Research on World Agricultural Economy
https://journals.nasspublishing.com/index.php/rwae

ARTICLE

The Relationship between the Wheat Market and the Financial Market in Malaysia Using a Dynamic Conditional Correlation Model (DCC-GARCH)

Wisam H. Ali Al-Anezi [1*], *Ali Y. Abdullah Al-Joaani* [2], *Abdulrazaq Shabeeb* [1], *Faez Hlail Srayyih* [1], *Faisal Ghazi Faisal* [3]

[1] *Department of Economics, College of Administration and Economics, University of Anbar, Ramadi 31001, Iraq*
[2] *Ministry of Finance, Ramadi 31001, Iraq*
[3] *Department of Finance and Banking , Al-Idrisi University College, Ramadi 31001, Iraq*

ABSTRACT

The research aims to identify the nature of the dynamic relationship between the returns of the wheat market (RPW) and the returns of the general index of the Malaysia financial market (RISX), and to verify the transmission of shocks and volatility between the returns of both markets during the monthly period from (1/1/2004) to (31/10/2024). Using the Dynamic Conditional Correlation GARCH (DCC-GARCH) model, the results showed an inverse relationship between the returns of both markets, with the correlation sensitivity reaching (−0.08%). This indicates a weak ratio, suggesting that diversifying the portfolio in both markets may increase gains to some extent. The predictive results indicated a positive correlation, which is also weak. As it refers to sensitivity to returns in both markets for dynamic changes that occur over time, there may not be an opportunity to achieve diversification when prices are imbalanced and to achieve returns in these markets. Therefore, the weak correlation between the returns of both markets indicates a decrease in their integration. The research recommended the need to increase the openness of the Malaysian securities market and to enhance its informational efficiency and transparency to

*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

ARTICLE INFO
Received: 15 November 2024 | Revised: 2 December 2024 | Accepted: 5 December 2024 | Published Online: 6 February 2025
DOI: https://doi.org/10.36956/rwae.v6i1.1480

CITATION
Al-Anezi, W.H.A., Al-Joaani, A.Y.A., Shabeeb, A., et al., 2025. The Relationship between the Wheat Market and the Financial Market in Malaysia Using a Dynamic Conditional Correlation Model (DCC-GARCH). Research on World Agricultural Economy. 6(1): 367–380.
DOI: https://doi.org/10.36956/rwae.v6i1.1480

increase the capacity and smoothness of the flow of information to and from the financial market.
Keywords: Dynamic Correlations; DCC-GARCH; Portfolio Diversification; Investor Interest

1. Introduction

Financial and commodity markets have witnessed increasing interconnectedness and significant fluctuations among asset classes in recent years. Advances in information technology, communications, and financial innovations, along with the easing of financial restrictions across countries, have all contributed to the increased interdependence of global financial markets, making them more susceptible to contagion emerging away from the host country. The impact of the financial crisis of 2008 and the COVID-19 pandemic of 2019 was felt worldwide [1], raising the need for alternative investments to diversify the risks associated with financial markets, It cannot be said that all financial markets in different economies exhibit the same degree of efficiency in allocating financial resources, based on the assortment or diversity of their advantages. Stupid money exacerbates abnormal stock returns, while smart money alleviates these anomalies [2] .

Recent research has not considered that other commodities, such as agricultural, industrial, and precious metals, may also impact the Malaysian economy, either economically or financially. Basic commodities serve as a diversification tool or a means of hedging, and hedging is considered strong diversification when the correlation with the main variable is zero or negative. This comes from the management of standard portfolios in standard textbooks on corporate finance [3]. The factor that led to increased discussion about the role of commodities, including wheat, in the process of allocating strategic assets, the global financial crisis of 2008 had tangible repercussions on various parts of the world, causing a major disaster for different economies, markets, and investors, as well as the rise in commodity prices since 2002 and their subsequent decline in July 2008 [4]. The agricultural sector plays a fundamental and strategic role in bearing significant responsibility for achieving food security [5], meeting local food demand, as well as providing essential inputs for other economic sectors. At the same time, the agricultural industry generates surpluses that can be exported to enhance foreign exchange reserves [6]. Investors who allocate more of their investment capital to the commodities market will change this capital flow's structure of correlation between the commodities and stock markets [7].

There are different channels through which shocks from a specific source (financial or commodity) can transfer to other assets and vice versa. For example, crude oil is a key factor in agriculture and individual company stocks, and inflation links energy, agriculture, and financial markets. Therefore, it is clear that a shock in any of the markets may also transfer to other markets, affecting investor returns and portfolio rebalancing [8]. Financial diversification is possible through assets that have relatively less integration, as assets that are less affected by the indirect effects arising from the financial sector have the potential to serve as a diversification factor [9]. In general, commodities can provide this function, as they are less tied to financial assets, and commodity prices are usually determined by supply and demand forces, while non-economic factors such as herd behavior, market sentiment, and future expectations play a crucial role in pricing assets in financial markets [10]. Due to the aforementioned factors, as well as the lack of previous studies on the relationship between the Malaysia financial market and the wheat market, this research aims to answer the following two main questions that represent the research problem:

1. Is there a dynamic conditional relationship between wheat market returns and the overall index returns of the Malaysian financial market?

2. To what extent do conditional fluctuations affect wheat market returns and the overall index returns of the Malaysian financial market?

The research aims to identify the nature of the dynamic relationship between wheat market returns and the returns of the general index of the Malaysia financial market, and to verify the transmission of shocks and fluctuations between them, in addition to determining whether the wheat market returns can be used as a predictor for fluctuations in the returns of the general index of the Malaysia financial market.

The importance of the research is evident in that it assists investors and portfolio managers in making appropriate diversification decisions and managing risks, by being guided by the results of correlation coefficients and their trends shown by the proposed model, in particular since wheat was chosen among other commodities because it represents one of the most important strategic goods and ranks first in most countries of the world as a commodity that represents global food security and can be a haven for investors in the Malaysian financial market.

