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Value-at-Risk and Expected Stock Returns: Evidence from Pakistan

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Abstract

This study investigates whether exposure to downside risk, as measured by value-at-risk (VaR), explains expected returns in an emerging market, i.e., Pakistan. We find that portfolios with a higher VaR are associated with higher average returns. In order to explore the empirical performance of VaR at the portfolio level, we use a time series approach based on 25 size and book-to-market portfolios. Based on monthly portfolio data for October 1992 to June 2008, the results show that VaR has greater explanatory power than the market, size, and book-to-market factors.

Keywords: Value-at-risk, emerging market, Fama-French factors.

JEL classification: C32, G32.

1. Introduction

The most important implications of the capital asset pricing model (CAPM) (see Sharpe, 1964; Lintner, 1969; Black, Jensen, & Scholes, 1972) are that (i) the expected return on a risky asset is linearly and positively related to its systematic risk, and (ii) only the asset's beta captures cross-sectional variations in expected stock returns; other variables have no explanatory power. However, the empirical evidence of the last few decades suggests that many alternative risk and nonrisk variables are able to explain average stock returns. These include size (Banz, 1981), the ratio of book equity to market equity (Fama & French, 1992, 1993, 1995, 1996; Stattman, 1980; Rosenberg, Reid, & Lanstein, 1985; Chan, Hamao, & Lakonishok, 1991), the price/earnings ratio (Basu, 1977), leverage (Bhandari, 1988), liquidity (Pastor & Stambaugh, 2003), and value-at-risk (VaR) (Bali & Cakici, 2004; Chen, Chen, & Chen, 2010).

Bali and Cakici (2004) investigate the relationship between portfolios sorted by VaR[1] and expected stock returns and find that VaR,

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[1] The k-day VaR on day t with probability $1 - \alpha$ is defined as prob. $[p_{t-k} - p_t \leq \text{VaR}(t, k, \alpha)] = 1 - \alpha$ where p_t is the day t price of the asset. VaR is based on both the mean and variance of returns, so it is not exactly a measure of risk but rather a measure of value-at-risk.

size, and liquidity explain the cross-sectional variation in expected returns, while beta and total volatility have almost no explanatory power at the stock level. Furthermore, the strong positive relationship between average returns and VaR is robust for different investment horizons and loss-probability levels.

VaR is a popular measure of risk value among finance practitioners and regulators of banks and financial institutions because it provides a single number with which to quantify the monetary loss associated with a portfolio exposed to market risk with a certain probability. If portfolios sorted by VaR result in higher returns associated with a higher VaR, then this can prove to be extremely valuable information for investors, portfolio managers, and financial analysts who can construct and recommend profitable portfolio strategies accordingly. The Basel II accord on banking supervision also recommends using VaR to measure the market risk exposure of banking assets. It is, therefore, an equally useful measure for market regulators and policymakers, making it important to investigate the asset pricing implications of VaR as a risk factor.

Apart from Bali and Cakici's (2004) pioneering study on the US and a recent study on Taiwan by Chen et al. (2010), there are no empirical studies on this aspect of asset pricing in the context of emerging and developed markets. The major objective of our study is to test whether the maximum likely loss as measured by VaR can explain the cross-sectional and time variations in average returns in Pakistan as an emerging market.

We have selected Pakistan for this analysis because it typifies an emerging market, exhibiting features such as higher returns associated with higher volatility, lower liquidity, a relatively high market concentration, and infrequent trading of many stocks.[2] Additionally, given that determining the validity of an economic or financial theory or model requires testing it under different conditions, this study aims to contribute to the literature by testing the relationship between VaR and expected returns accordingly. Our analysis reveals that constructing VaR as the common risk factor enables a better explanation for time variations in average portfolio returns sorted by size and book-to-market factors as compared to the Fama-French common factors.

[2] Khawaja and Mian (2005) elaborate further on some features of the market; Iqbal (2012) provides an overview of the stock market in Pakistan.

2. Literature Review

Over the last six decades, downside risk has been studied from the perspective of explaining asset returns. The concept of measuring downside risk dates back to Markowitz (1952) and Roy (1952). Markowitz (1952) provides a quantitative framework for measuring portfolio risk and return. The study utilizes mean returns, variances, and covariances to develop an efficient frontier on which every portfolio maximizes the expected return for a given variance or minimizes the variance for a given expected return.

Roy (1952) explains the same equation as Markowitz, connecting the portfolio variance of returns to the variance of returns of the constituent securities. As Markowitz (1959) points out, investors are interested in minimizing the downside risk because this would help them make better decisions when faced with nonnormal security return distributions. Consequently, he suggests assessing downside risk using (i) a semivariance computed from the mean return or below-mean semivariance (SV_m) and (ii) a semivariance computed from a target return or below-target semivariance (SV_t). The two measures compute a variance using only the returns below the mean return (SV_m) or target return (SV_t). In addition, the study compares several risk measures, including standard deviation, expected value of loss, expected absolute deviation, probability of loss, and maximum loss.

Quirk and Saposnik's (1962) study establishes the theoretical dominance of the semivariance over the variance. Mao (1970) argues in favor of using the semivariance given that investors will be interested specifically in the downside risk. Bawa (1975) and Fishburn (1977) identify the lower partial moment as a general family of below-target risk measures (one of which is the SV_t) that describe below-target risk in terms of risk tolerance. Bawa and Lindenberg (1977), whose study develops a mean lower partial moment (MLPM) model based on downside risk, present the CAPM as a special case of the MLPM, pointing out that the latter must explain the data at least as well as the CAPM. Harlow and Rao (1989) provide empirical support for the Bawa-Lindenberg downside risk model.

Nawrocki's (1999) study of downside risk differentiates between the two types of semivariance risk measures presented by Markowitz (1959). Eftekhari and Satchell (1996) and Claessens, Dasgupta, and Glen (1995) observe nonnormality in emerging markets. Bekaert, Erb, Harvey, and Viskanta (1998) note that skewness and kurtosis are significant risk factors for emerging market equities. Harvey and Siddique (2000) and Bekaert and Harvey (2002), respectively, argue that skewness is a significant risk factor in both developed and emerging markets.

Estrada (2000, 2002) investigates different risk measures and finds that semi-standard deviation is the relevant measure of risk for emerging markets. Dittmar (2002) determines the influence of a security's skewness and kurtosis on investors' expected returns. Bali and Cakici (2004), Bali, Gokcan, and Liang (2007), and Bali, Demirtas, and Levy (2009) consider VaR an alternative risk factor that helps explain the cross-section of stock returns. Chung, Johnson, and Schill (2006) argue that a set of co-moments taken together may be more reliable than individual co-moments. Ang, Chen, and Xing (2006) demonstrate how the downside beta term helps explain cross-sectional variations in average stock returns.

Iqbal, Brooks, and Galagedera (2010) evaluate the CAPM and MLPM for an emerging market over the period September 1992 to April 2006. Their empirical results support both models when performed against an unspecified alternative, but support the CAPM when an MLPM alternative is specified. Blitz, Pang, and van Vliet (2013) study the significant effects of volatility in emerging markets. De Groot, Pang, and Swinkels (2012) demonstrate the significant presence of value, momentum, and size effects in frontier emerging markets over the period 1997 to 2008; the authors argue that transaction costs or risk do not adequately explain these three market factors.

