COMPARE VALUE AT RISK AND RETURN OF ASSETS PORTFOLIO STOCK, GOLD, REIT, U.S. & IRAN MARKET INDICES

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ABSTRACT

Nowadays investors follow investment in asset like, stocks, gold, and real-estate investment trusts in the world. This study surveys three types of main assets portfolio of stock, gold, and REIT. This article use from S&P500, Gold price, S&P United States REIT of U.S as a development and Iran stock market, Gold price as an emerging country. Samples are collected from 2004 to2014 daily index U.S market and Iran market for 10 years. In this case, we use GARCH model for estimating return and variance with conditional variation. Then use Mont carol simulation for determination Value at Risk with three likelihood. Then calculate correlation of portfolios with multiple regression. Finally, compared Value at Risk and return and correlation for each portfolio (four types of portfolios). Then compare different type of portfolio and select best portfolio via R-Sharp criteria.

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Keywords: Value at risk, Return, Assets portfolio, GARCH model, R-Sharp.

Contribution/ Originality

This study contributes in new approach of assessment and comparing investment's risk and return in different countries.

1. INTRODUCTION

Securitized Real estate, stock and gold are important assets for investors. The attention of investors have been concerned by the liquidity and relationship of these three assets. It is well-known in investment science that risk can be qualified by diversification. Portfolio is very useful for hedging the risk in financing asset management and used to make asset management stable. According to classical portfolio theory, Markowitz's mean variance model is studied by many investigators and profitable results have been attained, and the variance-minimizing is also important to minimize the risk in portfolio (Markowitz (1990); Pliska (1997) and Ross (1999)). Recently, value-at-risk (VaR) is used generally in finance to estimate the risk of worst-scenarios. VaR is a risk sensitive norm based on percentiles and is one of the standard criteria in asset management (Jorion, 2006). VaR is a kind of risk values of the properties prices at an identified risk level probability and for decide on portfolios to dispose of bad scenarios in investment. Many researchers and financial agents usually use VaR by numerical approximations since the VaR portfolios analyze is not easy mathematically (Julijana, 2013). VaR presents a way for evaluation of risk and risk decision

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making management. In this paper, VaR and return of each portfolio is calculated then with return and VaR four portfolio compare together for selection bad scenario in REIT, stocks and gold portfolios in US and Iran.

Since Bachelier showed the price of financial time series as a random walk model (Bachelier, 1900) many useful methods have been made, such as the ARCH (Engle, 1982) GARCH (Bollerslev, 1986) model, etc. Since the mid-1980s and the introduction of generalized ARCH (or GARCH) models, these models have become extremely common among both academics and practitioners. GARCH models led to a fundamental adjustment to the approaches used in finance, through an efficient modeling of volatility (or variability) of the prices of financial assets. Several classes of nonlinear time series models have been recommended, but none of them has made interest comparable to that in GARCH models. The attention of the academic investigations in these models is explained that they are simple enough to be practical in usage, but also powerful in theoretical issues, many of them unsolved (Francq Jean-Michel Zako¨ıan, 2010). The ARCH and GARCH models, which represent autoregressive conditional heteroskedasticity and *generalized* autoregressive conditional heteroskedasticity, are designed to deal with just in financial applications where the dependent variable is the return on an asset or portfolio and the variance of the return represents the risk level of those returns. They have developed widespread tools for dealing with time series heteroskedastic models. The goal of such models is providing a volatility measure-like a standard deviation-that can be used in financial decisions with concerning risk analysis, portfolio range and derivative pricing (Bollerslev *et al.*, 1992). You can find highly significant GARCH effects in equity markets, not only for individual stocks, but for stock portfolios and indices, and equity futures markets as well (Engle, 1982).

2. LITERATURE REVIEW

In this study we intent compare different types of portfolio in US and Iran with VAR and return. A well-known study by Berkowitz and O'Brien investigates the VaR models used by six US financial institutions (Berkowitz and O'Brien, 2002).

