Beta Anomaly and Comparative Analysis of Beta Arbitrage Strategies

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Abstract

Over a long period of time, stocks with low beta have consistently outperformed their high beta counterparts across developed and emerging markets alike. We explore the presence of low beta anomaly and its robustness after controlling for size, value and momentum factors in the Indian stock markets. We have chosen the universe of past and present constituent stocks of the Nifty 500 index in our study for the period 2001 to 2014. We study relative risk-adjusted performance and portfolio characteristics of three different zero-cost, long-short beta arbitrage strategies including beta neutral and negative net beta version of strategies. We find all the beta arbitrage strategies deliver superior risk adjusted performance in the Indian markets, though of different magnitude, with a clear tilt away from the value factor and towards the momentum factor. However, we don't find any tilt towards size factor. Our study provides the framework for choosing an implementable beta arbitrage strategy consistent with the investor's investment objective.

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1. Introduction

An investment strategy based on investing in a portfolio that consists of low risk, stable stocks that consistently outperforms a matching portfolio of high risk, volatile stocks as well as market portfolio on risk adjusted basis. This phenomenon is widely known as risk anomaly or volatility puzzle.

In this study, we explore the presence of low beta anomaly and its robustness, after controlling for size, value and momentum factors, in the Indian stock markets. We have chosen the past and present constituent stocks of the Nifty 500 index for our study over a period 2001 to 2014.

We answer the following questions with respect to the Indian equity markets:

1. Does beta anomaly exist after removing small and illiquid stocks from the universe?
2. Does beta anomaly remain robust after controlling for size, value and momentum factors?
3. What are the alternative ways of implementing beta arbitrage strategies and how to compare different beta arbitrage strategies?

We establish the following: (a) Beta anomaly is robust even after eliminating small and illiquid stocks from the universe. (b) Beta anomaly is robust after controlling for size, value and momentum factors, and is not proxy for any other factors. (c) We compare relative attractiveness of alternative beta arbitrage strategies and we find that all beta arbitrage strategies deliver different magnitudes of superior risk-adjusted performance in Indian markets with a clear tilt away from the value factor and towards the momentum factor. We don't find any tilt towards size factor. (d) While all strategies offer superior risk-adjusted performance, they have very different ex-post beta and therefore, choice of strategy is a function of the investment objective.

This study highlights key differences in characteristics of alternative beta arbitrage strategies and it provides a simple framework for choosing an implementable beta arbitrage strategy consistent with the investment objective.

Risk anomaly is one of the strongest anomalies. It has remained largely unexplored by researchers and under-exploited by practitioners till the dawn of the twenty first century. This anomaly is against the very spirit of a strictly positive relationship between risk and return depicted by classical asset pricing theories like the capital asset pricing model (CAPM). According to CAPM, systematic risk as measured by beta is the sole driver of the expected return. In the CAPM world, market portfolio is the portfolio with the highest Sharpe ratio, which implies excess return per unit of risk. Rational investors must hold a combination of market portfolio and long/short position in risk-free asset to meet their unique risk preferences. Risk-averse investors de-lever their holding in the market portfolio by investing a fraction of their capital in the market portfolio and remaining capital in risk-free assets. On the contrary, investors with a higher risk appetite use leverage - by borrowing money to increase expected returns on the market portfolio. In the imperfect real world outside the CAPM framework, various categories of investors including retail investors, mutual funds and pension funds may not have unconstrained access to leverage. Such investors tend to exhibit preference for high beta security in anticipation to earn higher expected returns compared to the market portfolio.

Early evidence of low risk anomaly and flatter security market line for US stocks can be traced back to the early 1970s. Black (1972) and Black, Jensen and Scholes (1972) first highlight that the security market line is much flatter than predicted by CAPM, because of the borrowing restrictions resulting in low beta stocks having a positive and higher alpha. Haugen and Heins (1975) were among the first to show that stocks with low volatility of historical returns tend to outperform those with higher volatility. However, during hay days of market efficiency and CAPM, these results were dubbed as a data mining exercise or an aberration.

Subsequently after a long gap, research on risk anomaly has picked up and since the beginning of the twenty first century, many researchers have explored low risk anomaly using various approaches. Studies differ mainly on two counts - choice of risk measure and method of portfolio construction approach. While popular risk measures include idiosyncratic volatility, standard deviation and beta, two popular portfolio construction approaches are portfolio construction based on ranking stocks using a risk measure and constructing a minimum variance portfolio using modern portfolio theory Markowitz (1952) framework. More recent literature is focused on finding rational and behavioral explanations to explain the risk anomaly or to explain it away. Ang, Hodrick, Xing and Zhang ((2006), (2009)) use idiosyncratic volatility calculated as standard deviation of residuals of daily stock returns regressed upon proxies for market, size, value and momentum factors as defined by Fama and French (1992) and Carhart (1997). They report an inverse relationship between idiosyncratic risk and expected returns across global markets. Clarke, De Silva and Thorley (2006) report that minimum variance portfolio in US markets provides comparable or better-than-market returns with 25% reduction in volatility. Blitz and Vliet (2007) find that volatility effect is stronger than beta effect. They further establish that volatility effect is a distinct effect and is by no means disguised in other classic effects such as size, value and momentum.