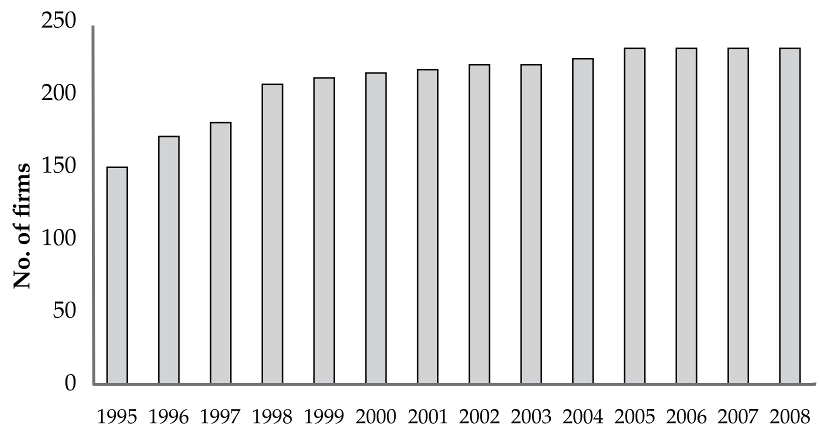
The disadvantage of the MLPM, which measures the relationship between asset returns and downside movement in the market, is that it yields a regression-based estimate, which may not be easily understood by common investors. The VaR, on the other hand, is a monetary value that readily captures downside risk. Accordingly, this study focuses on providing empirical evidence on the efficacy of VaR as a risk measure for Pakistan's emerging market. In addition to providing time series evidence, we carry out a cross-sectional regression analysis of VaR and average portfolio returns sorted with respect to VaR. This differentiates the study from Bali and Cakici (2004), for example, who do not provide estimates for the cross-sectional relationship between VaR and expected returns.

3. Data, Sample Selection, and Variables

Our primary source of data is the Karachi Stock Exchange (KSE)—the largest of Pakistan's three stock exchanges. Conducting asset-pricing tests based on daily data is problematic, given that daily returns tend to be nonnormal and that stocks are traded infrequently in this market. We have, therefore, used monthly data on continuously compounded stock returns for 231 stocks traded on the KSE from October 1992 to June 2008 (see Appendix 1).

The number of firms in the sample varies over the sample period. Figure 1 shows the number of firms at the end of December for each year of the sample period. We have 149 firms in the first year and 231 stocks at the end of June 2008, which provides us with a reasonable volume of data for analysis. The sample includes both financial and nonfinancial firms across all sectors of the KSE. As with other studies that use price databases, firm survival may be an issue, implying that the data overstates the importance of certain factors in such cases. In order to minimize this likelihood, we have applied a smaller level of significance—1 percent instead of 5 and 10 percent—in the statistical tests conducted.

Figure 1: Number of firms included in the sample over the sample period



The variables employed include: (i) size, (ii) systematic risk (beta), (iii) book-to-market equity, and (iv) VaR. These are explained below.

Following the literature, we measure firm size using the natural logarithm of the market value of equity, i.e., the stock price multiplied by the number of shares outstanding as of the sample selection date (each December).

In constructing systematic risk (beta), we follow Fama and French (1992) and sort all the sample stocks by size to determine the KSE size quintile breakpoints, based on which the stocks are allocated into five size portfolios. We then subdivide each size quintile into another five portfolios based on pre-ranking betas for all the sample stocks. The pre-ranking betas are calculated using two to five years' (as available) data on the monthly returns ending in December of year *t* based on the market model. In all, 162 post-ranking monthly returns for each of the 25 portfolios are computed for the period January 1995 to June 2008.

Following Fama and French (1992), we estimate the pre-ranking betas as the sum of the slopes yielded by regressing the monthly return on the current and previous months' market returns:

$$R_{jt} = \beta_{0j} + \beta_{1j} R_{mt} + \beta_{2j} R_{mt-1} + u_{jt} \tag{1}$$

where R_{jt} is the monthly return on stock j in period t, $\beta_{1j} + \beta_{2j}$ is the pre-ranking beta for stock j, R_{mt} is the monthly return on the KSE value-weighted index in period t, and u_{jt} is the residual series from the time series regression.

Book-to-market equity or BE/ME is the ratio of the book value of equity plus deferred taxes to the market value of equity. This study uses each firm's market price and equity data as of the end of December for each year to compute its BE/ME. Given the absence of reliable historical data on book values, we have employed December 2000 values (which fall roughly in between the sample period) to construct book-to-market portfolios.

In order to construct portfolios sorted by VaR, we sort the sample stocks by 99, 95, and 90 percent VaR levels and obtain the average returns and average VaR for each decile portfolio. The VaR is estimated using the historical simulation method.[3] The mean and cutoff return for each confidence level is estimated using 24–60 monthly returns (as available). The 99, 95, and 90 percent confidence level VaRs are then measured by the lowest, third lowest, and sixth lowest observations drawn from these monthly returns in December of each year, starting from 1995.

4. Methodology

This section explains how the relationship between VaR and expected returns is determined.

4.1. VaR and the Cross-Section of Expected Returns

In order to capture the relationship between VaR and expected returns, we investigate whether stock portfolios with a higher maximum likely loss (as measured by VaR) earn higher expected returns. Starting from 1995 through December of each subsequent year, we sort the sample of 232 KSE stocks by 99, 95, and 90 percent VaR levels to determine the

[3] There are several parametric and nonparametric methods of estimating VaR; see Iqbal, Azher, and Ijaz (2013) for a comparison of predictive abilities. Examining the sensitivity of the study's results to different VaR estimates could be an interesting direction for future research.

decile breakpoint for each VaR stock. Based on these breakpoints, we then allocate the stocks among 99, 95, and 90 percent VaR deciles. Decile 1 comprises the 10 percent of stocks with the lowest VaR; decile 10 represents those stocks with the highest VaR. We also compute the equally weighted average returns for the stocks in each decile. The portfolios are rebalanced every December for the subsequent years.

4.2. VaR and Time Series Variations in Expected Returns

Given the drawbacks of the CAPM, Fama and French (1992) have developed an alternative asset-pricing model, which we employ to study the usefulness of the VaR factor. Fama and French (1993) study the common risk factors in stock returns using six portfolios formed by sorting the stocks by size (ME) and BE/ME. Following this method, we rank the 232 sample stocks for January of each year *t* from 1995 to June 2008 according to size. The median stock size is used to divide the stocks into two groups: small (S) and big (B). The stocks are sorted separately into three portfolios based on the breakpoints for the bottom 30 percent (L), the middle 40 percent (M), and the top 30 percent (H). Thus, we construct six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) from the intersection of the two ME groups and the three BE/ME groups.

The Fama and French small-minus-big (SMB) factor is constructed as the difference between the average return on a portfolio of three small-cap stocks, i.e., (S/L + S/M + S/H)/3, and the average return on a portfolio of three big-cap stocks, i.e., (B/L + B/M + B/H)/3. The high-minus-low (HML) factor is constructed as the difference between the average return on two high-BE/ME portfolios, i.e., (S/H + B/H)/2, and the average return on two low-BE /ME portfolios, i.e., (S/L + B/L)/2.

Following Fama and French (1993, 1995, 1996), we use the excess market return over the risk-free return (RM-RF) as a measure of the market factor in stock returns. The RF is constructed using the 30-day repo rate obtained from DataStream. The excess returns on the 25 portfolios sorted by size and BE/ME are employed as dependent variables in the time series regressions.

In order to examine the empirical performance of VaR based on the 25 Fama and French (1993) portfolios, we follow Bali and Cakici (2004) and construct an HVaRL factor (high VaR minus low VaR), which is meant to mimic the risk factor in returns related to VaR and is defined as the difference between the simple average of the returns on high VaR and low VaR portfolios. The construction of the 95 percent VaR portfolios is similar to that of Fama and French's size portfolios: for December of each year *t* from 1995 through June 2008, we rank 232 stocks by their 95 percent VaR level. The median 95 percent VaR is used to divide the selected stocks into two groups: high VaR and low VaR.

