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**HOW MUCH DOES VOLATILITY INFLUENCE
STOCK MARKET RETURNS? – EMPIRICAL
EVIDENCE FROM INDIA**

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How Much Does Volatility Influence Stock Market Returns? – Empirical Evidence from India

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Abstract

The purpose of this paper is to establish and estimate the extent of the volatility anomaly (VA), i.e., low volatility stocks achieve high average returns over time, in the Indian stock market. We examine the impact of the beta, variance, relative beta, and relative variance measures on the expected stock returns for a cross-section of NIFTY500 companies, for the 10-year period July 2010 to June 2020. We comprehensively examine the data through robustness checks by undertaking the same procedure on a rolling year basis for different subsamples. We also consider the 6-month Covid pandemic phase from January to June 2020 to examine the role of risk and time on stock returns. Our empirical findings suggest that the VA is predominant in the medium to long term (5 to 10 years), but it seems to be negligible in the ultra-short and short time frames (6 months to 3 years). The overall findings suggest that the VA is most significant when the time period considered is 3 years or more. These results can prove to be highly useful for investors as well as portfolio managers.

Keywords: *Volatility anomaly; investing; alpha; emerging markets; relative beta*

JEL Codes: *G11, G12, G15*

Acknowledgement

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INTRODUCTION

India is among the fastest-growing economies in the world with a colossal amount of foreign direct and indirect investment into the country. Hence, it is important to examine whether these resources are being allocated efficiently and if this is reflected in the stock prices. The growth of the Indian stock market has been more than impressive in the last two decades, especially in terms of market capitalization, number of listed firms and turnover rates. Numerous studies have investigated the efficiency of the Indian stock market (Dicle *et al.*, 2010; Kumar *et al.*, 2011; Narayan *et al.*, 2014; Narayan *et al.*, 2015; Narayan and Ahmed, 2014; Kayal and Maheswaran, 2018; Kayal and Mondal, 2020). Evaluating stock market dynamics in the Indian context deserves attention for several reasons. Firstly, as a developing nation, India has become the economic powerhouse of the world and has endless potential to expand and deliver more. Secondly, the National Stock Exchange (NSE) is the largest derivatives exchange in the world in terms of the volume of contracts traded, the second-largest exchange in the world in terms of the number of contracts traded in single stock futures and ranked first in terms of contracts traded in index options and currency futures. Thirdly, according to the International Monetary Fund (IMF), India is the eleventh largest economy in the world by nominal GDP and the third-largest by purchasing power parity (PPP). Over the past two decades, the stupendous growth of the Indian stock market has been accompanied by a surge in low-risk/high-return investment strategies as well as in the volume and size of investments by both domestic and international investors. Hence, studying its volatility anomaly (VA) and thereby the risk-adjusted expected return pattern is very important to support investors in making their investment decisions and monetary policy specialists for policy formulation. Further, the study would be relevant for investors who may wish to invest in Asian countries. As most Asian countries (except a few) are emerging in nature, the VA is not a phenomenon confined to just India. We would expect similar return patterns across many other countries in Asia. Foreign and domestic

investors can use this anomaly to develop low-risk-high-return (LRHR) strategies to invest in Asian financial markets.

The relationships between risks and returns lie at the heart of modern finance. Traditional finance gurus often talk about the widely prevalent notion that high risks could yield higher returns. In other words, stocks exhibiting higher volatility measured by *variance*, and stocks with higher systematic risk measured by *beta*, could yield higher returns for investors. But evidence from equity markets all over the world has presented quite a different picture in the last two decades. The *Capital Asset Pricing Model* (CAPM), originally put forward by Sharpe (1964) and Lintner (1965), postulates that the risk of an asset should be measured by the extent to which it contributes to the volatility of a well-diversified portfolio. According to the CAPM, higher *beta* assets should demand a higher average return to compensate investors for bearing higher risk. In contrast, the actual relationship between *beta* and return is much flatter than predicted by the CAPM (Black, 1972; Black *et al.*, 1972; Haugen and Heins, 1975). Motivated by empirical results, Baker *et al.* (2011) contended that high *beta* and high volatility stocks have consistently underperformed when compared with low *beta* and low volatility stocks. Their findings have not only contradicted CAPM but have also clearly underscored the very proven principle behind risks and returns: low-risk portfolios seem to have yielded greater reward than high-risk portfolios.

The observation that low-*beta* stocks outperform high-*beta* stocks, has received a lot of research attention and triggered the need for a profound investigation into the same, especially in the context of the Indian stock market. More specifically, low-volatility stocks, i.e., stocks that fluctuate less over time, having lower *variance* and lower *beta*, are the ones that have provided a higher expected return to investors in the long run. This long-term risk-return relationship is termed as the *Volatility Anomaly* (De Jong and Palkar, 2016). Substantial evidence from international markets like the United States and China

shows that future stock returns of previously low return-variability stocks significantly outperform those of previously high return-variability stocks. Consistent with this view, this paper showcases how the average returns on stocks within a specified period can be explained in the context of the Indian stock market using symmetric and asymmetric risk measures such as (i) *variance*, (ii) *beta*, (iii) *relative variance*, (iv) *relative beta*, (v) *downside beta*, (vi) *downside semi-variance*, and (vii) *Value at Risk*. Our main goal throughout the paper is to understand the implication of the first four risk measures on stock returns, the other two are considered for cross verifying our results.

Our theoretical analysis begins by studying the dynamics of risk and why the aforementioned risk standards are chosen to explain the trend pattern in expected stocks returns. Risk pertains to the uncertainty of getting back the money (or even more) one invests. It should not be surprising that most investors are more concerned about downside risk than upside risk. The downside risk is the risk of the actual return being below the expected return. It is common knowledge that India mostly comprises institutional investors who are risk-averse. They certainly want to make a profit but at the same time do not want to incur losses. According to Estrada (2002; 2007) and Post *et al.* (2009), downside risk measures fare better than traditional risk measures in explicating the variability in long-term stock returns.

We shed light on two categories of risk measures. The symmetric and standard risk measures include *variance* and *beta*. The asymmetric risk measures such as *relative variance* and *relative beta* are used to account for downside risk. Ang *et al.* (2006) delineated three proxies for downside risk: *downside beta*, net *beta* (upside *beta* minus *downside beta*) and *relative downside beta*. While *downside beta* is the most appropriate measure of downside risk, future stock returns cannot be sorted on this basis because, by construction, regular *beta* and *downside beta* are not independent of each other. Thus, *relative variance* (difference between negative semi-*variance* and *variance*) and

relative downside beta (difference between *downside beta* and *beta*) qualify as the most appropriate measures of downside risk since they accurately capture the incremental impact of *downside beta* over regular *beta* and *downside variance* over regular *variance*.

We establish our empirical results for a cross-section of stocks listed on the National Stock Exchange (NIFTY500 index) over the 10-year period from July 2010 to June 2020. From the daily stock price data of these companies, we calculate the daily stock returns. Going forward, we use the various risk measures to examine the pattern of mean returns on these stocks. For each risk proxy, we divide the data into five quintiles from '1' being the lowest to '5' being the highest. Subsequently, for each risk measure, we check whether low-quintile stocks provide higher mean returns than the high-quintile stocks and whether the VA manifests. Furthermore, we comprehensively examine the 10-year data through several robustness checks by undertaking the same procedure on a rolling year basis for different subsamples.

Our approach to checking for higher returns yielded by stocks bearing higher volatility and systematic risk closely follows Ang *et al.* (2006). We have differentiated our work from its companion papers by conducting our study on a rolling year basis for different time horizons, namely, very short term (less than a calendar year), short term (more than 1 year and less than 3 years), medium-term (more than 3 years and less than 5 years), and long term (5 years and more). Finally, we also examine the data from the 6-month Covid pandemic phase from January to June 2020. Our findings suggest that the VA is more of a medium to long term phenomenon than a short term one. A possible explanation is that the market typically requires 3 years or more for risk adjustment and volatility smoothening to yield higher returns.

Modern investors are perpetually concerned with risk-adjusted returns. The low-risk anomaly explanations focus on an investor's risk appetite. Time-varying market volatility alters their investment

opportunity set by influencing the expectation of future market returns or changing the risk-return trade-off. Hence, the importance of understanding stock returns in terms of risk measures cannot be stressed more. The bonus from the LRHR strategies is attributable to the compounding effect – the lower volatility pressure on investment returns enhances the performance of less volatile stocks. The real benefits of possessing low-volatility stocks accrue over longer periods of time (Janani *et al.*, 2022), as the well-known power of compounding suggests (Ang *et al.*, 2006).

The rest of the paper is arranged along the following lines. We present the Literature review in the following section. We elaborate on the data and methodology next, followed by empirical results and discussion. Then we conduct extensive robustness checks as well as pinpoint potential extensions. Finally, based on the observations, a few policy conclusions are drawn.

LITERATURE REVIEW

An enormous amount of research has been devoted to the fact that around the world low volatility stocks have higher average returns than high volatility stocks (Ang *et al.*, 2006, 2009; Clarke *et al.*, 2006; Blitz and van Vliet, 2007; Baker *et al.*, 2011; Baker and Haugen, 2012). The outperformance of low volatility stocks over high volatility ones is economically exceptionally large, amounting to 12 per cent per annum on an average (Walkshäusl, 2013). As a result, Baker *et al.* (2011) proclaimed that “*the outperformance of low-risk portfolios is perhaps the greatest anomaly in finance*”. Baker *et al.* (2011), as well as Frazzini and Pedersen (2014), found compelling evidence of this anomaly in the U.S. stock market data. Furthermore, Collver *et al.* (2013), as well as Baker and Haugen (2012), observed that results from global equity markets mostly concurred with those of the U.S while they tested the VA in multiple developed and emerging countries. While investigating the same in Germany’s stock market, Koch (2010) discovered strong

evidence that low-risk stocks generate considerably higher returns than high-risk ones by around 9 percent per annum. Consistent with the preceding evidence, Saengchote (2017) detected that Thai stocks having low beta exhibited positive abnormal returns whereas high-beta stocks exhibited negative abnormal returns for the 12-year period of 2004 to 2015.

