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Expected Shortfall and Value at Risk as Alternative of Market Beta to Explain Cross-Sectional Stock Returns

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ABSTRACT

The objective of this study is to risk-return model with Value at Risk (VaR) and Expected Shortfall (ES) as the systematic risk factors. Notably, it is tested whether VaR and ES can be used as an alternative to market beta in the traditional Capital Asset Pricing Model (CAPM), a three and five-factor model. Data is collected for non-financial companies listed on the Pakistani Stock Exchange. VaR and ES are calculated at two levels of significance, i.e., 95% and 99%. Results showed that the traditional market beta of CAPM, three and five-factor model is not following the risk-averse behaviour of investors. Conversely, VaR and ES showed a positive relationship with stock returns supporting the 'high-risk, high return' theory. Furthermore, investment, profitability and size factors become redundant with VaR and ES as systematic risk factors. Therefore, it is recommended that VaR and ES may be used the alternative to market beta to predict the cross sections of stock excess returns.

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Introduction

Over the last few decades, there is a substantial increase in the financial models concerning asset pricing theory. These models are developed to predict risk-return in relation to making efficient investment decisions. CAPM was the seminal work by Lintner (1965) and Sharpe (1964) that identified market exposure as a primary systematic risk factor in predicting cross-sectional stock returns. CAPM argued that the co-movement (beta) between stock and market returns could explain differences in cross-sectional stock returns. However, various studies documented that the CAPM beta does not present such cross-sectional differences (Chiah et al., 2016). Furthermore, CAPM assumes a positive relationship between the stock return and market returns. However, the literature showed mixed results for this relation. For instance, Benz (1981) found the negative risk and return relationship with the increase in firm size.

Such irregularities in CAPM evolved the literature of multifactor models of asset pricing. Multifactor models argue that the irregularities in CAPM are due to risk factors that cannot be diversified. Investors require compensation in the presence/absence of such factors. Therefore, such anomalies are needed to control using an appropriate variable in single-factor CAPM. For instance, Benz (1981) found that the irregularity of CAPM can be controlled by using firm size. Similarly, Basu (1983) found that the price-earning ratio and market beta better predict the stock returns than the CAPM model. Fama and French's (1993) three-factor model is among the most cited multifactor models that used both size and value factors to control CAPM anomalies. Several studies have shown that the three-factor model outperformed single-factor CAPM (Fama & French, 1998; Griffin, 2002; Javid & Ahmad, 2011; Peter et al., 2017).

The five-factor model of Fama and French (2015) is another popular enhancement of the three-factor model. Fama and French (2015) added investment and profitability factors. They included these two factors due to empirical results showing a strong association of profits and investment with stock returns. Chiah et al. (2016) demonstrate the superior performance of the five-factor model. Following the multifactor theory, this research also postulates that irregularities are associated with single-factor CAPM due to the inability of market exposure to control idiosyncratic risks that are not minimised by a well-diversified portfolio. This research argues that it is inappropriate to use market exposure as a proxy for systematic risk. Instead, these are the tails of distribution that can better control systematic and idiosyncratic risks in explaining the differences in cross-sectional stock returns (Khan et al., 2021).

VaR and ES represent the risk base in the tail distribution of asset returns. VaR is defined as the security's or asset's worst expected loss for a certain time horizon at a certain level of significance (Naqvi et al., 2019). Based on the left tail of the asset return distribution, VaR provides the risk of asset or portfolio of assets with maximum loss prediction (Lin et al., 2010). Contrarily, Expected Shortfall (ES) estimates the worst expected loss average at a specified confidence interval.

We argued that both VaR and ES could be an alternative to market beta and other risk factors in explaining the stock returns. Like CAPM beta, which calculates the systematic risk based on whole distribution, VaR and ES, following the extreme value theory (EVT), conduct systematic risk, but it checks the data's left tail behaviour. Schedule et al. (2016) explained that ES and VaR provide superior risk estimation and are less prone to model misspecifications. Therefore, VaR and ES-based models can provide superior explanations to cross sections of stock returns. The research's primary objective is to compare the VaR and ES-based models with traditional single, three and five-factor models.

