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Downside Risk-Based Six-Factor Capital Asset Pricing Model (CAPM): A New Paradigm in Asset Pricing

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Abstract: The importance of downside risk cannot be denied. In this study, we have replaced beta in the five-factor model of using downside beta and have added a momentum factor to suggest a new six-factor downside beta capital asset pricing model (CAPM). Two models are tested—a beta- and momentum-based six-factor model and a downside-beta- (proxy of downside risk) and momentum-based six-factor model. Beta and downside beta are highly correlated; therefore, portfolios are double-sorted to disentangle the correlation. Factor loadings, i.e., size, value, momentum, profitability, and investment, are constructed. The standard methodologies are applied. Data for sample stocks from different non-financial sectors listed in the Pakistan Stock Exchange (PSX) are taken from January 2000 to December 2018. The PSX-100 index and three-month T-bills are taken as proxies for market and risk-free returns. The study uses three subsamples for robustness—period of very high volatility, period of stability, and period of stability and growth with volatility. The results show that the value factor is redundant in both models. The momentum factor is rejected in the beta-based six-factor model only. The beta-based six-factor model shows very low R² in periods of highly volatility. The R² is high for the other periods. In contrast, the downside beta six-factor model captures the downside trend of the market in an effective manner with a relatively high R². The risk-return relationship is stronger for the downside beta model. These reasons lead us to believe that, overall, the downside beta six-factor model is a better option for investors as compared to the beta-based six-factor model in the area of asset pricing models.

Keywords: asset pricing model; downside risk; anomalies; Fama–Macbeth regressions

1. Introduction

Investors seek to optimize investment decisions by building efficient portfolios in a mean-variance framework [1]. They achieve efficient portfolios by using a risk-based pricing model as the first principle about the nature and preference of investment opportunities. The risk–return-based model is linear, and the expected excess returns are dependent on factor loadings. These factor loadings are sources of risk that price an asset and define the risk side of mean-variance-based portfolios mimicking these risk factors [2]. An insight into this matter leads to different pricing
models that stem mostly from general equilibrium asset pricing models. The first asset pricing model was presented by [3] and is known as the capital asset pricing model (CAPM). It is generally recognized as the most widely used model [4,5], as it is used by 73.5% of CFOs in the US and 45% of the CFOs in Europe. It marked the birth of asset pricing models and, concurrently, it opened the debate on validity and tests of the CAPM. Both theoretical and empirical discussions have led us to three viewpoints about the CAPM. There are three major perspectives identified in this area [6].

1.1. The Three Perspectives of CAPM

The first perspective was by [7,8], and completely rejects the CAPM theoretically. It observes that the true market portfolio in the CAPM is not observable; thus, the CAPM cannot be tested at all. Ross [9] advocated replacing the CAPM with Arbitrage Pricing Theory (APT). He proposed the APT model to advocate for a linear relationship between returns and macroeconomic factors that affect the asset’s risk. These factors may include stock market index.

The second perspective does not reject the CAPM altogether, but it argues that anomalies are present. This means that beta is not the only predictor in the CAPM. Rather, size, value, time effects, and momentum are additional factors to be added into the model [10]. The outcome of this perspective is witnessed in the form of the multi-factor CAPM of [11,12]. Furthermore, Fama and French [13] added investment and a profitability factor to extend the CAPM to a five-factor model.

The third perspective addresses the theoretical and statistical weaknesses, such as the proxy of risk measure and the issue of normality. Stock prices exhibit non-normality, which, in turn, advocates for the importance of higher moments in the CAPM world [14–19] extended the single-factor CAPM to a skewness-based CAPM. Harvey [20] shows that higher moments like skewness, co-skewness, and kurtosis are priced in the individual emerging markets. However, this relationship is not observed in the developed markets.

Another problem is that of the y-intercept, which does not equate to the risk-free rate. Black [21] developed a zero-beta CAPM without assuming risk-free rate. Instead, he developed a zero-beta portfolio with return and no risk attached to it. Gibbons [22] rejected the zero-beta CAPM. Merton [23] developed an inter-temporal Capital Asset Pricing Model that assumes that investors take a risky hedge position against shortfalls in consumption. In the third perspective, an important theoretical weakness of the CAPM is the proxy of risk measure.

Introducing Downside-Risk-Based CAPM

Another solution may be replacing the CAPM’s beta with downside risk based on [24] safety-first rule. This is due to the fact that investors dislike downside risk and do not give equal weight to both upside and downside. The CAPM, on the other hand, assumes that the investor is indifferent to upside and downside risk [25]. The proxy of downside risk in the asset pricing model was first developed as a semi-variance. Hogan and Warren [26] gave the first official version of a downside-risk-based CAPM (DCAPM). As a second breakthrough, Bawa [27] developed proxy for downside risk as lower partial moment (LPM) based on stochastic dominance.

