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A Comparison of Forecasting Accuracy between Two Dynamic Conditional Correlation (DCC) Models*

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İki Dinamik Koşullu Korelasyon (DCC) Modeli Arasındaki Tahmin Doğruluğunun Karşılaştırılması

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Abstract

This study compares two commonly used DCC-family models to predict the linkage between the US equity and REIT markets within a global minimum-variance portfolio. Equity and REIT portfolios are constructed using variance-covariance matrices, which represent forward-looking covariance information. These matrices are constructed out-of-sample with ex-ante forecasting. By assessing the predictive precision of each model, the study aims to determine which one produces the lowest forecasting errors and performs better economically. According to a statistical comparison, ex-ante correlation forecasts based on the Asymmetric DCC model were more accurate than those based on the standard DCC model. An empirical comparison of the economic performance of these two models in a dynamic portfolio allocation framework reveals that, despite its complexity, the Asymmetric DCC model exhibits similar economic performance characteristics to the standard DCC model. Despite the lack of emphasis on the economic overperformance of the Asymmetric DCC model, investors who recalibrate their portfolios weekly will benefit from reduced forecast errors and the ability to create more efficient portfolios by using an asymmetric model instead of a standard model.

Keywords: *Forecasting error, asymmetric DCC-GARCH, dynamic correlation.*

Makale Bilgileri

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Öz

Bu çalışma, genel bir minimum varyans portföyü içinde ABD hisse senedi ve GYO (Gayrimenkul Yatırım Ortaklığı) piyasaları arasındaki bağlantıyı tahmin etmek için yaygın olarak kullanılan iki Dinamik Koşullu Korelasyon (DCC) modelini karşılaştırmaktadır. Hisse senedi ve GYO portföyleri, varyans-kovaryans matrisleri ile örneklem dışı olarak oluşturulmuş, ex-ante tahminle ileriye dönük kovaryans bilgisini temsil etmektedir. Çalışmanın amacı, her iki modelin tahmin hassasiyetini değerlendirip hangisinin daha düşük tahmin hataları ürettiğini ve ekonomik olarak daha iyi performans gösterdiğini belirlemektir. İstatistiksel karşılaştırmaya göre Asimetrik DCC modele dayanan ex-ante korelasyon tahminleri, standart DCC modele göre daha küçük hatalar üretmektedir. Bu iki modelin ekonomik performansı, dinamik bir portföy tahsisi çerçevesinde ampirik olarak karşılaştırıldığında, Asimetrik DCC modelinin standart DCC modeline benzer ekonomik performans özellikleri sergilediği ortaya konulmuştur. Asimetrik DCC modelinin ekonomik performansına rağmen portföylerini haftalık olarak yeniden kalibre eden yatırımcılar, daha az tahmin hatasından ve daha verimli portföyler oluşturma becerisinden faydalanabilirler.

Anahtar Kelimeler: *Tahmin hatası, asimetrik DCC-GARCH, dinamik korelasyon.*

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1. Introduction

Predicting the conditional correlation between diverse asset classes plays a pivotal role in several critical areas, including portfolio diversification, risk management, asset pricing, capital allocation, and hedging. Portfolio managers who actively manage their investments are particularly keen on forecasting the ever-changing relationship of the stock market with REIT (Real Estate Investment Trust) asset classes. This dynamic relationship holds the potential for timely portfolio rebalancing, allowing portfolio adjustments to account for risk fluctuations. The importance of timely rebalancing cannot be over-stated since it can enable investors to potentially outperform their benchmarks or reduce portfolio risk significantly. An extensive body of scholarly research, largely originating from the Dynamic Conditional Correlation (DCC) model pioneered by Engle (2002), has delved into the efficiency and efficacy of dynamic correlation estimations. Several studies have confirmed the proficiency of DCC models in capturing dynamic correlations. This type of estimation models, however, have a common limitation of offering insights into historical data generation processes due to their retrospective nature. Active fund managers require forecasting models that can make forward-looking predictions about the future, particularly those that incorporate the DCC framework.