Baker and Haugen (2012), Blitz and Vliet (2007), and Blitz, Pang and Vliet (2013) demonstrate that risk anomaly is a global phenomenon. Baker, Bradley and Wurgler (2011) use beta as well as volatility sorting, using only large cap stocks in US market and demonstrate that low beta-high alpha and high beta-low alpha phenomenon persists even in large cap stocks. They offer a series of explanations, rational as well as behavioural, to explain persistence of such anomaly. They argue that institutional investors' mandate to focus on beating a benchmark, coupled with borrowing and short-selling restrictions, hinders their ability to exploit a low beta, high alpha opportunity. As a result, they take exposure to high beta, low alpha stocks.

Moreover, behavioural biases such as preference for lottery, overconfidence and representativeness cause investors to chase high beta stocks. This leads to price increase in high beta stocks leading to lower returns in the subsequent periods. Bali and Cakici (2008) argue that the negative relationship shown by Ang, Hodrick, Xing and Zhang (2006) between idiosyncratic volatility and expected return is due to small, illiquid stocks only. If these small stocks are excluded from the sample, a puzzling negative relationship between idiosyncratic volatility and expected returns turns insignificant. Bali, Cakici and Whitelaw (2011) create a variable to capture lottery-like payoff and show that an inverted risk-return relationship between idiosyncratic risk and expected return is due to investors' preference for lottery-like payoffs. They also demonstrate that such inverted relationship between risk and return cannot be explained by skewness in distribution of returns. Fu (2009) argues that an inverted relationship between idiosyncratic risk and expected return is due to short term reversals. In line with Black (1993), Frazzini and Pedersen (2010), and Hong and Sraer (2012) also attribute an anomalous flat-to-negative relationship between risk and return to borrowing restrictions and short selling constraints. Brennan (1993), Karceski (2002), Falkenstein (2009), Blitz, Pang and Vliet (2013) and Baker and Haugen (2012) argue that there is an agency problem associated with delegated portfolio management and also argue that the call option-like fund manager's compensation structure tilts their preference towards high risk stocks. Clarke, De Silva and Thorley (2010) construct an additional factor based on idiosyncratic volatility 'volatile-minus-stable (VMS)' after controlling size effect and show that VMS is an important factor in explaining a cross-section of security returns.

While there are several strands of research emerging on this exquisite anomaly of markets, we extend the strand of beta arbitrage based investment strategy. Black, Jensen and Scholes (1972) and Black (1993) first provide a framework and evidence on how unconstrained investors can exploit a flatter-than-expected security market line. More recently, Frazzini and Pedersen (2014), in their seminal work, extend the scope of beta arbitrage by constructing betting against beta (BAB) portfolios across several asset classes and markets. They report large and significant risk-adjusted returns. By design, 'betting against beta' portfolios are market neutral on ex-ante basis because of active use of levering of low beta portfolios and de-levering of high beta portfolios. Asness, Frazzini and Pedersen (2014) demonstrate that betting against beta strategies are not merely industry bets as suspected by many. They establish it by constructing industry neutral BAB factor.

The rest of the paper is organized as follows. Section 2 discusses data and methodology, Section 3 discusses results and Section 4 offers the conclusion.

2. Empirical Model

We follow Baker, Bradley and Wurgler (2011), Blitz, Pang and Vliet (2013), Frazzini and Pedersen (2014) and Garcia-Feijoo, Kochard, Sullivan and Wang (2015) to build our empirical model.

1. At the end of every month t, we calculate beta for each stock by regressing excess monthly return of stocks with excess monthly market returns using previous thirty-six months’ data, including month t.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{m,t} - r_{f,t}\right) + \epsilon_{i,t} \quad (1)$$

At the end of month t, we sort stocks in ascending order based on beta, to construct quintile portfolios. We construct three different versions of beta arbitrage portfolios by going long on low beta stocks and short on high beta stocks, and compare performance and characteristics of all three beta arbitrage portfolios.

2. We construct the first variant of zero-cost, beta arbitrage portfolio by going long on lowest beta quintile portfolio and going short on highest beta quintile portfolio (lb-hb) as widely captured in popular literature (i.e. Blitz and Vliet (2007), Baker, Bradley and Wurgler (2011)). This strategy is a zero-cost strategy, but is not a beta neutral strategy. This strategy typically results in substantial net negative beta exposure.

