ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF Vol. 13, No. 1, 143–158, 2017

THE LOW-RISK ANOMALY: EVIDENCE FROM THE THAI STOCK MARKET

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ABSTRACT

In many developed countries, low-risk stocks tend to earn superior risk-adjusted returns compared to high-risk stock. Using data on the Stock Exchange of Thailand between 2004 and 2015, this paper shows that the abnormal returns associated with investing in low-beta stocks are significant and robust. The zero-cost portfolio that longs low-beta stocks and shorts high-beta stocks delivers monthly four-factor alpha of 1.26%. This paper provides suggestive evidence that, in addition to leverage constraints, the low-risk anomaly can be caused by institutional designs that favour stocks that are index constituents.

Keywords: beta, Capital Asset Pricing Model (CAPM), leverage constraints, benchmarking, index inclusion

INTRODUCTION

Asset pricing theory suggests that investors should not be able to earn abnormal returns in excess of the "fair" compensation they receive for the risks they take on. Such systematic abnormal excess returns have come to be known as returns "anomalies", and are often linked to firm characteristics such as size, growth opportunities, past returns, investments, profitability (e.g., Fama & French (1993); Jegadeesh & Titman (1993); Novy-Marx (2013); Titman, Wei, & Xie (2013)) or

Publication date: 30 August 2017

To cite this article: Saengchote, K. (2017). The low-risk anomaly: Evidence from the Thai stock market. *Asian Academy of Management Journal of Accounting and Finance, 13*(1), 143–158. https://doi.org/10.21315/aamjaf2017.13.1.6

To link to this article: https://doi.org/10.21315/aamjaf2017.13.1.6

market conditions (e.g., Pástor & Stambaugh (2003); Ang, Hodrick, Xing Zhang (2006)). The relationship between such anomalies and identifiable characteristics allow us to gain better understanding of risk determinants, as well as form profitable trading strategies.[1] However, one class of anomaly that is of particular interest is the "low-risk" anomaly, where assets with low risk (e.g. beta or idiosyncratic volatility) seem to outperform assets with high risk. Consider Figure 1, where average Sharpe-Lintner betas of stocks listed in the Stock Exchange of Thailand between January 2004 and December 2015 are plotted against their excess returns. In the Capital Asset Pricing Model that is often taught in finance classes, the relationship between systematic risk and returns is positive, but the figure reveals an opposite picture. In other words, high-risk assets are overpriced, and low-risk assets are underpriced.[2]

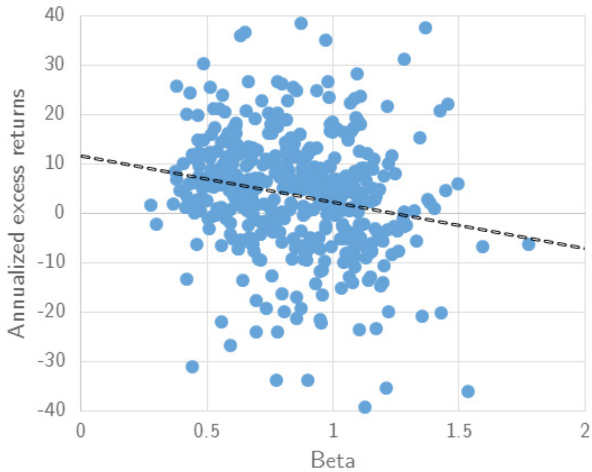

Figure 1. Relationship between stock beta and annualised excess returns. This scatter diagram plots the average excess returns for each stock in the Stock Exchange of Thailand against the calculated Sharpe-Lintner beta over the period of January 2004 to December 2015. Excess returns are calculated as the monthly return minus the one-month Thai Treasury bill rate, annualised and presented as percentage points. To be included in the sample, stocks must have at least 60 months of returns, leaving 453 unique stocks in total. An ordinary least squares regression is fitted to the data points and the resulting best-fit line is plotted as the dotted line in the diagram.

