included in the MSCI World Developed Index, excluding the United States and Israel, and our sample consists of 17,949 firms. We use daily and monthly returns of the main market indexes as the proxy for market returns for each country, collected from DataStream.

In addition, we construct aggregated portfolios by including all firms available from Datastream as follows. The Europe aggregate portfolio contains 6274 firms from sixteen countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The Pacific aggregate portfolio contains 7789 firms from Australia, Hong Kong, Japan, New Zealand, and Singapore. Finally, the Global aggregate portfolio includes all firms of the twenty-two countries in our sample. The Global aggregate comprises 17,949 firms, including the Europe and Pacific aggregates, plus 3886 firms from the Canadian stock market.

We obtain daily and monthly returns of these aggregate markets from Applied Quantitative Research (AQR).[7] According to AQR, the stock portfolios are formed on a monthly basis for each country, and aggregates are computed by weighting each country's portfolio by the country's total lagged ($t-1$) market capitalization.

We construct equally weighted portfolios for twenty-two countries and three aggregates to assess the beta anomaly. We use the one-month US Treasury Bill Rate as a proxy for the risk-free rate, and all returns are in US dollars and measured as excess returns above the risk-free rate. We do not include any currency hedging to estimate returns. The one-month US Treasury bill rate and risk factors for each of the twenty-two countries and three aggregates that include market (MKT), size (SMB), book-to-market (HML), momentum (UMD), and quality (QMJ) are collected from AQR.[8]

2.2. Variable construction

2.2.1. Beta

We follow the approach suggested by Frazzini and Pedersen (2014) to estimate ex-ante betas. At the end of each month, we calculate the time-series betas for each stock using the following equation:

$$\beta_i^{ts} = \rho \frac{\sigma_i}{\sigma_m} \tag{1}$$

where σ_i and σ_m are the estimated volatilities, and proxied by standard deviations, for stock i and the stock market, and ρ is their correlation. We estimate volatilities and correlations using the previous one-year and five-year daily data, respectively.[9]

We estimate volatilities and correlations separately because correlation appears to move more slowly than volatilities (e.g., De Santis and Gerard, 1997; Frazzini and Pedersen, 2014). We use one-day log returns to estimate volatilities, while we use overlapping three-day log returns to calculate correlation to control for nonsynchronous trading, which only affects correlation. Overlapping three-day return is estimated using the following equation:

$$r_{i,t}^{3d} = \sum_{k=0}^{2} ln\left(1 + r_{t+k}^{i}\right) \tag{2}$$

We require 130 trading days of non-missing data to estimate volatilities and 780 trading days of non-missing data to estimate correlations. Lastly, to account for outliers, we follow Vasicek (1973) shrinkage time series estimates of beta β_i^{ts} toward the cross-sectional mean β^{xs}:

$$\hat{\beta}_i = w_i \hat{\beta}_i^{ts} + (1 - w_i)\hat{\beta}^{xs} \tag{3}$$

For simplicity, we set $w = 0.6$ and $\beta^{xs} = 1$ as in Frazzini and Pedersen (2014) for all periods.[10]

2.2.2. Stock quality

Asness et al. (2019) provide a valuation model showing how stock prices increase with their quality, which is a characteristic based on stocks' profitability, growth, and safety. They further introduce the quality-minus-junk (QMJ) factor, which is a time series of returns on a portfolio that is long in high-quality stocks and short in low-quality stocks. They show that the QMJ factor earns significant risk-adjusted returns in the US and across twenty-four countries.

We follow Geppert and Zhao (2018) and define stocks' loading on the QMJ factor in each market as a proxy for the quality level of the stocks. Previous studies document that firm characteristics and factor loading are highly correlated (Fama and French, 1993; Daniel and Titman, 1997; Davis et al., 2000; Daniel et al., 2001). For instance, Daniel et al. (2001) show that firms with high loading on a priced factor have lower prices because their

[5] Formerly known as Thomson Reuters.

[6] This is the total return, which shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are reinvested to purchase additional units of an equity at the closing price applicable on the ex-dividend date. Gross dividends are used where available, and the calculation ignores tax and re-investment charges. Adjusted closing prices are used throughout to determine prices and returns.

[7] The data was originally constructed by Frazzini and Pedersen (2014), and now regularly updated by AQR Capital Management website at https://www.aqr.com/Insights/Datasets. The three aggregate markets evaluated in this study include all stock markets (except the Israel's stock market) that were used to construct the aggregate portfolios sourced for AQR.

[8] According to AQR, the factors portfolio construction follows approaches in Fama and French (1992, 1993, 1996), Asness and Frazzini (2013), and Frazzini and Pedersen (2014) and is based on common stocks obtained from the CRSP dataset and the Compustat/XpressFeed Global database (supplemented by Moody's data). See Asness and Frazzini (2013) and Asness et al. (2019) for a detailed description of their construction.

[9] We use daily data, as the accuracy of the covariance improves with the sample frequency.

[10] The shrinkage factor selection does not affect how stocks are sorted into beta-portfolios, as common shrinkage does not change the beta's ranks (Frazzini and Pedersen, 2014).

future cash flows are discounted at higher rates. This suggests a correlation between factor loadings and the corresponding firm characteristics. Furthermore, Fama and French (1993) find that sensitivity to value and size risk factors can proxy for book-to-market and size characteristics of firms. They show that returns of value stocks covary strongly with the HML returns, and small stock returns covary with the SMB portfolio returns. Similarly, Daniel and Titman (1997) show that a portfolio with high sensitivity to the HML factor behaves like a value stock portfolio.[11] In our study, we assume that a portfolio with high sensitivity to the QMJ factor behaves like a portfolio of quality stocks, and the sensitivity to the QMJ factor proxies the expected stock quality for the following month. Specifically, at the end of month t, we estimate the sensitivity of stocks' returns to the QMJ factor, denoted β_{QMJ}, as the slope coefficient from a rolling regression of excess stock returns on the QMJ factor using one year of daily returns covering days $t-260$ to t. We require at least 180 daily returns over the previous year to compute the quality loadings.

2.2.3. Control variables

In our regression analyses, we control for firm characteristics variables known to explain the cross-section of expected stock returns. They include size (Banz, 1981), book-to-market ratio (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993), reversal (Jegadeesh, 1990; Lehmann, 1990) and illiquidity (Amihud, 2002). Moreover, we control for MAX as Bali et al. (2011) show that the maximum daily return of the previous month (MAX) is negatively associated with future stock returns of the following month. The construction of these variables are explained as follows.

Size (Ln MV): the natural logarithm of the market capitalization of a firm in millions of dollars each month, where the market capitalization or market value of equity (MV) is computed as the product of the stock price and the number of shares outstanding (NS) at the end of December of the prior year.

Book-to-market (Ln B/M): the natural logarithm of book-to-market ratio (B/M), calculated following Fama and French (1992), as the book value of equity divided by the market value of equity at the end of December of the prior year.[12]

Momentum (Mom): the intermediate-term momentum in each month, as defined in Jegadeesh and Titman (1993), is estimated as the cumulative return of prior months from month $t-12$ to month $t-2$ inclusive.[13]

Reversal (Rev): the short-term return reversal in each month, following Jegadeesh (1990) and Lehmann (1990), estimated as stock return in month $t-1$.

Illiquidity (Illiq): the Amihud (2002) illiquidity of the stock in each month, calculated as the absolute monthly stock return divided by its dollar trading volume in millions of dollars:

$$Illiq_{it} = \frac{|R_{it}|}{VolD_{it}} \tag{4}$$

where $Illiq_{it}$ is the illiquidity measure for each stock i in month t, R_{it} is the return on stock i in month t, and $VolD_{it}$ is the monthly trading volume in dollars in month t.

MAX: a proxy for lottery demand calculated as the maximum daily return during the month. We follow Bali et al. (2011, 2017) and require a minimum of 15 daily price observations in a month to estimate MAX.

Table 1
Summary statistics.

Variable	No Obs	Mean	Median	Std Dev	Min	Max
Price	3,108,121	96.55	5.72	467.15	0.00	4796.46
Return	3,097,303	1.22	−0.05	19.21	−100.00	411.22
β	2,495,289	0.85	0.81	0.29	−1.88	6.58
Quality	2,860,882	−0.73	−0.53	1.02	−8.60	7.95
NS	3,119,457	418,231	37,411	2,018,543	1.00	99,195,620
MV	3,016,572	1567.15	73.62	9002.41	0.01	861,069.6
B/M	2,404,641	1.27	0.75	4.41	0.00	100.00
Mom	2,888,506	9.21	0.03	63.88	−100.00	425.72
Rev	3,079,629	1.22	−0.05	19.19	−100.00	411.22
Illiq	2,892,585	0.10	0.00	0.72	0.00	8.50
Max	3,094,536	8.48	4.69	11.87	−50.11	100.92

This table reports the descriptive statistics of variables used in this study across the whole sample. The sample period is from January 1990 to March 2021. Price is the stock closing price at the end of the month, and Return is the monthly stock return. Beta (β) for each month is estimated according to Frazzini and Pedersen (2014) and defined in Eq. (1). Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. NS is the monthly average number of shares outstanding; MV is the market capitalization in millions of dollars, calculated at the end of last December; B/M is the book-to-market ratio calculated following Fama and French (1992), Mom is the intermediate-term momentum, defined by Jegadeesh and Titman (1993) and estimated as the monthly cumulative return over the past year except the previous month. Rev is the short-term reversal following Jegadeesh (1990) and Lehmann (1990) and estimated as the previous month's return. Illiq is the Amihud (2002) stock illiquidity measured as the absolute monthly stock return divided by its dollar trading volumes in millions, defined in Eq. (4). MAX is estimated according to Bali et al. (2011) as the maximum daily return during the previous month. Return, Mom, Rev and MAX are expressed in percentage, and Illiq is rescaled by 10^4.

Table 1 reports the summary statistics of the variables used in this study over the period from January 1990 to March 2021. All variables are in US dollars; Return, Mom and Rev are expressed as percentages; and Illiq is rescaled by 10^4.

The average stock price in our sample is 96.55 US dollars, with a median value of 5.72 US dollars. The average monthly return is 1.22%, but the median value is −0.05%. The minimum (maximum) monthly return is −100% (411%). The mean (median) β and quality for all stocks in our sample are 0.85 (0.81) and −0.73 (−0.53), respectively. The quality values range from −8.60 to 7.95, whereas β ranges from −1.88 to 6.58 over the twenty-two countries in the sample.

Since the sample includes twenty-two different stock markets and around 18,000 firms over 375 months, there could be considerable variation across countries. Table 2 reports the mean values of all variables, including the number of firms for each country in the sample.

The total number of firms in the sample is 17,949, and the two country portfolios that record the highest number of firms are Canada, with 3886 firms, and Japan, with 3377 firms. In contrast, the two country portfolios with the fewest firms are Portugal, with 41 firms, and Austria, with 66 firms.[14] The average monthly stock return, including all stocks, is 1.22%. The country portfolios that record the lowest returns are Italy, Japan, and Spain, with average monthly returns of 0.44%, 0.63%, and 0.64%, respectively. The average β for all stocks is 0.85, and it ranges from 0.71 for France to 0.95 for Australia. Our proxy for stock quality shows an average value of −0.73. The lowest mean quality value is −1.01 for Japan, while the highest is −0.07 for Ireland. The mean values of MV vary significantly across different countries, ranging from an average of over $4.8 billion for Spain to $453 million for Greece.

11 Daniel and Titman (1997) show that the higher B/M portfolios have higher HML factor loadings since characteristics and sensitivities are highly correlated. They note that portfolios sorted on other variables forecast those factor loadings because of the high correlation between characteristics and loadings.

12 The results of regression analyses are robust when we estimate MV and B/M using available figures of NS, BV and MV at the end of the prior month.

13 We also estimate intermediate-term momentum of a stock in month t as the cumulative return from month $t-6$ to month $t-2$ inclusive. The results of regression analyses are robust to both momentum measures.

14 Austria and Portugal are the two only countries with less than 100 firms in the sample.

Table 2
Firm variables for each country.

