APPLIED FINANCE LETTERS

VOLUME 06, ISSUE 01, 2017

RETURNS TO LOW RISK INVESTMENT STRATEGY

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Abstract: The paper studies the low-risk anomaly in the Indian equity market represented by stocks listed on National Stock Exchange (NSE) for the period January 2001 to June 2016. The study provides evidence that low-risk portfolio returns are robust across various risk measures as well as market cap buckets though the intensity of the returns differs. The returns from low-risk investment are not only economically but also statistically significant. They outperform the high-risk portfolio as well as the benchmark portfolio. They deliver higher returns even after controlling for the well-known size, value and momentum factors. The returns are highest for low-risk large cap stocks portfolio sorted for stock volatility as a risk measure. Most of the low-risk portfolios consist of growth and winner stocks. The study provides a framework for an implementable low risk investing strategy.

Keywords: low risk anomaly, volatility effect, idiosyncratic risk, market efficiency, beta.

1. Introduction

The basic goal of portfolio management is to provide higher returns for a given degree of risk or deliver a certain level of return for lower risk. To meet this goal, academics and portfolio managers have formulated various investment strategies. An investor needs to take high risk to earn higher returns – this conviction has survived from the time finance theory led by CAPM has evolved as a structured body of knowledge. But empirical evidence started mounting challenging positive risk-return relationship within the asset class and it was refereed as low risk anomaly where the low-risk investments delivered high returns. Investments in low volatility stocks have delivered higher risk adjusted and absolute returns over a period of time across global markets than high volatility stocks and value weighted benchmark portfolios. It has attracted enough attention for further investigation and application in portfolio management.

Thus, the objective of this research is to provide answers to the following research questions:

1. Does low-risk anomaly exist in the Indian stock market? Is it significant?

2. Is the strength of the low-risk anomaly sensitive to the choice of risk measure?

3. Is the strength of the low-risk anomaly sensitive to the market cap size buckets?

4. How strong is the low-risk investment alpha after controlling for the value, size and momentum factors?

The study considers three risk measures to construct portfolios – volatility (TVOL), idiosyncratic volatility (IVOL) and CAPM beta (Beta). The standard deviation of returns of a stock measures volatility (total risk). CAPM beta measures systematic risk while idiosyncratic volatility measures firm-level unsystematic risk.

The study establishes the following for the Indian equity market: (a) Returns from low-risk stocks portfolio exceed high-risk stocks portfolio returns as well as equally weighted benchmark market portfolio returns over the full market cycle on risk adjusted basis. These returns are positive, as well as statistically and economically significant. (b) Return to low-risk investment strategy is independent of market cap size and the risk measure used to construct portfolios though the intensity of returns differs. (c) Low volatility investing gives higher returns than low idiosyncratic risk investing or low beta investing. (d) Considering the market cap bucket, a low volatility large cap portfolio delivers highest positive excess return. (e) The low beta small cap portfolio delivers negative excess returns. (f) Low-risk investment gives positive excess returns even after controlling for size, value and momentum factors. (g) The low-risk portfolio mostly consists of growth and winner stocks.

Early evidence of low-risk anomaly was documented back in 1970s. Low-risk anomaly indicates that over a period of time, safer stocks (low risk) deliver higher risk adjusted returns than riskier stocks. A flatter than expected risk-return relationship was documented by Black, Jensen, and Scholes (1972). Haugen and Heins (1975) report early evidence for negative risk return relationship. Later, Fama-French (1992) explained that only beta as a systematic risk measure failed to explain the flat market line. They introduced the size and value factors.

Studies on low-risk anomaly differ on the ground of method of portfolio construction and the choice of risk measure. The three common risk measures found in the literature are volatility, idiosyncratic volatility, and CAPM beta. The two portfolio construction approaches are ranking stocks using a risk measure or constructing a minimum variance portfolio using Markowitz (1952) framework. There are studies that either explain the low-risk anomaly or refute it. The possible explanations for the low-risk anomaly can be categorized into economic and behavioural aspects.

Studies conducted by Haugen & Heins (1975), Blitz and Vliet (2007), Clarke, De Silva and Thorley (2006), Ang, Hodrick, Xing and Zhang (2006, 2009), Baker, Bradley and Wurgler (2011), Soe (2012), Baker and Haugen (2012), Blitz, Pang and Vliet (2013) and Frazzini and Pedersen (2014) found that the historical returns of low-risk securities were higher than high-risk securities.

Refuting the above, the studies conducted by Malkiel and Xu (1997), Malkiel and Xu (2002), Fu (2009), Spiegel and Wang (2005), Martellini (2008) support the view that high-risk stocks give higher average return though it varies over time. Bali and Cakici (2008) attribute inverse relationship between idiosyncratic risk and return to illiquid, small stocks. Bali, et al. (2011) attribute the negative risk-return relationship due to investor's demand for lottery like pay-offs. Scherer (2011) argues that excess returns of a minimum variance portfolio are attributable to size and value factors and volatility effect is merely a proxy for value effect.

