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RESEARCH ARTICLE

Measuring the Correlations between Stock Market Returns and Commodity Returns in the United States Using GARCH-M Models

Wisam H. Ali Al-Anezi [1*], *Ali Y. Abdullah Al-Joaani* [2], *Faisal Ghazi Faisal* [3], *Bha Aldan Abdulsattar Faraj* [4], *Abdulrazaq Shabeeb* [1]

[1] *Department of Economics, College of Administration and Economics, University of Anbar, Ramadi 31001, Iraq*

[2] *Al-Nisour University College, Baghdad 10011, Iraq*

[3] *Department of Finance and Banking, Al-Idrisi University College, Ramadi 31001, Iraq*

[4] *Department of Finance and Banking Sciences, College of Financial and Administrative Sciences, University of Al Maarif, Ramadi 31001, Iraq*

ABSTRACT

The research aims to measure the correlations between stock market returns (Returns of the Standard & Poor's 500 Index (RS&P500) and Returns of the Dow Jones Index (RDJI) and commodity markets returns (Returns of gold (RPG), Returns of U.S. corn (RC) and Returns of soybeans (RS)) for the United States of America, using daily data for the period from January 2, 2015, to November 22, 2024, and by employing the GARCH-M model. The results indicate the returns from financial markets and agricultural commodity markets in the United States tend to move in the same direction but at different rates, and that investing in the gold market is considered a haven for investment in the financial markets in the United States, while investing in agricultural commodity markets in the United States does not reduce risks in the financial markets but rather increases them, as they are positively correlated. The study also found that indirect effects between financial markets and agricultural commodity markets in the United States were mostly driven by short time horizons, followed by medium and long time horizons, which highlights

*CORRESPONDING AUTHOR:
Wisam H. Ali Al-Anezi, Department of Economics, College of Administration and Economics, University of Anbar, Ramadi 31001, Iraq; Email: wisamali@uoanbar.edu.iq

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the importance of considering the evolving nature of correlations when making asset allocation decisions, as well as their importance for investors, portfolio managers, and government departments (policymakers) with regard to managing risks.

Keywords: Market Volatility; Dynamic Correlations; GARCH-M; DCC-GARCH; CCC-GARCH; Portfolio Diversification

1. Introduction

In recent decades, researchers have increasingly focused on the relationship between other commodity markets, such as precious metals and agricultural and industrial goods, and financial markets and their economic and financial impacts. Commodities serve as a diversification tool or a means of hedging, and hedging is considered a strong form of diversification when the correlation with the main variable is zero or negative. This stems from portfolio management in corporate finance textbooks [1], which has led to increased discussion about the role of commodities in the strategic asset allocation process, particularly following the global financial crisis of 2008, the repercussions of which were felt across various parts of the world, leading to significant disasters for several economies, markets, and investors, as well as the rise in commodity prices apparent since 2002, and their subsequent decline in July 2008 [2].

Investors who allocate a greater proportion of their investment capital in the commodity market will change the flow of capital and the correlation structure between commodity markets and stock markets [3] by studying the correlation between various commodities (agricultural, energy, and metals) and the U.S.

Stock market, ref. [4] found that agricultural commodities play a significant role in the portfolios of risk-averse investors, as they tend to be less volatile during market crises. Since the emergence of financial liberalization and the integration of capital markets, the financing of commodity markets has been observed, and the development of commodity markets has paved the way for international diversification across markets [5].

Consequently, we conclude that markets, in general, are characterized by their interconnections with one another. The relationship between financial and commodity markets is close, and is strengthened as the economy develops. Financial markets are now referred to as the mirror reflecting the economy, and there is a mutual influence between them and commodity markets. Commodity markets affect, and indeed are affected by changes occurring in financial markets, and vice versa [6]. Therefore, the analysis of indirect effects through financial markets and commodity markets in the United States is essential, given that its economy is one of the largest and most developed in the world, in addition to its transition from an industrial economy to a global financial economy in light of developments in artificial intelligence. The fluctuations that occasionally affect its markets are reflected in their returns, a portion of which is invested in its markets. Thus, this study will inform us whether the returns of financial market assets (RS&P500 and RDJI) have any correlation with the returns of commodity assets (gold, corn, soybeans), and will further explore advanced techniques such as the Constant Conditional Correlation (CCC-GARCH) and the Dynamic Conditional Correlation (DCC-GARCH) models, to understand the evolving interactions between financial markets and commodity markets.

