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The Volatility Effect: Evidence from India

Nehal Joshipura and Mayank Joshipura

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The Volatility Effect: Evidence from India

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Abstract:

In this paper, we examine the low risk anomaly and its potential explanations in the Indian stock market. Using alternative risk measures of standard deviation and beta, we find evidence in favour of the low risk anomaly after controlling for size, value and momentum. Despite our finding of the anomaly being similar to that in other markets, we uncover several new results in contrast to the prior literature. First, we do not find statistically significant volatility effect after controlling for beta effect. Second, our evidence for volatility effect is not dominated by small and illiquid stocks. Third, our results show that low volatility portfolio outperforms benchmark portfolio not only in down market conditions but also in up market. Besides, we provide performance chasing behavior of mutual fund investors as an additional explanation to portfolio managers' preference for high volatility stocks. The performance chasing behavior leads the investors to choose past performers in portfolio though their future expected returns may be lower.

Keywords: Volatility effect, Betting against beta, Market efficiency, Low risk anomaly, Lottery effect, Limits of arbitrage

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1. Introduction

Finance theory suggests a positive relationship between risk and return. But, researches like Haugen & Heins (1975), Blitz & Vliet (2007), Blitz, et al. (2013) show that portfolio consisting of low volatility stocks outperforms the high volatility counterpart as well as the equally weighted benchmark portfolio over the full market cycle leading to low risk anomaly. This volatility effect is found to be present during different time periods and in different markets in the empirical evidences.

Shifting attention to explanations for the existence of low risk anomaly, we observe the possible explanations are ranging from economic and market frictions to behavioural biases.

Our study attempts to contribute to the body of knowledge in several ways.

First, we attempt to contribute to the existing body of literature by providing evidence of low volatility and low beta anomaly in universe carefully chosen to eliminate small and illiquid stocks. This helps to understand the validity of Bali & Cakici (2008) claim that negative expected returns are associated with small and highly illiquid stocks. We check if the anomaly still exists using large and liquid stock's universe.

Second, we attempt to find volatility as well as beta effect in line with Blitz & Vliet (2007). Our results don't show statistically significant volatility effect after controlling for beta. In our sample, volatility effect is present but not significant once controlled for beta effect. This evidence indicates that both volatility and beta effects are comparable and there is a little evidence for idiosyncratic risk based volatility effect as shown by Ang, et al. (2009).

Third, analysis of regression coefficients for Fama-French-Carhart factors shows the characteristics of the low and high volatility portfolios. In our sample large, growth and winner stocks dominate low volatility portfolio and small and risky stocks dominate high volatility portfolio. This provides clear evidence against Scherer (2011) who argues that large part of excess return of minimum variance portfolio over benchmark portfolio can be explained using Fama-French factors. Also he claims that the volatility effect is mainly a proxy for value effect. So the paper further tries to offer evidence against that. Bali and Cakici (2008).

Fourth, our study attempts to address issue raised in Poullaouec (2010) that large part of outperformance of minimum variance strategy is attributable to the period of 2000 to 2003 and is directly linked to the aftermath of dotcom bubble. Our study starts from January 2004 and still finds clear evidence for low risk anomaly.

Last, but not the least, our study shows that volatility effect is highly significant not only on risk-adjusted basis but delivers superior absolute returns over equally weighted universe portfolio as well as popular value weighted benchmark Nifty 200 index.

The paper is organized as follows. Section 2 covers detailed literature review. Section 3 discusses data and methodology. Section 4 shows results, Section 5 discusses possible explanations and Section 6 offers conclusion.

2. Review of Literature

Initial evidence on flatter than expected systematic risk and return relation as predicted from CAPM by Sharpe (1964) comes from Black (1972). Haugen & Heins (1975) claim that the relation was not merely flat but negative. Further Fama & French (1992) report flat relationship between beta and cross section of returns in U.S. markets for the period of 1963-1990. Haugen & Baker (1991) and Haugen & Baker (1996) offer initial evidence on inverse relation between risk and return. More recently, Clarke, et al. (2006) and Blitz & Vliet (2007) report evidence for low risk anomaly using minimum variance portfolio and simple ranking based volatility portfolios respectively. Besides Blitz & Vliet (2007) report low beta anomaly and offer both economic and behavioural explanations as a cause of it.

More recent studies on low risk anomaly can be classified based on choice of

1) portfolio construction method - minimum variance vs. volatility sorting
2) choice of risk measures - standard deviation, beta, idiosyncratic risk
3) choice of portfolio construction and holding period - short vs. long

We can further classify various studies based on the way they attempt to explain or explain away the low risk anomaly:

1) studies that attempt to explain volatility effect either by economic reasoning or by behavioural reasoning and

2) studies that attempt to explain away the low risk anomaly.

We discuss some of the major studies and their propositions below.

Clarke, et al. (2006) show evidence for low risk anomaly based on the 1,000 largest U.S. stocks over the 1968-2005 period. They report volatility reduction of 25% while delivering better than market portfolio return for low risk portfolio.

Blitz & Vliet (2007) find evidence of low risk anomaly using both standard deviation as well as beta as risk measures using simple ranking based methodology to sort stocks into different volatility decile portfolios based on 1 to 5 year historical volatility of monthly returns and beta using different combinations of construction and holding periods. They report volatility reduction even greater than reported by Clarke, et al. (2006). They report clear evidence for inverted relationship between risk and expected return using standard deviation as well as beta. However, they find volatility effect stronger and more consistent than beta effect. Blitz, et al. (2013) find similar evidence for emerging markets as well.

Ang, et al. (2006), Ang, et al. (2009) report evidence for inverted relationship between idiosyncratic volatility as opposed to systematic and total risk for a very short term-one month volatility measure in U.S. as well as other global markets.

Most recently, Frazzini & Pedersen (2014) report evidence for betting against beta and attributed to leverage constrained investors seeking superior returns bid up the high beta stocks that in turn results into lower expected returns on high beta stocks.

Among others, Choueifaty & Coignard (2008), Baker, et al. (2011), Baker, et al. (2013), Soe (2012), Carvalho, et al. (2012) also find evidence for low risk anomaly.

On one hand, evidence for low risk anomaly is growing and practitioners are busy latching onto the prospect of delivering higher returns without facing higher risks. On the other hand, some recent studies also report findings in favour of classic positive risk-return relationship or dispute the methodological choices of other studies reporting flat or inverted risk-return relationship.