There is extensive evidence that DCC-type models perform better than conventional correlation models when used in-sample and out-of-sample (Elton and Gruber, 1973; Huang and Zhong, 2013; Kalotychou et al., 2014; Peng and Schulz, 2013). The argument in these studies is that portfolio managers achieve more efficient portfolios and enhance risk-adjusted returns by using a DCC-type model that accurately captures the time varying nature of correlations. As an example, Huang and Zhong (2013, hereafter HZ) investigate the potential diversification advantages of REITs, in a portfolio of Treasury Inflation-Protected Securities (TIPS) and commodities over the period from 1970 to 2010. They empirically document out-of-sample performance of portfolios for a pre-specified (target) return (5%, 10%, 15%, 20%) and conclude that when the DCC model is used to form these portfolios, the average standard deviation of portfolios rebalanced every 20, 50, and 100 days were consistently smaller than that of historical correlation model (See Table 9 in HZ).

Another important paper in forecasting the dynamic correlation is by Peng and Schulz (2013). Using data from eight countries, the authors examine both out-of-sample and in-sample forecasting frameworks when forecasting portfolio performance for REITs. Portfolios are formed using either a fixed covariance matrix or a dynamic one, constructed using DCC. Using daily returns from 1999 to 2010, they conclude that the portfolios constructed based out-of-sample correlation forecasts from the DCC are less risky compared to the portfolios of static covariance matrix. The authors also point out that, although dynamic covariance matrix-based active portfolios produce higher returns than static covariance matrix-based passive portfolios, the transaction costs associated with active portfolio management offset the benefits.

Furthermore, Case et al. (2012) constructs dynamic portfolios that include REITs and other asset classes. Based on the monthly return correlation, their analysis compares listed REITs with non-listed REIT stocks. Portfolios are constructed using 60-month rolling correlations and dynamic correlations generated by a DCC method. Their findings reveal that the realized returns from the dynamic portfolio employing the DCC-GARCH model, outperform those from the dynamic portfolio employing the rolling correlation model by an annual margin of 20 basis points. In addition, the DCC-GARCH model suggests a more stable allocation of assets.

The present study reexamines this research subject by evaluating DCC-family models' predictive capabilities within a global minimum-variance portfolio context. Variance-covariance matrix forecasts, which represent forward-looking covariance information, are used to construct portfolios with equity and REIT market. Specifically, at the time t, a rebalancing is carried out on the portfolio to be held during $t+1$ using the ex-ante predictions for $t+1$ based on out-of-sample data. Consequently, the asset weights in the portfolio for $t+1$ are determined based on the forecasted variance-covariance matrix for $t+1$. By adopting an out-of-sample structure with ex-ante forecasting, this study presents a comprehensive and pragmatic approach to addressing this matter. An assessment of two widely employed DCC models for forecasting the weekly correlation between the US equity and REIT markets is conducted to determine which model yields the best portfolio performance. Essentially, the primary research questions of this investigation are as follows: Which of the two DCC-type models will result in the lowest statistical error in estimating dynamic correlation over time? Within the context of a dynamic portfolio allocation framework, which model can demonstrate superior economic performance? The objective is to identify the approach that produces portfolios with optimal combination of high returns and minimal risk.

As evidenced by the empirical results, the Asymmetric DCC approach consistently outperforms the other model under both statistical and economic evaluation criteria. An investor seeking to recalibrate her portfolios on a weekly basis will benefit from reduced forecast errors and the ability to create more efficient portfolios by using the asymmetric model instead of the standard one.