The relationship between equity market returns and commodity returns has been the subject of significant interest in financial economics, particularly in portfolio diversification, risk management, and formulating macroeconomic measures. While traditional asset pricing theories suggest that commodities and stocks may have low correlations due to their different economic drivers, empirical evidence suggests that these relationships may vary over time, particularly during financial crises and economic uncertainty [7].

Volatility clusters and time-varying risk premiums play a crucial role in shaping the dynamics of this relationship [8]. In this context, the GARCH-M models provide a solid methodological framework for studying the interaction between return volatility and risk behavior by recording the effects of volatility on various asset classes [9, 10].

Although numerous studies have individually analyzed the volatility of equity and commodity markets, there is still a knowledge gap in understanding how risk behavior and volatility effects influence the correlation dynamics between different asset classes in the US market.

This study aims to fill these gaps by using GARCH-M models to analyze the time-varying nature of correlations between major U.S. stock indices (such as the S&P 500) and major commodity classes (such as crude oil, gold, and agricultural commodities). The results will provide insights into the hedging potential of commodities against stock market fluctuations and contribute to a better understanding of portfolio risk management strategies.

This study is organized as follows: The first section provides an introduction to the relationship between financial and commodity markets, while the second section provides a literature review on these topics. The third section discusses the methodology, while the fourth section covers the study results and their further discussion. Finally, the fifth section provides a summary of the findings and their significance for investors, portfolio managers, and government administrations (policymakers).

2. Literature Review

The relationship between financial markets and commodity markets has been extensively examined by researchers, as indirect measures are viewed as a fundamental concept underlying risk measurement and portfolio management and diversification [11]. Indirect measures provide an empirical gauge of the degree of integration among different asset classes [12], as assets have the potential for diversification if they are less affected by the indirect effects arising from other assets. Recent studies emphasize commodities in general because they are less impacted by the indirect effects of financial assets due to different pricing mechanisms, and thus have the potential for diversification [13]. One of the studies concerned with exploring indirect effects across financial and commodity markets is that by [14], the aim was to verify the transmission of indirect effects through crude oil, precious metals, and the U.S. dollar exchange rate. By using generalized standard deviation decomposition and impulse response functions, they found significant transmission of volatility between oil and gold returns. The study by Nguyen et al [15] studied the relationship between financial markets and commodity markets (gold, oil, food, agriculture, energy, and minerals) in the United States using GARCH models for the period from 1992 to 2017. The Local Gaussian correlation model was also used, and the study found an increasing correlation between basic commodity markets and stock markets after the mortgage crisis [15].

Wang et al. [16] aimed to determine whether commodity indices could be used as predictors for stock market fluctuations. Relying on the Rogers International Commodity Index (RICI), including the Agricultural Commodity Index (RICIA), the Metals Index (RICIM), and the Energy Index (RICIE) as independent variables, and the U.S. stock market index as the dependent variable, and using ARCH (1), it was found that there are stable long-term relationships between certain commodity and stock markets, with commodity indices generally leading stock market indices. The results also showed that commodity indices such as agricultural (RICIA) and metals (RICIM) are influenced by the U.S. stock market and that commodity indices do not have hedging effects on stock markets under normal conditions, thus they cannot be used as hedging tools. However, during severe financial crises or high volatility in stock markets, the Metals Index (RICIM) can be used as a safe-haven asset and integrated into investment portfolios to reduce risks [16].

Öztek and Öcal [17] examined financial crises and the nature of the correlation between commodity markets and stock markets, relying on the agricultural commodities index, the precious metals index, and the S&P 500 index. Using a multivariate MGARCH model and specifications of both smooth transition conditional correlation (STCC-GARCH) and double smooth transition conditional correlation (DSTCC-GARCH), their study aimed to model the time-varying correlations between commodity markets and stock markets, revealing the dynamic nature of correlations during the financing of commodity markets and, indeed, following the financial crisis of 2008. Their findings provided evidence against an upward trend in correlations for the agricultural commodities sub-index, indicating that the increase in correlation could not be solely attributed to the 2008 financial crisis. In contrast, for the precious metals sub-index, market volatility plays an important role in the dynamic nature of the correlation, alongside the upward trend [17]. Meanwhile, a study by Alshenawy and Abdo [18] aimed to verify the dynamic correlations between the S&P 500 index, crude oil price, natural gas price, and gold price. Using a DCC-GARCH model, their study found significant and varying correlations over time for these asset classes, demonstrating the potential diversification benefits they offer, and emphasizing the need for adaptive portfolio management based on dynamic correlations. This highlights the importance of considering the evolving nature of interdependencies when making asset allocation decisions and the significance of integrating advanced multivariate techniques like DCC-GARCH in financial analysis and portfolio management [18].

