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Forecasting Portfolio Risk Estimation by Using Garch And Var Methods

1. Noor Azlinna Azizan, Faculty of Technology, Universiti Malaysia Pahang, Lebuhraya Tun Razak, 26300 Kuantan, Pahang, Malaysia.
Tel: 609 549 2634
2. Lee Chia Kuang, Faculty of Technology, Universiti Malaysia Pahang, Lebuhraya Tun Razak, 26300 Kuantan, Pahang, Malaysia.
3. Zeenat Ahmed, Institute of Mathematical Scicences, Universiti of Malaya, Malaysia.
*Corresponding author: Email: azlinna@ump.edu.my

Abstract

Risk management or risk predicting are closely related with the market volatility which affect the return of portfolio estimation. Portfolio managers around the world concerned with risk estimation because portfolio risk management is part of their decision-making process. According to Hull (2006), VaR is widely used by fund managers "to provide a single number summarizing the total risk in a portfolio of financial assets." Motivates from this, we conducted an analysis to compare the effectiveness of VaR analysis and GARCH method in forecasting risk estimation. Risk manager can used the best methods in reducing their customers risk volatility and rank the risk level.

Keywords: Forecasting, Value at Risk, GARCH, Portfolio estimation, Risk.

1. Introduction

Value at risk (VaR) is widely used by banks, securities firms, commodity merchants, energy merchants, and other trading organization. Such firms could track their portfolio market risk by using historical volatility as a risk metric. VaR has become a very popular measure of market risk. VaR is the loss on the portfolio that will not be exceeded with a specified probability over a specified time horizon. VaR is an extremely powerful risk measure, because looks at downside risk, that is well suited for asymmetrical distribution, and because in principle it can calculated assuming any kind of distribution of portfolio returns. VaR is widely used for controlling traders, for determining capital requirements and for disclosure to external subjects, both investors and regulators. (Raffaele.Z &Massimiliano.P, 2000)

Adapting VaR measures for asset managers (rather than traders) involves finding a proper way to model future scenarios, preserving the multivariate properties of asset returns, when time horizon is relatively long. According to Raffaele.Z &Massimiliano.P, (2000) the VaR concept has been further extended to the portfolio value at risk (PVaR) measure used to evaluate the maximum potential loss of a portfolio with a given probability over a specified period (Manganelli & Engle, 2002).

Accordingly, our paper explores the question of whether VaR analysis is better than GARCH model in forecasting risk. We will compare different VaR analysis methods such as historical simulation method and normal distribution. They are several importances; first, practitioners are rediscovering the importance of portfolio risk management as part of their decision-making process. Second, Levy and Levy (2004) show that this model can be used for making portfolio selection decisions and third according to Hull (2006, p. 435) notes, VaR is widely used by fund managers "to provide a single number summarizing the total risk in a portfolio of financial assets." Finally, the economic losses arising from ignoring estimation risk can be particularly large (see, e.g., Best and Grauer (1991), Chopra and Ziemba (1993), and Chan, Karceski, and Lakonishok (1999)).

2. Methodology

Description of the data

The data set consists of daily stock indices between 2000 and 2009 for the following market:

a) Malaysia Kuala Lumpur composite Index (KLCI).
b) India: Bombay Stock Exchange (BSE).
c) Japan: Nikkei Stock Average 225.

d) Singapore: Straits Times Index.

3. Data Analysis and Discussions

3.1 Distributions of Returns

The following tables display the results for normality test for the data tested.

Table 1: Normality test results

Return	**Malaysia**	**Singapore**	**India**	**Japan**
Test Stat	6877.7579	1377.4592	1869.6736	377.8534
p.value	0.000	0.000	0.000	0.000

Dist. under Null: chi-square with 2 degrees of freedom
Based on table 1, the null of normality is rejected using this test since P value is less than 0.05 and it is significant.

Table 2: Descriptive Statistics for daily returns

Return	**Mean**	**Std Dev**	**Skewness**	**Kurtosis**
MALAYSIA	0.00029333	0.008987	-0.2071	11.886
JAPAN	-0.00001288	0.012090	-0.2467	5.026
INDIA	0.00083497	0.015889	-0.6754	7.437
SINGAPORE	0.00020421	0.010596	-0.3972	6.901

From the above table 2, we can see that daily return of market indexes have high Kurtosis for daily series. This means that the daily returns are not normally distributed, and the mean of daily return series is very close to zero. Daily returns for Malaysia has low standard deviations compare to other market indexes and India has the highest standard deviation so it will be more risky. When the data is not normal, unconditional volatility is not realistic. Conditional volatility is empirically observed and probably is the culprit behind fat-tailed asset returns.

