Value-at-Risk Analysis for Measuring Stochastic Volatility of Stock Returns: Using GARCH-Based Dynamic Conditional Correlation Model

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Abstract
To assess the time-varying dynamics in value-at-risk (VaR) estimation, this study has employed an integrated approach of dynamic conditional correlation (DCC) and generalized autoregressive conditional heteroscedasticity (GARCH) models on daily stock return of the emerging markets. A daily log-returns of three leading indices such as KSE100, KSE30, and KSE-ALL from Pakistan Stock Exchange and SSE180, SSE50 and SSE-Composite from Shanghai Stock Exchange during the period of 2009–2019 are used in DCC-GARCH modeling. Joint DCC parametric results of stock indices show that even in the highly volatile stock markets, the bivariate time-varying DCC model provides better performance than traditional VaR models. Thus, the parametric results in the DCC-GARCH model indicate the effectiveness of the model in the dynamic stock markets. This study is helpful to the stockbrokers and investors to understand the actual behavior of stocks in dynamic markets. Subsequently, the results can also provide better insights into forecasting VaR while considering the combined correlational effect of all stocks.

Keywords
value-at-risk, DCC, GARCH, market risk, volatility, stock returns

Introduction
Nowadays, it has been a big challenge for the investors to predict the risk and return associated with the specific index or portfolio in dynamic markets. Higher market risk is because of the presence of unpredictability or volatility in stock prices. The reason for high volatility in stock returns is always the unstable country’s conditions, both politically and economically (Afzal et al., 2019). Increasing market risk on stock has brought new challenges to find an effective way of predicting risk in dynamic conditions. Value-at-risk (VaR) is the most widely used standardized volatility measurement tool for the measurement of market risk (Jorion, 1996).

In dynamic markets, neither the stock returns could be identical nor could the future trend be predicted historically. Therefore, traditional volatility models, such as historical simulation, variance–covariance, and Monte-Carlo simulation method (Marshall & Siegel, 1997), are not capable of giving the right estimation of market risk; either they are based on assumptions or have the issues of underestimation and overestimation (Sampid & Hasim, 2018). Indeed, limited tools have been developed that could predict the volatility correctly without any issues of underestimation or overestimation. In doing so, this study desires to find an efficient stochastic model that can predict better estimation of risk and return in dynamic stock markets, thereby winning the interest of investors in wealth creation. Therefore, this study suggests that employing dynamic conditional models can capture better volatility of stock returns without any assumptions or problems of underestimation or overestimation of market risk, thereby maximizing the investors’ confidence. Subsequently, modeling the dynamic correlation structure gives insight into both markets’ volatility clustering and synchronization in financial series. Hence, under dynamic correlation structure, dynamic conditional correlation (DCC) and generalized autoregressive conditional heteroscedasticity (GARCH) are found to be efficient and practicable methods to capture the market volatility and compare the forecasting results of VaR. While looking for
the model assumptions, this model can predict better VaR with time-varying correlation rather than using a constant correlation. In this dynamic structural model, an integrated model DCC-GARCH(1,1) has been used for the estimation of VaR and conditional correlation estimation. The findings of the study suggest that adopting an integrated hybrid tool of DCC and GARCH can give better insights of risk estimation in dynamic conditions. Furthermore, this study contributed to the literature in a way of introducing an effective method of risk estimation in dynamic conditions.

This study has been expanded in the following section: section “Previous Research on VaR and Measurement Tools” describes the theoretical background of relevant studies; section “Data and Empirical Results” is based on the details of materials and methods; section “Key Findings” describes the key finding of the study; and the last section consists of the conclusions, implications, and future research directions.

Previous Research on VaR and Measurement Tools

VaR has been popular and is widely adopted as a market risk analysis tool, and it measures the volatility of stock indices. It summarizes the maximum possible loss that financial assets can have at a certain period under a certain confidence level. In 1993, VaR analysis was initially presented in a report “the practice and rules of derived products” published by Group 30. Afterward, in 1994, J.P. Morgan Company applied the VaR model to measure the market risk in stock exchanges. Nowadays, VaR has been adapted by different financial institutions, for instance, banks, fund managers, insurance companies, and stockbrokers. There have been a wide range of studies found on the method of VaR that address its significance in volatility measurement, particularly in stocks (Ackermann et al., 1999; Beder, 1995; Carhart, 1997; Favre & Galeano, 2002; Fung & Hsieh, 1997; Marshall & Siegel, 1997). The Monte-Carlo simulation and variance–covariance methods are based on the assumption that the returns are identically distributed and are independent of each other. Similarly, historical simulation relies on historic data believing that the same trend will get repeated in the future, yielding the desired outcome (Hull & White, 1998).