James et al. [19] indicated that there are correlations between stock indicators in the financial market in the United States through the estimation of daily data for the period between 2000 and 2020, using spectral characteristic models to determine the optimal investment portfolio among these sectors, the results of this study showed that diversification across sectors is essential compared to diversification within a single sector [19]. One study by Urom et al. [20] found that there was a transmission of waves from real economic activity to financial and commodity markets in the United States during the period from March 12, 2011, to May 2, 2020 [20].

Kocaarslan et al. [21] examined forecasts of the volatility in the oil, currency, and stock markets in the BRICS group and the United States via VAR-A-DCC-EGARCH (1.1) and VAR-DCC-EGARCH models. They found that the forecasts in the stock, gold, and oil markets in the United States are asymmetric, and diversification among these markets can be beneficial, considering them to be safe havens for each other; it was also found that Brazil and Russia exhibit common movements with the markets in the United States compared to India and China [21]. A further study by Gao and Mei [22] found that there is a correlation between the stock markets in the United States and eleven stock markets in Asia by examining three different samples and using cointegration models between those markets; at the same time, this same study demonstrated that there is a weak connection (SSE) between the American and Chinese stock markets due to the restrictions imposed on the transfer of foreign capital [22].

Han [23] presented the behavioural patterns between the American and Chinese stock markets and the energy market, finding a strong pattern between the financial and energy markets [23]. Kim et al. [24] were able to identify links between the U.S. stock market and those of six OECD countries during the global financial crisis via the DCC-EGARCH model [24]. Siedlecki and Papla used the conditional correlation coefficient to measure the contagion of financial crises between the stock market in the United States and several global stock markets, as well as economic activity from December 1999 to March 2013. It was found that the reaction of the real economy lags behind the decline in the stock market by about one to three months in the United States. The American stock market leads other markets, and there is a strong contagion between them [25]. Ruan et al. [26] found that there is a mutual relationship between the stock markets in Shanghai and those in Hong Kong using daily closing prices from January 1, 2007, to December 31, 2016 [26].

This study contributes to existing empirical literature by examining the general and bilateral indirect effects of market returns in the United States. In this way, it provides novel empirical insights into the temporal and frequency-based dynamics of indirect effects on financial and commodity markets.

3. Theoretical Framework

This study is based on several important financial theories and econometric models that explain the dynamics of relationships between asset returns, the interaction between equity and commodity markets, and the mechanisms of volatility transfer:

1-Modern portfolio theory (MPT) — Markowitz [27] Investors seek to maximize returns while minimizing risk through diversification. Commodities are often seen as alternative investments with low correlation to equities, which increases portfolio efficiency [28].

2-Capital Asset Pricing Model (CAPM) — Sharpe and Lintner [29] The CAPM framework emphasizes the role of market factors in asset pricing, in which risk and return have a positive relationship. Investors tend to invest capital in higher-risk investments to achieve higher returns. According to CAPM, an asset's expected return is positively correlated with its risk exposure, which is why investors must be compensated for taking on higher risks with higher returns.

3-Efficient Market Hypothesis (EMH) — Fama EMH claims that asset prices take full account of all available information [30], making it difficult to predict future price movements by integrating these theoretical perspectives, this study will provide a comprehensive econometric analysis of the relationship between stock and commodity returns in the United States, with implications for investors, policymakers, and risk management professionals.

4. Methodology

4.1. Description of the Data Used in the Study

To capture the volatility of returns, the current study employed daily sample data covering the period from January 2, 2015, to November 22, 2024. The time series determined the Standard & Poor's 500 Index (RS&P500) returns, Dow Jones Index (RDJI), gold returns (RPG) and US corn (RC), and soybean yields (RS). The market indicators were retrieved from the following website [31].

4.2. Multivariate Model (GARCH-M)

With the wide application of single-variable (GARCH) models, there was a need to develop their application to include a multi-variable (GARCH-M) model. The latter represents a more reliable model when predicting the movements of financial asset returns, which is important when pricing financial assets in the portfolio because financial fluctuations move together over time across financial markets [32]. Therefore, the GARCH-M model provides an explanation of how common variations move over time by building a common variance matrix. Accordingly, the multi-variable (GARCH-M) model helps one to make better decisions in different areas of financial market applications [18].