The article assumes that the correlation between wheat market returns and the overall index returns of the Malaysia financial market has an upward trend and that there are mutual relationships or trends between the returns of both markets. In other words, fluctuations occurring in one market affect the performance of the other market in Malaysia.

As a methodology, the deductive method was adopted by linking the results to the causes and interpreting the data in light of economic theory. The inductive method was also relied upon by quantitatively measuring the relationship between financial and commodity markets, based on measurement methods according to the standard approach in an attempt to prove the research hypothesis and achieve its objectives.

The remainder of this paper is structured as follows. Section 2 introduces the literature review. Section 3 describes materials and methods. The results are presented in Section 4. and Section 5 conclusions, recommendations, and future works.

2. Literature Review

There is a large number of research studies in developed countries exploring the correlations between financial markets and commodity markets, where Mensi et al.[11] investigate the relationships of returns and interconnections between the (S&P 500) index and the prices of commodities (wheat, oil, gold, and beverages). Their results indicated that shocks occurring in the (S&P 500) index significantly affect the markets for crude oil, gold, and wheat. In the same way, Creti, Joëts and Mignon[7] analyze the evolution of the relationship between equity rights (stocks) and (25) commodities, and their results revealed that the correlations and flows between stock prices and basic commodities increase in the post-crisis period. Kang, McIver and Yoon[12] also examined the transmission of infection between West Texas Intermediate (WTI) crude oil and wheat, rice, corn, gold, and silver, and their study concluded that there is an indirect transmission of returns and volatility among the studied commodities.

A study by Sadorsky[13] analyzed the fluctuations and correlations between stock prices and the prices of wheat, copper, and oil in emerging markets of 21 countries. Their study found that the correlations between emerging market stock prices and wheat, copper, and oil prices increased after 2008 and did not return to their values before 2008. A study by Gozgor, Lau and Bilgin[14] examined the transmission of commodity market volatility in the United States and its correlations with risks and uncertainties in financial markets. Their results showed that crude oil returns are positively correlated with four types of agricultural commodity returns. Additionally, high-risk perception in financial markets leads to a decline in corn and soybean returns, while increased uncertainty in financial markets is negatively associated with corn and soybean returns. Furthermore, the effects of risk and uncertainty perceptions on wheat market returns are not statistically strong and vary across different sub-periods. Recent studies conducted by Maitra, Guhathakurta and Kang[15] and Mensi et al.[16] have analyzed the transmission of indirect effects in commodity markets. Their findings revealed that indirect effects and the hedging potential of various assets are sensitive to crises such as the global financial crisis, the European debt crisis, the collapse of oil prices, and the spread of COVID-19. Most of the current previous studies have been limited to the time-varying relationship between financial and commodity markets, and most of them are studies of developed Western economies. Additionally, most studies have focused on events before the COVID-19 pandemic, such as the global financial crisis of 2008 and the European debt crisis. We are adding to the current empirical research by studying the relationship between wheat market returns and the overall index returns of the Malaysian financial market during the pre-pandemic period, the pandemic period, and the post-pandemic period. We provide new empirical insights into the time dynamics and frequency of indirect effects across financial assets and commodities. A study by Gunera [17] examined the cycles and dynamic correlations between agricultural markets and financial markets, analyzing the cyclical relationship between stock markets and commodity markets in the United States. It also studied the conditional dynamic correlations between them. The study found that stock markets and commodity markets alternated in their influence on each other nine times during the study period. The results indicated that the COVID-19 pandemic had little long-term impact, while the global financial crisis of 2008 marked a turning point in counter-cyclical behavior, allowing individuals and investors to benefit from commodities by aligning their investments with these cycles. The relationship between stock markets and commodity markets is interconnected, which leads to improved financial risk management. A study by N. Nordin, S. Nordin and Ismail [18] addressed the impact of commodity prices, interest rates, and exchange rates on the performance of the Malaysian stock market, focusing on palm oil prices, oil prices, and gold prices as key commodities influencing stock market performance. The results showed significant cointegration relationships and a substantial impact of palm oil prices on the Malaysian stock market index, while no significant impact was observed from oil prices and gold prices. However, interest rates and exchange rates did affect the performance of the Malaysian stock market.

The unique contribution of our study is represented by measuring the relationship between wheat prices and the stock market in Malaysia.

3. Materials and Methods

The research includes a time series spanning nineteen years of monthly data from 1/1/2004 to 31/10/2024, with a total of 250 observations for both the returns of the wheat market (RPW) and the returns of the general index of the Malaysia financial market (RISX). This is aimed at understanding the nature of the relationship between the returns of both markets by applying the Dynamic Conditional Correlation GARCH (DCC_GARCH) model proposed by Engle [19], which is defined as a model that assumes conditional correlation is not constant and evolves. It is considered one of the modern standard analytical tools in the field of modeling the cointegration relationship between two or more series. This model allows us to track the conditional correlation in the series over time and periodically, whether the time series is (daily, weekly, monthly, annually, etc.), in addition to the model's distinguished characteristics as follows [20]:

1. This model relies on estimating its parameters based on residuals, and thus the assumption of (non-constant variance of inputs) is a fulfilled condition [21].
2. There are explanatory variables, as this model allows for their addition in the mean equation, thus its results are well-specified.
3. This model does not necessitate the search for many variables, as it relies on the returns of different assets.

This model is estimated in two stages [21]:

- The first stage involves estimating the (Generalized Autoregressive Conditional Heteroskedasticity) GARCH (1,1) model to generate deviations and estimate residuals.
- The second stage involves calculating the residuals and using them as inputs to determine the parameters of the (DCC_GARCH) model.