2. Data and Empirical Methodology

The time frame of this study spans the beginning of 2001 to the end of 2016, using weekly index price observations from the US. The dataset comprises index returns, acquired from Refinitive Eikon, denominated in US Dollars (USD). The variables Equity represents the S&P 500 Composite Price Index returns and REITs denotes the FTSE/NAREIT Equity REITs Price Index returns, both in percentages. In the calculation of continuously compounded returns, $r_{i,t} = \log(index_{i,t}) - \log(index_{i,t-1})$, the term i represents either the equity or REIT index. A descriptive analysis of the variables is presented in Tables 1.

Table 1. Descriptive Statistics

	Equity	REITs
Mean (%)	0.0851	0.1076
Median (%)	0.1805	0.3157
Maximum (%)	11.3559	20.6801
Minimum (%)	-20.0838	-20.0892
Std. Dev. (%)	2.3940	3.5353
Skewness	-0.8595	-0.4651
Kurtosis	11.3012	11.2766
Jarque-Bera Test Statistic	2348***	2266***
N	784	784
$CORR_{equity}$		0.7021

Data are weekly index returns for the period from December 2001 to December 2016 and obtained from *DataStream* in USD. *Equity* are percentage returns on S&P500 Composite Price Index and *REITs* are FTSE/NAREIT Equity REITs Price Index (NAREQR$(PI)). Mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jarque-Berra test of normality, and unconditional correlation of index returns are reported.

***, **, and * indicates statistical significance at 1%, 5%, and 10% levels, respectively.

We use two versions of Engle's (2002) correlation model; namely, Asymmetric Dynamic Conditional Correlation (ADCC), and Dynamic Conditional Correlation (DCC). Initially, in order to assess the statistical performance of these models, we conduct a comparative evaluation of the loss functions derived from each model. The loss function is the difference between the forecast of the correlation and the realized correlations. Next, the economic significance of these models is evaluated in an asset allocation problem. We examine the optimal allocation of asset weights within the global minimum variance portfolio. The evaluation of covariance's informational value is quantified as the increment in portfolio returns attainable without a corresponding rise in volatility.

The dataset is divided into three distinct sub-periods: *training timeframe, statistical assessment timeframe, and economic assessment timeframe*. The defined time intervals are as follows. The training timeframe encompasses 2002 to 2005, the statistical assessment timeframe spans from 2006 to 2011, and finally the economic assessment timeframe extends from 2012 to 2016.

We use the initial 262 weekly observations in the training timeframe in order to construct the first forecast of the following point in time, which is the first week of the statistical assessment timeframe. For example, all observations up until 31 December 2005, the whole training time- frame, are used to get a forecast of the conditional correlation between the two asset classes for the first week of January 2006, and so on.

After forecasting time-varying correlations for 2006 to 2016, we use the forecasts to compare the loss functions from each model using forecasts of the *statistical assessment timeframe*. Subsequently, the two DCC models are utilized to construct the minimum risk portfolio based on forecasts within the defined *economic assessment timeframe*. In other words, first, the ex-ante forecasts of statistical assessment timeframe are used to quantify our models based on error statistics, and then we evaluate the economic significance of the models for an active portfolio manager using variance-covariance matrix forecast in the economic assessment timeframe.

2.1. DCC- Family Forecasting Models

DCC-family models postulate that the matrix of covariance can be expressed as the product of the matrix representing the time-varying correlation of standardized disturbances and the matrix representing the square root of their variances: $H_t = D_t R_t D_t$. Here, R_t denotes the matrix representing time-varying linkages of standardized disturbances. $D_t = diag[\sqrt{h_t}]$. Here h_t refer to standardized disturbance variances. There are two steps involved in estimating the model. The variance process is estimated first, followed by the correlation process. Variance processes $\left(D_{t+k} = diag[\sqrt{h_{ii,t+k}}]\right)$ are forecasted using Equations 1 and correlation processes (R_{t+k}) are forecasted separately using Equations 2&3. According to Engle and Sheppard (2001), separate forecasting of variance and correlation gives the least biased forecast, see e.g. Orskaug (2009).