Portfolios	No firms	Price	Return	β	Quality	NS	MV	B/M	Mom	Rev	Illiq	Max
All sample	17,949	96.55	1.22	0.85	−0.73	418,231	1567.15	1.27	9.21	1.22	0.10	8.48
Australia	1874	6.74	1.44	0.95	−0.77	396,373	865.24	0.84	10.79	1.46	0.10	10.78
Austria	66	36.93	0.77	0.74	−0.20	61,250	1521.14	1.03	8.44	0.78	0.02	4.21
Belgium	116	130.61	0.77	0.77	−0.29	56,063	2394.25	1.06	8.42	0.78	0.05	4.43
Canada	3886	19.10	2.70	0.92	−0.74	67,263	535.17	1.63	12.66	2.70	0.38	16.70
Denmark	144	50.15	0.92	0.83	−0.29	51,552	1527.79	0.93	11.35	0.91	0.02	5.25
Finland	130	11.40	1.05	0.77	−0.22	161,252	2234.89	0.77	11.62	1.05	0.02	5.45
France	714	113.66	0.88	0.71	−0.55	67,333	2738.26	0.94	7.64	0.88	0.08	5.88
Germany	834	92.67	0.89	0.72	−0.55	51,573	2145.08	1.89	8.16	0.89	0.15	7.08
Greece	126	8.27	1.12	0.86	−0.64	102,588	453.76	1.69	11.79	1.11	0.20	6.94
Hong Kong	1897	2.79	0.98	0.81	−0.85	2,319,027	1481.91	1.43	10.38	0.98	0.02	7.59
Ireland	919	1212.26	0.66	0.73	−0.07	153,439	1221.66	1.21	5.77	0.67	0.00	2.60
Italy	314	19.74	0.44	0.82	−0.52	549,410	2849.99	0.94	4.28	0.42	0.00	5.16
Japan	3377	28.23	0.63	0.84	−1.01	121,396	1431.49	1.18	6.71	0.62	0.00	5.43
Netherlands	111	48.65	0.84	0.84	−0.53	189,868	4232.17	0.82	8.41	0.83	0.02	4.92
New Zealand	151	2.52	1.16	0.94	−0.10	305,477	518.46	0.79	11.47	1.17	0.07	5.15
Norway	330	34.25	1.12	0.89	−0.52	181,005	1332.24	1.10	9.96	1.09	0.04	6.81
Portugal	41	8.61	0.88	0.89	−0.15	659,738	1428.30	2.21	6.59	0.88	0.29	6.22
Singapore	490	1.47	0.93	0.90	−0.72	1,032,907	924.41	1.29	8.35	0.92	0.08	8.29
Spain	208	16.48	0.64	0.80	−0.55	454,006	4873.27	1.30	7.80	0.64	0.01	4.31
Sweden	767	11.59	1.31	0.87	−0.39	128,603	1117.09	0.67	12.06	1.31	0.02	8.46
Switzerland	296	243.27	0.76	0.76	−0.33	59,348	4208.85	1.17	9.21	0.77	0.01	4.10
UK	1158	550.88	0.84	0.83	−0.67	708,011	3593.77	1.69	7.97	0.83	0.00	5.91

This table reports the time-series averages of the monthly cross-sectional means of various firm characteristics variables for each country portfolio. The sample period is from January 1990 to March 2021. Price is the stock closing price at the end of the month, and Return is the monthly stock return. Beta (β) for each month is estimated according to Frazzini and Pedersen (2014) and defined in Eq. (1). Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. NS is the monthly average number of shares outstanding; MV is the market capitalization in millions of dollars, calculated at the end of last December; B/M is the book to market ratio calculated following Fama and French (1992), Mom is the intermediate-term momentum, defined by Jegadeesh and Titman (1993) and estimated as the monthly cumulative return over the past year except the previous month. Rev is the short-term reversal following Jegadeesh (1990) and Lehmann (1990) and estimated as the previous month's return. Illiq is the Amihud (2002) stock illiquidity measured as the absolute monthly stock return divided by its dollar trading volumes in millions, defined in Eq. (4). MAX is estimated according to Bali et al. (2011) as the maximum daily return during the previous month. Return, Mom, Rev and MAX are expressed in percentage, while Illiq is rescaled by 10^4.

3. The beta anomaly across international stock markets

In this section, we investigate the beta anomaly's existence and its extent in three aggregate and twenty-two country portfolios.

3.1. The beta anomaly across aggregate portfolios

For each aggregate portfolio, Global (excluding the US), Europe, and Pacific, and at the end of each month, we sort all stocks in ascending order based on the previous month's beta and construct quintile portfolios. We then form a portfolio that is long in the lowest beta quintile and short in the highest beta quintile: the low–high beta portfolio. All portfolios are equally weighted and rebalanced every calendar month. Fig. 1 plots the monthly cumulative returns of one US dollar invested in the low–high beta portfolios in January 1993 across three aggregate portfolios over time.[15]

The performance of the low–high beta portfolios from January 1993 to March 2021 shows that, on average, low-beta stocks earned higher returns than high-beta stocks, since the cumulative returns of all three aggregate low–high beta portfolios are positive. An equally weighted low–high beta portfolio that includes all twenty-two stock markets (the Global aggregate) earns higher excess returns than its Europe and Pacific counterparts. The low–high beta portfolio that longs \$1 in the low beta portfolio and shorts \$1 in the high beta portfolio for the Global aggregate is worth \$358.04 by March 2021. The low–high portfolio for the Pacific aggregate is worth \$107.24 by March 2021. However, the low–high portfolio for the Europe aggregate is only worth \$3.92 by March 2021.

Table 3 reports the time-series means of the cross-sectional average of monthly portfolio excess returns and alphas relative to several common risk factors of each beta quantile portfolio for the Global, Europe, and Pacific aggregate portfolios. The factor models are the CAPM, Fama and French (1993) three-factor model (FF3), and the Fama and French (1993) and Carhart (1997) four-factor model (FFC4). Table 3 also presents the excess returns and alphas for the low–high beta portfolios as well as β (ex-ante), β (realized), Quality and annualized Volatility and Sharpe ratios in each aggregate market. The β (ex-ante) is the one-month-lag betas estimated following Frazzini and Pedersen (2014), whereas β (realized) is the slope of a time-series regression of monthly stock excess returns on market excess returns for each beta-sorted portfolio.[16] The t-statistics are adjusted for autocorrelation and heteroskedasticity using the Newey and West (1987) method with five lags. Panels A, B, and C report the results for the Global, Europe, and Pacific portfolios, respectively.

The results of Table 3 show that the average excess returns of the beta-sorted portfolios tend to decrease from the low-beta quintile (P1) to the high-beta quintile (P5) across all aggregate portfolios. For the Global portfolio (Panel A), the excess returns decrease monotonically from 1.49% monthly for the low-beta quintile (P1) to 0.92% for the high-beta quintile (P5), and the average return difference between the low-beta and the high-beta quintiles (low–high) is 0.57% (t-statistic = 2.07). For the Europe portfolio (Panel B), the monthly excess returns decrease from 0.89% for the low-beta quintile (P1) to 0.75% for the high-beta quintile (P5), and the return of the low–high beta portfolio is 0.14% per month. For the Pacific portfolio (Panel C), the monthly excess returns decrease from 0.86% for the low-beta quintile (P1)

15 Although the sample data start in January 1990, we use the first three years of data to estimate beta.

16 The estimation of realized β is only conducted to compare and examine the performance of our estimated β (ex-ante), and neither portfolio analysis nor regression analysis focus on the realized β estimation.

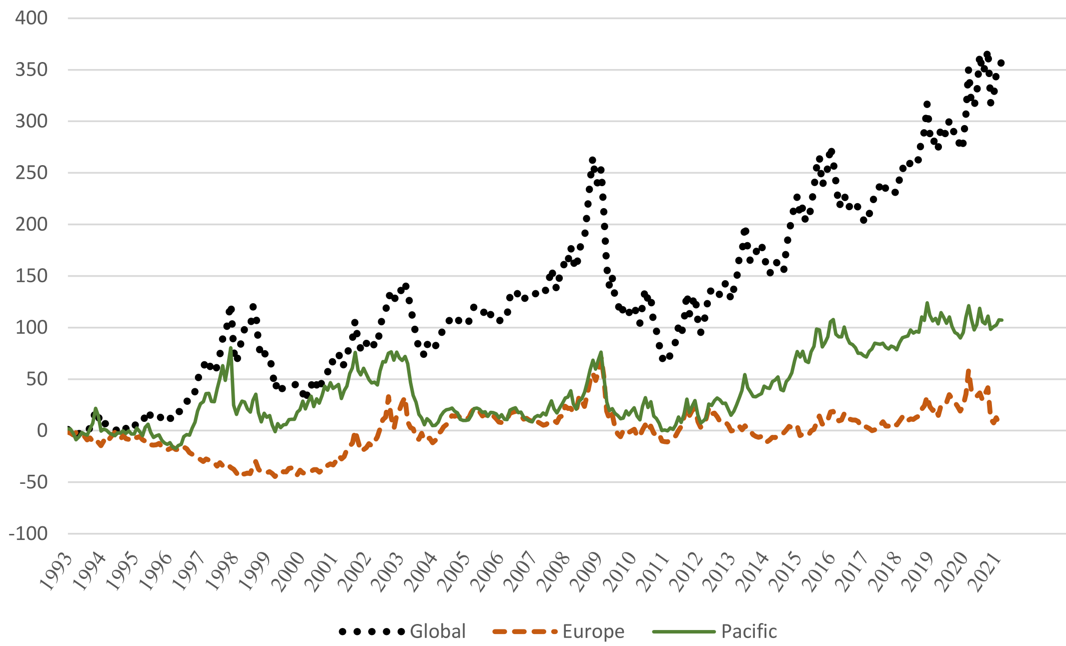

Fig. 1. Performance of the low-minus-high beta portfolios over time. The figure plots the monthly cumulative returns of a portfolio that is long 1 US dollar in the low beta portfolio and short 1 US dollar in the high beta portfolio in January 1993 for three aggregate portfolios: Global (excluding the US), Europe, and Pacific. Aggregate portfolios are defined in Section 2.1. Quintile portfolios are formed every month from January 1993 to March 2021 by sorting stocks based on the previous month's beta. Beta (β) is estimated according to Frazzini and Pedersen (2014). The low–high beta portfolio is long in the lowest beta quintile and short in the highest beta quintile. Portfolios are equally weighted and rebalanced every calendar month.

Table 3
Beta-sorted portfolios at the aggregate level.

Panel A: Global aggregate (excluding US)						
Beta portfolios	P1 (low)	P2	P3	P4	P5 (high)	P1–P5 (low–high)
Excess return	1.49	1.25	1.08	0.99	0.92	0.57
	(5.00)	(3.78)	(3.04)	(2.52)	(1.87)	(2.07)
CAPM α	1.20	0.85	0.62	0.46	0.27	0.93
	(6.71)	(5.38)	(3.92)	(2.77)	(1.12)	(4.50)
FF3 α	1.19	0.83	0.57	0.40	0.20	0.99
	(9.24)	(7.93)	(5.09)	(3.37)	(1.02)	(4.70)
FFC4 α	1.14	0.81	0.58	0.47	0.49	0.64
	(8.45)	(7.22)	(5.06)	(3.80)	(2.56)	(3.08)
β (ex-ante)	0.51	0.69	0.81	0.95	1.22	−0.71
β (realized)	0.60	0.81	0.95	1.09	1.34	−0.74
Quality	−0.19	−0.40	−0.64	−0.93	−1.43	1.24
Volatility	13.02	15.36	17.52	19.67	25.55	16.92
Sharpe ratio	1.37	0.97	0.74	0.60	0.43	0.40
Panel B: Europe aggregate						
Beta portfolios	P1 (low)	P2	P3	P4	P5 (high)	P1–P5 (low–high)
Excess return	0.89	1.03	0.96	0.88	0.75	0.14
	(3.73)	(3.42)	(2.89)	(2.44)	(1.76)	(0.52)
CAPM α	0.60	0.61	0.46	0.28	−0.01	0.61
	(4.06)	(3.97)	(3.34)	(2.29)	(−0.05)	(3.46)
FF3 α	0.55	0.53	0.39	0.21	−0.08	0.62
	(4.93)	(5.81)	(5.31)	(2.81)	(−0.68)	(3.60)
FFC4 α	0.42	0.47	0.40	0.31	0.30	0.11
	(3.46)	(4.98)	(5.08)	(3.94)	(2.57)	(0.64)
β (ex-ante)	0.50	0.63	0.74	0.87	1.11	−0.61
β (realized)	0.49	0.71	0.86	1.03	1.29	−0.80
Quality	−0.10	−0.25	−0.38	−0.57	−1.03	0.93
Volatility	11.61	14.69	16.66	18.99	23.72	17.28
Sharpe ratio	0.92	0.84	0.69	0.56	0.38	0.10

(continued on next page)

Table 3 (*continued*).

Panel C: Pacific aggregate

Beta portfolios	P1 (low)	P2	P3	P4	P5 (high)	P1–P5 (low–high)
Excess return	0.86	0.97	0.86	0.74	0.50	0.36
	(2.97)	(2.81)	(2.43)	(1.92)	(1.06)	(1.27)
CAPM α	0.65	0.67	0.51	0.35	0.02	0.63
	(4.32)	(4.64)	(4.06)	(2.56)	(0.10)	(2.73)
FF3 α	0.67	0.65	0.47	0.28	−0.05	0.73
	(5.00)	(5.89)	(5.50)	(3.12)	(−0.33)	(3.13)
FFC4 α	0.65	0.67	0.54	0.42	0.22	0.43
	(4.45)	(6.03)	(6.33)	(4.68)	(1.39)	(1.77)
β (ex-ante)	0.56	0.73	0.85	0.97	1.21	−0.64
β (realized)	0.59	0.84	0.94	1.08	1.32	−0.73
Quality	−0.22	−0.55	−0.84	−1.18	−1.73	1.51
Volatility	13.48	16.89	18.23	20.75	26.42	18.38
Sharpe ratio	0.77	0.69	0.56	0.43	0.23	0.23

This table reports the results of univariate portfolios sorted on beta for three aggregate portfolios: Global (excluding the US) in Panel A, Europe in Panel B, and Pacific in Panel C. Aggregate portfolios are defined in Section 2.1. For each aggregate portfolio and every month from January 1993 to March 2021, quintiles are formed by sorting stocks based on the previous month's beta. Portfolios are equally weighted and rebalanced every calendar month. The table reports average monthly excess returns and alphas estimated with respect to CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4) models. It also presents the average of betas, volatilities, and Sharpe ratios for each portfolio. β (ex-ante) is the one-month lag beta estimated according to Frazzini and Pedersen (2014), β (realized) is the slope of a regression of monthly excess returns on market excess returns, Quality is the estimated coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns, and volatility is the standard deviation of monthly returns. Volatilities and Sharpe ratios are annualized, and excess returns and alphas are in percentage. Numbers in brackets are t-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

to 0.50% for the high-beta quintile (P5), and the return of the low–high beta portfolio is 0.36% per month.