There are multiple reasons underlying the existence of the VA. For example, Baker *et al.* (2011) argued that the low volatility effect arises because sophisticated investors must follow a benchmark; and consequently, are unable to take advantage of an arbitrage opportunity whereas it is possible to systematically earn higher returns while assuming lower risk. This anomaly can persist because institutional investors cannot fully exploit the excess returns, they could gain from investing in such stocks. 'Limits on arbitrage' (Dutt and Humphery-Jenner, 2013) could be another reason for this anomaly. However, they pointed out that 'limits on arbitrage' would be less dominant in emerging markets as an explanation for the VA. This is mainly due to the existence of fewer and stable stocks in the emerging market equity index and the limited availability of quality stocks for investments. It encourages large investors to choose low-volatility, stable stocks and thereby arbitrage away any potential excess profits. Further, media attention can also have an impact on investors' attention and influence investors' choices. In this case, also, the VA disappears for stocks with high media attention (Biltz *et al.*, 2020) as too much attention could arbitrage away potential excess profits. However, it is also true that, in the case of arbitrage asymmetry, limited arbitrage opportunities would eliminate more underpricing than overpricing (Stambaugh *et al.*, 2015). Therefore, it is generally observed that quality stocks in emerging markets are overpriced, stable, and create high risk-adjusted returns. That possibly explains the reason for the VA in emerging markets like India. Similarly, different forms of regulations and constraints on short selling (which is prevalent in most of the emerging stock markets including India) support the argument of arbitrage asymmetry that leads to the VA (Stambaugh *et*

al., 2015). Also, trading frictions in emerging markets could also be high and therefore arbitrage can be costly (Shleifer and Vishny, 1997). This will again possibly contribute in favour of the VA argument. Another reason this anomaly exists could also be irrational investors' sentiment and its impact on volatility. In a recent study, Haritha and Rishad (2020) have highlighted that positive sentiment due to irrationality could lead to higher speculative activities and thereby overvaluation of stocks. This sentiment also reduces volatility in the long-run due to the bullish outlook on overvalued stocks. Although the authors' argument wasn't directly motivated to establish the VA, we could identify a clear connection between volatility and returns.

Risk-based explanations pose certain difficulties in describing the observed return pattern, as the return difference between low and high-risk stocks cannot be accurately captured by common asset pricing models. This is precise because low volatility stocks have typically low market *betas*, whereas high volatility stocks exhibit high market *betas*. Consistent with this view, Black *et al.* (1972) were among the first to contend that high-*beta* stocks have lower returns than equilibrium and that low-*beta* stocks earned higher returns than expected. This gives rise to the fact that low-risk stocks should be considered as a unique asset class while strategically allocating assets (Blitz and van Vliet, 2007).

This study is strongly connected with that by Ang *et al.* (2006). They acknowledged that stocks that are highly sensitive to innovations in aggregate stock market volatility have low mean returns. They further point out that using other measures of aggregate volatility risk (such as sample volatility, extreme value volatility estimates, and realized volatility estimates calculated from high-frequency data) results in little spread in the cross-section of average stock returns. Our main upshot is that both *beta* and *variance* are significantly valued risk factors in the cross-section of returns.

Our paper concentrates on the extensive impact of low volatility and low risk on expected stocks-returns within a time frame. The appealing feature of our medium of analysis is to study this impact with respect to risk-based measures. In congruence with this, Baker *et al.* (2011) posited behavioural explanations for this anomaly. They contended that the volatility effect may be partially elaborated by the irrational preference for high volatility stocks by individual investors and partially by the institutional investor's mandate to beat a given benchmark which tends to limit investments in low volatility stocks. In addition to this, the 'low volatility effect' seems to be related to operating performance and investment. Less volatile stocks would most likely exhibit strong operating performance as low volatility improves a firm's access to capital. In an efficient market there should be a connection between stock returns and (positive) earnings surprises, but not merely between stock returns and earnings per se (Core *et al.*, 2006).

Finally, our study is also related to the literature on rare and unexpected events. Starting with Rietz (1988), many researchers have modelled the possibility of occurrence of rare disasters, such as wars, global pandemics, or economic depressions, to unfold the equity premium puzzle (e.g., Barro, 2006; Gabaix, 2008, 2012). Similarly, this paper also investigates the impact of the Coronavirus pandemic on stock returns. A point worth noting is that such unexpected events or disasters are extremely rare.

DATA AND METHODOLOGY

Data

The data in this study consists of daily stock prices for 362 companies partly constituting the NIFTY500 index for the 10-year period starting from 1st July 2010 to 30th June 2020. Daily stock price data is not available for many companies prior to 2010. This sample represents approximately 72 percent of the overall population, which is a large proportion to work with. Increasing the time frame would further reduce

the sample size. The period under study is chosen with the objective that stock price fluctuations can be observed for certain ups and downs in the market such as the post-2008 financial crisis period and the period of the coronavirus pandemic starting from December 2019. Also, a 10-year period would possibly reflect both bear and bull market scenarios.

Methodology

The standard risk measures used in this study include *variance* and *beta*. *Variance* is calculated for each company's stock price by taking the average of squared deviations from their mean returns. *Variance* explains the degree of spread or variability in the data. *Beta* is a measure of systematic risk of a stock compared to the market as a whole. It is calculated as the ratio between the *covariance* of expected return on a stock and return on the market, and the *variance* of average expected returns on the market

$$\beta_j = \frac{\text{Cov}(\text{market}, \text{stock})}{\text{Var}(\text{market})} = \frac{\text{cov}(\bar{r}_j, \bar{r}_M)}{\sigma_M^2} \quad (1)$$

Where, β = beta;

$\text{Cov}(\text{market}, \text{stock})$ = Covariance between market and stock

$\text{Var}(\text{market})$ = Variance of market

Following this, to evaluate the effectiveness of *relative variance* and *relative beta* on mean returns, we should calculate the *downside deviation*, i.e., the *variance* of the negative returns to the stocks. *Relative variance* is defined as the difference between *variance* and *downside variance* (or deviation). *Downside beta* is one of the most direct measures of downside risk. It is calculated as the ratio of *covariance* of expected return on a stock and return on the market, and *downside deviation*. *Relative beta* is defined as the difference between *downside beta* and *beta*. It underestimates the risk for low-*beta* stocks and overestimates the risk for high-*beta* stocks. This explains why low-*beta* stocks seem to be systematically underpriced and high-*beta* stocks seem overpriced in empirical tests of CAPM in the mean-*variance*

framework (Black *et al.*, 1972; Fama and MacBeth, 1973; Reinganum, 1981; and Fama and French, 1992).

The observation that investors are more worried about downside risk than upside risk when it comes to decision-making leads to the possibility that they might treat downside risk differently from market risk. In this context, Markowitz (1959) suggested that *downside semi-variance* would be a more appropriate risk measure as compared to *variance*. *Downside semi-variance* is defined as the variability of a stock up to its mean level. Compared to *variance*, *downside semi-variance* concentrates on the bad outcomes of stock returns. Mathematically, it is represented as follows:

$$SV(<) = \frac{1}{n} \sum_{j=1}^n (r_j < \bar{r}_j) (\bar{r}_j - r_j)^2 \quad (2)$$

Where each observation r_j is lower than the mean value of all observations (\bar{r}_j)

Another integral measure that is related to the risk of loss of investments, is the *Value at Risk (VaR)*. This *VaR* is defined as the maximum amount of loss that one can expect for a given confidence interval and a given time horizon. Suppose a portfolio has a 4.3 percent *VaR* at a 5 percent probability level for one month. This would imply that over the next month there is a 5 percent chance that the portfolio could lose more than 4.3 percent of its value or there is a 95 percent chance that the portfolio will lose less than 4.3 percent. Also, a positive *VaR* indicates a loss, whereas a negative *VaR* indicates a profit. Our calculation of *VaR* at 95 percent confidence limit for the data under study shows negative values, indicating a profit for these stocks. Mathematically, it is represented in equation 3.

$$VaR_{\alpha}^{percent} = z_{\alpha} \sigma \quad (3)$$

We begin our analysis by investigating the risk-return relation for constituent stocks of the NIFTY500 Index. To explain the low volatility–

high return relationship, we group the stock returns data in terms of the highest mean returns and then sort them based on each of the risk measures - *variance*, *beta*, *relative variance*, and *relative beta*. Further, we divide all stocks into five quintiles, 1 being the lowest quintile and 5 being the highest. Based on the quintile breakpoints for the variables, stocks are segregated into low and high volatility stocks as well as safe and risky stocks. We find that low *beta* and low volatility stocks (and not lowest *beta* and least volatile stocks) generate high expected returns within the mentioned time frame. To provide more clarity, stocks falling under the first three quintiles are considered as low *beta* stocks since their *beta* values are roughly below the market beta and the ones falling under the 4th and 5th quintiles are the high *beta* stocks with *beta* values usually above the market beta. A similar description holds true in the case of low and high volatility stocks.

In addition to the 10-year period of analysis, we cross-verify the presence of the VA by conducting the same procedure over a period of 7 years, 5 years, and 3 years on a rolling basis as well as for a period of 6 months when the world was hit by the unexpected Coronavirus pandemic.

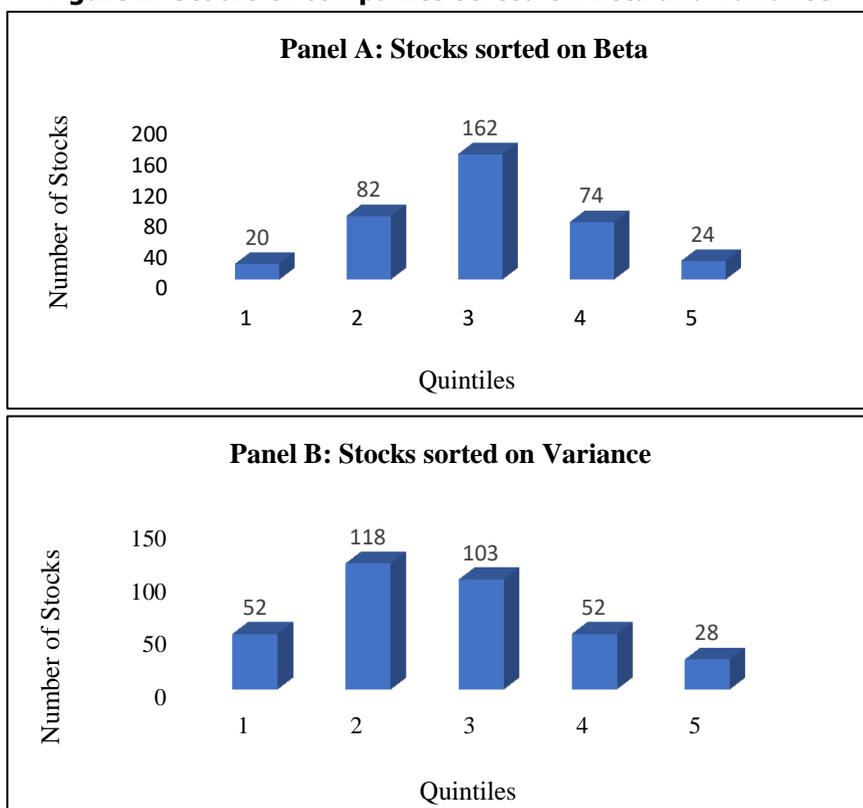
EMPIRICAL RESULTS

Our theoretical reasoning coupled with a study of the past literature clearly suggested that low-*beta* stocks and low-*variance* stocks outperform the high-*beta* and high-*variance* ones. In this section, we provide strong empirical support for the VA. Initially, we sort the stocks based on the *beta*, *variance*, *relative beta*, and *relative variance* and present the existence of the VA in each case. Later, we sort the stocks on the basis of *Value at Risk (VaR)*, *downside semi-variance* and *downside beta*, and provide interpretations.