Later, Fishburn [28] extended [26] LPM into an LPM with an unlimited scope of n-order. The Bawa–Fishburn LPM encompasses all classes of investors—risk-averse, risk-seeking, and risk-neutral. Additionally, it is not tied to the condition of normality and is flexible to include skewness and kurtosis. Moreover, Bawa and Lindeberg [29] extended symmetric partial moments to an asymmetric generalized co-LPM or GCLPM for n-degree LPM structures accommodating asymmetric distributions.

These methodologies use risk-free rate as a benchmark of downside risk for DCAPM. Later on, Harlow and Rao [30] used mean returns as a benchmark for defining downside risk, while [31,32] added an endogenous co-semi-variance matrix, which is constructed on all elements of the covariance matrix to deal with the endogeneity problem.
1.2. The Evidence for CAPM and DCAPM

In the area of asset pricing, the major studies comparing the CAPM and DCAPM models go back to the 2000s. The most notable among them are those of [25,31,33–36]. All of these studies prefer the DCAPM to the CAPM in a single-factor framework. The study of [33] is particularly worth mentioning. Their study tested alternative models using a new methodology as well as standard Fama and MacBeth regressions.

Furthermore, Ang et al. [34] found that some of the profitability of investing in momentum strategies can be explained as compensation for bearing high exposure to downside risk. This highlights the importance of the momentum factor. Post and Van Vliet [35] used second-order stochastic dominance and formed portfolios based on size, value, and momentum. Resultantly, the criterion reported the successful rationalization of the persistent mean-variance inefficiencies in the 1970s and the early 1980s.

1.3. The Research Gap

This study accepts the importance of the size, value, investment, and profitability factors, as [13] outlined in their recent study. However, the momentum factor, as incorporated by [11], is ignored by [13]. Furthermore, the importance of downside risk as the replacement of the risk proxy used in the CAPM cannot be ignored at all. The recent evidence in favor of the DCAPM and its variant models, adding to its intuitive and flexible theoretical modeling, advocates that investors set the DCAPM as a base model. This means replacing the CAPM’s beta with downside beta as a proxy of risk.

The theoretical appeal rests in the premise that investors dislike downside risk and do not give equal weight to both upside and downside risk, as assumed in the CAPM. Moreover, the DCAPM is flexible to incorporate the different thresholds the investors seek for downside risk protection, while the CAPM treats all of them similarly. The CAPM and its variants are applicable only to risk-averse investors, while the DCAPM and its variants cater to all types of investors, i.e., risk-averse, risk-seeking, and risk-neutral [25]. Lastly, the DCAPM can accommodate all factors, like size, value, momentum, investment, and profitability, and can be tested and validated with a multi-factor CAPM for the same factors mentioned.

This makes this study first of its kind, as it compares the two alternative six-factor models—CAPM and DCAPM—using size, value, momentum, investment, and profitability factors to test them for the first time. However, the CAPM beta and DCAPM downside beta have high correlation among them, and their effects have to be disentangled. Therefore, this study uses a double sorting procedure to address this issue, which makes this study more robust. Consequently, the study may suggest a suitable asset pricing model for investors in evaluating portfolios or individual stock compared to the rest of the market. Furthermore, investors can reevaluate how their portfolios are constructed and can evaluate the reasonableness of future expectations. In this way, in holding unnecessary cash, investors, especially fund managers, may feel less obligation towards more productive investment decisions.

The paper has four sections; Section 1 is the introduction and literature review, Section 2 covers the data and methodology, Section 3 shows the results and discussion, and Section 4 is the conclusion.

2. Data and Methodology

The sample of this study is the Pakistan Stock Exchange (PSX), which was established in 11 January, 2016 by merging three stock exchanges—the Karachi Stock Exchange (KSE), the Lahore Stock Exchange (LSE), and the Islamabad Stock Exchange (ISE). Financial Times Stock Exchange (FTSE) classifies the PSX as a Secondary Emerging Market. Morgan Stanley classified the PSX as Morgan Stanley Capital International (MSCI)Emerging Market in May 2017. In 2002, the KSE was declared the “Best Performing Stock Market of the World”, and, again, the PSX was among the world’s best performing stock markets between 2009 and 2016. The Pakistan Stock Exchange (PSX) was ranked the fifth best performing market in the world in 2016. However, it regressed to the worst
performing stock market with a fall of 28% from its peak in May 2017 till December 2017. Recovering from its December 2017 position, in 2018, the stock market showed mixed trends.

