Forecasting Value at Risk (VAR) in the futures market using Hybrid method of Neural Networks and GARCH model

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ABSTRACT

This study proposes a hybrid model, which combines GARCH and Neural Network, for estimating VAR in Nasdaq 100 and Dow Jones futures index market. Empirical results demonstrated that the hybrid method has certain outperformed the conventional method (historical simulation, variance/covariance and the Monte Carlo simulation) in estimating VAR. In terms of accuracy, the hybrid method is superior to any of the conventional methods, especially in the Nasdaq 100 futures index market. In terms of conservativeness, the hybrid method was superior to the HS method in both markets, and hybrid method is superior to the conventional methods in the Nasdaq 100 futures index. In terms of efficiency, the hybrid method were more efficient than HS method when applied to in both futures index, and hybrid method is superior to the conventional methods in the Dow Jones futures index.

Keywords: Neural Networks, GARCH Model, Value at Risk
INTRODUCTION

The conventional estimation method on VAR (Value at Risk) includes the historical simulation (HS), variance/covariance (VCV), and Monte Carlo simulation (MCS) methods. Jorion [1996] documented VAR summarizes the worst expected loss over a target horizon and within a given confidence interval. Linsmeier and Pearson [2000] defined VAR is a measure of losses resulting from normal market movements. Badik [2005] pointed out VAR is the value of the negative result (loss) that for a certain period and with a certain probability will not be exceeded. Consequently, estimating VAR requires determining the two parameters of holding period and confidence level. Duffie & Pan [1997] developed the idea of applying VAR to compare the risks of stocks or investment portfolios, market price and historic prices, and to compare risks between different markets.

Most financial asset returns exhibit a fat-tail distribution, but conventional VAR estimation models assume that returns are normal distribution. Fama [1965] proposed that the distribution of stock price and stock return usually follows a leptokurtic and fat-tailed distribution. Notably, Hull & White [1998] studied the statistical characteristics of asset returns and discovered that normal distribution was associated with systematic errors, particularly in situations involving returns with a fat-tailed distribution. According to Mahoney, Sundaramurthy & Mahoney [1996], historical simulation method can solve fat tails or determination of nonlinear investment portfolio values derived from the assumption of normal distribution. Thus, compared with the assumption of normal distribution returns, historical simulation method would lead to better conclusions.

Recently, Neural Network simulation has been extremely popular in forecasting stock prices, but has almost never been applied to VAR estimation. On the other hand, stock price data usually exhibits time series correlation, Neural Network simulation forecasting of stock prices cannot be influenced by time series correlation. This paper proposes a hybrid model, which combines GARCH and Neural Network simulation, for estimating VAR. The hybrid method first to adopt the GARCH model to determine significant independent variables, then employing these variables as Neural Network input variables to improve the forecasting efficiency of Neural Network simulation, and further to compare the forecasting performance between the conventional and hybrid models in terms of estimating VAR.

CONVENTIONAL METHOD

Historical Simulation Method

The historical simulation method directly observes the empirical distribution of investment portfolio return. This method first identifies the assets included in the portfolio and observes the historic data of each asset over a specific period (Stambaugh [1996]). Historical data are applied to the weight of the current portfolio to simulate possible portfolio changes during the observation period. Portfolio VAR can be obtained given a certain confidence level.

This method is easy to understand and explain since it makes no statistical assumptions about the distribution of returns (Badik [2005]). The main difficulty in implementing historical simulation is that it requires a time series of the relevant market factors covering on the last N days. This can be problematic in situations where reliable data is not readily available. Another disadvantage is that the N days considered in the calculation may be atypical owing to market events.

Variance/Covariance Method

The simplest and perhaps most widely used method of modeling changes in portfolio value is the variance/covariance method popularized by RiskMetrics (Glasserman, Heidelberger &
Shahabuddin [2002]). The most notable feature of variance/covariance method is its assumption that future returns on assets are normal distribution, and that investment portfolio gain or loss is also normal distribution in order to simplify VAR estimation. Thus, the VAR over a specific holding period and at a certain confidence level can be directly estimated based on investment portfolio standard deviation. VAR is calculated by multiplying the distributed standard deviation by the standardized normal distribution z-value, so when α is fixed (1-α is confidence coefficient), VAR is affected only by the standard deviation. If we know the variation and correlated coefficient of asset returns, we can estimate the VAR of the investment portfolio. Britten-Jones and Schaefer [1999] and Glasserman et al. [2000] are good references for the delta-gamma approach.