Bollerslev first introduced the GARCH-M model to measure risk and forecast, and it is often used to predict financial indicators closely related to risk [33]. The expression of this model can be represented by the following structure [34]:

$$r_t = \mu_t + \epsilon_t \tag{1}$$

$$\epsilon_t = H_t^{1/2} Z_t \tag{2}$$

Where:

r_t: is the vector n×1for logarithms n of variables n in time t.

ϵ_t: Residual vector n×1 for variables n in time t, with expected mean E(ϵ_t) = 0, and variance matrix COV. (ϵ_t) = H_t.

μ_t: Vector n×1of the expected values of conditional returns of n variables in time t.

H_t: n×n matrix of conditional variations of ϵ_t in time t.

Z_t: vector n×1 for random errors follows normal distribution with mean E(Z_t) = 0, E($z_t z_t$T) = 1

The main concept underlying this category of models is to divide the matrix of conditional deviations into two parts: conditional standard deviation and conditional correlations, as follows [35, 36]:

$$H_t = D_t R_t D_t \tag{3}$$

where D_t represents the diagonal conditional standard deviation matrix on the structure [37]:

$$D_t = diag\left(h_{1t}^{1/2}, \ldots, h_{nt}^{1/2}\right) \tag{4}$$

while R_t represents the matrix of conditional correlations, the models of this category can be classified into two groups: the first with a fixed correlation matrix, and the second when the correlation matrix is time-varying.

- **Conditional Static Correlation Model (CCC-GARCH):**
  This model is considered one of the most important multivariate models and better than the GARCH model, as proposed by Bollerslev , and which was later circulated by Jeantheau . Assuming that (P_{ij}) is the constant conditional correla-

tion coefficient, we can write the conditional correlation of the matrix H_t as follows[35]:

$$H_t = D_t R_t D_t = P_{ij}\sqrt{h_{jj.t}h_{ii.j}} \tag{5}$$

$D_t = diag\left(\sqrt{h_{ii.t}}\right)$
$R = \ (P_{ij})_{N\times N}$
R expresses the constant conditional correlation matrix P_{ij}, where the (CCC) model contains the GARCH model for each conditional variation, $h_{ii.t}$, in D_t.

- **Estimating the Dynamic Conditional Correlation Model (DCC-GARCH):**

The modelling of each asset is achieved using the GARCH (1,1) univariate process, with the ARMA (0,0) average equation and multivariate natural errors, where the DCC-GARCH model captures dynamic correlations between assets by applying the DCC (1,1) structure to conditional correlations.

For each asset (i), the conditional mean equation is presented as follows[38]:

$$r_{\{i,t\}} = \mu_i + \phi_i * \left(r_{\{i,t-1\}} - \mu_i\right) + \theta_i * \epsilon_{\{i,t-1\}} + \epsilon_{\{i,t\}} \tag{6}$$

This represents the return of the asset (i) in a time t, where is the fixed average, and are the coefficients of AR and MA respectively, which $\epsilon_{\{i,t\}}$ is the error term.

The GARCH (1,1) univariate model for each asset (i) is defined as follows[39]:

$$h_{\{i,t\}} = \omega_i + \alpha_i * \epsilon_{\{i,t\ -1\}^2} + \beta_i * h_{\{i,t-1\}} \tag{7}$$

The conditional variation of the asset (i) in time t is indicated by the fact that, where, is the deviation, is the ARCH coefficient, and is the GARCH coefficient.

That the structure of the DCC is given by[40] as:

$$q_t = (1-a-b)*Q + a*\left(\epsilon_{\{t-1\}} * \left(\epsilon_{\left\{t-1\right\}}'\right)\right) + b*q_{\{t-1\}} \tag{8}$$

t is the matrix of dynamic conditional correlations in time, Q is the unconditional correlation matrix, a and b are the coefficients of DCC, and u_t is the uniform residue vector.

5. Results and Discussion

In this section, we will attempt to explore the indirect effects across financial and commodity markets in the United States of America, using self-regression models conditional on the heterogeneity of the variation heterogeneity of the generalized multivariate errors (GARCH-M), as represented by the static conditional correlation model (CCC-GARCH) and the dynamic conditional correlation model (DCC-GARCH). The multivariate time series of our study consists of **2490** views for each asset.