k-step-ahead GARCH forecasting model used in our empirical analysis is as follows:

$$h_{(t+k|t)} - \sigma^2 = \left(\alpha + \tfrac{1}{2}\gamma + \beta\right)^{k-1} \left(h_{(t+1|t)} - \sigma^2\right) \tag{1}$$

Based on this theoretical background, one-step-ahead ADCC and DCC forecasting models are as follows:

$$Q_{t+1} = [1-(g+b+a)]\bar{\rho} + a\theta_t\theta_t + g\theta_t\theta_t + bQ_t \tag{2}$$

$$Q_{t+1} = [1-(b+a)]\bar{\rho} + a\theta_t\theta_t + bQ_t \tag{3}$$

$$\theta_t = \varepsilon_t D_t^{-1} = \frac{\varepsilon_t}{\sqrt{h_t}} \tag{4}$$

In order to calculate a forecasting error of DCC-family model forecasts, we use an ADCC model estimating (in-sample) realized correlations. The ADCC model is as follows:

$$Q_t = [1-(g+b+a)]\bar{\rho} + a\theta_{t-1}\theta_{t-1} + gI_{t-1}\theta_{t-1}\theta_{t-1} + bQ_{t-1} \tag{5}$$

$$\theta_t = \varepsilon_t D_t^{-1} = \frac{\varepsilon_t}{\sqrt{h_t}}$$

where Q_t is time-varying covariance, $\bar{\rho}$ is the market *i*'s residuals' fixed correlation with the market

The standardized fluctuations, denoted as θ_t, are computed based on conditional volatility in the initial-stage estimation. The estimation of Q_t is done using all available information until time *t*.

2.2. Statistical Evaluation of Forecasting Models

The forecast performance of each model is compared using four commonly used statistics of loss function: the mean error (*ME*), the mean absolute error (*MAE*), the root mean squared error (*RMSE*), and the mean absolute percentage error (*MAPE*). In conjunction with these four loss-metrics, we use a test by Diebold and Mariano (1995, *DM*) to assess the statistical precision of the methodologies.[1]

- $ME = \frac{1}{N}\sum_{\tau=1}^{N}(\hat{\rho}_\tau - \hat{\rho}_n)$
- $MAE = \frac{1}{N}\sum_{\tau=1}^{N}|\hat{\rho}_\tau - \hat{\rho}_n|$
- $RMSME = \left[\frac{1}{N}\sum_{\tau=1}^{N}(\hat{\rho}_\tau - \hat{\rho}_n)^2\right]^{0.5}$
- $MAPE = \frac{1}{N}\sum_{\tau=1}^{N}\left|\frac{\hat{\rho}_\tau - \hat{\rho}_n}{\hat{\rho}_n}\right|$
- $DM(s_i) = \frac{d_i}{\sqrt{\frac{\hat{\omega}_{ii}}{T_i}}}$

2.3. Economic Evaluation of Forecasting Models

The optimization problem of global minimum variance portfolio can be formulated as follows:

$$\min_{\omega_{t,t+1}} \sigma_t^2 = \omega'_{t,t+1} H_{t,t+1} \omega_{t,t+1} \tag{6}$$

$$subject\ to\ \ \omega'_{t,t+1}\mu_{t,t+1} = r_P \quad and \quad \sum_{j=1}^{N} \omega_{j,t+1} = 1$$

where, j = equity and REIT index and $\omega_{t,t+1}$is the portfolio weight vector of $t+1$, $H_{t,t+1}$ is the time-varying covariance matrix of time $t+1$. $\mu_{t,t+1}$ is assumed to be a vector representing the anticipated returns in excess of the risk-free rate, and finally $r_{P,t,t+1} > 0$ is the portfolio rate of return. Weights, covariances, risk-free rate, and portfolio rate of returns for time $t+1$ are determined at time t.