We first compared the original CAPM, three and five-factor models in explaining the differences in cross-sectional stock returns. Then we modified the CAPM, three-factor, and five-factor model by replacing market beta with VaR and ES. We compared the VaR and ES-based models with traditional models to find the best-fitted model. It also tested whether four firm-specific factors used in the five-factor model become redundant in VaR and ES-based models. We tested these comparisons for the data from Pakistan Stock Exchange. Though most previous studies compared the five-factor and three-factor models with CAPM, few studies investigated the role of VaR and ES in this respect.

Particularly, comparing the VaR and ES-based models with different significance levels while controlling idiosyncratic risk factors provided in the five-factor model is a theoretical research gap. Moreover, to the best of the author's knowledge, no study has yet investigated the ES-based model in Pakistan. Nasir et al. (2021) worked on a similar objective of comparing VaR and ES with CAPM beta in the three and five-factor models. Their study focused on the time series dependency of returns to risk factors. This study adds to the body of knowledge by taking a different approach to check the cross-sectional risk and return relationship. Pakistan is a developing country where the stock market shows variations. In such volatile markets, the study of the distribution's tails could be more helpful in explaining the stock returns. Thus, the outcome of this research will contribute both theoretically and practically. The objective of comparing VaR and ES-based models with CAPM, three and five-factor models will provide theoretical contributions. While the unique settings of an emerging market, i.e., Pakistan, will offer practical implications for investors intending to invest in Pakistan Stock Exchange.

Literature Review and Theoretical Background

Markowitz (1952) provided the groundwork for asset pricing by explaining the asset allocation based on mean-variance analysis. His efficient frontier allows selecting the portfolio providing specific returns at the lowest risk. Their portfolio theory was based on the reduction of risk through diversification. After that, Lintner (1965) and Sharpe (1964) extended their work and argued that expected stock returns are non-diversifiable systematic risk functions. The proposed CAPM uses market exposure as a single factor in predicting cross-sections of stock returns. However, the implication of CAPM is based on the efficient market hypothesis; when a market reflects all the true information timely, then expected returns could be measured by adjusting additional compensation against additional systematic risk.

In actual practice, markets are not efficient, and information is not adjusted accurately and timely. Consequently, CAPM may provide an inaccurate estimation of expected returns. The emergence of models based on Arbitrage Pricing Theory (APT) focuses on the multifactor model to control the non-diversifiable anomalies, which were ignored by CAPM. Three-factor model by Fama and French (1993) is one of the famous multifactor models. Fama and French (1993) added value and size factors to the market beta factor of CAPM. They argued that investors require more compensation against small-size and value stocks. Various studies explored other anomalies in predicting expected stock returns, but the three-factor model remained the most cited and eminent multifactor model.

In 2015, in addition to the three-factor model, Fama and French tested the significance of two more factors, i.e. profitability and investment (Fama & French, 2014). Various studies have shown the superiority of three and five-factor models in explaining cross-sectional stock returns (Fama & French, 2017; Lohano & Kashif, 2018). However, this research argues that traditional market beta used in single-factor and multifactor models is not an appropriate benchmark of systematic risk to compensate. Instead, these are the fat tails of the distribution that can better represent the risk to explain the variations in stock returns (Aziz & Ansari, 2017; Huang et al., 2012); stated tail effects can be captured by using Value at Risk (VaR). VaR is the worst expected loss for a certain time horizon (Diamandis et al., 2011). It can help developing countries where stock markets are more volatile from the tail sides as a proxy of risk. For instance, Chen et al. (2014) found that VaR significantly explains the variations in the cross-sectional stock returns in the case of an emerging market, i.e. Taiwan Stock Exchange. Similarly, Aziz and Ansari (2017) indicated a positive relationship between VaR and risk premium.