The alphas of the beta-sorted portfolios follow similar patterns across three aggregate portfolios and decrease monotonically from the low-beta quintile to the high-beta quintile.[17] For the Global portfolio, the low–high portfolio generates positive and statistically significant alphas of 0.93% (t-statistic = 4.50), 0.99% (t-statistic = 4.70) and 0.64% (t-statistic = 3.08) relative to the CAPM, FF3 and FFC4 models, respectively.

The alphas decrease almost monotonically for the Europe and Pacific portfolios from the low-beta quintile to the high-beta quintile in Panels B and C, respectively. In Panel B, the low–high portfolio has positive and statistically significant CAPM and FF3 alphas of 0.61% (t-statistic = 3.46) and 0.62% (t-statistic = 3.60), respectively. Overall, FFC4 alphas also decrease from quintile P1 to quintile P5, yet the low–high portfolio indicates a positive but insignificant alpha of 0.11% (t-statistic = 0.64). In Panel C, the low–high portfolio records positive and statistically significant CAPM and FF3 alphas of 0.63% (t-statistic = 2.73) and 0.73% (t-statistic = 3.13), and FFC4 alpha is positive (0.43%) and marginally significant (t-statistic = 1.77). Similarly, the Sharpe ratio decreases monotonically from P1 to P5 across all aggregate portfolios. For example, it is 1.37 (0.92) for P1 and 0.43 (0.38) for P5 in Panel A (B). By construction, the average β (ex-ante) increases monotonically from quintile P1 to quintile P5. The β (realized) follows the same pattern, rising from 0.60 to 1.34, from 0.49 to 1.29, and from 0.59 to 1.32 in Panels A, B, and C, respectively, showing that β (ex-ante) can predict β (realized). In contrast, Quality decreases monotonically from quintile P1 to quintile P5. Quality values decrease from −0.19 to −1.43, from −0.10 to −1.03, and from −0.22 to −1.73 in Panels A, B and C, respectively. This pattern is consistent with our argument that high-beta (low-beta) stocks are more likely to be junk (quality) stocks.[18] Similar to the betas, the annualized volatility rises from quintile P1 to quintile P5 from 13.02% to 25.55% in Panel A, from 11.61% to 23.72% in Panel B, and from 13.48% to 26.42% in Panel C.

The results in Fig. 1 and Table 3 show that the beta anomaly is economically and statistically significant in aggregate stock portfolios.[19] For example, for the Global (Pacific) aggregate portfolio the low–high beta portfolio earns monthly excess returns and CAPM alphas of 0.57% (0.36%) and 0.93% (0.63%), respectively. The results support prior studies that show the existence of the beta anomaly across international stock markets (Auer and Rottmann, 2019; Frazzini and Pedersen, 2014; Walkshausl, 2014; Zaremba, 2016). Furthermore, consistent with prior literature, the results indicate that higher quality stocks are related to low-beta stocks, while lower quality stocks are linked to high-beta stocks.[20] In addition, the results in Table 3 are consistent with Fama and French (1992, 2016), indicating that the beta anomaly becomes stronger after controlling for size and value premiums.

3.2. The beta anomaly across country portfolios

To explore the beta anomaly at the country level, we group firms into twenty-two country portfolios and conduct an analysis of all trading data available between January 1990 and March 2021.

Every month and for each country, we form quintile portfolios by sorting stocks based on the previous month's beta. Then, we construct the low–high beta portfolio, which is long in the lowest beta quintile portfolio and short in the highest beta quintile portfolio. Table 4 reports the average monthly excess returns and alphas of each country's low–high beta portfolio. We estimate alphas relative to CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4). We also report each country's average beta, volatility, and Sharpe ratio of the low–high beta portfolio. The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West's (1987) standard errors with five lags.

17 For example, the CAPM alpha is 1.20% and statistically significant (t-statistic = 6.71) for the low-beta quintile, while it is 0.27% and not statistically significant (t-statistic = 1.12) for the high-beta quintile.

18 We thank the anonymous reviewer for this comment.

19 In unreported tests, we replicate Table 3 using beta-decile portfolios instead of beta-quintile portfolios. The time-series means of the cross-sectional average of monthly portfolio excess returns and alphas relative to several common risk factors are economically and statistically significant in the Global, Europe, and Pacific aggregates. The results indicate that the beta anomaly is robust to both quantile and decile beta-portfolios. The results are available upon request.

20 Asness et al. (2019) and Geppert and Zhao (2018) show that high-beta stocks are riskier and more likely to be junk stocks, while low-beta stocks are less risky and more likely to be quality stocks.

Table 4
The beta anomaly at the country level.

Low–high beta portfolios	Excess return	*t*-stat	CAPM α	*t*-stat	FF3 α	*t*-stat	FFC4 α	*t*-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Australia	0.16	(0.46)	0.62	(2.05)	0.69	(2.43)	0.44	(1.25)	−0.66	−0.57	22.94	0.09
Austria	−0.45	(−1.06)	0.06	(0.28)	0.11	(0.49)	−0.09	(−0.47)	−0.54	−0.77	23.71	−0.23
Belgium	−0.04	(−0.15)	0.16	(0.75)	0.19	(0.87)	−0.05	(−0.22)	−0.52	−0.64	20.18	−0.03
Canada	0.78	(2.34)	1.16	(3.76)	1.13	(3.44)	0.76	(2.16)	−0.89	−0.56	21.37	0.44
Denmark	0.15	(0.41)	0.75	(2.20)	0.76	(2.15)	0.17	(0.45)	−0.53	−0.52	18.61	0.10
Finland	−0.25	(−0.72)	0.31	(1.09)	0.33	(1.21)	0.32	(1.17)	−0.46	−0.49	22.25	−0.14
France	0.28	(0.89)	0.77	(3.46)	0.73	(3.48)	0.33	(1.54)	−0.58	−0.85	22.45	0.15
Germany	0.08	(0.25)	0.57	(2.94)	0.56	(3.08)	0.10	(0.49)	−0.54	−0.72	21.12	0.05
Greece	0.05	(0.09)	0.19	(0.46)	0.36	(0.95)	0.05	(0.14)	−0.61	−0.70	32.81	0.02
Hong Kong	0.42	(1.11)	1.07	(3.67)	1.21	(3.96)	0.93	(2.99)	−0.62	−0.78	26.74	0.19
Ireland	−0.06	(−0.09)	0.46	(0.73)	0.47	(0.77)	0.41	(0.63)	−0.50	−0.71	35.31	−0.02
Italy	0.06	(0.19)	0.29	(0.98)	0.32	(1.10)	0.12	(0.39)	−0.48	−0.60	22.23	0.04
Japan	−0.01	(−0.03)	0.15	(0.67)	0.27	(1.22)	0.16	(0.78)	−0.58	−0.72	19.27	−0.01
Netherlands	0.06	(0.16)	0.67	(2.33)	0.77	(2.63)	0.53	(1.87)	−0.60	−0.84	25.15	0.03
New Zealand	0.20	(0.65)	0.44	(1.43)	0.44	(1.45)	0.34	(1.10)	−0.43	−0.23	19.81	0.12
Norway	0.63	(1.30)	1.32	(3.55)	1.32	(3.58)	0.93	(2.46)	−0.62	−0.75	30.07	0.25
Portugal	0.85	(1.23)	1.34	(2.32)	1.76	(3.11)	1.59	(2.45)	−0.71	−0.92	46.85	0.22
Singapore	0.42	(0.94)	0.84	(2.49)	0.79	(2.46)	0.46	(1.55)	−0.77	−0.73	23.10	0.22
Spain	0.04	(0.10)	0.64	(2.15)	0.66	(2.19)	0.37	(1.26)	−0.58	−0.84	26.28	0.02
Sweden	0.34	(1.10)	0.88	(3.73)	0.87	(3.68)	0.49	(1.99)	−0.53	−0.45	17.73	0.23
Switzerland	−0.09	(−0.25)	0.48	(1.94)	0.52	(2.22)	0.14	(0.57)	−0.49	−0.78	19.84	−0.05
United Kingdom	0.40	(1.61)	0.70	(2.87)	0.76	(3.22)	0.27	(1.06)	−0.57	−0.63	16.62	0.29

The table reports the results of univariate portfolios sorted on beta at the country level. For each country and every month, quintile portfolios are formed by sorting stocks based on the previous month's beta. The low–high beta portfolio is long in the lowest beta quintile and short in the highest beta quintile. Portfolios are equally weighted and rebalanced every calendar month. The table reports the average monthly excess returns and alphas of the low-minus-high (low–high) beta portfolios for twenty-two country portfolios. Alphas are estimated with respect to the CAPM, Fama–French three-factor (FF3) and Fama–French–Carhart four-factor (FFC4) models. It also presents the average beta, volatility, and Sharpe ratio for each low–high beta portfolio. β (ex-ante) is the one-month lag beta estimated according to Frazzini and Pedersen (2014), β (realized) is the slope of a regression of monthly excess returns on market excess returns, and volatility is the standard deviation of monthly returns. Volatilities and Sharpe ratios are annualized, and excess returns and alphas are in percentage. Numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

Results in Table 4 show that all alphas relative to CAPM and FF3 are positive in all twenty-two countries. Indeed, the low–high beta portfolios generate significant abnormal stock returns in fourteen country portfolios, as measured by either CAPM or FF3 alphas. Our results are consistent with Fama and French (1992, 2016), who find that the beta anomaly becomes stronger after controlling for size and value factors. Table 4 also shows that β (ex-ante) can predict β (realized) (or CAPM beta) since all low–high portfolios document consistent β (ex-ante) and β (realized). The results in Table 4 are consistent with the results for aggregate portfolios, showing that the beta anomaly also exists at the country level.

4. The link between stock quality and the beta anomaly

Asness et al. (2019) find that high quality stocks (labelled as quality stocks) have positive risk-adjusted returns, whereas low quality stocks (labelled as junk stocks) have negative risk-adjusted returns. They refer to this phenomenon as the stock quality effect. They show that quality stocks have higher risk-adjusted returns as market prices fail to fully reflect the quality characteristics. Hence, this phenomenon arises from mispricing, as quality stocks are underpriced and junk stocks are overpriced. In addition, although quality stocks deliver higher risk-adjusted returns, they appear safer, not riskier, than junk stocks, benefiting from the flight to quality.

Liu et al. (2018) show that the beta anomaly exists only among overpriced stocks. Since junk stocks are overpriced (Asness et al., 2019), the beta anomaly should exist only in junk stocks. Indeed, Geppert and Zhao (2018) document a negative relationship between beta and stock quality in the US market and show that the beta anomaly no longer exists after controlling for stock quality.

In this section, we investigate the relation between the beta anomaly and stock quality and examine whether the beta anomaly is more prevalent among low-quality stocks in non-US markets. We perform portfolio and Fama and MacBeth (1973) regression analyses for different stock quality groups between January 1994 and March 2021.

4.1. The impact of quality on the beta anomaly at the aggregate level

To examine the impact of quality of the beta anomaly, we do double-sort analyses based on quality level and beta for each aggregate portfolio. Specifically, in each month and for every aggregate portfolio, first, we sort stocks in ascending order based on their quality level into groups, and form bottom, middle, and top-quality groups for each aggregate portfolio. Top (bottom) quality stocks are those in the top (bottom) 33% of the quality score. We focus on the bottom (junk) and top (quality) groups. Then, we form quintile portfolios within these quality groups by sorting stocks based on the previous month's beta and constructing a low–high beta portfolio. The low–high beta portfolio is long in the lowest beta-quintile and short in the highest beta-quintile. Portfolios are equally weighted and rebalanced every calendar month. Table 5 shows average monthly excess returns and alphas of CAPM, FF3, and FFC4 for portfolios formed among the quality groups. Panel A shows the low–high beta portfolios among junk stocks, while Panel B illustrates the low–high beta portfolios among quality stocks. We also present average betas, volatility, and Sharpe ratios for the low–high beta portfolios.

Panel A of Table 5 shows positive excess returns and alphas of the low–high beta portfolios relative to the CAPM, FF3, and FFC4 for junk stocks in the three aggregate portfolios. The Global aggregate documents excess returns of 1.30% (t-statistic = 4.15), CAPM alpha of 1.48% (t-statistic = 4.73), FF3 alpha of 1.69% (t-statistic = 5.42), and FFC4 alpha of 1.25% (t-statistic = 3.90). The Europe aggregate documents a CAPM alpha of 0.79% (t-statistic = 3.29), FF3 alpha of 0.88% (t-statistic = 3.90) and FFC4 alpha of 0.34% (t-statistic = 1.52). Finally, the Pacific aggregate shows excess returns of 0.70% (t-statistic = 2.26), CAPM alpha of 0.80% (t-statistic = 2.50), FF3 alpha of 0.93% (t-statistic = 3.01) and FFC4 alpha of 0.58% (t-statistic = 1.65). The excess returns of low–high beta portfolios constructed using only junk stocks are more than double the returns of low–high beta portfolios constructed using all stocks for all three aggregates (reported

Table 5
The beta anomaly among junk and quality stocks at the aggregate level.