After the promulgation of the Stock Exchanges (Corporatization, Demutualization, and Integration) Act 2012, the three stock exchanges were successfully corporatized and demutualized on August 27, 2012. In December 2016, the PSX sold 40% strategic shares to a Chinese consortium for 85 million USD. A total of 558 companies were listed on the PSX in 2018. Foreign institutional investors and domestic institutional investors stand at 1886 and 883, respectively.

The data are built on monthly closing prices of listed stocks on the Pakistan Stock Exchange (PSX). The sample consists of 218 companies. The closing prices of stocks of non-financial sectors from the period January 2000 to December 2018 were taken in this study following [12,13]. This is attributed to the fact that financial sector reporting standards are different from those of the non-financial sectors. The sources of data are DataStream, the State Bank of Pakistan, and annual statements of companies.

2.1. Factor Construction

This study follows the methodologies of [13] for calculating the various factors, which are size, value, profitability, and investment. The PSX-100 index returns are taken as a market portfolio proxy. The market capitalization of companies is taken as a proxy for the size factor. The proxy for value stocks is the book equity to market equity ratio (BE/ME), which is calculated from the annual statements of the sample companies. The momentum factor is calculated using the average of the last twelve months’ returns. Operating profit is used to calculate the profitability factor. The investment factor is taken as the change in total assets.

The sample is sorted according to the size proxy from small (S) to big stocks (B) and then split into two equal halves. Each half is again sorted according to the respective factor loading, like BE/ME ratio, and then again broken down into 15%, 70%, and 15% break points as high (H), medium (M), and low (L) stocks, respectively. The size factor is defined as the SMB:

$$SMB = \frac{[(SH + SM + SL)] - (BH + BM + BL)]}{3}$$

where SH indicates stocks with small size and high BE/ME, SM indicates stocks with small size and medium BE/ME, and SL indicates stocks with small size and low BE/ME. The BH, BM, and BL follow the big stocks and value combinations.

The value factor is defined as the HML:

$$HML = \frac{[(SH + SL)] - (BH + BL)]}{2}$$

The momentum factor is defined as the WML:

$$WML = \frac{[(SW + SL)] - (BW + BL)]}{2}$$

where SW is small-sized and winner stocks, SL is small-sized and loser stocks, BW is big-sized and winner stocks, and BL is big-sized and loser stocks.

The profitability factor is defined as RMW:

$$RMW = \frac{[(SR + SW)] - (BR + BW)]}{2}$$

where SR is small-sized and robust stocks, SW is small-sized and weak stocks, BR is big-sized and robust stocks, and BW is big-sized and weak stocks.

The investment factor is defined as CMA:

$$CMA = \frac{[(SC + SA)] - (BC + BA)]}{2}$$

where SC is small-sized and conservative stocks, SA is small-sized and aggressive stocks, BC is big-sized and conservative stocks, and BA is big-sized and aggressive stocks.
2.2. Double-Sorted Portfolios

The purpose of double sorting the dependent variables is to remove the effect of high correlation between the beta and downside beta following the methodology of [33]. First, the study estimates beta and downside beta for every respective stock available using 48 months of data following [2]. The sample is split into equal high-beta (H) and low-beta stocks (L), which are again sorted into two sub-samples based on downside beta and beta. The second split follows the former procedure from high (H) downside beta to low (L) downside beta. Twelve-month rolling regression is applied, and the sample is treated in the same manner for each rolling regression.

Therefore, this sorting procedure yields four types of portfolios: High beta and high downside beta (HH), high beta and low downside beta (HL), low beta and high downside beta (LH), and low beta and low downside beta (LL) portfolios [25,33]. All portfolios are equally weighted portfolios. This approach has three major advantages. First, the criterion for sorting is outlined as a high-or low-risk measure. Second, it disentangles correlation between beta and downside beta. Last, it helps in assessing the risk–return relationship between HH and LL portfolios, as outlined by [33]. This is achieved by assessing the difference between the results of HH and LL for portfolio returns and the risk measure. The differences of HH and LL returns and HH and LL risk measures are studied for the risk–return relationship. In this case, it should be positive.

2.3. Addressing Econometric Issues

Responding to Roll [7] criticism of the unobservability of a true market portfolio, this study, following [37]), uses the KSE-100 index returns as the proxy of the market portfolio. The issue of measurement error is resolved by following the procedure of [38,39] of factor formation based on pre- and post-formation factor loadings and realized factor loadings.

The issue of selection bias is addressed by constructing portfolios including the listed companies in the specific time period and then rolling forward using a rolling window of 12 months. Initially, the portfolios were constructed using 48 months of data, and then the data were rolled forward by 12 months; again, the portfolios were constructed for the sample in that given period and then rolled forward by 12 months till the end of period. The beta/downside beta of the previous year was used as the instrumental variable. To address the problem of heteroscedasticity and the autocorrelation problem, this study used the Newey–West estimators adjusted for ordinary least squares (OLS), which correct for both heteroscedasticity and autocorrelation [40].

