Modelling Volatility in Measuring Market Risk with Value-at-Risk (VaR): Evidence From Pakistan

SHAKEEL AHMAD
MBA (Scholar) Department of Management Sciences
Bacha Khan University, Charsadda, Pakistan
shakeelahmad.bkuc@hotmail.com

MUHAMMAD NISAR KHAN
Lecturer in Finance, Department of Management Sciences
Bacha Khan University, Charsadda, Pakistan
nisarmgmt@bkuc.edu.pk

DR. MUHAMMAD ILYAS
Lecturer in Finance, Institute of Business Studies and Leadership
Abdul Wali Khan University, Mardan
Milyas_79@awkum.edu.pk

DR. IHTISHAM KHAN
Assistant Professor in Finance, Institute of Business Studies and Leadership
Abdul Wali Khan University, Mardan
ihteshamkhan@awkum.edu.pk

Abstract
This research work is done to examine the best volatility forecasting model for measuring market risk. The models used for finding the volatility of stock returns were SMA, EWMA and GARCH. The proxy used for measuring market risk is value-at-risk (VaR) method. Variance-Covariance method is used for the calculation of VaR to measure market risk. The daily data of stock return has been used in this study and collected from Pakistan Stock Exchange (PSX). The analysis start with ADF test to check the order of integration of all selected variables. After applying augmented dickey fuller (ADF) test for stationarity, the variables were stationary at level. The regression test were then applied to check that which forecasting model is best to measure the market risk through VAR, the regression analysis result exhibits that volatility forecasting model simple moving average (SMA) is 99% best model used for measuring market risk.

Keywords: PSX-100 index, SMA, EWMA, GARCH, market risk and Value-at-risk (VaR)

1. Introduction
From the past several years’ financial risk management play very important role in the financial market. Market risk is risk of adverse change in price or rates such as stock prices, exchange rates, interest rates and energy prices (Szylar, 2013). This market risk
can measure by various methods but in this paper we used value-at-risk method because it is most popular and most widely used method and give more accurate results than other methods. During 1990’s VaR was broadly approved for calculating market risk. Its basis drawn back from 1922. VaR method calculate market risk by concluding in what way greatly the company worth might decay over a specified dated with a specified possibility as outcome of fluctuations in market prices. It is broadly used by monetary institutions, stock supervisors, and nonfinancial companies to regulate the market risk in a portfolio of financial instruments. This paper emphasis on the statistical models of volatility (SMA, EWMA and GARCH models) in financial market of Pakistan stock exchange PSX-100 index Pakistan. A question is to be raised and answered that is which econometric volatility forecasting model is best for measuring market risk?

There are two significant studies that have put encouragements to excite the assessment of financial risk management. The first supportive study is to approximate and forecast volatility. From the past decade’s volatility has one of the utmost important and vigorous research area in time series econometrics and empirical finance. We define volatility is a statistical measure of the trend of a market or security to increase or decrease harshly within a specified period of time. Volatility has a giant use in finance and at an elementary level is a proxy for the riskiness of an asset. Volatility forecasting models have been firstly deliberate by Engle (1982) in the educational world. Many new studies track Engle’s original volatility forecasting work. In this paper volatility measured by three most popular volatility models SMA, EWMA and GARCH.

Another study is established by JP Morgan called Risk Metrics technique (1994). In 1994 the concept of VaR was first introduce by JP Morgan he defines “The expected worst-case loss at a precise confidence level (e.g. 95%, 99%) over specified period of time. VaR will come to be the typical measure that financial experts will custom to measure market risk. There are different methods for the calculation of value-at-risk but in this paper we used variance-covariance method which is most popular method. The main objective of this paper is to determine the impact of different econometric models of volatility forecasting on measuring market risk with VaR, these econometric volatility models are SMA, EWMA and GARCH. This paper is arranged in the following order, section 1 give explanation of the data used in the study, section 2 give argues about methodology and test used, section 3 shows the actual results of the research, and in section 4 there is conclusion of the study.