The easy availability of the necessary data makes VAR computation relatively easy, and hence it is the most widely used method (Badik [2005]). Despite its ease of calculation, it may be difficult to explain to senior management due to its reliance on the statistical properties of normal distribution when used to calculate. Another significant drawback is the assumption of normality of asset returns, which does not always hold.

**Monte Carlo Simulation method**

The Monte Carlo simulation method assumes that the volatility of investment portfolio returns follows a certain stochastic process, meaning the paths of stock prices can be computationally simulated hundreds, thousands, or even millions of times to establish portfolio returns distribution and estimate VAR (Stambaugh [1996]). Monte Carlo simulation is basically an empirical method based on the law of large numbers, with a larger number of iterations leading to an average close to the theoretical value.

Monte Carlo simulation is a natural alternative for handling nonlinear portfolios (Jin & Zhang [2006]), and is designed to simulate the stochastic process of asset price and risk factors, with each simulation yielding a period-end asset value. Iterated simulations can be used to produce the distribution of period-end portfolio values can be created. The simulated distribution can then be used to derive the VAR with the given confidence level.

In terms of precision, it is perhaps the most effective of all methods, particularly in situations involving more complex instruments (Badik [2005]). It is also extremely flexible, since it makes no definite assumptions regarding asset returns. The Monte Carlo simulation procedure can be quite complex and time consuming, requiring expensive intellectual and technological skills.

**Empirical studies of VAR**

Alexander & Leigh [1997] used the simple weighted average, exponential weighted moving average (EWMA), and GARCH models to estimate VAR. Maximum likelihood estimate (MLE), root mean square error (RMSE), back-testing, and forward testing methods were applied for the model testing, and demonstrated that the exponential weighted moving average method tended to underestimate VAR, and GARCH did not differ significantly in terms of statistical verification but yielded a more correct 99% VAR estimate.

Hull & White [1998] pointed out that under Historical Simulation, better VAR estimates could be obtained when the daily change of market factors estimated using the GARCH or EWMA models was used to adjust historical changes. Papageorgiou & Paskov [1999] compared the speed and accuracy of the Monte Carlo and quasi-Monte Carlo methods by estimating 34 European stock index options and foreign exchange call options. Moreover, Chang, Chen & Hsieh [2007] used the percentile of cluster and the percentile statistics method to estimate VAR, demonstrated that the percentile of cluster method was more accurate and conservative than the percentile of statistics method.
GARCH MODEL

In financial market, most research has been used GARCH model for modeling volatility of time series data. Gokcan [2000] forecasting volatility of emerging stock markets used by GARCH model, Lien, Tse & Tsui [2002] using GARCH model for forecasting the time-varying hedge ratio. Berkowitz & Brien [2002] indicate that the GARCH model of profit and loss generally provides for lower VARs and is better at predicting changes in volatility.

Engle [1982] propose an autoregressive conditional heteroskedasticity (ARCH) model which relates the error variance to the square of a previous period's error. In the ARCH model, the volatility $\sigma^2$ is expressed in a discrete stochastic process of the form

$$\sigma^2_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i}$$

where $\sigma^2$ is the volatility of return at time $t$, $\omega$, $\alpha_i$ are constant parameters, $\omega > 0$ and $\alpha_i \geq 0$, $\varepsilon_i$ denote the returns residuals and assume that $\varepsilon_i = \sigma_i z_i$, where $z_i \sim iid(0,1)$.

Bollerslev [1986] introduced an alternative process to the ARCH model is the popular generalized autoregressive conditional heteroskedasticity (GARCH) model. The GARCH(p, q) model (where p is the order of the GARCH terms and q is the order of the ARCH terms ) is given by

$$\sigma^2_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2_{t-i}$$

where $\beta_i$ is constant parameters, $\beta_i \geq 0$ and $\alpha_i + \beta_i < 1$.