Black et al. (1972), Frazzini and Pedersen (2014) and Hong and Sraer (2012) attribute the existence of a flat relationship between risk and return to borrowings and short selling restrictions. Brennan (1993), Karceski (1993), Falkenstein (2009), Blitz et al. (2013), Baker et al. (2012) show the existence of agency problem and decentralized investing approach. The borrowing restrictions and short selling constraints make institutional investors ignore low risk, high positive alpha stocks. Agency problems associated with portfolio construction motivate fund manager to increase their investments in high-risk stocks. This in turn enhances their personal compensation structure. It also makes the fund managers care more about out-performing in the bull market rather than under-performing in the bear market. It results in an increase in demand for high beta stocks which reduces the required rate of returns. Moreover, behavioural biases such as preference for lotteries, over confidence and representativeness motivate investors to demand high-risk stocks. This leads to increase in price for high-risk stocks.

Different studies have used different risk measures to explain the low-risk anomaly. Clarke, De Silva and Thorley (2010) constructed volatility-minus-stable (VMS) factor on the basis of idiosyncratic volatility. After controlling for size effect, VMS is able to explain the cross section of security returns. Frazzini et al. (2014) extend the scope of beta arbitrage by constructing Betting against Beta (BAB) factor. BAB portfolios across several asset classes and markets give higher returns. Garcia-Feijoo, Kochard, Sullivan, and Wang (2015) constructed the alternative (Alt- BAB) factor to further extend the scope of beta arbitrage.

In the Indian market, Agarwalla, et al. (2014) studied the returns of BAB (betting against beta) factor. They study found that BAB factor earns significant positive returns. Joshipura and Joshipura (2016, 2017) conducted a robust test and found that low volatility and low beta stocks earned higher returns than high volatility and high beta stock respectively as well as beat the benchmark market portfolio even after controlling for size, value and momentum factors.

Thus the literature in India as well as abroad provide evidence of the low-risk anomaly. The present study intends to further explore these findings. Data comprises of National Stock Exchange (NSE) listed stocks from January 2001 to June 2016 bifurcated into large cap, mid cap and small cap size buckets. It studies returns to volatility, idiosyncratic volatility and CAPM beta sorted portfolios.

The paper is organized as follows. Section I discusses data and methodology. Section II discusses results. Section III discusses the limitations and future scope of the paper. Section IV provides the conclusion to the paper.

2. Data and Methodology

According to World Federation of Exchanges (WFE), in 2015, the National Stock Exchange (NSE) was the leading stock exchange in India and the fourth largest in the world by equity trading volume. NSE India has a market capitalization of $1.87 trillion[1] in 2016-17. It has an average daily turnover of $3,185.5 million. The number of companies listed on NSE is 1,808 in 2015-16. NSE holds a leadership position across asset classes in the Indian and global exchange sectors. This demonstrates the robustness and liquidity of the exchange. The study includes data of all past and present stock constituents of NSE India. The period of study is from January 2001 to June 2016. We collected data from Capitaline database.

[1] $1 =Rs 64

We collected monthly data on stock prices[2], volume, market capitalization and earning to price.

The total number of stocks vary from period to period due to listing / de-listing of stocks on the exchange. This universe consisted of approximately 1,000 stocks, on average.

We collected Fama-French (1992) and Carhart (1997) momentum factors and risk free rate for the Indian Stock Markets from the IIM Ahmedabad data library.
We calculated the monthly log-return of stocks, volatility, idiosyncratic risk and CAPM beta for all stocks. We calculated the risk measures for each month using past 36 months excess log return of stocks. To separate the stocks into various size buckets, we first sorted the stocks in a particular month on the basis of its market capitalization. We then cumulated 75% of the total market capitalization in the large cap bucket. Companies falling in the next 20% of the total market capitalization were included in the mid cap bucket. The small cap bucket consisted of companies falling in the remaining 5% of the total market capitalization. We did this on a month-on-month basis. These were the breakpoints to allot stocks to the large cap, mid cap and small cap size buckets.

We calculated the stock returns and the three risk measures for 150 months in monthly iteration from January 2004 to June 2016. We eliminated from the sample any company with less than 12 monthly returns. Also, we eliminated companies that did not have a return in the month following the portfolio construction month (37th month). On monthly basis, we constructed equally weighted quintile portfolios from January 2004 onwards. We sorted stocks on volatility to construct low to high volatility portfolios. We repeated the same to form idiosyncratic volatility and CAPM beta sorted portfolios.

P1 quintile portfolio of every iteration of every market cap size bucket as well for every risk measure consists of low-risk stocks. Similarly, P5 quintile portfolio consists of highest risk stocks. We calculated monthly excess returns for the month following portfolio construction (37th month).

For the resulting time series, we calculated average annualized equally weighted excess returns, the standard deviation of returns, Sharpe ratio, CAPM alpha and ex-post beta. We considered equally weighted entire NSE listed equity stocks as proxy to market portfolio (EWI) on similar lines Blitz et al. (2007)

We used the three-factor and four-factor Fama-French-Carhart regression[3] to test the robustness of the results and the strength of low risk investing strategy. Also, it helped to separate the effect of low risk investing from other effects. We used market capitalization to measure size for calculation of SMB (small-minus-big) factor. Earnings-to-price was used for calculation of VMG (value-minus-growth) factor. We calculated past 12-months total returns minus 1-month returns to know the WML (winner-minus-loser) factor returns. In case of Fama-French Model, we regressed the returns of portfolios against market returns, SMB and VMG. In case of Fama-French-Carhart Model, we regressed the returns of the portfolios against market returns, SMB, VMG and WML. It controlled for any influence of these factors on the returns.