3. We construct a second variant of zero-cost, beta arbitrage portfolio as betting against beta (BAB) portfolio following Frazzini and Pedersen (2014) by levering low beta quintile portfolios and de-levering high beta quintile portfolios. We shrink stocks’ beta towards their cross-sectional mean, by assigning 60% weightage to the estimated beta of stock from previous 36-months returns ($\beta_{regression}$) and 40% weightage to cross section estimate of beta (β_{prior}), which is set as 1 as prescribed by Vasicek (1973).

$$\beta_{shruk} = 0.4 \times \beta_{prior} + 0.6 \times \beta_{regreession} \quad (2)$$

We construct BAB portfolio as zero-cost, beta neutral portfolio by levering low beta portfolio and de-levering high beta portfolio to push both extreme quintile portfolios to unity.

$$r_{BAB,t+1} = \frac{r_{L,t+1} - r_{f,t+1}}{\beta_{L,t}} - \frac{r_{H,t+1} - r_{f,t+1}}{\beta_{H,t}} \quad (3)$$

However, our approach is slightly different as we construct equally weighted BAB portfolios and we don't use any weighting to assign different weights to stocks within quintile portfolio.

4. We follow Gracia-Feijoo, Kochard, Sullivan and Wang (2015) to construct a third variant of beta arbitrage portfolio, which is an alternative betting against beta portfolio (Alt-BAB) in a much simpler manner than BAB portfolio by going long on low beta portfolio and going short on high beta portfolio in the following manner, by avoiding levering or delivering low and high beta portfolios respectively, or pushing both low beta and high beta portfolio to unity. We call it Alternative BAB (ABAB) portfolio.

$$r_{BAB,t+1} = (r_{L,t+1} - r_{f,t+1}) - \left(\frac{r_{H,t+1} - r_{f,t+1}}{(\beta_{H,t}/\beta_{L,t})}\right) \quad (4)$$

We repeat this process every month. We then measure returns, standard deviation, ex-post, realized beta, alpha and Sharpe ratio for the resultant time series of quintile portfolios over the entire study period.

In addition, we perform bivariate analysis using double sort, a robust non-parametric technique to evaluate whether beta effect is indeed a separate effect or the one which is disguised in one of the other well-known effects such as value, size and momentum. We first sort stocks on one of the control factors (size, value or momentum) and construct quintile portfolios. Then, we sort stocks on beta within each control factor quintile portfolio. We construct our factor neutral beta quintile portfolios that represent every quintile of control factor.

3. Data and Methodology

3.1. Data

We obtained adjusted monthly closing stock price, earnings to price, market cap, trading volume and turnover data from Capitaline database for all past and present constituents of Nifty 500 index for the period of January 2001 to December 2014. Nifty 500 stocks cover close to 95% of free float market capitalization of the stocks listed on NSE. These stocks represent almost the full universe of the Indian market and at the same time, exclude penny and highly illiquid stocks from the sample. We have taken Fama-French and Momentum factors for the Indian Stock markets and risk-free rate for Indian markets from the IIM Ahmedabad data library from its website (Agarwalla, Jacob, & Varma, 2013).

3.2. Methodology

3.2.1. Univariate Analysis

We calculate average returns for each quintile portfolio for month t + 1 for the beta sorted quintile portfolios constructed at the end of period t. We repeat this process every month. We then measure returns, standard deviation, ex-post beta, CAPM style, single factor alpha and Sharpe ratio for the resultant time series of quintile portfolios over the entire study period.

3.2.2. Bivariate Analysis

We perform bivariate analysis using double sort, a robust non-parametric technique to evaluate whether the beta effect is indeed a separate effect or the one which is disguised in one of the other well-known effects such as value, size and momentum. We first sort stocks on one of the control factors (size, value or momentum) and construct quintile portfolios. Then, we sort stocks on beta within each control factor quintile portfolio. We construct our factor neutral beta quintile portfolios that represent every quintile of control factor.

3.2.3. Fama-French three factor and Fama-French-Carhart four factor regressions.

We compare performance of all three long-short, beta arbitrage portfolios using single factor CAPM style alpha, calculated using equation and Fama-French, three-factor alpha and Fama-French-Carhart, four-factor alpha using equations 5 and 6 respectively. We also analyze factor loadings of alternative beta arbitrage strategies.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,m}(r_{m,t} - r_{f,t}) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \epsilon_{i,t} \quad (5)$$
$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,m}(r_{m,t} - r_{f,t}) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{HML}(WML) + \epsilon_{i,t} \quad (6)$$

4. Empirical Results

We discuss results of our study in this section. Appendix 1 reports summary statistics of number of stocks used for each iteration in the study with their median price to earnings multiple and median market capitalization.