Bali & Cakici (2008) argue that the significant negative relationship reported by Ang, et al. (2006) is due to presence of small and illiquid stocks with lottery like payoffs. Removing these stocks form the sample makes the anomaly insignificant. Martellini (2008) finds that positive relationship between risk and return is in tack. However, one must note that the study uses only surviving stocks and therefore systematically ignores stocks delivering significant negative returns before disappearing. Fu (2009) claims that one should focus on expected rather than historical volatility. And he reports a positive relationship between risk and return by using EGARCH models to estimate idiosyncratic volatility. Scherer (2011) argues that large part of excess return of minimum variance portfolio over benchmark portfolio is attributable to systematic exposure to size and value factors and volatility effect is mere proxy for value effect. Poullaouec (2010) shows that while MSCI MV index has outperformed MSCI World index by 0.5% per annum over a period of 1988 to 2010, large chunk of this outperformance comes from a period of June 2000 to June 2003, period representing the aftermath of dotcom crisis and therefore superior returns of minimum variance strategy are concentred during extreme bearish periods. Bali, et al. (2011) further contest results of Ang, et al. (2009) by arguing that inverted risk-return relationship is attributable to lottery like payoffs associated with high idiosyncratic volatility stocks and they substantiate their results by developing lottery like variable MAX.

They try to establish that MAX is an independent variable and not mere proxy for idiosyncratic volatility.

Turning attention to explanations of low risk anomaly, we have two sets of explanations to explain the low risk anomaly. One based on economic reasons and market frictions; and the other based on behavioural biases in investing.

Baker, et al. (2011) and Baker, et al. (2013) provide some explanation for the presence and sustainability of low risk anomaly. They attribute benchmarking mandate given to institutional investors as limits to arbitrage leads to high beta-low alpha and low beta-high alpha combinations. Blitz & Vliet (2007) and Blitz, et al. (2013)) attribute such sustainable outperformance to restricted borrowing as reported by Black (1972), decentralized investment approach and behavioral biases such as preference for lotteries, over confidence and representativeness.

3. Data and Methodology

3.1. Data

The data set for the study includes all past and present constituent firms of Nifty 200 index of National Stock Exchange (NSE) from the *Capitaline* database for the period from

January 2001 to June 2015. The study uses monthly stock returns, volume, earnings to price and market cap data.

Why Nifty 200?

There are many reasons for choosing past and present constituents of Nifty 200 as universe.

- Nifty 200 represents about 87.45% of free float market capitalization of the stocks listed on NSE as on March 31, 2015. Besides, the total traded value for the last six months ending March 2015, of all index constituents is approximately 81.48% of the traded value of all stocks on NSE. NSE is the largest stock exchange of India by daily dollar volume traded. In the light of these facts, Nifty 200 is a fair representation of Indian Markets.
- Bali & Cakici (2008) attribute volatility effect to inferior performance of small and illiquid stocks with high idiosyncratic volatility. Our objective in this study is to control for these effects by eliminating such stocks right in the beginning.
- Besides, many return irregularities are known to disappear or become less pronounced when the universe is restricted to large cap stocks, which is important considering lack of depth in Indian markets.
- IRDA (Insurance Regulatory and Development Authority), the Indian Insurance regulator, contemplates restricting ULIP and other equity investments restricting to constituents of Nifty 200 and BSE 200 indices.

- Most of the equity research and FII investment is focused in top 200 stocks only and chances of fair price discovery by market forces are much higher for them.

3.2. Methodology

This study follows Blitz & Vliet (2007) and Blitz, et al. (2013) methodology with slight changes.

At the end of every month, we construct equally weighted decile portfolios by dividing the stocks into 10 groups after sorting stocks on the past three-year volatility of monthly returns. Portfolios are constructed such that top-decile portfolio (LV) consists of lowest historical volatility stocks, whereas bottom-decile portfolio (HV) consists of stocks with highest historical volatility. For each decile portfolio, we calculate excess monthly return (over risk free rate) over the month (holding period) following portfolio formation. We use only log returns to make them additive. For the resulting time-series of returns for all the iterations, we calculate average return, standard deviation of returns, Sharpe ratios and CAPM style alpha as well as ex-post beta considering equally weighted index portfolio (EWI) as proxy for market portfolio. We use equally weighted portfolio as proxy for market portfolio throughout the study.

We additionally calculate CAPM alphas and betas using Nifty 200 as proxy for market to make it more relevant and comparable with publicly available benchmark. To compare the strength of volatility effect and separate it from other well-known classic effects such as size, value and momentum, we use following three approaches.

First, we sort portfolio returns based on their end-of-the-month market-cap (size) and then divide the sorted returns based on volatility. Similar approach is followed for earnings-to-price (value) sort and past 12-month minus 1-month total return (momentum) sort followed by volatility sort. For the size and value measures, stocks with lowest value are assigned to top decile, whereas for momentum, stocks with highest value are assigned to top-decile. We calculate excess returns to risk free return, standard deviation, Sharpe ratio, CAPM alpha and beta for resultant time series of decile portfolio returns for each factor in similar manner as the one proposed for volatility decile portfolios. We compare characteristics of volatility decile portfolios with all other factor decile portfolios.

Second, we use both three-factor (FF) and four-factor Fama-French-Carhart regressions to disentangle volatility from other effects. For Fama-French-Carhart regression, we use market capitalization as measure of size for calculating small-minus-big (SMB) and earnings-to-price as a measure of value for calculating value-minus-growth (VMG) factors for Fama-French regression. In addition, we use total returns for past 12-months minus 1-month returns as a measure of momentum for calculating winner-minus-loser (WML). For calculating SMB, VMG and WML factors, we use the difference of return between top 30% and bottom 30% of the stocks sorted on size, value and momentum measures respectively. By regressing returns of volatility sorted portfolios on these factors, we control for any systematic exposure to SMB and VMG in case of Fama-French and SMB, VMG and WML factors in case of Fama-French-Carhart regression. The resultant alpha in volatility decile portfolio is now not overlapping with other well-known effects.

Now we describe the tests to calculate significance in difference of Sharpe ratios, one factor CAPM alphas, three-factor Fama-French alphas and four factor Fama-French-Carhart alphas.