Stocks Sorted by Beta and Variance

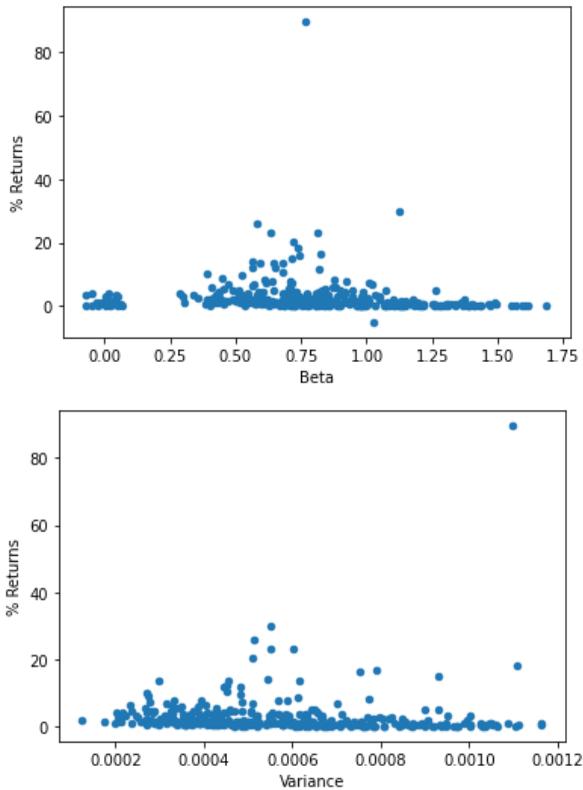
To check the existence of VA, we sort the stocks of 362 companies of *beta* and *variance*. Early studies that explain the empirical failure of the CAPM include Brennan (1971), Black *et al.* (1972), and Haugen and Heins (1975). Later Ang *et al.* (2006; 2009) argued that volatility gives negative premiums for equity returns and that stocks with high sensitivity to aggregate volatility risk earn low returns. Our findings help elucidate these anomalous relations between volatility and stock returns.

Figure 1: Stocks of companies sorted on *Beta* and *Variance*



Panel A and Panel B exhibit the number of stocks in each of the 5 quintiles following sorting by *beta* and *variance* respectively.

Figure 2: Pattern of Returns (in 100s) for all *beta* and *Variance* Values



The left and right boxes present the return pattern for all *beta* and variance values respectively. The returns for beta mostly lie within the range of 100-2500 percent (2nd and 3rd quintiles). The right box clearly shows that low volatility stocks provide high average returns. Thus, the mean returns are higher for lower beta and variance values, validating the presence of VA.

Figure 1 presents the graphical pattern of sorting stocks on the basis of *beta* and *variance*. Panel A shows the number of stocks in each quintile when they are *beta*-sorted. Out of 362 companies, the stocks of 263 companies that form the low-*beta* quintiles (1st, 2nd, and 3rd) give higher mean returns as compared to stocks in the high-*beta* quintiles (4th and 5th), as highlighted in figures 1 and 2. The VA holds true for this risk

proxy since a low *beta*, i.e., low systematic risk, is associated with higher expected returns in the future (Baker and Haugen, 2012). Panel B shows the number of stocks in each of the five quintiles when they are sorted according to *variance*. While dividing all the *variance* values into five quintiles, we find that all the stocks are confined to three quintiles (1st, 2nd, and 5th). Out of 362 stocks, the lowest quintile giving the highest mean returns contained 353 stocks, which makes it difficult to make any inferences. To resolve this issue, we further divide these 353 stocks into five quintiles. Out of these, stocks of 273 companies lie in the low *variance* quintiles (1st, 2nd and 3rd) and display higher mean returns as compared to stocks falling under high-*variance* quintiles (4th and 5th), as displayed in figures 1 and 2. The VA exists since low *variance*, i.e., low risk and less stock price fluctuation is associated with high average returns. In the case of both these risk measures, our empirical findings are consistent with the argument that the low-*beta* and low-*variance* stocks outperform and provide higher mean returns in the long run as compared to the high-*beta* and high-*variance* stocks (Lakonishok and Shapirom, 1984; Heston *et al.*, 1999; Baker *et al.*, 2011; De Jong and Palkar, 2016).

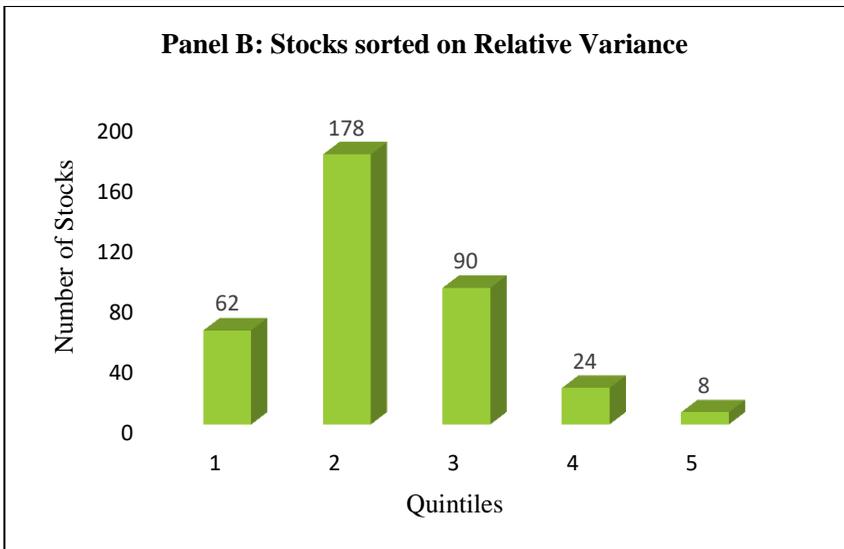
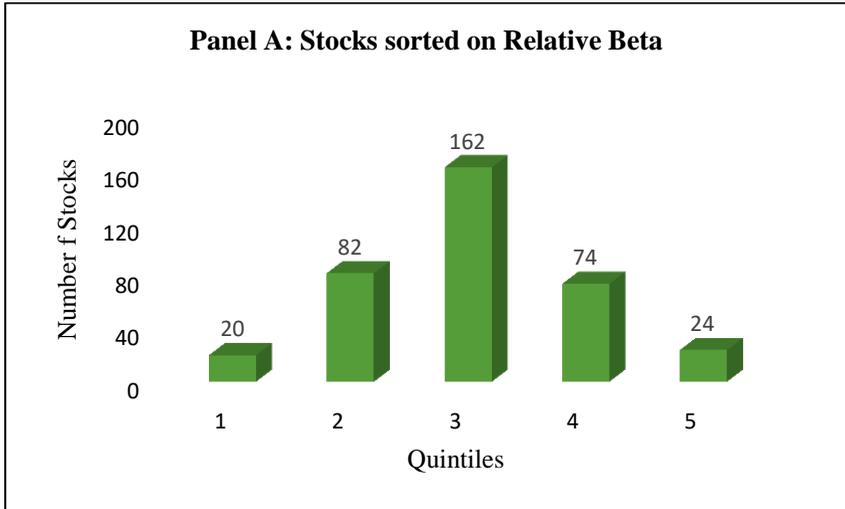
Stocks sorted by Relative Beta and Relative Variance

While dealing with cross-sectional data the importance of downside risk measures cannot be stressed. Hence, we need risk measures that specifically take into consideration the liability traits of investment decisions (Leibowitz, 1986). In this section, we re-examine the risk-return relation, using asymmetric risk proxies like *relative beta* and *relative variance*. By construction, quintile 1 represents the stocks with the lowest downside risk, making them least risky and quintile 5 on the other hand represents the stocks with the highest downside risk, and thus the riskier ones.