Traditionally, historical simulations, Monte-Carlo simulations, and variance–covariance methods assume that stock returns are normally distributed. Therefore, the fluctuations in asset prices show persistent volatility over time. However, volatility is not considered to be persistent in real-life dynamic conditions (Bansal et al., 2014). Recent studies have also described some practical VaR measurement models that can better address the nonpersistent nature of volatility. While addressing the normality issues in time series volatility, Engle (1982) has introduced a unique ARCH model. Later on, based on this ARCH model, Bollerslev (1986) has presented the GARCH with the estimation of parameters (p,q) that make it easier than the ARCH model for volatility measurement.

Similarly, Füss et al. (2007), in their study on volatility measurement, suggested that the GARCH-based VaR models appear to be superior and outperform the traditional VaR estimation methods. While working on funds’ risk, Zhou et al. (2010) considered multiple distributions for the effectiveness of the GARCH model over the traditional VaR models. Thus, results have shown that generalized difference distribution outperforms the t-distribution and normal distribution. Furthermore, to overcome the weaknesses of asymmetric and long-memory volatility effects, several extensions of the GARCH family have been introduced, such as Exponential GARCH (EGARCH), Glosten–Jagannathan–Runkle GARCH (GJR-GARCH), Fractionally Integrated GARCH (FIGARCH), Fractionally Integrated Asymmetric Power ARCH (FIAPARCH), and Hyperbolic GARCH (HYGARCH). Unfortunately, this GARCH family has some limitations to measure the time-varying effect of volatility in dynamic conditions (Franq & Zakoian, 2010; Yang, 2011).

Researchers have found that in dynamic conditions, the correlations among stock indices are asymmetric across the market movements and the return distribution tails are fatter (Ang & Chen, 2002; Boyer et al., 1997; Kolari et al., 2008; Longin, 2000; Longin & Solnik, 2001; Tastan, 2006). Therefore, forecasting returns seemed to be underestimated or overestimated using GARCH family models alone. To address the appropriateness of VaR with time-varying effects in dynamic conditions, one possible solution is to apply the DCC model for volatility measurement as proposed by Engle in 2002 and further modified in 2006. Studies on DCC show that the DCC-GARCH model is found to be more accurate in yielding the conditional variances (Engle, 2002; Tse & Tsui, 2002). Modeling the DCC structure can provide insight into both markets’ synchronization and volatility clustering in financial series. Thus, by using a conditional correlational and time-varying effect, this DCC model provides a better estimation of the dynamic correlation structure for capturing the volatilities and forecasting returns more efficiently than other models (Celik, 2012).

Data and Empirical Results

The data used in this study consist of three stock indices of the Pakistan Stock Exchange (PSX), that is, KSE100, KSE30, and KSE-ALL, and Shanghai Stock Exchange (SSE), that is, SSE180, SSE50, and SSE-Composite. A total of 2,528 equal daily log-returns for each index are used as sample data, because an equal number of observations for each asset class is necessary for DCC modeling for conditional correlation (Asai & McAleer, 2009). Data were gathered from the official websites of PSX and SSE from the period of 2009 to 2019.

Table 1 shows the summary statistics of each index used in this study that explains the time frame of research and the total number of observations used. The distribution of data is slightly skewed to the left; the negative skew values in all indices show that there are more chances to earn negative
returns than positive returns. For the kurtosis, we have a value of less than 3 in the case of PSX, which implies that the distribution of the data is platykurtic, but in the case of SSE the kurtosis is greater than 3, which shows that the distribution of SSE data is leptokurtic. Skewness and kurtosis are essential for volatility as kurtosis is the measure of the level of a distribution expressed as fat tails. Investors who are risk-averse always prefer to have low kurtosis distribution or simply the returns that are near to distribution mean (Shanmugam & Chattamvelli, 2016). If there is positive skewness, then it becomes possible to get high kurtosis by avoiding excessive negative returns in the future with the possibility of having more positive returns. When we have negative skewness, investors can face extreme negative returns due to the impact of a high excess kurtosis (Jondeau & Rockinger, 2003).