The fact that stocks with low risk seem to earn better returns is appealing for asset managers; after all, this is opposite of the "high-risk, high-return" mantra that is the fundamental principle of finance. There are several candidate theories that seek to explain this anomaly: some rely on behavioral biases and sentiments that affect retail investors (e.g. Barberis & Huang (2008), Kumar (2009), and Antoniou, Doukas & Subrahmanyam (2015)), some on limits to arbitrage through leverage constraints that are binding even for some institutional investors (e.g. Black (1972) and Frazzini & Pedersen (2014)), or a combination of both (e.g. Hong & Sraer (2016)).

The objective of this paper is to document the low-risk anomaly in Thailand and understand the forces that drive the abnormal returns so as to provide insights into if and how market participants can benefit from this anomaly. Consistent with evidence found in developed markets, Thai stocks with low beta also exhibit positive abnormal returns while high-beta stocks exhibit negative abnormal returns over the 12-year period of 2004 to 2015. The zero-cost portfolio that longs low-beta stocks and shorts high-beta stocks delivers monthly four-factor alpha of 1.26%, a very significant amount even after taking into account trading costs. The evidence on the nature and timing of low-beta returns do not fully support the leading explanations that are proposed for developed markets. Using stock trade data from the Stock of Exchange of Thailand between 2004 and 2008 that classifies investors by type, this paper shows that investors tend to be more active in high-beta stocks, particularly non-retail investors. High-beta stocks in Thailand tend to have larger market capitalisation and are more likely to be index constituents. As mutual funds tend to be evaluated based on index-based returns benchmark, this finding is consistent with Baker, Bradley and Wurgler (2011) who argue that the low-beta anomaly is driven by such benchmarking. Moreover, stocks that are included in indices tend to be in higher demand (e.g. Jain (1987), Kaul, Mehrotra & Morck (2000) and Chen, Noronha, & Singal (2004)).[3]

LITERATURE REVIEW

The idea that high-risk assets may be overpriced is not new: Black (1972) shows that, with borrowing restrictions (e.g. margin requirements), low-beta stocks can perform better than predicted by the Sharpe-Lintner Capital Asset Pricing Model (CAPM), while high-beta stocks can perform worse. Empirically, several studies (e.g. Black, Jensen, & Scholes (1972) and Fama & French (1992)) have documented that the relationship between beta and returns of the CAPM is flatter than the model implies. The empirical shortcomings of the CAPM has led to numerous papers that either attempt to extend the model by including other risk factors (e.g. Fama & French (1993), Jegadeesh & Titman (1993); Novy-Marx (2013)) or critique the assumptions behind the model (e.g. Shleifer & Vishny (1997); Gromb & Vayanos (2002); Acharya & Pedersen (2005)), but the main focus of academic studies had not been on the anomaly itself.

The low-risk anomaly received greater attention when Ang et al. (2006) and Ang, Hodrick, Xing and Zhang (2009) find that high-risk stocks (in their papers, risk is defined as idiosyncratic volatility rather than beta) tend to earn very low average returns. The low-risk anomaly has been discussed under both systematic (beta) and idiosyncratic risk measures, but portfolios that have low systematic risk also tends to have low idiosyncratic risk. However, as systematic risk exposure tends to be similar across similar businesses, one may argue that the low-risk returns are attributable to stocks that are in relatively more stable industries. Baker, Bradley and Taliaferro (2014) find that the superior performance comes from both picking low-beta stocks (micro effect) in low-beta industry/ country (macro effect). This finding is further corroborated by Asness, Frazzini and Pedersen (2014) who document that low-risk investing strategy delivers positive returns even as industry-neutral bets. In addition, the positive returns have also been found in many developed countries and across several asset classes (e.g. Baker et al. (2014) and Frazzini & Pedersen (2014)).