The objective of this study is to explore the difference between the well-researched systematic risk factors i.e. Market beta and VaR as the estimation capacity of cross-sectional stock returns of Pakistani firms. Furthermore, this study explores the comparison between two significant extreme value models i.e. VaR and ES. A significant number of studies have investigated the CAPM, three and five-factor models for Pakistani listed firms. For instance, Kashif, Ilyas, et al. (2018) found that CAPM misspecified the cross-sectional stock returns while the three factors and five-factor models better explain the differences in stock returns. Kashif, Saad, et al. (2018) provided evidence of contrarian strategy. They found that single-factor CAPM is misspecified due to not controlling the effects of contrarian strategy. Conversely, the three and five-factor models explained the risk-adjusted abnormal returns due to contrarian strategy. Asad and Cheema (2017) found that the q-factor model is superior to the CAPM and three-factor model in the Pakistan Stock Exchange. They also found that the size effect is only relevant for small firms while large firms are not affected.

Similarly, Fatima et al. (2017) reported the significant impact of value and size factors on returns of firms' prices PSX. Javid and Ahmad (2011) investigated the changes in beta during bearish/bullish market conditions. They observe an increase in market beta with a bullish trend in the market and a decrease in market beta with a bearish trend. Their results further revealed that the three-factor model better predicted the cross-sectional stock returns as compared to CAPM. Various other studies also compared the three and five-factor models and found their superiority (Ameer, 2013; Lohano & Kashif, 2018; Peter et al., 2017; Zada et al., 2018; Zhang et al., 2019). Thus, the literature on asset pricing in Pakistan shows that multifactor models better predict stock returns than single-factor CAPM.

Contrary to traditional CAPM and three-factor models, Iqbal and Azher (2014) used VaR as a proxy of risk in predicting Pakistani stock returns. Their results showed that significant risk premiums are associated with VaR. However, VaR is a parametric approach assuming a normal distribution of returns with non-normal skewness or excess kurtosis (Khan et al., 2020). In violation of such assumptions, a nonparametric approach is required to calculate risk from the tail of the distribution. Conditional Value at Risk or expected shortfall (ES) is one such nonparametric approach (Chen, 2008).

Similar to VaR, ES focus on the tail of the distribution and measures the average of some percentage of worst expected losses (Khan et al., 2019). VaR is a percentile of the loss distribution, while ES shows the average losses scheduled within that percentile. In this way, VaR can be defined as the lower boundary of ES. Sarykalin, Serraino and Uryasev (2008) contended that ES is a better proxy of risk than VaR, especially in optimisation problems. VaR does not control the losses exceeding its value. In comparison, ES controls its effect by taking the average and portraying a comprehensive picture of the distribution's tails. Similarly, ES contains good mathematical properties such as continuous and convex functions compared to VaR which can have discontinued functions (Sarykalin et al., 2008). Therefore, it can be more appropriate to use ES as a risk measure rather than VaR.

This research intends to compare parametric VaR and nonparametric ES performances with traditional asset pricing models. The study further tests the significance of cross-sectional models of VaR and ES, by including non-systematic risk factors such as profitability, investment, size and value. To the best of the author's knowledge, no study has yet tested and compared these implications of VaR and mainly ES-based models at different significance levels in the Pakistan Stock Exchange. Therefore, this research will help the investor predict stock returns using an appropriate proxy of systematic risk.

Research Methodology

We have collected data from the 527 listed non-financial firms of the Pakistan Stock Exchange (PSX) from 1998 to 2015. Daily stock price data is extracted from the business recorder and the Pakistan stock exchange website. We use daily stock returns to calculate market beta, value at risk and expected shortfall values separately. Accounting information is collected from the State Bank of Pakistan (SBP) annual publications. Daily stock returns are calculated using the following formula

$$R_i = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (01)$$

Ri represents the daily stock return while Pt and Pt-1 are the current and previous trading dates' stock prices. From the annual data, the following single-factor CAPM model as proposed by Sharpe (1964), Lintner (1965) and Black (1972) is analysed using the ordinary least square (OLS) regression model.