2.4. Fama and MacBeth Regressions

The study adopts the standard [38] method to test the alternative models. It is a two-pass method. The first pass process is based on the methodology of [39], in which parameters are estimated using time-series data:

\[ R_{pt} - R_{ft} = \alpha + \beta_{pt}(R_{mt} - R_{ft}) + \beta_{SMB}(R_{SMB}) + \beta_{HML}(R_{HML}) + \beta_{WML}(R_{WML}) + \beta_{CMA}(R_{CMA}) \] (1)

where (1) represents the six-factor CAPM:

\[ R_{pt} - R_{ft} = \alpha + D\beta_{pt}(R_{mt} - R_{ft}) + \beta_{SMB}(R_{SMB}) + \beta_{HML}(R_{HML}) + \beta_{WML}(R_{WML}) + \beta_{CMA}(R_{CMA}) \] (2)

where (2) represents the six-factor DCAPM, where D\( \beta \) is the downside beta.

The second pass is a cross-sectional analysis where the parameters in Equations (1) and (2) are treated as variables:

\[ R_{pt+1} = \lambda + \lambda_{pt}(\beta_{pt}) + \lambda_{SMB}(\beta_{SMB}) + \lambda_{HML}(\beta_{HML}) + \lambda_{WML}(\beta_{WML}) + \lambda_{RMW}(\beta_{RMW}) + \lambda_{CMA}(\beta_{CMA}) \] (3)

where (3) represents cross-sectional analysis of the six-factor CAPM:
\[ R_{p,t+1} = \lambda + \lambda_p(D\beta_{pt}) + \lambda_{SMB}(\beta_{SMB}) + \lambda_{HML}(\beta_{HML}) + \lambda_{WM}(\beta_{WM}) + \lambda_{RMW}(\beta_{RMW}) + \lambda_{CMA}(\beta_{CMA}) \]  

(4)

where (4) represents cross-sectional analysis of the six-factor DCAPM.

The [4] coefficient statistics for specific lambdas are:

\[ \bar{\lambda}_j = \frac{1}{T} \sum_{t=1}^{T} \tilde{\lambda}_{jt} \]  

(5)

and

\[ \sigma(\bar{\lambda}_j) = \sqrt{\frac{1}{T(T-1)} \sum_{t=1}^{T} (\tilde{\lambda}_{jt} - \bar{\lambda}_j)^2} \]  

(6)

and then they form the t-stat as:

\[ t(\bar{\lambda}_j) = \frac{\bar{\lambda}_j}{\sigma(\bar{\lambda}_j)} \]  

(7)

The t-stat is calculated using (7), and it is consequently tested whether \( \lambda j > 0 \); the risk–return relationship with restriction is tested for the one-tail test.

3. Results and Discussions

The results are reported for the alternative six-factor CAPM and six-factor DCAPM in Panels A and Bin each table in appendix A, respectively, for different time periods. Each panel contains eleven columns. Column 1 is the sample period, column 2 is the portfolio types HH, HL, LH, and LL, and column 3 is the returns for each portfolio type. Column 4 in each panel reports the results of \( \beta \) and \( D\beta \), and the next five columns account for the five factors: Size, value, momentum, profitability, and investment. The last two columns report the \( R^2 \) and adjusted \( R^2 \) of each model for each portfolio type. The rows show the parameter values of each variable with the methodology of [38] with the t-stat in brackets. The test is a one-tail test that signifies the relationship of each factor with returns as more than zero. The last rows in each panel report the difference between portfolios with high (HH) and low (LL) return/factor loadings as a test for the risk–return relationship. There are four tables in total, showing results for four different time periods. Table A1 shows the result for the time period of 2004 to 2018. Tables A2–A4 show results for the time periods of 2004–2008, 2009–2012 and 2013–2018, respectively.

The first breakup of the sample period of 2004–2008 is based on the crashes of the PSX (then KSE) in 2005 and the end of 2008 to assess the alternative models in highly volatile conditions. This period also marks high political instability. The period highlights the transfer of power from military to civilian democratic government. The second sample, 2009–2012, is the period where there was a lot of talk about reforms for the stock market, which eventually led to the promulgation of the Stock Exchanges (Corporatization, Demutualization, and Integration) Act 2012. Resultantly, the stock exchanges were corporatized and demutualized on 27 August 2012. The last period of 2013 to 2018 marks two general elections in this period, with a boom of the economy in the shape of the large Chinese investment in the form of the China–Pakistan Economic Corridor (CPEC). Figure 1 gives a guide to the performance of the Pakistan Stock Exchange from 2000 to 2018.
3.1. Regression Results of $\beta$ and $D\beta$ Six-Factor Model for the Period 2004–2018