To test the statistical significant of difference between Sharpe ratios over equally weighted universe (EWI) portfolio for each volatility decile portfolio, we use Jobson & Korkie (1981) with Memmel (2003) correction.

$$Z = \frac{SR_1 - SR_2}{\sqrt{\frac{1}{T}\left[2(1-\rho_{1,2}) + \frac{1}{2}\left(SR_1{}^2 + SR_2{}^2 - SR_1 SR_2\,(1+\rho_{1,2}{}^2)\right)\right]}} \qquad \text{(I)}$$

Here SR_i is the Sharpe ratio of portfolio i,

$\rho_{i,j}$ is the correlation between portfolios i and j,

and T is the number of observations.

We calculate CAPM alpha using EWI return as proxy for market by using following classic one factor regression.

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,m}\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{p,t} \qquad \text{(II)}$$

where $R_{p,t}$ is return on portfolio p in period t. $R_{f,t}$ is risk free return in period t. α_p is the alpha of portfolio p, $R_{m,t}$ is market portfolio return in period t, $\beta_{p,m}$ is the beta of portfolio p with respect to market portfolio and $\varepsilon_{p,t}$ is the idiosyncratic return of portfolio p in period t. We use equally weighted universe as proxy for market portfolio in this study unless otherwise specified.

We calculate three-factor alpha by adding SMB (size) and VMG (value) proxies to the regression. We add WML (momentum) proxy in addition to size and value to the regression to calculate four-factor alpha.

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,m}(R_{m,t} - R_{f,t}) + \beta_{p,SMB} * R_{SMB} + \beta_{P,VMG} * R_{VMG} + \varepsilon_{p,t} \qquad \text{(III)}$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,m}(R_{m,t} - R_{f,t}) + \beta_{p,SMB} * R_{SMB} + \beta_{P,VMG} * R_{VMG} + \beta_{P,WML} * R_{WML} + \varepsilon_{p,t} \qquad \text{(IV)}$$

Where, R_{SMB}, R_{VMG} and R_{WML} represents the return on size, value and momentum factors in our universe and $\beta_{p,SMB}$, $\beta_{P,VMG}$ and $\beta_{P,WML}$ represents betas of portfolio p with respect to size, value and momentum factors in our universe.

Third, we use bivariate analysis. It is a strong non-parametric technique to disentangle volatility effect from other effects. It is robust to situations involving time-varying coefficients in three and four factor models that are assumed to be constant in the regressions as mentioned above. In double sorting, we first rank stocks on one of the control factors (size, value, momentum) and then by volatility within control factor (size, value, momentum) sorted stocks decile portfolio and then construct volatility decile portfolios to represent every decile of control factor. For example, to control for size effect, we first sort stocks based on size and divide them into size decile portfolios. Within each size decile portfolio, we sort stocks on volatility; next we construct top-decile volatility-sorted portfolio such that it has 10% least volatile stocks from every size decile. Similarly, we control for the size effect. We construct other volatility decile portfolios also to represent stocks of all size.

We perform two additional robustness tests to further substantiate our results. First, sorting stocks based on beta using past three years monthly returns rather than volatility. We calculate beta for each stock using equally weighted universe (EWI) as proxy to market portfolio. We compare CAPM alphas for portfolios sorted on both volatility and beta. Second, we use double sorting. We sort the stocks using volatility by controlling for beta. We first sort the stocks on beta and the within each beta decile stocks are again sorted on volatility. Finally, all top decile portfolios within each beta decile portfolio are having lowest volatility stocks controlled for beta. This method helps to evaluate whether volatility effect and beta effect represent the same effect comparing magnitude and strength.

4. Results and Discussion

4.1. Main Results – Univariate Analysis

Table 1 reports main results of univariate analysis for the volatility sorted decile portfolios.

Top two decile portfolios (P1 and P2), consisting of lower volatility stocks, report significant above average returns. Such outperformance over universe portfolio loses steam and turns into significant underperformance as we move towards bottom decile portfolios (P9 and P10) – the decile portfolios consisting of high volatility stocks. These portfolios report significantly below average returns. Returns decline monotonically when we move from low decile portfolio to high decile portfolio with an exception of sixth decile portfolio. The difference between average returns between top and bottom decile portfolios is whopping 10.10%.

Table 1: Main results (Annualized)

Table 1 reports main results of univariate analysis for the decile portfolios ranked on past three-year volatility. This analysis is a result of rolling iterations of the 36-month formation and 1-month holding period over the entire study period.

Panel A reports the average excess return across all iterations, their standard deviation, regression beta and alpha with the significance for difference of Sharpe ratio and alpha for each decile portfolio based on historical volatility with CNX200 as Proxy for market portfolio. Panel B reports the return difference for each decile with Universe portfolio during the upmarket and downmarket periods as well as maximum drawdown as defined to be the return difference from peak to through.

Panel A: Decile portfolios based on historical volatility												
	P1 (LV)	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10 (HV)**	**P1-P1O (LV-HV)**	**EWI (universe)**
Excess return	11.40%	11.46%	8.68%	6.46%	5.89%	10.96%	5.70%	5.53%	1.52%	1.30%	10.10%	6.89%
Standard Deviation	17.84%	21.24%	24.66%	28.52%	29.37%	32.32%	32.62%	34.64%	40.47%	45.14%	35.16%	29.14%
Sharpe ratio	0.64	0.54	0.35	0.23	0.20	0.34	0.17	0.16	0.04	0.03		0.24
t-value for difference over Universe	7.05	7.94	4.06	-0.40	-1.60	4.88	-3.04	-3.12	-7.66	-6.44		
Beta	0.51	0.68	0.80	0.94	0.97	1.08	1.09	1.14	1.34	1.45	-0.94	
Alpha	0.08	0.07	0.03	0.00	-0.01	0.04	-0.02	-0.02	-0.08	-0.09	0.17	
t-value	2.66	2.88	1.37	0.00	-0.37	1.60	-1.09	-0.82	-2.40	-1.91	2.58	
Panel B: Risk Analysis of portfolios based on historical volatility												
Return up (Return difference over Universe)	-2.16%	-1.36%	-0.96%	-0.60%	-0.34%	0.73%	0.33%	0.68%	1.39%	2.29%	-4.46%	0.00%
Return down (Return difference over Universe)	4.09%	2.93%	1.78%	0.79%	0.30%	-0.23%	-0.73%	-1.28%	-3.14%	-4.51%	8.60%	0.00%
Max drawdown	-43.21%	-45.16%	-60.46%	-64.24%	-70.12%	-65.39%	-69.74%	-68.44%	-74.20%	-78.51%		-64.71%

The results become more noteworthy when we focus on a risk-adjusted performance rather than absolute returns. Ex post standard deviations increase monotonically for successive decile portfolios. The volatility of top decile portfolio is about sixty per cent of that of universe portfolio and almost half of that of bottom decile portfolio.

