**Range-based DCC models for volatility forecasting:**

**Evidence from India**

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Table of Contents

[1. OBJECTIVES 3](#_Toc89740871)

[2. INTRODUCTION 4](#_Toc89740872)

[3. LITERATURE REVIEW 5](#_Toc89740873)

[Note: Research Gaps 8](#_Toc89740874)

[4. METHODOLOGY 9](#_Toc89740875)

[4.1 The DCC-GARCH model: 9](#_Toc89740876)

[4.2 The Range-GARCH model: 11](#_Toc89740877)

[4.3 The DCC-Range-GARCH model: 12](#_Toc89740878)

[5. DATA 13](#_Toc89740879)

[Table 1 14](#_Toc89740880)

[6. RESULTS 15](#_Toc89740881)

[6.1 In-sample comparison of models 16](#_Toc89740882)

[Table 2 16](#_Toc89740883)

[Table 3 17](#_Toc89740884)

[Table 4 17](#_Toc89740885)

[6.2 Comparison of variance forecasts 19](#_Toc89740886)

[Table 5 19](#_Toc89740887)

[Table 6 20](#_Toc89740888)

[Table 7 21](#_Toc89740889)

[6.3 Comparison of covariance forecasts 22](#_Toc89740890)

[Table 8 22](#_Toc89740891)

[Table 9 23](#_Toc89740892)

[7. CONCLUSION & POLICY IMPLICATIONS 24](#_Toc89740893)

[8. REFERENCES 25](#_Toc89740894)

# OBJECTIVES

It is evident that incorporating high and low prices in the estimation of volatility and covariance forecasts lead to more robust estimates (Fiszeder and Perczak, 2016; Molnar 2016; etc.)

To involve OHCL data of a given day to calculate volatility estimates using the DCC Framework, we suggest the following:

1. Improve on the DCC Model using the DCC-Range-GARCH Model by incorporating the high and low prices.
2. To compare the performance of DCC-GARCH and DCC-RGARCH models in accurately predicting volatility using variance and covariance criterions.

# INTRODUCTION

Models that can describe the dynamic properties of two or more asset returns play an important role in finance and financial econometrics. Multivariate volatility models, right from the basic calculation of standard deviation as a measure of volatility to Implied Standard Deviation(ISD) models can be very useful to predict and test the temporal dependence of asset returns.

One of the most popular multivariate volatility models is the dynamic conditional correlation (DCC) model introduced by Engle (2002) and Tse and Tsui (2002). The advantages of the DCC model are the positive definiteness of the conditional covariance matrices and the ability to describe time-varying conditional correlations and covariances in a parsimonious way. The parameters of the DCC model can be estimated in two stages, which makes this approach relatively simple and possible to apply even for very large portfolios. The DCC model has become extremely popular and has been widely applied and modified (e.g. Heaney and Sriananthakumar, 2012; Lehkonen and Heimonen, 2014; Bouri et al., 2017; Bernardi and Catania, 2018; Dark, 2018; Karanasos et al., 2018). Most volatility models are return-based models, i.e. they are estimated on returns, which are calculated based only on closing prices. Meanwhile, the use of daily low and high prices leads to more accurate estimates and forecasts of variances (see e.g. Chou, 2005; Brandt and Jones, 2006; Lin et al., 2012; Fiszeder and Perczak, 2016; Molnár, 2016) and covariances (see e.g. Chou et al., 2009; Fiszeder, 2018). Daily low and high prices are almost always available alongside closing prices in financial series. Therefore, making use of them in volatility models is very important from a practical viewpoint.

# LITERATURE REVIEW

This paper looks into various volatility models like the DCC model, DCC-GARCH model, DCC-RGARCH as well as DCC-Range-GARCH model and analyses which ones perform with better robustness by analysing their models as well as volatility forecasts. It follows the methodology provided by Fiszeder et al.(2019) as mentioned in the Methodology section. We try to improve upon their result by using other estimation methods like the one given by Garman and Klass(1980) and Rogers and Satchell(1991) as opposed to the standard Parkinson(1980) estimator used in the paper.

Diebold and Mariano(1995) proposed and evaluated explicit tests of the null hypothesis of no difference in the accuracy of two competing forecasts. Other authors before them like Chinn and Meese(1991) stressed upon the direction of change, Cumby and Modest(1987) stressed market and country timings, etc. The authors however allowed for forecast errors to be non-Gaussian with non-zero mean and with both serial and contemporaneous correlation; and their tests are applicable to a very wide range of loss functions and structures.

Harvey et al(1997) analyzed the hypothesis of equal accuracy in forecast performance, given two forecasts of the same quantity. They point out drawbacks in the Diebold and Mariano(1995) test statistic, stating that the test can be seriously over-sized, even for very large samples, when the forecast errors are generated by heavy-tail distributions. They then suggest modifications to the Diebold-Mariano and the Morgan-Granger-Newbold tests, which apply to forecasts more than one step ahead, as well as not relying on the assumption of forecast unbiasedness.