In Appendix A, Table A1 shows the results for the whole sample, i.e., from 2000 to 2018. The reason that the results start from 2004 instead of 2000 is because the study uses 48 months’ data, which are then rolled forward by 12 months. In Panel A, the differences between the returns and beta of HH and LL are 5.77 and 1.62, respectively. For HH portfolios, SMB and HML are rejected at the 5% and 1% significance levels, while the other factor signifies the acceptance of the null hypothesis. The differences of HML and CMA factors for HH and LL portfolios yield a negative relationship with portfolio returns. The $R^2$ and adjusted $R^2$ for HH and LL are high, but the model falls short for HL and LH portfolios to a minimum value of 36.4% for adjusted $R^2$ for LH portfolios. This shows that the six-factor CAPM holds for high-risk and low-risk portfolios, but offers no solution for the mid-beta portfolios.

Similarly, in Panel B, the differences between the returns and downside beta of HH and LL are 5.77 and 1.75, respectively. The results highlight the relationship between risk and return as positive, which is the generally accepted principle. Only two factors, SMB for HL portfolios and WML for LH portfolios, are rejected at the 10% significance level, while the rest of the factors contribute to the model. However, the 10% significance level is generally accepted, thus indicating that the null hypothesis is not rejected in these factors. Overall, $R^2$ and adjusted $R^2$ are high for all portfolio types compared to the six-factor CAPM, especially for HL and LH portfolios, as the values are above 60%.

The results for beta and downside beta with returns are similar to those of [13,33]. The SMB and HML results for six-factor CAPM advocate redundancy for HH portfolios; this result for HML is similar to those of the [13]. However, adding the momentum factor makes the SMB factor less important. The CMA has the same relationship in both panels and validates the [13]. The results of the six-factor DCAPM highlight the importance of all the factors, which was initially reported by the studies of [10–12]. The six-factor DCPAM advocates the incorporation of size, value, and momentum anomalies along with profitability and investment factors coming from the dividend discount model. Overall, the six-factor DCAPM is a better model compared to the six-factor CAPM in terms of $R^2$ and adjusted $R^2$.

3.2. Regression Results of $\beta$ and $D\beta$ Six-Factor Model for the Period 2004–2008

The results for the sub-sample of 2004–2008 are reported in Table A2 of Appendix A. This period represents high volatility due to the political and financial instability, with market crashes in 2005 and 2008. The latter is considered a major crash where the trading was suspended for four months. Moreover, the political volatility was at its height, as the country was in a transitional period from a dictatorship to a democratic setup. Panel A provides results for the six-factor CAPM and Panel B provides results for the six-factor DCAPM for the time period 2004–2008. The null hypothesis is rejected at the 5% level of significance at many points in Panel A.
It is reported that HH portfolios have the highest rejection of factors: Beta, HML, and CMA at the 5% level. HL has two rejections for beta and WML, and LH has HML, but at 10% significant level. LL portfolios reject the WML factor at the 5% level. The R² and adjusted R² are very low in this period, which is marked by high volatility. The six-factor CAPM performs relatively poorly as compared to the total sample in Table A1, indicating that the model is primarily limited to stable conditions.

In Panel B, only HML for HL and CMA for LH portfolios are rejected at the 5% significance level. The R² and adjusted R² are relatively low as compared to the 2004–2018 period; however, in contrast to the six-factor CAPM, the six-factor DCAPM has a much better R² and adjusted R² with no value less than 60%. This is an impressive figure considering the market conditions of Pakistan. Thus, these results show that even in the time of turbulence, the six-factor DCAPM is more workable than the six-factor CAPM. This also backs up our argument that investors do not give equal weight to upside and downside beta, as this difference is most pronounced in highly volatile conditions, as stated by Table A2 [25].

3.3. Regression Results of β and DβSix-Factor Model for the Period 2009–2012

In Appendix A, Table A3 also has Panel A for the six-factor CAPM and Panel B for the six-factor DCAPM, but for the period after the crash, i.e., 2009–2012. The year 2012 includes the economic reforms of the KSE. Economic reforms moved the market towards stabilization, and these positive changes are also reflected in the results. As can be seen in Panels A and B, in 2009 to 2012, R² improved as compared to R² for all portfolios from 2004 to 2008. Again, our results show that the DCAPM holds better than the CAPM, as in Panel A, HML is rejected for both HH and LL portfolios and WML is rejected for LL portfolios at the 5% significance level.