2. Literature Review
(Ahmed et al., 2005) examined the stock return volatility of Kuala Lumpur’s stock exchange in Malaysia by using the GARCH model to study the volatility behaviour of returns. The result showed that GARCH was the appropriate model for calculating the volatility of returns. Iqbal and Azher (2010) investigate the accuracy of volatility models SMA, EWMA and GARCH for Pakistan stock market. They collected daily data from January 1992 to June 2008 from KSE-100 index. He calculates VaR through historical simulation. He selected Kupiec (1995) Likelihood Ratio procedure of backtesting. He found that at 95% confidence level GARCH method gave more accurate VaR. (McMillan et al., 2006) studied the UK stock market for volatility forecasting and to investigate the performance of ten different models employed, which included asymmetrical well as symmetric variants. In the situation of monthly returns series, RWM delivered better
volatility forecasts compared with the other models. Concerning the weekly returns series, the simple moving average (SMA), recursive smoothing and RWM performed better while, in the situation of daily returns series, the GARCH model, exponential smoothing and the SMA model provided better forecasts for volatility. The research study found that the most reliable models for forecasting volatility were the GARCH and SMA models. Marra (2015) determined the best volatility forecasting model. He compared volatility models SMA, EWMA, DHM, ARMA and ISDM. His consequences revealed that SMA model is the best model volatility forecasting for the shorter period used, the extra penetrating to shorter-term variations in volatility and hence the more possible this model is to over-estimate future volatility. EWMA work for longer period of time but some time EWMA break and under-estimate the risk. He also concluded that some model are best for equity indices and some are better predicting interest rate and currencies rate. SMA is the best model for indices. Angelovska (2010) described in his research study about the volatility forecasting models. He selected SMA, EWMA and GARCH models for modelling and volatility estimating of high developing stock markets and he set up that simple moving average (SMA) and exponentially weighted moving average (EWMA) implemented reliably over the time. But in comparison of SMA and EWMA model, SMA model was best fit for measuring market risk. Kayahan and Kandemir, (2015) clarified in his research that the volatilities of exchange rates of GBP/TRY and EUR/TRY was expected by the help of SMA, EWMA and GARCH models. By the companion of their volatilities estimates they found that the EWMA model proved well performed for both exchange rates compared to SMA and GARCH while GARCH perform better than SMA. Tse (1991) and Tung (1992) examined the data of Singaporean and Japanese stock exchange and set up that an exponentially weighted moving average (EWMA) model produced more accurate volatility predictions than simple moving average (SMA). Fernando and Leonel (2007) explained three model of forecasting volatility in his research the models are GARCH, EWMA and stochastic volatility (SV). In his research they used these models for volatility prediction to calculate the market risk of a portfolio of assets. They compare the efficiency of these models and result shows that volatility calculated by EWMA in measuring market risk through VaR was more reliable and give more accurate volatility forecasting than others. Guo (2012) studied two different volatility methods in his research paper. The methods were EWMA and GARCH model he collected two different actual stock data (Pectro Chian and TCL) from two different stock exchange market (Shanghai stock exchange and Shenzhen exchange market) respectively to analyse two volatility prediction methods (EWMA and GARCH). After completion of all calculation he compares the result of two methods and concluded that the GARCH model is superior to EWMA model in both the instance of Petro China and TCL. Lehar and Scheicher (2002) done research work on determination of more appropriate predicting volatility model they found that greater complex volatility models like GARCH and Stochastic volatility are not capable to increase on persistent volatility models for VaR calculation, even though these models perform well for option pricing. McMillan (2000) tried to done his research work on ten different volatility forecasting models comprising random walk, simple moving average and Generalized Auto Regressive Conditional Heteroscedasitcity (GARCH) models in
estimating UK stock market returns at different incidences. He set up that the progress of every model was different depending on the length of incidences, the sequence as well as the type of loss function being applied. The random walk model was giving more accurate result than others at the monthly incidence, whereas GARCH and SMA models were giving more accurate result for daily forecasts.