NEURAL NETWORK SIMULATION METHOD

Neural Network (NN) is an artificial intelligence (AI) methods Kai & Wenhua [1997] Neural Network is a highly non-linear, large scale, continuous, time-based and dynamic system. The knowledge of Neural Network is stored in the relationship among numerous nodes in the form of a weigh matrix. This method has become extremely important in making stock market predictions. Backpropagation neural networks comprise input, hidden and output layers (see also Figure 1).

A common advantage shared by Neural Network applications is their ability to deal with uncertain and robust data. Therefore, Neural Network can be efficiently used in stock markets to predict either stock prices or returns. Neural Network is particularly flexible and efficient in situations when certain data are unavailable. Previous studies have demonstrated that Neural Network outperforms classical forecasting and statistical methods. The combination of several Neural Network can obtain extremely accurate value predictions, because the combined methods can focus on different data set characteristics that are important for calculating output (Zekic [1998]; Afolabi & Olude [2007]). Meissner & Kawano [2001] combined GARCH with Neural Network
model capturing the volatility smile of options on high-tech stocks. Kastra & Boyd [1995] used backpropagation neural networks and ARIMA to forecast futures trading volume, and found that neural network forecasting ability is also benchmarked relative to the ARIMA model. Furthermore, Franses & Griensven [1998] investigated the performance of artificial neural networks (ANNs) for technical trading rules for forecasting daily exchange rates, showed that ANNs perform well, and frequently outperform linear models.

**DATA AND METHODOLOGY**

The research subject comprised daily data from the USA futures market, including the Nasdaq 100 and Dow Jones futures index, with the data period spanning 2000/01/03~2005/12/30, and the estimation period spanning 2006/01/03~2006/12/29, employing the rolling-window method, and with data being source from Futures & Index (Tick data) databases.

Previous studies of VAR all used conventional methods (history simulation, variance/covariance, and Monte Carlo simulation method) to estimate VAR. This study instead uses the hybrid Neural Network and GARCH models for VAR estimation to compare the performance between the conventional and hybrid methods.

**Hybrid Method**

This study proposes a hybrid model for estimating VAR that combines GARCH and Neural Network. Adopting the GARCH model requires determining which independent variables are significant then employing these significant variables as Neural Network input variables. A hybrid model incorporating the variance/covariance method (NN_VCV), or the Monte Carlo simulation method (NN_MCS), according to a hybrid model for forecast result, which combine variance/covariance (VCV) or Monte Carlo simulation (MCS) to estimate VAR.

GARCH model dependent variable: close index, independent variables: 5-day Bias, 10-day MA (Moving Average), 12-day RSI (Relative Strength Index), and KD indicator. The Neural Network simulation method is based on Back-propagation Network (BPN), which is used to identify the relationship between input and output variables. The input layer comprises five neurons, including 5-day Bias, 10-day MA, 12-day RSI, and KD indicator. The output layer is close index. The training data comprise 1,497 records, while the production data comprise 257 records.

**Assessment methods for VAR models**

Engel & Gifyock [1999] present a range of summary statistics that address a number of different aspects of the usefulness of VAR models focus on conservatism, accuracy and efficiency, and compare the performance of specific implementations of each of the VAR model. In this paper, the hybrid and convention methods were compared in terms of accuracy, conservativeness and efficiency (Engel & Gifyock [1999]), using a confidence level of 95%. These three terms were also used in Goorbergh & Vlaar [1999], Billio & Pelizzon [2000], Guermat & Harris [2002], Lin, Chang Chien & Chen [2005], Liu [2005], Liu, Lee & Wu [2005], and Chang, Chen & Hsieh [2007].

**Accuracy.** We define accuracy as the extent to which the rate of failure of the specific model is close to the preset significance level. Accuracy are concerned with whether the VAR estimates are large enough to cover the true underlying risks. We present the results for two accuracy measures: binary loss function and LR Test of Unconditional Coverage.