$$R_i - R_f = \alpha_i + \beta_1 \text{Market\_}\beta_i + \varepsilon_i \quad (02)$$

Ri – Rf represents the stock excess returns. Market risk is represented by Market-β. Equation 2 will test the cross-section effect of market beta on excess stock return for sample data. Similarly, Equation 3 represents Fama and French (1992, 1993, and 1996) three factor model. It analyses the effect of systematic risk factor, along with size and value on stock returns.

$$R_i - R_f = \alpha_i + \beta_1 \text{Market\_}\beta_i + \beta_2 \ln(ME) + \beta_3 BM + \varepsilon_i \quad (03)$$

Where Log of Market Equity (Ln(ME)) is represented as size, value factor is the book to market ratio (BM). The five-factor model introduced by Fama (2015) which is illustrated by equation four.

$$R_i - R_f = \alpha_i + \beta_1 \text{Market\_}\beta_i + \beta_2 \ln(ME) + \beta_3 BM + \beta_4 OP + \beta_5 INV + \varepsilon_i \quad (04)$$

The investment factor (INV) represents the change in the value of the total asset from the previous two years to the previous year, profitability factor (OP) is taken as the operating profit of the previous year from the financial reports divided by the book to market ratio of prior years. The first part of this research explores the performance of the above three models for sample data.

The second part of the current research replaces market beta with VaR to estimate various asset pricing models. It is argued that using VaR as an alternative to the market can better predict cross-sectional stock returns. VaR is the maximum expected loss at a certain confidence level for a level of investment. The Parametric VaR of security can be calculated using the following formula.

$$VaR\ \alpha = [N*(1-\alpha)]^{th} \text{ return value of the arranged distribution} \quad (05)$$

We have calculated separate VaR and ES for each stock; we have used the historical method to compute VaR values. We arranged the security returns and used [N*(1- α)]th return value of the minimum side of the distribution as the VaR. "N" is the total number of observations, and we used daily returns for the estimation period of one year as prescribed by the BASEL III accord. We used two values of the level of confidence "α", i.e. 95% and 99%. A 95% confidence interval is common among managers and researchers; it gives a high value of VaR, and a 99% level of confidence is used as the benchmark rate of the BASEL III accord (Mager, 2012). We have used the simple Using VaR, we modified single-factor, three-factor and five-factor models in the following way. We used the normal distribution of past returns to calculate VaR. The normality assumption is supported by the central limit theorem. The normal distribution is the most common distribution for VaR calculation; BASEL III accord allows banks to use a normal distribution with variance-covariance, historical distribution or Monte Carlo simulation approach to measuring VaR. The selection of the method is the bank's discretion (Mager, 2012). The method of calculating VaR and ES is according to extreme value theory, which uses various methods to check the extreme thresholds in the given data

$$R_i - R_f = \alpha_i + \beta_1 VaR + \varepsilon_i \quad (06)$$

$$R_i - R_f = \alpha_i + \beta_1 VaR + \beta_2 \ln(ME) + \beta_3 BM + \varepsilon_i \quad (07)$$

$$R_i - R_f = \alpha_i + \beta_1 VaR + \beta_2 \ln(ME) + \beta_3 BM + \beta_4 OP + \beta_5 INV + \varepsilon_i \quad (08)$$

The third part of this research provides an explanation of various asset pricing models concerning the expected shortfall as the systematic risk control mechanism. The formulation of ES is provided in equation nine:

$$Conditional\ VaR\ or\ ES = \frac{\Sigma[X|X \leq VaR_{\propto}]}{N} \quad (09)$$

Equation (9) represents the ES of stock returns calculations. It defines the extreme expected losses and provides the average work expected loss that investors sustain. The "X" operator represents the stock returns and for the calculation of ES, these returns are below the threshold level of VaR. Some of "X" is divided by the number of observations which is denoted by "N". we have used daily returns for a year as the estimation period. We used two values of the level of confidence, i.e. 95% and 99% with the normal distribution of past returns.