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[2] All stock price data is adjusted for corporate action- Section I Data and Methodology

[3] Risk free rate and Fama-French and momentum factors data has been taken from IIMA Data Library- Section I Data and Methodology

Using the following classic one-factor regression, we calculated CAPM alpha with equally weighted Entire NSE market (EWI) as a proxy for market:

$$Rp,t\text{-}Rf,t= \alpha p+ \beta p,m\ (Rm,t\text{-}Rf,t)+\varepsilon p,t \tag{1}$$

where Rp,t, Rf,t , Rm,t and Ɛp,t are the return on the portfolio p, risk-free rate, the return of the market portfolio and idiosyncratic volatility respectively in time t. The alpha of the portfolio is represented by αp.

The Fama-French 3 factor and Fama-French-Carhart 4 factor analysis is conducted by adding SMB, VMG and WML factors to the above equation 1.

$$Rp,t\text{-}Rf,t= \alpha p+\beta p,m\ (Rm,t\text{-}Rf,t)+ \beta p,smb*RSMB +\beta p,vmg*RVMG+\varepsilon p,t \tag{2}$$

$$Rp,t\text{-}Rf,t= \alpha p+\beta p,m\ (Rm,t\text{-}Rf,t)+ \beta p,smb*RSMB +\beta p,vmg*RVMG+ \beta p,wml*RWML+\varepsilon p,t \tag{3}$$

where RSMB, RVGM and RWML represent the return on size, value and momentum factors respectively and βsmb, βvmg and βwml represent betas of the portfolio of size, value and momentum factors of the study respectively.

3. Main Results

3.1 Results of TVOL and IVOL sorted portfolios

Panel A of Table I exhibits results of portfolios of large cap stocks sorted on volatility (TVOL). The excess return for low volatility quintile portfolio P1 is higher (8.28%) as compared to P5 (-15.28%) and market portfolio (-0.59%). There is a monotonic increase in the standard deviation from P1 (18.89%) to P5 (41.86%). The Sharpe ratio reduces from P1 (0.44) to P5 (-0.37) and it is also negative (-0.02) for the equally weighted market portfolio (EWI). The ex-post beta for P1 is the lowest (0.61). The CAPM alpha for P1 is the highest (8.67%) as well as economically and statistically significant. The differential gain by investing in low volatility portfolio and shorting high volatility portfolio (long-short strategy) is 23.56%. This is an exceptionally good return. The results show very clearly that there is a negative relationship between volatility and risk adjusted returns.

Panel B, Panel C and Panel D of Table I exhibits the above-mentioned results for mid cap, small cap, and entire NSE portfolios respectively sorted on volatility. These tables also show similar results as for large cap stock portfolios. The excess returns are diminishing, the standard deviation is increasing, the Sharpe ratio is decreasing, the ex-post beta is increasing and the CAPM alpha is decreasing from P1 to P5 in mid cap, small cap as well as EWI portfolios. The only exception in Table I Panel B is P3. Though the excess returns and alpha of P3 is greater than P2, it has a higher risk (measured by standard deviation and ex-post beta of the portfolio).

We observe a similar trend of returns from IVOL quintile portfolios as of TVOL quintile portfolios. The returns to low IVOL portfolio are economically and statistically significant though the intensity of the returns is different than TVOL portfolio.

Table I: Quintile portfolios based on historical volatility (Annualized Results) for Large Cap, Mid Cap, Small Cap and Entire NSE universe

	P1	P2	P3	P4	P5	P1-P5	EWI
Panel A: Historical Volatility sorted Large Cap Portfolios							
Excess Returns	8.28%	1.97%	1.50%	0.25%	-15.28%	23.56%	-0.59%
Std. Deviation	18.89%	23.38%	29.15%	31.48%	41.86%	31.30%	27.05%
Sharpe Ratio	0.44	0.08	0.05	0.01	-0.37		-0.02
Ex-post beta	0.61	0.82	1.03	1.12	1.45	-0.84	
Alpha	8.64%	2.45%	2.11%	0.91%	-14.42%	23.06%	
t-value	3.24	1.11	0.86	0.36	-3.48	3.79	
Panel B: Historical Volatility sorted Mid Cap Portfolios							
Excess Returns	7.03%	2.10%	2.89%	-2.00%	-12.97%	20.00%	-0.58%
Std. Deviation	20.79%	28.26%	30.69%	35.86%	43.11%	26.23%	31.00%
Sharpe Ratio	0.34	0.07	0.09	-0.06	-0.30		-0.02
Beta	0.64	0.89	0.97	1.14	1.36	-0.72	
Alpha	7.40%	2.62%	3.46%	-1.33%	-12.18%	19.58%	
t-value	4.07	1.68	2.13	-0.73	-4.72	5.03	
Panel C: Historical Volatility sorted Small Cap Portfolios							
Excess Returns	4.64%	-0.74%	-1.99%	-8.15%	-18.65%	23.29%	-5.01%
Std. Deviation	29.56%	35.55%	39.99%	42.31%	47.00%	21.80%	38.43%
Sharpe Ratio	0.16	-0.02	-0.05	-0.19	-0.40		-0.13
Beta	0.76	0.92	1.03	1.09	1.20	-0.44	
Alpha	8.43%	3.84%	3.19%	-2.67%	-12.64%	21.06%	
t-value	5.58	2.64	2.63	-2.01	-4.93	5.46	
Panel D: Historical Volatility sorted Entire NSE Portfolios							
Excess Returns	4.79%	1.83%	-1.42%	-6.16%	-16.94%	21.73%	-3.57%
Std. Deviation	24.55%	32.07%	36.22%	40.53%	45.57%	25.19%	35.29%
Sharpe Ratio	0.20	0.06	-0.04	-0.15	-0.37		-0.10
Beta	0.68	0.90	1.02	1.14	1.26	-0.59	
Alpha	7.20%	5.05%	2.22%	-2.08%	-12.42%	19.62%	
t-value	4.26	3.93	1.89	-1.72	-4.68	4.86	