However, in Panel B, the null hypothesis is accepted for all factors of all portfolios. This is further defended, as the R² values for all portfolios in Panel B have improved values compared to those in Panel A. In addition, the rejection of the momentum and value effects reinforces the analysis given by [13], that when investment and profitability are added to the model, the effects of value and momentum factors are reduced. The difference between the coefficients of risk and return in both panels is positively correlated with a stronger positive correlation in the DCAPM.

3.4. Regression Results of β and DβSix-Factor Model for the Period 2012–2018

The results for the time of 2013–2018 are reported in Table A4 of Appendix A. This period encompasses four major events: The Stock Exchanges (Corporatization, Demutualization, and Integration) Act 2012, the general elections in 2013, the very large Chinese investment, including 40% strategic shares purchased for 85 million USD by a Chinese consortium, and, again, the general elections in 2018. The period’s beginning and ending are marked by volatile conditions in Pakistan due to the general elections. During this period, relative stability and growth were witnessed in the PSX.

In Panel A, HML and WML are again rejected for HH portfolios at the 5% significance level. As compared to this, Panel B does not follow the pattern, and no factor is rejected at the 5% significant level, thus signifying that the DCAPM again held better than the CAPM. This justification is further fortified, as the value of R² is more for the DCAPM than for the CAPM. However, it is observed that the R² is high despite the two general elections, which made the market very volatile. This can be attributed to the fact that the PSX was formed in this period by merging one national stock exchange, i.e., Karachi Stock Exchange, and two regional stock exchanges, i.e., those of Lahore and Islamabad, into one major stock exchange for Pakistan. Resultantly, the stock market is broader now.

If we sum up our results, the six-factor downside CAPM performs better than the six-factor CAPM. It is endorsed by the –return relationship, which is more pronounced in the six-factor DCAPM setup than in its counterpart. In the events of the market crashes in 2005 and 2008, the six-factor CAPM failed to hold, while the six-factor DCAPM performed relatively better with the value of R² in an acceptable range. This is due to the fact that when there is turmoil, market returns tend to fall below the expected level, which increases the downside risk. In such cases, investors need a model that can capture this phenomenon more accurately. The six-factor DCAPM is a suitable model
especially in these circumstances where the market shows high volatility, thus rendering the investors to care for the safety-first concept.

In most of the results, the HML factor was rejected at the 5% level of significance, which shows that it does not contribute enough towards the model. This argument is in line with [13]. Likewise, Zaremba and Konieczka [41] reported that the value factor performs poorly on the Polish market. Barillas and Shanken [42] compared different asset pricing models, and they reported that the model containing the value factor performs the best. The differences in results might be attributed to the differences in proxies used for the value factor. Asness et al. [43] tested a modified version of HML, and argue that HML remains a highly significant factor that is not explained by other factors.

Similarly, WML is also not a significant factor in many portfolios.

This may be the reason that this result reinforces the point given by [7] and backs up the study by Fama and French, who then did not include WML in their analysis.

Overall, we can safely say that the six-factor DCAPM is better than the six-factor CAPM in terms of both R\(^2\) and risk–return relationship. As far as the inclusion of the HML factor is concerned, while using multivariate regression, overall analysis is taken. Therefore, even if some factors are redundant, but the R\(^2\) is up, as it is in our case, we include them. The results for the base factor, i.e., replacing beta with downside beta, are consistent with those of [3,31,35,40].

4. Conclusions

In this study, the CAPM’s beta was replaced with downside beta in the [13] five-factor model and extended to a six-factor model by adding the momentum factor. The motivation for downside beta comes from the study of [33], while the factor loadings are based on studies by [11–13]. This yielded two new asset pricing models: Beta- and downside-beta-based six-factor models. The models were tested on the volatile market of Pakistan.

As beta and downside beta are highly correlated, this study follows the methodology of [33]. Double-sorted portfolios were constructed: HH (high beta and high downside beta), HL (high beta and low downside beta), LH (low beta and high downside beta), and LL (low beta and low downside beta). The factor loadings—size, value, momentum, profitability, and investment—were constructed using the methodologies of [11,13]. The models were tested on the Pakistan Stock Exchange. The sample period was from January 2000 to December 2018, and was broken down into three major subsamples to measure the effects of different market conditions on the alternative models. Standard [38] regressions were estimated, and the results are stated along with R\(^2\) and adjusted R\(^2\). We are interested in beta and downside beta of greater than zero. The t-stat was one-tailed, based on the [38] methodology, and was set at the 5% significance level.