$$R_i - R_f = \alpha_i + \beta_1 ES + \varepsilon_i \quad (10)$$
$$R_i - R_f = \alpha_i + \beta_1 ES + \beta_2 \ln(ME) + \beta_3 BM + \varepsilon_i \quad (11)$$
$$R_i - R_f = \alpha_i + \beta_1 ES + \beta_2 \ln(ME) + \beta_3 BM + \beta_4 OP + \beta_5 INV + \varepsilon_i \quad (12)$$

Results and Discussions

Table 1 of descriptive statistics shows that the average beta of the sample stocks is 0.372 with high variations of 0.423. It is also notable that some of the stocks documented negative beta as the minimum value of beta is -1.417. It refers to the inefficiency of the single-factor model as the basic assumption is violated. Results also show that the average VaR95 value is -0.48 compared to the value VaR99 (-1.25). This indicates that the results of VaR could provide different statistics at the varied level of significance for VaR.

Table 1: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum Value	Maximum Value
Beta	0.40	0.42	-1.41	2.48
ln(ME)	1.99	1.03	0.00	3.00
BM	0.24	0.85	-4.50	2.78
INV	0.11	0.24	-0.50	4.13
OP	0.09	0.74	-6.62	7.27
VaR 95	-0.05	0.05	-0.81	0.00
VaR 99	-0.13	0.12	-1.59	0.00
ES 95	-0.00	0.00	-0.03	0.00
ES 99	-0.00	0.00	-0.01	0.00

Table 2 shows the results of single-factor models with stock excess returns as the dependent variable and market beta, VaR and ES as independent variables. Results show that market beta (model 1) has a significant negative relation with excess returns. Such a significant negative relationship is also consistent with (Theriou et al., 2005). These results negate the notion of risk aversion and a positive risk-return relationship. Hence, the implication of the CAPM model in the Pakistan Stock Exchange to predict stock returns is inappropriate. One of the reasons for the negative beta can be the inclusion of cyclic stocks in our sample.

Table 2. One Factor Cross-Sectional Risk and Return Model

This table represents the single-factor OLS regression model with the traditional CAPM model in Model 1, and from models 2 to 5, ES and VaR are used as the systematic risk factors. VaR and ES are tested at both 95% and 99% levels of confidence. Non-italic values are coefficients. Italic formatted values in parathesis represent p-values for significance. Bold formatted values are insignificant values

Ri - Rf					
Models	**1**	**2**	**3**	**4**	**5**
Market Beta	-0.002				
	(0.000)				
VaR-95		0.0031			
		(0.000)			
VaR-99			0.0034		
			(0.000)		
ES-95				0.0864	
				(0.000)	
ES-99					0.3410
					(0.000)
Constant	0.0012	0.0005	0.0008	0.0008	0.0009
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R2	0.50	0.50	0.52	0.51	0.62
F-Value	258.16	47.1	58.013	44.33	66.68
Chi-Square	516.32	94.26	116.02	88.66	133.36

Table 2 also shows that the other four models portray significant positive effects of VaR and ES on stock returns. Results are also showing that the risk premium of VaR99 (0.0034) and ES99 (0.3410) is more significant than VaR95 (0.00309) and ES95 (0.0864), respectively. It is consistent with the theory that an increase in the risk of tail effects requires compensation. It shows that VaR and ES can control the impact of cyclic stock. Adj. R2 of these models are also high as compared to the classical CAPM model. It is also notable that all four models (particularly Model 2 VaR 95%) documented an intercept value close to zero, indicating a shallow autonomous effect on stock market excess returns. Thus, it can be concluded that VaR and ES-based models can better predict the expected stock returns as compared to CAPM in Pakistan Stock Exchange. Notably, ES based model showed the highest explanatory power as its adjusted R2 is 0.62.