4.3. Regression Analysis With Several Factors

We carry out a series of regressions to ascertain the role of the various factors (RM-RF, SMB, HML, and HVaRL) in explaining returns. These include (i) one-factor models (which use RM-RF, SMB, HML, or HVaRL as a single explanatory variable at a time), (ii) two-factor models (which use RM-RF along with SMB, HML, or HVaRL), (iii) three-factor models (which use RM-RF along with SMB and HML, or SMB and HVaRL, or HML and HVaRL), and (iv) four-factor models (which use RM-RF, SMB, HML, and HVaRL).

5. Empirical Results

This section presents the results of each regression analysis.

5.1. VaR and the Cross-Section of Expected Returns

Table 1 presents the average returns on the VaR portfolios for all ten deciles as well as the estimated regression coefficients $\hat{\alpha}$ and $\hat{\beta}$, corresponding t-statistics, and R^2 values. The cross-sectional regression of average portfolio returns on the average VaR of the portfolios is given as:

$$R_j = \alpha + \beta VaR_j + u_j \tag{2}$$

$j = 1, 2, \dots 10$

As Table 1 shows, when portfolios are formed according to their 99, 95, and 90 percent VaR, average stock returns are positively correlated with VaR. In other words, stocks with a higher maximum likely loss (measured by VaR) generally yield higher average returns. From the lowest to the highest 1 percent VaR decile, the monthly average return on VaR portfolios increases from 0.96 to 7.83 percent, which amounts to an 82.45 percent annual return differential. This increase is not monotonic: for example, moving from the eighth to the ninth decile portfolio using the 99 percent VaR results in a lower average return.

The overall evidence supporting a positive risk-return relationship is fairly strong. This is in contrast to Bali and Cakici (2004) who estimate an annual return differential of only 11.52 percent between the highest and lowest VaR portfolios. Our result is, however, consistent with the general observation that emerging markets yield higher returns than developed markets. The result is also important from an investment allocation perspective.

We find a similarly strong positive relationship between average returns and VaR, using the 95 and 90 percent confidence levels. The results show that, the greater a portfolio's potential losses as captured by VaR, the higher will be the expected return. Portfolios of higher-VaR stocks appear to yield higher returns than lower-VaR portfolios.

To gauge the statistical significance of the relationship between the average VaR and average returns on the VaR portfolios, we regress the average returns from the decile portfolios on the average VaR for the 99, 95, and 90 percent levels, respectively. The results indicate that the VaR coefficients are highly significant with a theoretically consistent positive sign. The R^2 values range from 83 to 86 percent.

Table 1: Average monthly portfolio returns, August 1992–June 2008

Decile	99% VaR	Return %	95% VaR	Return %	90% VaR	Return %
Low VaR	2.85	0.96	0.32	1.03	0.74	1.66
2	17.72	2.39	10.85	3.42	5.88	0.82
3	21.67	4.07	13.95	1.92	9.13	4.08
4	25.16	3.73	16.03	2.88	11.08	3.65
5	28.57	3.38	17.87	4.74	12.59	4.03
6	31.89	5.23	20.36	5.57	14.10	4.32
7	35.44	5.14	22.48	5.43	16.09	4.46
8	40.45	5.89	25.34	5.47	18.20	6.62
9	47.64	4.68	28.62	6.19	20.64	6.39
High VaR	60.68	7.83	34.76	6.48	24.51	7.09
Coefficient	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$
	0.93	0.11	0.94	0.18	0.75	0.27
t-statistic	2.45**	8.04*	1.95***	9.79*	1.07	6.76*
R^2	0.86		0.83		0.86	

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. We obtain R^2 by regressing a cross-section of the average returns to the ten deciles on a constant and the average VaR of the portfolios. The t-statistics are based on heteroskedasticity-consistent standard errors and tested to determine if the estimated coefficients are significantly different from 0.
Source: Authors' calculations.

5.2. VaR and Time Series Variations in Expected Stock Returns

Panel A of Table 2 provides some descriptive statistics for RM-RF, SMB, HML, and HVaRL at a 95 percent confidence level. The normality of the Fama-French and VaR factors is rejected in all cases. However, the time series sample is large enough to justify statistical tests asymptotically.

Panel B calculates the correlation between RM-RF, SMB, HML, and HVaRL in order to determine the direction and magnitude of the relationship between HVaRL and the three Fama-French factors. There is a positive correlation of 0.59 and 0.53 between the market and HVaRL factors and between HML and HVaRL, respectively. The size factors, however, are weak correlates of HVaRL. Overall, the correlation between HVaRL and the Fama-French factors is not very large, making it possible to estimate any independent influence on portfolio returns without fear of collinearity.

Table 2: Descriptive statistics and Pearson correlation coefficients for HVaRL and Fama-French factors

	Descriptive statistics			
Panel A	**RM-RF**	**SMB**	**HML**	**HVaRL**
Observations	162	162	162	162
Mean	0.003	-0.007	-0.006	-0.011
Median	0.006	-0.008	-0.005	-0.016
Maximum	0.240	0.126	0.186	0.217
Minimum	-0.416	-0.162	-0.135	-0.142
Standard deviation	0.097	0.046	0.048	0.052
Skewness	-0.510	-0.010	0.294	0.730
Kurtosis	4.800	3.943	4.579	5.450
	Pearson correlation coefficients			
Panel B	**HVaRL**	**RM-RF**	**SMB**	**HML**
HVaRL	1.000			
RM-RF	0.590	1.000		
SMB	-0.019	-0.586	1.000	
HML	0.533	0.393	-0.041	1.000

Source: Authors' calculations.

Table 3 shows the correlation between returns for the 25 portfolios and HVaRL, RM-RF, SMB, and HML. RM-RF and HVaRL capture more common variation in stock returns on average than SMB and HML.

Table 3: Correlation of 25 portfolio returns with RM-RF, SMB, HML, and HVaRL

Portfolio	HVaRL	RM-RF	SMB	HML
S1BM1	0.603	0.317	0.282	0.011
S1BM2	0.640	0.462	0.097	0.311
S1BM3	0.258	0.377	-0.033	0.405
S1BM4	0.551	0.425	0.109	0.499
S1BM5	0.574	0.231	0.373	0.529
S2BM1	0.405	0.295	0.160	0.057
S2BM2	0.522	0.545	-0.068	0.216
S2BM3	0.434	0.335	0.165	0.351
S2BM4	0.586	0.569	0.010	0.396
S2BM5	0.745	0.521	-0.002	0.576
S3BM1	0.482	0.558	-0.250	0.236
S3BM2	0.382	0.493	-0.117	0.230
S3BM3	0.512	0.514	-0.082	0.274
S3BM4	0.694	0.685	-0.168	0.462
S3BM5	0.730	0.718	-0.286	0.580
S4BM1	0.566	0.521	-0.094	0.294
S4BM2	0.633	0.589	-0.198	0.500
S4BM3	0.497	0.596	-0.266	0.384
S4BM4	0.658	0.673	-0.221	0.508
S4BM5	0.746	0.830	-0.482	0.555
S5BM1	0.301	0.573	-0.510	-0.013
S5BM2	0.611	0.820	-0.460	0.282
S5BM3	0.592	0.903	-0.541	0.378
S5BM4	0.562	0.759	-0.394	0.317
S5BM5	0.654	0.942	-0.573	0.491
Average	0.557	0.570	-0.142	0.353

Note: S1BM1 denotes a portfolio that belongs to the smallest size quintile and the lowest BE/ME quintile. The other portfolios are similarly labeled.
Source: Authors' calculations.

5.3. *Regression Analysis With Several Factors*

This section presents the results of the four- and three-factor models (see Appendix 2 for the results of the one- and two-factor models).

5.3.1. Four-Factor Model

Table 4 presents the parameter estimates, averages, t-statistics, adjusted R^2 values, and standard errors of estimates for the time series regression of excess stock returns on the four factors RM-RF, SMB, HML, and HVaRL (with a 95 percent confidence level).