While there are several potential explanations for this anomaly, the most often-cited theory stems from leverage constraints. Shleifer and Vishny (1997) provides a simple framework that helps us understand how limited arbitrage capital that is constrained by borrowing capacity can allow prices to diverge far from their fundamental values. The intuition has been developed further in Gromb and Vayanos (2002), Acharya and Pedersen (2005), Brunnermeier and Pedersen (2009), Garleanu and Pedersen (2011) and Rytchkov (2014). Frazzini and Pedersen (2014) extend the model of Black (1972) and derive a zero-cost, market-neutral pricing factor called BAB (betting against beta) – that is, a portfolio that longs low-beta stocks and shorts high-beta stocks.[4] In their model, agents that cannot borrow must overweight high-beta stocks in order to achieve higher returns, making the security market line flatter (similar to Black (1972)), but the slope depends on the tightness of the funding constraints. Other forms of institutional frictions can also impose limits to arbitrage. For example, Baker et al. (2011) argue that distortions created by returns benchmarking can induce the anomaly.

Other leading explanations posit that investors/agents are prone to behavioral biases or market sentiments. For example, Kumar (2009) finds that some individuals exhibit preference for stocks with lottery-like payoffs, while Bali, Cakici and Whitelaw (2011) also find that portfolios with lottery-like payoffs tend to exhibit poor returns. Antoniou et al. (2015) find evidence that sentiment affects the security market line; noise traders appear to be more bullish about high-beta stocks when market sentiments are good. Combining both market sentiments and limits to arbitrage, Hong and Sraer (2016) propose a model where the direction of the risk-return relationship depends on disagreement about the market's prospect;

when disagreement is high, high-beta assets tend to be more prone to speculative overpricing when there are short-sale constraints.

DATA AND METHODOLOGY

Data

The data used in the analysis comes from several sources. Equity market data is retrieved from Thompson Reuters Datastream and contains total return, market capitalisation and the book-to-market ratio of all common stocks in the Stock Exchange of Thailand (SET) at monthly frequency between January 2001 and December 2015, and the monthly return of the SET50 index which is used as the proxy for market returns. The index is a market capitalisation-weighted price index of 50 listed companies on SET, selected based on large market capitalisation, high liquidity and availability of free-float stocks for general. Stocks that are classified as under rehabilitation plan as well as stocks that do not trade consecutively for three months are excluded from the sample. Because historical returns are used to estimate the stock beta (methodology to be described subsequently), the final sample runs from January 2004 to December 2015 and contains 453 stocks in total. Risk-free rate used for calculations of excess returns and market risk premium is the one-month Thai government Treasury bill retrieved from Bloomberg. The market capitalisation and book-to-market ratio are used for construction of Fama and French (1993) size small-minus-big (SMB) and value high-minus-low (HML) factor-mimicking portfolios respectively. Past returns are used to construct the Carhart (1997) momentum up-minus-down (UMD) factor.[5]

METHODOLOGY

To rank the stocks based on their ex-ante beta, the beta is estimated based on historical volatility and stock return's correlation with market return. Following Frazzini and Pedersen (2014) procedure for monthly data, each stock's beta is calculated using the following formula:

$$\hat{\beta}_i^{ts} = \hat{\rho}_i(\hat{\sigma}_i / \hat{\sigma}_m)$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are estimated volatilities for stock and the market using one-year (12 months) rolling window. $\hat{\rho}_i$ is the estimated correlation between stock *i* and the market, calculated over a three-year (36 months) horizon. With the ex-ante betas, stocks can be ranked in each month into 5 groups based on their previous months' beta, construct equally-weighted portfolios, and examine the properties of returns using various specifications of the linear factor pricing model of the following general form:

$$r^e_{j,t} = \alpha_j + \beta'_j f_t + \varepsilon_{j,t}, \qquad j = 1,...,5$$

where $r^e_{j,t}$ is the equally-weighted excess returns of stocks in portfolio j, f_t is the vector of factors of the pricing model, β_j is the vector of the factor loadings on portfolio j,, and α_j the systematic abnormal excess returns associated with strategy of portfolio j (our outcome of interest). All returns are computed as monthly percentage point. Stocks are sorted based on their ex-ante estimated beta in ascending order, so portfolio 1 corresponds to stocks with lowest beta and portfolio 5 highest beta. The linear factor pricing model specifications to be used are Sharpe-Lintner CAPM single-factor model, Fama and French (1993) three-factor model and Carhart (1997) four-factor model. All standard errors in the linear pricing regressions are adjusted for heteroskedascity and autocorrelation using Newey-West standard error with lag of 12 months.