The results show that the HML factor is rejected in total and in the sub-sample periods for both the beta- and downside-beta-based six-factor models. The SMB, CMA, and beta factors were also rejected only once in the sub-sample. The rejection of WML in beta-based six-factor model was greater compared to other factors while it was less than the HML factor. Furthermore, it was witnessed that beta was also rejected in one sub-sample. In contrast, the factor remained valid for the DCAPM six-factor extension. The R\(^2\) was very low for the beta model in the highly volatile period; however, the downside beta model captured the downside trend in a more effective manner. For the total sample and sub-sample periods, the R\(^2\) of the downside-beta-based six-factor model was higher than its counterpart. The results were very pronounced for HH and LL portfolios. The risk–return relationship is reported as the difference of returns and risk measures; for the HH and LL portfolios. This difference was stronger in the downside risk six-factor model as compared to beta-based model. The HML results for the beta model were consistent with the [13] study, while the base factor, i.e., replacing beta with downside beta, was consistent with [3,31,33,40].

The downside-beta-based six-factor model can be used in investment decisions for operators in the stock exchange. Companies’ strategies and policies are integrated with the PSI in the form of factor loadings of size, profitability, and, particularly, investment. In other words, corporate governance laws should be fully implemented; otherwise, the valuation of an asset will suffer. If this happens, then the investor will move from efficient to inefficient decision-making. Furthermore, the
models in this study are static in nature; if the model is taken as dynamic (inter-temporal), then it might be an even better option in the downside risk framework. Other suitable factors can also be dissected based on the dividend discount model.

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## Appendix A

### Table A1. Results for Fama-MacBeth Regression based on Beta and Downside Beta Multi-Factor Models from 2004 to 2018.

| Portfolio | Returns (%) | β | SMB | HML | WML | RMW | CMA | R² | AdjR² |
|-----------|-------------|----|-----|-----|-----|-----|-----|-----|-------|
| HH        | 14.22       | 1.33 | 0.17** | 0.08*** | 0.77 | 0.55 | 1.06 | (0.565) | (-1.996) | (-2.917) | (0.497) | (0.671) | (0.145) | 0.740 | 0.686 |
| HL        | 11.13       | 0.99 | 0.51 | 1.28 | 0.37 | 0.42 | 0.82 | (0.936) | (0.997) | (0.323) | (-1.144) | (0.234) | (0.384) | 0.522 | 0.423 |
| LH        | 9.08        | -0.09 | 0.8 | 0.95 | 0.24 | 0.67 | 0.71 | (0.353) | (-1.204) | (-1.011) | (-1.429) | (-1.369) | (-1.480) | 0.474 | 0.364 |
| LL        | 8.45        | -0.29 | 0.13 | 0.75 | 0.43 | 0.51 | 1.98 | (0.693) | (0.241) | (0.521) | (-1.234) | (0.777) | (0.141) | 0.759 | 0.709 |

### Panel B

| Portfolio | Returns (%) | Dβ | SMB | HML | WML | RMW | CMA | R² | AdjR² |
|-----------|-------------|----|-----|-----|-----|-----|-----|-----|-------|
| HH        | 14.22       | 1.8 | 0.22 | 1.52 | 0.57 | 0.6 | 1.02 | (0.318) | (0.803) | (0.477) | (0.654) | (-0.553) | (0.115) | 0.8172 | 0.7791 |
| HL        | 11.13       | 0.23 | 0.45* | 1.32 | 0.34 | 0.43 | 0.94 | (0.687) | (-1.670) | (0.070) | (0.340) | (0.534) | (0.047) | 0.6262 | 0.5483 |
| LH        | 9.08        | -1.62 | 1.11 | 0.94 | 0.21* | 0.69 | 0.62 | (0.115) | (-1.112) | (0.182) | (-1.661) | (0.288) | (0.544) | 0.6396 | 0.5645 |
| LL        | 8.45        | 0.05 | 0.13 | 0.76 | 0.45 | 0.51 | 1.17 | (0.608) | (-1.114) | (0.660) | (-0.783) | (0.830) | (-0.043) | 0.7907 | 0.7471 |

**High–Low** | 5.77 | 1.75 | 0.09 | 0.76 | 0.12 | 0.09 | -0.15 | ***shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.**
Table A2. Results for Fama-MacBeth Regression based on Beta and Downside Beta Multi-Factor Models from 2004 to 2008.

| Panel A | Portfolio | Returns (%) | β    | SMB | HML | WML | RMW | CMA | R² | AdjR² |
|---------|-----------|-------------|------|-----|-----|-----|-----|-----|----|-------|
|         | HH        | 15.83       | 2.33** | 1.04 | 0.31** | 0.37 | 0.35 | 0.74** |   |       |
| 2004–2008 | HL       | 11.43       | 1.3* | 1.09 | 0.56 | 1.41* | 0.59 | 0.22 |   |       |
|         | LH        | 6.97        | 1.27 | 0.68 | 0.53* | 1.81 | 0.71 | 0.46 |   |       |
|         | LL        | 5.312       | 1.21 | 0.73 | 0.75 | 0.53** | 0.6 | 0.72 |   |       |
|         | High–Low  | 10.518      | 1.12 | 0.31 | −0.44 | −0.16 | −0.25 | 0.02 |   |       |