Here, we first study the descriptive statistics of market returns to get an idea of the salient facts of the studied time series, as shown in the following table:

We note from the statistical results in **Table 1** that the average returns of the markets are positive, while the unconditional volatility of each series is measured by standard deviations (Std. Dev.), and the sample differences range from 0.0038421% (RPG) to 0.0071589% (RC). The torsion coefficients (skewness) indicate that the examined series is far from being normally distributed, and we also note that the distribution of returns at the level of the entire market took an elongated form, which explains the problem of the thickness of the tails; the Kurtosis coefficient exceeded the value of the three that correspond to the normal distribution, which means that the chains of returns deviate from the normal distribution, as the distribution gathers more around the average. This is confirmed by the Jarque-Bera test statistics, which indicate that the returns do not follow the normal distribution in all markets during the study period, as illustrated in **Figure 1**:

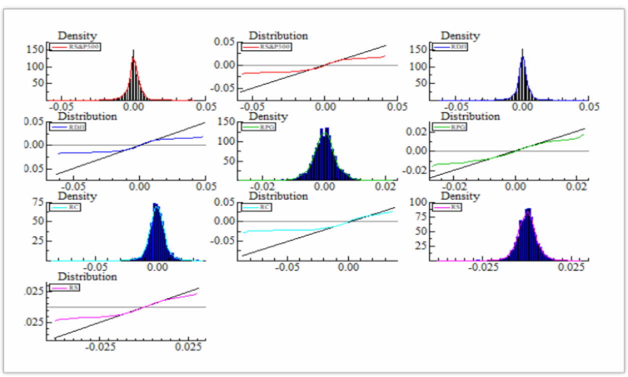

Figure 1. The results of testing the normal distribution of the series of daily returns of the U.S. markets.

Table 1. Descriptive statistics of market returns during the study period.

	RS&P500	RDJI	RPG	RC	RS
Mean	0.000185	0.000158	0.000143	8.9356e−006	−1.1882e−005
Median	0.000286	0.000298	0.000201	0.000000	0.000166
Maximum	0.038944	0.046749	0.020381	0.033518	0.027909
Minimum	−0.055441	−0.060114	−0.025613	−0.082949	−0.048171
Std. Dev.	0.004041	0.004285	0.0038421	0.0071589	0.0056394
Skewness	−0.80794	−0.94602	−0.20856	−1.3822	−0.54909
Kurtosis	15.727	22.645	2.8573	16.618	5.3698
Jarque-Bera	225931.0	353573.0	862.93	129446.0	3116.7
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2490	2490	2490	2490	2490
Q(2)(10)	16.3471**	14.0009**	9.50888**	8.27316**	6.87563*
ARCH (10)	158.12**	166.04**	10.946**	7.0152**	12.959**
ADF	−28.73**	−28.00**	−20.06**	−28.23**	−29.41**

Notes: (***) and (**) and (*) indicate statistical significance at the levels (1%, 5%, and 10%, respectively), and ARCH (10) represents the Lagrange multiplier tests for heteroscedasticity up to the 10th lag, while Q2(10) represents the Ljung-Box statistics for squared returns. ADF refers to the augmented Dickey-Fuller unit root tests for the residuals after estimating the ARCH model, which includes both trend and intercept in the equation.

The results of the Jarque-Bera test also show the application of the types of multi-variable GARCH-M models, to measure the volatility of returns using the daily data series of market returns. We can then observe unconditional correlations between markets using the correlation matrix and, as shown in **Figure 2**, there is a strong correlation between market returns.

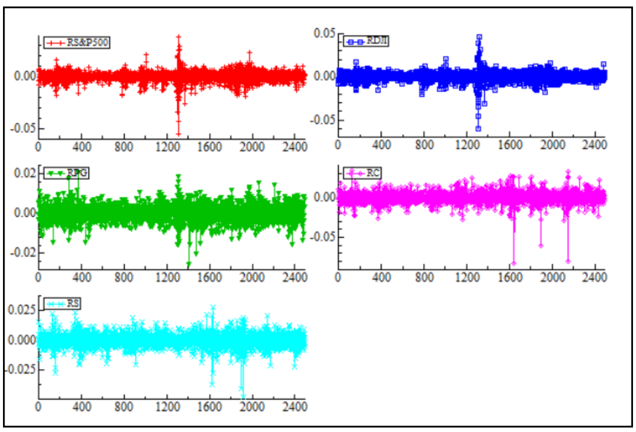

Figure 2. The movement of daily returns of financial and commodity markets in the USA.

In **Figure 2**, we applied natural logarithms to a time series of market returns and calculated daily logarithmic returns to stabilize the variance and achieve stability, as these conversions allow us to focus on changes in asset prices instead of their absolute levels.