Our first constraint ensures that there exists for each $r_{P,t,t+1}$ value a unique finite solution. The second constraint is interpreted as choosing a set of portfolio allocation weights $\omega_{t,t+1}$ such that the portfolio variance $\omega'_{t,t+1} H_{t,t+1} \omega_{t,t+1}$ is minimized given that the investor wants the global minimum variance portfolio return. Given that a vector of returns of r on the risky assets, we assume that $E(r) = \mu$ and $Var(r) = H$, where H is positive definite (hence invertible).

We employ three risk-adjusted techniques to assess the performance of portfolios generated by various models: Sharpe ratio (SR) developed by Sharpe (1966), Jensen's alpha ratio (JaR) developed by Jensen (1968), and Treynor ratio (TR) developed by Treynor (1965).

- $SR = \frac{R_P - R_{RF}}{\sigma_P}$
- $TR = \frac{R_P - R_{RF}}{\beta_P}$
- $JaR = R_P - [R_{RF} + \beta_P(R_M - R_{RF})]$

[1] Forecasting accuracy of models can be tested using equal predictive accuracy (EPA) tests and superior predictive accuracy (SPA) tests. EPA tests test whether two forecasting procedures have equal accuracy. There is a crucial difference between EPA and SPA. Null hypothesis for the former is that all forecasting procedures will be equally accurate while composite hypothesis for the latter is that one forecasting procedure will be outperformed by alternative forecasts. Granger and Newbold (1977); Meese and Rogoff (1988); Diebold and Mariano (1995); Harvey *et al.* (1997); West (1996) are some studies introducing tests for equal forecasting accuracy. Based on a SPA test known as the reality check by White (2000), Hansen and Lunde (2005) proposes another test for better forecasting. Several forecasts are compared against a benchmark to determine which model provides superior predictions.

3. Empirical Results

3.1. Correlation Forecasting

Figure 1 reports the forecasts of dynamic correlations of equity and REITs. The figure compares these correlation forecasts with the time-varying realized correlations for each of forecasting models. The realized correlations are the estimates of the Asymmetric DCC model given in Equation 5.[2][3]