3.2 Estimation of ARCH/GARCH Models

ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the previous innovations. To Test ARCH Effects we used the Lagrange multiplier (LM) principle can be applied. Consider the null hypothesis of no ARCH errors versus the alternative hypothesis that the conditional error variance is given by an ARCH (q) process. The test approach proposed in Engle [1982] is to regress the squared residuals on a constant and q lagged values of the squared residuals. From the results of this auxiliary regression, a test statistic is calculated as: $(N-q)\cdot R^2$

There is evidence to reject the null hypothesis if the test statistic exceeds the critical value from a chi-square distribution with q degrees of freedom.
Null Hypothesis H_0 :no ARCH effects

Table 3: Test for ARCH Effects for index return: Lagrange Multiplier (LM) Test

Index	**Malaysia**	**Singapore**	**India**	**Japan**
Test Stat	256.8870	149.8258	481.9420	150.1772
p.value	0.0000	0.0000	0.0000	0.0000

The above table 3, stated that the value of test Statistics for the four returns are very big if we compare it with statistical table for χ^2 with 33 degrees of freedom , so F is significant, so reject H_0 .There are ARCH effects. To avoid this problem we model all the market tested daily return using GARCH model.

The following tables 4(a),(b),(c) and (d) are the results for GARCH model for all the market tested.

Table 4(a): Results of GARCH model for daily return (Malaysia)

Model	**coefficient**	**Std.Error**	**t value**	**Pr(>|t|)**
ϕ_1	0.086901	0.03602	3.920	4.301×10^{-4}
β_1	0.6900000	0.04727	14.807	0.000
α_1	0.400000	0.04632	8.635	0.000
α_0	0.000001	2.604×10^{-7}	3.915	4.669×10^{-5}

AIC = -14395.62

Table 4, provides some descriptive statistics of KLCI daily return. The sample size data are 2086 observations. Our results show that GARCH(1,1) model is the most significant compare to other GARCH model with higher order rank and this is prove by the lowest AIC =14395.62. So our GARCH (1,1) model is the following.

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\sigma_t^2 = 0.000001 + 0.4 a_{t-1}^2 + 0.7 \sigma_{t-1}^2$$

where ε_t is a sequence of independent and identically distributed (iid) random variables with mean zero and variance 1, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$.

Table 4(b): Results of GARCH model for Singapore daily return

Model	**coefficient**	**Std.Error**	**t value**	**Pr(>|t|)**
ϕ_1	0.0751	0.04841	3.931	5.31×10^{-4}
β_1	0.7000	0.04035	17.348	0.000
α_1	0.4000	0.0426	9.380	0.000
α_0	1.283×10^{-6}	3.765×10^{-7}	3.407	0.0003341

AIC = -13416.12

For AIC value we choose the model with the smallest AIC value, from table 4(b) above the model has the smallest AIC value, which show that there is GARCH (1, 1) effects then

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\sigma_t^2 = 0.000001 + 0.4 a_{t-1}^2 + 0.7 \sigma_{t-1}^2$$

Where ε_t is a sequence of independent and identically distributed (iid) random variables with mean zero and variance 1, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$.

Table 4(c): Results of GARCH model for India daily return from

Model	value	Std.Error	t value	Pr(>|t|)
ϕ_1	0.09204535	0.02871	3.206	6.824×10^{-4}
β_1	0.70000000	0.05851	11.964	0.000
α_1	0.40000000	0.05033	7.948	1.554×10^{-15}
α_0	0.00001014	1.961×10^{-6}	5.170	1.282×10^{-7}

AIC = -11954.27

For AIC value we choose the model with the smallest AIC value, from table 4(c) above the model has the smallest AIC value, which show that there is GARCH (1, 1) effects, then

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\sigma_t^2 = 0.00001 + 0.4\, a_{t-1}^2 + 0.7\, \sigma_{t-1}^2$$

Table 4(d): Results of GARCH model for Japan Daily return

Model	Coefficient	Std.Error	t value	Pr(>|t|)
θ_1	0.08036	0.02679	3.000	1.366×10^{-3}
β_1	0.7000	0.06306	11.101	0.000
α_1	0.4000	0.04474	8.941	0.000
α_0	2.642×10^{-6}	8.318×10^{-6}	3.176	7.579×10^{-4}

AIC = -12673.89

For AIC value we choose the model with the smallest AIC value, from table 4(d) above the model has the smallest AIC value, which show that there is GARCH (1, 1) then

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\sigma_t^2 = 0.0000026 + 0.4\, a_{t-1}^2 + 0.7\, \sigma_{t-1}^2$$