The procedural steps for DCC-GARCH(1,1) are described as follows:

1. The daily log-returns of series have been calculated as

   \[ R_t = \begin{bmatrix} \log \left( \frac{S_{1,t}}{S_{1,t-1}} \right), \ldots, \log \left( \frac{S_{N,t}}{S_{N,t-1}} \right) \end{bmatrix} = (R_{1t}, \ldots, R_{Nt}) \]  

   where \( S_t \) represents the return of stock 1, \( S_{N,t} \) represents the return of the \( N \)th stock, \( t \) represents the time period, and \( R_t \) represents the total return of a specific stock at time \( t \). While using log-returns, Figure 1 shows the shreds of evidence of the existence of volatility clustering in three selected stock indices of PSX and SSE. Hence, modeling of conditional volatility can be done by considering the fact of volatility presence.

2. Financial data are always nonstationary or have normality issues; therefore, to check the normality of data, Shapiro test has been applied to each set of the data separately. The \( p \)-value for each asset after Shapiro test is less than 5% in all the selected indices, which indicates the data are not normally distributed (Hanusz & Tarasińska, 2015). The data are then normalized by considering \( M = 0 \) and variance = 1. On the normalized data set, Shapiro test shows the \( p \)-values higher than 5%, which indicates the data are now normally distributed around the mean, and they are ready for risk-modeling.

3. Afterward, it is necessary to check whether the data have more or less volatility clustering. To check the volatility clustering, the Ljung–Box test \((Q_k)\) has been applied to the squared log-returns of each index that

\begin{table}
\centering
\caption{Summary Statistics of PSX and SSE Stock Indices.}
\begin{tabular}{|l|c|c|c|c|c|c|c|c|}
\hline
& KSE10 & KSE30 & KSE-ALL & SSE180 & SSE50 & SSEComp \\
\hline
Test statistics & Time frame & June 12, 2009 to October 31, 2019 & & & & & \\
Observations (no. of days) & 2,528 & & & & & \\
Mean & 0 & 0 & 0 & 0 & 0 & 0 \\
variance & 0 & 0 & 0 & 0 & 0 & 0 \\
Skewness & -0.301 & -0.163 & -0.244 & -0.637 & -0.418 & -0.875 \\
Kurtosis & 2.171 & 1.819 & 2.779 & C & 7.610 & 8.171 \\
SD & 0.001 & 0.001 & 0.001 & 0.002 & 0.002 & 0.002 \\
\hline
\end{tabular}
\end{table}
indicates the presence of volatility clustering in each asset class (Peña & Rodríguez, 2002). Lagrange-multiplier test $Q_k$ also confirmed the presence of arch effect in the series of log-returns of each asset class (see Table 2). The Ljung–box test checks confirm the presence of autocorrelation in the data based on the number of lags $m$. The purpose is to test whether the autocorrelation $\gamma_1, \ldots, \gamma_m$ of $z_t$ is 0 or not.

The Ljung–box test can be described in the form of hypothesis:

$$H_0: \gamma_1 = \ldots = \gamma_m = 0$$

$$H_1: \text{atleast one } \gamma_i \neq 0, i = 1, \ldots, m$$

The test statistic is as follows:

$$Q_m = n(n+2) \sum_{i=1}^{m} \frac{\rho_i^2}{n-1}$$

The Ljung–Box test statistics have been shown in Equation 2, where $n$ shows the total number of samples used in this study. $\rho_i$ represents the correlation samples of $z_t^2$ at Lag 1; furthermore, $m$ shows the lags that are being considered for testing, and $Q_m$ is asymptotically distributed as a chi-square distribution having a degree of freedom represented by $m$ in the null hypothesis. For a significance level $\alpha$, we reject $H_0$ if

$$Q_m > \chi^2_{\alpha, m}$$

where $\chi^2_{\alpha, m}$ is the $\alpha$-quantile of the chi-square distribution with $m$ degrees of freedom. Hence, after testing the null hypothesis $H_0$ (no Arch effect present), $H_0$ is rejected because the $p$-value is greater than 5%. Thus, $H_1$ is accepted because the arch effect is present in a series of data (Burns, 2005).