Table 4: Four-factor model: Regression of excess stock returns on RM-RF, SMB, HML, and HVaRL

BE/ME quintile

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.485)					**t-statistics**				
Small	0.562*	0.518*	0.680*	0.476*	0.424*	6.01	4.84	4.94	4.66	3.32
2	0.437*	0.588*	0.366*	0.581*	0.302*	4.56	6.27	4.78	7.45	2.78
3	0.372*	0.531*	0.443*	0.517*	0.407*	3.97	5.49	4.92	6.66	4.77
4	0.349*	0.235*	0.331*	0.408*	0.495*	4.13	3.20	4.45	5.41	6.16
Big	0.413*	0.577*	0.732*	0.564*	0.846*	3.78	8.86	13.26	7.45	17.98
	HVaRL slope (average = 0.432)									
Small	1.167*	0.793*	-0.547**	0.245	0.634*	7.87	4.67	-2.51	1.51	3.14
2	0.354**	0.335**	0.061	0.191	1.117*	2.33	2.25	0.51	1.55	6.49
3	0.391**	0.018	0.316**	0.521*	0.779*	2.63	0.12	2.22	4.23	5.76
4	0.460*	0.460*	0.193	0.415*	1.148*	3.44	3.95	1.64	3.47	9.00
Big	0.421**	0.463*	0.219**	0.305**	0.370*	2.43	4.48	2.51	2.54	4.96
	SMB slope (average = 0.328)									
Small	1.327*	0.861*	0.772*	0.830*	1.658*	8.42	4.77	3.33	4.82	7.72
2	0.796*	0.593*	0.685*	0.734*	0.412**	4.93	3.75	5.31	5.59	2.25
3	0.028	0.450*	0.409*	0.337**	-0.111	0.18	2.76	2.70	2.58	-0.77
4	0.283**	0.007	0.033	0.143	-0.762*	1.99	0.06	0.27	1.13	-5.62
Big	-0.616*	-0.124	-0.15	-0.003	-0.360*	-3.34	-1.14	-1.62	-0.02	-4.55
	HML slope (average = 0.084)									
Small	-1.040*	-0.16	0.753*	0.505*	0.866*	-8.14	-1.09	4.00	3.62	4.97
2	-0.418*	-0.247***	0.183***	0.098	0.592*	-3.20	-1.93	1.76	0.92	4.00
3	-0.119	-0.028	-0.066	0.142	0.499*	-0.94	-0.22	-0.54	1.34	4.28
4	-0.072	0.294*	0.170***	0.289*	0.493*	-0.63	2.93	1.68	2.81	4.49
Big	-0.614*	-0.230**	0.005	-0.074	0.283*	-4.11	-2.59	0.07	-0.72	4.40
	Adjusted R^2 (average = 0.518)					**SSE**				
Small	0.642	0.484	0.262	0.441	0.574	0.06	0.07	0.10	0.07	0.09
2	0.296	0.411	0.323	0.509	0.613	0.07	0.07	0.05	0.05	0.08
3	0.340	0.277	0.350	0.614	0.686	0.07	0.07	0.06	0.05	0.06
4	0.377	0.488	0.397	0.571	0.833	0.06	0.05	0.05	0.05	0.06
Big	0.430	0.711	0.822	0.593	0.920	0.08	0.05	0.04	0.05	0.03

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. The table reports statistics for the period January 1995 to June 2008.
Source: Authors' calculations.

The table shows that the slope coefficients of RM-RF are positive and highly significant (with p-values of less than 0.01). It is worth noting that 22 of the 25 slopes for HVaRL are significant and, barring one, all have the correct positive sign. Ten of these slopes are significant at 1 percent, especially for the largest book-to-market quintile portfolios. The number of significant coefficients corresponding to HVaRL is higher than those for the size and book-to-market factors; its average coefficient is also much larger. The four-factor model yields a greater average adjusted R^2 value (0.518) than the other models.

These results are in line with the findings of Bali and Cakici (2004). The smaller size portfolios appear to be strongly related to average portfolio returns compared to portfolios comprising larger sizes. Thus, smaller firms may require higher returns for the greater risk with which they are associated. The signs of the HML factor are not stable.

5.3.2. Three-Factor Model

In order to gauge the importance of the VaR factor, we consider if it can serve as a substitute for any of the Fama-French factors. Tables 5, 6, and 7 present panel estimates from the three-factor model in which the excess returns on 25 portfolios were regressed on RM-RF along with (i) SMB and HML, (ii) HVaRL and SMB, or (iii) HVaRL and HML.

Table 5 indicates that all the RM-RF coefficients are highly significant. The size and book-to-market factors follow in importance with fewer significant coefficients. The average adjusted R^2 value is 0.485, which is slightly lower than that for the four-factor model, including VaR.

Compared to HML, most of the SMB slope coefficients are statistically significant, implying strong size effects but slightly weak book-to-market effects during the testing period; this is consistent with Chen et al. (2009). Once SMB and HML are added to the one-factor model, the average adjusted R^2 value increases from 0.359 (Table A1 in Appendix 2) to 0.485 (Table 5), which shows that the factors SMB and HML also help explain the time series variation. These findings are consistent with Fama and French (1993), Al-Mwalla (2012), Al-Mwalla and Karasneh (2011), and Mirza (2008).

Table 5: Three-factor model: Regression of excess stock returns on RM-RF, SMB, and HML (panel A)

BE/ME quintile

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.656)					**t-statistics**				
Small	1.023*	0.831*	0.464*	0.573*	0.674*	11.89	9.34	4.25	7.15	6.58
2	0.577*	0.720*	0.390*	0.656*	0.742*	7.60	9.71	6.54	10.73	7.80
3	0.526*	0.539*	0.567*	0.723*	0.714*	7.06	7.15	7.97	11.33	9.76
4	0.530*	0.416*	0.407*	0.571*	0.948*	7.79	6.94	6.98	9.38	12.29
Big	0.579*	0.760*	0.818*	0.685*	0.993*	6.67	14.10	18.68	11.38	25.18
	SMB slope (average = 0.534)									
Small	1.880*	1.237*	0.513**	0.946*	1.959*	11.33	7.20	2.43	6.12	9.91
2	0.963*	0.752*	0.714*	0.825*	0.942*	6.58	5.25	6.20	6.99	5.13
3	0.213	0.459*	0.559*	0.585*	0.258***	1.49	3.16	4.07	4.75	1.83
4	0.501*	0.225***	0.125	0.339*	-0.217	3.82	1.95	1.11	2.89	-1.46
Big	-0.416**	0.094	-0.046	0.141	-0.184**	-2.49	0.91	-0.55	1.22	-2.43
	HML slope (average = 0.207)									
Small	-0.706*	0.067	0.596*	0.575*	1.048*	-4.98	0.46	3.31	4.35	6.21
2	-0.317**	-0.151	0.201**	0.152	0.912*	-2.53	-1.24	2.05	1.51	5.81
3	-0.007	-0.023	0.023	0.291*	0.722*	-0.06	-0.19	0.20	2.77	5.99
4	0.059	0.426*	0.226**	0.408*	0.822*	0.53	4.30	2.35	4.07	6.47
Big	-0.493*	-0.097	0.068	0.012	0.389*	-3.45	-1.10	0.95	0.13	5.98
	Adjusted R^2 (average = 0.485)					**SSE**				
Small	0.504	0.416	0.237	0.436	0.550	0.08	0.08	0.10	0.07	0.09
2	0.276	0.396	0.327	0.505	0.512	0.07	0.07	0.05	0.05	0.08
3	0.316	0.282	0.334	0.572	0.622	0.07	0.07	0.06	0.06	0.07
4	0.334	0.440	0.391	0.541	0.749	0.06	0.05	0.05	0.05	0.07
Big	0.412	0.676	0.816	0.579	0.908	0.08	0.05	0.04	0.05	0.04

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. The table reports statistics for the period January 1995 to June 2008.
Source: Authors' calculations.