RESULTS

First, this study examines whether raw returns of beta-sorted portfolio exhibit the low-risk anomaly. Table 1 presents the excess returns of stocks in each portfolio along with the corresponding average beta, market capitalisation and book-to-market ratio. The raw returns are indeed decreasing in the stock beta, as evident in the scatter diagram earlier (Figure 1). Figure 2 plots the excess returns by portfolio for convenient visual inspection. On average, low-beta stocks tend to be smaller, while the average book-to-market ratio is similar across portfolios. Of course, the returns differences can be attributed to different risk characteristics, so in the next step the differences are further investigated under several specifications of the linear factor-pricing model.

Table 1
Summary statistics of beta-sorted portfolios

This table provides descriptive statistics of the beta-sorted portfolio over the period of January 2004 to December 2015 (144 months). At the beginning of each calendar month, stocks in the Stock Exchange of Thailand are ranked based in ascending order based on their estimated beta at the end of the previous month. All stocks are given equal weights within each portfolio, and portfolio are rebalanced every month. Portfolio 1 contains stocks with the lowest beta, and portfolio 5 the highest. Beta is estimated using covariance and standard deviation calculated over rolling windows of 36 months and 12 months respectively. Market capitalisation is measured in millions of baht, and book-to-market ratio is obtained at the monthly frequency.

Portfolio	Excess returns (monthly, %)	Estimated beta	Market capitalisation (THB million)	Book-to-market ratio
1	0.59	0.38	6,254.77	1.03
2	0.50	0.60	11,957.56	1.09
3	0.50	0.78	17,098.99	1.04
4	0.37	0.99	27,347.93	1.03
5	–0.49	1.42	25,112.22	0.95

Figure 2. Monthly excess returns of beta-sorted portfolios. This scatter diagram plots the average monthly excess returns for beta-sorted portfolio over the period of January 2004 to December 2015. Excess returns are calculated as the monthly return minus the one-month Thai Treasury bill rate, presented as percentage points. At the beginning of each calendar month, stocks in the Stock Exchange of Thailand are ranked based in ascending order based on their estimated beta at the end of the previous month. All stocks are given equal weights within each portfolio, and portfolio are rebalanced every month. Portfolio 1 contains stocks

with the lowest beta, and portfolio 5 the highest.

Table 2
Returns of beta-sorted portfolios

The following table reports the returns of the beta-sorted portfolio over the period of January 2004 to December 2015. At the beginning of each calendar month, stocks in the Stock Exchange of Thailand are ranked based in ascending order based on their estimated beta at the end of the previous month. All stocks are given equal weights within each portfolio, and portfolio are rebalanced every month. Portfolio 1 contains stocks with the lowest beta, and portfolio 5 the highest. The sixth column is a self-financing, long-short portfolio that longs portfolio 1 and shorts portfolio 5. In the top half of the table, monthly excess returns of the portfolios are reported along with annualised volatility and Sharpe ratio. The benchmark risk-free rate used is the one-month Thai Treasury bill. The bottom half of the panel reports the alphas corresponding to different specifications of the linear factor pricing model. The CAPM alpha is the single-factor Capital Asset Pricing Model which uses the return on the SET50 index as proxy for market returns. The three-factor model adds the Fama and French (1993) SMB and HML factor-mimicking portfolios, while the four-factor model adds the Carhart (1997) UMD factor. Excess returns and alphas are in monthly percent, and *t*-statistics are reported in square parentheses. All standard errors in the linear pricing regressions are adjusted for heteroskedascity and autocorrelation using Newey-West standard error with lag of 12 months. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	(1)	(2)	(3)	(4)	(5)	(1)–(5)
Excess returns	0.593**	0.497	0.503	0.373	–0.495	1.088**
	[2.135]	[1.555]	[1.097]	[0.645]	[–0.681]	[2.003]
Volatility (annualised)	11.55	13.30	19.06	24.02	30.22	22.57
Sharpe ratio (annualised)	0.62	0.45	0.32	0.19	–0.20	0.58
Alphas						
Sharpe-Lintner CAPM	0.546**	0.436*	0.406	0.247	–0.656*	1.203***
	[2.076]	[1.717]	[1.278]	[0.811]	[–1.928]	[3.597]
Three-Factor	0.455**	0.245**	0.178	–0.00197	–0.924***	1.378***
(Fama & French, 1993)	[2.304]	[2.126]	[1.275]	[–0.0128]	[–4.545]	[4.223]
Four-Factor	0.492**	0.308**	0.263*	0.148	–0.767***	1.259***
(Carhart, 1997)	[2.327]	[2.519]	[1.858]	[0.979]	[–4.645]	[4.179]