**Binary Loss Function (BLF).** The binary loss function is based on whether the actual loss is larger or smaller than the VAR estimate. Here we are simply concerned with the number of exceptions rather than the magnitude of these exceptions. The actual profit or loss $R_{t+1}$ exceeds the VAR estimate then has a value equal to 1; all others profits and losses have a zero value. That is
The aggregate number of failures close to the BLF value of the confidence level is more accurate.

**LR Test of Unconditional Coverage (LR_{uc}).** The average BLF offers a point estimate of the probability of failure. Kupiec [1995] presents a likelihood ratio test based on the binomial experiment that can be applied to determine if the rate of failure is statistically compatible with the expected level of confidence. The likelihood ratio test statistic of the unconditional coverage is given by:

\[
LR_{uc} = -2 \ln \left[ (1-p)^{N-p} \right] + 2 \ln \left[ \left( \frac{1-N}{T} \right)^{N-p} \left( \frac{N}{T} \right)^{p-N} \right]
\]

where LR_{uc} is conform to \( \chi^2_{(1, \alpha)} \), p is the specified probability of failure equal to 1 minus the model’s specified level of confidence, T is sample size, N is frequency of failure. If the LR_{uc} null hypothesis \( H_0 : p = \alpha \) is accepted that \( \text{VAR} \) estimate is accuracy.

**Conservativeness.** Hendricks [1996] proposes a root mean squared relative bias (RMSRB) to measure the degree to which the risk measures tend to vary around the all model average risk. The RMSRB is computed as:

\[
RMSRB = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left( \frac{\text{VAR}_t - \text{VAR}}{\text{VAR}} \right)^2}
\]

where \( \text{VAR}_t = \frac{1}{N} \sum_{i=1}^{N} \text{VAR}_t^i \), \( \text{VAR}_t^i \) is \( i^{th} \) model’s VAR at time \( t \), \( T \) is the time periods, \( N \) is number of \( \text{VAR} \) models. RMSRB is a negative indicator, with smaller RMSRB indicating greater conservativeness.

**Efficiency.** A well fitness model of risk measure needs to be more than just appropriately conservative and accurate. It should be considered correlated with the true risk exposure of the portfolio. Engel & Gizyck [1999] point out efficiency is more important which \( \text{VAR} \) measures are used both by supervisors and the internal management of financial firms to influence investors’ incentives. A more efficient \( \text{VAR} \) model provides more precise resource allocation signals to the financial institutions (Engel & Gizyck [1999]; Liu [2005]).

The Mean Relative Scaled Bias (MRSB) (Engel & Gizycki [1999]) is aimed at determining which model, once the desired risk coverage level is suitably obtained, produces the smallest \( \text{VAR} \) measure. There are two steps involved in calculating the MRSB measure. First, the scaling should be calculated by multiplying the \( \text{VAR} \) for each model by the multiple needed to obtain the 95% coverage as described in the multiple to obtain coverage measure. Engel & Gizycki [1999] proposed scaling factor \( X_i \) of the multiple to obtain coverage as:

\[
F_i = T_i (1 - \alpha) \quad \text{where} \quad F_i = \sum_{t=1}^{T} \begin{cases} 1 & \Delta R_{t,i+1} < X_i \times \text{VAR}_t^i \\ 0 & \Delta R_{t,i+1} \geq X_i \times \text{VAR}_t^i \end{cases}
\]

where \( X_i \) of is the scaling factor of \( i^{th} \) model, \( \Delta R_{t,i+1} \) represents the actual profit or loss, \( T_i \) is the
sample size and $\alpha$ is the VAR confidence level.

The second step is to compare the scaled VAR numbers with the average relative size by using the mean relative bias calculation. The MRSB measure is calculated as follows:

$$MRSB = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \frac{X_t \times \text{VAR}_t - \bar{X_t} \times \text{VAR}}{X_t \times \text{VAR}}}$$

(7)

MRSB is a negative indicator, the most efficient model will be the one that produces the smallest relative bias.

**EMPIRICAL RESULTS**

When calculating the VAR in this study, a rolling window of 257 observations is used for the estimation of each model. Equation (2) is used to estimate the results of parameter for the GARCH model. Table 1 reveals that all variables were significant at P-Value <0.1, SSR= 391.693.9, AIC=8.048, Schwarz’s SBC=8.076, $R^2$ =0. 9912, Adjusted $R^2$ =0. 9911, F-statistic=24,045.86.