In the next step, it is important to check the correlation pattern of return. Figure 2 shows the autocorrelation function (ACF) of actual returns of PSX and SSE, and Figure 3 shows the ACF of squared returns of PSX and SSE. Actual returns are serially uncorrelated, and then the 5% lags in the ACF plot are expected to fall outside the limits mentioned as red-dotted lines in the ACF plots (Finlay et al., 2011). In Figure 2, we can see that the lags falling outside the

### Table 2. Multivariate-Arch Test on the Log-Returns.

| Multivariate arch | KSE-100 | KSE-30 | KSE-ALL | SSE180 | SSE50 | SSEComp |
|-------------------|---------|-------|---------|--------|-------|---------|
| $p$-value         | 0       | 0     | 0       | 0      | 0     | 0       |
| $Q_{(12)}$        | 727.28  | 846.54| 651.06  | 2,821.8| 2,552.7| 3,653.6 |
| $p$-value         | .0006   | .0007 | .0172   | .00    | .00   | .00     |
| $Q_{(12)}$        | 458.58  | 457.22| 424.42  | 629.04 | 599.81| 700.73  |

Note. $p > .05$. 

![Figure 2. ACF observations of actual returns. Note. ACF = autocorrelation function.](image)
series do not make any pattern and show random walk in all the selected stock indices of PSX as well as SSE. We can conclude that the actual returns are serially uncorrelated, but in Figure 3, the lags falling outside the limits (red-dotted lines) do make some patterns (Madsen, 2007). We can see that initial lags are greater, and then the ACF is decreasing. This is just because the lags falling outside the limits and inside the limits are making patterns, so the squared returns are not uncorrelated. The squared returns only can be uncorrelated if the actual returns are serially independent, but this is not the case here, which means the actual returns are dependent. Because of the uncorrelation of actual returns, correlation modeling is being done using the DCC-GARCH model by Engle (2002).

5. Before applying the DCC volatility matrix, first, GARCH mean and variances should be calculated (Sampid & Hasim, 2018). Bollerslev (1986) proposed the GARCH model that allows the dependence of the conditional variance to its previous lags. The GARCH(1,1) model has the following form:

\[ \gamma_{u,t} = \gamma_{u} + \alpha_{u,t} \sigma_{u,t} + \beta_{u,t-1} \]

\[ \lambda_{u,t} = \alpha_{u} + \beta_{u} \gamma_{u,t-1} + \gamma_{u} \lambda_{u,t-1}, \text{for } u = 1, \ldots, N, t = 1, \ldots, T \]

where in Equation 4 \( \gamma_{u,t} \) represents the log-returns of daily stock prices, \( \gamma_{u} \) represents the conditional log-return mean, \( \alpha_{u,t} \) represents the mean residuals, \( \gamma_{u,t} \) shows the white noise having variance 1 and 0 mean, and \( \lambda_{u,t} \) shows the conditional volatility series; \( \alpha, \beta, \text{ and } \gamma \) in Equation 5 are described as the key parameters of GARCH(1,1) estimation, \( T \) represents the available sample size, and \( N \) represents the number of stock values. Thus, the covariance matrix of DCC at time \( t \) is as follows:

\[ \Sigma_{t} = G_{t} \Sigma_{t} G_{t}^{-1} \]

And the DCC conditional correlation matrix is then \( P_{t} \):

\[ P_{t} = G_{t}^{-1} \Sigma_{t} G_{t}^{-1} \]

In Equation 7, \( G_{t} \) represents the diagonal matrix of the \( N \) conditional volatilities of the stock returns, that is, \( G_{t} = \text{diag} \{ \sqrt{\lambda_{11,t}}, \ldots, \sqrt{\lambda_{NN,t}} \} \) and \( \lambda_{u,t} \) is the \( (u,v) \)th component of the volatility matrix. Based on the above assumptions, the DCC model can be expressed as follows:

\[ P_{t} = (1 - \Omega_{1} - \Omega_{2}) \bar{P} + \Omega_{1} P_{t-1} + \Omega_{2} \varphi_{t-1} \]