Similarly, Table 3 compares the three-factor model based on the market beta, VaR and ES. Results show that market beta (model 6) depicts a negative relation between market returns and stock excess returns in the traditional three-factor model. The traditional three-factor model (model 6) also revealed a positive coefficient for size. These results are inconsistent with the theory as market beta and size effect should possess positive and negative beta, respectively. This indicates that adding the size and value effect to single-factor CAPM is still ineffective in predicting stock returns in the case of the Pakistan Stock Exchange.

Table 3 is also showing that a positive risk premium is associated with both VaR and ES. However, size effects become redundant in model 7 (VaR95) and model 9 (ES95). Conversely, model 8 (VaR99) and model 9 (ES99) have a significant adverse effect indicating more risk premium for small stocks than large stocks, supporting the risk-averse behaviour of investors. Table 3 also shows that substantial risk premium is associated with value stocks in all five models (models 6-10). Results also show that the constant term is insignificant for models 7 (VaR95) and 9 (ES95). These results indicate that the significance level for VaR and ES affects the redundancy and autonomous effect of size and constant term, respectively.

Table 3. Cross-Sectional Ordinary Least Square Model of Three Factor Model

The table posits the three-factor models using the ordinary least square model. Model 6 is the traditional three-factor model using systematic risk factor (Market beta), size and value as the idiosyncratic risk factors. VaR-95 and ES-95 are taken as the systematic risk factor at a 95% confidence interval. VaR-99 and ES-99 are systematic risk factors at a 99% level of confidence. Non-italic values are coefficients. Italic formatted values in parathesis represent p-values for significance. Bold formatted values are insignificant values

	Ri - Rf				
Models	**6**	**7**	**8**	**9**	**10**
BETA	-0.0035				
	(0.000)				
VaR-95		0.0039			
		(0.000)			
VaR-99			0.00583		
			(0.000)		
ES-95				0.1072	
				(0.000)	
ES-99					0.4855
					(0.000)
LnME	0.0044	0.0000	-0.00152	-0.0007	-0.0014
	(0.000)	(0.851)	(0.021)	(0.271)	(0.034)
BM	0.0007	0.0004	0.0004	0.0004	0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
C	-0.0097	0.0002	0.0048	0.0025	0.0045
	(0.000)	(0.813)	(0.006)	(0.143)	(0.010)
Adj. R2	0.55	0.44	0.58	0.42	0.63
F-Value	252.78	42.16	34.63	22.15	30.78
Chi-Square	1009.7	168.65	138.51	88.59	123.11

Similarly, Table 4 provides regression analyses using market beta, VaR and ES as the systematic risk factor in five-factor model. The five-factor model also provided similar results to the three-factor model in market beta, VaR and ES, size, and value effect. Results showed insignificant investment factors for all five models. Similarly, except for VaR95 (model 12), all the models also revealed a negligible impact on profitability. It indicates that in Pakistan Stock Exchange, no risk premium is associated with investment and profitability.

We also applied quantile regression to the five-factor model using ES, VaR and market beta to obtain a robust analysis. Tables 1 to 4 provide models based on ordinary least squares, using average returns as the dependent variable. Quantile regression offers a comparison to OLS regression with median stock returns as the dependent variable; Table 5 provides the results of the 20th, 50th and 80th deciles of excess returns. Results show that in 80th quantile regression, five-factor models (model 25-30) based on the market beta, VaR and ES provided similar results. The only difference is the insignificant risk premium of VaR95 in model 27. All the models showed insignificant size effects and significant effects on value stocks, investment and profitability. It is also found that the constant term is significant but very small for Models 26-30 of the 80th quantile regression. This finding concludes that the traditional five-factor model can be applied to distinguish cross-sectional stock returns from high excess returns.