Before proceeding further with the analysis, the returns characteristics of the beta-sorted portfolios as presented in Table 2. Portfolio 1, which has the lowest beta, also has the lowest volatility (here, annualised), while portfolio 5 which has the highest beta has the highest volatility. The relationship between risk and return is decreasing under both measures of risk, consistent with Baker et al. (2011) and Frazzini and Pedersen (2014). In addition, the Sharpe ratio is also decreasing in beta. A zero-cost investment strategy which longs low-beta stocks (portfolio 1) and shorts high-beta stocks (portfolio 5) returns 1.09% per month with annualised Sharpe ratio of 0.58.

Table 2 also presents the alphas of the portfolios under different specifications of the linear factor pricing model. The Sharpe-Lintner CAPM alpha suggests that the abnormal returns associated at either extremes of the beta spectrum are statistically significant. Stocks with lowest beta earn 0.55% more per month than predicted by the model, while stocks with highest beta earn 0.66% less.[6] The zero-cost, long-short portfolio earns an astonishing 1.2% abnormal returns per month, far in excess of any trading costs that could be involved in executing the strategy.

One concern that may arise from results in Table 1 is that average market capitalisation of stocks in the portfolios is different, which could consequently affect returns. The three-factor model incorporates these characteristics. With the inclusion of the size premium, the alphas the portfolios decrease slightly but the alphas remain statistically significant. Finally, the inclusion of the momentum factor still leaves the results intact. The long-short portfolio delivers monthly four-factor alpha of 1.26%, statistically significant at 1% level. Overall, the superior returns of the low-risk strategy are statistically significant and robust to several specifications of the linear factor-pricing model.

UNDERSTANDING THE LOW-RISK ANOMALY

What could be the economic forces behind the low-risk anomaly in Thailand? In this section, the issue is further explored. Two leading explanations for the anomaly are behavioural biases and leverage constraints, as discussed in Literature Review.

Many classes of investors in Thailand face leverage constraints where securities borrowing and selling is expensive for retail investors, and many institutional investors face explicit borrowing constraints.[7] Consequently, they may be forced to invest in riskier assets in order to generate returns for their investors.[8]

To investigate the leverage constraints, the BAB factor proposed by Frazzini and Pedersen (2014) is employed. The steps in the construction the BAB factor involve partitioning the universe of stocks into two groups: low-beta and high-beta. The stocks in each group are then weighted based on beta-sorted ranks which are scaled by average portfolio beta so that average beta in each group is exactly one. The factor-mimicking portfolio longs low-beta stocks and shorts high-beta stocks. When the two groups are netted off against each other, the resulting portfolio is both zero-cost and zero-beta (i.e. market-neutral). The BAB factor is negatively correlated with stock market returns, as shown in Figure 3. No proxy for funding liquidity (like the TED spread in the U.S.) is available in Thailand, but suppose one argues that funding liquidity tightens during periods when stock market performs poorly, then the correlation between the BAB factor and funding liquidity has the opposite sign to what is expected and demonstrated in Frazzini and Pedersen (2014), where BAB factor performs worse when funding liquidity tightens.