Panel A: Low–high beta portfolios among junk stocks

Aggregate	Excess return	*t*-stat	CAPM α	*t*-stat	FF3 α	*t*-stat	FFC4 α	*t*-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Global	1.30	(4.15)	1.48	(4.73)	1.69	(5.42)	1.25	(3.90)	−0.72	−0.39	19.75	0.79
Europe	0.48	(1.78)	0.79	(3.29)	0.88	(3.90)	0.34	(1.52)	−0.61	−0.59	16.61	0.34
Pacific	0.70	(2.26)	0.80	(2.50)	0.93	(3.01)	0.58	(1.65)	−0.55	−0.32	20.05	0.42

Panel B: Low–high beta portfolios among quality stocks

Aggregate	Excess return	*t*-stat	CAPM α	*t*-stat	FF3 α	*t*-stat	FFC4 α	*t*-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Global	−0.43	(−1.42)	−0.12	(−0.54)	−0.17	(−0.70)	−0.29	(−1.29)	−0.66	−0.63	17.16	−0.30
Europe	−0.02	(−0.08)	0.30	(1.81)	0.24	(1.44)	0.05	(0.29)	−0.49	−0.60	14.63	−0.01
Pacific	−0.36	(−1.09)	−0.14	(−0.59)	−0.14	(−0.55)	−0.32	(−1.28)	−0.54	−0.72	18.16	−0.23

This table presents the performance of the low–high beta sorted portfolios for junk and quality stocks at the aggregate level. For each aggregate portfolio and every month from Jannuary 1994 to March 2021, all stocks are sorted into three different quality groups, and the bottom and top groups, as junk and quality subsamples, are selected. The aggregate portfolios are Global, Europe and Pacific and defined in Section 2.1. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. The quintile portfolios are formed every month by sorting stocks based on the previous month's beta for both subsamples. Portfolios that are long in the lowest beta-quintile and short in the highest beta-quintile (low–high beta portfolio) are formed. The portfolios are equally weighted and rebalanced every calendar month. Panel A (B) reports the average monthly excess returns and alphas of the low-minus-high (low–high) beta portfolios among junk (quality) stocks. Alphas are estimated with respect to CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4) models. The table also presents average betas, volatility, and Sharpe ratio of the low–high beta portfolios. β (ex-ante) is the one-month lag beta estimated according to Frazzini and Pedersen (2014), β (realized) is the slope of a regression of monthly excess returns on market excess returns, and volatility is the standard deviation of monthly returns. Volatilities and Sharpe ratios are annualized, and excess returns and alphas are in percentage. Numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

in Table 3). The excess returns are 1.30% (0.57%), 0.48% (0.14%) and 0.70% (0.36%) for junk (all) stocks in the Global, Europe, and Pacific aggregates, respectively. Likewise, the alphas of low–high beta portfolios constructed using only junk stocks are greater than those constructed using all stocks, as reported in Table 3. The FF3 alphas are 1.69% (0.99%), 0.88% (0.62%) and 0.93% (0.73%) for junk (all) stocks in the Global, Europe and Pacific aggregates, respectively. Similarly, the FFC4 alphas are 1.25% (0.64%), 0.34% (0.11%) and 0.58% (0.43%) for junk (all) stocks in the Global, Europe and Pacific aggregates, respectively.

In contrast to junk stocks, Panel B of Table 5 shows negative excess returns and CAPM, FF3, and FFC4 alphas for low–high beta portfolios among quality stocks in the Global and Pacific aggregates. The Europe aggregate has negative excess returns but insignificant positive alphas. The three aggregates report statistically insignificant values for both excess returns and alphas. For example, the Global aggregate documents excess returns of −0.43% (t-statistic = −1.42), CAPM alpha of −0.12% (t-statistic = −0.54), FF3 alpha of −0.17% (t-statistic = −0.70), and FFC4 alpha of −0.29% (t-statistic = −1.29). The performance of the low–high beta portfolios is markedly poor in all three aggregates.

In brief, the finding that the beta anomaly is stronger among junk stocks indicates that both the raw and risk-adjusted profitability of buying low beta stocks and selling high beta stocks improves when considering only junk stocks. As a robustness test, we further form beta-decile portfolios within the quality groups and construct a low–high beta deciles for each aggregate portfolio. The results reported in Table A.1 in the Appendix are qualitatively similar to our findings based on quintile sorting approach i.e. the beta anomaly is significant among junk stocks but insignificant among quality stocks.

4.2. The impact of quality on the beta anomaly at the country level

So far, we show the impact of stock quality on the beta anomaly at the aggregate level. In this section, we examine whether this phenomenon persists at the country level. We repeat the double-sort analysis performed in the previous section for the twenty-two country portfolios. Every month and for each country portfolio, first, we sort stocks into three quality terciles. Then, within the junk (bottom tercile) and quality (top tercile) groups, we form quintile portfolios by sorting stocks based on the previous month's beta and construct a low–high beta portfolio for each country. The low–high beta portfolio is the equally weighted portfolio that is long in the lowest beta-quintile and short in the highest beta-quintile and rebalanced every calendar month. Table 6 presents average monthly excess returns and alphas of CAPM, FF3, and FFC4 for each country's low–high beta portfolios. Panel A shows the low–high beta portfolios among junk stocks, while Panel B illustrates the low–high beta portfolios among quality stocks. We also present average betas, volatility, and Sharpe ratios.

Panel A of Table 6 shows positive CAPM and FF3 country alphas for twenty-one of twenty-two low–high beta portfolios among junk stocks. The only exception is Spain. Eleven low–high beta portfolios have statistically significant CAPM and FF3 alphas. The results indicate that the security market line is downward-sloping in almost all countries among the junk stocks. In contrast, Panel B shows negative excess returns for quality stocks in fifteen of twenty-two country portfolios, and all countries have either negative or insignificant CAPM and FF3 alphas. The results suggest that the security market line is either flat or upward sloping in all countries among the quality stocks, since the excess returns of low-minus-high beta portfolios are not positive and statistically significant. In fact, 15 of 22 low–high beta country portfolios report negative excess returns (though insignificant) among the quality group in Panel B. The results indicate that the beta anomaly does not exist within the quality group, as high-beta stocks are not related to higher expected returns. Comparing results in Panels A and B indicates that the performance of the low–high beta portfolios among junk stocks is positive and higher than those among quality stocks. Junk portfolios record higher excess returns for eighteen countries and higher Sharpe ratios for nineteen countries than quality portfolios. These results show that in these countries, the beta anomaly is more prevalent among junk stocks compared to quality ones.

In brief, we do not find evidence of the beta anomaly if the sample includes only quality stocks. Contrasting the results in Table 4 that examine beta anomaly for the whole sample, Table 6 shows insignificant or negative abnormal returns for the low–high beta portfolios among quality stocks. Hence, we postulate that the strategies that buy low beta stocks and sell high beta stocks are not profitable if we exclude junk stocks. In other words, the abnormal returns of the beta anomaly exist only among junk

Table 6
The beta anomaly among junk and quality stocks at the country level.

Panel A: Low–high beta portfolios among junk stocks

Country	Excess return	*t*-stat	CAPM α	*t*-stat	FF3 α	*t*-stat	FFC4 α	*t*-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Australia	0.49	(1.41)	0.70	(2.09)	0.96	(2.71)	0.64	(1.66)	−0.63	−0.29	22.83	0.26
Austria	−0.12	(−0.24)	0.23	(0.52)	0.31	(0.65)	0.08	(0.18)	−0.50	−0.55	32.30	−0.04
Belgium	−0.10	(−0.23)	0.08	(0.19)	0.15	(0.37)	−0.13	(−0.32)	−0.54	−0.68	27.80	−0.04
Canada	0.95	(2.63)	1.21	(3.33)	1.29	(3.43)	0.81	(1.86)	−0.93	−0.38	24.11	0.47
Denmark	0.24	(0.46)	0.60	(1.18)	0.59	(1.18)	0.49	(1.04)	−0.53	−0.32	28.19	0.10
Finland	0.05	(0.12)	0.40	(0.87)	0.52	(1.15)	0.54	(1.21)	−0.45	−0.34	30.71	0.02
France	0.62	(1.53)	1.03	(2.67)	0.97	(2.92)	0.49	(1.50)	−0.58	−0.66	24.30	0.31
Germany	1.03	(2.74)	1.41	(4.38)	1.44	(4.65)	1.04	(3.06)	−0.54	−0.60	26.13	0.47
Greece	1.68	(2.28)	1.85	(3.05)	2.01	(3.37)	1.34	(2.16)	−0.63	−0.70	44.86	0.45
Hong Kong	0.58	(1.29)	0.86	(1.91)	1.01	(2.44)	0.78	(1.88)	−0.60	−0.46	24.76	0.28
Ireland	0.47	(0.54)	0.85	(1.08)	0.83	(1.05)	0.66	(0.84)	−0.49	−0.77	46.28	0.12
Italy	0.24	(0.68)	0.42	(1.27)	0.48	(1.54)	0.34	(1.03)	−0.43	−0.46	24.69	0.12
Japan	0.33	(1.43)	0.40	(2.00)	0.46	(2.50)	0.36	(1.98)	−0.44	−0.43	14.44	0.27
Netherlands	1.09	(1.61)	1.44	(2.18)	1.43	(2.11)	1.02	(1.58)	−0.54	−0.57	33.97	0.38
New Zealand	0.13	(0.18)	0.13	(0.17)	0.13	(0.18)	−0.12	(−0.16)	−0.43	0.00	36.25	0.04
Norway	0.88	(1.40)	1.48	(2.57)	1.48	(2.61)	0.67	(1.17)	−0.62	−0.75	41.04	0.26
Portugal	2.08	(1.65)	2.20	(1.78)	2.26	(1.95)	1.75	(1.45)	−0.65	−0.37	77.03	0.32
Singapore	0.55	(1.72)	0.75	(2.49)	0.89	(3.04)	0.70	(2.12)	−0.81	−0.34	24.52	0.27
Spain	−0.41	(−1.05)	−0.20	(−0.58)	−0.17	(−0.49)	−0.48	(−1.44)	−0.41	−0.38	25.25	−0.19
Sweden	0.23	(0.63)	0.70	(1.76)	0.71	(1.89)	0.28	(0.73)	−0.54	−0.39	23.22	0.12
Switzerland	0.32	(0.96)	0.72	(2.26)	0.64	(2.06)	0.31	(0.89)	−0.49	−0.65	21.74	0.18
United Kingdom	0.13	(0.44)	0.37	(1.26)	0.47	(1.62)	−0.03	(−0.11)	−0.59	−0.56	19.60	0.08

Panel B: Low–high beta portfolios among quality stocks

Country	Excess return	*t*-stat	CAPM α	*t*-stat	FF3 α	*t*-stat	FFC4 α	*t*-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Australia	−0.58	(−1.19)	−0.17	(−0.43)	−0.12	(−0.37)	−0.54	(−1.33)	−0.62	−0.57	27.37	−0.25
Austria	−0.23	(−0.47)	0.01	(0.03)	−0.06	(−0.12)	−0.05	(−0.09)	−0.35	−0.38	29.29	−0.10
Belgium	0.16	(0.43)	0.23	(0.61)	0.21	(0.58)	0.08	(0.22)	−0.35	−0.24	25.24	0.08
Canada	−0.18	(−0.40)	0.13	(0.31)	0.07	(0.15)	−0.31	(−0.70)	−0.87	−0.45	27.08	−0.08
Denmark	0.08	(0.20)	0.43	(0.87)	0.42	(0.88)	0.17	(0.34)	−0.42	−0.30	22.08	0.05
Finland	0.43	(0.74)	0.92	(1.64)	0.76	(1.39)	0.45	(0.87)	−0.43	−0.48	32.62	0.16
France	−0.13	(−0.41)	0.19	(0.73)	0.08	(0.34)	−0.05	(−0.19)	−0.43	−0.53	21.09	−0.08
Germany	−0.04	(−0.10)	0.21	(0.65)	0.18	(0.60)	0.00	(0.01)	−0.38	−0.38	20.59	−0.02
Greece	−1.00	(−1.57)	−0.93	(−1.53)	−0.77	(−1.37)	−0.89	(−1.58)	−0.36	−0.27	31.28	−0.38
Hong Kong	−0.47	(−0.95)	−0.14	(−0.35)	−0.12	(−0.29)	−0.24	(−0.58)	−0.49	−0.54	25.24	−0.22
Ireland	−0.09	(−0.17)	0.14	(0.26)	0.15	(0.28)	0.00	(−0.01)	−0.38	−0.36	29.09	−0.04
Italy	−0.25	(−0.51)	−0.13	(−0.28)	−0.17	(−0.39)	−0.35	(−0.87)	−0.35	−0.32	25.26	−0.12
Japan	−0.37	(−1.70)	−0.28	(−1.93)	−0.31	(−2.08)	−0.31	(−2.03)	−0.38	−0.54	14.14	−0.31
Netherlands	−0.14	(−0.34)	0.05	(0.11)	0.09	(0.22)	0.04	(0.10)	−0.41	−0.31	27.27	−0.06
New Zealand	0.11	(0.24)	0.28	(0.60)	0.30	(0.65)	0.41	(0.82)	−0.39	−0.16	33.80	0.04
Norway	−0.36	(−0.64)	0.09	(0.19)	0.09	(0.20)	−0.12	(−0.24)	−0.42	−0.56	30.79	−0.14
Portugal	2.35	(1.10)	2.48	(1.15)	2.53	(1.17)	2.29	(1.11)	−0.53	−0.36	107.26	0.26
Singapore	0.03	(0.06)	0.31	(0.80)	0.28	(0.73)	0.07	(0.18)	−0.64	−0.48	23.17	0.01
Spain	−0.13	(−0.30)	0.05	(0.13)	0.03	(0.08)	−0.03	(−0.07)	−0.34	−0.34	25.06	−0.06
Sweden	−0.45	(−1.07)	−0.07	(−0.17)	−0.07	(−0.16)	−0.19	(−0.43)	−0.47	−0.31	22.81	−0.23
Switzerland	−0.24	(−0.82)	−0.02	(−0.07)	0.07	(0.32)	−0.08	(−0.35)	−0.29	−0.35	15.58	−0.18
United Kingdom	0.06	(0.18)	0.26	(0.94)	0.25	(0.91)	−0.01	(−0.02)	−0.41	−0.46	17.90	0.04

This table presents the performance of the low–high beta sorted portfolios for junk and quality stocks at the country level. For each country and every month, all stocks are sorted into three different quality groups, and the bottom and top groups, as junk and quality subsamples, are selected. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. Quintile portfolios are formed every month by sorting stocks based on the previous month's beta within both subsamples. Portfolios that are long in the lowest beta-quintile and short in the highest beta-quintile (low–high beta portfolio) are formed for twenty-two country portfolios. Portfolios are equally weighted and rebalanced every calendar month. The table reports the average monthly excess returns and alphas estimated with respect to the CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4) models. Panel A (B) shows country portfolios among junk (quality) stocks. The table also presents average betas, volatility, and Sharpe ratio. β (ex-ante) is the one-month lag beta estimated according to Frazzini and Pedersen (2014), β (realized) is the slope of a regression of monthly excess returns on market excess returns, and volatility is the standard deviation of monthly returns. Volatilities and Sharpe ratios are annualized, and excess returns and alphas are in percentage. Numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

stocks. Our results align with the mispricing hypothesis of Asness et al. (2019) and suggest that junk stocks may be overpriced, which is also consistent with Liu et al. (2018), as they argue that the beta anomaly only exists among overpriced stocks.