Engle assumes through his (DCC) model that for (N) time series consisting of multiple variables following a normal distribution with a mean equal to zero and variance (H_t), the (DCC_GARCH) model is as follows [19]:

$$r_t = \mu_t + \varepsilon_t = \frac{\varepsilon_t}{\Omega_{t-1}} N\left(0.H_t\right) t = 1.2 \ldots .T \quad (1)$$

Where r_t represents an $(1 \times N)$ matrix of returns, and (ε_t) represents an $(1 \times N)$ matrix with a zero mean made up of the residuals from the autoregressive estimation of the returns of each variable. Additionally, (Ω_{t-1}) represents a matrix of all available information up to time (t), thus (H_t) can be expressed as follows[22]:

$$H_t = D_t R_t D_t \tag{2}$$

It is known that (D_t) represents a diagonal matrix of size $(N \times N)$ for the time-varying standard deviations of the returns on all assets in the sample, while (R_t) represents the time-varying conditional correlation matrix $(N \times N)$. Based on this, the (DCC_GARCH) model estimates the conditional volatilities and correlations in two steps[21]:

First: Determining the mean and conditional variance equation for each asset in the sample through the univariate (DCC_GARCH) model, where (D_t) is specified as follows[23]:

$$D_t = diag\left(\sqrt{h_{ii.t}}\right) \tag{3}$$

Where: $(\sqrt{h_{ii.t}})$ represents the conditional variance for each asset, estimated using the GARCH (1,1) model.

Secondly: the time evolution of the conditional correlation is estimated through the matrix (R_t) as follows[22, 24]:

$$R_t = diag(\mathfrak{Q}_t)^{-1/2}\mathfrak{Q}_t diag\ (\mathfrak{Q}_t)^{-1/2} \tag{4}$$

$$\mathfrak{Q}_t = (1-\theta_1-\theta_2)\ \bar{\mathfrak{Q}} + \theta_1\left(\mu_{t-1}\mu'_{t-1}\right) + \theta_2\mathfrak{Q}_{t-1} \tag{5}$$

It is known that: $(\mathfrak{Q}_t)$ represents the conditional variance matrix of order $(N \times N)$, which is symmetric and positive, while $(\bar{\mathfrak{Q}})$ represents the unconditional variance matrix, and (θ_1, θ_2) represents the unknown parameters to be estimated in the (DCC) model. The parameter (θ_1) reflects the impact of (previous shocks) on (current conditional variance), while the parameter (θ_2) reflects the impact of (previous conditional variance) on (current conditional variance). To ensure model stability, the parameters (θ_1, θ_2) must be positive and satisfy the following conditions:

$$\theta_1 + \theta_2 < 1; \theta_1 > 0; \theta_2 \geq 0 \tag{6}$$

Additionally, (μ_{t-1}) represents the standardized residuals at time $(t-1)$, while $(\mu_{t-1}\mu'_{t-1})$ represents the unconditional variance matrix of the errors (μ_{it}) of order $(N \times N)$, which reflects the (joint variance) resulting from previous shocks. Meanwhile, the conditional variance matrix $(\mathfrak{Q}_{t-1})$ reflects the variances and joint correlations among assets at the time $(t-1)$. The matrix $(\mathfrak{Q}_t\ )^{-1/2}$ represents a diagonal matrix consisting of square roots of the inverses of the diagonal elements of $(\mathfrak{Q}_t)$ and is calculated as follows[25]:

$$diag\ (\mathfrak{Q}_t\ )^{-1/2} = diag\left(\frac{1}{\sqrt{q_{ii,t}}} \cdots\cdots\cdots \frac{1}{\sqrt{q_{mn,t}}}\right) \tag{7}$$

The dynamic conditional correlation coefficient of two random variables is given as follows[22, 26]:

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}, i, j = 1, 2, \ldots\ldots, n, \ and\ i \neq j \tag{8}$$

Equation (8) refers to how to calculate the (conditional correlation coefficient) between returns (i) and (j) using elements from the conditional variance matrix $(\mathfrak{Q}_t)$, which is used to convert (conditional joint variance) into (conditional correlation) between assets. By substitution, we find[27]:

$$\rho_{12,t} = \frac{(1-\theta_1-\theta_2)\ \bar{q}_{12} + \theta_1\mu_{1,t-1}\mu_{2,t-1} + \theta_2 q_{12,t-1}}{\sqrt{[(1-\theta_1-\theta_2)\ \bar{q}_{11} + \theta_1\mu^2_{1,t-1} + \theta_2\ q_{11,t-1}]}\sqrt{\left[(1-\theta_1-\theta_2)\ \bar{q}_{22} + \theta_1\mu^2_{2,t-1} + \theta_2\ q_{22,t-1}\right]}} \tag{9}$$

Where (q_{ij}) are the elements forming the matrix $(\mathfrak{Q}_t)$ with (i) rows and (j) columns. Engle suggested the possibility of estimating the (DCC) model using the maximum likelihood method (log-likelihood), where (θ) represents the parameters in (D_t) and $(\varnothing)$ represents the parameters in (R_t). Thus, the equation is presented as follows[28–30]:

$$\ell_t(\theta, \varnothing) = [-\tfrac{1}{2}\sum_{t=1}^{T}(n log\ (2\pi) + log\ |D_t^2| + \varepsilon'_t D_t^{-2}\varepsilon_t)] + [-\tfrac{1}{2}\sum_{t=1}^{T}(log\ |R_t| + \mu'_t R_t^{-1}\mu_t - \mu'_t\mu_t)] \tag{10}$$

The first part of the log-likelihood function represents volatility, which is the sum of the probabilities of each variable in the (GARCH) model. The log-likelihood function can be maximized in the first part through the estimated parameters in (D_t), while the second part in Equation (10) can be maximized by estimating the correlation coefficients.

4. Results

4.1. Descriptive Statistics of Wheat Market Returns and the Overall Index Returns of the Malaysia Financial Market

Table 1 shows a summary of the descriptive statistics for the returns of the Malaysia Stock Market Index (RISX) and the Wheat Market (RPW), providing valuable insights into the characteristics of both markets over the study period. There is significant volatility in the returns of both markets, indicating relative instability. We observe that the average returns of both markets were positive, with the financial market index (RISX) achieving a higher average return of (0.00505), while the Wheat Market (RPW) recorded a lower average return of (0.00157). The results also show that investment in the Malaysian financial market is more exposed to risk, as evidenced by the high standard deviation (Std. Dev.) value of (0.081), while the Wheat Market exhibits lower volatility with a low standard deviation of (0.007). Additionally, the positive values of the skewness coefficient related to the returns of both markets indicate a rightward skew in the distribution of their returns, suggesting a significant likelihood of achieving high returns in these markets, as shown in **Table 1**.