Pagan and Schwert(1990) analyzed and compared various statistical models for monthly stock return volatility. They bring out the importance of nonlinearities in the behaviour of most stocks, which cannot be captured by any conventional ARCH or GARCH models, especially due to the nonstationary nature of stock volatility, implying that the standard parametric models are not sufficiently extensive. Non parametric models provide more robust results because they can reflect asymmetric relationships between volatility and past returns.

Engle(2002) in his paper, developed the DCC-GARCH model where parameters were estimated using closing prices. This model has the flexibility of a univariate GARCH model coupled with the parsimonious parametric models for correlations.

Glosten et. al. (1993) use a modified GARCH-M model popularly known as the GJR model to find a relation between expected value and volatility of the nominal excess return on stocks. They found results supporting that there is a negative relationship between conditional expected monthly return and the conditional variance of monthly return. Nelson (1991) also developed another asymmetric GARCH model called an EGARCH model. The two models above can be used to construct DCC models namely the DCC-EGARCH and the DCC-GJR model.

Molnar (2016) formulated the Range-GARCH model. This incorporated the high and low prices along with the traditional return from closing prices in the simple GARCH model. The paper also showed that the Range-GARCH is in-fact superior to the simple GARCH model based on closing prices. This Range-GARCH model is used as a basis to specify the DCC model proposed by Engle (2002) in this paper, to give a new specification of DCC, the DCC-Range-GARCH model or DCC-RGARCH model.

Andersen et al.(2003), demonstrate the use of simple Gaussian vector autoregressive models to forecast the high daily and lower frequency return volatilities and return distributions using integrated high-frequency intraday data. They also demonstrated the fact that their models work better than simple GARCH models and attributed this to the fact that the GARCH model presents a slow response to sudden changes in the market. Same fact is furthered by Hansen et al.(2012). They introduce a new framework named Realized GARCH which is used to model both returns and realized volatility together. Empirical application on Dow Jones Industrial Average stocks and exchange traded funds showed a significant improvement over a simple GARCH model.

Poon and Granger(2003) conduct an analysis of the several volatility models in terms of their forecast accuracy, by analyzing 93 relevant papers and building upon various models, right from the basic ARIMA models to the ISD(Implied Standard Deviation) and the SV(Stochastic Volatility) model forecasts. They found out that ISD methods provide the best forecasting ahead of Historic Volatility(HISVOL) models and GARCH models, especially because ISDs use a richer dataset involving option prices as well.

Su and Wu(2014) suggest a new range-based Markov-switching dynamic conditional correlation (MS - DCC) model to be used for estimating minimum variance hedging ratios, which addresses the limitations of the linear functional forms of the standard conditional covariance estimation methods, with both in-sample and out-of-sample performance indicating that the use of range-based MS-DCC model for hedging is superior to using the standard OLD regression, return-based DCC, range-based DCC and return-based MS-DCC models.

L. C. G. Rogers and Fanyin Zhou (2008) mention that no doubt that volatility is a central concept in the theory and application of quantitative finance. It is always worth computing the new estimator, if only as a comparison with the simple open-close estimator. Widely differing numerical values may indicate a departure from log-normality that requires further investigation. It is clear that if we are trying to produce an estimate of the covariance matrix of more than two Brownian motions, estimating each entry, then the matrix will be rank 2 and nonnegative definite. Simulation experiments showed that the estimator behaved as expected for log-Brownian data, but that the performance on simulated variance gamma data was poor.

Peter Molnar (2012) reviews alternative price range estimators and discusses their empirical properties and limitations. Volatility modelling and forecasting become one of the most developed parts of financial econometrics. Range, the difference between high and low prices is a natural candidate for the volatility estimation.

The Garman-Klass volatility estimator combines the Parkinson volatility estimator with simple squared return. Range-based volatility estimators were derived to be as precise volatility estimators as possible. Andersen, Bollerslev, Diebold, and Ebens (2001) find that ”although the unconditional daily return distributions are leptokurtic, the daily returns normalized by the realized standard deviations are close to normal.” But the conclusion is that these models cannot estimate volatility precisely enough and the noise in the volatility estimates causes the heavy tails.

Mark B. Garman and Michael J. Klass (1980) examines the problem of estimating capital asset price volatility parameters from the most available forms of public data. Their purpose is to develop the estimation consequences of the model, given the data restrictions. Classical estimator advantages are its simplicity of usage and its freedom from obvious sources of error or bias and principal disadvantage is the fact that it ignores other readily available information which may contribute to estimator efficiency. One criticism of the High/Low Estimators which are based solely on the quantity (u-d) is that they ignore the joint effects between the quantities u, d, and c, which may be utilized to further increase efficiency. But an estimator is "best" when it has minimum variance and is unbiased.