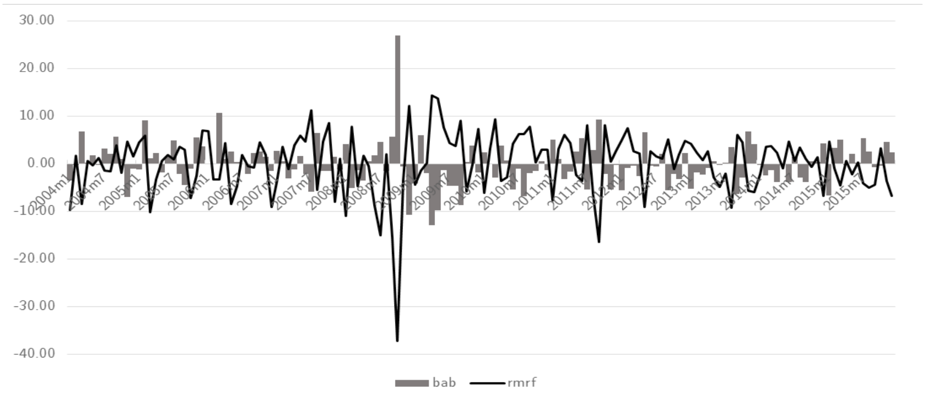

Figure 3. BAB factor versus equity market risk premium. This graph plots the monthly values of the BAB factor and equity market risk premium measured as percentage points. BAB factor is displayed as bars and equity market risk premium as line. The Pearson correlation coefficient between the two factors is –0.7256 and statistically significant at 1% level.

Table 3 shows the results of the linear factor-pricing model with the addition of the BAB factor. As expected, the loading on the BAB factor declines as portfolio beta increases. However, the alphas associated with the portfolios, while lower than the baseline model, are still non-zero and statistically significant, suggesting that the BAB factor cannot fully explain the anomaly. Taken together with Figure 3, the results in Table 3 suggest that leverage constraints can at best partially explain the low-risk anomaly in Thailand.

The next leading explanation is investor behavioural biases. There are several mechanisms through which behavioral biases can affect stock prices, but one mechanism that could be tested here is investor sentiment. Antoniou et al. (2015) find that during periods where market sentiments are pessimistic, average returns on high-beta portfolios are higher than low-beta portfolios, while the low-risk anomaly is found during optimistic periods, where unsophisticated investors are more bullish about prices of high-beta stocks and bid up their prices. However, Figure 3 reveals an opposite pattern: when stock market returns perform well (arguably optimistic market sentiments), the low-risk portfolio performs worse. Investor sentiment does not seem to the driving force in Thailand either.

