Beta and Biased Beliefs

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Abstract

Relying on 116 million firm days from 50 stock markets and guided by behavioral theories, I provide evidence for the conjecture that the puzzling beta anomaly is the result of mispricing partly caused by expectational errors and biased beliefs. First, long/short return spreads across the globe are several times larger surrounding a broad range of firm-specific news announcements. Second, the anomaly is largely explained by a composite local mispricing factor. Third, the anomaly is positively related to lagged local market gains. Fourth, local consumer confidence positively predicts alphas. Fifth, the anomaly is concentrated in heavily traded stocks.

Keywords: beta anomaly, risk/return trade-off, investor biases, behavioral finance, international stock markets

JEL Classification Codes: G02, G12, G14, G15

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1 Introduction

The beta anomaly may be "a particularly compelling" candidate for "the greatest anomaly in finance" (Baker et al. (2011, p. 40)). Stocks with low market beta strongly outperform stocks with high market beta on a risk-adjusted basis, which contradicts the fundamental risk and return trade-off at the heart of standard asset pricing theory. To explain this puzzle, a broad range of drivers have been proposed, thereby leaving a blurry picture on its underlying causes. Moreover, most of the literature on the determinants of the anomaly focuses only on the U.S. stock market.[1] This may raise further questions about the generalizability of return predictive mechanisms, as recently highlighted in Harvey et al. (2016), McLean and Pontiff (2016) or Linnainmaa and Roberts (2016). I shed new light on this issue by providing evidence for the conjecture that the beta anomaly represents mispricing driven by market participants' biased beliefs. My analysis gains power from synthesizing information from 50 stock markets and from conceptually diverse tests.

While the link between the beta anomaly and several well-known biases in investors' beliefs or decision processes is intuitive and well theorized, it is still largely untested. I first discuss the implications of the four most plausible biases, all of which may work simultaneously or reinforce each other, before describing my empirical tests and findings.

First, and as highlighted by Daniel and Hirshleifer (2015, p.81) in their literature review, "overconfidence provides a natural explanation for (...) betting-against-beta effects." Overconfidence, broadly characterized as the excessive belief in own, often mistaken, valuations, has been shown to be present among all types of market participants, and is "perhaps the most robust finding in the psychology of judgment" (DeBondt and Thaler

[1] More generally, Karolyi (2016, p. 27) concludes that "there is a large and persistent US (home) bias in academic research in Finance."

(1995, p. 389)). A direct consequence of overconfidence is dispersion of beliefs (e.g., Hong and Stein (2007)). Overconfident disagreement coupled with frictions such as short-selling constraints (e.g., Miller (1977), Stambaugh et al. (2012, 2015)) can give rise to overpricing as market valuations will primarily reflect the most optimistic views. High beta stocks have more uncertain outcomes and thus create greater scope for overconfidence (e.g., Baker et al. (2011)), possibly resulting in low future returns relative to low beta stocks. Separately, overconfident investors with excessive beliefs in their own skill are likely to be attracted to volatile stocks as these securities offer particularly large rewards to both stock selection and market timing talent (e.g., Blitz et al. (2014), Cornell (2009)).

Second, biased beliefs may also arise from base rate neglect as a consequence of the representativeness heuristic (Tversky and Kahneman (1983)). Especially during boom phases, stocks with high beta (or, more general, high risk) will likely account for a substantial fraction of the stocks with the highest ex post returns. Market participants who place too much weight on confirming, exciting anecdotes instead of taking the full expected return distribution into account may thus tend to equate "speculative investments" with "great investments" (e.g., Baker et al. (2011), Falkenstein (2010)). This belief could be exacerbated by social interactions, in which investors may place asymmetric weight on their gains relative to their losses, as modeled in Han and Hirshleifer (2015).

Third, the anomaly may be related to mental accounting. For instance, Shefrin and Statman (2000) develop a behavioral portfolio theory in which investors match distinct mental accounts with different goals. Based on this security-potential/aspiration idea, Blitz and van Vliet (2007) propose that some investors may be risk-averse in their asset allocation but more speculative in their individual security selection. Consistent with this conjecture, "high risk, low return" anomalies appear to exist within (e.g., Frazzini and Pedersen (2014)) but not across asset classes (e.g., Baker and Wurgler (2015)).

Fourth, both cognitively constrained retail investors (e.g., Barber and Odean (2008)) and many mutual fund managers (e.g., Falkenstein (1996), Fang et al. (2014)) have been shown to excessively buy attention grabbing stocks. Following short-term price pressure, these stocks often tend to underperform (e.g., Da et al. (2011), Engelberg et al. (2011)). Due to their extreme payoffs, high beta stocks are likely to attract attention. For instance, high (low) beta stocks receive high (low) residual media coverage (Jacobs (2016a)).

Empirically, I set the stage by constructing a data set that consists of about 50,200 stocks from 50 countries, which account for about 116 million firm days between 1st January 1990 and 1st January 2014. In the average country month, a zero-cost portfolio that buys the 20% stocks with the lowest pre-ranking beta and sells the 20% stocks with the highest beta generates an annualized local Fama and French (1993) alpha of more than 6% (4.5%) in the case of equally (value) weighted returns. This finding is statistically highly significant and robust to a large number of modifications. In sum, the beta anomaly represents a pervasive global phenomenon, which complements the insights of prior work (Baker et al. (2014), Baker and Haugen (2012), Blitz and van Vliet (2007), Blitz et al. (2013), Frazzini and Pedersen (2014)).

This finding calls for a unified explanation. I thus explore to what extent the cross-section and time-series of the anomaly across the globe may be attributable to expectational errors and other well documented investor biases.

First, I analyze the cross-sectional market reaction around millions of firm-specific events. More specifically, I study abnormal returns to earnings announcements and dividend announcements across the globe. For the U.S. market, I additionally exploit data on 8-K filings, 10-K filings, newswire stories, and newspaper articles. The theory of biased expectations suggests that announcement returns are predictable, as discussed in detail in Engelberg et al. (2015). If investors systematically overestimate (underestimate) the prospects of high (low) beta firms, then information shocks will force them to at least partly update their biased beliefs, thereby creating predictable patterns in cross-sectional returns during a narrow event window. Indeed, I find that abnormal returns strongly decline with beta. This pattern is observable for each of the event groups, economically large, and statistically highly significant. In sum, the beta anomaly is several times larger than usual around firm-specific news, which is difficult to reconcile with rational expectations-based theories of price formation or competing explanations of the beta puzzle.

The results are also interesting from another perspective. Both Savor and Wilson (2014) and Lucca and Moench (2015) find that on days when macroeconomic news is scheduled for announcement beta is positively priced in the cross-section of U.S. stock returns. On non-announcement days, the risk-return relation is non-existent or even negative, which is part of an "important puzzle" (Savor and Wilson, 2014, p. 173). My news analysis suggests that the aggregation level of news may play a crucial role for our understanding of the beta anomaly. While investors may have correct expectations about market-level news, which may be the predominant effect on the few days with macroeconomic announcements, they seem to have erroneous expectations about firm-level news, which appears to be in line with the judgment biases discussed above.

Second, a single country-specific composite mispricing factor based on the Stambaugh et al. (2015) cross-sectional mispricing metric can explain much of the abnormal returns associated with the beta anomaly. Recent work provides compelling evidence that the score captures price distortions caused by market participants' expectational errors (e.g., Akbas et al. (2015), Jacobs (2016b), Stambaugh and Yuan (2016)). Adding a local mispricing factor to a local three-factor Fama and French (1993) model reduces the average alpha by 75% (40%) in the case of equally weighted (value weighted) returns.

Third, motivated by Cooper et al. (2004), I distinguish between up market states and down market states, defined as the lagged three-year local market return being positive or negative. As I will discuss in the respective section, the behavioral biases outlined above are likely to be positively related to lagged aggregate market gains, which may eventually result in larger long/short alphas. In contrast, some alternative explanations of the anomaly make different predictions. I find strong support for my conjecture. Overall, the beta anomaly exists in up market states only.

Fourth, I extent the insights of Antoniou et al. (2016) and Shen and Yu (2013) to an international level. The authors show that U.S. investor sentiment, as mainly proxied for by the Baker and Wurgler (2006) index, positively predicts the beta anomaly. I use country-level consumer confidence to confirm this finding for a broad range of countries.

Fifth, alphas are stronger (weaker) among stocks with high (low) residual turnover. Previous work has established a strong link between turnover and the biases that may underlie the beta anomaly. This finding is thus consistent with the idea that the cross-sectional variation of the anomaly is positively related to the degree of investors' behavioral biases.

I contribute to the controversial debate about the underlying mechanism of the beta anomaly. Black (1972, 1993), Brennan (1971), and Frazzini and Pedersen (2014) highlight the role of leverage or funding constraints. Hong and Sraer (2016) propose a behavioral model that builds on short selling constraints in combination with time-varying disagreement about the macro-economy. Baker et al. (2011), Brennan (1993), Falkenstein (2010), and Karceski (2002) highlight agency issues and other consequences of delegated portfolio management, such as fixed-benchmark strategies, tournament behavior, or manager compensation schemes. Bali et al. (2016) propose price pressure induced by investors' preference for lottery-like stocks as a driver of the beta anomaly (see also Bali et al. (2011), Barberis and Huang (2008), Kumar (2009), Wang et al. (2016)). Schneider et al. (2016) on the one hand and Novy-Marx (2014) as well as Fama and French (2016) on the other hand argue that the anomaly is partly rooted in hidden tilts towards firm-level downside risk and (mainly) profitability, respectively. This list is not exhaustive.[2]

My findings provide most support for the few recent papers that advocate a behavioral explanation of the beta anomaly in the U.S. stock market (e.g., Antoniou et al. (2016), Bali et al. (2016), Hong and Sraer (2016)). My results may help to enhance our understanding of the puzzle. For instance, consistent with Bali et al. (2016), a part of the beta anomaly across the globe appears to be a manifestation of the effect of lottery demand on stock returns. However, controlling for lottery-like payoffs, a substantial fraction of the average global alpha and of the abnormal event-time returns remains unexplained. My findings suggest that this part is more attributable to judgement biases than to lottery preferences. Consistent with Hong and Sraer (2016), differences of opinion appear to be a mechanism through which the anomaly may be generated. However, while Hong and Sraer (2016) highlight the role of disagreement about the common factor of firms' cash flows, my analysis suggests that disagreement about firm-specific cash flows is a key factor as well.

Finally, at least some of my findings may also be consistent with the implications of theories that highlight market frictions instead of behavioral biases. In fact, the behavioral finance view on anomalies rests on both investor psychology, which allows inefficiencies to arise, and limits to arbitrage, which allows inefficiencies to persist (e.g., Barberis and Thaler (2003)). My main contribution is to provide novel and comprehensive evidence on the investor psychology channel within the context of a large global data set.

[2]For instance, further (partial) explanations are based on money illusion in combination with high expected inflation (Cohen et al. (2005)) or on excessive arbitrage trading activity (Huang et al. (2015)). A related stream of the literature with a slightly different focus argues that a positive risk-return relation can be established once the basic CAPM is extended (e.g., Jagannathan and Wang (1996), Lettau and Ludvigson (2001)).