Their results represent that these models are in some cases poorly accurate because banks occasionally experienced much losses more than their replicas predicted, which recommends these models are deprived at dealing with fat tails and risky events. Lehar et al. discover that more complex volatility models (GARCH and Stochastic volatility) are unable to progress on constant volatility models for VaR estimate, although they use for option pricing (Lehar *et al.*, 2002). According to Brooks and Persaud, the relation performance of different models depends on the loss function used. Brooks and Persand (2003) however ,GARCH models provide reasonably accurate VaR. Ming-Chih,et al., engle and engle et al. found that process of estimating dynamic correlation conditional model is time varying and provides dynamic of volatility modeling (Ming-Chih *et al.*, 2006); (Engle, 2002); (Engle, 2001). The results of ledoit and audino research represents important criteria like accurate of forecasting, standard residual, estimating Value at Risk and selecting portfolio. Multifactor GARCH model has better performance (Ledoit *et al.*, 2003); (Audrino and Barone-Adesi, 2003). Ling and Naranjo applied the multivariate model to explore the integration relationship between the US commercial real-estate market and the stock market. They realize that the market for traded real- estate companies, including REITs, is combined with the stock market (Ling and Naranjo, 1997).

3. HYPOTHESES

This article has two hypotheses. At first comparing different portfolios in both country and second finding the best portfolio in both country. One of them is as development and other is as an emerging market.

4. METHODOLOGY

This article use from S&P500, Gold price of U.S and S&P United States REIT data and Tehran stock market, Gold and real state price of Iran. Samples are collected from 2004 to2014 daily index U.S and Iran market for 10 years. This research shows market risk of a hypothetical equity index portfolio with a Monte Carlo simulation

technique with using a Student's t copula and Extreme Value Theory (EVT). The process first excerpts the filtered residuals from each return series with an asymmetric GARCH model, then generates the sample marginal cumulative distribution function (CDF) of each asset using a Gaussian kernel estimate for the interior and a generalized Pareto distribution (GPD). Then it estimates the upper and lower tails. A Student's t copula is proper to data and used to induce correlation between the simulated residuals of each asset. Finally, the simulation evaluates the Value-at-Risk (VaR) of the hypothetical global equity portfolio over a one month horizon.

The initial level of each index has been normalized to unity to enable the comparison of relative performance, and no dividend changes are explicitly taken into account. In research for subsequent modeling, convert the closing level of each index to daily logarithmic returns .

Since the first step in the overall modeling approach involves a repetitive application of GARCH filtration and EVT to characterize the distribution of each different equity index return series, it is useful to examine the details for a particular index. Modeling the tails of a GPD distribution requires the data to be approximately independent and identically distributed. However, most financial return series exhibit some degree of autocorrelation and, more importantly, heteroskedasticity.The first instruction autoregressive model compensates for autocorrelation, the GARCH model recompenses for heteroskedasticity.

In particular, the last term joins asymmetry (leverage) into the variance by a Boolean indicator that takes the value 1 if the prior model residual is negative and 0 otherwise (Ross, 1999).

Additionally, the standardized residuals of each index are modeled as a standardized tudent's t distribution to compensate for the fat tails often associated with equity returns. residuals are filtered from each return series, standardize the residuals by the corresponding conditional standard deviation. These standardized residuals represent the fundamental zero-mean, unit-variance. series upon which the EVT estimation of the sample CDF tails is based.

residuals = residuals / sqrt(variances)