Piotr Fiszeder and Grzegorz Perczak took a new look at variance estimation based on low, high and closing prices. It has been a subject of plenty of studies, Anderson and Bollerslev (1998) have shown us that daily squared return is an inefficient estimator. The best-known volatility measures constructed on the basis of open, low, high and closing prices estimators of Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991) and Yang and Zhang (2000) these are more than seven times more efficient than the daily squared return estimator. Authors estimate the bias and analytically assess effectiveness of various, popular estimators of variance in paper. Density and characteristic functions are used to evaluate well known and density and characteristic functions. However in many studies the issue of the joint density of the random vector (Ct, Xt) is considered Eg. Cox and Miller (1965) and Harrison(1985). Estimators based on low, high and closing prices can be applied in the future to the construction of the GARCH models; it will be possible to obtain even more accurate volatility estimates.

To test the significance of differences in the likelihood function of various models, two tests have been taken. First, is the **Rivers and Vuong (2002)** test for non-nested model selection. Second is the **Clarke (2007)** test for non-nested model selection. The latter test has been proven to be more efficient than the Vuong test when distribution of individual log-likelihood ratios is highly peaked.

## Note: Research Gaps

The estimator used for variance in the given paper is based on the Parkinson(1980) estimator, which takes into account only the High and Low prices of that particular time frame, fail to take into account the joint effects between the high, low and closing prices which could be used to further improve the robustness and efficiency as it leaves the crucial data about opening and closing prices. Some more robust estimators like the Garman and Klass(1980) estimator which do take into account all the above mentioned data as well as volume effects and the Rogers and Satchell(1991) estimator improves upon both the previous results as it assumes the presence of a drift term ‘c’, which helps in creating an unbiased estimator.

It is well known that GARCH model tends to overestimate the persistence value( in periods of sudden jumps or dips in the market. This creates a possibility of wrong predictions. Thus improvements over the traditional GARCH model are needed. These regime shifts have to be incorporated into the model to get more accurate predictions.

The DCC-Garch model utilises only the closing prices to calculate its parameters. However, the high and low prices of the day contain more information about volatility than just the closing prices and thus a new specification of the DCC model called the DCC-Range-GARCH can be used to get more robust results.

# METHODOLOGY

This paper involves the following models, described as follows:

## 4.1 The DCC-GARCH model:

In this paper we extend the DCC model by Engle (2002) by introducing the range (the difference between low and high prices) to the model. First, we present the standard DCC model based on closing prices. In order to better distinguish this model from its competitors used in the paper, which are based on different univariate models, we will refer to it as the DCC-GARCH model.

Let us assume that (𝑁 × 1 vector) is the innovation process for the conditional mean and can be written as:

Where:  is the set of all information available at time t − 1,

is the multivariate normal distribution and

is the 𝑁 ×𝑁 symmetric conditional covariance matrix.

The DCC(𝑃, 𝑄)-GARCH(𝑝, 𝑞) model by Engle (2002) is as follows:

where:

,

conditional variances (for 𝑘 = 1, 2, …, 𝑁) are described as univariate GARCH models (Eqns. (5) – (6)),

is the standardized 𝑁×1 residual vector assumed to be serially independently distributed given as  ,

is the time varying 𝑁×𝑁 conditional correlation matrix of ,

is the unconditional 𝑁×𝑁 covariance matrix of (according to Engle, 2002) and

is the diagonal 𝑁×𝑁 matrix composed of the square root of the diagonal elements of .

The parameters are non-negative and satisfy the condition    *.*

The univariate GARCH(𝑝, 𝑞) model applied in the DCC-GARCH model can be written as:

Where:

,

weaker conditions for non-negativity of the conditional variance can be assumed (see Nelson and Cao, 1992).

The requirement for covariance stationarity of is

A nice feature of the DCC-GARCH model is that its parameters can be estimated by the quasi-maximum likelihood method using a two-stage approach (see Engle and Sheppard, 2001).

Let the parameters of the model be written in two groups , where is the vector of parameters of conditional means and variances and is the vector of parameters of the correlation part of the model. The log-likelihood function can be written as the sum of two parts:

Where represents the volatility part:

while can be viewed as the correlation component:

can be written as the sum of log-likelihood functions of 𝑁 univariate GARCH models:

This means that in the first stage the parameters of univariate GARCH models can be estimated separately for each of the assets and the estimates of can be obtained. In the second stage residuals transformed by their estimated standard deviations are used to estimate the parameters of the correlation part conditioning on the parameters estimated in the first stage .

## 4.2 The Range-GARCH model:

In the new specification of the DCC-RGARCH model we use the Range-GARCH model introduced by Molnár (2016). The RGARCH(𝑝, 𝑞) model can be formulated as:

where is the Rogers and Satchel estimator (1991) estimator calculated as:

In this formulation, other variance estimators such as the Garmen and Klass (1980) and Parkinson(1980) estimator can be also be used. We use the Roger Satchell estimator as it incorporates a drift term (mean return not equal to zero) and as a result it provides a better volatility estimation when the underlying in trending.