Table I reports univariate analysis for the resultant time series of volatility sorted quintile portfolios constructed for large cap, mid cap, small cap and entire NSE universe in Panel A, B, C and D respectively. Each Panel reports annualised excess returns, standard deviation, Sharpe ratio, ex-post beta and CAPM style alpha with their t-value.

3.2 Results of Beta sorted portfolio

The results of ex-ante beta sorted portfolios are a bit different. The excess return for low beta large cap quintile portfolio P1 (3.36%) is marginally lower by 1.47% than P2 (4.83%) portfolio. Also, the excess return of low beta mid cap quintile portfolio P1 (3.92%) is marginally lower by 0.17% than P2 (4.09%) portfolio.

But the excess returns of the highest beta portfolio P5 (-14.34%) of large cap, mid cap (-8.51%) and the entire universe market portfolio (-0.59%) are lower than P1. The standard deviation is increasing monotonically from P1 to P5. The Sharpe ratio reduces from P1 to P5 but increases marginally in P2 (0.20) from P1 (0.17). It is also negative (-0.02) for the equally weighted market portfolio (EWI). The ex-post beta is increasing from P1 to P5. The CAPM alpha is higher and statistically significant for P2 and P3 as compared to P1 portfolios.

We observe in Table II that the P1 of beta sorted small cap stocks portfolio deliver negative excess returns. The excess returns from P2 and P3 are less negative than P1 though risk increases from P1 to P5.

Table II: Excess Returns of various portfolios sorted on different risk measures (Fig.in %)

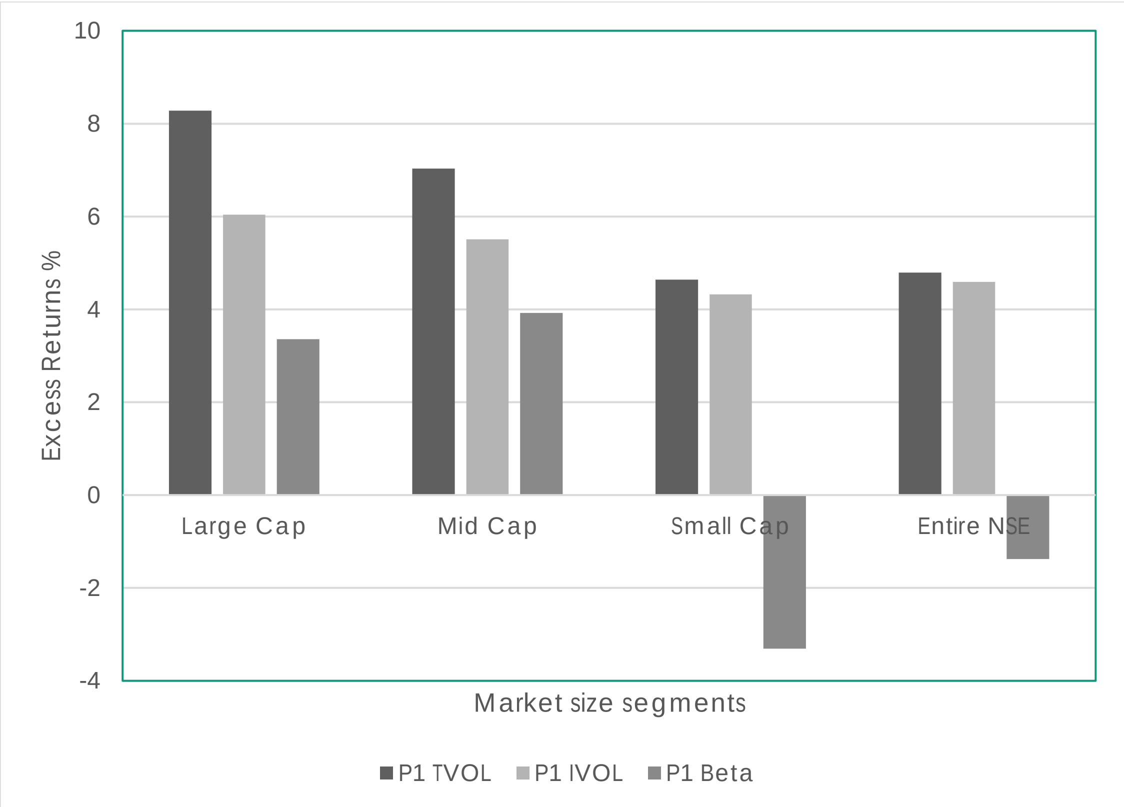
	Volatility (TVOL)				Idiosyncratic Volatility (IVOL)				Ex-ante Beta (β)			
	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE
P1	8.28	7.03	4.64	4.79	6.04	5.51	4.32	4.59	3.36	3.92	-3.31	-1.38
P2	1.97	2.10	-0.74	1.83	4.39	5.09	0.15	1.31	4.83	4.09	-1.68	1.46
P3	1.50	2.89	-1.99	-1.42	-2.22	-1.36	-4.64	-2.45	3.12	1.04	-0.73	-1.18
P4	0.25	-2.00	-8.15	-6.16	-0.12	-0.30	-6.35	-4.09	-0.29	-3.53	-6.0	-4.44
P5	-15.28	-12.97	-18.65	-16.94	-11.38	-11.91	-18.41	-17.25	-14.34	-8.51	-13.26	-12.35
P1-P5	23.56	20.00	23.29	21.73	17.42	17.41	22.73	21.83	17.70	12.44	9.94	10.97