Table 1 Estimate parameter result of GARCH model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>P-Value,</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-17.6053</td>
<td>3.1394</td>
<td>-5.6079</td>
<td>0.0000***</td>
</tr>
<tr>
<td>5-day Bias</td>
<td>879.4733</td>
<td>48.0766</td>
<td>18.2932</td>
<td>0.0000***</td>
</tr>
<tr>
<td>10-day MA (Moving Average)</td>
<td>0.9938</td>
<td>0.0023</td>
<td>424.1620</td>
<td>0.0000***</td>
</tr>
<tr>
<td>12-day RSI (Relative</td>
<td>27.9354</td>
<td>1.5898</td>
<td>17.5713</td>
<td>0.0000***</td>
</tr>
<tr>
<td>Strength Index)</td>
<td>10.8588</td>
<td>1.2573</td>
<td>8.6365</td>
<td>0.0000***</td>
</tr>
<tr>
<td>KD indicator</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

: P-Value <0.1,      : P-Value <0.05,    : P-Value <0.001

The simplest generalized autoregressive conditional heteroskedasticity (GARCH) model of dynamic variance can be written as (Christoffersen [2003])

$$\sigma_{t+1}^2 = \omega + \alpha R_t^2 + \beta \sigma_t^2 , \text{with} \ \alpha + \beta < 1$$

(8)

The result of parameter estimation for the GARCH(1,1) model in different future markets in Table 2. Equation (8) is used to estimate these parameters ($\alpha$, $\beta$, $\omega$) of daily variance for VAR forecasting, and the estimate value $\alpha+\beta < 1$. These parameters value are used to calculate variance of the index return in each market. The Neural Network estimate value in Table 3 shows the Correlation coefficient and mean square error (MSE) on two categories of future market.

Table 2 Estimate parameter result of GARCH model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Nasdaq 100 futures</th>
<th>Dow Jones index futures</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.020900</td>
<td>0.090500</td>
</tr>
<tr>
<td>B</td>
<td>0.914800</td>
<td>0.731500</td>
</tr>
<tr>
<td>$\Omega$</td>
<td>0.000004</td>
<td>0.000007</td>
</tr>
<tr>
<td>$\alpha+\beta$</td>
<td>0.935700</td>
<td>0.822000</td>
</tr>
<tr>
<td>MLE</td>
<td>874.800000</td>
<td>916.300000</td>
</tr>
</tbody>
</table>

Table 3 Correlation coefficient and MSE of Neural Network estimate value

<table>
<thead>
<tr>
<th>Market</th>
<th>Correlation coefficient</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nasdaq 100 futures</td>
<td>0.9697</td>
<td>29.2894</td>
</tr>
<tr>
<td>Dow Jones index futures</td>
<td>0.9778</td>
<td>336.1866</td>
</tr>
</tbody>
</table>
Figure 2 and 3 show the VAR derived by various methods given maximum tolerable loss of 5% for the Nasdaq 100 and Dow Jones futures index. These methods used to forecast VAR included historical simulation (HS), variance-covariance methodology (VCV), Monte Carlo simulation method (MCS), Neural Network with variance/covariance methodology (NN_VCV) and Neural Network with Monte Carlo simulation method (NN_MCS).

Fig. 2 VAR estimated by each model for the Nasdaq 100 futures index

Fig. 3 VAR estimated by each model for the Dow Jones futures index
The BLF test for accumulated failures of each VAR model in Table 4, the conventional method of VCV and MCS show that accumulate number of failures over the BLF value in the Nasdaq 100 futures. The hybrid method is superior to any of the conventional methods, because of in both futures markets had to conform to BLF value.