It is also noted from **Table 1** that the value of the kurtosis coefficient is greater than three, which corresponds to the normal distribution, indicating the presence of outliers in the displayed time series, meaning there are temporary spikes and drops in returns. Based on the Jarque-Bera test statistics, we reject the hypothesis of normal distribution of returns, as its value is large for both markets, meaning that the return series does not follow a normal distribution. We also examine through **Table 1** in more depth the returns of both markets to determine if they are suitable for modeling volatility (and more specifically), we study the presence of autocorrelation in squared returns and the effects of (ARCH) in the studied time series. We observe that the (Ljung-Box) tests applied to the squared returns up to (10) lags (Q210) reject the null hypothesis of no serial correlation, providing evidence of autocorrelation between the two markets. Additionally, the ARCH Lagrange Multiplier (LM) tests reject the null hypothesis of no (ARCH) effects, indicating significant (ARCH) effects, as well as the necessity to ensure the degree of stationarity of the returns of both markets as a prerequisite for applying (ARCH) models. Therefore, we relied on the Augmented Dickey-Fuller (ADF) unit root tests after estimating the (ARCH) model. Its results indicated no unit root in the monthly return data series of both markets under investigation, thus confirming the stationarity of the series. To further ascertain the degree of stationarity of the time series, the strength of this stability, and the duration of the correlation between the two studied markets, we will plot the Autocorrelation Function (ACF), which provides evidence of serial correlation among the observations, As shown in **Figure 1.**

It can be observed from **Figure 2**, The Partial Autocorrelation Function (PACF), which indicates the dependence among observation values over the long-term, using a lag length of (100), that serial autocorrelations are showing a clear pattern of persistence and slow decay, which is one of the characteristics of long memory processes between the values of both markets. Additionally, the PACF indicates the existence of some dependence between the long-term observation values. It is also noted that the time series of returns for both markets mostly fall within the confidence intervals, except for some lag periods that fall outside the confidence intervals, which are usually (95% or 99%), such as lag period (71) for the returns of the Malaysia stock market index, lag periods from (1–10), lag periods (12–13), as well as lag periods from (70–100) for the returns of the wheat market (RPW). This indicates a statistically significant autocorrelation at those periods between the displayed series values, which is a feature that can be captured by GARCH models. However, the lag periods that fall within the confidence intervals indicate the stability of the time series. Nevertheless, one cannot accept the stability of these series definitively due to the presence of fluctuations in their behavior. This necessitates reliance on standard statistical tools capable of interpreting these fluctuations and building a standard model to predict the correlations between both markets during the research period.

Table 1. Descriptive statistics of wheat market returns and the general index returns of the Malaysia financial market.

	RISX	RPW
Mean	0.00508	0.00158
Median	−0.00031	0.00046
Maximum	1.03557	0.030763
Minimum	−0.15937	−0.044638
Std. Dev.	0.081095	0.007052
Skewness	9.3177	0.32943
Kurtosis	116.271	13.9177
Jarque-Bera	1594.8	30813.1
Probability	0.0000	0.0000
Observations	250	250
Q2(10)	0.069620	292.960**
ARCH (10)	0.006225	11.290**
ADF	−6.998**	−3.330*

Notes: (***) and (**) and (*) indicate statistical significance at levels (1%, 5%, and 10%) respectively, and ARCH (10) represents Lagrange multiplier tests for heterogeneous volatility up to the 10th lag, while Q2 (10) represents 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.

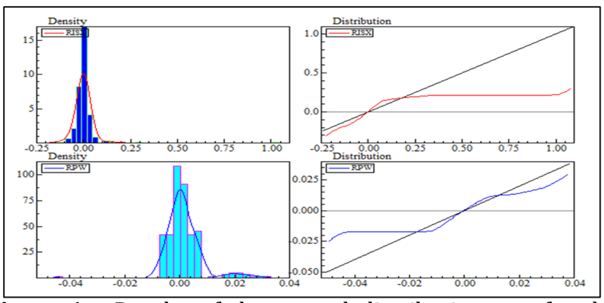

Figure 1. Results of the normal distribution test for the monthly return series of the studied markets.

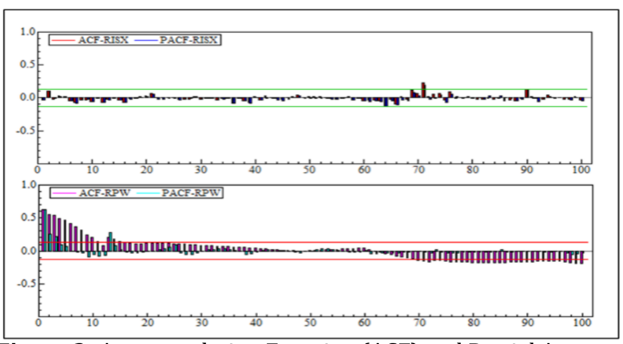

Figure 2. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the studied market returns.

The return series for both markets is suitable for further modelling, and the Dynamic Conditional Correlation (DCC-GARCH) model is appropriate for analyzing the volatility and conditional relationships (correlations) between the two studied markets. As a preliminary study regarding the existence of conditional correlations between the monthly returns of both markets, we present the movement of returns during the research period through **Figure 3**, which shows a strong correlation between the returns of both markets, indicating that the returns of both markets are subject to the same forces driving toward equilibrium. The reason for the increase in the returns of the Malaysia Stock Market Index in 2015 is the change in the method of calculating the index. The correlation between the returns of both markets during the research period can be represented.

Figure 4 shows an inverse relationship between the returns of the Malaysia stock market index and the returns of the wheat market, meaning that the returns of both markets tend to move in opposite directions and to varying degrees. This relationship may provide investors with an opportunity to diversify their portfolios and reduce overall risks, indicating that wheat has the potential to mitigate risks in the Malaysian financial market.