2 The beta anomaly across the globe

I gather daily data for both active and dead stocks from CRSP (in the case of the U.S.) as well as from Datastream (for all international markets). I obtain accounting data from Compustat and Worldscope, respectively. In addition, I collect analyst data from I/B/E/S.

I follow previous work in cleaning the Datastream data. The most important screens can be summarized as follows. I condition on firms with non-missing identifier, return, and market capitalization data. The home country of a firm has to equal the country in which its stock is traded. The stock needs to survive the generic filter rules proposed in Griffin et al. (2010), which are intended to identify non-common equity. To exclude delisted firms, I follow the method proposed in Ince and Porter (2006). As a second check, I condition on the period before the Worldscope "inactive date". To eliminate remaining data errors, I drop daily (monthly) returns over 100% (300%) which are reversed on the following day (in the next month). Return data and market capitalization data are winsorized at the 0.1% and the 99.9% level. Returns account for dividends as well as for capital actions.

To exclude micro-caps, I further condition on stocks with a lagged market capitalization of at least ten million USD. The asset pricing tests require a sufficient number of stocks both in the cross-section and in the time series. I thus concentrate on countries for which there are at least 50 eligible stocks at least 60 months in a row. The sample period starts on 1st January 1990 and ends on 1st January 2014. The start date aims at balancing the trade-off between maximising the time-series and maximising the cross-section. The final data set consists of 50,221 stocks from 50 countries.

In the baseline analysis, returns are expressed in local currency and beta is computed relative to a country-level value-weighted stock market index. Following Hong and Sraer (2016), I compute Dimson (1979) betas which account for non-synchronous trading. More precisely, I regress the stock's excess return on the contemporaneous excess market return as well as five lags of the excess market return. Beta is then computed as the sum of the six OLS coefficients. I use a rolling regression approach based on daily excess returns over the previous twelve months, during which I require at least 200 valid return observations. In each country month, I sort firms on beta in ascending order and construct a zero-cost portfolio that goes long firms in the bottom quintile and short firms in the top quintile.[3] To compute risk-adjusted returns, I rely on a self-constructed Fama and French (1993) three-factor models. I use country-specific models, as prior work such as Griffin (2002) points to the importance (and potentially superiority) of local factors.

On a country-by-country basis, Panel A of Table 1 provides descriptive statistics and also shows the local three-factor alphas. In all asset pricing tests of this paper, I document both equally weighted portfolio returns as well as value weighted portfolio returns, both of which have their merits.[4] There is strong evidence for the beta anomaly around the globe. In total, 82 of the 100 alpha estimates are positive. Assuming independence and a chance result of 50%, the corresponding p-value obtained from a binominal distribution is less than 0.001.

Please insert Table 1

In Panel B, I pool the time-series of monthly country-specific long/short returns. The

[3] I focus on portfolio quintiles due to the low number of eligible firms in some countries, especially in earlier years. In tests unreported for brevity, I find that using deciles or more accentuated stock weighting procedures, as sometimes used in the literature (e.g., Frazzini and Pedersen (2014)), tends to yield stronger findings. In this respect, the reported magnitude of the anomaly may be considered to be conservative.

[4] Value weighted returns are dominated by the largest and thus economically most important stocks, but, especially in smaller markets, can be driven by a few firms. Equally weighted returns give much weight to small stocks, but may provide a better impression of how widespread an anomaly is.

empirical relation between betas and excess returns is flat and indistinguishable from zero. To provide an estimate of the average risk-adjusted performance difference between high and low beta stocks across the globe, I pool the time-series of country-specific abnormal long/short portfolio returns. The latter are defined as the intercept plus the fitted value of the residual of the three-factor model regressions from Panel A. These factor alphas have several advantages. Fist, they quantify the economic magnitude of the anomaly, which is hard to intuitively grasp from excess returns. Second, abnormal returns make sure that the noise-induced mismatch between ex ante (estimated) and ex post (realized) betas is picked up by the realized factor loadings. Third, focusing on risk-adjusted returns also makes the country-level long/short estimates, which may differ in beta spreads or their exposure to size and value factors, comparable. I thus rely on factor alphas (as opposed to excess returns) in the remainder of the paper.

Based on the average country month and equally (value) weighted portfolio returns, low beta stocks outperform high beta stocks by about 51 (37 bp) per month. The corresponding t-statistics based on double-clustered standard errors are 4.30 and 2.98, respectively. The short leg of the portfolio contributes more to the anomaly, which is consistent with the potential mechanisms outlined in the introduction.

Table 2 reports results from three different sets of sensitivity checks. In Panel A, I modify the measurement of returns or alphas. In specification 1, I compute all returns (including the Fama/French factors) in USD. In specification 2, I report the CAPM alpha. In specification 3, I add a short-term reversal factor and a long-term reversal factor.

Please insert Table 2

In Panel B, I modify the way beta is computed. In specification 4, I subtract the the average industry beta before forming portfolios. In specification 5, I compute traditional (instead of Dimson (1979)) betas. In specification 6, I alternatively use low frequency betas based on monthly data over the previous 60 months. In specification 7 (8), I compute beta relative to the MSCI World Index (Global Investable Market Index).

In Panel C, I modify the country universe. In specification 9 (10), I condition on MSCI developed (emerging or frontier) markets. In 11 (12), I focus on large (small) markets.

In each specification, the long/short portfolio generates economically meaningful and statistically significant alphas. In addition, I have verified that the main insights from the tests reported in the next section hold for each of these twelve modifications. For instance, my findings on the role of behavioral biases also hold for the subsample of emerging markets, in which competing explanations based on the consequences of delegated portfolio management may be less powerful. My findings also hold for large and small stock markets alike. In sum, inferences do not change, which justifies using the baseline approach in the remainder of the paper.

3 Biased beliefs as a driver of the beta anomaly?

3.1 Firm-level news

In the rational expectations framework, fundamentally relevant firm-specific news is random and should not have systematic return predictive ability. This contrasts with the implications of the biased belief framework. If investors tend to have too optimistic (pessimistic) expectations regarding high (low) beta stocks, then new firm-specific information will force them to rapidly update their beliefs. As a consequence, long/short portfolio spreads should be particularly large surrounding important news announcements.

Empirically, a benefit of this event-driven approach is that one can concentrate on a narrow time window during which expected returns are small irrespective of the asset pricing model. In order to be consistent with my prior tests, I define the abnormal announcement return as the difference between the actual buy-and-hold return over the event days t=-1 to t=1 and the expected buy-and-hold return implied by a local Fama and French (1993) factor model. Factor loadings are estimated based on daily returns and rolling regressions over the months t-12 to t-2. To mitigate the impact of outliers driven by noisy factor loadings, abnormal returns are winsorized at the 0.5% and the 99.5% level.[5]

I gather global earnings announcement dates and dividend declaration dates from Worldscope, Compustat, and CSRP. If the announcement falls on a non-trading day, the date is set to the next trading day. In total, about 1,087,000 million earnings announcements and 292,000 dividend announcements are included in my analysis. The dividend events exclude those observations where earnings and dividends are announced on the same day. My main findings are presented in Tables 3 (earnings) and 4 (dividends).

Please insert Tables 3 and 4

In specification (1) of Panel A in both tables, all observations are pooled. Consistent with prior literature including Barber et al. (2013) and Hartzmark and Solomon (2013), the average earnings (dividend) announcement generates a significantly positive abnormal three day event-time return of 6 (33) bp. However, my focus is on cross-sectional differences. Thus, I start by regressing the pooled global abnormal returns on the pre-ranking beta quintile. In specifications (2) to (5) of Panel A in both tables, I additionally consider the following country subsets: Americas (Argentina, Brazil, Canada, Chile, Colombia, Mexico, United States), Asia (China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Sri Lanka, Taiwan, Thailand, Vietnam), Pacific (Australia, Hong Kong, Japan,

[5] In tests untabulated for brevity, I find that using raw returns does not change inferences.

New Zealand, Singapore), and Europe/Middle East/Africa (all other countries displayed in Table 1). This market classification is inspired by MSCI and represents an attempt to balance the trade-off between the number of distinct subsamples and the number of observations per subsample.

The results show a clear picture. Irrespective of the event type and the geographic region, abnormal returns strongly decline with beta. The findings are all economically meaningful and, in nine out of ten estimates, significant at the one percent level. For instance, with respect to global earnings announcements, low beta firms (quintile 1) are estimated to generate a three-day abnormal return of about 35 bp. In contrast, high beta firms yield about -21 bp. The regression coefficient for the beta quintile has a t-statistic of -16.50, with standard errors being double clustered by firm and day. With respect to global dividend announcements, low (high) beta firms are estimated to yield an abnormal return of 43 (21) bp. The regression coefficient for the beta quintile has a t-statistic of -6.51. Panel B verifies that findings are virtually unchanged if I include country fixed effects. In general, the difference in three-day abnormal return spreads are large compared to the unconditional magnitude of the anomaly as presented in Table 1, suggesting that much of the anomaly is the result of biased expectations about firm-level news.

However, as outlined in the introduction, beta may be correlated with other firm characteristics that may partly subsume the beta anomaly. Thus, I construct five quintile-based control variables whose construction is described in the Online Appendix. More specifically, I consider the maximum daily return in the previous month as a proxy for lottery-like payoffs (e.g., Bali et al. (2016)). I also include profitability (e.g., Novy-Marx (2014)) and coskewness (e.g., Harvey and Siddique (2000), Schneider et al. (2016)). Beta may also be related to a firm's sensitivity to aggregate funding liquidity. Motivated by Frazzini and Pedersen (2014), I compute the TED spread beta, i.e. the slope coefficient from a regression of daily excess stock returns on the TED spread.[6] As a second proxy, and motivated by Chen and Lu (2015), I use the stock-level return sensitivity to financial sector leverage.

Panels C of Table 3 and Table 4 show the multivariate regression results. The major insight is that, while the control variables do have return predictive ability, the role of beta is only marginally affected. For instance, with respect to worldwide events, the implied abnormal return difference between the lowest and highest beta quintile is still about 44 bp (t-stat 13.01) in the case of earnings announcements and 25 bp (t-stat 6.95) in the case of dividend announcements. In sum, inferences remain unchanged.

The rich set of data available for the U.S. stock market allows me to explore about 1.7 million further firm-level events. More specifically, I study the market reactions to 10-K filings, 8-K filings[7], news stories as relied on in Chan (2003) as well as national newspaper articles as used in Hillert et al. (2014). I then imitate the regression approach used in the previous section. The results are presented in table 5.

Please insert Table 5

The major insight is that the findings carry over. For each event type and in each regression specification, there is a statistically significant and economically meaningful negative relation between pre-ranking beta and announcement returns. Implied abnormal return differences are in the area of 40 bp over a three day horizon.

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[6] In tests untabulated for brevity, I find that alternatively using the monthly stock return sensitivity to the monthly standard deviation of daily TED spread changes does not change inferences.

[7] *www.sec.gov/answers/form8k.htm* defines an 8-K filing as a"'current report' companies must file with the SEC to announce major events that shareholders should know about".