Figure 3 shows the results of sorting the stocks based on *relative beta* and *relative variance*. Panel A shows the number of stocks in each quintile when they are *relative beta*-sorted. We observe the exact same

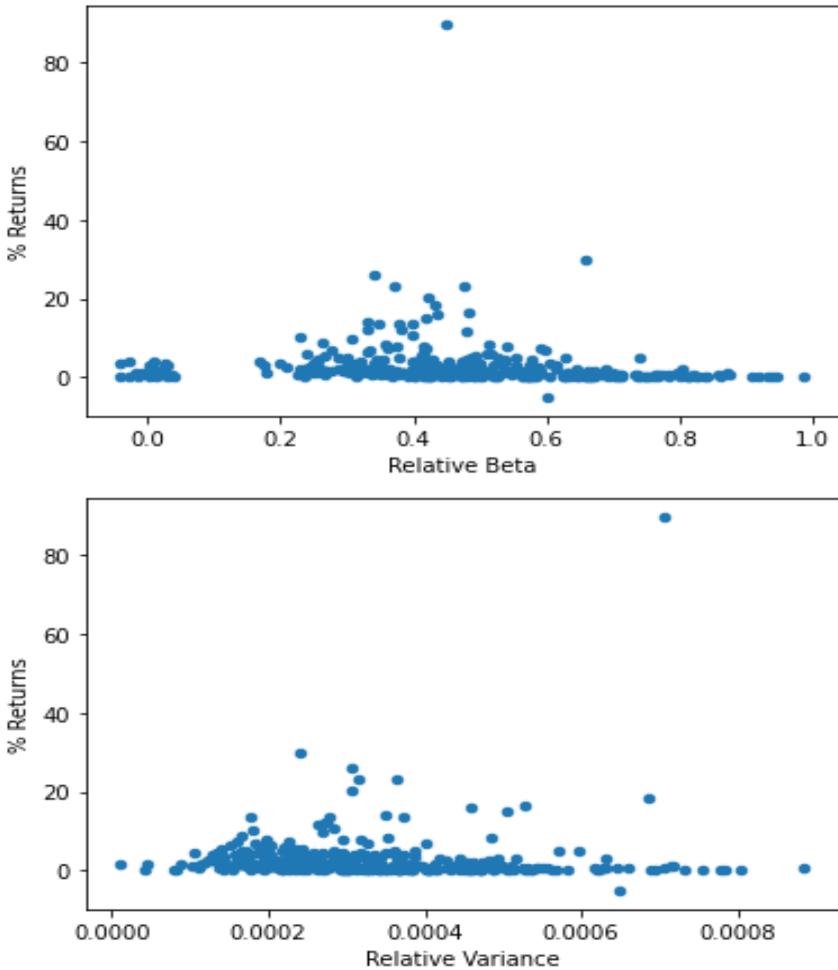
return pattern as for the *beta*-sorted stocks, as displayed in figures 1 and 2. The VA is predominant here since low-*relative beta* signifies lower downside risk and shortfall which is associated with higher expected return here. Panel B shows the number of stocks in each of the quintiles when they are sorted by *relative variance*. Out of the 362 companies, the stocks of 241 companies belonging to the low-*relative variance* quintiles (1st, 2nd and 3rd) compound into higher mean returns over time as compared to stocks under the high-*relative variance* quintiles (4th and 5th). This is graphically represented in figures 3 and 4. The VA evidently holds true in this setting since low-*relative variance* signifies more safety which is associated here with higher expected return (Grootveld and Hallerbach, 1999). We can observe that the lowest-quintile stocks are safer than the highest-quintile ones in terms of future expected returns. High-risk stocks exhibit much higher time-series variation, resulting in lower compound returns over time (Bollerslev, 1987; Vuolteenaho, 2002). In the backdrop of both these risk measures, we can comfortably say that the low *relative beta* and low *relative variance* stocks are safer as well as fare better than the high *relative beta* and high *variance* ones in terms of giving higher expected returns (similar to the findings by Shefrin, 2001; Fong, 2018).

Figure 3: Stocks of Companies Sorted on Relative Beta and Relative Variance



Panel A and Panel B exhibit the number of stocks in each of the 5 quintiles following sorting by *relative beta* and *relative variance* respectively.

Figure 4: Pattern of Returns (in 100s) for all *Relative Beta* and *Relative Variance* Values



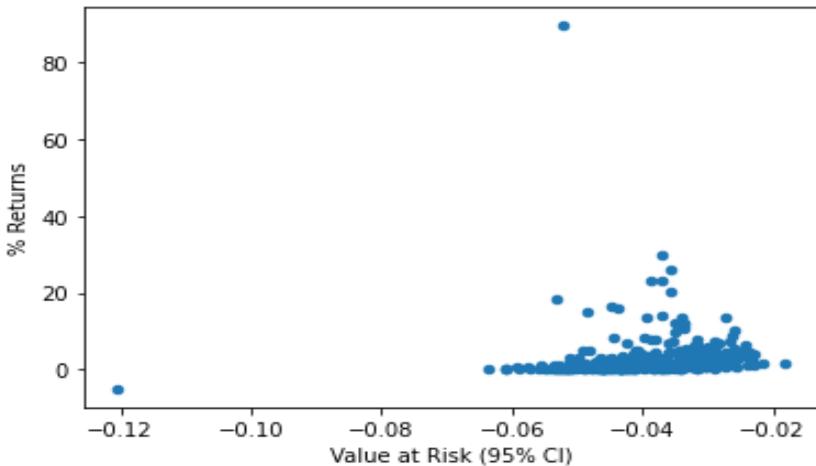
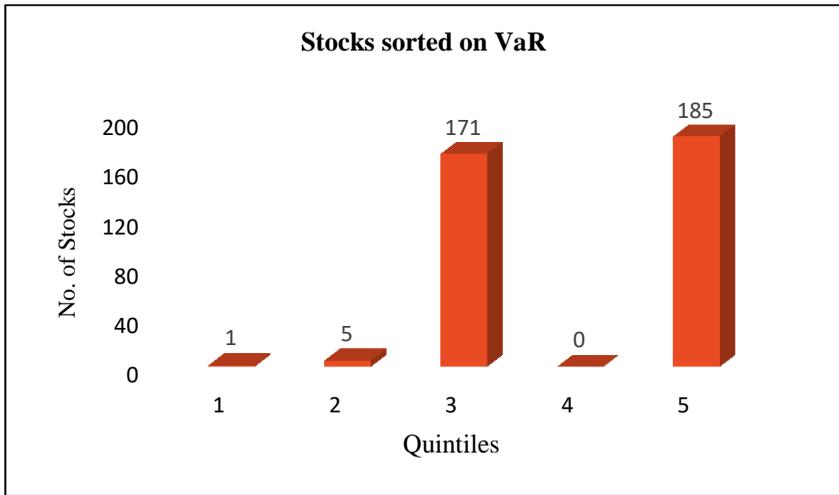
The left and right boxes present the return pattern for all *relative beta* and *relative variance* values respectively. Returns mostly lie within the range of 100-2500 percent for *relative beta* values in the range 0.25-1.00 (2nd and 3rd quintile). The right box unveils the return pattern for all *relative variance* values. In the right box, returns mostly fall within the range of 100-3000 percent. We can easily comment that less volatile stocks provide higher mean returns, validating the prominence of the VA.

Stocks Sorted by Value at Risk (VaR), Downside Semi-Variance and Downside Beta

A related analysis can be made for downside risk measures like *Value at Risk (VaR)*, *Downside Semi-Variance* and *Downside Beta*. *VaR* shows the worst expected loss over a target horizon within a given confidence interval. It summarizes the exposure to market risks and the probability of adverse changes in financial variables, in a single number. *Semi-variance* (Markowitz, 1959), measures the variability of returns below the mean. *Downside beta* is the sensitivity of stock returns to the market. It may change with the level of the market returns, leading to an asymmetric risk profile (Post *et al.*, 2012).

VaR is the maximum loss that a firm can observe within a specified confidence limit and for a given time horizon. Here we consider the confidence limit to be 95 percent. *VaR* estimation highly depends on a good forecast in the light of unexpected and rare events, or catastrophic risks, since it is quantified from the lowest stock returns (Danielsson and De Vries, 2000). A positive *VaR* indicates a loss, whereas a negative *VaR* indicates a profit. Since our *VaR* calculations generate negative values, the higher the *VaR* the higher is the profit and also therefore the expected returns on the stocks. This concept is projected in Figure 5. Out of the 362 stocks, 355 stocks belong to the 3rd and 5th quintiles. The pattern of mean returns is expressed in the right box of figure 5.

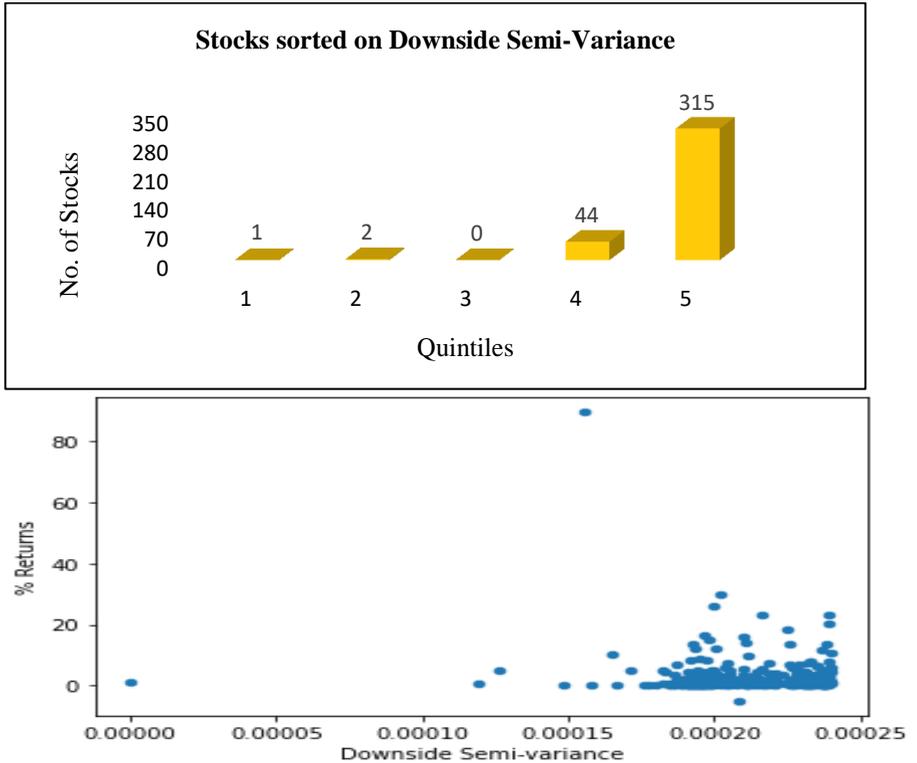
Figure 5: Pattern of Returns (in 100s) for All Stocks Sorted on VaR Values



The left box exhibits the number of stocks in each quintile when sorted by VaR . Since we obtain negative values from VaR calculations, the higher the quintile or value of VaR , the higher is the expected future return. We find that 355 stocks giving higher mean returns lie within the higher VaR quintiles (3rd and 5th). The box on the right shows the return pattern for all VaR values. We observe that the highest expected returns are obtained for stocks belonging to the 3rd and 5th quintiles.