**Table A3. Results for Fama-MacBeth Regression based on Beta and Downside Beta Multi-Factor Models from 2009 to 2012.**

| Panel A | Portfolio | Returns (%) | β    | SMB | HML | WML | RMW | CMA | R² | AdjR² |
|---------|-----------|-------------|------|-----|-----|-----|-----|-----|----|-------|
| 2009–2012 | HH        | 7.71        | 1.1  | 0.22* | 0.17** | 0.47 | 0.33 | 0.59 |   |       |
|         | HL        | 7.33        | 0.37 | 0.7 | 1.32 | −0.39 | −0.34 | −0.44 |   |       |

***shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.
### Panel B

| Portfolio | Returns (%) | DJβ | SMB | HML | WML | RMW | CMA | R² | AdjR² |
|-----------|-------------|-----|-----|-----|-----|-----|-----|-----|-------|
| 2009–2012 |             |     |     |     |     |     |     |     |       |
| HH        | 7.71        | 1.6 | 0.34| 1.56*| 0.17| 0.3 | 0.69|     |       |
|           |             | (0.053) | (1.454) | (−1.613) | (0.16) | (0.490) | (0.438) | 0.838 | 0.8043 |
| HL        | 7.33        | 0.39 | 0.7 | 1.36*| −1.4***| −0.37| −9.64|     |       |
|           |             | (0.705) | (0.51) | (−1.751) | (3.08) | (−1.230) | (−0.537) | 0.8114 | 0.7721 |
| LH        | 3.64        | −1.3 | 0.97| 1.63*| 0.38| −0.15| 0.15|     |       |
|           |             | (−0.363) | (0.09) | (−1.761) | (0.62) | (−1.424) | (0.225) | 0.7263 | 0.6693 |
| LL        | 2.082       | −1.33 | 0.5 | 0.57 | 1.01 | 0.41 | 0.57|     |       |
|           |             | (0.429) | (1.03) | (0.852) | (0.16) | (0.648) | (0.845) | 0.6861 | 0.6207 |
| High–Low  | 5.628       | 2.93 | 0.04| 0.99| −0.84| −0.11| 0.12|     |       |

***shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.
Table A4. Results for Fama-MacBeth Regression based on Beta and Downside Beta Multi-Factor Models from 2013 to 2018.

| Portfolio | Returns (%) | β  | SMB    | HML    | WML    | RMW    | CMA    | R²     | AdjR² |
|-----------|-------------|----|--------|--------|--------|--------|--------|--------|-------|
| **HH**    | 6.61        | 2.501 | 1.96   | 0.13** | 0.44** | 0.28   | 0.17   | 0.787  | 0.743 |
| **HL**    | 6.155       | 1.58  | 0.69   | 0.25   | 0.63   | 0.57   | 0.39   | (0.731) | (0.578) |
| **LH**    | 5.09        | 3.02  | 0.34   | 0.67   | 0.64   | 0.45   | 0.69   | (1.962) | (0.832) |
| **LL**    | 5.322       | 1.56  | 0.84   | 0.26*  | 1.03   | 0.9    | 0.59   | (0.520) | (0.330) |
| **High–Low** | 1.288 | 0.9412 | 1.12   | -0.13  | -0.59  | -0.62  | -0.42  | 0.794  | 0.751 |

| **Panel B** | **Portfolio** | **Returns (%)** | DJβ | SMB    | HML    | WML    | RMW    | CMA    | R²     | AdjR² |
|-------------|---------------|----------------|-----|--------|--------|--------|--------|--------|--------|-------|
| **HH**      | 6.61          | 1.8041         | 0.93 | 1.42*  | 0.46   | 0.3    | 0.25   | (0.459) | (0.062) |
| **HL**      | 6.155         | 1.4991         | 0.66 | 0.3    | 0.39   | 0.58   | 0.38   | (1.311) | (0.007) |
| **LH**      | 5.09          | 1.3571         | 0.37*| 0.71   | 0.67   | 0.51   | 0.75   | (0.074) | (0.069) |
| **LL**      | 5.322         | 0.523          | 0.83 | 0.26   | 1.03   | 0.9    | 0.59   | (1.367) | (0.934) |
| **High–Low** | 1.288     | 1.2811         | 0.1  | 1.16   | -0.57  | -0.6   | -0.34  | 0.8265 | 0.7904 |

***shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%. 

2013–2018
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