Table 3
Explaining abnormal returns using BAB factor

The following table reports the factor loadings of the linear pricing model for the beta-sorted portfolio over the period of January 2004 to December 2015. At the beginning of each calendar month, stocks in the Stock Exchange of Thailand are ranked based in ascending order based on their estimated beta at the end of the previous month. All stocks are given equal weights within each portfolio, and portfolio are rebalanced every month. Portfolio 1 contains stocks with the lowest beta, and portfolio 5 the highest. The sixth column is a self-financing, long-short portfolio that longs portfolio 1 and shorts portfolio 5. The linear factor pricing model augments the Carhart (1997) four-factor model with BAB factor as proposed by Frazzini and Pedersen (2014). BAB factor is constructed as self-financing, zero-beta portfolio that longs low-beta stocks and shorts high-beta stocks. The factor-mimicking portfolio is rebalanced every month. Alphas are in monthly percent, and t-statistics are reported in square parentheses. All standard errors in the linear pricing regressions are adjusted for heteroskedascity and autocorrelation using Newey-West standard error with lag of 12 months. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	(1)	(2)	(3)	(4)	(5)	(1)–(5)
RMRF	0.774^{***}	0.617^{***}	0.887^{***}	1.066^{***}	1.321^{***}	-0.547^{***}
	[21.27]	[14.26]	[26.90]	[18.76]	[12.57]	[–5.585]
SMB	0.707^{***}	0.616^{***}	0.847^{***}	1.018^{***}	1.191^{***}	-0.485^{***}
	[8.807]	[6.551]	[9.143]	[14.51]	[11.97]	[–5.120]
HML	0.567^{***}	0.592^{***}	0.664^{***}	0.684^{***}	0.695^{***}	–0.128
	[14.41]	[9.185]	[8.070]	[8.470]	[5.843]	[–1.208]
UMD	-0.139^{***}	-0.0857^{***}	-0.0923^{***}	-0.149^{***}	-0.133^{**}	–0.00593
	[–5.285]	[–3.272]	[–2.655]	[–4.140]	[–2.442]	[–0.125]
BAB	0.524^{***}	0.0391	-0.0812^{*}	-0.214^{***}	-0.347^{***}	0.872^{***}
	[10.12]	[1.128]	[–1.739]	[–3.729]	[–2.771]	[8.164]
Alpha	0.395^{***}	0.301^{**}	0.278^{*}	0.187	-0.703^{***}	1.098^{***}
	[3.104]	[2.469]	[1.911]	[1.217]	[–4.468]	[5.576]

Notes. RMRF = market factor (market return minus risk-free rate); SMB = size factor (small [market cap] minus big); HML = value factor (high [book-to-market ratio] minus low); UMD = momentum factor (up [trend] minus down); BAB = betting against beta factor

The results here are rather perplexing: the low-risk anomaly is present and robust in Thailand, yet leading explanations do not seem to explain the anomaly very well in this setting. So in the next step, the analysis turns to identity of the groups of investors that participate in each risk stratum in the market. Using stock trade data in SET that allows classification of traders by investor group (here, retail investors, mutual funds, and other groups which comprise proprietary trading and foreign investors) available from 2004 to 2008, this paper examines the average monthly trade value of stocks in each portfolio. The results are displayed in Table 4. Investors in all groups tend to invest in high-beta stocks more. However, non-retail investors tend to invest in high-beta stocks disproportionately more than retail investors. To the extent that behavioural bias explanations are typically associated with activities of retail investors, the anomaly here seems to be more related to non-retail investors.

Table 4
Trades by investor group of beta-sorted portfolios

This table provides characteristics of the beta-sorted portfolio over the period of January 2004 to December 2008 (60 months). At the beginning of each calendar month, stocks in the Stock Exchange of Thailand are ranked based in ascending order based on their estimated beta at the end of the previous month. All stocks are given equal weights within each portfolio, and portfolio are rebalanced every month. Portfolio 1 contains stocks with the lowest beta, and portfolio 5 the highest. Beta is estimated using covariance and standard deviation calculated over rolling windows of 36 months and 12 months respectively. Market capitalization and trade value (both buy and sell transactions) are measured in millions of baht. Stocks that are SET100 index constituents are identified. Other groups of investors include proprietary trading by securities companies and foreign investors.

Portfolio	Monthly trade value (THB million)			Estimated Beta	Market Capitalisation (THB million)	Index Constituents (%)
	Retail	Mutual	Others			
1	111.60	2.64	12.45	–0.09	2,564.88	1.7
2	50.61	6.79	21.84	0.19	4,077.62	5.4
3	143.67	21.80	80.05	0.42	7,590.62	14.8
4	399.94	87.55	352.89	0.73	21,262.81	26.7
5	1,048.81	137.47	570.60	1.36	27,360.12	35.3