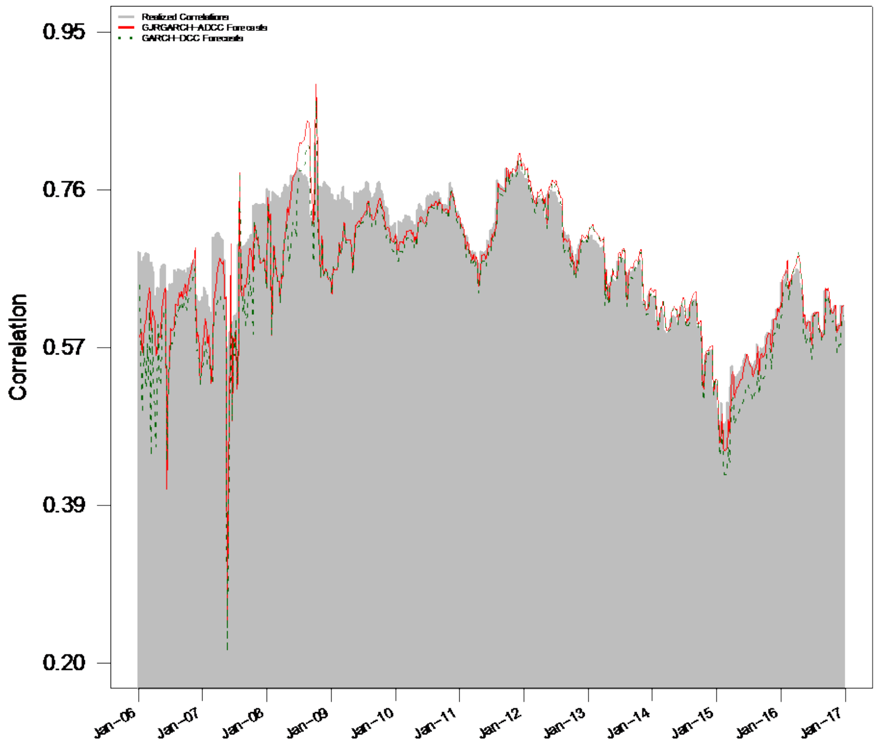

Figure 1. Comparison of Time Varying Correlations

This figure depicts realized (estimated) and forecasted correlations by the traditional forecasting models and two DCC- family models. Realized correlations by both traditional and the DCC-family models are represented by the grey area. Correlation forecasts from traditional models are to be compared with *ex-post* realized (estimated) correlations, and correlations forecasts from the DCC-family models are to be compared with *ex-post* correlation estimates from the ADCC model.

Figure 1 indicates that the DCC-family models effectively explain fluctuations in the dynamic correlation. Hence, the portfolio that is updated according to the forecast of correlation matrix from the DCC-family models would be expected to capture the risk aspects of the portfolio in a timelier manner.[4]

A portfolio manager who needs to make a decision regarding the rebalancing frequency of her portfolio may prefer to update her portfolio more frequently since more frequently rebalanced portfolios would absorb more information about the markets and be better protected against market shocks through timelier diversification.[5]

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[2] Realized correlations are the ADCC model correlation estimates. However, results are robust to the DCC model correlation estimates. All available information until time *t* is used to estimate the realized correlation for time *t*.

[3] It should be emphasized that the forecasting errors between realized (ex-post) and forecasted (ex-ante) correlations depicted in Figure 1 are small. The small forecasting errors are as a result of our forecasting procedure, one step (week) ahead forecasting. Errors in forecasting into the short distant future such as one step ahead will be smaller than those made in forecasting into the more distant future. Exhibit 2 of Schnaars (1986) compares the magnitude of forecasting error for different time horizons and report that the forecasting errors get larger as forecasting time horizon increases.

[4] A more frequently updated portfolio due to the use of DCC-family models is expected to cause additional transaction cost. Real economic benefits of active portfolio strategies occur only when the cost of rebalancing is more than offset by the perceived benefit associated with rebalancing the portfolio. All portfolio returns reported in this study are net of the cost of rebalancing the portfolio.

[5] Although more frequently rebalanced portfolios may lead to higher return and/or lower risk portfolios, we do not suggest that an active portfolio manager should update her portfolio more frequently. The cost of rebalancing is an important factor affecting the overall performance.

3.2. Statistical Comparison of Forecasting Models

Table 2 reports forecasting error statistics. The empirical findings demonstrate that, in terms of forecasting accuracy, the Asymmetric DCC model outperforms the standard DCC model by yielding smaller errors according to ME, MAE, RMSE, and MAPE. Additionally, the DM test provides evidence to reject the null hypothesis of equal accuracy, in favor of the alternative hypothesis that the Asymmetric DCC model exhibits superior accuracy.

Table 2. Loss Function Comparison of Forecasting Models

	Asymmetric DCC Model	DCC Model
Mean Error	**-0.3834**	-0.6429
Mean Absolute Error	**0.6820**	0.7980
Root Mean Squared Error	**1.0702**	1.1881
Mean Absolute Percentage Error	**-0.02171**	-0.0412
DM stat	-3.3020	
DM p-value	0.0005	

The table reports results of forecast error statistic for each model using standardized forecast error measures. The smallest forecasting error is given in bold text. The DM test tests the null hypothesis of equal accuracy against an alternative hypothesis of the DCC model is less accurate than the Asymmetric DCC model.

So far, our statistical comparisons methods report the relative statistical performance of all models on average terms, and they do not inform whether the superiority of a model is consistent over time. Overall, on a statistical performance basis, the Asymmetric DCC model generally outperforms the standard DCC model. Nonetheless, it remains plausible that certain significant and sporadic errors may have influenced one of the model's forecasts, resulting in larger average forecast errors, either in a more favorable or unfavorable direction. And in turn, we may have erroneously concluded that one model produces smaller forecasting errors. Thus, it is essential to show that the superiority of a forecasting model is consistent over time.