Based on all table 4 (a), (b), (c) and (d) all market can be modeled by GARCH (1, 1). This means volatility is a function of lagged squared returns and lagged variances of one day. The coefficient of the ARCH effect (α1) is statistically significant at 1% significance level. This indicates that news about volatility from the previous periods has an explanatory power on current volatility. Similarly, the coefficient of the lagged conditional variance (β1) is significantly different from zero, indicating volatility clustering in all markets return series. The sum of (α1 + β1) coefficients is unity, suggesting that shocks to the conditional variance are highly persistent. This implies that wide changes in returns tend to be followed by wide changes and mild changes tend to be followed by mild Changes. A major economic implication of this finding for investors is that stock returns volatility occurs in cluster and as it is predictable.

From Table 4(a) (b), (c) and (d), we also notice that asymmetry (gamma) coefficient is positive. The sign of the gamma reflects that a negative shock induce a larger increase in volatility greater than the positive shocks. It also implies that the distribution of the variance of all market returns is left skewed, implying greater chances of negative returns than positive. The positive asymmetric coefficient is indicative of leverage effects evidence in Nigeria stock returns.

3.3 Value at Risk (VaR)

This section summarizes the steps for calculating Value-at-Risk (VaR) for a portfolio of equity assets using S-PLUS 7.0 and S+FinMetrics 2.0. VaR is computed using empirical quantiles, and the normal distribution. Some basic concepts of asset returns and portfolios, and defines the market risk concepts value-at-risk (VaR) and expected tail loss (ETL) (which is also called expected shortfall (ES)).

3.3.1 Asset Returns

The portfolio consists of i = 1, . . . , N equity assets. Let P_{it} denote the price of asset i at time t. The one-period simple return on asset i between times t − 1 and t is

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}}$$

3.3.2 Value-at-Risk Defined

Consider a one period investment in an asset with simple return R. Let $\$W_0$ denote the initial dollar amount invested. The value of the investment after one period in terms of the simple return is $\$W_1 = \$W_0(1+R)$

3.3.3 VaR Based on Simple Returns

For $\alpha \in (0,1)$, let q_α^R denote the α × 100% quintiles of the probability distribution of the simple return R. Usually, q_α^R is a low quartile such that α = 0.01 or α = 0.05. As a result, q_α^R is typically a negative number. The α × 100% dollar Value-at-Risk
($\$\mathrm{VaR}_\alpha$) is

$$\$\mathrm{VaR}_\alpha = -\ \$\mathrm{W}_0 \cdot q_\alpha^R$$

In words, $\$VaR_\alpha$ represents the dollar loss that could occur with probability α. By convention, it is reported as a positive number (hence the minus sign). The VaR as a percentage of the initial portfolio value is simply the (negative) low quartile of the simple return distribution:

$$VaR_\alpha = \frac{\$\mathrm{VaR}_\alpha}{\$\mathrm{W}_0} = -q_\alpha^R$$

3.3.4 Expected Tail Loss Defined

The α × 100% expected tail loss (ETL), in terms of the log return, is defined as ETLα = −E[r|r < $-VaR_\alpha$]
In words, the ETL is the expected (negative) return conditional on the return being less than the ·100% percentage VaR. If the initial investment is $\$W_0$, then the dollar ETL is \$ET L = $\$W_0$ × ET Lα

3.3.5 Historical Simulation

A different approach for VaR assessment is called Historical Simulation (HS). This technique is nonparametric and does not require distributional assumptions. This is because HS uses essentially only the empirical distribution of the portfolio returns.

Historical simulation is one of the popular ways of estimating VaR. It involves using past data in a very direct way as guide to might happen in the future. This data consists of the daily movements in all market variables over the period of time. The first step in this method is to identify the market variables affecting the portfolio. Then collect data on the movements in these market variables over the period of time.

The first simulation trial assumes that the percentage changes in each market variable are the same as those on the first day covered by the data, the second simulation trial assumes that the percentage changes in the portfolio value, ΔP is calculated for each probability distribution ΔP.
This defines a probability distribution for daily change in the value of portfolio.
Define v_i as the value of a market variable on day I and suppose that today is day m . The I th scenario assumes that the value of the market variables tomorrow will be $v_m \frac{v_i}{v_{i-1}}$

Historical simulation (HS) simply refers to the empirical distribution of the observed returns. As a result, the × 100% VaR based on HS is just the × 100% empirical quartile of the return distribution. (same idea is in Hull. J. C. 2006)