Table 6 shows that adding HVaRL and SMB to the one-factor model yields significant coefficients for RM-RF, while HVaRL captures slightly more time variation in the test portfolios than SMB. Five of the HVaRL slope coefficients and eight of the SMB slope coefficients are insignificant. All the HVaRL coefficients have the correct positive sign while some of the SMB coefficients have a negative sign.

Table 6: Three-factor model: Regression of excess stock returns on RM-RF, HVaRL, and SMB (panel B)

BE/ME quintile

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.493)					**t-statistics**				
Small	0.465*	0.503*	0.751*	0.524*	0.505*	4.21	4.74	5.25	4.98	3.72
2	0.398*	0.565*	0.383*	0.590*	0.357*	4.07	6.02	5.01	7.63	3.17
3	0.361*	0.529*	0.436*	0.531*	0.453*	3.89	5.52	4.90	6.87	5.09
4	0.342*	0.262*	0.347*	0.435*	0.541*	4.10	3.52	4.68	5.69	6.41
Big	0.355*	0.555*	0.732*	0.557*	0.873*	3.12	8.45	13.42	7.43	17.70
	HVaRL slope (average = 0.465)									
Small	0.765*	0.731*	-0.256	0.440*	0.969*	4.60	4.56	-1.19	2.78	4.74
2	0.192	0.239***	0.132	0.229***	1.346*	1.30	1.69	1.15	1.96	7.93
3	0.345**	0.007	0.291**	0.576*	0.972*	2.46	0.05	2.16	4.95	7.23
4	0.433*	0.574*	0.259**	0.527*	1.338*	3.44	5.10	2.32	4.57	10.50
Big	0.183	0.374*	0.221*	0.276**	0.480*	1.07	3.77	2.69	2.45	6.45
	SMB slope (average = 0.335)									
Small	1.241*	0.848*	0.834*	0.871*	1.729*	6.64	4.71	3.44	4.89	7.52
2	0.761*	0.572*	0.700*	0.743*	0.460**	4.60	3.60	5.40	5.67	2.41
3	0.018	0.448*	0.403*	0.349*	-0.070	0.12	2.76	2.67	2.67	-0.47
4	0.277***	0.031	0.047	0.166	-0.721*	1.96	0.25	0.38	1.29	-5.04
Big	-0.666*	-0.143	-0.150	-0.009	-0.337*	-3.46	-1.29	-1.62	-0.07	-4.04
	Adjusted R^2 (average = 0.494)					**SSE**				
Small	0.494	0.483	0.191	0.398	0.510	0.08	0.07	0.10	0.07	0.10
2	0.254	0.401	0.314	0.509	0.576	0.07	0.07	0.05	0.05	0.08
3	0.341	0.281	0.353	0.612	0.651	0.07	0.07	0.06	0.05	0.06
4	0.380	0.463	0.390	0.552	0.813	0.06	0.05	0.05	0.05	0.06
Big	0.373	0.701	0.823	0.594	0.910	0.08	0.05	0.04	0.05	0.03

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. The table reports statistics for the period January 1995 to June 2008.
Source: Authors' calculations.

Interestingly, in Table 7, HVaRL captures greater time variation than RM-RF and SMB as indicated by their significant coefficients. Only three of the HVaRL coefficients are insignificant compared to five and ten, respectively, in the case of RM-RF and SMB. The average adjusted R^2 value is 0.476. Again, while the HML factor carries both signs, HVaRL has a robust positive sign in all cases.

Table 7: Three-factor model: Regression of excess stock returns on RM-RF, HVaRL, and HML (panel C)

BE/ME quintile

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.346)					**t-statistics**				
Small	0.001	0.154***	0.353*	0.125	-0.277*	0.02	1.92	3.54	1.64	-2.64
2	0.100	0.337*	0.076	0.270*	0.127	1.40	4.92	1.31	4.52	1.65
3	0.360*	0.341*	0.270*	0.374*	0.454*	5.50	4.92	4.19	6.75	7.59
4	0.229*	0.232*	0.317*	0.347*	0.818*	3.83	4.51	6.09	6.56	13.25
Big	0.674*	0.630*	0.795*	0.565*	0.999*	8.50	13.76	20.43	10.67	28.50
	HVaRL slope (average = 0.571)									
Small	1.725*	1.155*	-0.222	0.594*	1.331*	10.82	7.12	-1.10	3.84	6.28
2	0.688*	0.584*	0.349*	0.499*	1.291*	4.72	4.22	2.97	4.14	8.27
3	0.403*	0.207	0.488*	0.663*	0.732*	3.04	1.48	3.75	5.91	6.06
4	0.579*	0.463*	0.207***	0.475*	0.828*	4.80	4.45	1.97	4.44	6.64
Big	0.162	0.410*	0.156**	0.304*	0.219*	1.01	4.44	1.99	2.84	3.09
	HML slope (average = 0.101)									
Small	-0.969*	-0.113	0.795*	0.550*	0.956*	-6.33	-0.73	4.10	3.70	4.69
2	-0.375*	-0.215	0.220***	0.137	0.614*	-2.68	-1.62	1.95	1.19	4.10
3	-0.118	-0.004	-0.044	0.16	0.493*	-0.93	-0.03	-0.36	1.49	4.25
4	-0.056	0.294*	0.172***	0.297*	0.452*	-0.49	2.95	1.71	2.89	3.78
Big	-0.647*	-0.237*	-0.002	-0.074	0.263*	-4.21	-2.67	-0.03	-0.73	3.87
	Adjusted R^2 (average = 0.476)					**SSE**				
Small	0.484	0.413	0.215	0.362	0.416	0.08	0.08	0.10	0.08	0.10
2	0.192	0.362	0.207	0.415	0.603	0.07	0.07	0.06	0.06	0.08
3	0.344	0.247	0.325	0.600	0.686	0.06	0.07	0.06	0.05	0.06
4	0.365	0.491	0.401	0.570	0.801	0.06	0.05	0.05	0.05	0.06
Big	0.393	0.711	0.820	0.595	0.910	0.08	0.05	0.04	0.05	0.03

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. The table reports statistics for the period January 1995 to June 2008.
Source: Authors' calculations.

It is interesting to note that the three-factor model captures slightly more common variation in terms of the adjusted R^2 value when using HVaRL with SMB or HML: the average adjusted R^2 value increases from 0.485 (Table 5) to 0.494 (Table 6).

6. Conclusion

Investigating the asset-pricing implications of VaR as a risk factor can be a difficult task, especially in the context of emerging markets where economic and political conditions may be volatile. However, VaR is now widely applied in the financial world and is popular among risk managers, banks, and financial institutions that wish to determine whether their investors are compensated adequately in terms of high returns. Our main aim has been to investigate the role of VaR at three different confidence levels (10, 5, and 1 percent) in Pakistan as an emerging market for the period August 1995 to June 2008.

The study compares the explanatory power of VaR with that of the size and book-to-market factors by adopting both a cross-sectional and time series approach. It also investigates the asset-pricing implications of downside risk as measured by VaR and examines the cross-section of expected returns for decile portfolios sorted by the VaR (10, 5, and 1 percent) of each stock. Portfolios with a higher VaR are found to yield a higher average return; the VaR factor thus significantly explains the cross-sectional variations in expected returns. As a measure of downside risk, therefore, VaR is associated with higher returns.

We also evaluate the performance of VaR at the portfolio level by using a time series regression approach. This involves applying one-, two-, three-, and four-factor models where the monthly returns associated with a portfolio constructed by sorting stocks with respect to size and book-to-market are regressed on the returns for a market portfolio of stocks as well as size, book-to-market, and VaR factors. Our empirical results show that VaR captures substantial time variation in stock returns in the one-factor and two-factor models. More importantly, it gains additional explanatory power after controlling for the characteristics of RM-RF, SMB, and HML in the four-factor model.