Risk-adjusted performance of the decile portfolios makes these results even more interesting. On one hand, returns keep on declining as we move from top-decile to bottom-decile portfolio (with an exception of portfolio P6), On the other hand, volatility keeps on increasing as reported earlier. This results in a significant decline in Sharpe ratio as we move from top to bottom decile portfolio. Sharpe ratio keeps on declining from 0.64 for top-decile to mere 0.03 for the bottom-decile portfolio. The decline in Share ratio is evident even in some of the middle decile portfolios where return differences are not significant. As in these cases, Shape ratio is dominated by standard deviation, which increases as we move from top to bottom-decile portfolio without any exception. Sharpe ratio of 0.64 for top-decile, low volatility stock portfolio is much higher compared to Sharpe ratio of 0.24 for the universe portfolio. This difference is highly significant, both economically and statistically. The converse is true for the bottom-decile high volatility stock portfolio. Here, Sharpe ratio is significantly lower compared to universe portfolio both in economic and statistical terms. It is worth mentioning that, going by these results, there is definite inverse relationship between pre-formation volatility and ex post risk adjusted returns and to a large extent absolute returns as well.

Bottom half of Panel A in Table 1 reports an alternative approach to test relation between pre-formation volatility and ex post returns for decile portfolios. We run CAPM regression using time-series of monthly returns of volatility sorted decile portfolios with universe portfolio as proxy for market portfolio. Low volatility portfolio has low ex-post beta of 0.51 and positive alpha of 7.91% which is economically and statistically significant. High volatility portfolio has high ex-post beta of 1.45 and a negative alpha of -8.72%, which again is economically and statistically significant, however, with negative sign. The alpha spread between low and high volatility portfolios (P1-P10) is massive 16.63%. This result provides clear evidence for low beta-high alpha and high beta-low alpha anomaly. Putting it differently, it provides evidence not only for flatter than expected SML but reversal in relationship between beta and return from positive to negative!

Panel B of Table 1 reports further details on performance of decile portfolios, especially during up market and down market periods. Out of total 138 months in our study, 82 are upmarket months, whereas 58 are down market months. First row of Panel B reports returns of decile portfolios over universe return during upmarket months, second row reports the same for the down market months. During up market months, low volatility portfolio underperforms universe portfolio by 2.16%, during the same period high volatility portfolio outperforms universe by 2.29%. The difference between performance of low volatility and high volatility portfolio is 4.46% and in favour of high volatility portfolio. The relation reverses during down market months where the low volatility portfolio outperforms by 4.09% and high volatility portfolio underperforms by 4.51%. The difference between performance of low volatility and high volatility portfolio is 8.6% and in favour of low volatility portfolio.

This indicates that high volatility portfolio tend to perform better during up market periods, whereas low volatility portfolio tends to perform better during down market periods. However, it is important to notice that the outperformance of low volatility portfolio during down market is sizably higher than the underperformance during down market. This in turn leads to net outperformance of low volatility portfolio over a period of full market cycle. The fact that we have considerably more upmarket months in our study period compared to down market months, it adds to the strength of our result. Finally, we report drawdown in the final row of Panel B as a proxy for worst entry-worst exit points.

As expected, maximum drawdown for all portfolios is concentred during the period around 2008 global financial crisis. Low volatility portfolio suffers maximum drawdown of -43.21% compared to -64.71% for universe portfolio and -78.51% for high volatility portfolio. Drawdown faced by low volatility portfolio is little over two third of the market and below sixty per cent of its high volatility counterpart.

Table 2: Main results (Annualized) for decile portfolios based on historical volatility with CNX200 as proxy for market portfolio													
Panel A: Decile portfolios based on historical volatility													
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P1O (LV-HV)	CNX 200	
Excess return (Annualized %)	11.40%	11.46%	8.68%	6.46%	5.89%	10.96%	5.70%	5.53%	1.52%	1.30%	10.10%	5.60%	
Standard Deviation %	17.84%	21.24%	24.66%	28.52%	29.37%	32.32%	32.62%	34.64%	40.47%	45.14%	35.16%	26.21%	
Sharpe ratio	0.64	0.54	0.35	0.23	0.20	0.34	0.17	0.16	0.04	0.03		0.21	
(t-value for difference over Universe)	7.75	7.63	4.37	0.44	-0.42	3.87	-1.11	-1.38	-4.56	-4.18		-	
Beta	0.58	0.73	0.88	1.03	1.05	1.15	1.14	1.19	1.40	1.51	-0.93		
Alpha	8.17%	7.35%	3.74%	0.71%	0.02%	4.52%	-0.69%	-1.11%	-6.31%	-7.13%	15.30%		
(t-value)	2.91	2.76	1.47	0.25	0.01	1.32	-0.18	-0.25	-1.24	-1.10	2.04		
Panel B: Risk Analysis of portfolios based on historical volatility													
	LV	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-10 (LV-HV)	CNX 200	
Return up (Excess return over CNX200)	3.90%	4.90%	5.14%	5.51%	5.67%	6.54%	6.03%	6.44%	6.81%	7.55%	-3.65%		
Return down (Excess return over CNX200)	-2.46%	-4.16%	-5.20%	-6.32%	-6.73%	-7.07%	-7.38%	-8.12%	-9.65%	-10.97%	8.51%		
Max drawdown	-43.21%	-45.16%	-60.46%	-64.24%	-70.12%	-65.39%	-69.74%	-68.44%	-74.20%	-78.51%		-60.40%	

Table 2 reports same results as Table 1 in all aspects but with popular public benchmark, Nifty 200, a value weighted proxy for market portfolio.

Analysing results of Table 1 and Table 2 provide preliminary evidence about presence of low risk anomaly in Indian stock markets; we shift our focus to see how strong the low volatility effect is compared to other known effects such as size, value and momentum.

4.2. Volatility Effect and other Investment Strategies

It is important to answer following two questions. How strong is the volatility effect with respect to other effects? And whether volatility effect is a proxy for some other effect or an independent effect in itself, i.e. low volatility portfolio consists of high proportion of value, momentum or small stocks.