Downside semi-variance measures the dispersion of returns below an expected value of investment return. Measuring downside risk using *semi-variance* provides an intuitive perception of the risk borne by investors (Boasson *et al.*, 2011). We know that *semi-variance* is calculated below a targeted level of return. Here, the benchmark level of return is taken as the mean of variances of all stocks, so the values represent returns below the mean of *variance*. The resultant values are plotted graphically as shown in the right box of Figure 6. In contrast with the results of all the previously used variables, the VA is not observed. Out of 362 stocks, 315 stocks lie in the 5th quintile, which exhibits neither the highest mean returns nor the least standard deviation of returns, as shown in the left box of Figure 6. Additionally, the graph on the right box of Figure 6 showing the return pattern for all values of *semi-variance*, clearly points to the fact that higher risks provide higher returns over the 10-year sample period considered. Contrary to our expectations, the data provide evidence against the VA for this downside risk measure.

Figure 6: Pattern of Returns (in 100s) for all Stocks Sorted on *Downside Semi-Variance* Values

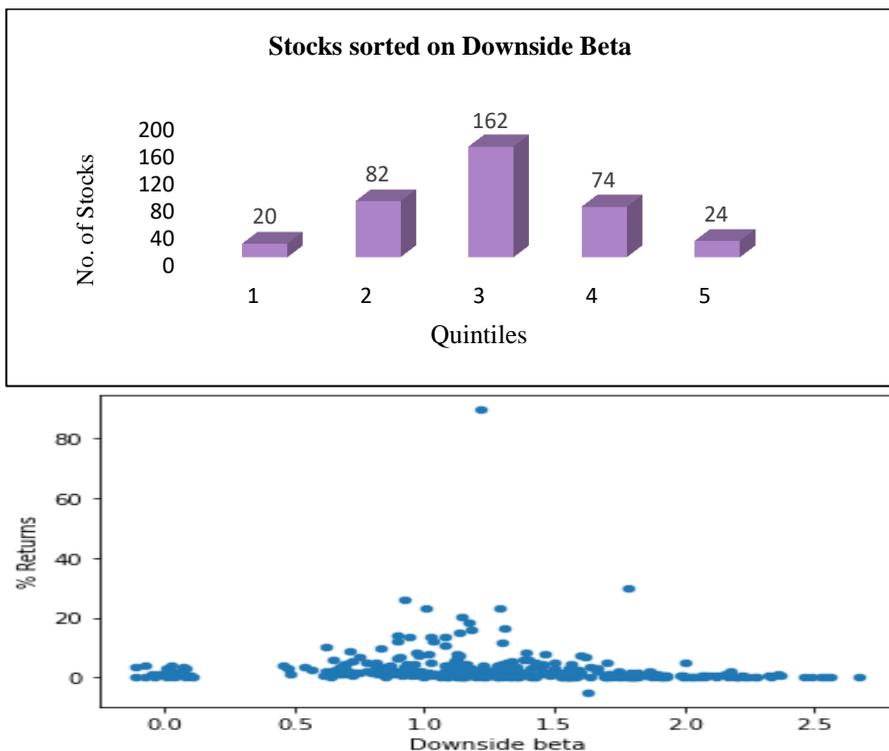


The left box of this figure shows the number of stocks in each quintile when sorted by *downside semi-variance*. The right box shows the return pattern for all *downside semi-variance* values. Since the returns are observed to be higher for higher values of *semi-variance*, we find that the VA is non-existent for this risk measure over the 10-year sample period. These results are consistent with the traditional notion of an association between higher risks and higher returns.

Downside beta is defined as the susceptibility of excess stock returns to excess market returns during market downturns. A market downturn is a period during which the excess market return is lower than its mean value during the past year (Atilgan *et al.*, 2018). The stocks of the 362 companies are sorted into five quintiles based on values of

downside beta. We can detect that these results are exactly the same as in the case of the *beta* and *relative beta*. This is not surprising since *relative beta* is the difference between *downside beta* and *beta*. This is clearly projected in Figure 7 along with the overall spread of returns for all values of *downside beta*. Our data provide persuasive evidence in favour of the VA for this risk measure.

Figure 7: Pattern of Returns (in 100s) for all Stocks Sorted On Downside Beta Values



The left box in the figure exhibits the number of stocks in each quintile when they are sorted by *downside beta*. Ignoring the extreme value, the dispersion of returns is within the range of 100-2500 percent for *downside beta* values in the range 0.50-1.75 (2nd and 3rd quintile). The right box shows the return spread for all *downside beta* values. We distinctly observe that the highest expected returns are obtained for stocks belonging to the 2nd and 3rd quintiles, validating the VA claim.

From these results, it is quite evident that the presence of VA is strong in the Indian stock market. A plausible reason is the limited availability of quality, stable, and liquid stocks. The Indian stock market has approximately 6000 stocks out of which only 10-15 percent are purely liquid stocks. Out of these only around 100 stocks are of high quality (Walkshäusl, 2013). Hence, retail as well as institutional investors prefer to invest only in these stocks. They are safe stocks in the sense that they are less volatile and yield decent and consistent returns over a long period of time. The equity market is divided into large, mid and small-cap stocks. Most of the safe stocks belong to the large-cap category. Since investors mostly invest in liquid stocks giving satisfactory returns during their investment periods, occasionally we witness excess demand in the market on the one hand as well as no demand for these stocks on the other. This is the primary reason why volatility fluctuates so much in the Indian stock market. When we invest in such stocks over a long period, we find that the volatility is smoothened out, and high average returns are earned by bearing lower idiosyncratic risk.

Further, we also observe some firm-level characteristics that are related to the VA. Since we focused on the documentation of the VA in India using different methods, we have not specifically analysed the firm-level characteristics in our study. However, carefully observing the set of companies for which we consistently observe high returns and low volatility, we find that most of the companies are high quality in nature (irrespective of small or large) indicated by their high profitability ratios, stable free cash flows, high returns on capital employed, low debt-to-equity ratios, high level of promoters' holdings, and such indicators. This observation is very similar to the findings of Walkshäusl (2013) as he observed the VA for high-quality firms.

ROBUSTNESS CHECK

From our analysis using a cross-section of companies from the NIFTY500 stock index for a period of 10 years, we learn that the VA clearly exists in the Indian stock market. As Warren Buffet observed, "*Risk cannot be defined until it has a specified time horizon.*" This makes it extremely important to check whether the VA persists over different time frames and to varying extents. Here, we consider sample periods of 7 years, 5 years and 3 years on a rolling basis, and the 6-month Covid pandemic phase from January-June 2020. The choice of 7-, 5-, and 3-years rolling windows is to show how VA performs over different time horizons (medium term to long term). The same process can also be repeated with 2, 4, 6, and 8 years. We have cross-checked the results and find them to be similar and VA holds for 4-, 6-, and 8-years windows.

Expected stock returns have been observed to change with time so that investment opportunities are not constant (Campbell and Viceira, 1999). This is due to the stochastic nature of expected returns, which enables us to understand their behaviour over time. Table 1 shows the number of stocks in each quintile sorted on *beta*, *variance*, *relative beta*, and *relative variance* for 7 years on a rolling basis from July 2010 to June 2020. There are four different sample data sets generated in this case, i.e., 2010-2017, 2011-2018, 2012-2019, and 2013-2020. Figure 8 exhibits the distribution of stocks giving the highest mean returns into quintiles when they are sorted on beta values. Figure 9 displays the return pattern of stocks for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 7-year period of 2013-2020.

Here, we notice that the highest mean returns are of the stocks in the 2nd and 3rd quintiles when they are beta-sorted, as shown in Figure 8 and the 2nd quadrant of Figure 9. This clearly indicates that low-risk stocks continue to provide higher expected returns for all the 7-year periods taken. The VA claim becomes even stronger when stocks are variance-sorted. The least risky stocks, i.e., the ones belonging to the 1st

and 2nd quintiles, have generated higher returns, especially during the 2013-2020 period. Around 99 percent of the least risky stocks provided the highest expected returns. Furthermore, the results for relative beta exactly replicate the results obtained for beta-sorted stocks. Thus, we can comfortably infer that the VA is observed for relative beta-sorted stocks for the specific time horizon, as shown in the 1st quadrant of Figure 9. Finally, in the light of the relative variance-sorted stocks, the highest mean returns are obtained for stocks falling under the 2nd and 3rd quintiles. Graphically, this is visible in the 4th quadrant of Figure 9. Therefore, the low-risk stocks fare better than the high-risk ones in terms of average returns for all the 7-year time frames.

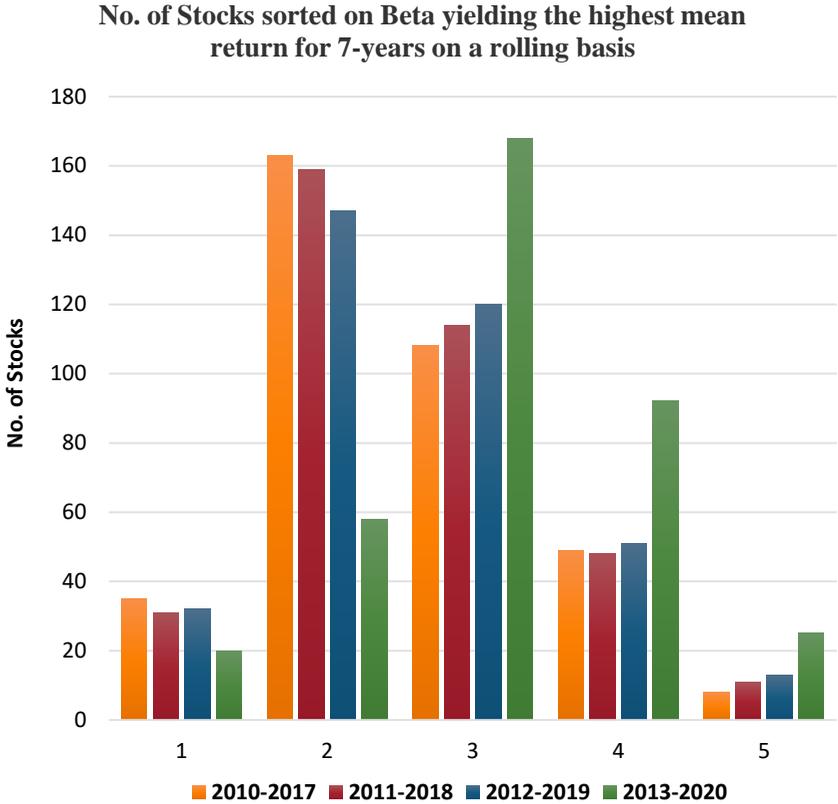
Similarly, we cross-verify and exhibit our empirical results for periods of 5 years on a rolling basis from July 2010 to June 2020. In this case, there are 6 different subsample data sets generated, i.e., 2010-2015, 2011-2016,, 2015-2020. Figure 10 shows the segregation of stocks yielding the highest mean returns into quintiles when they are sorted on *beta* values, whereas Figure 11 displays the return pattern of stocks for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 5-year period of 2015-2020. The outcomes for the subperiod of 5 years on a rolling basis almost replicate the outcomes obtained for the subperiod of 7 years. Our empirical evidence ascertains the veracity of the VA for a period of 5 years. The data is expressed numerically in Table 2 and graphically in Figures 10 and 11.