Please insert Figure 1

Figure 1 illustrates the main findings from the tests in this section. Taken in their entirety, three conclusions can be drawn. First, beta anomaly spreads are all else equal several times larger on firm days surrounding important stock-specific news announcements than during regular firm days. Second, these findings are consistent with the conjecture that the beta anomaly is, at least in part, mispricing driven by biased expectations. Third, the results are difficult to reconcile with alternative hypotheses about the underlying drivers of the beta anomaly, as outlined in the introduction.

3.2 Composite mispricing factor

If the beta phenomenon represents mispricing, then it may be subsumed by a factor designed to capture inefficiences caused by biased beliefs and market frictions. To take this idea to the data, I implement country-specific versions of the composite mispricing metric proposed in Stambaugh et al. (2015). The evidence in Akbas et al. (2015), Jacobs (2016b), and Stambaugh, Yu, and Yuan (2012, 2014, 2015) collectively suggests that the score represents a state of the art approach to quantify price distortions. The score condenses the information from 11 well-established or recently proposed anomalies. Reference papers as well as construction details are provided in the Online Appendix.

For each country month, I construct a mispricing factor that goes long (short) firms in the bottom (top) quintile of Stambaugh et al. (2015) mispricing. I then regress the country-level beta anomaly on a standard local Fama and French (1993) factor model (as in Table 1) augmented with the country-specific mispricing factor. On a country-by-country basis, the main findings are displayed in Panel A of Table 6.

Please insert Table 6

The beta anomaly loads strongly on the mispricing factor. In total, 89 of the 100 mispricing coefficient estimates (50 countries, two return weighting schemes) are positive. Almost two thirds of these positive coefficients are statistically significant at least at the 10% level. The alpha is positively statistically significant in 18 out of 100 cases only, as opposed to 42 observations in the baseline analysis.

To assess the big picture, Panels B and C pool the time-series of country-specific abnormal returns generated by the three-factor model augmented with the mispricing factor. The approach mimics the procedure in Panel B of Table 1. However, the sample size is slightly reduced due to stricter data requirements for the construction of the mispricing factor. To facilitate comparison, I thus construct a matched sample of abnormal returns generated by the three-factor model only. This matched sample produces an average alpha of 54 bp (t-stat 4.56) in the case of equally weighted returns and an average alpha of 42 bp (t-stat 3.49) in the case of value weighted returns. The inclusion of the mispricing factor has strong effects on these estimates. The equally weighted alpha dramatically drops to 13 bp, which is not significant anymore (t-stat 1.19). With respect to value-weighted returns, the drop is weaker yet still remarkable (26 bp, t-stat 2.42). Consistent with the notion that overpricing is more prevalent than underpricing (e.g., Stambaugh et al. (2015)), the mispricing factor is particularly able to explain the poor performance of high beta stocks.

In Panels D and E, I control for previously proposed determinants of the beta anomaly by constructing analogous country-specific versions of a maximum daily return factor, a TED spread sensitivity factor, a financial sector leverage factor, a profitability factor, and a coskewness factor. The regression approach then mimics the procedure in Panel B. There are two main insights. First, in their enterity, the control factors are able to explain a substantial fraction of the beta anomaly. The Online Appendix shows country-level regression results which indicate that this finding is primarily driven by the maximum daily return factor. This is consistent with the lottery-demand based explanation proposed in Bali et al. (2016). However, the combined impact of all control variables is about as strong as the impact of the single composite mispricing factor, as demonstrated in Panels B and C. Moreover, and second, the mispricing factor matters over and above these previously proposed determinants. In sum, to a large extent, the beta anomaly appears to be a manifestation of mispricing.[8]

3.3 Market states

The impact of the behavioral biases discussed in the introduction on the expected return of beta-sorted portfolios is likely to be amplified (reduced) after periods of rising (falling) market valuations. For instance, aggregate overconfidence, coupled with self-attribution bias (e.g., Daniel et al. (1998)), has been argued to increase following market gains (e.g., Cooper et al. (2004), Gervais and Odean (2001)). High past market returns also attract attention (e.g, Yuan (2015)), in particular among less sophisticated investors (e.g., Lamont and Thaler (2003), Grinblatt et al. (2011)) who moreover tend to trade more aggressively during these periods. Opposite patterns are found in down market periods (e.g., Karlsson et al. (2009), Sicherman et al. (2016)). Following market gains, at least some stocks with high systematic risk will have generated high returns, which is likely to strengthen the inappropriate use of the representativeness heuristic. Many investors' return expectations also appear to be extrapolative as their return expectations are positively correlated with

[8]Moreover, Fama and MacBeth (1973) regressions shown in the Online Appendix suggest that aggregate cross-sectional Stambaugh and Yuan (2016) mispricing is also a significant cross-country determinant of the beta anomaly.

past stock market returns (e.g., Greenwood and Shleifer (2014)). Moreover, expectations of risk-adjusted returns tend to be procyclical as well (e.g., Amromin and Sharpe (2009)).

In sum, high (low) beta stocks may be more overvalued (undervalued) following aggregate market gains. In contrast, some other explanations for the beta anomaly do not predict larger (smaller) long/short alphas in up (down) market states. Hong and Sraer (2016) argue that their main aggregate disagreement measure can be high during both down markets and up markets (see their figure 1). The demand for lottery-type stocks (Bali et al. (2016)) has been argued to be particularly strong during bad economic times (e.g., Kumar (2009)).

Empirically, I follow Cooper et al. (2004) and Hou et al. (2009) by defining up (down) market states as months in which the lagged three-year value-weighted country market return is positive (negative). Naturally, the stricter data requirements slightly reduce the sample. About 74% of the remaining country months are classified as up market states. On a country-by-country basis,

I then regress the time-series of abnormal returns (defined as in Table 1) on two dummies for up markets and down markets. The results in Panel A of Table 7 show a clear picture. In about 85% of all (country, return weighting) combinations, alpha point estimates are larger in up markets states than in down market states. Assuming a chance result of 50%, the corresponding p-value is less than 0.001. About 90% of the alphas in up markets are positive, but less than 40% in down markets.

Please insert Table 7

In Panels B and C of Table 7, I again pool the observations. In down market states, the beta anomaly is non-existent or even negative in the average country month. In contrast, the alpha is large and highly significant in up market states. The average monthly alpha difference between both states exceeds 100 bp for both equally weighted and value weighted returns, which is significant at the one percent level.[9]

To control for previously proposed determinants of the beta anomaly, Panels D and E rerun the analysis of Panel B and C. However, the portfolio sorting is based on the portion of beta that is orthogonal to the maximum daily return in the previous month, profitability, the sensitivity to TED spread and financial sector leverage, as well as coskewness.[10] Panel C shows that inferences remain unchanged. The average alpha difference between up and down market states is still estimated to be 79 bp (value weighted returns) or 101 bp (equally weighted returns).

3.4 Consumer confidence

There is ample evidence that non-rational behavior and mispricing increase with investor sentiment (e.g., Baker and Wurgler (2006), Stambaugh et al. (2012, 2014, 2015)). The line of reasoning is similar as in the case of up market states. For the U.S. stock market, Antoniou et al. (2016) and Shen and Yu (2013) indeed document that the CAPM appears to work much better in pessimistic sentiment periods than in optimistic sentiment periods. In this section, I extent their main idea to my large international sample.

Inspired by Lemmon and Portniaguina (2006) and Schmeling (2009), I proxy for

[9]Moreover, Fama and MacBeth (1973) regressions shown in the Online Appendix suggest that the lagged local market return is also a significant cross-country determinant of the beta anomaly.

[10]More specifically, in each country month, I regress beta on the same control variables as in the firm-level news analysis in section 3.1, and sort stocks based on the residual from this cross-sectional regression. This slightly reduces the sample size. To facilitate comparison with the univariate findings in Panel B, I therefore also estimate a matched univariate sample.

country-specific sentiment with local consumer confidence indices, as provided by Datastream. I am able to gather quarterly updated sentiment data for 32 countries. Separately for each country, and as common in the literature (e.g., Stambaugh et al. (2012)), I define local high and low sentiment periods simply by a median split, lagged by one period (i.e., a quarter). Sentiment and market states are only moderately positively correlated, suggesting that the sentiment classification contains distinct information.[11] I consequently run an analysis analogously to the one for market states. The main results, which are displayed in table 8, are as predicted.

Please insert Table 8

In more than two thirds of the observations, the country-level alpha point estimates in Panel A are larger following positive than following negative sentiment (p-value about 0.004). The pooled results in Panels B and C show a similar picture. With respect to equally weighted returns, the average alpha is about 21 bp (t-stat 1.14) following negative sentiment, but 87 bp (t-stat 5.05) following positive sentiment, which results in a difference of 66 bp (t-stat 2.92). The respective numbers for value weighted returns are 21, 51, and 30 bp (t-stat 1.01., 3.91, and 1.59). Panels D and E show that inferences remain unchanged when controlling for previously proposed determinants of the beta anomaly. In sum, the results are again consistent with a mispricing story.

[11] Conditional on up market states, about 55% (45%) of country quarters are classified as high (low) sentiment periods. Conditional on down market states, about 33% (67%) of country quarters are classified as high (low) sentiment periods.

3.5 Trading activity

The cross-sectional variation of the beta phenomenon may be positively related to cross-sectional variation in investor biases possibly underlying the anomaly, in particular with respect to the short leg of the portfolio.

Stock-level turnover appears to be a natural, albeit clearly noisy, proxy for the biases outlined in the introduction. High trading volume is a direct consequence of overconfidence (e.g. Gervais and Odean (2001), Hong and Stein (2007), Statman et al. (2006)). Aggressive trading is also predicted by models based (partly) on the representativeness heuristic or extrapolative expectations (e.g., Fischer and Verrecchia (1999), Hong and Stein (2007)). Finally, both theory and empirical evidence suggest a strong bidirectional link between stock-level trading volume and (excessive) attention (e.g., Barber and Odean (2008), Hou et al. (2009), Merton (1987), Miller (1977)).

As trading volume may not only contain a noise trading component, but also a liquidity component, I use residual turnover. More specifically, I rely on the residual obtained from monthly cross-sectional regressions of logarithmized stock-level turnover on the bid-ask spread measure developed in Corwin and Schultz (2012), the spread measure proposed in Chung and Zhang (2014), lagged logarithmized market capitalization and lagged inverse stock price.[12] I then compute the beta anomaly separately for stocks with above and below median residual turnover. Table 9 shows the main findings.

Please insert Table 9

[12]Due to limited data availability, turnover and, in particular, the two spread measures cannot be computed for all firm months. To keep the cross-section of stocks reasonably large, I set missing values of the spread measures to zero and include two dummy variables that equal one when the respective variable is missing, and zero otherwise. Using raw instead of on residual turnover does not change inferences.

Panel A provides country-by-country results. In more than 77% of the (country, return weighting scheme) pairs, the beta anomaly anomaly is stronger among stocks with high residual turnover than among stocks with low residual turnover (p-value less than 0.001). Panel B and C show the global perspective. The high turnover sample generates an average alpha of about 70 bp, whereas the low turnover sample yields only about 25 bp. The alpha difference between both samples is economically large and highly statistically significant. Further inspection shows that this result is mainly driven by the short leg. In line with with the mispricing hypothesis, high beta stocks that are heavily traded appear to be particularly overvalued.