In Equation 8, \( \bar{P} \) shows the unconditional correlation matrix of \( \theta_{1}, \theta_{2}, \text{ and } \theta_{2} \), which are positive real numbers satisfying \( 0 < \Omega_{1} < 1 \). \( \varphi_{t-1} \) stands for the correlation matrix of returns depending on \( \{ \theta_{t-1}, \ldots, \theta_{t-1} \} \) for some integer \( n \) and is as follows:

\[ \varphi_{n,t-1} = \frac{\sum_{u=1}^{n} \theta_{u,t-u} \theta_{v,t-u}}{\sqrt{\left( \sum_{u=1}^{n} \theta_{u,t-u} \right) \left( \sum_{v=1}^{n} \theta_{v,t-u} \right) \left( \sum_{u=1}^{n} \theta_{u,t-u} \right) \left( \sum_{v=1}^{n} \theta_{v,t-u} \right)}} \]

where the optimal parameters can be viewed as the smoothing parameter; the larger the value of \( n \), the smoother will be the correlational effect (Sampid & Hasim, 2018). Engle (2002) has proposed the modified version of the DCC model,
The correlation matrix explained in Equation 8 can be further defined as follows:

\[ p_t = (1 - \Omega_1 - \Omega_2) \Omega_1 p_{t-1} + \Omega_2 q_{t-1} q'_{t-1} \]  \hspace{1cm} (11)

In Equation 10, \( \Omega_1 \) and \( \Omega_2 \) show the positive real numbers and \( 0 < \Omega_1 + \Omega_2 < 1 \); \( p_t \) stands for a positive-definite matrix. To renormalize the correlation matrix at each time \( t-1 \), Equation 10 uses the parameter \( q_{t-1} \) (for more information, see Tsay, 2018).

Table 3 shows the forecasted VaR of all three indices of each selected stock exchange at different quantiles of standard residuals calculated using the DCC-GARCH model. Quantile shows the probability of volatility scores of all three indices. The joint VaR value at \( \alpha = 5\% \) is 1.38229 for PSX and 0.87883 for SSE, showing a combined portfolio result.

| Index  | 1%    | 5%    | 10%   | 95%   | 99%   |
|--------|-------|-------|-------|-------|-------|
| KSE100 | -2.283| -1.636| -1.269| 1.661 | 2.369 |
| KSE30  | -2.33 | -1.69 | -1.292| 1.659 | 2.319 |
| KSE-ALL| -2.366| -1.707| -1.286| 1.64  | 2.417 |
| SSE180 | -0.172| -0.129| -0.076| 0.932 | 0.984 |
| SSE50  | -1.760| -1.752| -1.743| 0.361 | 0.541 |
| SSEComp| -0.613| -0.519| -0.401| 0.702 | 0.717 |

Note. VaR = Value-at-Risk.

Key Findings

As the study desired to measure future market risk using VaR, therefore, volatility forecasting has been calculated to find out the accurate measures of stock returns. In doing so, realized and forecasted correlation results of the DCC-GARCH model show the forecasting of returns of combined stocks. Using DCC, this study has come across a key finding of estimating more realized forecasted results than the traditional models.

Figure 4 shows the realized conditional correlation between the selected indices of PSX and SSE from the period 2009 to 2019. Figure 5 shows the forecasted correlation of each stock index separately. In all, 20 lags from the estimated correlation matrix and 10 lags from the forecasted matrix have been selected to present the conditional correlation between the stock indices better. Cor\_30\_all is the correlation between KSE30 and KSE-ALL indices, cor\_KSE100\_all is the correlation between KSE100 and KSE-ALL, and, finally, cor\_100\_30 is the correlation between KSE100 and KSE30, respectively. Similarly, cor\_180\_50 is the correlation between SSE180 and SSE50 indices, cor\_180\_comp is the correlation between SSE180 and SSE-Composite indices, and, finally, cor\_50\_comp is the correlation between SSE50 and SSE-Composite indices.

The DCC model of Engle (2002) can better estimate the time-varying correlation between the asset classes. The main finding of this article is even in the highly volatile stock markets, and the bivariate time-varying dynamic conditional correlation model provides better performance than traditional models. See Figure 6 as the comparison of capturing volatilities across the sample indices that endorse the findings of this article.

Figure 6 shows the volatility capturing of each selected stock index in comparison with the simple GARCH model and DCC model used for capturing the volatility. We can notice that the volatility captured by the GARCH(1,1) method is underestimated, but volatility captured through the DCC model is more accurately addressed. The GARCH family models alone are unable to capture the volatility effectively. The DCC model is a much more effective model to address the volatility as the parameters estimated by the DCC model indicate the effectiveness of the model in the selected stock market.