As a robustness test, we perform a double-sort portfolio analysis by constructing five quality portfolios in the first step and report the relationship between future excess returns and beta after controlling for stock quality in all 25 portfolios in Appendix. Table A.2 shows the time-series means of monthly equal-weighted excess returns for portfolios within the three aggregates. The results are consistent with the findings reported in this section that the beta anomaly exists among junk stocks but not among quality stocks.

The results from Panel A for Global aggregate show a monotonic decreasing pattern for the excess returns and alphas of the low–high beta portfolios from low quality (Quality 1) to high-quality stocks (Quality 5) that ultimately become negative for the high-quality stocks, suggesting that the beta anomaly exists among the lower quality or junk stocks. For example, the low–high beta portfolio shows monthly excess returns of 1.29% (t-statistic = 3.44), CAPM alpha of 1.44% (t-statistic = 3.82), FF3 alpha of 1.70% (t-statistic = 4.46), and FFC4 alpha of 1.15% (t-statistic = 2.93) among the junk stocks in quintile 1 (Quality 1). However, the performance of the low–high beta portfolio decreases from quintile 1 to 5. For quintile 5 (Quality 5), the excess return, CAPM alpha, FF3 alpha and FFC4 alpha are −0.74%

Table 7
Fama–MacBeth regressions among quality and junk stocks at the aggregate level.

Variable	Panel A: Global aggregate				Panel B: Europe aggregate				Panel C: Pacific aggregate			
	Junk		Quality		Junk		Quality		Junk		Quality	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.009	0.007	0.013	0.012	0.007	0.007	0.003	0.008	0.010	0.011	0.001	0.005
	(1.00)	(0.75)	(2.38)	(2.96)	(1.53)	(1.49)	(1.07)	(2.26)	(1.34)	(1.68)	(0.37)	(1.26)
β	0.005	0.005	0.014	0.012	−0.005	−0.001	0.004	0.007	−0.004	−0.002	0.016	0.014
	(0.54)	(0.57)	(2.16)	(2.02)	(−0.88)	(−0.13)	(0.67)	(1.12)	(−0.74)	(−0.32)	(2.16)	(2.16)
Ln MV	−0.004	−0.003	−0.003	−0.003	0.000	0.000	0.000	−0.001	−0.002	−0.002	−0.002	−0.002
	(−2.18)	(−1.67)	(−4.09)	(−4.41)	(0.04)	(−0.95)	(−0.76)	(−3.16)	(−2.62)	(−3.93)	(−3.31)	(−4.19)
Ln B/M	0.016	0.017	0.001	0.004	0.010	0.009	0.007	0.008	0.015	0.014	0.009	0.008
	(3.46)	(2.85)	(0.31)	(1.12)	(4.27)	(4.39)	(4.69)	(3.70)	(5.75)	(5.78)	(3.83)	(3.45)
Mom		−0.002		0.003		0.009		0.009		0.000		0.000
		(−0.54)		(1.08)		(3.83)		(3.83)		(0.06)		(0.06)
Rev		0.005		−0.005		0.003		0.020		−0.005		−0.002
		(0.28)		(−0.51)		(0.50)		(2.07)		(−0.91)		(−0.49)
Illiq		0.664		−0.185		−73.148		−29.334		0.156		0.047
		(1.73)		(−1.16)		(−1.54)		(−0.61)		(0.34)		(1.59)
Max		−0.036		0.033		−0.044		−0.072		−0.052		−0.041
		(−2.64)		(0.63)		(−2.96)		(−3.55)		(−3.33)		(−2.55)

This table presents the result of the Fama–MacBeth regressions over quality and junk subsamples at the aggregate level. For each aggregate portfolio and every month from January 1994 to March 2021, all stocks are sorted into three different quality groups, and the bottom and top groups, as junk and quality subsamples, are selected. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. Within each subsample, we run a firm-level cross-sectional regression of monthly stock excess returns on lagged values of beta (β) and firm characteristics as control variables. The table reports the time-series averages of the monthly cross-sectional regression slope coefficients of junk and quality stocks for the three aggregate portfolios. Panels A, B, and C illustrate the Global (excluding the US), Europe, and Pacific aggregate portfolios, respectively. Aggregate portfolios are defined in Section 2.1. The set of control variables includes the natural logarithm of firms' market capitalization (Ln MV), the natural logarithm of book-to-market ratio (Ln B/M), momentum (Mom), reversal (Rev), illiquidity (Illiq), and MAX. Details of these variables and their construction are provided in Section 2.2.3. Numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

(*t*-statistic = −2.12), −0.44% (*t*-statistic = −1.53), −0.50% (*t*-statistic = −1.57), and −0.65% (*t*-statistic = −2.19), respectively. Our results are consistent with Geppert and Zhao (2018) and indicate that stock quality is a key driver of the beta anomaly.

4.3. Regression analysis for aggregate portfolios

Findings in the previous section suggest that stock quality plays an essential role in the relation between future stock returns and beta. However, the portfolio analysis does not allow for simultaneously controlling multiple effects or factors at a time. In this section, we run regression analysis in two quality subsamples (junk and quality), which enables us to include those controls. Specifically, we perform Fama and MacBeth's (1973) regressions of future stock excess returns on beta (β) and combinations of firm characteristic variables to control for other effects in determining the relationship between β and stock expected returns. We consider β, Ln MV, Ln B/M, Mom, Rev, Illiq, and Max, defined in Section 2.2.3, as independent variables.

Within each aggregate portfolio, all stocks are sorted into three quality terciles at the end of each month *t*. To form junk and quality subsamples, we select the bottom (low-quality) and top (high-quality) groups. Then, we run the following monthly cross-sectional regression among the stocks in each subsample:

$$R_{it} = \lambda_0 + \lambda_1 \beta_{it-1} + \Lambda X_{it-1} + \varepsilon_{it} \quad (5)$$

where R_{it} is stock excess returns in month *t*, β_{it-1} is stock betas computed at the end of month *t-1*, and X_{it-1} is a vector of firm characteristics variables.

Table 7 presents time-series averages of the monthly estimates of the cross-sectional regression coefficients for the three aggregate portfolios. We show the results for the junk and quality subsamples. Model (1) includes *β*, Ln MV, and Ln B/M as explanatory variables, and Model (2) includes Mom, Rev, Illiq, and Max plus explanatory variables in Model (1). Panels A, B, and C illustrate the Global, Europe, and Pacific aggregate portfolios, respectively. The *t*-statistics are adjusted following Newey and West (1987) using five lags.

Panel A of Table 7 shows that when the Global aggregate includes only junk stocks, the β coefficients are small and statistically insignificant, suggesting a flat relationship between future returns and β. For example, the β coefficient is 0.005 (*t*-statistic = 0.54) and 0.005 (*t*-statistic = 0.57) in Models (1) and (2), respectively. In contrast, β becomes positive and statistically significant when the Global aggregate includes only quality stocks. The β coefficient is 0.014 with a *t*-statistic of 2.16 in Model (1) and 0.012 with a *t*-statistic of 2.02 in Model (2). Our results indicate that the beta anomaly only exists among junk stocks in the Global aggregate.

Panel B of Table 7 shows negative and insignificant β coefficients of junk stocks in the Europe aggregate. While β is positive, it was insignificant for quality stocks. For example, the beta coefficient of junk stocks is −0.005 (*t*-statistic = −0.88) and −0.001 (*t*-statistic = −0.13) in Models (1) and (2), respectively. For quality stocks, the beta coefficient is 0.004 (*t*-statistic = 0.67) and 0.007 (*t*-statistic = 1.12) in Models (1) and (2), respectively. The flat relationship between future returns and β is observed for quality and junk subsamples in the Europe aggregate. Finally, Panel C illustrates a negative β coefficient for junk stocks and a positive and significant β coefficient for quality stocks in the Pacific aggregate. For instance, the β coefficient of junk stocks is −0.004 (*t*-statistic = −0.74) and −0.002 (*t*-statistic = −0.32) in Models (1) and (2), respectively, indicating a flat security market line for the junk stocks. In contrast, β becomes positive and statistically significant when the Pacific aggregate contains only quality stocks. The β coefficient is 0.016 with a *t*-statistic of 2.16 in Model (1) and 0.014 with a *t*-statistic of 2.16 in Model (2). The results show that market risk is priced among quality stocks for the Pacific aggregate.

The results in Table 7 illustrate that the beta anomaly is evident only among junk stocks in both Global and Pacific aggregates, whereas there is a flat relationship between future returns and β for quality and junk subsamples for the Europe aggregate. The results demonstrate that stock quality plays an important role

Table 8
Fama–MacBeth regressions among quality and junk stocks at the country level.

Country portfolio	Panel A: Junk stocks				Panel B: Quality stocks			
	Intercept	*t*-stat	β	*t*-stat	Intercept	*t*-stat	β	*t*-stat
Australia	0.03	(2.00)	0.00	(−0.02)	0.02	(2.14)	0.02	(2.12)
Austria	−0.02	(−0.26)	0.00	(−0.23)	−0.02	(−1.59)	0.02	(1.01)
Belgium	−0.01	(−0.33)	−0.03	(−1.58)	0.02	(1.94)	−0.02	(−1.38)
Canada	−0.02	(−1.07)	−0.10	(−0.45)	0.04	(4.93)	0.00	(−0.07)
Denmark	0.01	(0.77)	−0.02	(−1.27)	0.01	(0.99)	0.01	(1.19)
Finland	0.01	(0.15)	0.07	(1.33)	0.01	(0.62)	0.01	(0.41)
France	0.00	(−0.38)	0.00	(0.42)	0.01	(2.32)	0.01	(1.16)
Germany	0.00	(−0.15)	0.04	(1.20)	−0.04	(−0.84)	0.05	(0.88)
Greece	0.00	(0.26)	−0.01	(−0.93)	−0.01	(−0.56)	0.01	(0.59)
Hong Kong	0.02	(1.27)	0.01	(0.69)	0.01	(1.75)	0.02	(2.02)
Ireland	0.16	(0.74)	5.16	(0.95)	0.37	(1.00)	0.83	(1.69)
Italy	0.00	(0.32)	0.00	(0.12)	0.01	(1.44)	0.00	(0.08)
Japan	0.00	(0.38)	0.00	(0.63)	0.00	(−0.20)	0.01	(2.39)
Netherlands	0.01	(0.34)	−0.01	(−1.01)	0.01	(0.62)	0.00	(0.25)
New Zealand	−1.07	(−0.92)	0.53	(0.71)	0.02	(1.90)	−0.02	(−1.38)
Norway	0.08	(0.69)	0.09	(0.62)	0.02	(1.71)	0.03	(2.07)
Portugal	0.11	(0.21)	−0.06	(−0.24)	0.04	(1.15)	−0.10	(−1.13)
Singapore	0.00	(0.00)	0.00	(0.00)	0.00	(0.59)	0.00	(0.18)
Spain	0.01	(0.90)	−0.01	(−0.75)	0.01	(0.72)	−0.01	(−0.77)
Sweden	0.01	(1.07)	0.00	(0.08)	0.02	(2.47)	0.00	(−0.10)
Switzerland	0.01	(1.26)	0.00	(0.41)	0.00	(0.56)	0.01	(0.53)
United Kingdom	0.00	(0.52)	0.01	(0.98)	0.00	(−0.01)	0.01	(1.02)

This table presents the results of the Fama–MacBeth regressions in quality and junk subsamples at the country level. For each country and every month, all stocks are sorted into three different quality groups, and the bottom and top groups, as junk and quality subsamples, are selected. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. Within each subsample and for each country, we run a firm-level cross-sectional regression of monthly stock excess returns on lagged values of beta (β) and firm characteristics as control variables. We then calculate the time-series averages of the monthly cross-sectional regression slope coefficients. The set of control variables includes the natural logarithm of firms' market capitalization, the natural logarithm of book-to-market ratio, momentum, reversal, illiquidity, and MAX. Details of these variables and their construction are provided in Section 2.2.3. For brevity reasons, we only report estimated intercepts and βs. Numbers in brackets are t-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

in explaining the beta anomaly even after taking into account various control variables in these aggregates.[21]

4.4. Regression analysis for country portfolios

We previously show that beta anomaly exists only among junk stocks for the aggregate portfolios; now we turn to examine the impact of stock quality on the beta anomaly while we control for firm-specific characteristics at the country level. We run the Fama and MacBeth (1973) regression analysis using country portfolios. Specifically, every month, all stocks are sorted into three quality terciles within each country's portfolio. Then, we perform monthly Fama and MacBeth (1973) regressions, defined in Eq. (5), among the stocks in the bottom (junk) and top (quality) terciles.