4 Conclusion

The beta anomaly is a pervasive global phenomenon that contradicts the risk-return trade-off underlying modern asset pricing theory. There is little consensus on the mechanisms behind this empirical puzzle. Guided by behavioral theories, I revisit the controversial debate. In their entirety, the findings from cross-sectional and time-series tests in stock markets around the globe suggest that expectational errors and behavioral biases play an essential part in generating the beta anomaly.

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Figure 1: Beta and the market reaction to firm-level news

Separately for the unconditional stock universe as well as for beta-sorted quintiles, the figure shows average abnormal returns around firm-specific news. The abnormal return is defined as the buy-and-hold return during the event days t=-1, t=0, and t=+1 minus the expected buy-and-hold return as implied by a local Fama and French (1993) model. Abnormal returns are winsorized at the 0.5% level and at the 99.5% level. The first picture is based on pooled global earnings announcements (see Table 3). The second picture is based on pooled global dividend announcements (see Table 4). The third picture is based on pooled further U.S. news events (see Table 5). T-statistics (in parentheses) are based on standard errors that are double-clustered by firm and date. Two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

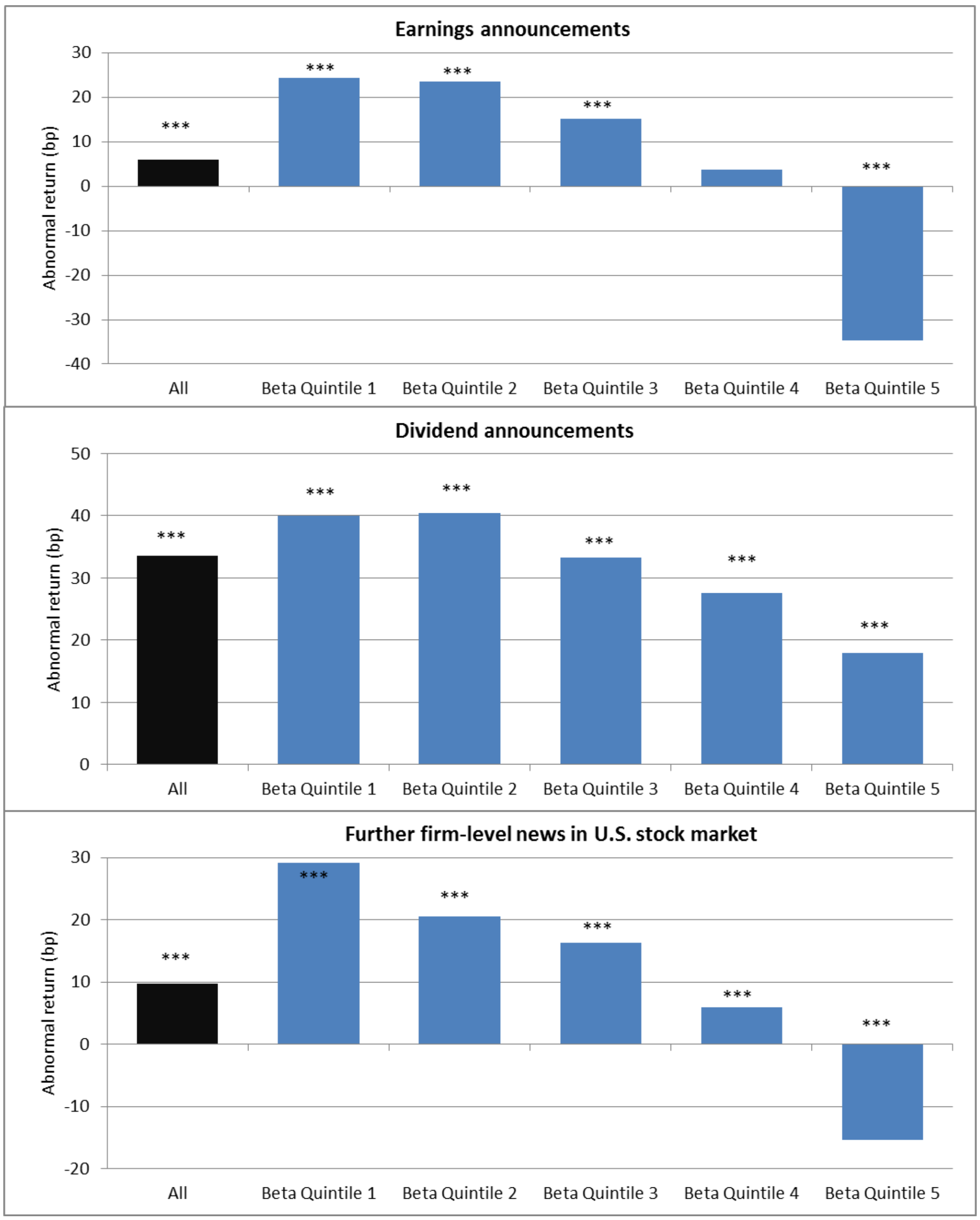

Table 1: Beta anomaly across the globe

Panel A reports monthly alphas (in %) obtained from regressing country-specific long/short beta portfolios on country-specific Fama and French (1993) three-factor models. T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Zero-cost portfolios go long (short) stocks in the bottom (top) quintile of historical Dimson (1979) betas, computed using daily excess returns over the previous twelve months. Firms within the portfolios are either equally weighted (EW alphas) or value weighted (VW alphas). Panel A additionally shows descriptive statistics for firms surviving all data screens. Firm size is expressed in million USD. The total number of firm months is expressed in 1,000s. In Panel B, the time-series of country-specific excess long/short portfolio returns or, alternatively, the time-series of abnormal returns, defined as the intercept plus the fitted value of the residual from the regressions in Panel A, are pooled. In Panel B, t-statistics (in parentheses) are based on standard errors that are double-clustered by country and month. In both panels, two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Descriptive statistics and three-factor alphas of long/short portfolios sorted on beta, country-by-country basis									
Country	Start	End	Firm months	Number firms	Mean firm size	EW alphas		VW alphas	
Argentina	Aug-94	Dec-13	12	102	578	0.327	(0.63)	-1.016*	(-1.88)
Australia	Jan-90	Dec-13	167	2,148	798	0.495**	(2.23)	0.541*	(1.65)
Austria	Dec-90	Dec-13	19	160	819	0.702**	(2.48)	0.377	(1.33)
Belgium	Jan-90	Dec-13	27	204	1,626	0.005	(0.02)	0.238	(0.89)
Brazil	Nov-97	Dec-13	18	201	3,065	0.669	(1.01)	-0.720	(-1.10)
Bulgaria	Mar-07	Dec-13	6	143	101	0.309	(0.28)	0.802	(0.46)
Canada	Jan-90	Dec-13	164	2,321	1,059	0.958***	(3.23)	0.676*	(1.82)
Chile	Jul-90	Dec-13	39	243	803	0.647**	(2.25)	0.322	(0.87)
China	Jul-94	Dec-13	255	2,456	1,051	0.647**	(2.52)	1.114***	(3.32)
Denmark	Jan-90	Dec-13	40	275	689	0.317	(1.41)	0.499*	(1.85)
Emirates	Oct-06	Dec-13	7	102	1,403	1.600***	(2.70)	0.333	(0.41)
Egypt	Jul-99	Dec-13	16	139	469	0.710	(1.24)	-0.415	(-0.49)
Finland	Jul-95	Dec-13	23	171	1,516	0.899***	(2.89)	0.543*	(1.73)
France	Jan-90	Dec-13	150	1,360	1,981	0.769***	(3.18)	0.619**	(2.33)
Germany	Jan-90	Dec-13	144	1,180	1,746	0.515**	(2.21)	0.439	(1.02)
Greece	Mar-90	Dec-13	50	381	378	0.700	(1.55)	1.107**	(2.01)
Hongkong	Jan-90	Dec-13	35	179	2,663	1.333***	(3.28)	1.051**	(2.39)
India	Jul-92	Dec-13	237	2,838	489	0.060	(0.18)	0.408	(0.92)
Indonesia	Apr-92	Dec-13	50	454	594	-0.141	(-0.36)	0.163	(0.29)
Israel	Jul-94	Dec-13	69	637	288	0.093	(0.33)	0.325	(0.74)
Italy	Jan-90	Dec-13	58	434	1,862	0.527**	(2.24)	0.761***	(2.84)

[continued overleaf]

Country	Start	End	Firm months	Number firms	Mean firm size	EW alphas		VW alphas	
Japan	Jan-90	Dec-13	828	4,546	1,071	-0.197	(-0.95)	-0.153	(-0.55)
Jordan	Oct-06	Dec-13	11	192	225	-1.005**	(-2.06)	-0.132	(-0.28)
Korea	Jan-90	Dec-13	288	2,393	376	1.152**	(2.05)	1.536**	(2.32)
Kuwait	Jan-06	Dec-13	12	161	844	0.876**	(2.13)	0.150	(0.26)
Malaysia	Jan-90	Dec-13	142	1,076	347	0.667***	(2.91)	0.895***	(3.45)
Mexico	Dec-92	Dec-13	25	201	1,720	0.172	(0.54)	0.016	(0.05)
Morocco	Jul-06	Dec-13	5	78	885	0.372	(0.78)	-0.115	(-0.26)
Netherlands	Jan-90	Dec-13	33	235	2,584	0.776***	(2.96)	0.102	(0.28)
New Zealand	Jul-94	Dec-13	16	189	263	0.646**	(2.10)	0.529*	(1.68)
Norway	May-01	Dec-13	33	354	917	-0.237	(-0.64)	-0.169	(-0.40)
Oman	Oct-06	Dec-13	7	97	228	2.030***	(3.82)	1.355***	(2.87)
Pakistan	Jul-93	Dec-13	30	258	182	0.488	(1.41)	0.265	(0.73)
Philippines	Jan-93	Dec-13	27	215	479	1.196***	(2.72)	0.741*	(1.74)
Poland	Jul-98	Dec-13	33	555	480	-0.415	(-1.12)	-0.230	(-0.51)
Portugal	Oct-90	Jul-05	9	115	424	1.034**	(2.12)	0.279	(0.45)
Romania	Jul-06	Dec-13	10	183	215	-1.054	(-1.19)	-0.965	(-1.12)
Russia	Jul-03	Dec-13	22	426	3,091	0.682	(1.15)	0.486	(0.55)
Singapore	Jan-90	Dec-13	87	724	519	0.530**	(2.24)	0.410	(1.10)
South Africa	Jan-90	Dec-13	65	688	962	1.185***	(4.22)	0.743**	(2.38)
Spain	Jan-90	Dec-13	32	205	3,516	0.766***	(3.17)	0.259	(0.95)
Sri Lanka	Nov-03	Dec-13	13	212	87	0.655	(1.16)	0.685	(1.08)
Sweden	Jan-90	Dec-13	56	604	1,257	0.920***	(2.73)	0.561	(1.25)
Switzerland	Jan-90	Dec-13	55	370	3,255	0.390*	(1.88)	0.578***	(2.67)
Taiwan	Jul-92	Dec-13	216	1,887	507	0.190	(0.60)	0.129	(0.36)
Thailand	Jul-94	Dec-13	81	640	358	0.747**	(2.14)	0.351	(1.06)
Turkey	Aug-94	Dec-13	53	381	535	-0.466	(-0.99)	-1.369**	(-2.28)
United Kingdom	Jan-90	Dec-13	277	2,788	1,847	0.132	(0.76)	0.277	(1.02)
United States	Jan-90	Dec-13	1,306	13,933	2,355	0.630***	(2.74)	0.601**	(2.10)
Vietnam	May-08	Dec-13	11	387	132	-0.703	(-0.72)	1.403	(1.01)
Panel B: Long/short returns and alphas, pooled data									
Excess returns, equally weighted									
N: 11,419	Long	0.369**	(2.30)	Short	0.264	(0.71)	Long-short	0.105	(0.41)
Excess returns, value weighted									
N: 11,419	Long	0.270**	(1.97)	Short	0.276	(0.77)	Long-short	-0.006	(-0.02)
Three-factor alphas, equally weighted									
N: 11,419	Long	0.139**	(2.15)	Short	-0.369***	(-4.72)	Long-short	0.509***	(4.30)
Three-factor alphas, value weighted									
N: 11,419	Long	0.083	(1.33)	Short	-0.284***	(-3.98)	Long-short	0.367***	(2.98)