2.1 Hypotheses

H1. SMA (volatility) and market risk are related
H2. EWMA (volatility) and market risk are related
H3. GARCH (volatility) and market risk are related

3. Data and Statistical Methodology

This study based on the sample data which is collected from of PSX-100 index. This study employ’s data including the closing observation of PSX-100 index. This study cover a period of 7 years from 2008-2014 daily data is used. The PSX-100 stock return is calculated through

\[ Rt = \ln \left( \frac{P_1}{P_0} \right) \]

For the daily returns the \( R_t \) represent the daily returns \( P_1 \) represented the closing price on the given day and \( P_0 \) represented the closing price on the day previous to \( P_1 \).

This study further analysed to calculate the volatility through SMA, EWMA and GARCH then calculate market risk through VaR (variance-covariance method). After these calculations, we regressed volatility (SMA), (EWMA) and GARCH with Market risk (VaR).

3.1 Testing Stationarity: Unit Roots Tests

Numerous economic and financial time series reveal a tendencies or non-stationarity in the mean. If the time series variables have trend, then we apply Unit root tests to determine non-stationarity in the time series data. The Unit root tests use for checking the null hypothesis that against the alternative they are called unit root tests since, under the null hypothesis, the specific polynomial has a root equal to unity. There are numerous techniques which have been established to check the stationarity of time series data. The most innovative and progressive are Augmented Dickey- Fuller (ADF) test due to Dickey and Fuller (1979).

3.2 Augmented Dickey-fuller (ADF) Unit Root Test

As it is the assumption of regression analysis that the data must be normal (no trend). We first checked the normality of data there are different tests to check the Stationarity. We used ADF (augmented dickey fuller test) to check the Stationarity of the data. The ADF test tests whether a unit root is present in an autoregressive model. It is established by the statisticians David Dickey and Wayne Fuller in 1979.

3.3 Regression Model

Market risk = \( \alpha + \beta \) (volatility) (SMA)

Market risk = \( \alpha + \beta \) (volatility) (EWMA)

Market risk = \( \alpha + \beta \) (volatility) (GARCH)

3.4 Variables

This research consists of four variables

i. Simple moving average  ii. Risk Metrics (EWMA)  iii. GARCH
iv. Market risk
3.4.1 Independent Variables

3.4.1.1 Simple Moving Average (SMA)

Simple moving average is most widely used and easily applicable model from all others model. In SMA model the volatility is calculated by adding previous observations (closing price of some security) for the specified period of time and then dividing by the total number of time period it’s two democratic which give equal weight to past data. The formula for finding volatility is given

\[
\sigma_n^2 = \frac{1}{m} \sum_{i=1}^{m} U_{n-i}
\]

The moving average is an arithmetic mean of all selected variables e.g. stock prices for the specific time. In SMA the term moving express that every new prices is added and the eldest ones subsequently removed. The SMA model is possibly the greatest commonly applicable volatility model in VaR calculations.

3.4.1.2 Exponentially Weighted Moving Average (EWMA)

One of the most popular volatility models in risk management framework is the RiskMetrics model which is introduced by Morgan in 1995. This methodology was established by Morgan and Reuters, 1996. This is the improvement is simple moving average. These measures allocate more weights to current data points and less weight to distant data points. The reason is that current volatility is more linked to recent past than to distant past. This method presents lambda, which is named the smoothing parameter that sorts the EWMA a virtuous sign of the history of the price variations.

The formula used for finding volatility is given below

\[
\sigma_n^2 = \lambda \sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2
\]

The first term exhibit volatility in the previous period and the second term exhibit news shock of the previous period. But in this study we estimate the decay factor by using maximum likelihood estimation.