Table 3: Comparison with Other Investment Strategies

Panel A: Decile portfolios based on size (arket apitalization)												
	P1 (SMALL)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (BIG)	P1-P1O (LV-HV)	EWI (Universe)
Excess return (Annualized %)	17.07%	17.07%	10.34%	8.60%	4.18%	2.09%	7.19%	2.30%	-1.42%	2.63%	14.44%	6.89%
Standard Deviation %	38.03%	34.24%	32.51%	30.00%	30.85%	28.38%	28.80%	28.54%	28.95%	24.35%	23.89%	29.14%
Sharpe ratio	0.45	4.09	-0.37	-1.55	-7.69	0.07	0.25	0.08	-0.05	0.11		0.24
(t-value for difference over Universe)	3.59	4.09	-0.37	-1.55	-7.69	-9.03	-3.35	-8.79	-10.54	-6.02		
Beta	1.22	1.12	1.09	0.99	1.03	0.94	0.96	0.94	0.94	0.77	0.44	
Alpha	8.79%	7.50%	2.95%	1.87%	-2.82%	-4.32%	0.66%	-4.14%	-7.85%	-2.64%	11.43%	
(t-value)	2.10	2.39	1.26	0.73	-1.22	-1.89	0.3	-1.78	-2.86	-0.95	1.91	
Panel B: Decile portfolios based on Value (earnings-to-price)												
	P1(Value)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (Growth	P1-10 (VMG)	EWI (Universe)*
Excess return (Annualized %)	11.45%	5.02%	8.42%	10.00%	10.15%	8.90%	10.93%	8.19%	5.35%	0.70%	10.75%	7.91%
Standard Deviation %	39.30%	34.50%	32.26%	31.84%	28.65%	28.96%	24.44%	25.01%	24.11%	28.60%	20.32%	28.60%
Sharpe ratio	0.29	0.15	0.26	0.31	0.35	0.31	0.45	0.33	0.22	0.02		0.28
(t-value for difference over Universe)	0.48	-4.78	-0.66	1.68	3.37	1.28	5.27	1.69	-1.64	-8.17		-
Beta	1.29	1.15	1.09	1.08	0.97	0.97	0.80	0.82	0.78	1.05	0.24	
Alpha	1.24%	-4.08%	-0.17%	1.47%	2.48%	1.20%	4.59%	1.69%	-0.83%	-7.60%	8.84%	
(t-value)	0.31	-1.32	-0.07	0.62	1.14	0.51	1.83	0.67	-0.31	-2.58	1.56	
Panel C: Decile portfolios based on Momentum (12 month minus 1 month)												
	P1(Winner)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (Loser)	P1-P10 (WML)	EWI (Universe)
Excess return (Annualized %)	17.86%	11.96%	13.00%	5.06%	7.29%	5.48%	6.09%	1.61%	7.93%	-6.87%	24.73%	6.89%
Standard Deviation %	30.70%	26.53%	26.53%	27.07%	27.56%	29.70%	30.63%	33.65%	36.35%	41.15%	30.84%	29.14%
Sharpe ratio	0.58	0.45	0.49	0.19	0.26	0.18	0.20	0.05	0.22	-0.17		0.24
(t-value for difference over Universe)	6.41	4.96	6.89	-1.76	1.03	-2.33	-1.74	-6.76	-0.70	-9.96		-
Beta	0.89	0.90	0.85	0.88	0.91	0.98	1.02	1.10	1.18	1.31	-0.42	
Alpha	11.70%	5.74%	7.13%	-1.02%	1.01%	-1.35%	-0.96%	-6.05%	-0.26%	-15.95%	27.64%	
(t-value)	2.38	1.73	2.43	-0.39	0.42	0.58	-0.40	-2.03	-0.07	-3.44	3.29	

* Universe statistics is different for Value sorted portfolios as stocks with negative E/P and stocks with P/E > 150 are eliminated in this case.

Table 3 reports results similar to the one reported in Table 1 but for other well-known factors such as size, value and momentum. Our results are consistent with earlier evidence for momentum and size effect with top-decile of size and momentum portfolios outperform the universe and bottom decile of size and momentum portfolios underperform the universe. Results are significant both economically and statistically.

However, evidence for value effect in our sample is rather weak or only partially consistent with global evidence. Top-decile of value portfolio reports higher Sharpe ratio and positive alpha it is statistically not significant. However, bottom decile of growth portfolio underperforms universe portfolio both using Sharpe ratio as well as CAPM alpha measures and such underperformance is statistically significant. Here too the underperformance is restricted to bottom-decile of the value portfolio only and is not evident for higher decile portfolios.

It is interesting to compare characteristics of top-decile of volatility portfolio with top-decile portfolios of size, value and momentum portfolios.

Let us first focus on risk adjusted performance of top decile portfolios of volatility, size, value and momentum. Sharpe ratio of top decile of volatility portfolio is considerably higher compared to size, value and momentum top-decile portfolios. The results are the same when we use alpha as measure of outperformance. Alpha of top decile volatility portfolio is third after alphas of top decile portfolios of momentum and size portfolio respectively. Top decile momentum portfolio reports the highest alpha of 11.7%, followed by 8.79% for size portfolio and 7.91% for the low volatility portfolio. All these alphas are economically and statistically significant. While alpha for low volatility portfolio is not the highest, it is statistically most significant among all. Alpha spreads for top and bottom decile portfolios of volatility-sorted portfolios are only next to momentum-sorted portfolios. We attribute this difference in ranking of top decile portfolios using Sharpe ratio and alpha to presence of greater idiosyncratic risk in top decile of momentum and size portfolio compared to top decile volatility portfolio.

Looking at the performance of various strategies during up and down market periods, it becomes further clear that volatility effect is very distinct from size and value effects. While, outperformance of top-decile size and value portfolios come during upmarket periods, top-decile of volatility portfolio delivers significant outperformance during down market periods and underperforms during up market periods.

For now, only momentum effect appears stronger to volatility effect. However, comparison of characteristics of top decile volatility portfolios with top decile portfolios of size, value and momentum portfolios really helps in understanding how volatility effect is very different than other well-known effects. This means ex-post volatility of bottom-decile portfolios is higher than universe portfolio, whereas the ex-post volatility of top-decile of volatility portfolio is only about sixty per cent of universe portfolio. Picture does not change using beta instead of volatility. While top-decile portfolios of size and value have beta considerable higher than universe portfolio, top-decile momentum portfolio has beta slightly lower than universe portfolio. Beta of top decile of low volatility portfolio is only half of the universe. Clearly, low volatility effect is very different than other classic effects and not proxy for that.