To ensure the positivity of the parameters of the RGARCH model must meet conditions analogous to those in the GARCH model (see Nelson and Cao, 1992). The RGARCH process is covariance stationary if the following condition is met:

It is worth emphasizing that the RGARCH model describes the dynamics of the conditional variance of returns, not the conditional mean of the price range, as in the case of the CARR model. The parameters of the RGARCH model can be estimated by the quasi-maximum likelihood method and the likelihood function is the same as in the return-based GARCH model.

## 4.3 The DCC-Range-GARCH model:

In this subsection we introduce our new DCC-Range-GARCH model (denoted by DCC-RGARCH). The DCC(𝑃, 𝑄)-RGARCH(𝑝, 𝑞) model can be presented as:

where ,

conditional variances (are described as for the RGARCH model (Eqs. (11)–(12)), is the standardized 𝑁×1 residual vector which contains the standardized residuals calculated from the RGARCH model as , the other variables are defined in the same way as in the DCC-GARCH model.

The parameters of the DCC-R-GARCH model can be estimated by the quasi-maximum likelihood method using a two-stage approach. The log-likelihood function can be written as the sum of two parts, the volatility part and the correlation part:

This means that in the first stage the parameters of univariate RGARCH models can be estimated separately for each of the assets. In the second stage the standardized residuals are used to maximize Eq. (20) in order to estimate the parameters of the correlation component.

# DATA

We will apply the aforementioned models to 3 different sets of financial data – five listed large cap equities, three currency pairs and three mid cap listed equities.

The five equities chosen for this are: Reliance Industries Ltd(RELIANCE), Tata Consultancy Services (TCS), HDFC Bank (HDFCBANK), Infosys (INFY) and ICICI Bank (ICICIBANK). We chose these particular equities as these are 5 largest companies by market capitalization that are publicly traded in India. The OHLC data for these 5 tickers has been taken from Yahoo Finance and the OHLC data is based on the trading activity of these tickers on NSE.

The second set of data consists of three currency pairs which are USD/INR, GBP/INR and EUR/INR. These currency pairs were chosen as they are the most heavily traded INR currency pairs in the Forex market. The OHLC data for currency pairs has also been taken from the Yahoo Finance website.

The third set of data consists of three Mid-cap stocks which are Vinati Organic Ltd, Tanla Platforms Ltd and L&T Finance Holdings Ltd. mid-cap stocks were chosen as they are usually more volatile than large cap stocks.

We evaluate the models with these three datasets of daily OHLC data for the 3-year period starting from Oct 2018 and ending in Oct 2021. This time duration has been chosen as this period covers both low volatility periods, like the period between Oct 2018 and March 2020, and very high volatility periods, like the COVID-19 market crash and subsequent recovery.

The descriptive statistics for the returns of these assets are summarized in Table 1. The returns are percentage returns calculated by the formula rt = 100(log(rt)/rt -1). The means for almost all the returns are positive with an exception of L&T Ltd. The standard deviation for currency exchanges is significantly lower than that of the midcap assets and stocks considered. Almost none of the distributions of the asset is symmetric and most of them display significant leptokurtosis.

### Table 1

**Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Assets** | **Mean x 102** | **Minimum** | **Maximum** | **Standard Deviation** | **Skewness** | **Excess Kurtosis** |
| **Currency Rates** |  |  |  |  |  |  |
| EUR/INR | 0.0145 | -0.0250 | 0.0281 | 0.0052 | 0.236\* | 2.774\* |
| USD/INR | 0.0179 | -0.0432 | 0.0272 | 0.0064 | -0.316\* | 4.432\* |
| GBP/INR | 0.0159 | -0.0187 | 0.0294 | 0.0047 | 0.430\* | 3.410\* |
| **Midcap Stocks** |  |  |  |  |  |  |
| Vinergy Capital Inc | 0.1430 | -0.1313 | 0.1733 | 0.0246 | 0.535\* | 6.040\* |
| Tanla Platforms Ltd | 0.3614 | -0.1047 | 0.1360 | 0.0332 | 0.172\* | -0.188 |
| L&T Ltd | -0.0790 | -0.2042 | 0.1267 | 0.0297 | -0.650\* | 5.598\* |
| **Stocks** |  |  |  |  |  |  |
| Infosys | 0.1241 | -0.1766 | 0.1136 | 0.0187 | -0.812\* | 13.250\* |
| TCS | 0.0999 | -0.0988 | 0.0939 | 0.0171 | -0.119\* | 4.172\* |
| HDFC Bank | 0.0566 | -0.1348 | 0.1097 | 0.0173 | -0.379\* | 10.149\* |
| ICICI Bank | 0.1006 | -0.1966 | 0.1289 | 0.0240 | -0.443\* | 8.212\* |
| Reliance | 0.1096 | -0.1410 | 0.1373 | 0.0207 | 0.034 | 8.861\* |

The sample period is between January 1, 2018, to October 31, 2021. \*Indicates that the null hypothesis (the skewness or excess kurtosis is equal to zero) was rejected at the 10% significance level.