Overall, our results imply that VaR is better able to capture cross-sectional and time series variations than size and book-to-market factors in Pakistan's emerging market. Currently, it is implemented by the State Bank of Pakistan and the Securities and Exchange Commission of Pakistan, primarily to supervise the risk exposure of banks, brokerage houses, and investment companies. Our results suggest that VaR could serve as a useful measure for quantifying the downside risk exposure of equity securities in Pakistan.

The study could be extended to compare VaR with other measures of risk such as beta, downside beta, lower partial moment, and liquidity. In addition, the analysis could be extended to examine the sensitivity of the relationship between expected returns and VaR to various parametric and nonparametric methods of estimating VaR.

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Appendix 1

List of firms used in the study

No.	Firm	No.	Firm
1.	Abbott Labs (Pak.)	33.	Bosicor Pakistan
2.	ABN Amro Bank (Pak.)	34.	Capital Assets Leasing
3.	Adamjee Insurance	35.	Central Insurance
4.	Agriauto Industries	36.	Century Insurance
5.	Al Abid Silk	37.	Century Paper
6.	Al Zamin Leasing Corp.	38.	Cherat Cement
7.	Al-Abbas Cement	39.	Clariant Pakistan
8.	Al-Ghazi Tractors	40.	Colgate Palmolive
9.	Al-Khair Gadoon	41.	Crescent Commercial Bank
10.	Allied Bank	42.	Crescent Steel
11.	Al-Mazeen Mutual Fund	43.	Crescent Textiles
12.	Al-Noor Modaraba Management	44.	D G Khan Cement Company
13.	American Life Insurance	45.	Dadabhoy Cement
14.	Arif Habib Securities	46.	Dadabhoy Sack
15.	Askari Bank	47.	Dadex Eternit
16.	Askari Leasing	48.	Dandot Cement
17.	Atlas Honda	49.	Dawood Capital Management
18.	Atlas Insurance	50.	Dawood Hercules
19.	Attock Cement Pakistan	51.	Dawood Lawrencepur
20.	Attock Petroleum	52.	Dewan Automotive Engineering
21.	Attock Refinery	53.	Dewan Cement
22.	Azgard Nine	54.	Dewan Farooque Motors
23.	Balochistan Glass	55.	Dewan Mushtaq Textiles
24.	Bank Al Habib	56.	Dewan Salman Fiber
25.	Bank Al-Falah Limited	57.	Dewan Sugar
26.	Bank of Punjab	58.	Dewan Textile Mills
27.	Bannu Woolen Mills	59.	Dreamworld
28.	Bata Pakistan	60.	East West Insurance
29.	Bestway Cement	61.	Ecopack
30.	Bhanero Textiles	62.	EFU General Insurance
31.	BOC Pakistan	63.	EFU Life Assurance
32.	Bolan Castings	64.	English Leasing

No.	Firm	No.	Firm
65.	Engro Chemicals	101.	Ibrahim Fibers
66.	Escorts Investment Bank	102.	ICI Pakistan
67.	Faisal Spinning Mills	103.	Ideal Spinning Mills
68.	Fateh Textile Mills	104.	Indus Motors
69.	Fauji Cement Limited	105.	Inter Asia Leasing
70.	Fauji Fertilizer	106.	International General Insurance
71.	Fauji Fertilizer Bin Qasim	107.	International Industries
72.	Faysal Bank	108.	International Multi Leasing
73.	Fazal Textile Mills	109.	Invest Capital Investment Bank
74.	Fecto Cement	110.	Investec Mutual Fund
75.	Ferozsons Laboratories	111.	Investec Securities
76.	First IBL Modaraba	112.	J K Spinning Mills
77.	First Interfund Modaraba	113.	J O V & Co.
78.	First Tristar Mod	114.	Jahangeer Siddiqui
79.	Gadoon Textiles	115.	Japan Power Generation
80.	Gammon Pakistan	116.	Javedan Cement
81.	Gatron Industries	117.	JDW Sugar Mills
82.	Gauhar Engineering	118.	JS Global Capital
83.	General Tyre and Rubber Co.	119.	JS Value Fund
84.	Ghani Glass	120.	Karachi Electric Supply Corp.
85.	Gharibwal Cement	121.	Karam Ceramics
86.	Gillette Pakistan	122.	KASB Modaraba
87.	GlaxoSmithKline Pakistan	123.	Khalid Siraj Textiles
88.	Gul Ahmed Textile Mills	124.	Kohat Cement
89.	Gulistan Spinning Mills	125.	Kohinoor Energy
90.	Gulistan Textile Mills	126.	Kohinoor Mills
91.	Habib ADM	127.	Kohinoor Spinning Mills
92.	Habib Metro Bank	128.	Kohinoor Textile Mills
93.	Habib Modaraba First	129.	Kot Addu Power
94.	Habib Sugar	130.	Lakson Tobacco
95.	Hala Enterprises	131.	Liberty Mills
96.	Hayeri Construct	132.	Lucky Cement
97.	Hinopak Motors	133.	Mandviwala Mauser
98.	Honda Atlas Cars	134.	Maple Leaf Cement
99.	Hub Power	135.	Mari Gas
100.	Huffaz Seamless Pipe	136.	MCB Bank

No.	Firm
137.	Meezan Bank
138.	Mehmood Textiles
139.	Millat Tractors
140.	Mirpurkhas Sugar
141.	Modaraba Al-Mal
142.	Murree Brewery
143.	Mustehkam Cement
144.	MyBank
145.	Nakshbandi Industries
146.	National Bank of Pakistan
147.	National Refinery
148.	Nestle Pakistan
149.	New Jubilee Insurance
150.	New Jubilee Life Insurance
151.	NIB Bank
152.	Nimir Industrial Chemicals
153.	Nishat (Chunian)
154.	Nishat Mills
155.	Noon Sugar Mills
156.	Oil and Gas Development Corp.
157.	Orix Investment Bank
158.	Orix Leasing Pak.
159.	Otsuka Pakistan
160.	Packages
161.	Pak Elektron
162.	Pak Suzuki Motor
163.	Pakistan Cement
164.	Pakistan Engineering
165.	Pakistan Hotels Dvpr.
166.	Pakistan Insurance
167.	Pakistan International Airlines
168.	Pakistan International Container Terminal
169.	Pakistan National Shipping
170.	Pakistan Oilfields
171.	Pakistan Petroleum

No.	Firm
172.	Pakistan PTA
173.	Pakistan Refinery
174.	Pakistan Services
175.	Pakistan State Oil
176.	Pakistan Synthetic
177.	Pakistan Tobacco
178.	Paramount Spinning Mills
179.	PICIC Growth Fund
180.	PICIC Investment Fund
181.	Pioneer Cement
182.	Prudential Dis. House
183.	PTCLA
184.	Quality Textile Mills
185.	Rafhan Maize Products
186.	Rupali Polyester
187.	S G Fibers
188.	Saif Textile Mills
189.	Samin Textile Mills
190.	Sana Industries
191.	Sanofi-Aventis
192.	Sapphire Fibers
193.	Sapphire Textile Mills
194.	Saudi Pak Commercial Bank
195.	Sazgar Engineering
196.	Searle Pakistan
197.	Security Investment Bank
198.	Security Paper
199.	Service Industries
200.	Shabir Tiles
201.	Shadman Cotton Mills
202.	Shaffi Chemical Industries
203.	Shaheen Insurance
204.	Shahtaj Sugar Mills
205.	Shakarganj Mills
206.	Shell Pakistan
207.	Siemens Engineering