Table 8 reports time-series averages of the monthly estimates of the cross-sectional regression coefficients for twenty-two country portfolios. For brevity, Table 8 only shows intercept and β coefficients.[22] We present the results for the junk and quality subsamples in Panels A and B, respectively. The t-statistics are adjusted following Newey and West (1987) using five lags.

Panel A of Table 8 shows insignificant β coefficients for junk stocks for all twenty-two country portfolios, indicating a flat relationship between future returns and β for junk stocks at the country level. In contrast, the results of Panel B on quality stocks show that four countries record positive and statistically significant β coefficients: the β is 0.02 (t-statistic = 2.12), 0.02 (t-statistic = 2.02), 0.01 (t-statistic = 2.39), and 0.03 (t-statistic = 2.07) for Australia, Hong Kong, Japan, and Norway, respectively. The statistically insignificant β coefficients for the remaining countries might be attributed to the small size of the samples in those countries, which impact the power of the statistical analysis. In summary, our results in Tables 7 and 8 show a flat relationship between future returns and beta among junk stocks, while the market risk is priced among quality stocks in the Global and Pacific aggregates as well as four countries at the country level. The results indicates that the beta anomaly is more prevalent among junk stocks compared to quality stocks.

5. The quality minus junk (QMJ) factor and the beta anomaly

So far, we demonstrate the role that stock quality, as a characteristic, plays in driving the beta anomaly in the international markets. In this section, we use a common return factor associated with stocks quality in the market and explore its ability to explain the returns associated with the beta anomaly. Asness et al. (2019) and Geppert and Zhao (2018) find that quality stocks tend to be low beta stocks, while junk stocks tend to be high beta stocks. Hence, we examine the hypothesis that the returns of the quality-minus-junk portfolios will be associated with the returns of the low–high beta portfolios.

5.1. The QMJ factor and the low-minus-high beta portfolios at the aggregate level

Asness et al. (2019) construct the QMJ factor, which is long in high-quality stocks and short in low-quality stocks, earning significant risk-adjusted returns in the US and across twenty-four countries.[23] Asness et al. (2019) attribute the abnormal returns of the QMJ factor to analyst overoptimism. Analysts tend

[21] The regression analysis, in Table 7, uses MAX as the proxy for lottery demand (Bali et al., 2011). In unreported tests, we use alternative proxies to control for lottery demand. Our results are robust to various measures of lottery demand such as total skewness, idiosyncratic skewness and idiosyncratic volatility. Those results are available upon request.

[22] Table A.3 of the Appendix includes the full version of Table 8, showing all coefficients of the control variables.

[23] To construct the QMJ factor, Asness et al. (2019) divide stocks into two size groups (small and large), and within each size group, stocks are sorted on their quality scores to build three portfolios (junk, medium, and quality). Then,

Table 9
The QMJ factor and the low-minus-high beta portfolios at the aggregate level.

Panel A: Alphas using models without the QMJ factor								
Low–high beta portfolios	Excess Return	*t*-stat	CAPM α	*t*-stat	FF3 α	*t*-stat	FFC4 α	*t*-stat
Global	0.57	(2.07)	0.93	(4.50)	0.99	(4.70)	0.64	(3.08)
Europe	0.14	(0.52)	0.61	(3.46)	0.62	(3.60)	0.11	(0.64)
Pacific	0.36	(1.27)	0.63	(2.73)	0.73	(3.13)	0.43	(1.77)
Panel B: Alphas using models with the QMJ factor								
Low–high beta portfolios	QMJ α	*t*-stat	CAPM+ QMJ α	*t*-stat	FF3+ QMJ α	*t*-stat	FFC4+ QMJ α	*t*-stat
Global	−0.14	(−0.64)	0.34	(1.54)	0.36	(1.52)	0.32	(1.40)
Europe	−0.58	(−3.83)	−0.04	(−0.24)	−0.20	(−1.23)	−0.25	(−1.68)
Pacific	−0.17	(−0.79)	0.19	(0.84)	0.17	(0.70)	0.08	(0.34)

This table reports the risk-adjusted performance of univariate portfolios sorted on beta using QMJ factor for aggregate portfolios. Quintiles are formed for each aggregate portfolio and every month from January 1993 to March 2021 by sorting stocks based on the previous month's beta. The low–high beta portfolio is long in the lowest beta quintile and short in the highest beta quintile. Quintile portfolios are equally weighted and rebalanced every calendar month. The table reports the average monthly excess returns and alphas of the low-minus-high (low–high) beta portfolios for three aggregates. Panel A shows alphas estimated with respect to CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4) models. Panel B reports alphas based on risk models that include QMJ: CAPM model augmented by QMJ factor (CAPAM+QMJ), FF3 model augmented by QMJ factor (FF3+QMJ), and FFC4 model augmented by QMJ factor (FFC4+QMJ). Excess returns and alphas are in percentage, and the numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

to selectively cover stocks they already have favourable views and drop stocks they view unfavourably based on their private information (McNichols and O'Brien, 1997). This leads to an upward bias of analysts' forecasts, which are more optimistic about junk stocks than about quality stocks, since potential dispersion in analyst beliefs is larger for junk stocks. To examine whether QMJ factor explains the returns associated with the beta anomaly, we calculate the abnormal returns of the low–high beta portfolios augmented with the QMJ factor.

Table 9 shows excess returns and alphas using models without (with) the QMJ factor in Panel A (B) for the three aggregate portfolios. To facilitate comparison, Panel A displays the excess returns and alphas relative to the CAPM, FF3, and FFC4 factor models of the low–high beta portfolios, previously shown in Table 3. We report alphas of the models augmented by the QMJ factor in Panel B. We denote the augmented models QMJ, CAPM+QMJ, FF3+QMJ, and FFC4+QMJ.

The results in Table 9 suggest that including the QMJ factor dramatically affects the abnormal returns of the aggregate portfolios. Panel A of Table 9 reports positive excess returns and alphas for all models in the three aggregates. However, all excess returns become negative when the models are augmented with the QMJ factor. For instance, in Panel B, the low–high beta portfolios show QMJ alphas of −0.14 (*t*-statistic = −0.64), −0.58 (*t*-statistic = −3.83), and −0.17 (*t*-statistic = −0.79) for the Global, Europe, and Pacific aggregates, respectively. We also observe a stark contrast corresponding to the alphas relative to the CAPM and FF3 models. When using models that exclude the QMJ factor, the alphas of the low–high portfolio are positive and significant, yet they become insignificant in all aggregates when augmented with the QMJ factor. For example, the CAPM+QMJ alphas are 0.34 (*t*-statistic = 1.54), −0.04 (*t*-statistic = −0.24), and 0.19 (*t*-statistic = 0.84), and the FF3+QMJ alphas are 0.36 (*t*-statistic = 1.52), −0.20 (*t*-statistic = −1.23), and 0.17 (*t*-statistic = 0.70) for the Global, Europe, and Pacific aggregates, correspondingly. The results of the FFC4 and FFC4+QMJ models follow a similar pattern.

Table 9 illustrates the impact of the QMJ factor on the abnormal returns of low–high beta portfolios, as the low–high beta portfolios do not earn positive abnormal returns once we consider the quality factor. The results confirm our previous finding that quality plays a significant role in the profitability of the beta anomaly across aggregate portfolios.

In our analysis in Table 9 we use FF3 and FFC4 models as the base factor models to report the alphas. One may argue that Fama and French (2015) five factors (FF5) that include investment and profitability factors in addition to their traditional FF3 factors might be more suitable for our analysis since profitability and investment factor may capture large part of the QMJ premium.[24] As a robustness analysis we repeat the analysis in Table 9 with FF5 augmented by the Carhart momentum factor.

The results, provided in Table A.4 of the Appendix, show that portfolios that are long in low-beta stocks and short in high-beta stocks generate statistically significant returns after controlling for the Fama and French (2015) five factors and well as FF5 model augmented with Carhart momentum factor. For example, the FF5 alphas are 0.62 (*t*-statistic = 2.71), 0.35 (*t*-statistic = 1.77) and 0.83 (*t*-statistic = 4.07), for the Global, Europe and Pacific aggregates, respectively. However, these alphas become insignificant after controlling for the QMJ factor. For instance, the FF5+QMJ alphas are 0.32 (*t*-statistic = 1.34), −0.14 (*t*-statistic = −0.86) and 0.27 (*t*-statistic = 1.29) for the Global, Europe and Pacific aggregates, respectively. The results in Table A.4 indicate that profitability and investment factors do not alter our previous results presented in Table 9 and provide further evidence that controlling for the quality factor make the abnormal returns of low–high beta portfolios insignificant.

5.2. The QMJ factor and the low-minus-high beta portfolios at the country level

In the previous subsection, we show that augmenting standard factor models with the quality factor explains the abnormal returns of the low–high beta portfolios in aggregate portfolios. In this subsection, we examine whether the explanatory power of the QMJ factor persists at the country level. We repeat the analysis performed in the previous subsection across twenty-two country portfolios.

the QMJ factor is the average return of the two quality portfolios minus the average return of the two junk portfolios. Specifically, the quality factor is long the top 30% high-quality stocks and short the bottom 30% junk stocks within the universe of large stocks, and similarly within the universe of small stocks. As such, the QMJ factor portfolio is designed to capture returns associated with stock quality while maintaining neutrality to market capitalization.

[24] We thank an anonymous reviewer for this comment.

Table 10
The QMJ factor and the low-minus-high beta portfolios at the country level.

Low–high beta portfolios	Excess Return	*t*-stat	QMJ α	*t*-stat	CAPM α	*t*-stat	CAPM+ QMJ α	*t*-stat	FF3 α	*t*-stat	FF3+ QMJ α	*t*-stat	FFC4 α	*t*-stat	FFC4+ QMJ α	*t*-stat
Australia	0.16	(0.46)	−0.46	(−1.53)	0.62	(2.05)	−0.06	(−0.20)	0.69	(2.43)	0.18	(0.52)	0.44	(1.25)	−0.14	(−0.42)
Austria	−0.45	(−1.06)	−0.78	(−2.15)	0.06	(0.28)	−0.19	(−0.79)	0.11	(0.49)	−0.18	(−0.71)	−0.09	(−0.47)	−0.26	(−1.22)
Belgium	−0.04	(−0.15)	−0.04	(−0.14)	0.16	(0.75)	0.17	(0.72)	0.19	(0.87)	0.18	(0.73)	−0.05	(−0.22)	−0.03	(−0.12)
Canada	0.78	(2.34)	0.18	(0.54)	1.16	(3.76)	0.58	(1.74)	1.13	(3.44)	0.66	(1.95)	0.76	(2.16)	0.46	(1.41)
Denmark	0.15	(0.41)	−0.05	(−0.15)	0.75	(2.20)	0.46	(1.37)	0.76	(2.15)	0.42	(1.32)	0.17	(0.45)	0.08	(0.24)
Finland	−0.25	(−0.72)	−0.06	(−0.18)	0.31	(1.09)	0.43	(1.59)	0.33	(1.21)	0.41	(1.55)	0.32	(1.17)	0.38	(1.40)
France	0.28	(0.89)	−0.36	(−1.45)	0.77	(3.46)	0.35	(1.48)	0.73	(3.48)	0.14	(0.64)	0.33	(1.54)	0.04	(0.20)
Germany	0.08	(0.25)	−0.58	(−1.95)	0.57	(2.94)	0.14	(0.57)	0.56	(3.08)	0.20	(0.87)	0.10	(0.49)	−0.07	(−0.29)
Greece	0.05	(0.09)	−1.24	(−2.62)	0.19	(0.46)	−0.56	(−1.35)	0.36	(0.95)	−0.35	(−0.90)	0.05	(0.14)	−0.28	(−0.72)
Hong Kong	0.42	(1.11)	−0.27	(−0.94)	1.07	(3.67)	0.27	(0.91)	1.21	(3.96)	0.34	(1.12)	0.93	(2.99)	0.26	(0.88)
Ireland	−0.06	(−0.09)	−0.73	(−1.44)	0.46	(0.73)	−0.25	(−0.52)	0.47	(0.77)	−0.24	(−0.49)	0.41	(0.63)	−0.26	(−0.53)
Italy	0.06	(0.19)	−0.65	(−2.01)	0.29	(0.98)	−0.07	(−0.22)	0.32	(1.10)	−0.08	(−0.26)	0.12	(0.39)	−0.09	(−0.27)
Japan	−0.01	(−0.03)	−0.42	(−2.40)	0.15	(0.67)	−0.27	(−1.51)	0.27	(1.22)	−0.30	(−1.65)	0.16	(0.78)	−0.30	(−1.75)
Netherlands	0.06	(0.16)	−0.07	(−0.23)	0.67	(2.33)	0.40	(1.37)	0.77	(2.63)	0.45	(1.56)	0.53	(1.87)	0.32	(1.12)
New Zealand	0.20	(0.65)	0.20	(0.63)	0.44	(1.43)	0.43	(1.40)	0.44	(1.45)	0.43	(1.43)	0.34	(1.10)	0.33	(1.07)
Norway	0.63	(1.30)	−0.10	(−0.26)	1.32	(3.55)	0.71	(2.29)	1.32	(3.58)	0.69	(2.21)	0.93	(2.46)	0.40	(1.21)
Portugal	0.85	(1.23)	1.27	(1.56)	1.34	(2.32)	1.61	(2.24)	1.76	(3.11)	1.75	(2.57)	1.59	(2.45)	1.35	(1.86)
Singapore	0.42	(0.94)	−0.28	(−0.90)	0.84	(2.49)	0.18	(0.59)	0.79	(2.46)	0.21	(0.71)	0.46	(1.55)	0.13	(0.48)
Spain	0.04	(0.10)	−0.08	(−0.23)	0.64	(2.15)	0.44	(1.45)	0.66	(2.19)	0.47	(1.54)	0.37	(1.26)	0.29	(0.97)
Sweden	0.34	(1.10)	−0.05	(−0.16)	0.88	(3.73)	0.58	(2.34)	0.87	(3.68)	0.42	(1.61)	0.49	(1.99)	0.25	(1.00)
Switzerland	−0.09	(−0.25)	−0.66	(−2.83)	0.48	(1.94)	−0.26	(−1.25)	0.52	(2.22)	−0.30	(−1.43)	0.14	(0.57)	−0.35	(−1.76)
United Kingdom	0.40	(1.61)	−0.10	(−0.44)	0.70	(2.87)	0.27	(1.08)	0.76	(3.22)	0.22	(0.92)	0.27	(1.06)	0.02	(0.07)