Table 4 presents the estimated parameters from the DCC model for all the selected indices of PSX and SSE, including the \( p \)-values of each parameter estimated. Results reveal that the parameters estimated in Table 4 by DCC-GARCH(1,1) are highly significant. The parameter \( \beta_1 \) is significantly positive that shows the connection of its risk measures with its conditional variance, which shows substantial and positive autocorrelation of returns of all indices. The persistence measurement is \( \alpha_1 + \beta_1 \), which should be less than 1, but here it is almost equal to 1 in the case of all stock indices whether they are PSX stock indices or SSE stock indices. That means the estimated correlations can be integrated with the DCC-GARCH process, and it is nonstationary. More significance is given to the joint \( \text{dcc}_1 \beta_1 \) parameters as individual parameters \( \alpha_1 \) and \( \beta_1 \) are of univariate GARCH model. In Table 4, \( \text{dcc}_1 + \text{dcc}_1 \beta_1 \) is less than 1, which shows the stationary condition of the DCC model, indicating that there is no more volatility clustering behavior present after the modeling on selected stock indices of PSX and SSE. The findings of the study are helpful to the stockbrokers and investors to understand the actual behavior of stocks in dynamic markets. Subsequently, the results can also provide better insights into the forecasting of VaR while considering the combined correlation effect of all stocks because all stocks are prorogated to have a serial correction and time-varying effects. Therefore, this model.
Afzal et al. gives reasonable estimates to the investors in a highly volatile market who are looking at estimating what kind of correlation and volatility dynamics is present in their potential portfolios to maximize returns.

**Conclusion**

The nature of the model is critical in addressing the volatility of any stock market portfolio. Investors are always wondering to find better forecast methods to select the potential portfolios for their investment. This article assessed the time-varying dynamics of Pakistan stock market indices by using the DCC model to estimate the conditional correlation and volatility capturing dynamics by the DCC-GARCH model of selected stock indices of PSX and SSE. A daily log-returns of three stock indices of PSX, that is, KSE100, KSE30, and KSE-ALL, and three stock indices of SSE, that is, SSE180, SSE50 and SSE-Composite, from the period 2009 to 2019 are used for DCC modeling in VaR analysis.

The DCC model has better estimated the time-varying correlation between all asset classes. Even in the highly volatile stock markets, the bivariate time-varying DCC
model provides better performance than traditional models. The joint $\alpha_1$ and $\beta_1$ parameters are more significant than the individual parameters $\alpha$ and $\beta$, that are of univariate GARCH model. This indicates that there is no more volatility clustering behavior. The volatility captured by the GARCH(1,1) method is underestimated, but the volatility captured through the DCC model is more accurately addressed. The GARCH family models alone are unable to capture the volatility effectively. The DCC model is a much more effective model to address the volatility as the parameters estimated by the DCC model indicate the effectiveness of the model in the selected stock market.

Thus, this study contributes to the body of knowledge in a way to introduce an efficient method of risk estimation in dynamic market. This model gives a new way of risk consideration rather than using traditional methods. Furthermore, it is suggested that only dynamic models should be considered for risk estimation in dynamic market. Similarly, investors and financial experts can increase their market confidence by adopting this DCC-GARCH model for market risk estimation in dynamic capabilities. Future work could be done on

Figure 6. Volatility capturing using simple GARCH and DCC-GARCH model.
Note. GARCH = generalized autoregressive conditional heteroscedasticity; DCC = dynamic conditional correlation.
Table 4. Estimated DCC Parameters of PSX and SSE Stock Indices.