3.4.1.3 GARCH (Generalized Auto Regressive Conditional Heteroscedasticity)

GARCH is an extension of an ARCH model. ARCH was first introduce by Engle (1982) and GARCH by Bollerslev (1986 GARCH is process that contains historical discrepancies in the clarification of upcoming discrepancies. Further precisely, GARCH is a time series econometric model that uses prior errors and prior discrepancy estimates to estimate upcoming discrepancies (Akgiray, 1989; Bollerslev et al., 1992). GARCH modeling takes into account excess kurtosis (fat tail behavior) and volatility clustering. It delivers correct estimates of variances and covariance of returns through its ability to model time-varying conditional variances. GARCH models is more appropriate for option pricing, inflation rate, and foreign exchange rate among others. GARCH model is broadly used in financial markets investigation however it has numerous kinds. Several further investigators have further different developments in this model. In GARCH (1, 1) we assign some weight to the long-run average variance rate. The equation for basic GARCH (1, 1) model:

\[
\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2
\]

Since weights must sum to 1

\[
\alpha + \beta + \gamma = 1
\]
Setting \( w = \gamma V \) the GARCH (1, 1) model is

\[
\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2
\]

\[
V_L = \frac{\omega}{1 - \alpha - \beta}
\]

Comparing EWMA with GARCH equation

\[
\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2, \quad \sigma_n^2 = \lambda \sigma_{n-1}^2 + (1 - \lambda) u_{n-1}^2
\]

Realised from the above equations, \( \beta \) factor is identical as \( \lambda \) (exponential factor) in EWMA equation. Correspondingly, \( \alpha \) factor is identical as \( (1 - \lambda) \) in EWMA equation. In GARCH equation, taking of \( \omega = 0 \) creates EWMA equation a superior form of GARH equation.

3.4.2 Dependent Variable

3.4.2.1 Market Risk

Market risk is defined as the risk of financial losses due to changes in the market prices. It also that risk by which the value of investment decrease. It is also known as systematic risk cannot be removed through diversification (Szylar, 2013).

3.4.2.2 Proxy of Market risk (Value-at-risk)

VaR method calculate market risk by concluding in what way greatly company worth might decay over a specified dated with a specified possibility as outcome of fluctuations in market prices. It is broadly used by monetary institutions, stock supervisors, and nonfinancial companies to regulate the market risk in a portfolio of financial instruments. Throughout 1990’s, VaR had been broadly approved for determining market risk in trading portfolios. Its basis drawn back from 1922. Leavens (1945) gave numerical case, which could be major VaR measure continually issued Markowitz (1952) and three months later Roy (1952) autonomously allotted VaR measures that were unexpectedly alike. There are many methods for calculating VaR i.e. variance-covariance method, historical simulation and monte-carlo simulation. Most researcher choose variance-covariance method therefore we also choose this method for manipulating VaR.

3.4.2.3 Variance-covariance method

Variance-Covariance is the straightforward method for calculating VaR this method was first used by RiskMetrics methodology and introduced by Morgan. It is also known as Linear VAR. This method is fairly simple and broadly used. The primary and the most significant fact of this method is that it’s only used when the data is normal. This method calculates VaR by supposing some theoretical distribution of time series returns. Generally normal distribution is used. This statements permits volatility to be described in terminologies of standard deviations (SD). Lastly VaR for portfolio can be calculated using following formula:

\[
\text{VaR} = \sigma \cdot Z
\]

Where: \( Z \) is specific value for the specific confidence interval ( \( Z \)- value calculated from confidence level using formula “NORMSINV” in Excel), \( \sigma \) - standard deviation of time series returns.
4. Results and Discussion
Volatility of stock market returns is calculated by using three well-known volatility models SMA, EWMA and GARCH. Market risk is calculated by most widely used method value-at-risk model (variance-covariance method) to check the stationarity of stock market returns volatilities and market risk ADF Augmented dickey fuller test is used for which Ho null hypothesis is that there is a unit root. Table 1, shows the result of ADF Augmented Dickey fuller test for unit root. Table 1 exhibits the augmented dickey fuller test results for Unit Root of market risk through Value-at-risk method using different volatility models (SMA, EWMA and GARCH) and Volatility of stock market through SMA, EWMA and GARCH.