Though the excess return of P1 is negative, it is less negative than P5 of beta sorted small cap portfolio. The same stands true for P1 of entire universe portfolio sorted by beta. The alpha of beta sorted P1 is less positive than P2 and P3 but it is negative for P5.

3.3 Other Results

As seen in Fig.1, volatility sorted large cap stocks earn the highest excess returns. The beta sorted small cap portfolio earn the least excess returns. The P1 of TVOL sorted large cap stocks give higher returns than P1 of IVOL or Beta sorted large cap stocks. The same stands true for mid cap, small cap and the entire universe market portfolio. The P5 of TVOL sorted small cap stocks earn highest negative excess returns, followed by IVOL and Beta.

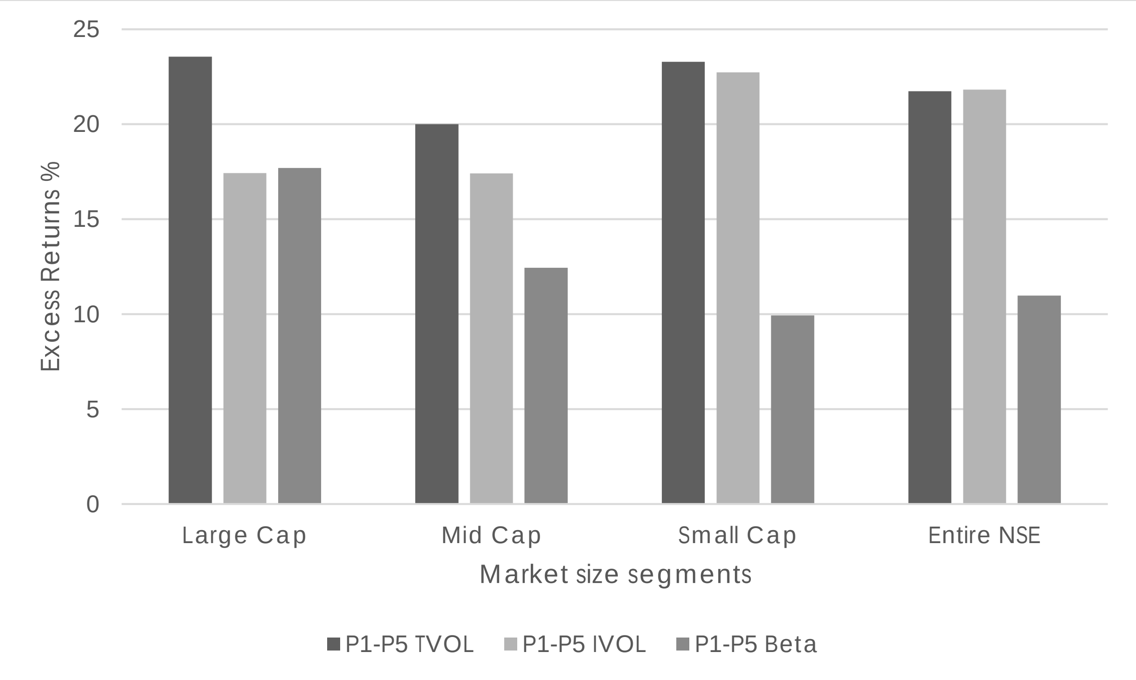
Fig.1: Various market sizes excess returns of lowest risk portfolio P1



3.4 Results of Long-Short Strategy

As observed in Fig. 2, the long- short strategy portfolios of all market size as well as risk measures deliver positive excess returns. The CAPM alpha is economically and statistically significant. The TVOL sorted large cap portfolio earn the highest excess returns. Whereas the Beta sorted small cap portfolio earn the least excess returns. The ex-post betas of this strategy in all market size bucket and risk measures are negative. Negative beta investment strategy indicates investment to hedge risk. This might not be preferable to the investment community. Also to successfully implement the long-short strategy requires leverage in investment which again might not be accepted by the mandates given to the investment houses. So though this strategy delivers high excess returns with zero risk, it might be rarely implementable.