Table 1: Number of Stocks Yielding the Highest Mean Return Sorted on Various Risk Measures (7 years)

This table summarizes the results for the number of stocks providing the highest mean return when sorted on *beta*, *variance*, *relative beta* and *relative variance* on a rolling 7-year basis. Panels A, B, C, and D respectively show the number of stocks in each quintile when they are sorted by *beta*, *variance*, *relative beta*, and *relative variance*. The VA significantly holds true here since 80-90% of low-risk and low-volatility stocks provide higher mean returns over a period of 7 years on a rolling basis.

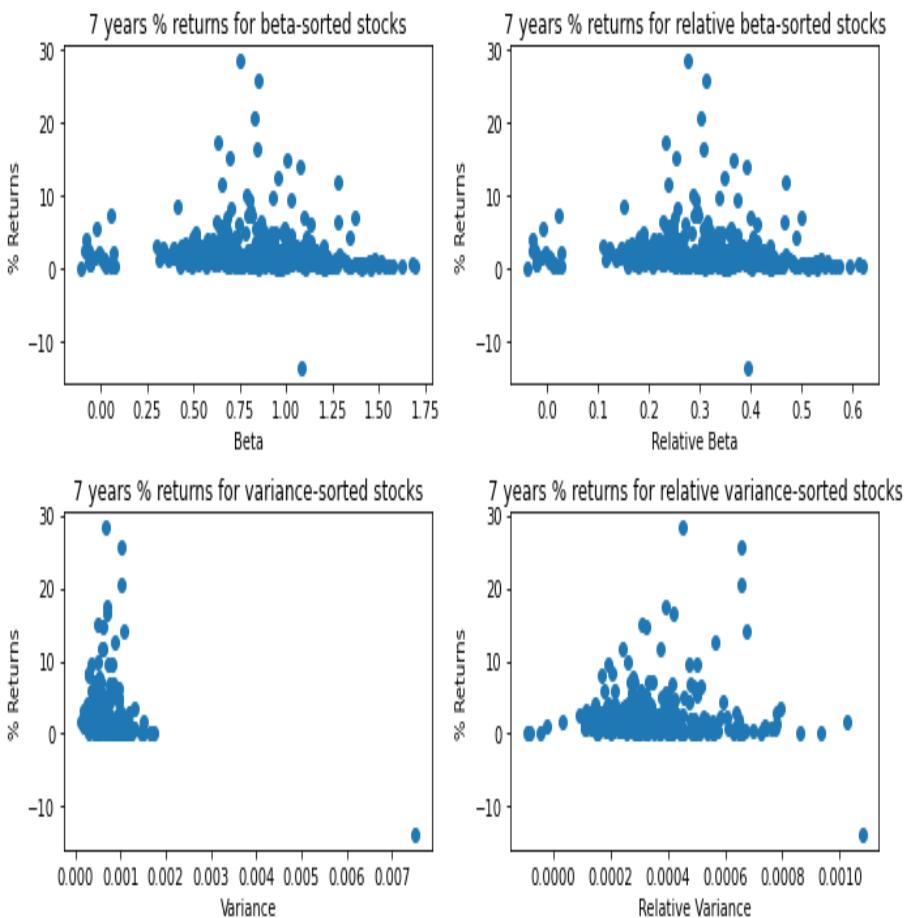
Highest Mean Return						
Quintiles 7-year Rolling	Low					High
	1	2	3	4	5	Low >
Panel A: <i>Beta</i> sorted						
<i>2010-2017</i>	35	163	108	49	8	Yes
<i>2011-2018</i>	31	159	114	48	11	Yes
<i>2012-2019</i>	32	147	120	51	13	Yes
<i>2013-2020</i>	20	58	168	92	25	Yes
Panel B: <i>Variance</i> sorted						
<i>2010-2017</i>	90	157	81	29	6	Yes
<i>2011-2018</i>	103	156	72	27	5	Yes
<i>2012-2019</i>	104	159	74	22	4	Yes
<i>2013-2020</i>	360	2	0	0	1	Yes
Panel C: <i>Relative Beta</i> sorted						
<i>2010-2017</i>	35	163	108	49	8	Yes
<i>2011-2018</i>	31	159	114	48	11	Yes
<i>2012-2019</i>	32	147	120	51	13	Yes
<i>2013-2020</i>	20	58	168	92	25	Yes
Panel D: <i>Relative Variance</i> sorted						
<i>2010-2017</i>	6	155	132	52	18	Yes
<i>2011-2018</i>	4	161	139	49	10	Yes
<i>2012-2019</i>	4	185	121	42	11	Yes
<i>2013-2020</i>	25	219	91	24	4	Yes

Figure 8: Beta-sorted stocks yielding the highest mean return for 7 years on a rolling basis



Evidently, the VA holds true for all time frames taken, since higher returns are obtained from stocks belonging to the 2nd and 3rd quintiles as compared to the high beta ones in the 4th and 5th quintiles.

Figure 9: Pattern of Returns (in 100s) for all values of Risk Measures for the 7-year Period 2013-2020



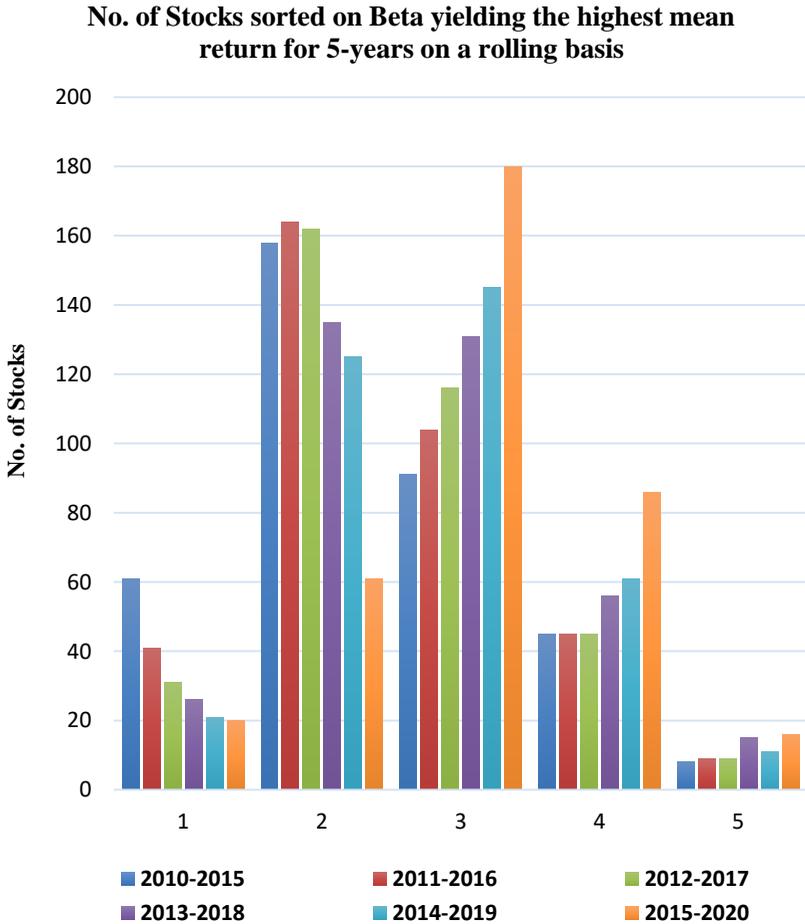
This figure depicts the pattern of mean returns for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 7-year period, 2013-2020. The 1st, 2nd, 3rd and 4th quadrants represent the return pattern for *beta*, *relative beta*, *variance*, and *relative variance* sorted stocks, respectively. Clearly, we find that the VA exists for this subsample period of 7 years.

Table 2: No. of Stocks Yielding the Highest Mean Return Sorted on Various Risk Measures (5 years)

This table summarizes the results for the number of stocks yielding the highest mean return when sorted on *beta*, *variance*, *relative beta* and *relative variance* on a rolling 5-year basis. Panels A, B, C, and D respectively show the number of stocks in each quintile when they are sorted by *beta*, *variance*, *relative beta*, and *relative variance*. The VA is prominent here since 70-95 percent of low-risk and low-volatility stocks provide higher mean returns over a period of 5 years on a rolling basis.