<table>
<thead>
<tr>
<th>Market</th>
<th>BLF (p=0.05, (\alpha=0.05))</th>
<th>Conventional method</th>
<th>Hybrid Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>HS</td>
<td>VCV</td>
</tr>
<tr>
<td>Nasdaq 100 futures</td>
<td>257</td>
<td>6~19</td>
<td>17</td>
</tr>
<tr>
<td>Dow Jones index futures</td>
<td>250</td>
<td>6~19</td>
<td>11</td>
</tr>
</tbody>
</table>

*: the number of failures over the BLF (Binary Loss Function) value

The Kupiec [1995] testing method was used to assess the accuracy of the VAR models. Table 5 lists the Kupiec [1995] likelihood ratio (LR\(_{\text{u}}\)) calculated using the accumulated failures. The result was further compared using \(\chi^2(1, \alpha=0.05)\) to verify the model accuracy. Given failure rate \(p=0.05\), the conventional method of VCV and MCS show that LR value larger than the \(\chi^2(1, \alpha=0.05)\)= 3.8415 in the Nasdaq 100 futures. The hybrid method for both futures index show the LR\(_{\text{u}}\) were lower than the \(\chi^2(1, \alpha=0.05)\)= 3.8415, which display the accuracy.

<table>
<thead>
<tr>
<th>Market</th>
<th>Conventional method</th>
<th>Hybrid Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HS</td>
<td>VCV</td>
</tr>
<tr>
<td>Nasdaq 100 futures</td>
<td>1.2865</td>
<td>6.9069*</td>
</tr>
<tr>
<td>Dow Jones index futures</td>
<td>0.1971</td>
<td>0.0208</td>
</tr>
</tbody>
</table>

*: the LR value larger than the Chi-square value, \(\chi^2(1, \alpha=0.05)\)= 3.8415

The Root Mean Squared Relative Bias (RMSRB) proposed by Hendricks [1996] was adopted to assess VAR model conservativeness. RMSRB is a negative indicator, with smaller RMSRB indicating greater conservativeness. Table 6 lists the RMSRB of each VAR model. The hybrid method was superior to the HS method in both markets, and hybrid method is superior to the conventional methods in the Nasdaq 100 futures index.

<table>
<thead>
<tr>
<th>Market</th>
<th>Conventional method</th>
<th>Hybrid Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HS</td>
<td>VCV</td>
</tr>
<tr>
<td>Nasdaq 100 futures</td>
<td>0.1225</td>
<td>0.1034</td>
</tr>
<tr>
<td>Dow Jones index futures</td>
<td>0.2110</td>
<td>0.0672</td>
</tr>
</tbody>
</table>

Mean Relative Scaled Bias (MRSB) is used to assess the efficiency of VAR models. MRSB can be used to identify the VAR model with the smallest VAR given some theoretical failure rate. MRSB is a negative indicator, while smaller MRSB indicates higher efficiency. Table 7 shows the MRSB for each VAR model, reveals that models based on the hybrid method were more efficient than HS method when applied to in both futures index, and hybrid method is superior to the conventional methods in the Dow Jones futures index.
Table 7 MRSB of each model

<table>
<thead>
<tr>
<th>Market</th>
<th>Conventional method</th>
<th>Hybrid Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HS</td>
<td>VCV</td>
</tr>
<tr>
<td>Nasdaq 100 futures</td>
<td>0.3553</td>
<td>0.2305</td>
</tr>
<tr>
<td>Dow Jones futures</td>
<td>0.3029</td>
<td>0.2979</td>
</tr>
</tbody>
</table>

CONCLUSION

This study proposes a hybrid model, which combines GARCH and Neural Network, for estimating VAR. Empirical results demonstrated that the hybrid method has certain outperformed the conventional method in estimating VAR.

In terms of accuracy, the hybrid method is superior to any of the conventional methods, because of in both futures index had to conform to BLF value. In terms of conservativeness, the hybrid method was superior to the HS method in both futures markets, and hybrid method is superior to the conventional methods in the Nasdaq 100 futures index. In terms of efficiency, the hybrid method were more efficient than HS method when applied to in both futures index, and hybrid method is superior to the conventional methods in the Dow Jones futures index.

To summarize, using hybrid Neural Network with GARCH method to compare with the conventional method in the estimation of VAR has certain advantages. Consequently, investors are suggested to use the hybrid method to estimate VAR when estimating the VAR of asset returns.

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