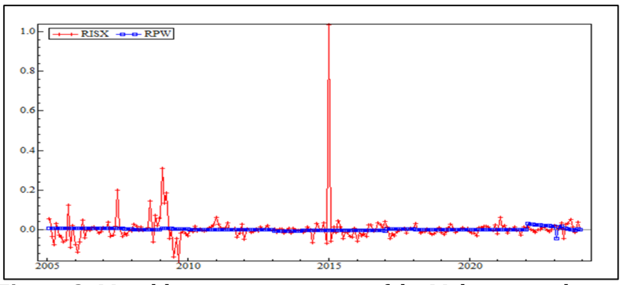

Figure 3. Monthly return movement of the Malaysia stock market index and wheat market.

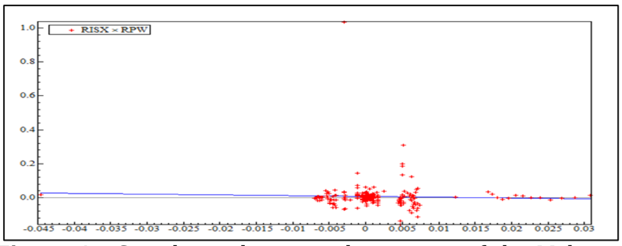

Figure 4. Correlation between the returns of the Malaysia stock market index and the wheat market returns.

It is worth noting that natural logarithms were applied to the time series of the variables and the monthly logarithmic returns were calculated to stabilize variance and achieve stability according to the following method[31].

$$y_t = Log\,(p_t) - Log\,(p_{t-1}) \quad (11)$$

Where: (y_t) is the logarithmic return, (P_t) is the price at time (t), (P_{t-1}) is the price at time $(t-1)$, and (Log) is the natural logarithm. These transformations allow us to focus on changes in the prices of variables rather than their absolute levels. **Figure 5** illustrates the time series graphs for both markets.

By examining **Figure 5**, we find that the visual impression indicates varying degrees of volatility and distinct periods of significant price movements. Large returns tend to be followed by large returns, while small returns tend to be close to low returns. Statistically, the clustering of volatility indicates a strong autocorrelation in the squared return. The displayed time series shows a temporal change in conditional variance and clustering of volatility, suggesting that the dynamics of these markets are influenced by various factors such as macroeconomic conditions, market events, and investor sentiment. This means that the data can be better modeled with a (DCC-GARCH) model.

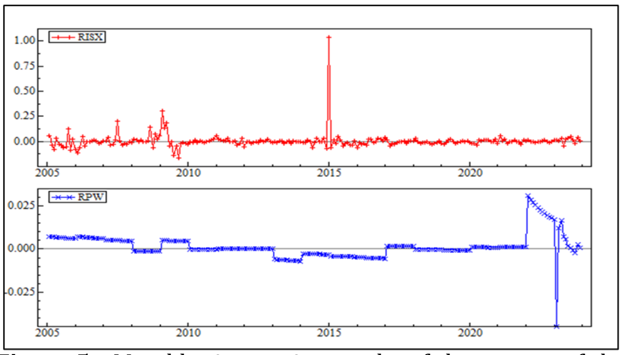

Figure 5. Monthly time series graphs of the returns of the Malaysia financial market and the wheat market returns.

4.2. Results of Estimating the GARCH (1,1) Model on the Returns of the Malaysia Stock Market Index and Wheat Market Returns

After diagnosing the return series of both markets, we estimate the GARCH (1,1) model under the assumption of normally distributed errors, as this is a fundamental step for applying multivariate GARCH models. **Table 2** summarizes the results:

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

		RISX	RPW
Mean Equation	C	0.0035***	−0.0013***
	AR (1)	0.4976**	0.7752**
Variance Equation	ω(Constant)	3.0030**	0.8124**
	α(ARCH)	1.0000**	0.1802**
	β(GARCH)	0.8791**	0.2671**
	α+β	1.2673	1.0548
+Log-likelihood		364.024	958.345

Notes: (***) and (**) and (*) indicate statistical significance at levels (1%, 5%, and 10%) respectively.

From **Table 2**, we observe that the GARCH (1,1) model applied to the returns of the Malaysia financial market index and the wheat market returns is statistically acceptable at a significance level of (5%). It also shows that the estimates are acceptable and significant at the (1%) level, which indicates that past returns play an important role in determining future returns. This is evident from the mean equation estimating the AR(1) autocorrelation. The alpha (α) value, which represents the effect of previous squared residuals (shocks) on current volatility, indicates a significant impact of past shocks on current volatility. It is noted that the returns of the Malaysia financial market index exhibited a high value for this coefficient, reaching (1.0000), which equals one, indicating a rapid response of the Malaysia financial market to effects and shocks in the short term. Additionally, the highest return rate was for the Malaysia financial market index at (3.0030). As for the term ARCH (β1(, which represents the effect of past fluctuations on current fluctuations, the returns of the wheat market (RPW) achieved a high value in the coefficient (β1) compared to the returns of the Malaysia stock market index. This means that the variance resulting from high fluctuations in the wheat market will be followed by another high variance in the subsequent period. Finally, the sum of the coefficients (α) and (β) reached one for both markets, confirming the presence of a heteroscedasticity problem in the two series, as well as emphasizing the persistence of volatility shocks in the future, which require time to dissipate their effects. This is because a high variance will be followed by another high variance in a later period, and thus the shock approaches infinity. Therefore, we conclude that there are dynamic conditional correlation properties in the return series of both markets, which necessitates dealing with the dynamic conditional correlation model (DCC-GARCH), which is what we aim for in what follows.