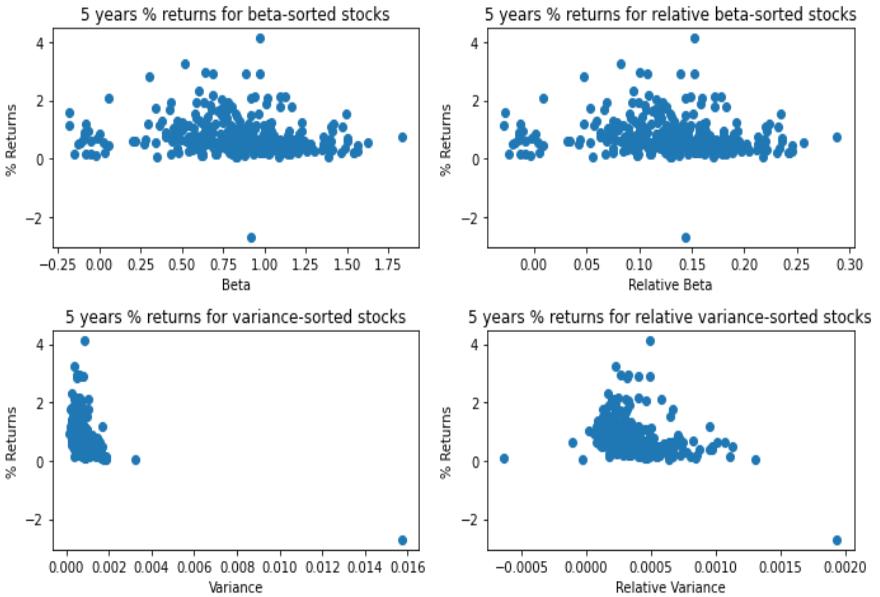
Highest Mean Return						
Quintiles 5-year Rolling	Low				High	
	1	2	3	4	5	Low > High
Panel A: <i>Beta</i> sorted						
<i>2010-2015</i>	61	158	91	45	8	Yes
<i>2011-2016</i>	41	164	104	45	9	Yes
<i>2012-2017</i>	31	162	116	45	9	Yes
<i>2013-2018</i>	26	135	131	56	15	Yes
<i>2014-2019</i>	21	125	145	61	11	Yes
<i>2015-2020</i>	20	61	180	86	16	Yes
Panel B: <i>Variance</i> sorted						
<i>2010-2015</i>	93	155	79	27	9	Yes
<i>2011-2016</i>	122	146	69	23	3	Yes
<i>2012-2017</i>	139	150	61	12	1	Yes
<i>2013-2018</i>	142	153	55	12	1	Yes
<i>2014-2019</i>	156	153	43	10	1	Yes
<i>2015-2020</i>	361	1	0	0	1	Yes
Panel C: <i>Relative Beta</i> sorted						
<i>2010-2015</i>	61	158	91	45	8	Yes
<i>2011-2016</i>	41	164	104	45	9	Yes
<i>2012-2017</i>	31	162	116	45	9	Yes
<i>2013-2018</i>	26	135	131	56	15	Yes
<i>2014-2019</i>	21	125	145	61	11	Yes
<i>2015-2020</i>	20	61	180	86	16	Yes
Panel D: <i>Relative Variance</i> sorted						
<i>2010-2015</i>	1	86	196	67	13	Yes
<i>2011-2016</i>	2	55	213	79	14	Yes
<i>2012-2017</i>	2	61	208	76	16	Yes
<i>2013-2018</i>	2	86	203	59	13	Yes
<i>2014-2019</i>	4	204	119	29	7	Yes
<i>2015-2020</i>	3	191	142	23	4	Yes

Figure 10: Beta-Sorted Stocks Yielding the Highest Mean Return for 5 Years on a Rolling Basis



This figure exhibits the number of stocks placed in quintiles when they are sorted according to *beta* for 5 years on a rolling basis from July 2010 to June 2020. There are 6 different subsample data sets generated, i.e., 2010-2015, 2011-2016,, 2015-2020. Unquestionably, we find that the VA holds true for all time horizons considered, since higher and promising returns are obtained from stocks belonging to the 2nd and 3rd quintiles as compared to the high beta ones in the 4th and 5th quintiles.

Figure 11: Pattern of Returns (in 100s) for all Values of Risk Measures for the 5-year period 2015-2020

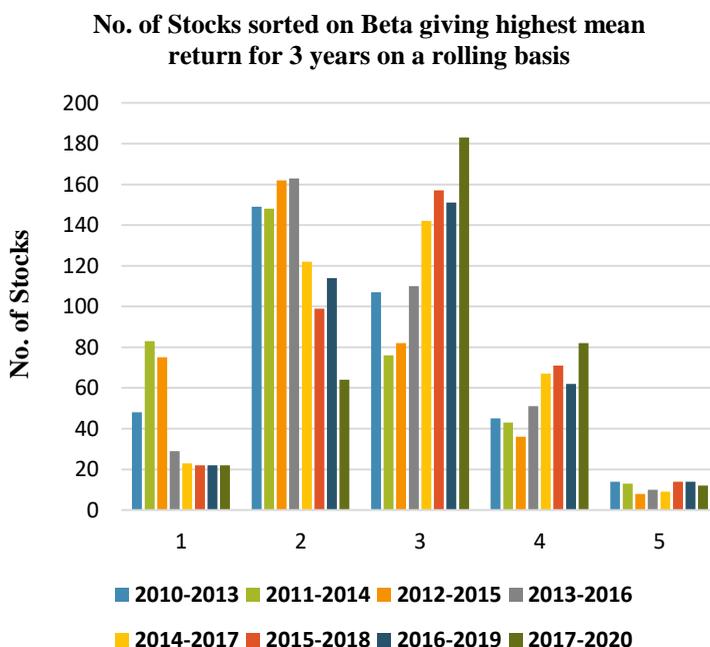


This figure exhibits the pattern of mean returns for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 5-year period, 2015-2020. The 1st, 2nd, 3rd and 4th quadrants represent the return pattern for *beta*, *relative beta*, *variance*, and *relative variance* sorted stocks, respectively. Undeniably, the VA is present for this subsample period of 5 years.

Hereafter, we cross-check our results for 3 years on a rolling basis from July 2010 to June 2020, shown in Table 3. We get 8 different subsample data sets, i.e., 2010-2013, 2011-2014,, 2017-2020. Figure 12 exhibits the distribution of stocks yielding the highest mean returns into quintiles when they are sorted on *beta*. Figure 13 depicts the mean return pattern of stocks for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 3-year period of 2017-2020. As before, we find that the highest returns are generated for stocks belonging to the 2nd and 3rd quintiles, but a noticeable aspect is that higher returns for *relative variance*-sorted stocks slowly move towards to the 4th quintile (especially during the 2013-2016 period). This leads us to

question whether VA assuredly exists for a period of 3 years. Although too early, it is reasonable to assume at this point that this anomaly might not always hold true for shorter time horizons. For other risk measures, our outcomes almost replicate the results obtained for the cases of 7 and 5 years. The 2nd and 3rd quintile stocks consistently show higher and promising returns for a majority of the risk measures. The results are depicted numerically in Table 3 and graphically in Figures 12 and 13.

Figure 12: Beta-sorted Stocks Giving Highest Mean Return for 3 Years on A Rolling Basis



This figure exhibits the number of stocks in each of the five quintiles when they are sorted on *beta* for 3 years on a rolling basis from July 2010 to June 2020. There are 8 different subsample data sets, i.e., 2010-2013, 2011-2014, 2012-2015,, 2017-2020. Assuredly, we find that the VA holds true for all time horizons considered since higher mean returns are achieved from stocks belonging to low beta quintiles (2nd and 3rd) as compared to the high beta ones (4th and 5th quintiles).

Table 3: No. of Stocks Giving Highest Mean Return Sorted on Various Risk Measures (3 years)

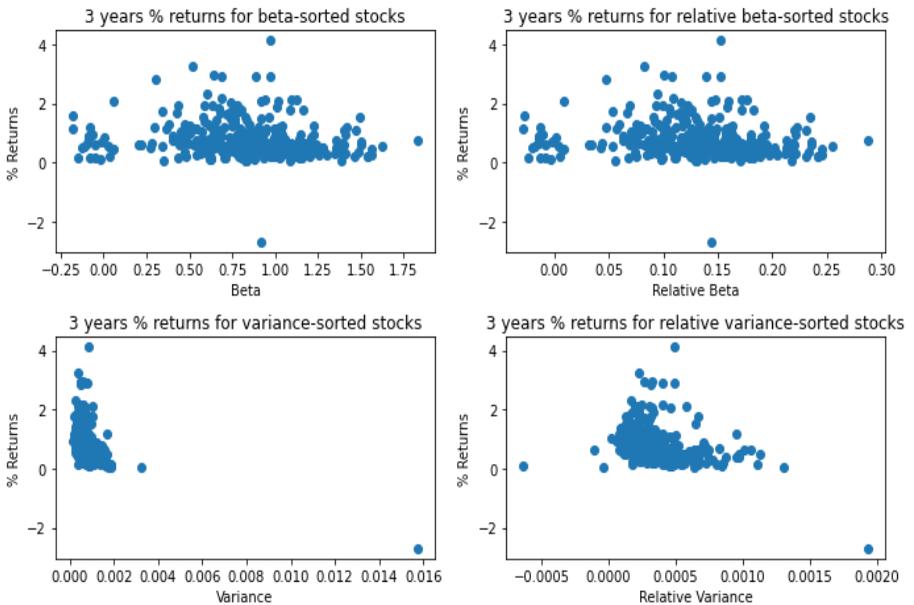
This table summarizes the results for the number of stocks providing the highest mean return when sorted on *beta*, *variance*, *relative beta*, and *relative variance* on a rolling 3-year basis. Panels A, B, C, and D respectively show the number of stocks in each quintile when they are sorted by *beta*, *variance*, *relative beta*, and *relative variance*. The VA clearly holds true here since 65-95 percent of low-risk and low-volatility stocks provide a higher mean return over a period of 3 years on a rolling basis.

Highest Mean Return						
Quintiles3-year Rolling	Low				High	
	1	2	3	4	5	Low > High
Panel A: Beta sorted						
<i>2010-2013</i>	48	149	107	45	14	Yes
<i>2011-2014</i>	83	148	76	43	13	Yes
<i>2012-2015</i>	75	162	82	36	8	Yes
<i>2013-2016</i>	29	163	110	51	10	Yes
<i>2014-2017</i>	23	122	142	67	9	Yes
<i>2015-2018</i>	22	99	157	71	14	Yes
<i>2016-2019</i>	22	114	151	62	14	Yes
<i>2017-2020</i>	22	64	183	82	12	Yes
Panel B: Variance sorted						
<i>2010-2013</i>	151	140	53	13	6	Yes
<i>2011-2014</i>	146	144	54	15	4	Yes
<i>2012-2015</i>	133	150	60	17	3	Yes
<i>2013-2016</i>	178	140	35	9	1	Yes
<i>2014-2017</i>	216	122	22	2	1	Yes
<i>2015-2018</i>	231	110	20	1	1	Yes
<i>2016-2019</i>	129	156	54	14	10	Yes
<i>2017-2020</i>	362	0	0	0	1	Yes
Panel C: Relative Beta sorted						
<i>2010-2013</i>	48	149	107	45	14	Yes
<i>2011-2014</i>	83	148	76	43	13	Yes
<i>2012-2015</i>	75	162	82	36	8	Yes
<i>2013-2016</i>	29	163	110	51	10	Yes
<i>2014-2017</i>	23	122	142	67	9	Yes
<i>2015-2018</i>	22	99	157	71	14	Yes
<i>2016-2019</i>	22	114	151	62	14	Yes
<i>2017-2020</i>	22	64	183	82	12	Yes