Table 4: Three Factor (Fama-French) and Four Factor (Fama-French-Cahart) Style Regression Analysis for Volatility Decile Portfolios											
Panel A: Three and four factor alphas for volatility decile portfolios											
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P10 (LV-HV)
3 factor alpha (annualized)	13.12%	10.25%	5.84%	2.14%	0.56%	3.10%	-2.49%	-4.89%	-12.05%	-15.57%	28.69%
t-value	5.25	4.44	2.59	0.91	0.25	1.34	-1.17	-1.82	-3.76	-3.46	4.92
4 factor alpha (annnualized)	9.78%	9.52%	4.63%	2.42%	-0.51%	3.69%	-2.28%	-4.11%	-10.08%	-13.06%	22.84%
t-value	3.90	3.89	1.95	0.97	-0.21	1.51	-1.01	-1.44	-2.99	-2.76	3.80
Panel B: Three and four factor regression coefficient analysis											
Fama French style regression coefficient for top and bottom decile volatility portfolios						Fama French-Cahart style regression coefficient for top and bottom decile volatility portfolios					
LV portfolio	coefficient	t-value	HV portfolio	Coefficient	t-value	LV portfolio	coefficient	t-value	HV Portfolio	coeffficient	t-value
FF alpha (monthly)	0.01	5.25	FF alpha (monthly)	-0.013	-3.46	FFC alpha(monthly)	0.01	3.90	FFC alpha(monthly)	-0.01	-2.76
EWI	0.66	21.98	EWI	1.333	24.70	EWI	0.67	23.45	EWI	1.32	24.60
SMB	-0.20	-3.32	SMB	0.383	3.59	SMB	-0.14	-2.38	SMB	0.34	3.09
VMG	-0.35	-5.93	VMG	0.084	0.79	VMG	-0.26	-4.40	VMG	0.02	0.17
						WML	0.16	4.02	WML	-0.12	-1.60

Table 4 reports another way of differentiating volatility effect from other effects using three factor Fama-French (FF) and four factor Fama-French-Carhart (FFC) regressions. First row of Table 3 reports three-factor alpha with corresponding t-value in second two. Surprisingly, three-factor alpha for top-decile volatility portfolio is 13.12%, which is considerable higher than CAPM alpha of 7.91%. Similarly, three-factor alpha of bottom-decile volatility portfolio is -15.57%, which is considerable higher than CAPM alpha of -8.72% but with negative sign.

Results are similar for four factor alpha with momentum as additional factor, besides size and value. Four factor Alphas for top-decile and bottom decile volatility portfolios are 9.78% and -13.06% respectively. These alphas are sizably more than CAPM alphas in magnitude with the same sign.

Panel 2 of Table 4 reports coefficients of three factor Fama-French and four factor Fama-French-Carhart factors for top and bottom decile volatility portfolios. Coefficients of both SMB and VMG factors in three-factor model are statistically significant but with negative sign. And that explains why three-factor alpha is much higher than CAPM alpha. Converse is true for High volatility portfolio where SMB and VMG factor both have positive coefficients, however, only SMB factor is statistically significant and not VMG.

It is evident that Low volatility portfolio consists of big and growth stocks rather than small and value stocks and high volatility portfolio consists of small stocks. Four-factor regression coefficients with momentum (WML) as added factor, helps explaining some part of positive alpha associated with low volatility portfolio. Four factor (FFC) alpha for top-decile volatility portfolio is 9.78% compared to three factor (FF) alpha. Coefficient of WML factor is positive and statistically significant in FFC regression for top-decile volatility portfolio and that explains some part of three-factor alpha. Four-factor (FFC) alpha for bottom-decile volatility portfolio is -13.06%, while three factor alpha is -15.57%. Coefficient of WML factor is negative but not significant. The fact that both three-factor and four-factor alphas are higher than CAPM alphas shows that volatility effect cannot be explained by size, value or momentum effect. Looking at the regression coefficients it is clear that large stocks dominate low volatility portfolio, whereas, small stocks dominate high volatility portfolio.

Table 5: Double-Sorted Results

Panel A: Annualized alpha from double sort on size (market capitalization) and volatility (past 3 years)											
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P10 (LV-HV)
Alpha	11.01%	9.49%	4.47%	3.62%	-0.81%	-0.37%	-2.64%	-1.83%	-12.57%	-7.99%	19.00%
t-stat	4.12	3.77	1.89	1.72	-0.34	-0.18	-0.78	-0.60	-3.91	-1.97	3.34
Panel B: Annualized alpha from double sort on value(earnings/price) and volatility (past 3 years)											
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P10 (LV-HV)
Alpha	4.99%	4.63%	4.51%	2.70%	2.30%	-2.43%	2.49%	-2.24%	-5.06%	-8.77%	13.76%
t-stat	2.06	2.01	2.15	1.15	1.10	-1.20	0.98	-0.79	-1.49	-2.13	2.58
Panel C: Annualized alpha from double sort on momentum(12 month minus 1 month returns) and volatility (past 3 years)											
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P10 (LV-HV)
Alpha	9.71%	6.94%	3.06%	1.20%	2.71%	-0.54%	-7.37%	-4.87%	-1.02%	-9.83%	19.54%
t-stat	3.75	3.05	1.38	0.58	1.20	-0.25	-2.74	-1.66	-0.24	-2.59	3.58

Table 5 reports results of double sorting approach. This is a robust non-parametric method that enables us to control for other effects. It also captures any time varying factor loadings for size, value and momentum factors that are assumed to be constant in Fama-French or Fama-French-Carhart multi factor models.

Panel A of Table 5 reports the results showing double sorted alphas of decile portfolios with their statistical significance. The difference here compared to alphas reported in Table 1 is that these alphas are based on portfolios constructed using double sort on size followed by volatility and therefore controlling for size effect. Every month, stocks are sorted based on size (market cap) and divided into decile portfolios. Each size decile portfolio is then sorted within itself based on volatility. Finally volatility decile portfolios are constructed using top decile stocks of each size decile portfolios. This robust arrangement helps us control for size effect. Putting it differently, each volatility decile portfolio now represents stocks with all different size. The similar process is followed for controlling value and momentum effects. Panel B and Panel C of Table 4 report these results.