By looking at **Figure 3**, we notice that there are varying degrees of volatility and distinct periods of movement. It is quite clear that large returns from the markets tend to be followed by large returns as well; small returns from the markets tend to be followed by low returns. Statistically, the combination of fluctuations indicates a strong subjective correlation in the quadratic return of these markets, because the quadratic return measures the moment of the second rank. The time series presented in **Figure 3** shows a temporal change in the conditional variation and a combination of fluctuations, which indicates that the dynamics of market returns are affected by various factors such as macroeconomic conditions, market developments, and the psychological state of investors. This means that the returns can be better modeled with a multivariate (GARCH-M).

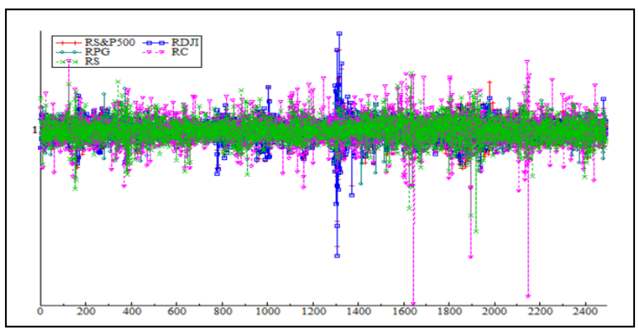

Figure 3. Returns of financial and commodity markets in the USA.

(1) Estimating the CCC-GARCH model:

Results of estimating the GARCH (1,1) model on the returns of the U.S. markets:After diagnosing the return series of the studied markets, we here estimate the GARCH (1,1) model under the assumption of normally distributed errors, as this is considered a fundamental step in the application of multivariate GARCH models, **Table 2** summarizes the results, which indicated a strong correlation between markets returns. This was confirmed by the values of α(ARCH) and β(GARCH):

This model was estimated using the student distribution because of the lack of a normal distribution of returns, where the returns' correlation was direct to varying degrees. There is a strong indirect correlation of 92% between the financial markets, while there is a moderate negative correlation between the financial markets and the gold market, which can be considered alternative investments and a haven for investments in financial assets. Conversely, the results of the CCC GARCH model confirmed a weak positive correlation between the financial and agricultural product markets, specifically the corn and soybean markets. This may be attributed to the significant development in the American financial markets that have not yet reached the agricultural product markets, in addition to the trading volume and the level of investments in both markets, as shown in **Figure 4** below:

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 ******************************
 ** MG@RCH(1) SPECIFICATIONS **
 ******************************
Conditional Variance : Constant Correlation Model
Multivariate Normal distribution.

Strong convergence using numerical derivatives
Log-likelihood = 52233.6
Please wait : Computing the Std Errors ...

 Robust Standard Errors (Sandwich formula)
                   Coefficient  Std.Error  t-value  t-prob
rho_21                0.919925  0.0044609    206.2  0.0000
rho_31               -0.011783   0.024970  -0.4719  0.6371
rho_41                0.054442   0.020333    2.677  0.0075
rho_51                0.079780   0.019889    4.011  0.0001
rho_32               -0.031721   0.025487   -1.245  0.2134
rho_42                0.059172   0.020210    2.928  0.0034
rho_52                0.082042   0.020518    3.998  0.0001
rho_43                0.041182   0.019356    2.128  0.0335
rho_53                0.064961   0.020622    3.150  0.0017
rho_54                0.473439   0.019550    24.22  0.0000
No. Observations :        2490  No. Parameters  :        30
No. Series       :           5  Log Likelihood  : 52233.621
Elapsed Time : 1 seconds (or 0.0166667 minutes).
```

Figure 4. Results of estimating the CCC-GARCH (1.1) model on the returns of American markets.

As shown in **Table 3**, the attached probability value of Hosking, Li and McLeod is less than the statistically significant level (5%), indicating that there is a subjective correlation in the error boxes at the delay periods 5, 10, 20, and 50, as is also shown in the following table:

(2) Estimating the DCC-GARCH model:

Table 4 shows the results of the dynamic conditional correlation model (DCC-GARCH), as it was found that there were dynamic conditional correlations over time that are negative between the fluctuations of the returns financial markets and gold market returns in the United States of America, meaning that there is no sensitivity to the returns in these markets to the changes that occur between them dynamically over time, these results are consistent with the results of the study [18]. In other words, events that affect the change of the return of one market index do not affect the change of the return of other market indices in the same direction, as these correlations indicate that the returns of each asset tend to move in opposite directions. This relationship may help investors to diversify their portfolios and reduce the overall risks they may be exposed to due to a financial crisis in this market.

On the other hand, the time-positive dynamic conditional correlations shown in **Figure 5**, which differ significantly from zero between the yield fluctuations in financial markets and agricultural commodity market returns in the United States, indicate that there is a sensitivity to the returns of these markets to the changes that take place between them dynamically over time; in other words, the events that affect the return change of one market index affect the change of other market indices in the same direction, where it was found that the sensitivity among other markets indices was weak.

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 ** MG@RCH(2) SPECIFICATIONS **
 ******************************
Conditional Variance : Dynamic Correlation Model (Engle)
Multivariate Normal distribution.

Strong convergence using numerical derivatives
Log-likelihood = 52628.4
Please wait : Computing the Std Errors ...

 Robust Standard Errors (Sandwich formula)
                   Coefficient  Std.Error  t-value  t-prob
rho_21                0.955005  0.0052286    182.7  0.0000
rho_31               -0.011231   0.060077  -0.1869  0.8517
rho_41                0.055204   0.050929    1.084  0.2785
rho_51                0.056187   0.050879    1.104  0.2696
rho_32               -0.037934   0.060534  -0.6267  0.5309
rho_42                0.061726   0.050512    1.222  0.2218
rho_52                0.059303   0.050618    1.172  0.2415
rho_43                0.050520   0.047488    1.064  0.2875
rho_53                0.068007   0.048547    1.401  0.1614
rho_54                0.407732   0.053982    7.553  0.0000
alpha                 0.031586  0.0028694    11.01  0.0000
beta                  0.952279  0.0051957    183.3  0.0000
No. Observations :        2490  No. Parameters  :        32
No. Series       :           5  Log Likelihood  : 52628.386
Elapsed Time : 2.767 seconds (or 0.0461167 minutes).
```