4.1. Univariate Analysis

Table 1 reports performance of beta quintile portfolios, zero cost, low beta minus high beta portfolio and universe portfolio.

Table 1: Main results (Annualized) for quintile portfolios based on historical beta

This table reports beta-sorted calendar-time portfolio returns. At the beginning of each month, stocks are sorted in ascending order based on their ex-ante beta at the end of the previous month. The ranked stocks are assigned to one of the five quintile portfolios. The portfolios are rebalanced every month. The first five columns report results of beta sorted quintile portfolios; the sixth column reports the result of zero cost, low-beta minus high-beta portfolio return, that is, long the low beta portfolio and short the high beta portfolio. The last column reports results of universe portfolio, which is an equally weighted portfolio of all the stocks. All the beta quintile portfolios are equally weighted by design. The first two rows report annualized excess returns and standard deviation of excess returns. Subsequent rows report Sharpe ratios for beta quintile portfolios, followed by t-value showing the difference between Sharpe ratio of the beta quintile portfolios over universe. The next two rows show average estimated beta (ex-ante) at the portfolio construction stage, beta (realized) is realized loading on the universe portfolio. CAPM-style alpha is the intercept in a regression on monthly excess return is annualized and reported with corresponding t-statistics for all portfolios.

	P1 (low beta)	P2	P3	P4	P5 (high beta)	low-beta minus high-beta	Universe (EWI)
Excess return (Annualized %)	6.30%	6.16%	3.11%	-0.04%	-8.84%	15.15%	1.34%
Standard Deviation %	22.55%	28.98%	33.19%	38.33%	45.80%	27.88%	33.18%
Sharpe ratio	0.28	0.21	0.09	0.00	-0.19	0.54	0.04
(t-value for difference over Universe)	8.12	9.53	5.15	-4.48	-9.71	2.97	
Beta (ex-ante)	0.47	0.76	0.96	1.20	1.61	-1.14	
Beta (realized)	0.65	0.86	1.00	1.16	1.35	-0.70	1.00
CAPM-style alpha	1.22%	-0.60%	-4.56%	-9.00%	-19.36%	20.58%	
(t-value)	0.51	-0.33	-3.74	-6.73	-5.14	3.51	

The first two rows report annualized returns over risk-free return and corresponding standard deviation of excess returns. Excess returns and standard deviations show a definite trend as we move from top quintile, low beta portfolio to bottom quintile, high beta portfolio. Annualized excess return of low beta portfolio is 6.3% and that is monotonically declining as we move towards high beta portfolio. High beta portfolio observes an annualized excess return of -8.84%. The trend is exactly the reverse for standard deviation. Annualized standard deviation of excess returns for low beta portfolio is 22.55% and it keeps on increasing, and the corresponding standard deviation of high beta portfolio is as high as 45.8%. Zero cost, low beta minus high beta, long-short portfolio reports an annualized excess return of 15.5% and standard deviation of 27.88%. Universe, a proxy for market portfolio reports annualized excess return of 1.34% and standard deviation of 33.88%. Clearly, a low beta portfolio turns out to be a high-return, low-risk portfolio. High beta portfolio turns out to be a low return, high risk portfolio. Low beta portfolio is a superior portfolio and dominates both high beta portfolio as well as universe portfolio.

The following two rows report Sharpe ratios and corresponding t-values showing significance of such Sharpe ratio in comparison to Sharpe ratio of universe portfolio. Sharpe ratio for low beta portfolio is 0.28, which is the highest among beta quintile portfolios with corresponding t-value of 8.12. Sharpe ratio keeps on declining. A high-beta portfolio has Sharpe ratio of -0.19 and corresponding t-value of -9.71%. The low beta portfolio registers superior risk-adjusted performance, whereas the high beta portfolio registers inferior risk-adjusted performance over the universe portfolio. Higher excess return and lower standard deviation both contribute to superior performance of low beta portfolio; converse is the case with high beta portfolio, where lower excess return and higher standard deviation both contribute to inferior performance. The stark difference in the performance of low beta portfolio and high beta portfolio is captured in zero-cost, long low beta and short high beta portfolio. Low beta minus high beta portfolio registers Sharpe ratio of 0.54, which is significantly higher compared to low beta portfolio.

However, such long-short portfolio is out of sync with the market. It has a negative correlation of returns, -0.82 in our sample. The next rows report both ex-ante beta (beta calculated for ranking purpose) and ex-post or realized beta of resultant time series of monthly rebalanced quintile portfolios. Ex-ante beta for low beta portfolio is 0.47, whereas realized beta is 0.65. For a high beta portfolio, ex-ante beta is 1.65, whereas realized beta is 1.35. It is evident that across quintile variation in realized betas is much lesser than ex-ante betas. However, it is worth noting that the low beta portfolio constructed using ex-ante beta ranking continues to have lowest realized beta and high beta portfolio constructed using ex-ante beta ranking continues to have the highest realized beta. The pattern remains the same for other quintile portfolios as well. The difference between the realized beta for the low beta and high beta, portfolio is -0.7, which is large and significant. These results indicate that betas predicted from past returns are a strong predictor of future betas.