Alpha for top-decile volatility portfolio after controlling for size effect is 11.01%, which is considerably higher and statistically more significant than top-decile volatility portfolio alpha of 7.91% without controlling for other effects. Looking at this outcome and keeping in mind that in our sample we have evidence for size effect, ideally, double sorted alpha, must be lower if low volatility portfolio is dominated by large number of small stocks. Instead, we see the exactly opposite, where low volatility portfolio alpha controlled for size effect is economically and statistically more significant than alpha without controlling for size effect. It implies that low volatility portfolio has greater proportion of large stocks rather than small within each size-sorted decile portfolio; if at all such minute observation is worth anything. Bottom-decile of volatility portfolio has alpha of -7.99% after controlling for size. This is slightly smaller than -8.72% without controlling for size effect. It shows that controlling for size does not lead to any improvement in performance of high volatility portfolio. Going by the results, we confirm that volatility effect is independent of size effect.

Alpha of top-decile volatility portfolio after controlling for value effect is 4.99% compared to 7.91% without controlling for value effect. It is still economically and statistically significant. Corresponding alphas for bottom-decile volatility portfolios are -8.77% and -8.72%. Positive alpha of top-decile volatility portfolio and negative alpha of bottom-decile volatility portfolio are sizeable and significant both in economic and statistical terms. This proves that volatility effect is not value effect but clearly an independent distinct effect than classic value effect.

Alpha of top-decile volatility portfolio after controlling for momentum effect is 9.71% compared to 7.91% without controlling for momentum effect. Corresponding alphas for bottom-decile volatility portfolios are -9.83% and -8.72%. Positive alpha of top-decile volatility portfolio and negative alpha of bottom-decile volatility portfolio are greater than volatility decile alphas and more significant both in economic and statistical terms. In nutshell, volatility effect is not even momentum effect but an independent effect.

The volatility effect remains economically and statistically significant even after controlling for all well-known effects including size, value and momentum.

4.3. Robustness Tests

We report the results of the robustness tests to further substantiate our results. First robustness test involves in place of volatility, sorting stocks on beta using past three years monthly returns. We calculate beta for each stock using equally weighted index (EWI) as proxy to market portfolio. We then report here the results of comparison between CAPM alphas for portfolios sorted on standard deviation and beta. Second robustness test involves sorting stocks on volatility after controlling for beta using double-sorting to evaluate whether volatility effect and beta effect represent the same effect comparing magnitude and strength of volatility effect vs. beta effect.

Table 6: Robustness Tests											
Panel A: CAPM style annualized alpha for decile portfolios sorted on volatility verses beta											
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P10 (LV-HV)
Alpha (Volatility sorted)	7.91%	6.80%	3.15%	-0.01%	-0.82%	3.53%	-1.80%	-2.33%	-7.70%	-8.72%	16.63%
Alpha (Beta sorted)	4.86%	5.53%	3.34%	0.93%	4.01%	2.89%	1.93%	-7.07%	-7.78%	-8.64%	13.50%
Panel B: Annualized alpha from double sort on beta (past 3 years) and volatility (past 3 years)											
	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P10 (LV-HV)
Alpha	1.06%	3.16%	3.16%	0.66%	1.75%	0.95%	0.01%	-4.16%	0.18%	-2.17%	3.23%
t-value	0.52	1.55	1.50	0.32	0.79	0.43	0.01	-1.57	0.05	-0.56	0.68

Table 6 reports results robustness tests performed to further substantiate the evidence. Panel A shows alpha comparison based on portfolios sorted on volatility vs. beta. Alphas for top-decile portfolios sorted by beta and volatility are 4.86% and 7.91% respectively. Alphas for bottom-decile beta and volatility sorted portfolios are -8.72% and -8.64% respectively. There is a clear beta effect similar to volatility effect discussed earlier but lesser magnitude in low risk portfolios and comparable in high-risk portfolios.

Panel B of Table 6 shows results of double-sorted decile portfolios, first on beta and then on volatility such as to control beta effect in decile portfolios. The results show that large chunk of alphas disappears and alphas don't remain statistically significant. However, going by numbers, still there is a clear trend. Alphas of the top three volatility-sorted decile portfolios are considerably higher compared to that of the bottom three volatility-sorted decile portfolios. The difference between alphas of top and bottom decile portfolios is 3.23%, though statistically not significant. In closing, we summarise that market misprices systematic risk decile and to some extent idiosyncratic risk too but large chunk of volatility effect is beta effect. This is explicable, since, by design, our universe eliminates small stocks, which have greater idiosyncratic volatility and lottery like payoffs. Besides, our choice of equally weighted universe as proxy of market portfolio makes our beta more representative of total volatility itself. These combined effects dwarf the idiosyncratic volatility effect as reported by other studies.

Table 7: Subperiod Analysis of decile portfolios from January 2004 to December 2007 based on historical volatility with CNX200 as Proxy for Market Portfolio for

	P1 (LV)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (HV)	P1-P1O (LV-HV)	CNX 200
Excess return (Annualized %)	23.68%	23.37%	24.13%	21.46%	24.98%	30.84%	23.88%	27.92%	33.04%	53.79%	-30.11%	23.42%
Standard Deviation %	19.32%	19.97%	22.37%	25.26%	26.53%	28.24%	26.46%	26.75%	29.07%	29.91%	20.72%	23.33%
Sharpe ratio	1.23	1.17	1.08	0.85	0.94	1.09	0.90	1.04	1.14	1.80		1.00
(t-value for difference over Universe)	2.44	1.71	1.00	-2.13	-0.82	0.98	-1.05	0.44	1.39	5.34		-
Beta	0.73	0.73	0.88	0.99	1.03	1.06	0.96	1.00	1.07	1.02	-0.29	
Alpha	6.57%	6.17%	3.61%	-1.73%	0.91%	6.05%	1.44%	4.49%	7.96%	29.94%	-23.37%	
(t-value)	1.37	1.14	0.75	-0.32	0.15	0.84	0.19	0.65	1.02	3.13	-2.26	