# RESULTS

We consider two DCC models in the analysis:

(1) The DCC-GARCH model by Engle (2002) summarized by Eqs. (1)–(6), where parameters are estimated based only on closing prices.

(2) The proposed DCC-RGARCH model summarized by Eqs. (14)–(19). In this specification the RGARCH model described by Eqs. (11)–(13) is applied in the DCC model instead of the univariate GARCH model.

The considered exchange rates, midcaps and stocks are not cointegrated (according to the Johansen test). Mean equations for returns are very simple: each mean equation is a constant, because in our data the sample return of any asset is not dependent on its own past returns nor on the past returns of other assets. We first compare the fit of the models estimated on the whole sample of data, and then compare the forecasts from these models. We analyse forecasts of variances and forecasts of covariances separately, because models for variances already exist whereas forecasting covariances is the paper’s main contribution.

## 6.1 In-sample comparison of models

The parameters of the considered models are estimated using the quasi-maximum likelihood method. The results of the estimation are presented in Tables 2–4 separately for exchange rates, midcap and stocks.

### Table 2

**Results of parameter estimation for stocks.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Parameter** | **DCC-GARCH** | | **DCC-RGARCH** | |
|  | **Estimate** | **Std. error** | **Estimate** | **Std. error** |
| γ10 | 0.000446 | 0.000379 | 0.000266 | 0.00039 |
| α10 | 9.25E-06 | 4.50E-06 | 7.81E-06 | 6.17E-06 |
| α11 | 0.13339 | 0.049256 | 0.319632 | 0.151019 |
| β11 | 0.832364 | 0.05893 | 0.71037 | 0.133175 |
| γ20 | 0.00088 | 0.00057 | 0.000641 | 0.000594 |
| α20 | 1.46E-05 | 5.34E-06 | 8.86E-06 | 7.32E-06 |
| α21 | 0.088606 | 0.022633 | 0.189927 | 0.062819 |
| β21 | 0.884946 | 0.023231 | 0.842658 | 0.04988 |
| γ30 | 0.00127 | 0.000447 | 0.00128 | 0.000449 |
| α30 | 2.05E-05 | 7.05E-06 | 1.72E-05 | 1.17E-05 |
| α31 | 0.079757 | 0.024802 | 0.299712 | 0.107963 |
| β31 | 0.853045 | 0.036287 | 0.7143 | 0.106576 |
| γ40 | 0.000991 | 0.000523 | 0.000841 | 0.00053 |
| α40 | 2.85E-05 | 1.29E-05 | 2.59E-05 | 1.17E-05 |
| α41 | 0.091531 | 0.031748 | 0.185476 | 0.062023 |
| β41 | 0.829901 | 0.057136 | 0.783371 | 0.066194 |
| γ50 | 0.00098 | 0.000432 | 0.000988 | 0.000433 |
| α50 | 1.42E-05 | 6.11E-06 | 5.84E-06 | 5.93E-06 |
| α51 | 0.076903 | 0.027642 | 0.170722 | 0.053914 |
| β51 | 0.877181 | 0.037421 | 0.841351 | 0.044568 |
| ζ1 | 0.014933 | 0.003295 | 0.016008 | 0.003564 |
| θ1 | 0.959962 | 0.010097 | 0.95579 | 0.011296 |

The sample period is January 1, 2018 to October 31, 2021, the parameters γk0 are constants, αk0, αk1, βk1 are parameters for the univariate GARCH model (Eq(6)), and the RGARCH model (Eq(12)). k=1, 2, 3, 4, 5 is for HDFC Bank, ICIC Bank, Infosys, Reliance and TCS, respectively, ζ1 andθ1 are the parameters of the correlation parts of both the DCC-GARCH and DCC-RGARCH models.

### 

### Table 3

**Results of parameter estimation for currency pairs.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Parameter** | **DCC-GARCH** | | **DCC-RGARCH** | |
|  | **Estimate** | **Std. error** | **Estimate** | **Std. error** |
| γ10 | 2.09E-05 | 0.000134 | 1.91E-05 | - |
| α10 | 2.39E-06 | 2.18E-06 | 2.34E-06 | - |
| α11 | 0.127024 | 0.07086 | 0.05 | - |
| β11 | 0.785997 | 0.143041 | 0.8 | - |
| γ20 | 0.000151 | 0.000162 | 0.000258 | 0.000133 |
| α20 | 9.65E-07 | 5.29E-07 | -9.34E-07 | 6.21E-07 |
| α21 | 0.088526 | 0.024374 | 0.939289 | 0.049367 |
| β21 | 0.888083 | 0.031312 | 0.053873 | 0.029199 |
| γ30 | 4.48E-05 | 0.000115 | 0.000165 | 0.000104 |
| α30 | 3.83E-07 | 1.88E-07 | 1.63E-06 | 9.34E-07 |
| α31 | 0.093789 | 0.019622 | 0.839876 | 0.073746 |
| β31 | 0.889839 | 0.022511 | 0.015425 | 0.076719 |
| ζ1 | 0.021476 | 0.006594 | 0.01632 | 0.006084 |
| θ1 | 0.96732 | 0.012673 | 0.966576 | 0.015665 |

The sample period is January 1, 2018 to October 31, 2021, the parameters γk0 are constants, αk0, αk1, βk1 are parameters for the univariate GARCH model (Eq(6)), and the RGARCH model (Eq(12)). k=1, 2, 3 is for EUR/INR, USD/INR and GBP/INR, respectively, ζ1 andθ1 are the parameters of the correlation parts of both the DCC-GARCH and DCC-RGARCH models.