The final two rows report CAPM-style single factor alpha for beta quintile portfolios and zero-cost low beta minus high beta portfolio as well as corresponding t-values. Single factor alpha for low beta portfolio is 6.75% with corresponding t-value of 3.59, which is large and significant. Alpha declines consistently as we move from low beta portfolio to high beta portfolio. Alpha for high beta portfolio is -10.65% with t-value of -3.41 that is substantially negative and significant. Zero-cost, long low beta and short high beta portfolio registers alpha of 16.08 with corresponding t-value of 3.41. This clearly shows that low beta stocks have high (positive) alpha whereas high beta stocks have low (negative) alpha. A long-only investment strategy of investing in a portfolio consisting of low beta stocks or long-short strategy of going long on low beta stocks and short on high beta stocks can be highly rewarding on absolute as well as risk-adjusted basis.

4.1. Bivariate Analysis

Now, we turn our focus to see the strength of beta anomaly after controlling for other known factors such as size, value and momentum by using double sorting approach.

Table 2: Bivariate Analysis Results - Double sorting to control for other effects

This table reports CAPM style one-factor alphas and realized market betas for beta quintile portfolios and zero-cost, long low beta, short high beta portfolio. Panel A, Panel B and Panel C report performance beta quintile portfolios after controlling for size, value and momentum factors respectively, where size is measured by market capitalization, value by E/P ratio and momentum as 12-months minus 1-month returns. Beta quintile portfolios are constructed in such a manner that they represent stocks from every slice of control factor, i.e. every size-controlled beta quintile portfolio represents stocks from each size quintile.

Panel A: Annualized Alpha from Double Sort on Size (Market Capitalization) and beta (past 3 years)						
	low beta	P2	P3	P4	high beta	lb-hb
Alpha	5.65%	4.99%	1.34%	-3.10%	-9.09%	14.70%
t-value	3.34	3.81	1.14	-2.71	-3.53	3.65
Panel B: Annualized Alpha from Double Sort on Value (Earnings/Price) and beta (past 3 years)						
	low beta	P2	P3	P4	high beta	lb-hb
Alpha	5.27%	3.20%	2.00%	-2.34%	-8.28%	13.55%
t-value	3.20	2.50	1.75	-1.88	-3.08	3.32
Panel C: Annualized alpha from Double Sort on Momentum (12 month minus 1 month returns) and beta (past 3 years)						
	low beta	P2	P3	P4	high beta	lb-hb
Alpha	5.67%	3.08%	2.35%	-2.15%	-9.11%	14.77%
t-value	3.09	2.16	1.96	-1.55	-3.31	3.41

Table 2 reports CAPM style alphas and corresponding t-values for double sorted beta quintile portfolios. Panel A presents results for beta quintile portfolios after controlling for size measured by market capitalization of each stock. Alpha for size controlled low beta portfolio is 5.65%, which is large and significant, and its t-value is 3.34. For a matching high beta portfolio, alpha is -9.09% which is large and significant but with negative t-value of -3.53. Panel B reports alpha and corresponding t-values for beta quintile portfolios by value effect. Alpha for low beta portfolio is 5.27% with t-value of 3.2, which is economically and statistically significant. Matching high beta portfolio delivers alpha of -8.08% with t-value of -3.08 which is large and significant. Alpha declines systematically as we move from low beta portfolio to high beta portfolio without any exception. Alphas in Panel C show similar results for momentum controlled beta quintile portfolios. Annualized alpha for low beta portfolio is 5.67% with t-value of 3.09, whereas matching high beta portfolio delivers alpha of -9.91% with t-value of -3.31. Alphas for both low and high beta portfolios are large and significant but have opposite signs. Alphas for zero cost, low-beta minus high beta portfolio for size, value and momentum factors are 14.70% (t-value of 3.65), 13.55% (t-value of 3.32) and 14.77% (t-value of 3.41) respectively; all are large and significant. These alphas are not materially different from one another. They are also not materially different from alpha of a matching portfolio without factor control. This shows that beta effect is robust, economically large and statistically significant after controlling for size, value and momentum effects. After establishing the robustness of beta anomaly using univariate and bivariate analysis, we look at relative performance of various long low-beta short high-beta arbitrage strategies. As we can see from Table 1, zero-cost, long-short, lb-hb portfolio, delivers large annualized alpha of 16.08%. However, it has the market beta of -0.7. The portfolio has zero cost but it is not a beta-neutral portfolio. From a practical perspective, such high negative beta may be an undesirable trait for most investors unless such portfolio is considered as a separate asset class and is used as an effective hedge to overall market facing portfolio.