This table reports the risk-adjusted performance of univariate portfolios sorted on beta using QMJ factor for each country. Quintile portfolios are formed for each country and every month from January 1993 to March 2021 by sorting stocks based on the previous month's beta. The low–high beta portfolio is long in the lowest beta quintile and short in the highest beta quintile. Portfolios are equally weighted and rebalanced every calendar month. The table reports the average monthly excess returns and alphas of the low-minus-high (low–high) beta portfolios for twenty-two countries. Alphas are estimated with respect to the CAPM, Fama–French three-factor (FF3), Fama–French–Carhart four-factor (FFC4) models as well as their QMJ-augmented versions: CAPM+QMJ, FF3+QMJ and FFC4+QMJ factor models. Excess returns and alphas are in percentage, and the numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

Table 10 presents excess returns and alphas of the low–high beta portfolios augmented by the QMJ factor for all countries. To facilitate comparison, we show the excess returns (Excess Returns) and alphas (CAPM α, FF3 α, FFC4 α) previously reported in Table 4. Table 10 shows alphas based on the QMJ, CAPM, CAPM+QMJ, FF3, FF3 +QMJ, FFC4, and FFC4+QMJ factor models.

Results in Table 10 show that the QMJ factor can explain the abnormal returns for all low–high beta portfolios, as no country portfolio shows statistically significant and positive alphas once we include the QMJ factor into the model. Furthermore, some country portfolios report statistically significant but negative alphas for the model that includes the QMJ factor. For example, the QMJ alphas are −0.78 (t-statistic = −2.15), −1.24 (t-statistic = −2.62), −0.65 (t-statistic = −2.01), −0.42 (t-statistic = −2.40), and −0.66 (t-statistic = −2.83) for Austria, Greece, Italy, Japan, and Switzerland, respectively. The abnormal returns of the low–high beta portfolios fall in all models augmented with the QMJ factor across the twenty-two country portfolios.

In addition, although FFC4 alphas show positive and significant abnormal returns for Canada, Hong Kong, Norway, and Portugal, they become insignificant once estimated using the FFC4+QMJ model. The FFC4 alphas are 0.76 (t-statistic = 2.16), 0.93 (t-statistic = 2.99), 0.93 (t-statistic = 2.46), and 1.59 (t-statistic = 2.45) for Canada, Hong Kong, Norway, and Portugal, correspondingly. However, they are statistically insignificant once we incorporate the QMJ factor. The FFC4+QMJ alphas are 0.46 (t-statistic = 1.41), 0.26 (t-statistic = 0.88), 0.40 (t-statistic = 1.21), and 1.35 (t-statistic = 1.86), respectively, for these country portfolios.

The findings in Table 10 are consistent with the results reported in the previous subsection for aggregate portfolios, showing that the quality factor can also explain the beta anomaly at the country level.[25]

[25] Our results are consistent with the results of the portfolio analysis reported by Geppert and Zhao (2018) and show that the beta anomaly becomes insignificant after controlling for quality.

6. Conclusion

This research assesses the beta anomaly and investigates its relationship with stock quality in international stock markets. We document the existence of the beta anomaly in aggregate and country portfolios and show that stock quality can explain the beta anomaly.

The literature argues that high-beta stocks are riskier and more likely to be junk stocks, while low-beta stocks are less risky and more likely to be quality stocks (e.g., Asness et al., 2019; Geppert and Zhao, 2018). Consistent with this argument, we show that the beta anomaly remains economically strong and statistically significant among junk stocks, while it disappears among quality stocks. For example, for the Global portfolio the monthly excess returns and FFC4 alpha are 1.30% and 1.25%, respectively, among junk stocks, whereas they are indistinguishable from zero for quality stocks.

In addition, after excluding junk stocks from the sample, the regression analysis illustrates a positive and significant relation between future stock returns and beta, which indicates that market risk is priced among quality stocks.

Finally, the abnormal returns of international portfolios that are long in low-beta stocks and short in high-beta stocks are significant. However, those abnormal returns no longer exist once alphas are estimated after controlling for the QMJ factor.

This research offers novel evidence on the relationship between market risk and expected stock returns in international stock portfolios. The findings of this paper provide implications for investors. An investment strategy that is long in low-beta stocks and short in high-beta stocks will generate economically and statistically significant abnormal returns and Sharpe ratio in aggregate and most country portfolios. However, those profits are restricted to low-quality stock portfolios and become insignificant within high-quality stock portfolios. The abnormal returns of a low–high beta portfolio almost double once estimated among junk stocks only. This study suggests that arbitrage opportunities are possible at both the aggregate and country levels and that stock quality should be taken into account to exploit the beta anomaly.

Table A.1
Low–high beta decile portfolios among junk and quality stocks at the aggregate level.

Aggregate	Excess return	t-stat	CAPM α	t-stat	FF3 α	t-stat	FFC4 α	t-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Panel A: Low–high beta portfolios among junk stocks												
Global	1.83	(4.70)	2.07	(5.08)	2.30	(5.62)	1.82	(4.18)	−0.94	−0.51	24.52	0.89
Europe	0.71	(2.01)	1.10	(3.37)	1.20	(3.85)	0.46	(1.56)	−0.77	−0.71	21.59	0.40
Pacific	0.93	(2.29)	1.04	(2.48)	1.17	(2.82)	0.74	(1.66)	−0.72	−0.38	25.06	0.44
Panel B: Low–high beta portfolios among quality stocks												
Aggregate	Excess return	t-stat	CAPM α	t-stat	FF3 α	t-stat	FFC4 α	t-stat	β (ex-ante)	β (realized)	Volatility	Sharpe ratio
Global	−0.53	(−1.40)	−0.18	(−0.60)	−0.27	(−0.81)	−0.45	(−1.46)	−0.86	−0.72	22.31	−0.28
Europe	0.12	(0.39)	0.51	(2.27)	0.38	(1.80)	0.14	(0.64)	−0.63	−0.73	18.76	0.07
Pacific	−0.37	(−0.88)	−0.11	(−0.37)	−0.12	(−0.37)	−0.36	(−1.15)	−0.69	−0.85	22.39	−0.20

This table presents the performance of the low–high beta sorted decile portfolios for junk and quality stocks at the aggregate level. For each aggregate and every month from Jannuary 1994 to March 2021, all stocks are sorted into three different quality groups, and the bottom and top groups, as junk and quality subsamples, are selected. The aggregate portfolios are Global, Europe and Pacific and defined in Section 2.1. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. The decile portfolios are formed every month by sorting stocks based on the previous month's beta for both subsamples. Portfolios that are long in the lowest beta-decile and short in the highest beta-decile (low–high beta portfolio) are formed. The portfolios are equally weighted and rebalanced every calendar month. Panel A (B) reports the average monthly excess returns and alphas of the low-minus-high (low–high) beta portfolios among junk (quality) stocks. Alphas are estimated with respect to CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4) models. The table also presents average betas, volatility, and Sharpe ratio of the low–high beta portfolios. β (ex-ante) is the one-month lag beta estimated according to Frazzini and Pedersen (2014), β (realized) is the slope of a regression of monthly excess returns on market excess returns, and volatility is the standard deviation of monthly returns. Volatilities and Sharpe ratios are annualized, and excess returns and alphas are in percentage. Numbers in brackets are t-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

This section illustrates additional portfolio and regression analyses to support our main findings. We present the following robustness tests: Table A.1 illustrates the low–high beta decile portfolios among junk and quality stocks at the aggregate level. Table A.2 shows a bivariate-dependent sort portfolio analysis of

Table A.2
The beta anomaly among different quality subsamples.

Portfolios	Quality 1 (low)	Quality 2	Quality 3	Quality 4	Quality 5 (high)
Panel A: Global aggregate					
β 1 (low)	2.22	1.88	1.75	1.34	1.57
β 2	1.17	1.08	1.32	0.98	1.49
β 3	0.91	0.96	0.98	1.12	1.61
β 4	0.66	0.98	0.92	1.06	1.77
β 5 (high)	0.93	0.82	1.20	1.15	2.31
Low–high beta portfolios					
Excess return	1.29	1.06	0.56	0.20	−0.74
	(3.44)	(3.97)	(2.25)	(0.80)	(−2.12)
CAPM α	1.44	1.23	0.80	0.48	−0.44
	(3.82)	(4.57)	(3.81)	(2.52)	(−1.53)
FF3 α	1.70	1.41	0.89	0.55	−0.50
	(4.46)	(5.16)	(4.13)	(2.87)	(−1.57)
FFC4 α	1.15	1.11	0.69	0.42	−0.65
	(2.93)	(3.80)	(2.99)	(1.94)	(−2.19)
Panel B: Europe aggregate					
Portfolios	Quality 1 (low)	Quality 2	Quality 3	Quality 4	Quality 5 (high)
β 1 (low)	1.01	1.04	0.85	0.62	0.68
β 2	0.84	0.98	0.99	0.82	0.89
β 3	0.57	0.85	0.80	0.97	0.99
β 4	0.62	0.92	0.95	0.93	0.77
β 5 (high)	0.62	0.66	0.82	0.66	0.69

Table A.2 (*continued*).

Portfolios	Quality 1 (low)	Quality 2	Quality 3	Quality 4	Quality 5 (high)
Low–high beta portfolios					
Excess return	0.39	0.38	0.03	−0.04	−0.01
	(1.37)	(1.73)	(0.13)	(−0.18)	(−0.03)
CAPM α	0.68	0.63	0.27	0.25	0.32
	(2.46)	(3.41)	(1.75)	(1.55)	(1.60)
FF3 α	0.79	0.66	0.30	0.27	0.22
	(2.98)	(3.76)	(1.97)	(1.64)	(1.12)
FFC4 α	0.21	0.43	0.16	0.13	−0.01
	(0.80)	(2.33)	(1.00)	(0.70)	(−0.04)
Panel C: Pacific aggregate					
Portfolios	Quality 1 (low)	Quality 2	Quality 3	Quality 4	Quality 5 (high)
β 1 (low)	0.84	1.17	1.12	0.53	0.57
β 2	0.58	0.72	0.93	0.70	0.52
β 3	0.51	0.70	0.65	0.66	0.89
β 4	0.37	0.64	0.56	0.65	0.92
β 5 (high)	0.18	0.44	0.64	0.74	1.07
Low–high beta portfolios					
Excess return	0.66	0.74	0.48	−0.21	−0.51
	(1.93)	(2.44)	(1.87)	(−0.77)	(−1.39)
CAPM α	0.72	0.80	0.59	−0.04	−0.28
	(2.08)	(2.54)	(2.37)	(−0.19)	(−1.03)
FF3 α	0.87	0.88	0.68	0.00	−0.30
	(2.53)	(2.67)	(2.65)	(0.01)	(−1.08)
FFC4 α	0.48	0.59	0.44	−0.16	−0.48
	(1.17)	(1.73)	(1.74)	(−0.71)	(−1.75)

This table presents the performance of the low–high beta sorted portfolios for different quality subsamples at the aggregate level. For each aggregate portfolio and every month from January 1994 to March 2021, all stocks are sorted into quintile quality groups and formed five quality subsamples. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. For each subsample, quintile portfolios are formed every month by sorting stocks based on the previous month's beta. The table shows the time-series means of monthly equal-weighted excess returns and alphas estimated with respect to CAPM, Fama–French three-factor (FF3), and Fama–French–Carhart four-factor (FFC4) models for the quintile portfolios. The section labelled Low–high beta portfolios presents the average returns and alphas for portfolios that are long with the low-beta quintile (β 1) and short with the high-beta quintile (β 5) for each quality subsample. Panels A, B, and C illustrate the Global (excluding the US), Europe, and Pacific aggregate portfolios, respectively. Aggregate portfolios are defined in Section 2.1. The t-statistics shown in brackets are adjusted following Newey and West (1987) using five lags.