### Table 4

**Results of parameter estimation for midcap stocks.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Parameter** | **DCC-GARCH** | | **DCC-RGARCH** | |
|  | **Estimate** | **Std. error** | **Estimate** | **Std. error** |
| γ10 | 0.000288 | 0.000604 | 0.000347 | 0.000619 |
| α10 | 3.52E-05 | 2.60E-05 | 2.70E-05 | 1.49E-05 |
| α11 | 0.099696 | 0.050493 | 0.095114 | 0.031593 |
| β11 | 0.857939 | 0.075292 | 0.857491 | 0.042741 |
| γ20 | 0.001899 | 0.001051 | 0.003646 | 0.001053 |
| α20 | 0.000183 | 6.13E-05 | 9.25E-05 | 5.64E-05 |
| α21 | 0.242236 | 0.055133 | 0.090566 | 0.032105 |
| β21 | 0.598422 | 0.09073 | 0.826024 | 0.073814 |
| γ30 | -0.000158 | 0.000758 | -0.0005 | 0.000771 |
| α30 | 2.18E-05 | 9.92E-06 | 2.93E-05 | 1.72E-05 |
| α31 | 0.058427 | 0.018538 | 0.135723 | 0.050217 |
| β31 | 0.917843 | 0.023507 | 0.848893 | 0.052287 |
| ζ1 | 0.037516 | 0.014352 | 0.035613 | 0.013042 |
| θ1 | 0.728839 | 0.080677 | 0.718536 | 0.077937 |

The sample period is January 1, 2018 to October 31, 2021, the parameters γk0 are constants, αk0, αk1, βk1 are parameters for the univariate GARCH model (Eq(6)), and the RGARCH model (Eq(12)). k=1, 2, 3 is for Vinary Capital, Tanla Platforms Inc and L&T Ltd, respectively, ζ1 andθ1 are the parameters of the correlation parts of both the DCC-GARCH and DCC-RGARCH models.

The estimation of parameters for the GARCH and R-GARCH models on closing price data (where the Parkinson estimator is used with the high-low range is used as an explanatory variable but the likelihood function is formulated based on closing prices). The estimates for αk1 are higher and those forβk1 are lower in RGARCH models as compared to GARCH model. This has a great impact on forecasting and modelling of volatility. This is because in RGARCH model shocks in previous period have a stringer impact on the current volatility than the corresponding GARCH model. This slow response to abrupt changes is often regarded as one of the major weaknesses of GARCH models as mentioned in the literature review section. Both of these models describe conditional variance of returns. One thing to note is that there is not much difference in terms of the correlation related coefficients between any of the two models for any asset class. This may be attributed to the fact that different use of the standardized residuals in Eqs. (4) and (19) of the DCC-GARCH and DCC-RGARCH models.

## 6.2 Comparison of variance forecasts

This section contains the forecast performance of the two univariate models that are DCC-GARCH and DCC-RGARCH. The forecasts models are evaluated based on two primary measures, namely mean absolute error (MAE) and mean squared error (MSE). The Diebold-Mariano test is employed to evaluate the significance of the obtained results. Pairwise comparison is done between RGARCH and GARCH. The results are presented in Table 5 and 6.

### Table 5

**Evaluation of variance forecasts: the MSE criterion**

|  |  |  |  |
| --- | --- | --- | --- |
| **MSE** | **GARCH** | **RGARCH** | **p-value of the DM test** |
| **Stocks** |  |  |  |
| HDFCBANK | 0.017376 | 0.017328 | 0.00023\*\*\* |
| ICICIBANK | 0.024074 | 0.024043 | 0.0034\*\*\* |
| INFY | 0.018726 | 0.018712 | 0.00312\*\*\* |
| TCS | 0.017109 | 0.017107 | 0.043\*\* |
| RELIANCE | 0.020724 | 0.020723 | 0.0466\*\* |
| **Currency rates** |  |  |  |
| EURINR | 0.005241 | 0.00524 | 0.0489\*\* |
| GBPINR | 0.006423 | 0.00642 | 0.0443\*\* |
| USDINR | 0.004706 | 0.004708 | 0.0567\* |
| **Midcap Stocks** |  |  |  |
| VIN | 0.02463 | 0.024608 | 0.0352\*\* |
| TANLA | 0.033287 | 0.033235 | 0.002\*\*\* |
| L&T | 0.029801 | 0.029796 | 0.0001\*\*\* |

The evaluation period is October 1, 2018, to October 31, 2020. The p-values of the Diebold -Mariano test are presented for the pair of RGARCH and GARCH. If the p-value is less than the significance level means that the RGARCH is more accurate in forecasts of variance.