| Parameters | Estimate | SE | p-value | t-value | Estimate | SE | p-value | t-value | Estimate | SE | p-value | t-value |
|------------|----------|----|---------|---------|----------|----|---------|---------|----------|----|---------|---------|
|            |          |    |         |         |          |    |         |         |          |    |         |         |
| KSE100     |          |    |         |         |          |    |         |         |          |    |         |         |
| $\mu$      | -0.012   | 0.019| -0.060  | 0.547   | -0.016   | 0.021| -0.790  | 0.430   | 0.010    | 0.019| 0.502   | 0.616   |
| $\omega$   | 0.004    | 0.002| 2.102   | 0.036   | 0.009    | 0.003| 3.237   | 0.001   | 0.007    | 0.002| 2.986   | 0.003   |
| $\alpha_1$ | 0.003    | 0.002| 1.592   | 0.111   | 0.004    | 0.003| 1.340   | 0.180   | 0.000    | 0.002| 0.007   | 0.994   |
| $\beta_1$  | 0.993    | 0.000| 35,607.000 | 0.000 | 0.988    | 0.000| 6,188,000 | 0.000 | 0.993    | 0.000| 37,315,000 | 0.000 |
| ar1        | -0.013   | 0.020| -0.642  | 0.521   | 0.027    | 0.020| 1.358   | 0.174   | -0.033   | -0.019| -1.697  | 0.090   |
| VaR        |          |    |         |         |          |    |         |         |          |    |         |         |
| 5%         | -1.636   | -1.269| 1.661  | 2.369   | -1.690   | -1.292| 1.659   | 2.319   | -1.707   | -1.286| 1.640   | 2.417   |
| 10%        |          |    |         |         |          |    |         |         |          |    |         |         |
| 95%        |          |    |         |         |          |    |         |         |          |    |         |         |
| 99%        |          |    |         |         |          |    |         |         |          |    |         |         |
| SSE30      |          |    |         |         |          |    |         |         |          |    |         |         |
| $\mu$      | 0.500    | 0.005| 93.608  | 0.000   | 0.501    | 0.005| 94.369  | 0.000   | 0.498    | 0.005| 92.647  | 0.000   |
| $\omega$   | 0.000    | 0.000| 2.019   | 0.044   | 0.000    | 0.000| 2.370   | 0.018   | 0.000    | 0.000| 1.977   | 0.048   |
| $\alpha_1$ | 0.036    | 0.002| 20.734  | 0.000   | 0.039    | 0.002| 16.623  | 0.000   | 0.035    | 0.002| 18.081  | 0.000   |
| $\beta_1$  | 0.960    | 0.000| 2,509.105 | 0.000 | 0.957    | 0.001| 1,600,820 | 0.000 | 0.962    | 0.000| 2,705,340 | 0.000 |
| ar1        | -0.880   | 0.083| -10.637924 | 0.000000 | 0.015    | 0.401| 0.038   | 0.970   | -0.875   | 0.067| -13.104 | 0.000   |
| VaR        |          |    |         |         |          |    |         |         |          |    |         |         |
| 5%         | -0.129   | -0.076| 0.932  | 0.984   | -1.752   | -1.743| 0.361   | 0.541   | -0.519   | -0.401| 0.702   | 0.717   |
| 10%        |          |    |         |         |          |    |         |         |          |    |         |         |
| 95%        |          |    |         |         |          |    |         |         |          |    |         |         |
| 99%        |          |    |         |         |          |    |         |         |          |    |         |         |
| SSEcomp    |          |    |         |         |          |    |         |         |          |    |         |         |
| $\mu$      |          |    |         |         |          |    |         |         |          |    |         |         |
| $\omega$   |          |    |         |         |          |    |         |         |          |    |         |         |
| $\alpha_1$ |          |    |         |         |          |    |         |         |          |    |         |         |
| $\beta_1$  |          |    |         |         |          |    |         |         |          |    |         |         |
| ar1        |          |    |         |         |          |    |         |         |          |    |         |         |
| VaR        |          |    |         |         |          |    |         |         |          |    |         |         |

Note. DCC = dynamic conditional correlation; SSE = Shanghai Stock Exchange.
the estimation of conditional correlation using the traditional GARCH family models together with the dependence measurement by copulas in volatile stock markets, where news impact is powerful. One can check the compatibility of copulas with individual stock dynamics.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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References

Ackermann, C., Mcenally, R., & Ravenscraft, D. (1999). The performance of hedge funds: Risk, return, and incentives. *Journal of Finance, 54*, 833–874. https://doi.org/10.1111/0022-1082.00129

Afzal, F., Haiying, P., Afzal, F., & Bhatti, F. G. (2019). Predicting the relationship, and/or publication of this article. The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The author(s) received no financial support for the research, authorship, and/or publication of this article.