For estimating the Semi-Parametric CDFs, assumed the standardized residuals from the previous step, estimation the empirical CDF of each index with a Gaussian kernel. Although non-parametric kernel CDF estimations are well fitting for the interior distribution where most of the data is found, they have a tendency to implement poorly when applied to the upper and lower tails. When apply EVT to those residuals that fall in each tail, the tails of the distribution has been better estimated. Specially, find upper and lower thresholds such that 10% of the residuals is reserved for each tail. Then fitting the amount by which those extreme residuals in each tail fall beyond the associated threshold to a parametric GPD by maximum likelihood. This approach is often referred to as the distribution of exceedances_ or _peaks over threshold_ method. The resulting piecewise distribution object allows interpolation within the interior of the CDF and extrapolation (function evaluation) in each tail. Extrapolation is very necessary, allowing estimation of quantiles outside the historical data, and is vital for risk management applications. Moreover, Pareto tail substances also provide aproaches to evaluate the CDF and inverse CDF (quantile function), and to enquiry the cumulative probabilities and quantiles of the borders between each section of the piecewise distribution.

Finally, the simulated returns is given for each index, an equally weighted of assets, portfolio compination of the individual indices. Since we work with daily logarithmic returns, the cumulative returns over the risk horizon are simply the sums of the returns over each intervening period. Also the portfolio weights are asummped fixed throughout the risk horizon. Note that although the simulated returns are logarithmic (continuously compounded), the individual logarithmic returns are converted to arithmetic returns (price change divided by initial price) and they create the portfolio return series, then weighting the individual arithmetic returns to obtain the arithmetic return of the portfolio, and finally are converted back to portfolio logarithmic return. With daily data and a short VaR horizon, the frequent conversions make little difference, but for longer time periods the disparity may be significant.

Results are obtained showing in table (1) & table (2). Value at Risk for three confidence levels are calculated.

Also coefficient relationship (ρ) and average of return each portfolio r_p in table (1) is noted.

Table-1. Value at Risk, return, coefficient relationship, & R-Sharp are calculated for different type of portfolio in U.S

	REIT&GOLD	GOLD&STOCK	REIT&STOCK	REIT&GOLD&STOCK
Simulated 90% VaR	6.17%	4.95%	6.37%	5.13%
Simulated 95% VaR	7.82%	6.35%	8.08%	6.78%
Simulated 99% VaR	11.37%	8.98%	13.35%	9.80%
R-Sharp %90	4.51	5.62	4.36	5.42
R-Sharp %95	3.55	4.38	3.44	4.10
R-Sharp %99	2.45	3.10	2.08	2.84
ρ	0.275	0.35	0.828	0.258
r_p	0.278	0.247	0.193	0.238

Table-2. Value at Risk, return, coefficient relationship & R-Sharp are calculated for different type of portfolio in Iran

	REIT&GOLD	GOLD&STOCK	REIT&STOCK	REIT&GOLD&STOCK
Simulated 90% VaR	2.69%	2.56%	3.52%	2.53%
Simulated 95% VaR	5.56%	5.55%	6.46%	5.12%
Simulated 99% VaR	19.05%	26.30%	23.58%	14.90%
R-Sharp %90	4.01	3.95	2.76	4.07
R-Sharp %95	1.94	1.82	1.50	2.01
R-Sharp %99	0.57	0.38	0.41	0.69
ρ	0.772	0.794	0.945	780
r_p	0.108	0.101	0.097	0.103

4.1. Assessment Performance Different Portfolio with R-Sharp Criteria

Following we measure performance of each portfolio with R-sharp criteria. This index is ratio return to Value at Risk. This index is calculated in three type of likelihood. the highest amount of ratio related to stock and Gold portfolio and also portfolio included three assets in Iran, in U.S. just portfolio two assets has the highest value.

5. CONCLUSION

This paper surveys risk and return of assets portfolio that refer to combination of Stock, Real state and Gold because people often tent to investing on this three assets. .Here we compare portfolios of this three assets in U.S. as a development country and market of Iran as an emerging country. In despite we expect with portfolio including of three asset in both country has more return and less risk, however we observe two assets portfolio has high return and low risk than the other options. Then we measure R-sharp criteria. This criteria shows investing in portfolio combination of two asset Stock and Gold can has higher ratio than the other options. In fact, this portfolio has higher coefficient relationship but has return higher than the portfolio contain of three assets.

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