### Table 6

**Evaluation of variance forecasts: the MAE criterion**

|  |  |  |  |
| --- | --- | --- | --- |
| **MAE** | **GARCH** | **RGARCH** | **p-value of the DM test** |
| **Stocks** |  |  |  |
| HDFCBANK | 0.011584 | 0.011577 | 0.004\*\*\* |
| ICICIBANK | 0.016674 | 0.016663 | 0.003\*\*\* |
| INFY | 0.012534 | 0.012527 | 0.0012\*\*\* |
| TCS | 0.012039 | 0.012035 | 0.0002\*\*\* |
| RELIANCE | 0.014214 | 0.014207 | 0.0012\*\*\* |
| **Currency Rates** |  |  |  |
| EURINR | 0.003836 | 0.003835 | 0.0455\*\* |
| GBPINR | 0.004652 | 0.004652 | 0.05\* |
| USDINR | 0.003438 | 0.003439 | 0.0502\* |
| **Midcap Stocks** |  |  |  |
| VIN | 0.016953 | 0.016934 | 0.002\*\*\* |
| TANLA | 0.026718 | 0.026659 | 0.0012\*\*\* |
| L&T | 0.021073 | 0.021071 | 0.0467\*\* |

The evaluation period is January 1, 2018, to October 31, 2021. The p-values of the Diebold -Mariano test are presented for the pair of RGARCH and GARCH. If the p-value is less than the significance level means that the RGARCH is more accurate in forecasts of variance.

According to the MSE criterion, the RGARCH’s forecasts comes out to be more accurate than that of GARCH for almost all the assets (except USD/INR currency rate). This result should be taken with a pinch of salt because as we have considered COVID data in our dataset, large outliers are expected to occur. These outliers may affect the MSE criterion results significantly. As for the MAE criterion, RGARCH again performs better than GARCH in almost all the assets with the exceptions of GBP/INR and USD/INR currency rates.

### Table 7

**Evaluation of variance forecasts: the logarithmic function**

|  |  |  |  |
| --- | --- | --- | --- |
| **LogLoss** | **GARCH** | **RGARCH** | **p-value of the DM test** |
| **Stocks** |  |  |  |
| HDFCBANK | 0.990047 | 0.743092 | <0.0001\*\*\* |
| ICICIBANK | 0.984043 | 0.735082 | <0.0001\*\*\* |
| INFY | 0.993379 | 0.708464 | <0.0001\*\*\* |
| TCS | 0.994327 | 0.738489 | <0.0001\*\*\* |
| RELIANCE | 0.974382 | 0.714619 | <0.0001\*\*\* |
| **Currency Rates** |  |  |  |
| EURINR | 0.992415 | 0.752069 | <0.0001\*\*\* |
| GBPINR | 0.99178 | 0.757655 | <0.0001\*\*\* |
| USDINR | 1.002277 | 0.769024 | <0.0001\*\*\* |
| **Midcap Stocks** |  |  |  |
| VIN | 0.958995 | 0.663628 | <0.0001\*\*\* |
| TANLA | 0.968785 | 0.78593 | <0.0001\*\*\* |
| L&T | 0.952166 | 0.709168 | <0.0001\*\*\* |

The evaluation period is January 1, 2018, to October 31, 2021.

To reduce the impact of outliers we employ the use of logarithmic loss function tabulated in Table 7. This is calculated in a similar manner as we have calculated the MSE results, with the sole change being that the proxy variance and the volatility forecasts are passed through a logarithmic function. The results further the results obtained through the MAE criterion that the RGARCH mode is superior in forecasting the variance.

## 6.3 Comparison of covariance forecasts

As the previous section, we here compare the covariance forecasts performance of both the models. Here too, we employ the use of MAE and MSE criterion to see which of the two models RGARCH and GARCH is a better forecaster. These results are tabulated in Table 8 and 9.