4.3. Results of Estimating the (DCC-GARCH) Model on the Returns of the Studied Markets

Table 3 shows the results of the Dynamic Conditional Correlation (DCC-GARCH) model between the volatility of returns on the Malaysia financial market index and wheat market returns. We relied on Engle's methodology and used the student distribution due to the absence of a normal distribution for the time series of both markets. It was found that there is a negative dynamic conditional correlation between the volatility of returns in both markets, indicating that the returns on the Malaysia financial market index and wheat market tend to move in opposite directions and to varying degrees. This relationship may provide investors with an opportunity to diversify their portfolios and reduce overall risks, as an investor can diversify their investments in the wheat market, which is considered a haven for investment in the Malaysian financial market. The sensitivity of the correlation between the returns of the two markets was (−0.08%), which is a weak percentage, suggesting that the gains from the decision to diversify the portfolio in both markets could increase. This negative correlation can be attributed to changes in risk appetite among investors; for instance, rising wheat prices may lead to a decrease in risk appetite, prompting investors to prefer less risky assets like gold, which negatively impacts the performance of stocks in the Malaysian financial market. Consequently, investors can use wheat as a safe-haven asset and integrate it into their investment portfolios to mitigate risks. The negative correlation indicates that a positive return in one market is associated with a negative return in the other market, reflecting a greater tendency for investors in one market to view the other market as an alternative.

Subsequent diagnostics of the (DCC-GARCH) model are critically important for verifying the adequacy of the multivariate (GARCH) specifications. Here, the efficiency of the (DCC-GARCH) model is checked by determining the sum of the remaining standardized squared autocorrelations and deriving their approximate distribution. This is done using the (Hosking) test and the (Li and McLeod) test to detect misspecification in the conditional mean or variance matrix, **Table 4** shows the p-value for the (Q) test, along with the (Hosking, Li, and McLeod) tests, which is greater than the 5% significance level, indicating no autocorrelation in the squared errors at lags (5), (10), (20), and (50).

Table 3. Results of estimating the DCC-GARCH (1.1) model on the returns of the studied markets.

** SERIES **

#1: RISX
#2: RPW

** MG@RCH(2) SPECIFICATIONS **

Conditional Variance : Dynamic Correlation Model (Engle)
Multivariate Student distribution, with 2.32848 degrees of freedom.
Strong convergence using numerical derivatives
Log-likelihood = 1592.14
Please wait : Computing the Std Errors ...
Robust Standard Errors (Sandwich formula)

	Coefficient	Std.Error	T-Value	T-Prob
rho_21	−0.008634	0.051963	−0.1655	0.8687
alpha	0.000000	1.0660e−017	0.01116	0.9911
beta	0.046819	1.1768	0.03979	0.9676
df	2.328477	0.044597	52.21	0.0000

No. Observations: 250 No. Parameters: 14
No. Series: 2 Log Likelihood: 1592.138
Elapsed Time: 0.047 seconds (or 0.000783333 minutes).

Table 4. Results of the (Q) test for the DCC-GARCH (1,1) model on the studied market returns.

Testing	Lags (Q)	Statistics			
		Consolidated Residues *		Unified Residual Quadrature **	
Hosking	5	9.99043	[0.9531793]	2.18045	[0.9999977]
	10	21.5774	[0.9892917]	11.6723	[0.9999879]
	20	85.5696	[0.2872672]	43.4277	[0.9994749]
	50	129.122	[0.9999670]	51.8478	[1.0000000]
Li and McLeod	5	10.1260	[0.9497685]	2.41631	[0.9999949]
	10	21.9985	[0.9871190]	12.3159	[0.9999751]
	20	85.0540	[0.3006315]	45.0653	[0.9989782]
	50	140.814	[0.9993761]	70.9637	[1.0000000]

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.

Figure 6 shows the dynamic conditional correlation between both markets, where the correlations between the fluctuations of returns in both markets, noting that they have experienced significant changes over time, alternating between increases and decreases. A sharp rise in correlations is particularly evident during financial crises and disturbances, indicating contagion between the two markets. The dynamic conditional correlations over time between the returns of the Malaysia financial market index and wheat market returns can be explained by their similar responses to regional and international conditions, such as fluctuations in oil prices and variations in global economic growth rates, not to mention their exposure to external shocks due to their economic openness and the ease of financial crisis contagion. Thus, these processes play a role in the joint movement of return fluctuations.

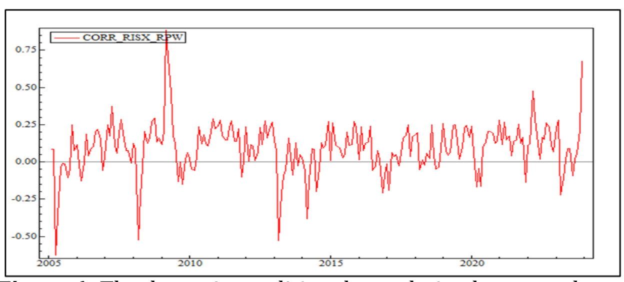

Figure 6. The dynamic conditional correlation between the returns of the Malaysia financial market index and wheat market returns.

To examine whether fluctuations arising from changes in the returns of one market can cause fluctuations in the returns of the other market, we will estimate the dynamic conditional correlation matrix based on the corrected (Engle) methodology. This is done by imposing an identification of the main diagonal elements in the correlation matrix. **Table 5** illustrates this as follows:

We observe from **Table 5** a negative correlation between the returns of the Malaysia stock market index and the returns of the wheat market, indicating that their returns move in opposite directions and to varying degrees. This relationship may provide investors with an opportunity to diversify their portfolios and reduce overall risks, as an investor can diversify their investments in both markets. The negative correlation suggests that positive returns in one market are associated with negative returns in the other market, indicating a greater tendency for investors in one market to treat the other market as an alternative. Therefore, investors can use wheat as a safe-haven asset and integrate it into investment portfolios to mitigate risks.

Table 5. Estimation of the dynamic conditional correlation matrix (E) for the returns of the studied markets.

Correlation Matrix		
	RPW	**RISX**
−0.038612	1.0000	RISX
1.0000	−0.038612	RPW

It can be concluded from the previous results that there are dynamic conditional correlations over time that vary between the returns of the Malaysia stock market index and the returns of the wheat market. These correlations can be confirmed by forecasting the dynamic conditional correlation matrix for the next 12 months.