Table 2: Robustness of the beta anomaly

The table shows the alphas from 12 sensitivity checks of the baseline analysis, as displayed in Panel B of Table 1. In (1), portfolio returns and the Fama and French (1993) factors are denominated in USD. As a proxy for the risk free rate, I rely on the U.S. one-month T-Bill rate (e.g., Fama and French (2012), Hou et al. (2011)). In (2), I use only the local market excess return as explanatory variable. In (3), I add a short-term reversal factor (based on the return in month t-1) and a long-term reversal factor (based on the cumulative return over t-60 to t-13). In (4), and separately for each country month, I subtract the average industry-level beta from each stock-level beta before forming portfolios. Industry classification is based on two digit SIC codes (United States) or Datastream level 1 industries (international markets). In (5), I compute traditional betas, i.e. I do not account for lagged market excess returns during the beta estimation process. In (6), betas are estimated from monthly returns over the previous 60 months. I require at least 24 valid return observations. In (7) and (8), I compute betas relative to the MSCI World and MSCI Global Investable Market Index, respectively. Betas are computed as in (6). All returns and the factors models are computed in USD. In (9) and (10), I condition on country months classified as MSCI developed markets and MSCI emerging markets or frontier markets, respectively. In (11) and (12), I condition on countries whose total one-month lagged market capitalization is larger or smaller than the mean country market capitalization in that month. In all specifications, standard errors are double-clustered by country and month. Two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

ID	Description	N	Equally weighted alphas		Value weighted alphas	
	Panel A: Modifications of return measurement					
(1)	US dollar-denominated returns	11,351	0.608***	(4.81)	0.453***	(3.54)
(2)	Local CAPM alpha	11,600	0.431***	(3.35)	0.347***	(2.73)
(3)	Three-factor model + reversal factors	10,822	0.520***	(4.58)	0.353***	(3.00)
	Panel B: Modifications of beta computation					
(4)	Industry-demeaned betas	11,419	0.420***	(4.08)	0.373***	(3.50)
(5)	Traditional beta from high frequency returns	11,419	0.580***	(4.66)	0.324***	(2.82)
(6)	Beta from monthly returns	10,939	0.468***	(4.36)	0.362***	(3.17)
(7)	Beta relative to MSCI World	10,981	0.395***	(3.56)	0.376***	(3.00)
(8)	Beta relative to MSCI ACWI	10,981	0.414***	(3.67)	0.399***	(3.14)
	Panel C: Modifications of country universe					
(9)	Developed stock markets	5,861	0.543***	(3.67)	0.436***	(3.28)
(10)	Emerging or frontier stock markets	5,550	0.472***	(3.21)	0.299*	(1.75)
(11)	Large stock markets	1,914	0.348*	(1.81)	0.444**	(2.36)
(12)	Small stock markets	9,505	0.541***	(4.49)	0.352***	(2.78)

Table 3: Beta and the market reaction to international earnings news

This table shows the main insights obtained from regressions aimed at testing for biased beliefs as a driver of the beta anomaly. The dependent variable in all regressions is the pooled firm-level abnormal earnings announcement return, defined as the buy-and-hold return during the event days t=-1, t=0, and t=+1 minus the expected buy-and-hold return as implied by a local Fama and French (1993) model. Abnormal returns are winsorized at the 0.5% level and at the 99.5% level. If the announcement falls on a non-trading day, the date is set to the next trading day. In all panels, t-statistics (in parentheses) are based on standard errors that are double-clustered by firm and date. Two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Specification	(1)	(2)	(3)	(4)	(5)
Region	World	Americas	Asia	Europe/Middle East	Pacific
Panel A: Abnormal returns around earnings announcements: Univariate results					
Beta quintile	-0.140***	-0.164***	-0.123***	-0.141***	-0.114***
	(-16.50)	(-10.39)	(-9.13)	(-11.11)	(-6.46)
Constant	0.486***	0.580***	0.318***	0.621***	0.360***
	(21.38)	(14.53)	(7.68)	(15.33)	(8.35)
N	1,087,615	453,382	218,604	202,537	213,092
Panel B: Abnormal returns around earnings announcements: Univariate results with country fixed effects					
Beta quintile	-0.142***	-0.165***	-0.122***	-0.144***	-0.115***
	(-16.63)	(-10.41)	(-9.07)	(-11.35)	(-6.48)
Panel C: Abnormal returns around earnings announcements: Multivariate results					
Beta quintile	-0.109***	-0.138***	-0.114***	-0.111***	-0.0591***
	(-13.01)	(-9.44)	(-7.71)	(-7.72)	(-3.44)
Maximum daily return quintile	-0.0955***	-0.121***	-0.0402***	-0.0961***	-0.0983***
	(-12.75)	(-9.08)	(-3.50)	(-6.82)	(-5.98)
Profitability quintile	0.0921***	0.140***	0.0538***	0.105***	0.0261**
	(13.01)	(10.93)	(4.75)	(7.69)	(2.00)
Coskewness quintile	-0.00713	-0.0172*	-0.001	-0.0222*	0.0126
	(-1.18)	(-1.69)	(-0.10)	(-1.70)	(0.99)
TED spread sensitivity quintile	-0.0206***	-0.0232*	-0.0259**	-0.0240*	-0.001
	(-3.02)	(-1.93)	(-2.18)	(-1.75)	(-0.04)
Financial sector leverage quintile	-0.0216***	-0.0301**	0.005	-0.002	-0.0561***
	(-2.95)	(-2.42)	(0.37)	(-0.15)	(-3.94)
Constant	0.543***	0.646***	0.313***	0.619***	0.537***
	(10.92)	(7.55)	(3.92)	(6.61)	(5.95)
N	936,568	409,339	185,213	157,095	184,921

Table 4: Beta and the market reaction to international dividend news

This table shows the main insights obtained from regressions aimed at testing for biased beliefs as a driver of the beta anomaly. The dependent variable in all regressions is the pooled firm-level abnormal dividend announcement return, defined as the buy-and-hold return during the event days t=-1, t=0, and t=+1 minus the expected buy-and-hold return as implied by a local Fama and French (1993) model. Abnormal returns are winsorized at the 0.5% level and at the 99.5% level. Dividend announcement dates that are also earnings announcement dates are excluded from the analysis. In all panels, t-statistics (in parentheses) are based on standard errors that are double-clustered by firm and date. Two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Specification	(1)	(2)	(3)	(4)	(5)
Region	World	Americas	Asia	Europe/Middle East	Pacific
Panel A: Abnormal returns around dividend announcements: Univariate results					
Beta quintile	-0.0547***	-0.0414***	-0.0900***	-0.146***	-0.0418
	(-6.51)	(-4.52)	(-4.87)	(-7.34)	(-1.64)
Constant	0.486***	0.333***	0.734***	1.026***	0.415***
	(21.26)	(12.93)	(12.38)	(16.05)	(6.17)
N	292,074	146,099	49,805	44,711	51,459
Panel B: Abnormal returns around dividend announcements: Univariate results with country fixed effects					
Beta	-0.0665***	-0.0440***	-0.0896***	-0.152***	-0.0211
	(-8.23)	(-4.80)	(-4.86)	(-7.56)	(-0.85)
Panel C: Abnormal returns around dividend announcements: Multivariate results					
Beta quintile	-0.0620***	-0.0482***	-0.0810***	-0.148***	-0.0281
	(-6.95)	(-4.78)	(-3.86)	(-5.99)	(-1.03)
Maximum daily return quintile	0.005	0.008	-0.031	-0.0405	-0.0494**
	(0.60)	(0.73)	(-1.52)	(-1.63)	(-2.04)
Profitability quintile	0.0498***	0.0218**	0.0597***	0.0636***	0.0320
	(6.59)	(2.42)	(2.94)	(2.74)	(1.45)
Coskewness quintile	-0.0207***	-0.0306***	-0.0155	0.001	0.010
	(-3.10)	(-3.98)	(-0.87)	(0.03)	(0.50)
TED spread sensitivity quintile	-0.0254***	-0.0154	-0.0347*	-0.0541**	-0.0178
	(-3.13)	(-1.49)	(-1.78)	(-2.35)	(-0.86)
Financial sector leverage quintile	0.008	-0.005	0.0109	0.0453*	-0.0127
	(0.89)	(-0.46)	(0.53)	(1.82)	(-0.55)
Constant	0.447***	0.415***	0.741***	0.979***	0.453***
	(9.21)	(7.27)	(5.41)	(6.28)	(3.08)
N	247,996	131,411	40,587	32,737	43,261

Table 5: Beta and the market reaction to further types of news in the U.S. stock market