Table 3: Performance of various beta arbitrage strategies

This table reports CAPM style one-factor alpha, realized market betas, 3-factor alphas controlling for size and value factor and 4-factor alphas after controlling for size, value and momentum factors for different zero-cost, beta arbitrage strategies. While lb-hb portfolio is zero-cost portfolio, it is not beta neutral, whereas both BAB and Alt-BAB are constructed by making them beta neutral on ex-ante basis at the end of each month.

	lb-hb	BAB	Alt-BAB
CAPM style alpha	16.08%	16.06%	10.81%
(t-value)	3.39	3.35	3.31
beta (realized)	-0.70	-0.05	-0.03
3-factor alpha	20.22%	19.63%	13.26%
t-value	4.70	4.36	4.33
4-factor alpha	16.37%	15.48%	10.43%
t-value	4.27	3.89	3.85

We report and analyze results of zero-cost, negative beta, long-short portfolio, with two alternative zero-cost, ex-ante, beta-neutral, long-short portfolios: BAB (betting against beta portfolio) constructed in the spirit of Frazzini and Pedersen (2014) and Alt-BAB (Alternative betting against beta) portfolio constructed in line with Garcia-Feijoo, Kochard, Sullivan and Wang (2015). The difference in the construction process of two beta-neutral portfolios is explained in the methodology section.

Table 3 reports market beta and one-factor, three-factor and four-factor alphas with corresponding t-values for all the three zero-cost long-short portfolios. CAPM-style one-factor alpha for long low-beta minus short high-beta portfolio is 16.08% with economically large and statically significant t-value of3.31. However, it has beta of -0.7 and that may not be consistent with many professional investment mandates. On the other end, BAB portfolio has one-factor alpha of 16.06% (t-value 3.35), which is very similar to the alpha of lb-hb portfolio, both in terms of magnitude and statistical significance. However, BAB has realized beta of -0.05 and it is largely beta-neutral.

Table 4: Output of Three and Four factors calendar time regression analysis

This table reports coefficients and corresponding t-values for three and four factor regressions for beta arbitrage portfolios lb-hb, BAB and Alt-BAB, and excess returns of low beta and high beta portfolios to understand the characteristics of beta arbitrage and low and high beta portfolios in terms of strength of their alpha and factor tilt towards classic size, value and momentum factors.

	lb-hb		BAB		Alt-BAB		$lb-r_f$		$hb-r_f$	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	coefficient	t-value	coefficient	t-value
4-factor alpha (annualized)	16.37%	4.27	15.48%	3.89	10.43%	3.85	5.08%	3.03	-11.29%	-4.49
r_m-r_f	-0.45	-10.22	0.18	4.10	0.13	4.11	0.74	39.28	1.19	41.79
SMB	-0.04	-0.48	-0.05	-0.65	-0.04	-0.83	-0.03	-0.90	0.01	0.13
HML	-0.40	-6.27	-0.34	-5.18	-0.23	-5.12	-0.12	-4.44	0.27	6.60
WML	0.31	6.19	0.33	6.44	0.23	6.43	0.13	6.15	-0.17	-5.33
	lb-hb		**BAB**		**Alt-BAB**		**$lb-r_f$**		**$hb-r_f$**	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	coefficient	t-value	coefficient	t-value
3-factor alpha (Annualized)	20.22%	4.70	19.63%	4.36	13.26%	4.33	6.76%	3.59	-13.47%	-4.92
r_m-r_f	-0.55	-12.01	0.07	1.54	0.05	1.55	0.70	35.24	1.25	43.09
SMB	-0.02	-0.24	-0.03	-0.37	-0.03	-0.54	-0.02	-0.61	0.00	-0.04
HML	-0.38	-5.27	-0.32	-4.26	-0.22	-4.21	-0.12	-3.66	0.26	5.77

The practical difficulty in constructing a BAB portfolio is that it requires active and dynamic lending and borrowing to push both low beta and high beta portfolios to unity in order to achieve beta-neutrality on ex-ante basis. This is an extremely difficult and expensive process to follow in emerging markets like India. An easier to implement Alt-BAB portfolio reports one-factor alpha of 10.81% (t-value = 3.31), that is large and statistically significant, but lower in economic terms compared to alphas of lb-hb and BAB portfolios. The results are robust when we look at three-factor alphas of all the three portfolios after controlling for Fama-French factors of size and value. Three factor alphas for lb-hb, BAB and Alt-BAB portfolios are 20.22% (t-value = 4.7), 19.63% (t-value = 4.36) and 13.26% respectively. It is worth noting that 3-factor alphas are greater economically and more significant statistically than corresponding one-factor alphas for all three beta arbitrage portfolios.