No.	Firm
208.	Sitara Chemical Industries
209.	Soneri Bank
210.	Southern Electric Power
211.	Standard Chartered Modaraba
212.	Sui Northern Gas
213.	Sui Southern Gas
214.	Sunshine Cotton Mills
215.	Syed Match Co.
216.	Taj Textile Mills
217.	Telecard
218.	Thal
219.	Tri-Pack Films
220.	Tri-Star Polyester

No.	Firm
221.	Trust Investment Bank
222.	Trust Modaraba
223.	Unicap Modaraba
224.	Unilever Pakistan
225.	Unilever Pakistan Foods
226.	United Bank
227.	United Sugar Mills
228.	Wazir Ali Industries
229.	Worldcall Telecom
230.	Wyeth Pakistan
231.	Zeal Pakistan Cement

Appendix 2

Results obtained from one-factor and two-factor models

One-factor model

Table A1 gives the estimates and averages obtained from the one-factor model in which the excess returns on 25 portfolios are regressed separately on RM-RF, SMB, HML, and HVaRL. It is evident from the table that, when these factors are employed individually, RM-RF captures more common variation in stock returns than HVaRL, SMB, or HML. All the market slopes are statistically significant. The average slope coefficient of RM-RF is 0.547. HVaRL captures a greater degree of time series variation in portfolio returns, even when used alone. These findings are consistent with Bali and Cakici (2004) and Chen et al. (2009). All the slope coefficients are statistically significant at the 1 percent level. The average slope of HVaRL is 1.002 and the t-statistics range from 3.38 to 14.14. The average adjusted R-squared value is 0.322.

The results also show that the portfolios with the highest book-to-market value are more sensitive to changes in HVaRL and have larger statistically significant coefficients than the other portfolios. Relative to the other factors, HVaRL has a higher degree of explanatory power for the portfolios in the large-cap stock quintile than SMB and HML. Specifically, the average adjusted R-squared value for HVaRL is 0.322 while the corresponding range for SMB and HML is 0.078–0.148, respectively.

SMB, which mimics the factor in returns related to size, has less explanatory power than HVaRL and HML. Nine of the slope coefficients are statistically insignificant and 18 of the adjusted R-squared values are less than 0.1. As expected, the SMB slopes are related to size: in every BE/ME for SMB, the slopes generally decrease from smaller to larger size quintiles. HML, when used alone, explains the large difference in contrast to SMB: three of its slope coefficients are statistically insignificant and 11 of the adjusted R-squared values are less than 0.1. Clearly, the slopes for HML are systematically related to BE/ME. In every size quintile of stocks, the HML slopes generally increase from lower to higher BE/ME quintiles.

Table A1: One-factor model: Regression of excess stock returns on RM-RF, SMB, HML, and HVaRL

BE/ME quintile

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.547)					**t-statistics**				
Small	0.361*	0.498*	0.436*	0.420*	0.329*	4.31	6.69	5.21	6.02	3.07
2	0.246*	0.480*	0.230*	0.455*	0.655*	4.00	8.34	4.66	8.83	7.82
3	0.465*	0.406*	0.416*	0.616*	0.781*	8.65	7.28	7.72	12.04	13.06
4	0.402*	0.436*	0.416*	0.555*	1.168*	7.82	9.33	9.68	11.57	18.78
Big	0.600*	0.714*	0.844*	0.647*	1.120*	8.99	18.40	26.81	14.93	35.69
	Adjusted R^2 (average = 0.359)					**SSE**				
Small	0.099	0.214	0.140	0.180	0.050	0.10	0.09	0.10	0.09	0.13
2	0.085	0.299	0.114	0.323	0.272	0.08	0.07	0.06	0.06	0.10
3	0.314	0.244	0.267	0.472	0.513	0.07	0.07	0.07	0.06	0.07
4	0.272	0.348	0.365	0.452	0.686	0.06	0.06	0.05	0.06	0.08
Big	0.331	0.677	0.817	0.580	0.888	0.08	0.05	0.04	0.05	0.04
	HVaRL slope (average = 1.002)					**t-statistics**				
Small	1.255*	1.272*	0.551*	1.002*	1.493*	9.54	10.58	3.38	8.36	8.86
2	0.615*	0.852*	0.541*	0.865*	1.731*	5.59	7.80	6.13	9.10	14.14
3	0.741*	0.581*	0.760*	1.152*	1.471*	6.97	5.25	7.55	12.14	13.35
4	0.803*	0.861*	0.639*	1.002*	1.943*	8.63	10.24	7.31	10.91	14.01
Big	0.587*	0.987*	1.029*	0.889*	1.443*	4.04	9.76	9.28	8.59	10.88
	Adjusted R^2 (average = 0.322)					**SSE**				
Small	0.360	0.410	0.061	0.301	0.326	0.09	0.08	0.11	0.08	0.11
2	0.159	0.272	0.186	0.338	0.554	0.07	0.07	0.06	0.06	0.08
3	0.229	0.143	0.259	0.478	0.526	0.07	0.07	0.07	0.06	0.07
4	0.315	0.394	0.247	0.424	0.550	0.06	0.06	0.06	0.06	0.09
Big	0.088	0.371	0.347	0.313	0.423	0.10	0.07	0.07	0.07	0.09
	SMB slope (average = -0.280)					**t-statistics**				
Small	0.653*	0.213	-0.082	0.218	1.087*	3.67	1.21	-0.44	1.36	5.05
2	0.268**	-0.126	0.226**	0.012	-0.008	2.01	-0.87	2.08	0.10	-0.04
3	-0.432*	-0.201	-0.139	-0.315**	-0.649*	-3.27	-1.51	-1.05	-2.16	-3.75
4	-0.152	-0.304**	-0.385*	-0.379*	-1.416*	-1.21	-2.55	-3.52	-2.85	-6.92
Big	-1.107*	-0.834*	-1.054*	-0.700*	-1.420*	-7.50	-6.54	-8.08	-5.41	-8.78
	Adjusted R^2 (average = 0.078)					**SSE**				
Small	0.072	0.003	-0.005	0.005	0.132	0.10	0.10	0.11	0.09	0.13
2	0.018	-0.001	0.020	-0.006	-0.006	0.08	0.08	0.06	0.08	0.12
3	0.057	0.008	0.001	0.022	0.075	0.08	0.08	0.08	0.09	0.10
4	0.003	0.033	0.066	0.042	0.225	0.07	0.07	0.06	0.08	0.12

Size quintile	Low	2	3	4	High	Low	2	3	4	High
Big	0.255	0.206	0.286	0.149	0.321	0.09	0.08	0.08	0.08	0.10
	HML slope (average = 0.712)					t-statistics				
Small	0.037	0.683*	0.948*	0.996*	1.510*	0.21	4.20	5.63	7.34	7.94
2	0.106	0.394*	0.485*	0.645*	1.469*	0.81	2.88	4.86	5.50	9.00
3	0.404*	0.389*	0.455*	0.846*	1.283*	3.15	3.06	3.70	6.66	9.01
4	0.464*	0.750*	0.547*	0.852*	1.589*	3.96	7.35	5.40	7.48	8.44
Big	-0.013	0.506*	0.724*	0.554*	1.190*	-0.08	3.79	5.22	4.29	7.16
	Adjusted R^2 (average = 0.148)					SSE				
Small	-0.006	0.094	0.160	0.247	0.278	0.11	0.10	0.10	0.08	0.12
2	-0.002	0.043	0.123	0.154	0.332	0.08	0.08	0.06	0.07	0.10
3	0.052	0.049	0.073	0.212	0.332	0.08	0.08	0.07	0.08	0.09
4	0.084	0.248	0.149	0.255	0.304	0.07	0.06	0.06	0.07	0.11
Big	-0.006	0.077	0.140	0.098	0.238	0.10	0.08	0.08	0.08	0.10

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. The table reports statistics for the period January 1995 to June 2008.
Source: Authors' calculations.