Fig. 2: Various market sizes excess returns of P1- P5



3.5 Discussion of the test of robustness of low risk anomaly

Table III Panel A, B, C and D report single-factor, 3-factor and 4-factor alphas with their t-values of volatility sorted quintile portfolios of various market size buckets as well as entire NSE market.

The 3-factor alpha controls for size and value whereas for 4-factor alpha controls for size, value and momentum. The results show that P1 portfolios of all market sizes and the entire universe market have economically and statistically significant positive alphas. The alphas for P5 portfolios are negative and statistically significant. This helps us to understand that the low risk investing strategy is independent of size, value and momentum factors in the Indian stock market. Even the long –short strategy for all market size buckets have economically and statistically significant positive alphas. An exception to the trend is Table III Panel B P3 (mid cap size bucket). P3 gives better and significant alpha as compared to P2.

We observe similar results for idiosyncratic volatility sorted portfolios of all market size.

But for portfolios sorted on ex-ante beta, we do not observe the same trend. CAPM alpha of P2 portfolios of large cap, mid cap and the entire market universe is greater, positive and statistically significant than the alpha of P1 portfolios. P3 portfolios of these three market segments also have higher alphas than P1 but they are statistically insignificant. The alphas for P5 portfolios are negative and statistically significant. P3 of Beta sorted small cap portfolios have the highest alpha followed by P2 and they are even statistically significant whereas P1 alphas are small and insignificant.

We infer from above revelations that value, size and momentum affect the statistical significance of the low-risk investment strategy. In most of the result, the three- and four-factor alphas are greater than the single factor alpha. This supports the robustness of the low-risk investment strategy. We can devise a better investment strategy by controlling these factors. By doing so, we can enhance returns of the portfolio. So, we conducted further analysis of extreme portfolios.

Table III: CAPM Alpha, Three Factor (Fama-French) alpha and Four Factor (Fama-French-Carhart) alpha for historical Volatility sorted Quintile Portfolios of Large Cap, Mid Cap, Small Cap and Entire NSE universe

	P1	P2	P3	P4	P5	P1-P5
Panel A: Historical Volatility sorted Large Cap Portfolios						
CAPM style Alpha	8.64%	2.45%	2.11%	0.91%	-14.42%	23.06%
t-value	3.24	1.11	0.86	0.36	-3.48	3.79
3 factor alpha	9.29%	2.76%	2.73%	1.38%	-16.60%	25.89%
t-value	3.49	1.25	1.11	0.55	-4.18	4.39
4 factor alpha	6.60%	1.79%	2.28%	2.14%	-13.16%	19.76%
t-value	2.72	0.81	0.91	0.85	-3.51	3.69
Panel B: Historical Volatility sorted Mid Cap Portfolios						
CAPM style Alpha	7.40%	2.62%	3.46%	-1.33%	-12.18%	19.58%
t-value	4.07	1.68	2.13	-0.73	-4.72	5.03
3 factor alpha	7.14%	2.81%	3.49%	-1.07%	-12.42%	19.55%
t-value	3.92	1.82	2.11	-0.58	-4.81	5.03
4 factor alpha	6.44%	1.56%	3.91%	-1.32%	-10.59%	17.03%
t-value	3.53	1.06	2.34	-0.71	-4.26	4.51
Panel C: Historical Volatility sorted Small Cap Portfolios						
CAPM style Alpha	8.43%	3.84%	3.19%	-2.67%	-12.64%	21.06%
t-value	5.58	2.64	2.63	-2.01	-4.93	5.46
3 factor alpha	9.88%	5.25%	3.01%	-2.61%	-15.38%	25.26%
t-value	7.09	3.85	2.42	-1.93	-6.57	7.24
4 factor alpha	9.69%	5.17%	3.11%	-2.51%	-15.32%	25.02%
t-value	6.89	3.74	2.47	-1.84	-6.46	7.08
Panel D: Historical Volatility sorted Entire NSE Portfolios						
CAPM style Alpha	7.20%	5.05%	2.22%	-2.08%	-12.42%	19.62%
t-value	4.26	3.93	1.89	-1.72	-4.68	4.86
3 factor alpha	9.26%	6.68%	2.85%	-3.20%	-15.65%	24.90%
t-value	6.45	6.20	2.45	-2.84	-6.90	7.49
4 factor alpha	8.50%	6.63%	2.96%	-2.85%	-15.29%	23.79%
t-value	6.09	6.06	2.51	-2.53	-6.67	-6.67

Table III reports univariate and multivariate analysis for the resultant time series of volatility sorted quintile portfolios constructed for large cap, mid cap, small cap and entire NSE universe in Panel A, B, C and D respectively. Each Panel reports annualised CAPM style alpha with their t-value, three factor (Fama-French) and four factor (Fama-French-Carhart) alpha with corresponding t value.