From **Tables 6** and **7**, we observe that the correlations in the final forecast have changed from those in the initial forecast, indicating that dynamic conditional correlations vary over time. The correlations between the returns of both markets can change as time progresses. We also note from the forecast that there is a positive correlation between the returns of both markets, suggesting that the returns in both markets are sensitive to the changes occurring between them dynamically over time. Therefore, there may be no opportunity for diversification when price discrepancies occur and returns are achieved in these markets. In other words, investing in these markets may be fraught with risks, and the diversification strategy may not be beneficial for investors and traders, as the price conditions of both markets move together in a coordinated manner. The correlation sensitivity reached 4% between the fluctuations of returns in both markets in the first month's matrix, and 8% in the last month's matrix, indicating that the gains from the decision to diversify the portfolio in both markets in the future could decrease.

Table 6. Initial correlation matrix forecasts for the studied markets' returns.

Conditional Correlation Forecast.	Step: 1	
	RPW	**RISX**
0.48913	1.0000	RISX
1.0000	0.48913	RPW

Table 7. Final correlation matrix forecasts for the studied markets' returns.

Conditional Correlation Forecast.	Step: 12	
	RPW	**RISX**
0.087054	1.0000	RISX
1.0000	0.087054	RPW

5. Conclusions, Recommendations, and Future Works

5.1. Conclusions

The research concluded that there was growth in financial investments in wheat commodities during the research period. This was indicated by the correlation value mechanism between the returns of both markets in the dynamic conditional correlation matrix. The attractiveness of investing in wheat commodities is attributed to the low correlation and interdependence with traditional asset classes, stocks, and bonds, allowing for portfolio diversification benefits. The rationale is that the price of wheat commodities is driven by different fundamentals such as weather conditions, supply constraints in physical production, and geopolitical events that determine various price patterns and dynamics relative to traditional assets. A large number of previous empirical studies have reached a consensus on the benefits of diversification by including commodities in investors' portfolios. The results of estimating the dynamic conditional correlation model indicated an inverse relationship between the returns of the wheat market and the returns of the general index of the Malaysia financial market, with a correlation sensitivity of (–0.08%), which is a weak percentage, indicating that gains from the decision to diversify the portfolio in both markets could increase. Meanwhile, the results of forecasting the correlation matrices between the returns of both markets indicated a positive correlation between the returns of the wheat market and the returns of the general index of the Malaysia financial market, with a correlation sensitivity of (4%) in the correlation matrix for the first month and (0.8%) in the correlation matrix for the last month. This indicates the existence of sensitivity of returns in both markets to the dynamic changes occurring between them over time. Therefore, there may not be an opportunity for diversification when prices are disrupted and returns are achieved in these markets. In other words, investing in these markets may be fraught with risks, and the diversification strategy may not be beneficial for investors and traders, as the price conditions of both markets move together in a coordinated manner. This means that the gains from the decision to diversify the portfolio in both markets could decline. Moreover, the weak correlation between the returns of both markets indicates the weakness of these markets and the low degree of their integration, leading to asymmetry in returns and providing opportunities for some investors to achieve extraordinary returns by diversifying their portfolios in non-integrated markets.

5.2. Recommendations

Therefore, we recommend increasing the openness of the Malaysia securities market and striving to enhance its informational efficiency and transparency, to increase the capacity and smoothness of information flow to and from the financial market, which grants local and foreign investors and brokers more ability to hedge and predict expected market fluctuations.

5.3. Future Works

Our research focused on studying the relationship between the financial market index and the wheat market in Malaysia to understand the types of correlations between them, using monthly data from (1/1/2004) to (31/10/2024). The Dynamic Conditional Correlation (DCC-GARCH) model was employed. Future research can be conducted addressing the relationship between financial and commodity markets, such as foreign exchange markets, interest rates, money supply, and inflation, as well as including other agricultural commodities and examining the effects of bonds on conditional volatility and exploring the impact of these factors on dynamic correlations. Future research could explore the applicability of the dynamic conditional correlation (DCC-GARCH) model to other asset classes, and new methods can be developed to enhance the portfolio based on time-varying correlations, increasing interest in studies that use daily data, as they provide more accurate and realistic results.

Author Contributions

W.H.A.A.-A.—estimation of the standard model and analysis of the results. A.Y.A.A.-J.—writing the methodology. A.S.—writing previous studies. F.H.S.—writing the conclusion. F.G.F.—data collection.

Funding

This research received no external funding.

Institutional Review Board Statement

This study used actual data for financial market indicators and the wheat market in Malaysia.

Informed Consent Statement

This study used actual data for financial market indicators and the wheat market in Malaysia.

Data Availability Statement

We obtained data from the financial market data is obtained from the website (https://sa.investing.com/markets/), and wheat market data was obtained from the website (https://www.indexmundi.com/commodities).

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Pandey, D., Verma, N., Islam, T., et al., 2021. The response of Consumer Food Price Index (CFPI) due to the impact of pandemic COVID-19 on Indian agriculture sector. Journal of Agricultural Sciences. 3(1), 29–35. DOI: https://doi.org/10.36956/njas.v3i1.370

[2] Akbas, F., Armstrong, W.J., Sorescu, S., et al., 2015. Smart money, dumb money, and capital market anomalies. Journal of Financial Economics. 118(2), 355–382. DOI: https://doi.org/10.1016/j.jfineco.2015.07.003

[3] Azar, S.A., Chopurian, N.A., 2018. Commodity indexes and the stock markets of the GCC countries. Arab Economic and Business Journal. 13(2), 134–142. DOI: https://doi.org/10.1016/j.aebj.2018.08.001

[4] Khan, A., Masih, M., 2014. Correlation between Islamic stock and commodity markets: An investigation into the impact of financial crisis and financialization of commodity markets; MPRA Paper no. 56979, 29 June 2014. Available from: https://mpra.ub.uni-muenchen.de/56979/1/MPRA_paper_56979.pdf

[5] Hammad, S.A., Outhman, N.Y., Hamad, M.F., et al., 2024. The impact of domestic public debt on agricultural government investment and economic growth: Evidence from Iraqi between 2004 and 2022. Research World Agricultural Economy. 5(3), 37–50. DOI: https://doi.org/10.36956/rwae.v5i3.1124