Two-factor model

In order to determine the relative efficacy of the VaR factor, we consider a set of two-factor models in which the monthly returns on the 25 portfolios are regressed on RM-RF along with SMB, HML, or HVaRL. The results are given in Table A2. Interestingly, the RM-RF and HVaRL two-factor model captures a greater degree of time variation in portfolio returns than the other two-factor models.

Panel A of the table gives the results of the excess stock returns regressed on RM-RF and HVaRL. When used alone, RM-RF has a low degree of explanatory power in terms of the adjusted R-squared value. However, when HVaRL is added to the regression, both variables capture a larger time series variation. RM-RF, when used alone, yields an average adjusted R-squared value of 0.359 (Table A1). In the two-factor regressions (Table A2, panel A), the average adjusted R-squared value is 0.452. The t-statistics for the RM-RF slopes are generally greater than 2.

As expected, 22 of the 25 HVaRL coefficients are statistically significant at the 1 percent level. The t-statistic ranges from –0.7 to 10.0. Panel B of Table A2 gives the regression results for the portfolios with RM-RF and SMB. The betas for stocks are all between 0 and 2. Six of the SMB slope coefficients are insignificant and the average adjusted R-squared value is 0.454.

Table A2: Two-factor model: Regression of excess stock returns on RM-RF and HVaRL or SMB or HML

BE/ME quintile

Panel A: RM-RF and HVaRL

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.352)					**t-statistics**				
Small	-0.056	0.147***	0.400*	0.158**	-0.220**	-0.64	1.85	3.86	2.00	-1.99
2	0.078	0.324*	0.089	0.278*	0.164**	1.07	4.74	1.54	4.68	2.04
3	0.353*	0.340*	0.267*	0.384*	0.483*	5.43	4.96	4.18	6.94	7.73
4	0.225*	0.249*	0.327*	0.365*	0.844*	3.81	4.77	6.29	6.78	13.23
Big	0.635*	0.616*	0.795*	0.561*	1.015*	7.68	13.29	20.63	10.67	27.94
	HVaRL slope (average = 0.614)									
Small	1.315*	1.107*	0.113	0.826*	1.735*	8.09	7.48	0.58	5.62	8.42
2	0.529*	0.493*	0.443*	0.558*	1.550*	3.90	3.88	4.08	5.05	10.37
3	0.353*	0.205	0.469*	0.731*	0.941*	2.92	1.61	3.95	7.10	8.09
4	0.555*	0.588*	0.280*	0.601*	1.019*	5.04	6.04	2.90	6.00	8.59
Big	-0.111	0.310*	0.155**	0.272*	0.330*	-0.72	3.60	2.16	2.79	4.89
	Adjusted R^2 (average = 0.452)					**SSE**				
Small	0.357	0.415	0.136	0.311	0.339	0.09	0.08	0.10	0.08	0.11
2	0.160	0.355	0.193	0.413	0.563	0.07	0.07	0.06	0.06	0.08
3	0.345	0.252	0.328	0.597	0.653	0.06	0.07	0.06	0.06	0.06
4	0.368	0.466	0.393	0.550	0.784	0.06	0.05	0.05	0.05	0.06
Big	0.329	0.700	0.821	0.597	0.902	0.08	0.05	0.04	0.05	0.04

Panel B: RM-RF and SMB

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.714)					**t-statistics**				
Small	0.827*	0.850*	0.629*	0.732*	0.964*	10.08	10.75	6.27	9.73	9.52
2	0.489*	0.678*	0.446*	0.698*	0.995*	7.12	10.26	8.32	12.78	10.69
3	0.524*	0.532*	0.574*	0.804*	0.914*	7.93	7.96	9.09	13.86	12.72
4	0.547*	0.534*	0.470*	0.684*	1.175*	9.04	9.49	8.92	12.05	15.27
Big	0.442*	0.732*	0.837*	0.688*	1.100*	5.55	15.27	21.48	12.89	28.40
	SMB slope (average = 0.596)									
Small	1.670*	1.257*	0.690*	1.118*	2.272*	9.70	7.59	3.28	7.09	10.69
2	0.869*	0.706*	0.774*	0.871*	1.214*	6.03	5.10	6.88	7.60	6.22
3	0.211	0.452*	0.566*	0.672*	0.473*	1.53	3.22	4.27	5.52	3.14
4	0.519*	0.352*	0.192***	0.461*	0.027	4.10	2.98	1.74	3.87	0.17
Big	-0.563*	0.065	-0.026	0.145	-0.068	-3.37	0.65	-0.32	1.30	-0.85
	Adjusted R^2 (average = 0.454)					**SSE**				
Small	0.430	0.419	0.189	0.373	0.444	0.08	0.08	0.10	0.08	0.10
2	0.251	0.393	0.313	0.501	0.411	0.07	0.07	0.05	0.05	0.09
3	0.320	0.286	0.338	0.554	0.539	0.07	0.07	0.06	0.06	0.07

Size quintile	Low	2	3	4	High	Low	2	3	4	High
4	0.337	0.379	0.373	0.496	0.684	0.06	0.06	0.05	0.06	0.08
Big	0.372	0.676	0.816	0.581	0.888	0.08	0.05	0.04	0.05	0.04

Panel C: RM-RF and HML

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	RM-RF slope (average = 0.484)					**t-statistics**				
Small	0.418*	0.433*	0.299*	0.268*	0.044	4.62	5.40	3.44	3.86	0.44
2	0.267*	0.478*	0.161*	0.391*	0.439*	3.99	7.61	3.09	7.14	5.47
3	0.457*	0.391*	0.388*	0.535*	0.631*	7.80	6.44	6.63	10.03	10.92
4	0.369*	0.344*	0.367*	0.462*	1.018*	6.63	7.24	8.01	9.46	16.76
Big	0.713*	0.729*	0.833*	0.639*	1.052*	10.31	17.26	24.30	13.52	33.50
	HML slope (average = 0.324)									
Small	-0.297	0.3365**	0.7084*	0.781*	1.474*	-1.61	2.06	4.00	5.51	7.11
2	-0.107	0.011	0.357*	0.332**	1.117*	-0.79	0.09	3.37	2.99	6.84
3	0.038	0.076	0.145	0.418*	0.779*	0.33	0.62	1.22	3.86	6.63
4	0.169	0.475*	0.253*	0.482*	0.775*	1.49	4.92	2.72	4.85	6.28
Big	-0.584*	-0.077	0.058	0.043	0.349*	-4.15	-0.90	0.84	0.45	5.47
	Adjusted R^2 (average = 0.405)					**SSE**				
Small	0.108	0.229	0.213	0.307	0.275	0.10	0.09	0.10	0.08	0.12
2	0.083	0.294	0.168	0.355	0.434	0.08	0.07	0.06	0.06	0.09
3	0.310	0.241	0.269	0.514	0.616	0.07	0.07	0.07	0.06	0.07
4	0.278	0.431	0.390	0.520	0.747	0.06	0.05	0.05	0.06	0.07
Big	0.393	0.677	0.816	0.577	0.905	0.08	0.05	0.04	0.05	0.04

Note: *, **, and *** = significant at 1, 5, and 10 percent, respectively. The table reports statistics for the period January 1995 to June 2008.
Source: Authors' calculations.

HML, when used together with RM-RF, captures a smaller degree of time series variation in stock returns compared to SMB. As panel C shows, ten of the HML coefficients are statistically insignificant and the average adjusted R-squared value is 0.405. As in Table A1, the slopes of SMB and HML are related to, respectively, size and BE/ME. In every BE/ME quintile, the SMB slopes generally decrease from smaller to larger size quintiles. In every size quintile of stocks, the HML slopes generally increase from negative values for the lowest BE/ME quintile to positive values for the highest BE/ME quintile.