Table 4. Five-Factor Models

This table provides the regression analysis using CAPM, ES and VaR as the systematic risk factors in the five-factor model. Non-systematic risk factors are size (LnME), value (BM), investment (INV) and

profitability (OP). VaR-95 and ES-95 are taken as the systematic risk factor at 95% confidence interval. VaR-99 and ES-99 are systematic risk factors at 99% level of confidence. Non-italic values are coefficients. Italic formatted values in parathesis represent p-values for significance. Bold formatted values are insignificant values					
			Ri - Rf		
Models	**11**	**12**	**13**	**14**	**15**
BETA	-0.004				
	(0.000)				
VaR 95		0.004			
		(0.000)			
VaR 99			0.006		
			(0.000)		
ES 95				0.1065	
				(0.0000)	
ES 99					0.483831
					(0.000)
LnME	0.0045	0.0000	-0.0015	-0.0007	-0.0014
	(0.000)	(0.839)	(0.024)	(0.291)	(0.038)
BM	0.0007	0.0004	0.0004	0.000417	0.00039
	(0.000)	(0.0000)	(0.000)	(0.0000)	(0.0000)
INV	-0.0002	-0.0001	-0.0001	0.0001	-0.0001
	(0.055)	(0.107)	(0.286)	(0.2858)	(0.2596)
OP	0.0000	0.0001	0.0000	0.0000	0.0001
	(0.585)	(0.035)	(0.536)	(0.407)	(0.482)
C	-0.0098	0.0002	0.0047	0.0023	0.00439
	(0.000)	(0.823)	(0.007)	(0.155)	(0.012)
Adj. R2	0.55	0.54	0.74	0.72	0.73
F-Value	168.96	29.34	23.34	15.07	20.82
Chi-Square	1013.7	176.03	140.02	90.43	124.89

Table 5. Five-Factor Model (Quantile Regression Model)

The table provides the 20th, 50th and 80th quantile regression analysis of the five-factor model Both VaR and ES are used with 95% and 99% confidence levels. Non-italic values are coefficients. Italic formatted values in parathesis represent p-values for significance. Bold formatted values are insignificant values					
Panel A: Twenty Percentile of Stock Excess Returns					
Models	**16**	**17**	**18**	**19**	**20**
Beta	-0.0003				
	(0.240)				
VaR95		0.0095			
		(0.000)			
VaR 99			0.0085		
			(0.000)		
ES-95				0.2372	
				(0.000)	
ES-99					0.9130
					(0.000)
LnME	0.0014	0.0006	-0.0005	-0.0004	-0.0012
	(0.037)	(0.110)	(0.295)	(0.380)	(0.003)
BM	0.0003	0.0004	0.0003	0.0004	0.0003
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
INV	-0.0001	-0.0001	-0.0001	-0.0001	-0.0000
	(0.000)	(0.000)	(0.660)	(0.0008)	(0.000)

OP	0.0001	0.00011	0.0000	0.0000	0.0001
	(0.356)	(0.263)	(0.982)	(0.853)	(0.592)
C	-0.0050	-0.0025	0.0009	0.0005	0.0027
	(0.005)	(0.014)	(0.505)	(0.660)	(0.009)
Panel B: Median Percentile of Stock Excess Returns					
Models	21	22	23	24	25
Beta	0.0003				
	(0.092)				
VaR95		0.0041			
		(0.000)			
VaR 99			0.0040		
			(0.000)		
ES-95				0.0814	
				(0.000)	
ES-99					0.422
					(0.000)
LnME	0.0003	0.0004	-0.0002	-0.00001	-0.0005
	(0.454)	(0.184)	(0.482)	(0.92)	(0.205)
BM	0.0003	0.0004	0.0003	0.0003	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INV	-0.0001	-0.0001	-0.00001	-0.00001	-0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OP	0.0001	0.0001	0.0001	0.0001	0.00001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.011)
C	-0.0007	-0.0008	0.0012	0.0005	0.0020
	(0.477)	(0.351)	(0.20)	(0.540)	(0.083)
Panel C: Eightieth Percentile of Stock Excess Returns					
Models	25	27	28	29	30
Beta	0.0004				
	(0.022)				
VaR-95		0.002			
		(0.274)			
VaR-99			0.0020		
			(0.036)		
ES-95				0.0587	
				(0.0142)	
ES-99					0.1960
					(0.0313)
LnME	-0.0008	-0.0004	-0.0007	-0.0007	-0.0008
	(0.085)	(0.260)	(0.103)	(0.095)	(0.052)
BM	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INV	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OP	0.0000	0.00001	0.00001	0.00001	0.00001
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
C	0.004	0.0031	0.0040	0.0038	0.0042
	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)