### Table 8

**Evaluation of covariance forecasts: the MSE criterion**

|  |  |  |  |
| --- | --- | --- | --- |
| **MSE** | **GARCH** | **RGARCH** | **p-value of the DM test** |
| **Stocks** |  |  |  |
| HDFC - ICICI | 0.022485 | 0.022454 | 0.0455\*\* |
| HDFC - INFY | 0.018041 | 0.017864 | 0.001\*\*\* |
| HDFC - TCS | 0.020091 | 0.019972 | 0.005\*\*\* |
| HDFC - RELIANCE | 0.017627 | 0.017558 | 0.001\*\*\* |
| ICICI - INFY | 0.019424 | 0.019343 | 0.0008\*\*\* |
| ICICI - TCS | 0.019753 | 0.019825 | 0.124 |
| ICICI - RELIANCE | 0.020911 | 0.020875 | 0.0023\*\*\* |
| INFY - TCS | 0.018174 | 0.018074 | 0.003\*\*\* |
| INFY - RELIANCE | 0.025463 | 0.025439 | 0.032\*\* |
| TCS - RELIANCE | 0.018554 | 0.018476 | 0.021\*\* |
| **Currency Rates** |  |  |  |
| EURINR - GBPINR | 0.016623 | 0.017162 | 0.0783\* |
| EURINR - USDINR | 0.011393 | 0.009628 | 0.0002\*\*\* |
| GBPINR - USDINR | 0.01447 | 0.013768 | 0.0012\*\*\* |
| **Midcap Stocks** |  |  |  |
| Vin-Tanla | 0.025023 | 0.02495 | 0.0034\*\*\* |
| Vin-L&T | 0.025791 | 0.025807 | 0.0764\* |
| Tanla-L&T | 0.03077 | 0.030661 | 0.0022\*\*\* |

The evaluation period is January 1, 2018, to October 31, 2021. The p-values of the Diebold-Mariano test are presented for the pair of RGARCH and GARCH. If the p-value is less than the significance level means that the RGARCH is more accurate in forecasts of variance.

### Table 9

**Evaluation of covariance forecasts: the MAE criterion**

|  |  |  |  |
| --- | --- | --- | --- |
| **MAE** | **GARCH** | **RGARCH** | **p-value of the DM test** |
| **Stocks** |  |  |  |
| HDFC – ICICI | 0.012034 | 0.012034 | 0.05\* |
| HDFC – INFY | 0.011734 | 0.011712 | 0.0465\*\* |
| HDFC – TCS | 0.011902 | 0.011895 | 0.0453\*\* |
| HDFC - RELIANCE | 0.011675 | 0.011662 | 0.0488\*\* |
| ICICI – INFY | 0.012713 | 0.012704 | 0.0042\*\*\* |
| ICICI – TCS | 0.012357 | 0.012364 | 0.067\* |
| ICICI - RELIANCE | 0.014303 | 0.014297 | 0.04995\*\* |
| INFY – TCS | 0.012239 | 0.012231 | 0.04898\*\* |
| INFY - RELIANCE | 0.013102 | 0.013102 | 0.05\* |
| TCS - RELIANCE | 0.012274 | 0.012269 | 0.04994\*\* |
| **Currency Rates** |  |  |  |
| EURINR - GBPINR | 0.004335 | 0.004353 | 0.069\* |
| EURINR - USDINR | 0.003766 | 0.003703 | 0.00321\*\*\* |
| GBPINR - USDINR | 0.003871 | 0.003847 | 0.00273\*\*\* |
| **Midcap Stocks** |  |  |  |
| Vin-Tanla | 0.017084 | 0.01707 | 0.0432\*\* |
| Vin-L&T | 0.017185 | 0.017191 | 0.0644\* |
| Tanla-L&T | 0.021268 | 0.021257 | 0.0455\*\* |

The evaluation period is January 1, 2018, to October 31, 2021. The p-values of the Diebold-Mariano test are presented for the pair of RGARCH and GARCH. If the p-value is less than the significance level means that the RGARCH is more accurate in forecasts of variance.

According to the MSE criterion, we see that the RGARCH model forecasts are more accurate than the GARCH ones in most cases except a few (ICICI-TCS, EUR/INR-GBP/INR and VIN-L&T) at 95% confidence. For the MAE criterion, we find a similar result as the MSE criterion. RGARCH is better for every asset except a few (ICICI-TCS, EUR/INR-GBP/INR and VIN-L&T) at 95% confidence.

# CONCLUSION & POLICY IMPLICATIONS

This study proposed a new specification of the DCC model called the DCC-RGARCH or DCC-Range-GARCH model which is a combination of two models namely the DCC by Engle(2002) and the Range-GARCH by Molnár(2016). It is similar to the DCC model but with a slight variation. It considers the estimator to be the log difference between the high and low prices. We compared the DCC-RGARCH with the DCC-GARCH proposed by Engle(2002) and show that both these models have similar correlation part but different conditional variance part. On the three data sets it was run on (stocks, currencies, midcap stocks) it was found that the Range-GARCH model was superior to the GARCH model in forecasting the variance and covariance. These results illustrate that using range data along with closing prices data for forecasting increases the forecasting accuracy of a model.

The DCC-Range-GARCH also has major implications for policy makers. This is because modelling volatility has always been a challenge for bureaucrats since it is usually difficult to separate out the noise from the useful information in financial time series data. The existing literature on Volatility modelling usually employs only the closing prices and ignores the intra-day volatility, which could potentially lead to misleading results and also lead to incorrect conclusions being made.

Allowing for intraday volatility using high and low prices allows for more robust estimators which can lead to better results and forecasting.

Thus, if policymakers employ a more accurate predictor of volatility like the DCC-Range-GARCH model, then they can model volatility more effectively and get more accurate forecasts for different scenarios thus allowing them to make a more informed decision when making fiscal or monetary policies.

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