Figure 2 depicts forecasting errors over time. As expected, forecast errors from both DCC-family models display large fluctuations and the forecast errors from the models produce large and small errors around the same time period. A forecast error of zero would mean a perfect forecast. Over-prediction of correlations by the forecasting models would produce positive forecast errors, while negative forecast errors would be generated in case of under-prediction. The figure shows that both positive and negative forecasting errors are present for both forecasting models, which highlights over- and under-prediction of the correlations and not surprisingly, the largest forecast errors take place during the 2008 global financial crisis.

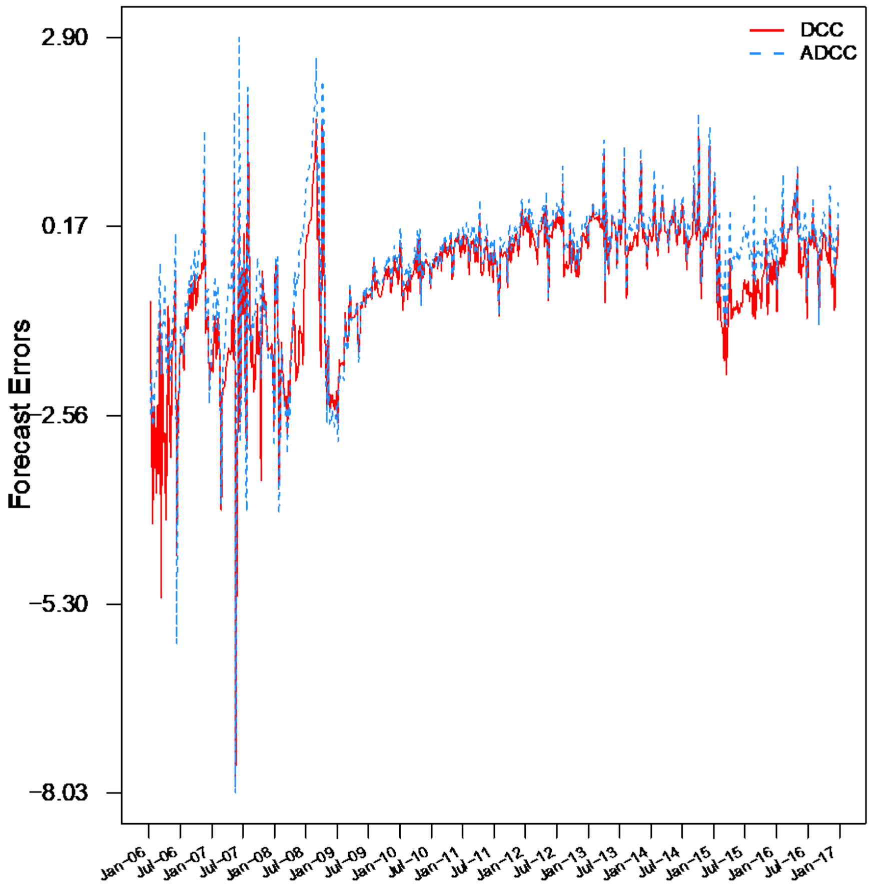

Figure 2. Comparison of Forecast Error in Different Models

The figure displays the loss functions of each model employed. The forecast error is the difference between correlations forecasts and realized (estimated) correlations. *DCC* and *ADCC* models are used to calculate correlation forecasts.

3.3. Economic Comparison of Forecasting Models

We optimize the global minimum portfolios consisting of stock and REIT indices.[6] Table 3 reports annualized mean and standard deviation of portfolios, and mean, maximum and minimum weights of stock and REIT indices in the portfolio as well as three portfolio performance evaluation statistics: SR, TR, and JaR. Based on the economic performance of the models presented in the table, it can be observed that both models yield nearly identical economic results, suggesting that there is no discernible superiority of one model over the other concerning economic performance.