Panel D: *Relative Variance* sorted

<i>2010-2013</i>	123	163	56	14	7	Yes
<i>2011-2014</i>	1	0	195	145	22	Yes
<i>2012-2015</i>	1	0	229	124	9	Yes
<i>2013-2016</i>	2	1	147	182	31	No
<i>2014-2017</i>	1	3	263	86	10	Yes
<i>2015-2018</i>	1	6	280	67	9	Yes
<i>2016-2019</i>	6	255	80	17	5	Yes
<i>2017-2020</i>	1	258	94	9	1	Yes

Figure 13: Pattern of Returns (in 100s) for all Values of Risk Measures for the 3-year period 2017-2020



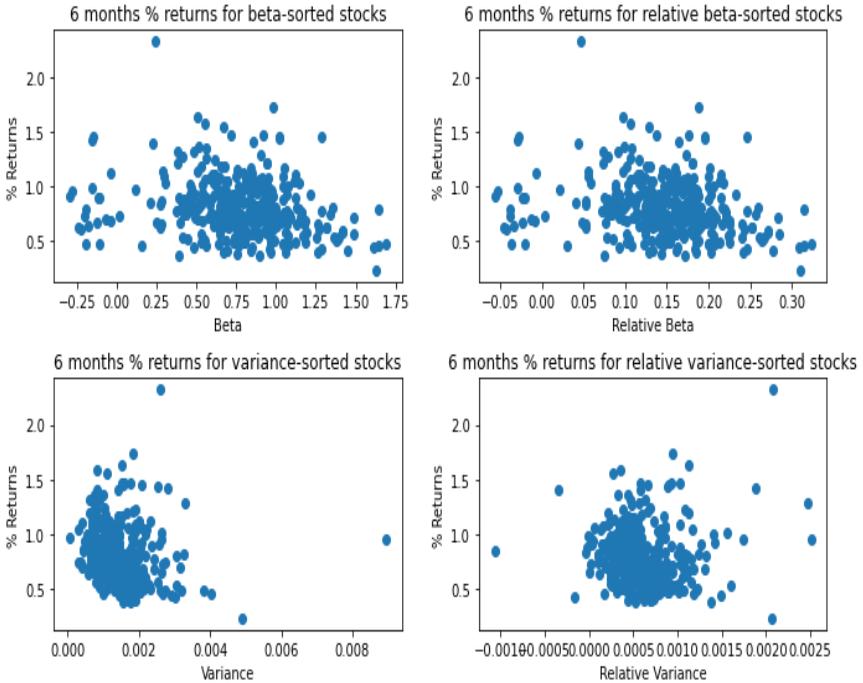
This figure presents the return pattern for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 3-year sample period, 2017-2020. The 1st, 2nd, 3rd and 4th quadrants represent the return pattern for *beta*, *relative beta*, *variance*, and *relative variance* sorted stocks, respectively. Except for *relative variance*, all other risk measures substantiate the existence of the VA for this subsample period of 3 years. For the period 2013-2016, the stocks in the 4th and 5th quintiles exhibit higher returns than the low *relative variance*-sorted quintiles.

Table 4: No. of Stocks Giving Highest Mean Return Sorted on Various Risk Measures (6 months)

This table summarizes the results for the number of stocks providing the highest mean return when sorted on *beta*, *variance*, *relative beta* and *relative variance* for a period of 6 months when the world witnessed the coronavirus pandemic. Panels A, B, C, and D respectively show the number of stocks in each quintile when they are sorted by *beta*, *variance*, *relative beta*, and *relative variance*. The VA does not exist for this subsample period of 6 months since the highest returns are found only in stocks falling under the 3rd quintile, not the 1st or even the 2nd quintile. *Variance*-sorted show the opposite picture.

Highest Mean Return						
Quintiles6-month Covid time	Low				High	
	1	2	3	4	5	Low > High
Panel A: Beta sorted						
<i>Jan-June 2020</i>	19	43	177	106	18	Yes
Panel B: Variance sorted						
<i>Jan-June 2020</i>	283	76	3	0	1	Yes
Panel C: Relative Beta sorted						
<i>Jan-June 2020</i>	19	43	177	106	18	Yes
Panel D: Relative Variance sorted						
<i>Jan-June 2020</i>	1	98	234	25	5	Yes

Figure 14: Pattern of Returns (in 100s) for all Values of Risk Measures for 6 Months Jan-June 2020



The following graph presents the return pattern for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 6-month subsample period, January-June 2020. The 1st, 2nd, 3rd and 4th quadrants represent the return pattern for *beta*, *relative beta*, *variance*, and *relative variance* sorted stocks, respectively. Except for *variance*, all other risk measures verify the non-existence of the VA for this ultra-short period. In the case of *variance*-sorted stocks, the results are contradictory.

Lastly, we aim to check whether the VA exists for a period of 6 months from January 2020 to June 2020 when the world was hit by the coronavirus pandemic. Table 4 shows the results for the same. Figure 14 graphically displays the return pattern of stocks for all values of *beta*, *variance*, *relative beta*, and *relative variance* for the 6-month Covid phase from January-June 2020. In the light of this rare event, we find that the highest expected returns have been generated only by stocks belonging to the 3rd quintile when they are sorted according to *beta*, *relative beta*,

and relative variance. This points to the fact that stocks in the 1st and 2nd quintiles did not yield high returns in this ultra-short period, as illustrated in Table 4 and Figure 14. This should not be surprising as we observed earlier that VA might not hold true for shorter time frames. Only when stocks are *variance*-sorted, we find this anomaly to prevail. This motivates us to find the reason underlying the two kinds of outcomes. One of the reasons could be that low-risk stocks can truly reward investors when they are patient since volatility is smoothed and returns are compounded over longer time periods. A factual reason is that in March 2020 the Indian stock market fell by approximately 46 percent and then recovered significantly by June. Due to such fluctuations, some low-risk stocks generated high returns in the bullish period while some low-risk stocks fell drastically in value and even went out of business. A few other reasons include the reduction in policy repo rate by 40 basis points by the Reserve Bank of India, the nationwide lockdown for almost 2 months which significantly impacted production and increased unemployment.

We also try to explore more generic reasons for the non-existence of the VA in the short run. The average investor in the global equity market probably has a horizon of three to five years or even longer (Blitz *et al.*, 2014). The differential treatment of short-term and long-term capital gains tax could be an underlying reason. Short-term capital gains are generally very high in almost all countries when compared to zero or a very low long-term capital gains tax. When investing for the long term, investors would generally prefer low-risk, stable, and fundamentally strong stocks. It is observed that compounding effects cause the long-term return spread between low-risk and high-risk stocks to widen by around 3 percent annually (Baker *et al.*, 2011). Further, Haritha and Rishad (2020) point out that positive sentiment due to irrationality could lead to higher speculative activities and thereby overvaluation of stocks. This sentiment increases the short-term volatility but reduces it in the long-run due to a bullish outlook on

overvalued stocks. All these reasons make a perfect case for the VA to be more of a long-run phenomenon than a short-run one.

CONCLUSION

This paper revisits the influence of risk and volatility on average stock returns over time. The fact that low-risk stocks generate higher expected returns is a remarkable anomaly in the field of finance. This anomaly has proved to be persistent globally over more than two decades. It contradicts the core concept of traditional finance that higher risks are generally associated with higher rewards. In this study, we have used various established risk measures to present a novel perspective on how the VA exists in the Indian stock market. After accounting for various risk measures and time horizons, we intend to show that anomalous empirical patterns do not necessarily fall in line with traditional asset pricing puzzles.

We observe that the traditional notion of “higher risks generally yield higher returns” is not always true. This has been proved in equity markets around the world such as in the USA and China. We attempt to show the existence of the low VA, i.e., whether low-risk and low-volatility stocks provide higher expected returns over a stipulated time frame, in the Indian stock market using a cross-section of companies from the NIFTY500 market index.

We first estimated the daily equity returns from the daily stock prices over a period of 10 years from July 2010 to June 2020. Thereafter, we subject these returns to the treatment of various established risk standards like *beta*, *variance*, *relative beta*, *relative variance*, *VaR*, *downside semi-variance* and *downside beta*. We divided the relevant data into quintiles (1 is the bottom quintile and 5 the top) based on the values of these risk measures. For the 10-year period, our results confirm the existence of the VA. Our results show that low-risk stocks (i.e., with low *beta*, *variance*, *relative beta*, and *relative variance*)

yield higher expected returns than the high-risk stocks. To cross-verify these findings for smaller time intervals, we have repeated this procedure for a period of 7 years, 5 years, and 3 years on a rolling basis. We observe that this anomaly undoubtedly exists for the cases of 7 and 5 years on a rolling basis. However, for the short period of 3 years and the ultra-short period of 6 months (January to June 2020) during the Covid lockdown period, this anomaly could not be confirmed. Hence, we can observe that the VA is a medium- to long-term phenomenon but not necessarily a short-term one. A satisfactory explanation is that the market typically would require 3 years or more for risk adjustment and volatility smoothening to accrue higher returns.

Emerging markets are generally known to be highly volatile in nature. Therefore, foreign investors are perpetually concerned with risk-adjusted returns especially when they are investing in emerging markets like India. This study shows that despite overall high volatility in emerging markets like India, there is an opportunity to generate high risk-adjusted returns due to the existence of the VA. The bonus from the low-risk-high-return strategies is attributable to the compounding effect – the lower volatility pressure on investment returns enhances the performance of less volatile stocks. The real benefit to possessing low-volatility stocks accrues over longer periods of time, as the well-known power of compounding suggests (Ang *et al.*, 2006). Further, our results can be useful for those investors who wish to invest in Asian countries. As most of the Asian countries are emerging economies (except a few), the existence of the VA may not be limited to only India. We can expect similar patterns across other Asian countries. Foreign (or even domestic) investors can use this anomaly to formulate low-risk-high-return strategies for investing in Asian financial markets.

This paper holds considerable potential for further development. For instance, this anomaly can be verified for equity markets in major developed, developing and emerging economies all over the world. This study can be extended by using other risk proxies such as expected

shortfall, jump risk, etc. Apart from risk and volatility measures, other factors like skewness asymmetry of stock returns, betting-against-*beta* strategy, cash flow variability, size, and quality of the firm and so on, can also be used to further explore and gain clarity on the VA phenomenon. These techniques are inspired from the works of Walkshäusl, 2013; Dutt and Humphery-Jenner, 2013; Frazzini and Pedersen, 2014; Schneider *et al.*, 2020; Atilgan *et al.*, 2020.

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