We also report four-factor alphas controlling for momentum factor in addition to size and value factors in the spirit of Carhart. Four-factor alphas of lb-hb, BAB and Alt-BAB factors are 16.37% (t-value = 4.27), 15.48% (t-value = 3.89) and 10.43% (t-value = 3.85) respectively. All are very similar to corresponding one-factor alphas in terms of their value with even greater statistical significance. These results show that low beta anomaly is unique and classic. Value, size and momentum factors combined together don't affect the strength or the statistical significance of the anomaly. On the contrary, three-factor alphas for all the three long-short, beta arbitrage portfolios are greater than their corresponding one-factor alphas. This encourages us to look at the characteristics of our beta arbitrage portfolios in terms of their size, value and momentum tilt.

Table 4 reports results of three-factor and four-factor regressions to understand the portfolio characteristics of lb-hb, BAB and Alt-BAB portfolios. Looking at the output of three and four-factor regressions, we can clearly witness that none of the three portfolios have any size tilt towards small stocks with SMB factor loading near zero, with a negative sign and statistically insignificant. However, the same is not the case with value factor. There is a clear tilt away from value stocks evident in all the three portfolios. HML factor loading of all the three portfolios is substantially large with a negative sign, and is statistically significant. Similarly, looking at four-factor regressions, we can clearly see that all the three portfolios have a clear momentum tilt with large and positive WML factor loading and it is highly significant statistically in each case.

These results are quite interesting. While none of the beta arbitrage long-short portfolios have any tilt towards size factor, these portfolios have clear negative tilt away from value factor and positive tilt for momentum factor. As we know, all these portfolios are a combination of long low-beta and short high-beta portfolios. It is important to see characteristics of both low and high-beta portfolios individually. This will help us understand which portfolio contributes to the size, value and momentum tilt of zero cost, long-short beta arbitrage portfolios. Both three-factor and four-factor loadings of low beta portfolios show that low beta portfolio has no size tilt. However, it is dominated by growth and winner stocks with negative HML factor loading and positive WML factor loading. Both HML and WML coefficients are similar in value and statistically significant, but with opposite sign. On the other end, a high-beta portfolio too has no size tilt, but has clear value tilt with large positive HML factor loading both in terms of size and statistical significance and negative WML factor loading, similarly large and significant. This clearly shows that a high-beta portfolio is dominated by value and loser or negative momentum stocks. We just want to highlight that HML loading is more significant than WML loading. Therefore, a long position in low-beta portfolio and short high-beta portfolio, both contribute to large and negative HML factor loading and comparably large but positive momentum factor loading of all zero-cost, beta arbitrage portfolios.

5. Limitations and Potential future work

This study compares alternative beta arbitrage strategies using portfolio level analysis only. Stock level analysis can provide valuable insights in explaining differences in performance and characteristics of alternative beta arbitrage strategies. Besides, this study uses equal weighting scheme while constructing beta quintile portfolios. Results with alternative weighting schemes such as value weighting scheme would add to the robustness of the results. In addition, this study does not analyze performance of beta arbitrage strategies in markets with borrowing constraints and changing liquidity scenarios.

Future work on beta arbitrage strategies may focus on stock level analysis of beta quintile portfolios and evaluating robustness of results to change in weighting schemes while constructing beta quintile portfolios. Besides, studying the impact of borrowing restrictions and varying liquidity scenarios on performance of beta arbitrage strategies in the Indian context will explain the difference in performance of beta arbitrage portfolios in different phases of the market cycle. Future work should focus on interaction of BAB factor with other known factors such as value, size and momentum to gain further insights into combining beta arbitrage strategies with other factor investment strategies to generate superior risk-adjusted returns.

2. Conclusion

Our results show clear evidence for beta anomaly in Indian stock markets. A low-beta portfolio delivers positive alpha and a high-beta portfolio delivers negative alpha. Beta anomaly is robust after controlling for size, value and momentum factors individually and collectively. Our comparison of three different versions of beta arbitrage portfolio establishes that all the portfolios deliver substantial alphas contributed by both long and short side of the portfolios. Moreover, all the portfolios have a clear tilt towards momentum and away from value factor, and no significant loading for size factor. While alphas of lb-hb and BAB portfolios are similar, BAB portfolio is largely beta-neutral, whereas lb-hb portfolio has large negative beta. Alt-BAB has comparatively lower alpha, but it turns out to be the best implementable strategy in emerging markets like India with short selling and borrowing restrictions along with funding constraints.

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Appendix 1: Summary statistics

This table reports the number of eligible stocks for each iteration with their median price to earnings multiple and median market capitalization.