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF test values</th>
<th>Order of integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility (SMA)</td>
<td>-4.975443</td>
<td>I(0)</td>
</tr>
<tr>
<td>Volatility (EWMA)</td>
<td>-5.270374</td>
<td>I(0)</td>
</tr>
<tr>
<td>Volatility (GARCH)</td>
<td>-7.866865</td>
<td>I(0)</td>
</tr>
<tr>
<td>VAR (SMA)</td>
<td>-4.975583</td>
<td>I(0)</td>
</tr>
<tr>
<td>VAR (EWMA)</td>
<td>-7.273517</td>
<td>I(0)</td>
</tr>
<tr>
<td>Var (GARCH)</td>
<td>-5.516290</td>
<td>I(0)</td>
</tr>
</tbody>
</table>

ADF augmented dickey fuller test exhibits that all the data are at level therefore we will go directly for regression.

4.1 Regression Analysis
Regression analysis shows the dependency of one variable upon another. Table 2, 3 and 4 shows the result of regression analysis.

<table>
<thead>
<tr>
<th>variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>1.08E-06</td>
<td>1.57E-06</td>
<td>0.683373</td>
<td>0.4963</td>
</tr>
<tr>
<td>Volatility (SMA)</td>
<td>1.644848</td>
<td>0.000128</td>
<td>12804.29</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared 0.999999
Adjusted R-squared 0.999999
F-statistic 2.64674
Prob(F-statistic) 0.000000

4.2 Interpretation of Regression Analysis
The results obtain in table 3 the equation can be derived as.

\[
\text{Market risk} = 1.08E-06 + 1.644848 \times \text{Volatility (SMA)}
\]

The equation suggests that there exists significant positive relationship link in market risk and volatility (SMA). The value of coefficient shows that a unit increase in volatility will bring 1.64 unit change in market risk.
Table 3: Regression Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.001873</td>
<td>0.002694</td>
<td>0.695398</td>
<td>0.4888</td>
</tr>
<tr>
<td>Volatility (EWMA)</td>
<td>1.578525</td>
<td>0.274054</td>
<td>5.759899</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.288049</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.279366</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>33.17644</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.3 Interpretation of Regression Analysis

The results obtained in Table 4 can be derived as:

Market risk = 0.001873 + 1.578525 * Volatility (EWMA)

The equation suggests that there exists a significant positive relationship link in market risk and volatility (EWMA). The value of the coefficient shows that a unit increase in volatility will bring 1.57 unit change in market risk.

Table 4: Regression Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.012997</td>
<td>0.001164</td>
<td>11.16762</td>
<td>0.0000</td>
</tr>
<tr>
<td>Volatility (GARCH)</td>
<td>0.264747</td>
<td>0.072319</td>
<td>3.660845</td>
<td>0.0004</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.140477</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.129995</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>13.40179</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000444</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.4 Interpretation of Regression Analysis

The results obtained in Table 5 can be derived as:

Market risk = 0.012997 + 0.264747 * Volatility (GARCH)

The equation suggests that there exists a significant positive relationship in market risk and volatility (GARCH). The value of the coefficient shows that a unit increase in volatility will bring 0.264 unit change in market risk.

5. Conclusion

Forecasting is the basis of all financial models and volatility is known as the recognition of that forecasting. Numerous features of financial return series create volatility essentially expectable. Conversely, volatility is stochastic in nature, a volatility model will completely capture the present and upcoming behaviour of volatility but there is no such past data. Throughout the sample period a model be able to estimate the behaviour of volatility examined and estimate precision. This research shows the best volatility model used for measuring market risk in Pakistan. There are different volatility models but SMA, EWMA and GARCH models are most popular and widely used for measuring market risk. There are few studies that have compared SMA, EWMA and GARCH.
models used in measuring market risk in developing market. In this research daily data is used. The daily data from January 2008 to December 2014 is used to find the best model in all of these for measuring market risk. It is concluded from the unit root test that all the data are at level therefore go directly for regression analysis. The regression analysis showed that the adjusted R-squared of SMA is 0.99999, EWMA is 0.279366 and GARCH is 0.129995 from this result it is concluded that SMA model is 99% best model for volatility forecasting to measure market risk. Other models EWMA and GARCH are also accurate but SMA is more accurate than others. These result are consistent to (Marra, 2015; Angelovska, 2010; (McMillan, 2006).

References
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