This table shows the main insights obtained from regressions aimed at testing for biased beliefs as a driver of the beta anomaly in the U.S. stock market. The dependent variable in all regressions is the pooled firm-level abnormal news announcement return, defined as the buy-and-hold return during the event days t=-1, t=0, and t=+1 minus the expected buy-and-hold return as implied by a local Fama and French (1993) model. Abnormal returns are winsorized at the 0.5% level and at the 99.5% level. If the announcement falls on a non-trading day, the date is set to the next trading day. In all panels, t-statistics (in parentheses) are based on standard errors that are double-clustered by firm and date. Two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Specification	(1)	(2)	(3)	(4)
Type of news	10-K filings	8-K filings	Newspaper	Newswire
Sample period	1/1994-12/2014	1/1995-12/2011	01/1989-12/2010	01/1980-12/2000
Panel A: Abnormal returns around U.S. firm specific news: Univariate results				
Beta quintile	-0.172***	-0.108***	-0.0984***	-0.100***
	(-7.80)	(-8.55)	(-5.65)	(-5.31)
Constant	0.264***	0.365***	0.507***	0.698***
	(5.37)	(10.28)	(9.03)	(12.60)
N	361,965	516,931	348,072	486,540
Panel B: Abnormal returns around U.S. firm specific news: Multivariate results				
Beta quintile	-0.126***	-0.0906***	-0.125***	-0.119***
	(-7.02)	(-7.23)	(-7.75)	(-5.99)
Maximum daily return quintile	-0.146***	-0.0477***	0.107***	0.165***
	(-8.34)	(-4.15)	(6.88)	(7.69)
Profitability quintile	0.0643***	0.0850***	-0.0107	-0.0243
	(5.18)	(7.52)	(-0.85)	(-1.51)
Coskewness quintile	0.0069	-0.0433***	-0.0338***	-0.0203
	(0.73)	(-4.61)	(-3.43)	(-1.52)
TED spread sensitivity quintile	-0.0054	-0.00369	-0.0202	-0.0213
	(-0.44)	(-0.32)	(-1.52)	(-1.25)
Financial sector leverage quintile	-0.0099	-0.0276**	-0.0551***	-0.0050
	(-0.74)	(-2.29)	(-3.83)	(-0.29)
Constant	0.420***	0.444***	0.715***	0.559***
	(4.67)	(6.05)	(6.91)	(4.31)
N	333,344	481,662	331,069	358,964

Table 6: Beta and a composite mispricing factor

The table shows the main insights from regressions aimed at testing whether the beta anomaly is subsumed by a composite country-specific mispricing factor, computed as in Stambaugh et al. (2015). In Panel A, I rely on the country-specific time series of a zero-cost portfolio that buys (sells) the 20% stocks with the lowest (highest) historical beta relative to the country excess return. I regress this time series on local Fama and French (1993) factors and a local mispricing factor. T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels B and C, the time-series of country-specific abnormal returns, defined as the intercept plus the fitted value of the residual, are pooled. Panels D and E mirror the approach in Panels B and C, but augment the model with country-specific versions of a maximum daily return factor, a TED spread sensitivity factor, a financial sector leverage factor, a profitability factor, and a coskewness factor. In Panels B to E, t-statistics (in parentheses) are based on standard errors that are double-clustered by country and month. In the case of equally weighted (value weighted) beta portfolio returns, the firms entering the mispricing factor as well as the control factors are equally weighted (value weighted) as well. In all panels, two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Country-by-country results										
Country	N	Mispricing factor	t-stat	Alpha	t-stat	Mispricing factor	t-stat	Alpha	t-stat
		Equally weighted portfolio returns				Value-weighted portfolio returns			
Argentina	137	0.345***	(2.73)	0.333	(0.61)	-0.070	(-1.17)	-0.297	(-0.63)
Australia	288	0.401***	(6.70)	0.016	(0.08)	0.313***	(4.76)	0.295	(0.93)
Austria	277	0.301***	(5.06)	0.297	(1.05)	0.039	(0.80)	0.343	(1.22)
Belgium	288	0.252**	(2.21)	-0.306	(-1.14)	0.104*	(1.72)	0.123	(0.48)
Brazil	190	0.268	(1.06)	0.287	(0.36)	0.001	(0.01)	-0.824	(-1.35)
Bulgaria	78	0.402	(1.43)	-0.407	(-0.32)	-0.214	(-1.49)	0.746	(0.42)
Canada	288	0.332***	(4.01)	0.640**	(2.16)	0.209**	(2.32)	0.505	(1.31)
Chile	246	0.086	(0.69)	0.299	(1.10)	0.097	(1.20)	-0.192	(-0.54)
China	222	0.250**	(2.06)	0.595**	(2.33)	0.084	(0.87)	1.134***	(3.29)
Denmark	288	0.224***	(3.31)	0.001	(0.00)	0.070	(1.15)	0.397	(1.46)
Emirates	78	0.389**	(2.57)	1.576**	(2.52)	0.165	(0.84)	0.289	(0.35)
Egypt	113	0.342**	(1.98)	1.635**	(2.57)	0.325*	(1.97)	1.382	(1.60)
Finland	222	0.369***	(3.75)	0.391	(1.20)	-0.065	(-1.31)	0.642**	(1.98)
France	288	0.842***	(12.44)	-0.409*	(-1.89)	0.358***	(5.84)	0.177	(0.65)
Germany	288	0.662***	(9.05)	-0.307	(-1.44)	0.337**	(2.11)	0.243	(0.62)
Greece	250	0.442***	(3.58)	0.115	(0.23)	0.306***	(3.14)	0.726	(1.34)
Hongkong	284	0.438**	(2.51)	1.240***	(3.07)	0.314**	(2.30)	0.844*	(1.93)
India	234	0.439***	(5.07)	-0.143	(-0.44)	0.270***	(2.90)	0.557	(1.24)
Indonesia	246	0.282***	(3.29)	-0.513	(-1.18)	0.158	(0.97)	-0.122	(-0.19)
Israel	183	0.222**	(2.58)	-0.015	(-0.05)	0.066	(0.71)	-0.277	(-0.62)
Italy	288	0.436***	(4.15)	0.0987	(0.37)	0.282***	(4.78)	0.600**	(2.31)

[continued overleaf]

Country	N	Mispricing factor	t-stat	Alpha	t-stat	Mispricing factor	t-stat	Alpha	t-stat
		Equally weighted portfolio returns				Value-weighted portfolio returns			
Japan	288	0.789***	(12.33)	-0.346**	(-2.09)	0.353***	(4.26)	-0.243	(-0.90)
Jordan	78	-0.058	(-0.52)	-1.466***	(-3.01)	-0.073	(-0.95)	-0.703	(-1.62)
Korea	284	0.811***	(7.85)	0.253	(0.55)	0.506***	(3.50)	1.016*	(1.72)
Kuwait	92	0.250***	(3.48)	0.822**	(2.10)	0.073	(0.81)	0.207	(0.34)
Malaysia	288	0.617***	(9.53)	-0.002	(-0.01)	0.408***	(5.12)	0.436*	(1.72)
Mexico	246	0.161	(1.22)	0.05	(0.15)	0.123**	(2.03)	-0.0138	(-0.04)
Morocco	85	-0.205	(-1.32)	0.495	(0.97)	0.102	(0.96)	-0.106	(-0.24)
Netherlands	288	0.413***	(4.78)	0.217	(0.80)	0.263***	(3.42)	0.079	(0.23)
New Zealand	195	0.0590	(0.79)	0.687*	(1.91)	0.175**	(2.32)	0.424	(1.33)
Norway	268	0.198*	(1.96)	-0.582	(-1.45)	0.0835	(1.12)	-0.289	(-0.72)
Oman	78	0.074	(0.54)	1.921***	(2.87)	0.226	(1.03)	0.800	(1.26)
Pakistan	215	0.220***	(3.17)	0.248	(0.67)	0.065	(1.12)	0.200	(0.54)
Philippines	234	0.258***	(3.03)	0.809*	(1.85)	0.127	(1.30)	0.543	(1.25)
Poland	184	0.296***	(3.32)	-0.721*	(-1.91)	0.199**	(2.49)	-0.267	(-0.59)
Portugal	140	0.237**	(2.29)	0.444	(0.76)	-0.178*	(-1.96)	0.675	(1.01)
Romania	80	-0.297*	(-1.72)	-1.139	(-1.21)	-0.155	(-1.07)	-1.386	(-1.38)
Russia	102	0.177	(0.93)	1.273**	(2.03)	0.0772	(0.34)	0.754	(0.73)
Singapore	288	0.338***	(4.54)	0.332	(1.39)	0.165*	(1.89)	0.392	(1.05)
South Africa	288	-0.148**	(-2.13)	1.298***	(4.42)	-0.115	(-1.61)	0.763**	(2.48)
Spain	288	0.240***	(3.18)	0.588**	(2.32)	0.302**	(2.45)	0.088	(0.31)
Sri Lanka	93	0.445*	(1.94)	0.334	(0.50)	0.034	(0.19)	0.915	(1.05)
Sweden	288	0.448***	(4.29)	0.110	(0.31)	0.175*	(1.93)	0.305	(0.64)
Switzerland	288	0.409***	(4.03)	-0.190	(-0.74)	0.300***	(6.25)	0.310	(1.50)
Taiwan	234	0.260**	(1.98)	-0.022	(-0.06)	0.262**	(2.38)	0.021	(0.05)
Thailand	257	0.570***	(5.96)	0.163	(0.46)	0.183**	(2.32)	0.299	(0.87)
Turkey	236	0.176*	(1.76)	-0.302	(-0.74)	0.203**	(2.16)	-0.617	(-1.13)
United Kingdom	288	0.544***	(5.97)	-0.923***	(-4.05)	0.383***	(4.40)	-0.083	(-0.31)
United States	288	0.780***	(7.29)	-0.396	(-1.60)	0.641***	(6.18)	-0.075	(-0.26)
Vietnam	68	0.823***	(4.89)	-1.334	(-1.54)	0.559	(1.51)	0.754	(0.50)
Panel B: Alphas, pooled data, equally weighted portfolio returns (N=10,825)									
FF3 + Mispricing	long	0.086	(1.37)	short	-0.045	(-0.64)	long-short	0.131	(1.19)
Matched FF3	long	0.144**	(2.24)	short	-0.398***	(-5.08)	long-short	0.542***	(4.56)
Panel C: Alphas, pooled data, value weighted portfolio returns (N=10,825)									
FF3 + Mispricing	long	0.069	(1.28)	short	-0.186***	(-2.96)	long-short	0.255**	(2.42)
Matched FF3	long	0.104*	(1.79)	short	-0.316***	(-4.28)	longs-short	0.420***	(3.49)
Panel D: Alphas, pooled data, equally weighted portfolio returns (N=10,649)									
FF3 + Controls + Mispricing	long	0.104*	(1.74)	short	0.008	(0.15)	long-short	0.095	(1.05)
Matched FF3 + Controls	long	0.119**	(1.96)	short	-0.139**	(-2.42)	long-short	0.258***	(2.61)
Panel E: Alphas, pooled data, value weighted portfolio returns (N=10,649)									
FF3 Controls + Mispricing	long	0.06	(1.31)	short	-0.133***	(-2.63)	long-short	0.195**	(2.26)
Matched FF3 + Controls	long	0.08	(1.63)	short	-0.198***	(-3.45)	long-short	0.280***	(2.92)

Table 7: Beta and market states

The table shows the main insights from regressions aimed at testing whether the beta anomaly is stronger in up market states, defined as the lagged three-year value-weighted country market return being positive, than in down market states. In Panel A, I regress the time-series of abnormal returns (defined as in Table 1) on two dummies for up markets and down markets (without a constant). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels B and C, the time-series of country-specific abnormal returns, defined as the intercept plus the fitted value of the residual, are pooled. Panels D and E mirror the approach in Panels B and C, but use the portion of beta that is orthogonal to the maximum daily return in the previous month, profitability, the sensitivity to the TED spread and financial sector leverage, as well as coskewness. In Panels B to E, t-statistics (in parentheses) are based on standard errors that are double-clustered by country and month. In all panels, two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Alphas, country-by-country results