3.3.6 Normal Distribution

Assume the N ×1 vector of log-returns r has a multivariate normal distribution with mean vector μ and covariance matrix Σ, r ~ N(μ, Σ)

where μ has elements μ_i (i = 1, . . . , N) and Σ has elements σ_{ij} (i, j = 1, . . . , N). For an individual asset, r_i ~ N(μ_i, σ_i)

The α × 100% quartile of the normal distribution for r_i is $q_\alpha = \mu_i + \sigma_i q_\alpha$

Where q_α is the α × 100% quartile of the standard normal distribution. The distribution of r_i given that $r_i \leq q_\alpha$ is truncated normal. The mean of this distribution is the normal ETLα. Greene (2004) shows that

$$E[r_i / r_i \leq q^i_\alpha] = \mu_i + \sigma_i \times \frac{\phi(z^i_\alpha)}{\Phi(z^i_\alpha)}$$

where $z^i_\alpha = (\mu_i - VaR_\alpha)/\sigma_i$ $\phi(Z)$ is the standard normal PDF and $\Phi(Z)$ is the standard normal CDF.

Given a random sample of size T of observed returns on N assets from the multivariate normal distribution, the mean vector μ and covariance matrix Σ may be estimated using the sample statistics

$$\hat{\mu} = T^{-1}\sum_{t=1}^{T} r_t, \quad \hat{\Sigma} = T^{-1}\sum_{t=1}^{T}(r_t - \hat{\mu})(r_t - \mu)'$$

The normal quartile may then be estimated using the plug-in method

$\hat{q}^i_\alpha = \hat{\mu}_i + \hat{\sigma}_i q^z_\alpha$ where $\hat{\mu}_i$ is the ith element of $\hat{\mu}_i$, and $\hat{\sigma}_i$ is the square root of the ith diagonal element of $\hat{\Sigma}$.

Similarly, the estimate of normal ETLα is

$$\hat{E}[r_i / r_i \leq q^i_\alpha] = \hat{\mu}_i + \hat{\sigma}_i \times \frac{\phi(\hat{z}^i_\alpha)}{\Phi(\hat{z}^i_\alpha)}$$

where $\hat{z}^i_\alpha = (\hat{\mu}_i - V\hat{a}R_\alpha) / \hat{\sigma}_i$, and $V\hat{a}R_\alpha = \hat{\mu}_i + \hat{\sigma}_i q^z_\alpha$

Standard errors for these estimates may be conveniently computed using the bootstrap.(same idea is in Eric ,Z. 2005)

VaR.01 for Malaysia, Singapore, India, Japan based on historical simulation and normal distribution:

	Malaysia	**Singapore**	**India**	**Japan**
Historical simulation	-0.0270196	-0.0301499	-0.0481094	-0.0315207
Normal distribution	-0.0206139	-0.0244462	-0.0361272	-0.0281373

With 1% probability the loss is about 2.7% , 3% , 4.8% and 3.1% or higher for (Malaysia, Singapore, India, Japan) respectively , based on historical simulation method.
With 1% probability the loss is about 2% , 2.4% , 3.6% and 2.8% or higher for (Malaysia, Singapore, India, Japan) respectively , based on normal distribution method.
Compare the above results, we found that for historical simulation method the 1% probability loss is higher than the normal distribution method.
We can also make a conclusion that the highest most risky market is India, follow by Japan, Singapore and Malaysia, this consistent with our data description statistic in chapter 3, where the standard deviation for India is the highest compare to other market.

4. Conclusion

Our results for Garch (1,1) model and VaR model for all the market tested showed that VaR has better in prediction the risk because VaR gives the percentage and rank of risk level.
The main objective of this study is to detect and forecast the risk movement and volatility of the Kuala Lumpur Composite Index (KLCI) data and other Asian markets like Singapore, India and Japan from 2000 to 2009. We also compared different VaR analysis method such as historical simulation method and normal distribution method in portfolio risk estimation. Besides that we compare the two VaR methods with GARCH model.
We discover that with 1% probability the loss is about 2.7% , 3% , 4.8% and 3.1% or higher for KLCI, Singapore, India, Japan respectively based on historical simulation method.
With 1% probability the loss is about 2%, 2.4% , 3.6% and 2.8% or higher for KLCI, Singapore, India and Japan respectively , based on normal distribution method.
Compare the above results, we found that for historical simulation method the 1% probability loss is higher than the normal distribution method. Whereas the GARCH method can only forecast by using the lag value without able to rank the risk level.

We concluded that the highest most risky market is India, follow by Japan, Singapore and Malaysia, this consistent with our data description statistic where the standard deviation for India is the highest compare to other market.

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