Figure 5. Results of estimating the DCC-GARCH model on market returns.

We note from **Figure 5** that the sum of the coeffi-

Table 2. Results of estimating the GARCH (1,1) model on the returns of the U.S. markets.

		RS&P500	RDJI	RPG	RC	RS
Mean Equation	C	0.000357 **	0.000311 **	0.00008 **	0.00010 **	0.00003 **
	AR(1)	−0.051478 **	−0.025942 **	0.00339 **	−0.01228	0.00332 **
Variance Equation	α(ARCH)	0.125009 **	0.127869 **	0.02749 **	0.10814 **	0.07254 **
	β(GARCH)	0.897009 **	0.893713 **	0.97386 **	0.90757 ***	0.93428 **
	α+β	1.02202	1.02158	1.00136	1.01572	1.00683
Log likelihood		10285.180	10389.019	10390.687	8984.981	9518.006

Table 3. Li and McLeod, Hosking test results for the CCC-GARCH model.

Testing	Lags *Q*	Statistics	
		Consolidated Residues*	Unified Residual Quadrature**
Hosking	5	187.626 [0.0001974]	356.587 [0.0000000]
	10	305.113 [0.0087397]	491.026 [0.0000000]
	20	548.858 [0.0606361]	787.974 [0.0000000]
	50	1189.194 [0.8857143]	1524.07 [0.0000001]
Li and McLeod	5	187.592 [0.0001987]	356.401 [0.0000000]
	10	305.096 [0.0087559]	490.826 [0.0000000]
	20	548.877 [0.0606566]	787.1442 [0.0000000]
	50	1190.89 [0.8785783]	1523.47 [0.0000001]

Note: The numbers in brackets in the third column are the statistics of (t), (5) Q, (10) Q, (20) Q, and (50) Q, indicating the tests of the rank (5, 10, 20, 50) for the serial variation of the uniform residue and the square of the uniform residue respectively, while the numbers in brackets in the fourth column are the values of (P). A score of (*) and (* *) indicates that the values of (P) have been corrected with a degree of freedom of (1 and 2), respectively.
Source: Prepared by the researchers based on the Ox-Metrics software.

cients (alpha and beta) was 0.983865, which indicates the existence of continuity in correlations in the long term between the returns of financial markets and the returns of commodity markets in the United States. This result reinforces the result obtained when analyzing the CCC-GARCH model.

It is clear from **Table 4** that the attached Hosting, Li and McLeod probability are statistically significant (less than 5% and 10%), indicating that there is a subjective correlation in the error boxes at the delay periods 5 and 10. The following figure illustrates the dynamic conditional correlations between market returns:

Figure 6 shows the correlations between the fluctuations of market returns, as the changes have been significant over time. It is also clear to us that there is a sharp rise in correlations, especially during times of crisis and financial turmoil. This means the transmission of infection between markets is thus confirmed by **Figure 7**, which shows the conditional differences between them.