[6] Our portfolio selection is constrained to include solely these two asset classes as our objective is to specifically assess the diversification impact of REITs for investors in the stock market. This approach ensures that any adjustments in the allocation of the REIT index within the portfolio exclusively reflect the diversification potential of this asset class.

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Table 3. Comparison of Portfolio Statistics of Forecasting Models

	DCC Var-Cov	ADCC Var-Cov
Mean of Portfolio Returns	0.0441	0.0441
SD of Portfolio Returns	0.7287	0.7288
Mean Weight Stock	0.5713	0.5713
Mean Weight REIT	0.4287	0.4287
Max Weight Stock	0.7036	0.7036
Max Weight REIT	0.6530	0.6532
Min Weight Stock	0.3470	0.3468
Min Weight REIT	0.2964	0.2964
Sharpe Ratio	0.0606	0.0606
Jensen's Alpha	0.0452	0.0452
Treynor Ratio	-52.4119	-52.4111

This table reports the statistics of the economic values of portfolio strategies using DCC-family forecasting models. Correlation forecast models used are DCC, and ADCC models. We use weekly data, which is equivalent to rebalancing the portfolio every week. All returns and standard deviations are annualized. Portfolio returns are free of transaction costs of rebalancing the portfolio.

A portfolio manager that uses the SR or JaR to analyze the investment portfolio's performance based on the DCC-type forecasting models of this study would be indifferent to the models. The Treynor ratio points out to the superiority of Asymmetric DCC model by a small amount, however, the difference is neglectable.

4. Conclusion

This research undertakes a comparative analysis of two prevalent models from the DCC-family to assess their efficacy in predicting the interconnection between the US equity market and the US REIT market. Our primary objective is to determine which model yields more precise forecasts with fewer errors and better economic performance by scrutinizing their predictive accuracy. As compared to the conventional DCC model, the Asymmetric DCC model achieves superior results by producing notably reduced errors in the out-of-sample correlation forecasts ex-ante correlations. The economic performance of these two models is then compared in relation to dynamic portfolio allocation within a comprehensive framework. The empirical findings reveal that, despite its increased complexity compared to the standard DCC model, the Asymmetric DCC model exhibits equivalent economic performance characteristics.

In detail, findings conclude that both DCC-family models capture the time-varying nature of the dynamic correlation in a timely manner. However, the statistical significance of errors in forecasts do not play an important role when constructing and rebalancing portfolios using the correlation forecasts by the two models, meaning they have similar economic performance, which indicates that none of the models lead to lower risk and/or higher return on portfolios over the other.

In the context of real-world out-of-sample portfolio optimization, where ex-ante forecasts of the variance-covariance matrix are employed, active portfolio managers may favor the use of forecasts derived from DCC-family models. This preference stems from these models' effectiveness in capturing the ever-changing nature of the correlation process.

From the perspective of an active portfolio manager, there is a trade-off to consider. They may opt for a model that provides a better understanding of the risk taken, even if it entails larger forecasting errors. This choice may lead them to prefer the asymmetric DCC model. Conversely, a passive manager who follows a buy-and-hold strategy is more inclined to opt for a traditional forecasting model.

One limitation of this study lies in its exclusive consideration of only two asset classes for portfolio construction. In practice, portfolio managers have access to a wide array of asset classes, enabling them to create considerably more diversified and efficient portfolios. Consequently, the portfolio's efficiency as depicted in this paper cannot be directly equated with that of conventionally diversified portfolios.

One other limitation of this study is its limited time frame, which, regrettably, does not include the recent global upheaval caused by Covid-19. During an economic recession, it would be of substantial interest to investors and portfolio managers to gain insight into how these models performed. Therefore, a subsequent study may warrant a more extensive portfolio, one which encompasses a diverse range of asset classes and leverages a broader range of datasets that are more contemporary in nature.

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