Country	N	Up market	t-stat	Down market	t-stat	Up market	t-stat	Down market	t-stat
		Equally weighted portfolio returns				Value-weighted portfolio returns			
Australia	288	0.748***	(3.25)	-2.299***	(-3.48)	0.781**	(2.43)	-2.095*	(-1.80)
Austria	277	0.501	(1.53)	1.068**	(2.03)	0.150	(0.56)	0.791	(1.45)
Belgium	288	0.273	(1.13)	-0.583	(-1.15)	0.125	(0.41)	0.485	(0.98)
Brazil	194	0.783	(0.93)	0.042	(0.05)	-0.535	(-0.67)	-1.736	(-1.02)
Canada	288	1.264***	(4.05)	-2.749***	(-4.55)	0.936**	(2.55)	-2.474	(-1.51)
Chile	257	0.379	(1.28)	-1.136	(-1.28)	0.028	(0.07)	-1.517**	(-2.15)
China	220	0.878**	(2.22)	0.478	(1.08)	1.486***	(2.90)	0.627	(1.28)
Denmark	288	0.627***	(2.69)	-0.725	(-1.37)	0.607**	(2.25)	0.137	(0.19)
Emirates	84	2.530**	(2.11)	0.631	(1.11)	1.573	(1.18)	-1.055	(-1.01)
Egypt	170	2.499***	(3.11)	-0.936	(-1.22)	1.191	(1.34)	-1.890	(-1.53)
Finland	222	1.441***	(3.41)	-0.120	(-0.25)	0.295	(0.84)	1.009*	(1.86)
France	288	1.110***	(4.26)	-0.425	(-0.68)	0.871***	(2.71)	-0.262	(-0.56)
Germany	288	0.655**	(2.43)	0.119	(0.24)	0.681	(1.47)	-0.250	(-0.33)
Greece	274	1.343**	(2.19)	-0.846	(-1.46)	1.133	(1.55)	0.200	(0.26)
Hongkong	288	1.461***	(2.97)	0.564	(0.69)	1.037**	(2.00)	1.135	(1.31)
India	251	1.130***	(2.87)	-2.461***	(-4.44)	1.490***	(2.95)	-1.793**	(-2.20)
Indonesia	248	0.413	(0.95)	-1.652	(-1.52)	0.351	(0.56)	-0.264	(-0.18)
Israel	232	0.277	(0.85)	-0.299	(-0.56)	-0.093	(-0.20)	1.219	(1.29)
Italy	288	0.807**	(2.58)	0.140	(0.40)	0.903**	(2.47)	0.565	(1.49)
Japan	288	0.565**	(2.07)	-0.773***	(-2.78)	0.688*	(1.73)	-0.789**	(-2.25)
Jordan	62	-1.814**	(-2.48)	-0.805	(-1.27)	0.710	(0.86)	-1.075**	(-2.51)
Korea	288	1.398***	(2.70)	0.600	(0.51)	2.117***	(3.17)	0.237	(0.22)

[continued overleaf]

Country	N	Up market	t-stat	Down market	t-stat	Up market	t-stat	Down market	t-stat
		Equally weighted portfolio returns				Value-weighted portfolio returns			
Kuwait	84	2.675***	(4.19)	0.117	(0.24)	2.192**	(2.17)	-0.699	(-0.95)
Malaysia	288	0.795***	(3.21)	0.136	(0.21)	1.077***	(3.89)	0.143	(0.19)
Mexico	253	0.113	(0.34)	1.464	(0.92)	0.014	(0.05)	0.0659	(0.02)
Morocco	85	0.955*	(1.77)	-2.348***	(-3.08)	0.388	(0.82)	-2.459**	(-2.36)
Netherlands	288	0.638**	(2.16)	1.178**	(2.14)	0.077	(0.17)	0.175	(0.26)
New Zealand	231	0.735**	(2.17)	0.307	(0.45)	0.518	(1.46)	0.575	(0.70)
Norway	268	-0.128	(-0.35)	-0.552	(-0.59)	0.487	(1.14)	-2.061**	(-2.29)
Oman	62	1.305*	(1.86)	1.382	(1.57)	0.379	(0.64)	0.846	(1.21)
Pakistan	221	1.171***	(2.88)	-0.963	(-1.29)	0.843*	(1.68)	-0.958	(-1.50)
Philippines	252	1.895***	(3.94)	-0.455	(-0.50)	1.293***	(2.64)	-0.561	(-0.70)
Poland	181	-0.144	(-0.39)	-0.892	(-1.09)	0.481	(1.01)	-1.465	(-1.56)
Portugal	145	1.553***	(2.91)	0.0611	(0.05)	0.989	(1.32)	-0.840	(-0.73)
Romania	90	-0.245	(-0.21)	-2.212*	(-1.70)	-1.196	(-1.25)	-0.635	(-0.42)
Russia	126	1.425*	(1.77)	-1.697	(-1.30)	0.970	(1.00)	-1.061	(-0.50)
Singapore	288	0.897***	(3.83)	-0.680	(-0.96)	1.193***	(3.24)	-2.172**	(-2.25)
South Africa	288	1.204***	(4.26)	0.101	(0.04)	0.735**	(2.25)	1.188	(0.91)
Spain	285	1.255***	(4.31)	0.007	(0.02)	0.601*	(1.84)	-0.139	(-0.24)
Sri Lanka	106	1.188**	(2.17)	-3.979	(-1.54)	1.348**	(2.07)	-3.596*	(-1.68)
Sweden	288	1.420***	(3.94)	-0.580	(-0.78)	1.081***	(2.74)	-0.999	(-0.77)
Switzerland	288	0.581***	(2.66)	-0.133	(-0.24)	0.488**	(2.10)	0.825*	(1.70)
Taiwan	258	0.393	(1.17)	-0.347	(-0.45)	0.595	(1.47)	-1.098	(-1.50)
Thailand	282	1.425***	(3.66)	-0.937	(-0.98)	0.984**	(2.41)	-1.219	(-1.63)
Turkey	275	-0.476	(-1.02)	-1.737***	(-2.79)	-1.442**	(-2.37)	-1.831	(-1.10)
United Kingdom	288	0.351*	(1.85)	-0.796	(-1.55)	0.292	(0.96)	0.213	(0.28)
United States	288	0.670***	(2.72)	0.464	(0.67)	0.627**	(2.01)	0.494	(0.73)
Panel B: Alphas, pooled data, EW returns, no further controls, down vs. up market (N=2,866 vs. N=8,194)									
	Down	-0.410*	(-1.86)	Up	0.824***	(6.99)	Diff	1.233***	(5.63)
Panel C: Alphas, pooled data, VW returns, no further controls, down vs. up market (N=2,866 vs. N=8,194)									
	Down	-0.392*	(-1.69)	Up	0.610***	(4.59)	Diff	1.002***	(4.02)
Panel D: Alphas, pooled data, EW returns, with controls, down vs. up market (N=2,295 vs. N=6,551)									
Full set of controls	Down	-0.205	(-1.13)	Up	0.803***	(7.75)	Diff	1.008***	(5.23)
Matched univariate	Down	-0.359	(-1.50)	Up	0.942***	(7.77)	Diff	1.301***	(5.50)
Panel E: Alphas, pooled data, VW returns, with controls, down vs. up market (N=2,295 vs. N=6,551)									
Full set of controls	Down	-0.202	(-1.05)	Up	0.590***	(5.20)	Diff	0.792***	(3.66)
Matched univariate	Down	-0.301	(-1.18)	Up	0.764***	(5.61)	Diff	1.065***	(3.88)

Table 8: Beta and consumer confidence

The table shows the main insights from regressions aimed at testing whether the beta anomaly is stronger following high than low sentiment as proxied for by country-specific consumer confidence indices. High (low) sentiment periods are defined as the one-quarter lagged sentiment index being higher than (lower than or equal to) the median value. In Panel A, I regress the time-series of abnormal returns (defined as in Table 1) on two dummies for positive and negative sentiment (without a constant). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels B and C, the time-series of country-specific abnormal returns, defined as the intercept plus the fitted value of the residual, are pooled. Panels D and E mirror the approach in Panels B and C, but use the portion of beta that is orthogonal to the maximum daily return in the previous month, profitability, the sensitivity to TED spread and financial sector leverage, as well as coskewness. In Panels B to E, t-statistics (in parentheses) are based on standard errors that are double-clustered by country and month. In all panels, two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Alphas, Country-by-country results

Country	N	High sentiment	t-stat	Low sentiment	t-stat	High sentiment	t-stat	Low sentiment	t-stat
		Equally weighted portfolio returns				Value weighted portfolio returns			
Argentina	128	0.796	(0.99)	1.002	(1.19)	-0.567	(-0.79)	0.079	(0.11)
Australia	288	0.479*	(1.88)	0.510	(1.38)	0.445	(1.29)	0.637	(1.21)
Austria	216	1.533***	(3.23)	0.014	(0.03)	0.868**	(2.25)	-0.203	(-0.55)
Belgium	288	-0.04	(-0.12)	0.047	(0.14)	-0.038	(-0.10)	0.491	(1.35)
Brazil	194	3.212***	(2.77)	-1.822**	(-2.31)	0.292	(0.22)	-1.712***	(-2.73)
Bulgaria	82	1.772	(1.06)	-1.085	(-0.73)	0.206	(0.09)	1.370	(0.60)
Chile	153	0.762	(1.58)	0.317	(0.64)	0.789	(1.48)	0.186	(0.53)
China	234	0.568	(1.31)	0.726*	(1.96)	1.212**	(2.30)	1.017**	(2.09)
Denmark	288	0.934***	(3.43)	-0.275	(-0.82)	0.812**	(2.37)	0.199	(0.49)
Finland	216	1.403***	(3.05)	0.505	(1.06)	0.577	(1.43)	0.608	(1.34)
France	288	0.682*	(1.69)	0.856***	(2.92)	0.532	(1.16)	0.706**	(2.44)
Germany	288	0.569	(1.60)	0.462	(1.47)	0.502	(1.03)	0.376	(0.60)
Greece	283	1.115	(1.59)	0.316	(0.58)	1.444*	(1.70)	0.796	(1.07)
Hongkong	165	2.125***	(3.62)	0.676	(1.06)	0.853	(1.46)	0.581	(0.80)
Indonesia	159	1.350***	(3.31)	0.138	(0.21)	0.596	(0.86)	0.592	(0.69)

[continued overleaf]