Table A.3
Fama–MacBeth regressions among quality and junk stocks at the country level (full results).

Panel A: Junk stocks

Country	Intercept	*t*-stat	β	*t*-stat	Ln MV	*t*-stat	Ln B/M	*t*-stat	Mom	*t*-stat	Rev	*t*-stat	Illiq	*t*-stat	MAX	*t*-stat
Australia	0.03	(2.00)	0.00	(−0.02)	0.00	(−3.69)	0.02	(3.25)	0.00	(0.83)	−0.01	(−1.16)	−2.21	(−1.61)	−0.04	(−0.91)
Austria	−0.02	(−0.26)	0.17	(0.71)	−0.02	(−0.73)	−0.05	(−0.90)	−0.03	(−0.21)	−0.46	(−2.24)	2.91	(0.13)	0.90	(0.60)
Belgium	−0.01	(−0.33)	−0.03	(−1.58)	0.01	(1.35)	−0.02	(−1.07)	0.01	(0.53)	0.06	(1.26)	19.34	(0.70)	−0.10	(−0.45)
Canada	−0.02	(−1.07)	−0.10	(−0.45)	19.34	(0.70)	0.01	(1.35)	0.06	(1.26)	−0.03	(−1.58)	0.01	(0.53)	0.00	(0.00)
Denmark	0.01	(0.77)	−0.02	(−1.27)	0.00	(0.74)	0.00	(−0.20)	0.00	(−0.24)	0.03	(1.12)	−4.59	(−0.55)	0.07	(0.98)
Finland	0.01	(0.15)	0.07	(1.33)	0.00	(−0.32)	−0.01	(−0.21)	−0.01	(−0.21)	0.19	(1.96)	−27.07	(−1.06)	−0.75	(−1.63)
France	0.00	(−0.38)	0.00	(0.42)	0.00	(−0.25)	0.02	(4.48)	0.01	(1.50)	0.00	(0.46)	−0.09	(−0.46)	−0.07	(−2.74)
Germany	0.00	(−0.15)	0.04	(1.20)	0.00	(−2.16)	0.01	(1.72)	0.02	(3.73)	0.01	(1.33)	0.30	(0.34)	−0.07	(−2.18)
Greece	0.00	(0.26)	−0.01	(−0.93)	0.00	(0.80)	0.01	(2.50)	−0.01	(−1.15)	0.01	(0.25)	2.05	(2.19)	−0.05	(−0.98)
Hong Kong	0.02	(1.27)	0.01	(0.69)	0.00	(−2.40)	0.01	(1.89)	0.00	(0.80)	−0.01	(−1.75)	1.25	(1.21)	−0.08	(−3.94)
Ireland	0.16	(0.74)	5.16	(0.95)	−0.54	(−0.95)	−0.14	(−0.59)	3.94	(1.02)	−7.99	(−0.98)	34.88	(1.20)	0.11	(0.47)
Italy	0.00	(0.32)	0.00	(0.12)	0.00	(−0.31)	0.01	(1.19)	0.01	(1.66)	0.03	(1.24)	20.66	(1.03)	−0.08	(−1.23)
Japan	0.00	(0.38)	0.00	(0.63)	0.00	(−1.29)	0.01	(4.33)	0.00	(0.64)	−0.01	(−1.27)	3.58	(3.83)	−0.08	(−6.01)
Netherlands	0.01	(0.34)	−0.01	(−1.01)	0.00	(0.78)	−0.01	(−0.73)	0.01	(1.22)	0.06	(2.14)	−183.8	(−1.90)	0.07	(0.79)
New Zealand	−1.07	(−0.92)	0.53	(0.71)	0.06	(1.09)	−0.01	(−0.39)	−0.20	(−1.19)	4.09	(1.07)	−9.73	(−0.85)	3.33	(1.05)
Norway	0.08	(0.69)	0.09	(0.62)	−0.01	(−1.21)	−0.01	(−0.53)	0.00	(0.00)	−0.08	(−0.65)	−15.66	(−0.53)	−1.24	(−1.36)
Portugal	0.11	(0.21)	−0.06	(−0.24)	−0.03	(−0.54)	0.12	(0.28)	−0.09	(−0.43)	−1.17	(−0.74)	267.12	(1.28)	−0.77	(−0.49)
Singapore	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Spain	0.01	(0.90)	−0.01	(−0.75)	0.00	(0.56)	0.01	(0.81)	0.01	(1.32)	−0.01	(−0.65)	52.12	(0.48)	−0.16	(−1.83)
Sweden	0.01	(1.07)	0.00	(0.08)	0.00	(−0.79)	0.01	(1.83)	0.00	(−0.06)	0.03	(2.00)	−0.07	(−0.15)	−0.04	(−1.03)
Switzerland	0.01	(1.26)	0.00	(0.41)	0.00	(−0.98)	0.00	(1.00)	0.01	(3.55)	0.02	(1.74)	−4.06	(−0.50)	−0.06	(−1.14)
United Kingdom	0.00	(0.52)	0.01	(0.98)	0.00	(−1.06)	0.01	(2.99)	0.01	(1.63)	−0.01	(−0.75)	−282.3	(−1.65)	−0.07	(−2.82)

Panel B: Quality stocks

Country	Intercept	*t*-stat	β	*t*-stat	Ln MV	*t*-stat	Ln B/M	*t*-stat	Mom	*t*-stat	Rev	*t*-stat	Illiq	*t*-stat	MAX	*t*-stat
Australia	0.02	(2.14)	0.02	(2.12)	0.00	(−5.03)	0.01	(4.17)	0.01	(1.58)	0.00	(−0.23)	0.00	(−0.05)	−0.06	(−2.60)
Austria	−0.02	(−1.59)	0.02	(1.01)	0.00	(−0.21)	0.01	(1.85)	0.00	(0.17)	0.00	(−0.06)	0.95	(0.30)	0.00	(−0.03)
Belgium	0.02	(1.94)	−0.02	(−1.38)	0.00	(0.11)	0.01	(1.69)	0.02	(3.02)	0.02	(0.69)	−0.56	(−1.75)	−0.04	(−0.51)
Canada	0.04	(4.93)	0.00	(−0.07)	0.00	(−4.49)	0.00	(−0.63)	0.00	(−0.16)	−0.01	(−1.21)	−0.06	(−0.45)	−0.01	(−0.23)
Denmark	0.01	(0.99)	0.01	(1.19)	0.00	(−0.70)	−0.01	(−1.13)	0.02	(3.39)	0.02	(1.23)	−0.12	(−0.57)	−0.06	(−1.35)
Finland	0.01	(0.62)	0.01	(0.41)	0.00	(−0.38)	−0.01	(−0.94)	0.01	(2.17)	0.08	(3.55)	0.75	(1.35)	−0.05	(−0.96)
France	0.01	(2.32)	0.01	(1.16)	0.00	(−2.42)	0.01	(2.41)	0.01	(3.36)	0.01	(0.84)	0.02	(2.15)	−0.11	(−4.71)
Germany	−0.04	(−0.84)	0.05	(0.88)	0.00	(−0.46)	0.03	(1.14)	0.04	(0.88)	−0.14	(−1.21)	0.11	(1.35)	0.10	(0.59)
Greece	−0.01	(−0.56)	0.01	(0.59)	0.00	(0.04)	0.02	(3.21)	0.00	(−0.51)	0.00	(0.07)	0.62	(1.40)	−0.11	(−2.21)
Hong Kong	0.01	(1.75)	0.02	(2.02)	0.00	(−3.20)	0.01	(2.20)	0.00	(−0.26)	0.01	(1.00)	0.04	(0.83)	−0.05	(−2.88)
Ireland	0.37	(1.00)	0.83	(1.69)	−0.10	(−1.52)	−0.36	(−1.57)	0.05	(0.24)	0.33	(0.66)	−3.21	(−0.13)	−0.78	(−1.88)
Italy	0.01	(1.44)	0.00	(0.08)	0.00	(−1.23)	0.01	(1.52)	0.01	(2.66)	0.03	(1.64)	5.93	(1.44)	−0.08	(−1.47)
Japan	0.00	(−0.20)	0.01	(2.39)	0.00	(−1.77)	0.01	(3.27)	0.00	(1.76)	−0.01	(−1.74)	0.03	(0.58)	−0.09	(−8.20)
Netherlands	0.01	(0.62)	0.00	(0.25)	0.00	(−1.41)	0.00	(0.29)	0.02	(3.35)	0.01	(0.63)	−0.06	(−0.07)	0.05	(0.95)
New Zealand	0.02	(1.90)	−0.02	(−1.38)	0.00	(−0.06)	0.00	(0.09)	0.01	(0.99)	0.05	(1.90)	−0.05	(−0.41)	−0.05	(−0.67)
Norway	0.02	(1.71)	0.03	(2.07)	0.00	(−2.23)	−0.02	(−2.19)	0.01	(1.15)	−0.01	(−0.41)	8.15	(1.59)	−0.16	(−2.33)
Portugal	0.04	(1.15)	−0.10	(−1.13)	0.01	(1.01)	−0.05	(−0.96)	−0.03	(−1.17)	0.00	(−0.05)	0.74	(0.29)	0.12	(0.37)
Singapore	0.00	(0.59)	0.00	(0.18)	0.00	(−0.87)	0.01	(4.77)	0.00	(1.08)	−0.01	(−1.49)	−0.01	(−0.20)	−0.04	(−2.37)
Spain	0.01	(0.72)	−0.01	(−0.77)	0.00	(1.20)	0.01	(1.96)	0.02	(3.26)	0.03	(1.20)	−1.14	(−0.85)	0.02	(0.30)
Sweden	0.02	(2.47)	0.00	(−0.10)	0.00	(−0.71)	0.01	(2.23)	0.01	(2.03)	0.01	(0.51)	0.37	(1.67)	−0.07	(−2.56)
Switzerland	0.00	(0.56)	0.01	(0.53)	0.00	(−0.26)	0.01	(3.27)	0.02	(5.13)	0.04	(2.59)	0.02	(0.10)	−0.08	(−2.64)
United Kingdom	0.00	(−0.01)	0.01	(1.02)	0.00	(−1.30)	0.01	(4.46)	0.01	(3.23)	0.01	(1.61)	−28.05	(−0.77)	0.01	(0.57)

This table presents the results of the Fama–MacBeth regressions in quality and junk subsamples at the country level. Every month and for each country, all stocks are sorted into three different quality groups, and the bottom and top groups, as junk and quality subsamples, are selected. Quality is estimated as the slope coefficient from a regression of excess stock returns on the QMJ factor using one year of daily returns. Within each subsample and for each country, we run a firm-level cross-sectional regression of monthly stock excess returns on lagged values of beta (β) and firm characteristics as control variables. We then calculate the time-series averages of the monthly cross-sectional regression slope coefficients. The set of control variables includes the natural logarithm of firm market capitalization (Ln MV), the natural logarithm of book-to-market ratio (Ln B/M), momentum (Mom), reversal (Rev), illiquidity (Illiq), and MAX. Details of these variables and their construction are provided in Section 2.2.3. Numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

the relationship between future excess returns and beta after controlling for stock quality. Table A.3 reports the results of Fama–MacBeth regressions for junk and quality stocks at the country level. Table A.4 shows the performance of the low-minus-high beta portfolios at the aggregate level using Fama–French five factor model augmented by QMJ factor.

Table A.4
The QMJ factor, Fama–French five-factor model, and the low-minus-high beta portfolios at the aggregate level.

Panel A: Alphas using models without the QMJ factor						
Low–high beta portfolios	Excess Return	*t*-stat	*FF5 α*	*t-stat*	FF5+mom *α*	*t-stat*
Global	0.57	(2.07)	0.62	(2.71)	0.45	(2.02)
Europe	0.14	(0.52)	0.35	(1.77)	0.05	(0.29)
Pacific	0.36	(1.27)	0.83	(4.07)	0.55	(2.77)
Panel B: Alphas using models with the QMJ factor						
Low–high beta portfolios	QMJ *α*	*t*-stat	*FF5+ QMJ α*	*t-stat*	FF5+mom+ QMJ *α*	*t*-stat
Global	−0.14	(−0.64)	0.32	(1.34)	0.28	(1.22)
Europe	−0.58	(−3.83)	−0.14	(−0.86)	−0.20	(−1.24)
Pacific	−0.17	(−0.79)	0.27	(1.29)	0.20	(1.05)

This table reports the risk-adjusted performance of univariate portfolios sorted on beta using Fama–French five-factor model augmented by QMJ factor for aggregate portfolios. Quintiles are formed for each aggregate portfolio and every month from January 1993 to March 2021 by sorting stocks based on the previous month's beta. The low–high beta portfolio is long in the lowest beta quintile and short in the highest beta quintile. Quintile portfolios are equally weighted and rebalanced every calendar month. The table reports the average monthly excess returns and alphas of the low-minus-high (low–high) beta portfolios for three aggregates. Panel A shows alphas estimated with respect to CAPM, Fama–French (FF5) five-factor model as well as FF5 model augmented by Carhart momentum factor (FF5+mom). The five-factor Fama–French (FF5) model includes investment and profitability factors in addition to FF3 factors. Panel B reports alphas based on risk models used in Panel A that include QMJ: FF5 model augmented by QMJ factor (FF5+QMJ) and FF5+mom model augmented by QMJ factor (FF5+mom+QMJ). Excess returns and alphas are in percentage, and the numbers in brackets are *t*-statistics, adjusted using Newey and West's (1987) standard errors with five lags.

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