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics, 20*(3), 339–350. https://doi.org/10.1198/07350010228618487

Favre, L., & Galcaneo, J.-A. (2002). Mean-modified value-at-risk optimization with hedge funds. *The Journal of Alternative Investments, 5*, 21–25. https://doi.org/10.3905/jai.2002.319052

Finlay, R., Fung, T., & Seneta, E. (2011). Autocorrelation functions. *International Statistical Review, 79*(2), 255–271. https://doi.org/10.1111/j.1751-5823.2011.00148.x

Francq, C., & Zakoïan, J. M. (2010). GARCH models: Structure, statistical inference and financial applications. In *GARCH models: Structure, statistical inference and financial applications*. https://doi.org/10.1002/9780470670057

Fung, W., & Hsieh, D. A. (1997). Empirical characteristics of dynamic trading strategies: The Case of hedge funds. *Review of Financial Studies, 10*(2), 275–302. https://doi.org/10.1093/rfs/10.2.275

Füss, R., Kaiser, D. G., & Adams, Z. (2007). Value at risk, GARCH modelling and the forecasting of hedge fund return volatility. *Journal of Derivatives & Hedge Funds, 13*, 2–25. https://doi.org/10.1057/palgrave.jdh.1850048

Hanusz, Z., & Tarasińska, J. (2015). Normalization of the Kolmogorov–Smirnov and Shapiro–Wilks tests of normality. *Biometrical Letters, 52*(2), 85–93. https://doi.org/10.1515/bile-2015-0008

Hull, J., & White, A. (1998). Incorporating volatility updating into the historical simulation method for value-at-risk. *The Journal of Risk, 1*(1), 5–19. https://doi.org/10.21314/JOR.1998.001

Jondeau, E., & Rockinger, M. (2003). Conditional volatility, skewness, and kurtosis: Existence, persistence, and comovements. *Journal of Economic Dynamics & Control, 27*(10), 1699–1737. https://doi.org/10.1016/S0165-1889(02)00079-9

Jorion, P. (1996). Risk 2 : Measuring the risk in value at risk. *The Journal of Finance, 51*(3), 57–82. https://doi.org/10.21314/JOR.1998.001

Kolari, J. W., Moorman, T. C., & Sorescu, S. M. (2008). Foreign exchange risk and the cross-section of stock returns. *Journal of International Money and Finance, 27*, 1074–1097. https://doi.org/10.1016/j.intmonfin.2007.07.001

Longin, F. M. (2000). From value at risk to stress testing: The extreme value approach. *Journal of Banking & Finance, 24*(7), 1097–1130. https://doi.org/10.1016/S0378-4266(99)00077-1

Longin, F. M., & Solnik, B. (2001). Extreme correlation of international equity markets. *The Journal of Finance, 56*(2), 649–676. https://doi.org/10.1111/0022-1082.00340

Madsen, H. (2007). Time-series analysis. In *Practical statistics: A quick and easy guide to IBM® SPSS® statistics, STATA, and other statistical software* (pp. 315–338). https://doi.org/10.4135/9781454838565.n8

Marshall, C., & Siegel, M. (1997). Value-at-risk: Implementing a risk measurement standard. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1212

Peña, D., & Rodríguez, J. (2002). A powerful portmanteau test of lack of fit for time series. *Journal of the American Statistical Association, 97*(458), 601–610. https://doi.org/10.1198/016214502760047122
Sampid, M. G., & Hasim, H. M. (2018). Estimating value-at-risk using a multivariate copula-based volatility model: Evidence from European banks. *International Economics, 156*, 175–192. https://doi.org/10.1016/j.inteco.2018.03.001

Shanmugam, R., & Chattamvelli, R. (2016). Skewness and Kurtosis. In *Statistics for scientists and engineers* (pp. 89–110). https://doi.org/10.1002/9781119047063.ch4

Tastan, H. (2006). Estimating time-varying conditional correlations between stock and foreign exchange markets. *Physica A: Statistical Mechanics and Its Applications, 360*(2), 445–458. https://doi.org/10.1016/j.physa.2005.06.062

Tsay, R. S. (2018). *Multivariate time series—R and financial applications*. https://www.wiley.com/en-cv/Multivariate+Time+Series+Analysis%3A+With+R+and+Financial+Applications-p-9781118617908

Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business & Economic Statistics, 20*(3), 351–362. https://doi.org/10.1198/073500102288618496

Yang, J. (2011). *Quantitative financial risk management*. https://doi.org/10.1007/978-3-642-19339-2

Zhou, X., Litke, A., & McLaughlin, A. (2010). A style-based market risk model for hedge fund portfolios. *Journal of Portfolio Management, 36*, 124–131. https://doi.org/10.3905/jpm.2010.36.4.124