Country	N	High sentiment	t-stat	Low sentiment	t-stat	High sentiment	t-stat	Low sentiment	t-stat
		Equally weighted portfolio returns				Value weighted portfolio returns			
Italy	288	0.941**	(2.56)	0.113	(0.39)	1.006**	(2.26)	0.516*	(1.81)
Japan	288	-0.258	(-0.90)	-0.139	(-0.49)	0.097	(0.27)	-0.393	(-1.00)
Korea	63	0.762**	(2.04)	0.004	(0.01)	0.385	(0.67)	1.467	(1.53)
Mexico	150	0.852*	(1.75)	1.450**	(2.40)	0.947*	(1.80)	0.379	(0.78)
Netherlands	288	0.990***	(2.67)	0.572	(1.55)	0.279	(0.49)	-0.067	(-0.14)
New Zealand	231	0.398	(0.94)	0.888**	(2.04)	0.119	(0.24)	0.929**	(2.10)
Norway	254	0.062	(0.16)	-0.121	(-0.20)	0.290	(0.65)	-0.228	(-0.35)
Philippines	81	2.141***	(2.72)	0.270	(0.25)	0.430	(0.40)	-0.065	(-0.06)
Portugal	149	2.087***	(3.07)	0.05	(0.07)	0.464	(0.46)	0.105	(0.14)
Romania	90	-0.884	(-0.63)	-1.224	(-1.12)	-1.355	(-1.01)	-0.576	(-0.58)
Russia	126	0.634	(0.62)	0.721	(0.75)	0.350	(0.26)	0.598	(0.50)
Spain	288	1.549***	(4.15)	0.014	(0.05)	0.894**	(2.23)	-0.349	(-0.82)
Sweden	249	1.743***	(3.34)	1.178**	(2.57)	0.730	(0.97)	1.215**	(2.02)
Switzerland	288	0.608**	(2.18)	0.172	(0.51)	0.465	(1.50)	0.692**	(2.34)
Turkey	282	0.044	(0.09)	-0.977	(-1.28)	-0.173	(-0.31)	-2.564**	(-2.55)
United Kingdom	288	0.478*	(1.89)	-0.214	(-0.80)	0.571	(1.45)	-0.017	(-0.04)
United States	288	0.725*	(1.91)	0.535*	(1.83)	0.669	(1.60)	0.532	(1.39)
Panel B: Alphas, pooled data, EW returns, no further controls, low vs. high sentiment (N=3,533 vs. N=3,428)									
	Low	0.205	(1.14)	High	0.868***	(5.05)	Diff	0.664***	(2.92)
Panel C: Alphas, pooled data, VW returns, no further controls, low vs. high sentiment (N=3,533 vs. N=3,428)									
	Low	0.208	(1.01)	High	0.514***	(3.91)	Diff	0.307	(1.59)
Panel D: Alphas, pooled data, EW returns, with controls, low vs. high sentiment (N=2,890 vs. N=2,872)									
Full set of controls	Low	0.307**	(2.32)	High	0.787***	(4.01)	Diff	0.481**	(2.10)
Matched univariate	Low	0.244	(1.35)	High	0.857***	(4.64)	Diff	0.613***	(2.73)
Panel E: Alphas, pooled data, VW returns, with controls, low vs. high sentiment (N=2,890 vs. N=2,872)									
Full set of controls	Low	0.245**	(1.97)	High	0.427***	(3.11)	Diff	0.182	(1.29)
Matched univariate	Low	0.318*	(1.70)	High	0.522***	(3.92)	Diff	0.204	(1.16)

Table 9: Beta and residual turnover

The table shows the main insights from regressions aimed at testing whether the beta anomaly is stronger among stocks with high residual turnover than among stocks with low residual turnover. I rely on the residual from a cross-sectional regression of logarithmized monthly stock-level turnover on the two spread measures proposed in Corwin and Schultz (2012) as well as in Chung and Zhang (2014), on lagged logarithmized market capitalization, and on lagged inverse stock price. All explanatory variables are winsorized at the 99% level. High (low) residual turnover stocks are defined as the average residual in the previous twelve months being larger (smaller) than the median in the country under consideration. I then compute the beta anomaly separately for both cross-sectional samples. Panel A shows the resulting monthly alphas on a country-by-country basis. T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels B and C, the time-series of country-specific abnormal returns, defined as the intercept plus the fitted value of the residual, are pooled. In Panels B and C, t-statistics (in parentheses) are based on standard errors that are double-clustered by country and month. In all panels, two-tailed statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Alphas, country-by-country results

Country	N	High turn.	t-stat	Low turn.	t-stat	High turn.	t-stat	Low turn.	t-stat
		Equally weighted portfolio returns				Value-weighted portfolio returns			
Argentina	201	0.043	(0.07)	0.447	(0.78)	-0.252	(-0.33)	0.335	(0.47)
Australia	288	0.888***	(3.22)	0.242	(1.03)	0.718*	(1.78)	0.858**	(2.57)
Austria	277	1.163***	(3.20)	0.481	(1.19)	0.666*	(1.95)	0.193	(0.55)
Belgium	227	0.100	(0.27)	0.135	(0.44)	-0.040	(-0.09)	-0.398	(-0.90)
Brazil	177	0.435	(0.65)	0.388	(0.46)	0.035	(0.05)	0.083	(0.09)
Canada	288	1.296***	(3.43)	0.722*	(1.94)	1.069**	(2.25)	0.707*	(1.69)
Chile	282	0.842**	(2.55)	0.460	(1.49)	0.726*	(1.97)	0.578*	(1.65)
China	234	0.884***	(3.23)	0.126	(0.44)	1.546***	(4.24)	0.645*	(1.93)
Denmark	288	0.631**	(1.99)	0.062	(0.24)	0.516	(1.30)	-0.077	(-0.21)
Emirates	87	2.440***	(3.10)	0.803	(1.10)	2.302***	(2.73)	-0.668	(-1.11)
Egypt	173	0.179	(0.28)	0.694	(1.09)	-0.547	(-0.67)	0.283	(0.30)
Finland	201	0.882*	(1.83)	0.009	(0.02)	-0.070	(-0.15)	-0.029	(-0.07)
France	267	1.081***	(3.30)	0.235	(1.06)	1.124***	(2.93)	0.466	(1.43)
Germany	211	0.600	(1.56)	0.440	(1.16)	0.029	(0.05)	-0.351	(-0.74)
Greece	283	0.630	(1.20)	0.247	(0.49)	1.138*	(1.77)	0.792	(1.43)
Hongkong	288	1.479***	(3.00)	1.096**	(2.44)	2.086***	(3.21)	0.812	(1.51)
India	227	0.618	(1.45)	0.154	(0.51)	0.597	(1.20)	0.334	(0.64)
Indonesia	261	0.398	(0.82)	-0.317	(-0.72)	0.791	(1.13)	-0.419	(-0.85)
Israel	232	0.950***	(2.73)	-0.621*	(-1.80)	0.816*	(1.72)	-0.245	(-0.53)

[continued overleaf]

Country	N	High turn.	t-stat	Low turn.	t-stat	High turn.	t-stat	Low turn.	t-stat
		Equally weighted portfolio returns				Value-weighted portfolio returns			
Italy	238	1.002***	(2.83)	0.232	(0.94)	1.139***	(2.95)	0.603*	(1.92)
Japan	285	-0.082	(-0.32)	-0.329*	(-1.81)	0.142	(0.42)	-0.182	(-0.60)
Jordan	87	-0.241	(-0.32)	-1.716***	(-4.02)	0.416	(0.57)	-1.604***	(-3.03)
Korea	288	1.130*	(1.69)	0.387	(0.74)	1.640**	(2.18)	1.332*	(1.75)
Kuwait	96	1.653***	(2.81)	0.057	(0.11)	0.813	(0.96)	-0.240	(-0.38)
Malaysia	288	0.712***	(2.62)	0.147	(0.67)	1.085***	(3.45)	0.474*	(1.92)
Mexico	253	0.408	(0.88)	0.033	(0.09)	-0.337	(-0.74)	0.132	(0.34)
Morocco	85	-0.053	(-0.10)	0.718	(1.01)	-0.999	(-1.37)	-0.064	(-0.11)
Netherlands	288	1.086***	(3.16)	0.371	(1.20)	0.895*	(1.86)	0.258	(0.61)
New Zealand	231	0.955**	(2.12)	0.089	(0.24)	0.443	(0.93)	0.478	(1.07)
Norway	268	-0.317	(-0.64)	-0.183	(-0.46)	0.415	(0.71)	-0.547	(-1.29)
Oman	87	3.139***	(4.22)	1.510***	(2.75)	2.378***	(3.00)	1.140**	(2.15)
Pakistan	246	1.227***	(2.88)	-0.122	(-0.27)	0.923*	(1.94)	0.081	(0.14)
Philippines	249	0.840	(1.38)	1.415**	(2.32)	1.959***	(2.88)	0.923	(1.44)
Poland	185	0.228	(0.45)	-0.583	(-1.40)	1.199**	(2.25)	0.018	(0.03)
Portugal	110	0.992	(1.41)	0.768	(1.08)	-0.059	(-0.05)	1.813	(1.66)
Romania	90	-0.706	(-0.60)	-1.039	(-0.83)	0.042	(0.03)	-2.531**	(-2.37)
Russia	119	1.218*	(1.95)	0.491	(0.71)	-0.199	(-0.26)	-0.045	(-0.04)
Singapore	288	0.661**	(2.08)	0.419	(1.63)	1.251***	(3.09)	0.410	(1.04)
South Africa	285	1.220***	(3.22)	0.792***	(2.65)	0.687	(1.58)	0.619	(1.53)
Spain	281	1.190***	(3.41)	0.553*	(1.89)	1.217***	(3.15)	0.360	(0.96)
Sri Lanka	116	0.618	(1.19)	0.617	(0.73)	1.329**	(2.07)	0.317	(0.31)
Sweden	288	1.247***	(2.72)	0.602**	(2.04)	0.716	(1.29)	0.582	(1.60)
Switzerland	282	0.945***	(3.22)	0.027	(0.13)	0.789**	(2.28)	0.185	(0.71)
Taiwan	258	-0.074	(-0.20)	0.027	(0.10)	-0.131	(-0.31)	-0.091	(-0.27)
Thailand	282	1.232***	(2.95)	0.432	(1.37)	1.631***	(3.61)	-0.161	(-0.47)
Turkey	282	-0.897*	(-1.68)	0.052	(0.09)	-1.080	(-1.58)	0.066	(0.08)
United Kingdom	288	0.46**	(2.00)	-0.204	(-1.14)	0.534	(1.56)	0.133	(0.43)
United States	285	0.659**	(2.28)	0.358**	(2.18)	1.010***	(2.94)	0.564**	(2.43)
Vietnam	68	-2.243*	(-1.71)	-0.435	(-0.53)	-1.505	(-1.20)	0.932	(0.48)
Panel B: Pooled data, equally weighted portfolio returns, N=10,988									
Long leg	High	0.187***	(2.83)	Low	0.159**	(2.03)	Diff	0.0278	(0.36)
Short leg	High	-0.527***	(-5.25)	Low	-0.090	(-1.63)	Diff	-0.436***	(-5.25)
Long-short	High	0.714***	(5.17)	Low	0.250***	(2.82)	Diff	0.464***	(5.06)
Panel B: Pooled data, value weighted portfolio returns, N=10,988									
Long leg	High	0.282***	(4.72)	Low	0.109	(1.54)	Diff	0.172***	(3.02)
Short leg	High	-0.426***	(-4.19)	Low	-0.153***	(-3.74)	Diff	-0.273***	(-3.07)
Long-short	High	0.708***	(4.64)	Low	0.263***	(2.88)	Diff	0.445***	(4.03)