Table IV reports the regression coefficients of P1 and P5 portfolios of Fama- French 3 factor regression. The FF alphas of all portfolios are significant other than P1 beta sorted portfolios. As we conducted the analysis for various market size buckets exclusively, we expected the results on size coefficient to be negligible. This happened to be true.

Table IV: Three Factor (Fama-French) Regression Coefficient Analysis for Large Cap, Mid Cap, Small Cap and Entire NSE universe portfolios sorted on Volatility, Idiosyncratic Volatility and Ex-ante Beta

	P1				P5			
	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE
Risk Measure –Volatility (Monthly data)								
FF Alpha	0.77%	0.59%	0.82%	0.77%	-1.38%	-1.03%	-1.28%	-1.30%
t-value	3.49	3.92	7.09	6.45	-4.18	-4.81	-6.57	-6.90
EWP	0.63%	0.64%	0.81%	0.75%	1.40%	1.34%	1.10%	1.14%
t-value	20.79	33.30	56.99	50.21	31.01	49.57	46.01	48.38
SMB	0.00%	0.08%	-0.01%	-0.08%	0.16%	-0.07%	0.06%	0.13%
t-value	-0.01	2.25	-0.49	-2.78	1.95	-1.44	1.33	2.86
VMG	-0.08%	-0.03%	-0.14%	-0.16%	0.14%	-0.09%	0.23%	0.24%
t-value	-1.91	-1.16	-5.70	-6.53	2.30	2.15	5.68	6.39
Risk Measure Idiosyncratic Risk (Monthly data)								
FF Alpha	0.62%	0.49%	0.83%	0.81%	-1.03%	-0.96%	-1.32%	-1.39%
t-value	3.46	3.89	6.84	7.38	-3.33	-5.26	-6.77	-7.43
EWP	0.75%	0.73%	0.86%	0.80%	1.22%	1.24%	1.04%	1.07%
t-value	31.04	45.63	57.56	58.80	28.69	53.89	43.54	45.69
SMB	-0.08%	-0.02%	-0.07%	-0.18%	0.10%	0.02%	0.14%	0.22%
t-value	-1.93	-0.77	-2.22	-6.80	1.32	0.39	2.90	4.73
VMG	-0.05%	0.02%	-0.12%	-0.13%	0.14%	0.03%	0.21%	0.24%
t-value	-1.34	0.94	-4.69	-5.88	2.38	0.97	5.24	6.29
Risk Measure – Beta (Monthly data)								
FF Alpha	0.34%	0.32%	0.05%	0.10%	-1.32%	-0.64%	-0.63%	-0.74%
t-value	1.23	1.86	0.37	0.73	-3.81	-2.68	-3.54	-4.03
EWP	0.63%	0.66%	0.80%	0.75%	1.38%	1.35%	1.19%	1.22%
t-value	16.90	29.89	47.61	43.32	29.08	45.22	54.32	52.85
SMB	0.07%	0.13%	0.10%	0.09%	0.17%	-0.18%	-0.12%	-0.07%
t-value	1.13	2.98	2.97	2.66	2.01	-3.15	-2.76	-1.56
VMG	-0.10%	-0.05%	-0.07%	0.06%	0.16%	0.14%	0.14%	0.17%
t-value	-1.92	-1.45	-2.41	-2.27	2.37	2.99	3.68	4.55

Table IV reports Fama-French Style regression coefficient of top and bottom quintile volatility, idiosyncratic volatility and beta portfolios with corresponding t value.

We observe that most of P1 consist of big stocks than small stocks. P5 consists of more small stocks than big stocks. The VMG factor in P1 has negative coefficients. It signifies that the portfolios consist of more growth stocks than value stocks. While the same does not stand true for P5. This explains that the low-risk effect is independent of small stock and value factor effect.

Table V lists the regression coefficients of P1 and P5 portfolios of Fama-French-Carhart 4 factor regression. The FF alphas of all portfolios are significant other than beta sorted low-risk portfolios. Additional factor added here is the momentum factor. It can be clearly observed that the P1 results are statistically significant for all market size segments. They consist of growth and winner stocks. While P5 consist of value and loser stocks.

So we can observe that positive risk-return relation is not holding true within the asset class though it is valid across asset classes. And such anomalous relationship is likely to prevail as long as market friction and behavioural biases continue to affect investment decision making.

Table V: Four Factor (Fama-French-Carhart) Style Regression Coefficient Analysis for Large Cap, Mid Cap, Small Cap and Entire NSE universe portfolios sorted on Volatility, Idiosyncratic Volatility and Ex-ante Beta