We perform sub-period analysis to validate Poullaouec (2010) claim, that low volatility strategy outperforms only during turbulent times and generally underperforms benchmark market portfolio during upward trending market. As we know the period of January 2001 to December 2007 saw a secular bull run in global markets including India before the start reversal from January 2008. Table 7 reports results of volatility decile portfolios with respect to popular benchmark index Nifty 200. Bottom decile portfolio outperforms top decile portfolio as well as market portfolio both in terms of Sharpe ratio as well as delivering positive alpha. This is no surprise as it is a known fact and is already reported in our main results in Table 1 itself. However, looking at performance of top decile portfolio with respect to benchmark Nifty 200 performance, we find that there is no difference between absolute returns of low volatility portfolio returns and returns of Nifty 200 returns. While low volatility portfolio delivers annualized returns of 23.68%, Nifty 200 delivers annualized returns of 23.42%. Annualized standard deviation of low volatility portfolio is 19.32% vis-à-vis annualized standard deviation of 23.33% for Nifty 200 portfolio. As a result risk adjusted returns as measured by Sharpe ratio is considerably higher and statistically significant compared to Nifty 200 portfolio. CAPM alpha for low volatility portfolio is 6.57% on an annualized basis; this is economically significant but not statistically significant. This results prove that low volatility portfolio does not show heavy underperformance to benchmark portfolio during good times. In fact, it delivers matching performance and marginally outperforms even in the period of secular bull-run in our study.

Possible Explanations

There are several possible explanations for low risk anomaly. We can categorize them into economic and market friction based explanations as well as behavioural explanations. For the sake of brevity, here we cover only a few more important explanations that are as much relevant in Indian markets as in global markets. However, we introduce performance chasing behaviour of mutual fund investors as one of the possible explanations due to which portfolio managers follow high beta stocks and are concerned only about outperformance during rising markets rather than falling markets.

4.4. Economic explanations

Borrowing restrictions for individual and institutional investors; benchmarking and minimizing tracking error as key performance criteria for portfolio managers; short selling constraints for all categories of investors; call option like compensation structure for portfolio managers where their reward is directly linked to the outperformance they deliver but no significant penalty for delivering negative returns - all these factors combined put limits on arbitrage. They together force investors to shift their choice towards highly volatile stocks and to systematically ignore low volatility stocks. This in turn leads to overpricing of high volatility stocks and under-pricing of low volatility stocks, ultimately leading to lower returns for high volatility stocks

and higher returns for low volatility stocks. Putting it differently, it leads to "high beta-low alpha and low beta-high alpha" scenario and flattening of security market line.

4.5. Behavioural explanations

Preference for lottery: Small and highly volatile stocks offer lottery like payoffs with skewed distribution of expected returns. These stocks have small probability of earning extremely high returns even when expected return is low. Investors, especially individuals, have known preference for lotteries, where expected value may be negative but there is an opportunity of winning jackpot, albeit with very small probability. This preference for lottery makes investors choose penny, highly volatile stocks with high idiosyncratic volatility in the hope of them turning out to be multi-bagger investment. This preference for lottery like stocks leads to systematic overpricing followed by lower returns.

Two stage investment decision making: Most investors follow two stage investment decision making process. First, asset allocation stage, where investors follow rational behaviour but when it comes to second stage decision of stock selection or fund selection within risky asset class like equity, they tend to prefer maximize return. Mental accounting makes investors think that money allocated to equity is risk capital and that drives choice of riskier securities within the risky asset class. Representativeness and overconfidence are the other two behavioural biases leading to preference for small and highly volatile stocks. Investors hope that they have superior stock picking ability and stocks they pick up may turn out to be the future Microsoft or Google of the world.

Performance Chasing Behaviour: There is enough evidence on performance chasing behaviour exhibited by mutual fund investors globally. This means that during upward trending markets asset under management (AUM) of funds grows not only due to increase in portfolio value, but also, due to significant net inflows as more and more investors pour money into funds. However, during good times, investors prefer only those funds, which deliver absolute outperformance; not only over benchmark, but over their peers also. Such focus on absolute outperformance leads portfolio managers to tilt their choice towards high beta stocks. It is easier to outperform benchmark as well as other funds in absolute terms with high beta portfolio rather than constructing portfolio that generates comparable alpha. High beta portfolio may lead to significant absolute negative returns in down markets. But such underperformance with respect to peers and benchmark does not matter as during such times investors flee from equity as an asset class and every fund faces significant shrinkage of their AUM. As most of the funds in India are open ended in nature, fund managers have practically no control over amount of available capital to manage. This separation of brain and capital makes fund managers prefer high beta stocks over their low beta counterpart and this contributes to systematic over-pricing of high beta stocks and under-pricing of low beta stocks. Naturally, this leads to lower alpha for high beta stocks and higher alpha for low beta stocks.

5. Conclusion

In closing, we find clear evidence for low risk anomaly. Portfolio consisting of low volatility or low beta stocks systematically outperforms benchmark portfolio as well as high volatility or high beta stocks portfolio. This outperformance is not only on risk adjusted basis but also on absolute basis over a period of our study. We also conclude that volatility effect is separate and significant effect and it is neither timid enough to be ignored nor it is a proxy for other well-known effects such as size, value and momentum. In fact, our low volatility portfolio consists of relatively large and growth stocks rather than small and value stocks. Besides, we conclude that a large part of our volatility effect is the same as beta effect and after controlling for beta we don’t find volatility effect significant. However, even after controlling for beta, low volatility portfolio retains positive alpha whereas high volatility portfolio retains negative alpha. None of them are significant and therefore we conclude that volatility effect is not due to idiosyncratic risk only as claimed by Ang, et al. (2006). And if at all idiosyncratic volatility affects, it may be adding to volatility effect. Evidence of volatility effect in our sample also rebuts the claim of Bali, et al.(2011) that low risk anomaly disappears once we eliminate small and illiquid stocks from the sample. Our universe consists of relatively large and liquid stocks only and we still find strong evidence for volatility effect. We also find evidence against Poullaouec (2010) and conclude that outperformance of low volatility portfolio over benchmark is not concentred during negative markets only. We find all the possible economic as well as behavioural explanations offered in existing literature for the persistence of low risk anomaly are also valid in Indian context. In addition, we add performance chasing behaviour of mutual fund investors as one of the possible explanation for low risk anomaly. We conclude with the claim that low risk anomaly is very strong and significant anomaly in the history of capital markets and it is going to stay for a long time unless economic and behavioural reasons as well as market friction that causes it or it becomes overcrowded investment place and loose its sheen. All these are unlikely to happen at least in the near future.

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