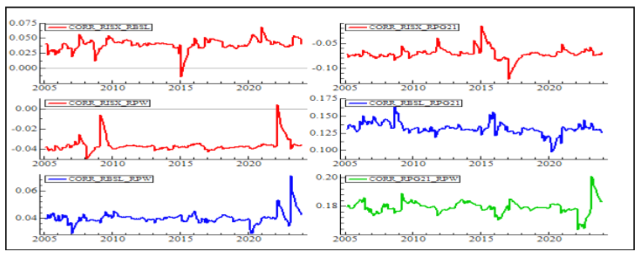

Figure 6. Dynamic conditional correlation for Engle between market returns.

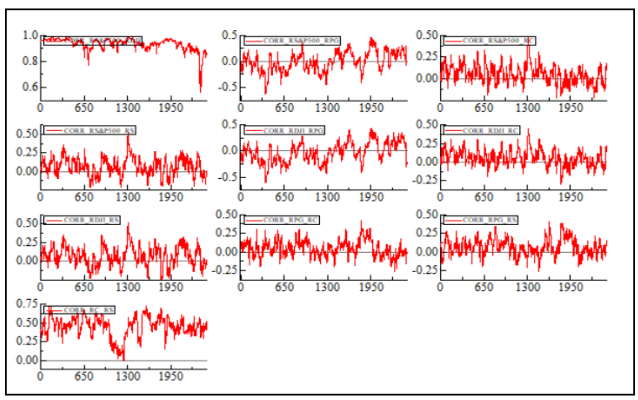

Figure 7. Conditional common variation between market returns according to the DCC model (Engle).

Table 4. Li and McLeod, Hosking test results for the DCC-GARCH model.

Testing	Lags Q	Statistics	
		Consolidated Residues*	**Unified Residual Quadrature****
Hosking	5	181.957 [0.0005444]	183.054 [0.0003623]
	10	304.490 [0.0093352]	279.000 [0.0857367]
	20	540.237 [0.0981827]	527.862 [0.1713198]
	50	1194.25 [0.8639909]	1213.66 [0.7518401]
Li and McLeod	5	181.914 [0.0005485]	183.032 [0.0003637]
	10	304.446 [0.0093784]	279.079 [0.0852275]
	20	540.281 [0.0979518]	527.907 [0.1709730]
	50	1195.83 [0.8567525]	1214.28 [0.7478258]

6. Conclusions

The returns from financial markets and agricultural commodity markets indicate that the returns of both these assets tend to move in the same direction but at different rates. This relationship may provide investors in the U.S. financial market with an opportunity to diversify their portfolios by investing in other markets to reduce the overall risks they might be exposed to due to future financial crises. Investing in the gold market is considered a haven for investment in the financial markets in the United States while investing in agricultural commodity markets does not appear to reduce risks in the financial markets but rather increases them as they are positively correlated, an outcome is that is consistent with the study by [15]. This means that investors cannot achieve investment diversification by investing in the assets of these markets simultaneously, which aligns with the result of the study by [12]. It may be noted that the correlation coefficients between the returns of financial markets and agricultural commodity markets are generally weak, indicating a divergence in the development between these markets and a low degree of integration. This necessitates further development of agricultural commodity markets in the United States to achieve more connections to make appropriate hedged investment decisions.

The study also found that indirect effects were mostly driven by short-time horizons, followed by medium- and long-time horizons, which highlights the importance of considering the evolving nature of correlations when making asset allocation decisions (financial and commodity), as well as their importance to investors, portfolio managers, and government departments (policymakers) of managing risks during periods of crisis. It is possible to apply the DCC-GARCH model to other markets and expand this study to include most markets that use other more sophisticated models to explore the impact of macroeconomic factors on dynamic correlations, and to develop new ways to improve the portfolio based on time-varying correlations as these give more accurate and realistic results in showing indirect effects between the returns of these markets.

The study also demonstrated that indirect effects were mostly driven by short-time horizons, followed by medium and long-time horizons. This highlights the importance of considering the evolving nature of correlations when making asset allocation decisions (financial and commodity) and their special importance for portfolio managers to build an ideal portfolio and predict fluctuations between markets. This research can be expanded to include exchange markets.

Author Contributions

Methodology, W.H.A.A.-A.; formal analysis, A.S.; data curation, F.G.F.; writing—original draft preparation, A.Y.A.A.-J.; writing—review and editing, B.A.A.F. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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