	P1				P5			
	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE
Risk Measure –Volatility (Monthly data)								
FF Alpha	0.55%	0.54%	0.81%	0.71%	-1.10%	-0.88%	-1.28%	-1.27%
t-value	2.72	3.53	6.89	6.09	-3.51	-4.26	-6.46	-6.67
EWP	0.67%	0.65%	0.82%	0.77%	1.35%	1.31%	1.10%	1.14%
t-value	23.92	32.70	53.86	50.36	31.19	48.30	43.03	45.17
SMB	0.01%	0.08%	-0.02%	-0.09%	0.15%	-0.07%	0.07%	0.14%
t-value	0.14	2.21	-0.60	-3.20	1.97	-1.37	1.34	2.94
VMG	-0.06%	-0.03%	-0.14%	-0.16%	0.12%	0.08%	0.23%	0.24%
t-value	-1.66	-1.08	-5.74	-6.86	2.09	2.09	5.67	6.41
WML	0.19%	0.05%	0.02%	0.07%	-0.24%	-0.14%	-0.01%	-0.03%
t-value	6.00	2.19	0.95	3.61	-4.98	-4.18	-0.19	-1.02
Risk Measure Idiosyncratic Risk (Monthly data)								
FF Alpha	0.55%	0.52%	0.86%	0.80%	-0.96%	-0.95%	-1.35%	-1.43%
t-value	3.08	4.01	6.99	7.22	-3.04	-5.08	-6.90	-7.56
EWP	0.76%	0.72%	0.85%	0.80%	1.20%	1.24%	1.05%	1.08%
t-value	30.84	42.98	53.78	55.27	27.56	50.84	41.47	43.53
SMB	-0.08%	-0.02%	-0.06%	-0.18%	0.10%	0.02%	0.13%	0.21%
t-value	-1.90	-0.73	-2.05	-6.78	1.29	0.41	2.74	4.61
VMG	-0.04%	0.02%	-0.12%	-0.13%	0.13%	0.03%	0.21%	0.24%
t-value	-1.20	0.90	-4.64	-5.87	2.28	0.94	5.20	6.28
WML	0.05%	-0.02%	-0.03%	0.01%	-0.06%	-0.02%	0.04%	0.04%
t-value	1.93	-1.06	1.32	0.36	-1.32	-0.54	1.32	1.32
Risk Measure – Beta (Monthly data)								
FF Alpha	0.06%	0.15%	-0.04%	-0.02%	-0.97%	-0.44%	-0.55%	-0.62%
t-value	0.22	0.96	-0.29	0.12	-3.06	-1.96	-3.15	-3.56
EWP	0.68%	0.70%	0.83%	0.78%	1.31%	1.31%	1.16%	1.18%
t-value	19.82	33.74	49.96	47.79	29.94	44.89	51.79	51.31
SMB	0.08%	0.12%	0.08%	0.07%	0.16%	0.17%	-0.11%	-0.05%
t-value	1.42	3.13	2.61	2.42	2.09	-3.24	-2.45	-1.25
VMG	-0.08%	-0.04%	-0.07%	-0.07%	0.13%	0.13%	0.14%	0.17%
t-value	-1.67	-1.38	-2.80	-2.66	2.17	3.03	3.96	4.91
WML	0.24%	0.16%	0.10%	0.12%	-0.30%	-0.18%	-0.10%	-0.13%
t-value	6.12	6.19	4.99	6.21	-6.04	-5.16	-3.53	-4.45

Table V reports Fama-French-Carhart Style regression coefficient for top and bottom quintile volatility, idiosyncratic volatility and beta portfolios with corresponding t value.

4. Limitations and Potential Future Study

The study observed the returns to the low-risk anomaly in various market cap size buckets forming equally weighed portfolios. In future, the results can be tested using a different weighing scheme like value weighted scheme. This will further check the robustness of the results. Bivariate analysis can also be performed. The portfolios can be double sorted for growth and momentum. This will check the robustness of the results and provide strategic investing alternatives. Stock level analysis can be done to understand the characteristics of stocks which are picked up by low-risk investment strategy to deliver high returns.

5. Conclusion

To conclude, a low-risk investment delivers positive excess return. The CAPM alpha for low-risk portfolios is positive as well as economically and statistically significant. High-risk portfolios deliver negative excess returns. They have statistically significant negative alphas. Low-risk stocks portfolio returns exceed not only high-risk stocks portfolio but also equally weighted benchmark portfolio returns over a full cycle period. The returns of the low-risk stocks portfolio are independent of size as well as the risk measure.

The excess returns to TVOL are greater than IVOL or Beta. The excess returns to large cap portfolio are greater than mid cap and small cap portfolio. The low-risk anomaly is robust even after controlling for size, value and momentum factors. It is not a proxy for either of these factors. The low-risk portfolios majorly consist of large, growth and winner stocks rather than small, value or loser stocks. This clearly proves that the low-risk anomaly exists in the Indian equity market.

A strategy of investing in lowest volatility large cap stocks portfolio controlling value give high excess returns with economically and statistically significant alpha. Another strategy delivered by the study is investing in small cap growth stocks with the lowest volatility or idiosyncratic volatility. Though our universe consists of all stocks listed on NSE, the low-risk stock portfolio picked up large, growth and liquid stocks to deliver high excess returns. Also, low risk anomaly is a combination of systematic as well as unsystematic risk and not restricted to any one risk measure. The reasons that have been listed in the existing literature for the presence of low-risk anomaly apply to the Indian markets. While positive risk-return relation is valid across asset classes, the relation is not holding true within the asset class. Such anomalous relationship is likely to persist as long as market friction and behavioural biases continue to affect investment decision making.

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