In fact, these high-beta stocks tend to have larger market capitalisation, which make them more likely to be member of stock indices (Table 4). If the investment performance of non-retail investors are evaluated relative to index-based benchmarks, then the fact that such investors tend to be disproportionately more active in large-cap stocks (which happen to have high beta) could be a friction induced by institutional design. In that case, this finding is consistent with Baker et al. (2011), who argue that investment managers happily invest in overpriced, high-beta stocks because it minimises their tracking error, a dimension which they are evaluated on. In addition, some classes of institutional investors – both domestic and foreign – may have explicit investment restrictions that permit to them to invest in only a subset of stocks, typically large-cap stocks which belong to some index. For this reason, such stocks tend to have higher demand relative to other stocks (e.g. Jain (1987), Kaul et al. (2000) and Chen et al. (2004)), so index inclusion could be another force that drives the low-beta anomaly.[9] Given the fact that Thai households are increasingly investing their wealth through mutual funds (up from 7.5% of GDP in 2000 to 30% in 2015), index-based benchmarking of fund returns could be good news for investors of non-index, low-beta stocks.[10]

CONCLUSION

This paper documents the existence of the low-beta anomaly in the Thai stock market. The abnormal returns are significant – both economically and statistically – and robust to several specifications of the linear factor pricing model. Further analyses suggest that leverage constraints may play a part in the existence of this anomaly, but frictions from benchmarking and index inclusion are more plausible explanations in this case. However, the results of the analyses on the cause of the anomaly should only be interpreted as suggestive evidence: to draw a definite conclusion, better data on funding liquidity and investor portfolio holdings are required.

For most other market anomalies, evidence suggests that profits associated with publicly available strategies tend to diminish as "arbitrage capital" grows (e.g. Chordia, Subrahmanyam & Tong (2014) and Hanson & Sunderam (2014)). However, in this case, given that most institutional investors that participate in the Thai stock market are not in the position to exploit this strategy, this provides an opportunity for the unrestricted investors. The low-beta strategy offers superior risk-adjusted returns and the best of both worlds–higher returns and lower volatility.

NOTES

1. Often, this is referred to as "style investing", where portfolio formation strategies are designed based on stock characteristics that earn anomalous returns not predicted by baseline pricing model.
2. The positive relationship between beta and return has been questioned long in the past (e.g. Black et al. (1972) and Fama & French (1992)) and received renewed attention recently (e.g. Ang et al. (2006), Ang et al. (2009), Baker et al. (2011), Baker et al. (2014) and Frazzini & Pedersen (2014)).
3. To illustrate why stocks with abnormally high demand can be bad for investors, consider a high-beta stock. High demand for such stock causes investors to bid

up its price. Note that investor demand – high or low – does not affect expected future cash flow that such stock would generate. With future payoffs the same, all else equal, higher purchase price translates into lower return than the asset-pricing model predicts in equilibrium. Conversely, if a low-beta stock has abnormally low demand, its price will be lower than it should be; all else equal, its return will be higher than predicted.

4. The BAB portfolio is not like a typical long-short portfolio in a sense that the weights of each stock and risk-free asset in the long and short groups are determined such that both groups have beta of one. When they are netted off against each other, the portfolio is market-neutral, i.e. has beta of zero.
5. All stocks in SET are used in the construction of the factors. SMB and HML factors are created from 2 x 3 sort and rebalanced annually using the market capitalisation and book-to-market ratio at the end of December in each year. UMD is calculated based on past cumulative returns from 2 to 12 months and sorted into 3 equal-size portfolios which are rebalanced monthly.
6. The beta loadings of the portfolios are unreported, but are similar in magnitude to the average ex-ante beta of the portfolios.
7. In particular, Securities and Exchange Act B.E. 2535 Section 126 prohibits mutual funds in Thailand from borrowing.
8. Explicit investment restrictions have been shown to artificially affect demand for risky assets and compel institutional investors to "reach for yield", as shown by Becker and Ivashina (2015).
9. Large-cap stocks in Thailand tend to receive more media coverage, and consequently investors may be disproportionately more inclined to invest in such stocks, bidding up their prices. However, the inclusion of the SMB factor in the linear factor pricing model partially mitigates the size-coverage effect. The author thanks the referee for suggesting the discussion of this issue.
10. As investment in mutual funds gains popularity, the proportion of retail investors trading value in the Thai stock market has declined steadily from 76% in 2003 to 50% in 2016.

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