Year-Month	No of stocks	Median PE	Median Market-cap (million INR)
200401	465	11.61	3209.5
200402	468	9.57	2911.1
200403	471	9.12	2734.7
200404	471	8.72	2630.9
200405	476	9.24	2876.9
200406	478	7.98	2568.5
200407	479	8.24	2510.2
200408	485	8.69	2859.1
200409	484	9.54	3213.4
200410	486	10.35	3553
200411	487	9.93	3586.5
200412	490	11.32	4210.1
200501	488	12.91	4585.4
200502	489	12.11	4856
200503	490	12.56	5013.2
200504	489	12.36	5263.4
200505	486	12.76	5191.1
200506	485	14.23	5470.2
200507	487	14.80	5699.8
200508	488	14.62	6191.5
200509	487	16.18	7065.7
200510	489	16.50	7342.2
200511	486	13.92	6818.4
200512	488	15.81	7556
200601	488	16.73	8062.1
200602	487	17.26	8605.8
200603	488	17.14	8569.5
200604	490	18.10	8918.8
200605	489	19.46	9909.8
200606	491	16.49	8418.9
200607	492	14.79	7516.5

Year-Month	No of stocks	Median PE	Median Market-cap (million INR)
200608	489	13.28	7689
200609	491	14.82	8514
200610	483	15.50	8906.3
200611	484	15.51	9607.1
200612	490	15.12	9665.7
200701	497	15.56	10411.7
200702	500	15.32	10664.2
200703	502	14.10	9614.6
200704	505	13.46	9085.3
200705	508	14.38	10221
200706	512	15.35	10633.6
200707	514	15.93	10375.8
200708	516	14.47	10873
200709	519	14.05	11064.3
200710	524	15.41	12198
200711	524	14.96	13157.2
200712	526	15.62	14177.3
200801	526	18.46	17079
200802	524	13.87	12929.6
200803	521	13.94	13285.3
200804	526	11.94	10934.4
200805	531	13.13	12363.7
200806	533	12.75	11829
200807	538	10.51	9923.1
200808	546	10.27	10282.3
200809	547	10.64	10478.9
200810	547	8.85	8476.4
200811	547	5.98	5779.6
200812	547	5.25	4940.8
200901	550	6.01	5740.9
200902	557	5.78	5033.7

Year-Month	No of stocks	Median PE	Median Market-cap (million INR)
200903	561	5.49	4729.6
200904	570	5.94	5338.4
200905	575	7.57	6494.1
200906	576	11.35	9560.6
200907	580	11.34	9448.2
200908	581	10.96	10575.6
200909	583	11.84	11775.7
200910	590	12.84	12784.5
200911	593	11.20	11247
200912	599	12.53	12488.7
201001	605	13.51	13840.2
201002	610	13.09	13715.3
201003	616	13.10	13176.8
201004	625	14.03	14432.6
201005	630	13.75	15055.9
201006	636	13.11	14744.4
201007	637	14.22	15705.1
201008	640	14.26	15980.2
201009	643	14.45	16738
201010	644	15.32	18071.7
201011	650	15.55	18573.6
201012	654	14.47	17380.1
201101	660	14.54	17879.7
201102	660	12.68	16109.9
201103	665	11.82	14004.7
201104	667	13.02	15545.7
201105	669	13.33	16680.2
201106	671	12.71	15531.4
201107	671	12.85	15267.9
201108	675	12.66	15482.1
201109	674	11.49	13593
201110	674	11.20	13176.3
201111	678	11.37	13743.2
201112	678	10.11	12340.2
201201	678	9.12	10668.6

Year-Month	No of stocks	Median PE	Median Market-cap (million INR)
201202	678	10.41	12901.9
201203	678	11.47	13786.1
201204	676	11.05	13371.7
201205	674	11.74	13145.1
201206	673	11.07	11838.6
201207	674	11.78	12536.5
201208	676	10.64	12044.4
201209	677	10.61	11785
201210	680	11.62	13412.5
201211	681	11.69	13470
201212	685	12.18	13249.3
201301	688	12.59	14517.4
201302	696	12.32	14650.1
201303	700	10.87	12177.1
201304	701	9.96	11880
201305	702	11.10	12600.5
201306	700	10.94	12202.6
201307	699	10.53	11363.2
201308	696	8.96	10060.7
201309	697	8.36	9992.2
201310	699	9.17	10364.1
201311	702	9.61	11386
201312	703	9.86	11883.6
201401	701	10.61	13471.9
201402	700	10.27	12745
201403	700	10.60	12772.5
201404	702	11.58	14553
201405	701	12.89	15120.2
201406	705	14.97	18413.2
201407	704	16.75	22120.3
201408	702	15.48	21312.5
201409	705	16.18	21465.1
201410	706	16.46	21569.7
201411	708	16.32	21632.9
201412	709	16.59	22677.6

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