[6] Kalhory, D.A., Hasan, T.M.L., Sakinaa, M.O., 2024. The attitude of full-time extension workers towards supervising the work of private agricultural projects in Sulaymani Governorate. Anbar Journal of Agricultural Sciences. 22(1), 28–40. DOI: https://doi.org/10.32649/ajas.2024.183694

[7] Creti, A., Joëts, M., Mignon, V., 2013. On the links between stock and commodity markets' volatility. Energy Economics. 37, 16–28. DOI: https://doi.org/10.1016/j.eneco.2013.01.005

[8] Ji, Q., Fan, Y., 2012. How does oil price volatility affect non-energy commodity markets?. Applied Energy. 89(1), 273–280. DOI: https://doi.org/10.1016/j.apenergy.2011.07.038

[9] Bai, Y., Green, C.J., 2010. International diversification strategies: Revisited from the risk perspective. Journal of Banking and Finance. 34(1), 236–245. DOI: https://doi.org/10.1016/j.jbankfin.2009.07.026

[10] Balli, F., Naeem, M.A., Shahzad, S.J.H., et al., 2019. Spillover network of commodity uncertainties. Energy Economics. 81, 914–927. DOI: https://doi.org/10.1016/j.eneco.2019.06.001

[11] Mensi, W., Beljid, M., Boubaker, A., et al., 2013. Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. Economic Modelling. 32(1), 15–22. DOI: https://doi.org/10.1016/j.econmod.2013.01.023

[12] Kang, S.H., McIver, R., Yoon, S.M., 2017. Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. Energy Economics. 62, 19–32. DOI: https://doi.org/10.1016/j.eneco.2016.12.011

[13] Sadorsky, P., 2014. Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. Energy Economics. 43, 72–81. DOI: https://doi.org/10.1016/j.eneco.2014.02.014

[14] Gozgor, G., Lau, C.K.M., Bilgin, M.H., 2016. Commodity markets volatility transmission: Roles of risk perceptions and uncertainty in financial markets. Journal of International Financial Markets, Institutions and Money. 44, 35–45. DOI: https://doi.org/10.1016/j.intfin.2016.04.008

[15] Maitra, D., Guhathakurta, K., Kang, S.H., 2021. The good, the bad and the ugly relation between oil and commodities: An analysis of asymmetric volatility connectedness and portfolio implications. Energy Economics. 94, 105061. DOI: https://doi.org/10.1016/j.eneco.2020.105061

[16] Mensi, W., Al Rababa'a, A.R., Vo, X.V., et al., 2021. Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. Energy Economics. 98, 105262. DOI: https://doi.org/10.1016/j.eneco.2021.105262

[17] Gunera, J.E.B., 2023. Cycles and dynamic correlations between agricultural and stock markets [Master's thesis]. Baton Rouge, LA, U.S.: Louisiana State University. pp. 1-59.

[18] Nordin, N., Nordin, S., Ismail, R., 2021. The impact of commodity prices, interest rate and exchange rate on stock market performance: An empirical analysis from Malaysia. Malaysian Management Journal. 18, 39–52. DOI: https://doi.org/10.32890/mmj.18.2014.9015

[19] Acatrinei, M., Gorun, A., Marcu, N., 2013. A DCC-GARCH model to estimate the risk to the capital market in Romania. Journal for Economic Forecasting. 1, 136–148.

[20] Al-Anezi, W.H.A., Mohammed, M.T., Asaad, B., 2021.

The impact of financial liberalization on the value of the bank: An applied study on private Iraqi banks for the period 2011-2017. Webology. 18(3), 462–476. DOI: https://doi.org/10.14704/WEB/V18SI03/WEB18108

[21] Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics. 20(3), 339–350. DOI: https://doi.org/10.1198/073500102288618487

[22] Bauwens, L., Laurent, S., Rombouts, J.V.K., 2006. Multivariate GARCH models: A survey. Journal of Applied Econometrics. 21(1), 79–109. DOI: https://doi.org/10.1002/jae.842

[23] Marozva, G., 2017. Africa stock markets cross-market linkages: A time-varying dynamic conditional correlations (DCC-GARCH) approach. Journal of Applied Business Research. 33(2), 321–328. DOI: https://doi.org/10.19030/jabr.v33i2.9904

[24] Amado, C., Teräsvirta, T., 2014. Conditional correlation models of autoregressive conditional heteroscedasticity with nonstationary GARCH equations. Journal of Business and Economic Statistics. 32(1), 69–87. DOI: https://doi.org/10.1080/07350015.2013.847376

[25] Al Mughairi, H., 2016. Essays on modelling the volatility dynamics and linkages of emerging and frontier stock markets [PhD thesis]. London, UK: Brunel University London. pp. 1-107.

[26] Chiang, T.C., Jeon, B.N., Li, H., 2007. Dynamic correlation analysis of financial contagion: Evidence from Asian markets. Journal of International Money and Finance. 26(7), 1206–1228. DOI: https://doi.org/10.1016/j.jimonfin.2007.06.005

[27] Kamel, A.B., Si Mohammed, 2017. Foreign exchange market contagion: Evidence of DCC and DECO Multivariate GARCH models. universite ibn khaldoun de tiaret. 14, 6–21. (in Arabic).

[28] Billio, M., Caporin, M., Gobbo, M., 2006. Flexible dynamic conditional correlation multivariate GARCH models for asset allocation. Journal of International Money and Finance. 2(2), 123–130. DOI: https://doi.org/10.1080/17446540500428843

[29] Ku, Y.H.H., Chen, H.C., Chen, K.H., 2007. On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. Applied Economics Letters. 14(7), 503–509. DOI: https://doi.org/10.1080/13504850500447331

[30] Billio, M., Caporin, M., Gobbo, M., 2003. Block dynamic conditional correlation multivariate GARCH models. Working Paper No. 03.03, April 2003.

[31] Ramon, H., 2008. Forecasting the volatility of Philippine inflation using GARCH models. BSP Working Paper Series, Series No. 2008-01.