Table 5 also shows that the traditional five-factor market beta becomes insignificant for median and 20th quantile regression analysis. Hence, it can be concluded that market beta becomes redundant for stocks having low excess returns. Conversely, VaR99, ES95, and ES99 showed consistent results (positive coefficient) for all three 20th, 50th and 80th quantile regression analyses. The constant term of VaR99 and ES95 in both the 20th and 50th quantile regression is also insignificant. These results conclude that VaR and ES-based models better predict the stock returns as compared to market beta regardless of the level of excess returns. Notably, in the case of VaR 99 for low excess return stocks (20th quantile regression), all the idiosyncratic risks except the value effect become redundant. Therefore, practitioners are recommended to use VaR and ES-based models in predicting the stock returns while making investment decisions in Pakistan Stock Exchange. The coefficient value of ES is more than VaR, which indicates the strong impact of ES against VaR but with the same direction and significant p-values.

Pakistani stock market is a highly volatile market in comparison with the established markets of developed economies. We prove it by empirically reporting the negative CAPM beta, which indicates the presence of cyclical stocks in PSX. The study provides a model based on VaR and ES, which follows the risk-averse assumption despite volatile cyclical stocks. This study provides an alternative measure of systematic risk compared to the well-established asset pricing models applied in well-established markets of developed countries. Our study provides a superior explanation of VaR and ES. Moreover, ES is a better estimator than VaR, and it is following the findings of (Sarykalin et al., 2008).

Conclusions

This study adds to the body of knowledge by providing an additional explanation of VaR and ES as the systematic risk factor against the well-established provisions of CAPM beta. CAPM, three and five-factor models are used as the traditional models. The CAPM defines risk that requires compensation under the risk-averse assumption, and it represents the stock price deviation from a well-established portfolio. In comparison, three and five-factor models argued that other idiosyncratic risks also explain stock returns significantly. These factors are size, value, investment and profitability. This research argues that market beta used in CAPM, three and five-factor models is not representative of systematic risk in the Pakistani stock market. Our results showed that market beta is negative and divergences from the 'high-risk, high return' theory. Cyclical stocks might be the reason for the negative effect of market beta. This study provided alternate models with systematic risk factors such as VaR and ES in single, three and five-factor models. Both ES and VaR showed a positive relationship with stock returns indicating high stock returns with increased risk value. It follows the ‘high risk, high return’ theory. There is a similar direction and significance of VaR and ES coefficients, but stock returns are more sensitive to ES coefficient change. We find these implications for the data from a developing country, i.e. Pakistan. In developing countries like Pakistan, stock markets are more volatile, increasing VaR and ES's importance in predicting stock returns. Our results also showed that Var and ES could also control the size, investment and profitability effects. Therefore, it is recommended that investors should rely on VaR and ES as a proxy of risk in estimating the cross-section stock returns to invest in the Pakistan Stock Exchange.

Limitations and Future Research

This study indicates that the difference is significant among CAPM beta, VaR and ES measures and the model can be applied to stock exchanges of various developed and developing economies. After applying this model to developed and developing stocks the overall market model based on VaR and ES can be formed to replace the CAPM estimates. The study deploys the normal distribution of returns to calculate VaR and ES. Future research can provide robust results with the help of contemporary methods which use other distributions to calculate VaR and ES. Due to the data unavailability, some stocks with missing annual data or daily return frequency data are dropped from the sample. The study assumes the normal distribution of data to calculate the value at risk. The objective is to check the penetration of value at risk and the expected shortfall to the controlling mechanism of systematic risk. More contemporary and current methods of VaR should be used for the robustness of results, but unfortunately, it is not in the scope of the current study.

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