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Risk Analysis of Round Fandoghi Pistachio Contracts in the Iran Mercantile Exchange Market

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Abstract

Iran Mercantile Exchange is striving to become a regional hub for price discovery of essential commodities and raw materials, providing producers with financial instruments and risk management tools. This study investigates the optimal hedge ratio in future and commodity deposit receipts (spot) contracts for Round Fandoghi pistachios. Using the BEKK-VAR-TARCH model, the impact of seasonal and daily volatility on returns and hedge ratios was assessed over the period from 19 October 2018 to 18 January 2022. The results showed that volatility on specific days of the week and during different seasons affect speculative and investment decisions in the commodity exchange. Particularly, sharp volatility during certain periods can lead to significant changes in returns and hedge ratios. These findings suggest that investors should update their investment strategies based on seasonal and daily volatilities. Additionally, the importance of utilizing financial instruments suited to market conditions for managing existing risks was confirmed. Ultimately, investors, speculators, and policymakers in the commodity exchange are advised to pay special attention to temporal changes and existing volatilities when composing their investment portfolios and adjusting hedge strategies. Furthermore, the use of futures contracts and derivative instruments is recommended as risk management approaches. This study contributes to a better understanding of volatility behavior and offers strategies for improved risk management in the Round Fandoghi pistachio market.

Keywords: Optimal commodity portfolio, Optimal hedge ratio, Seasonal data behavior

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Introduction

The primary priority of Iran Mercantile Exchange (IME) is focus on becoming a regional price reference for essential commodities and intermediary raw materials (Iran Mercantile Exchange, 2024). IME serves as a principal venue for hedging price volatility risks. Risk hedging enables a production unit to control the costs of the raw materials needed for manufacturing. A hedge is an investment aimed at reducing the risk posed by unfavorable price changes of an asset (Geman, 2005). Typically, hedging encompasses taking a compensatory or reverse position against the guaranteed position. By utilizing this strategy, a producer can more effectively manage product pricing (Geman, 2005). Common hedging techniques involve taking a compensatory position in derivatives contracts associated with the current position. Another form of hedging can occur through diversification. The need for hedging arises when a producer lacks control over the pricing of raw materials or finished products. The capacity to decide on the level of risk one is willing to accept or transfer via commodity exchanges is known as comprehensive risk tolerance (Iran Mercantile Exchange, 2024). In essence, hedging incurs costs, and a complete hedge eliminates all risks in a position or investment portfolio (Geman, 2005).

Hedging risks in agricultural products through the creation of a diversified portfolio has received limited promotion and attention. IME offers various hedging instruments. The exchange uses futures contracts and commodity deposits (spot contracts) to manage price volatility. Futures contracts and Commodity Deposit Receipts (CDRs) are two essential financial instruments in commodity and derivative markets, designed to manage risk and facilitate investment. A futures contract is a legally binding agreement between a buyer and a seller to trade a commodity at a predetermined price on a specified future date. These contracts are particularly useful for managing price risks, benefiting farmers, investors, and other market participants. Settlement and delivery of the commodity take place upon the contract's expiration. Conversely, a commodity deposit certificate represents ownership of goods stored in approved warehouses, and these receipts are traded on the IME. Commodity deposit receipts allow for immediate settlement without requiring physical delivery, with prices determined by the commodity's current market value, making them an efficient tool for spot transactions. Due to their instant settlement, market-based pricing, and ability to transfer ownership without physical delivery, commodity deposit receipts can serve as effective proxies for spot market transactions. They facilitate fast settlement and ownership transfer based on actual market conditions, reducing the risks associated with storage and delivery. This feature positions commodity deposit receipts as a viable alternative to spot market trading and plays a key role in optimizing inventory management and investment in physical goods (Iran Mercantile Exchange, 2024).

Pistachio is one of the two main agricultural products traded on the IME; however, during October 19, 2018, to January 18, 2022, the traded value of this product declined from approximately 865 billion Rials to around 19 billion Rials, while the trading volume dropped from about 984 tons to just 3.4 tons (Iran Mercantile Exchange, 2024). In 2008 and 2009, 100 tons of pistachios produced by Sirjan Agricultural Company were offered. However, in 2016, about 30 tons of pistachios were traded, and during the same year, Kashiri Kolaei & Hosseini Yekani (2016) showed that despite no change in overall pistachio exports, demand for pistachios would increase in Khorasan Razavi, Yazd, and Semnan provinces of Iran, while provinces such as Fars, Qom, and Qazvin would lose market share. During the review period, only Round Fandoghi pistachios were traded on the IME, though other varieties such as Akbari pistachios saw minimal trade (Iran Mercantile Exchange, 2024). It is also noteworthy that due to frost damage in Kerman in 2021, round pistachio production significantly declined (Pakdaman *et al.*, 2023), though it is likely that pistachios will return to the IME within a year once orchards recover from frost damage (Tajabadipour & Afarasteh, 2022). On the other hand, considering the large number of pistachio producers and the generally competitive production conditions, producers wish to see pistachio trading remain active on the IME to facilitate price discovery. However, in terms of exports, where the market is near-monopolistic, this preference does not exist. Given that pistachio is one of the most important agricultural products in Iran, the findings of this study could be used to inform future transactions for re-entering Round Fandoghi pistachios to the IME.

Various studies have shown that price volatility and hedge effectiveness vary across agricultural and energy commodity markets. GARCH, ARIMA, and neural networks have been widely used for price analysis and forecasting, with factors such as wholesale prices, risk-free interest rates, and government policies having significant impacts. Additionally, combining futures contracts with insurance and using hedge indices like BDI and CRBI can improve hedge efficiency. Moreover, the relationship between crude oil and agricultural commodity prices turned positive after 2006, with market liquidity reductions leading to collective price shocks. However, there is still a gap in the knowledge regarding risk analysis of the pistachio commodity in the IME, highlighting the need for further research in this area.

To support IME's objectives of promoting transparency and competition in the market, this study seeks to assess the risks faced by pistachio producers. For this purpose, we examined the risk hedging for Round Fandoghi pistachios using two instruments, i.e. futures contracts and investment deposits, by analyzing daily data from October 19, 2018, to January 18, 2022.This investigation answered the question of how the optimal portfolio between the two contracts has evolved throughout the study period.

Literature Review

Extensive studies have been conducted on the risk and price volatility of agricultural products in the commodity exchanges of Iran and the world. This section reviews several recent studies over the past decade.

Kavoosi Kalashami & Kavoosi Kalashami (2017) utilized the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to analyze the price variance of rice in wholesale and retail markets from April 1999 to March 2014. Their results indicated a positive effect of wholesale rice prices on price variance fluctuations. Baghestani *et al.* (2016) analyzed and forecasted monthly and weekly data for soybean meal from October 2004 to March 2013 using the Group Method of Data Handling (GMDH) neural network and Autoregressive Integrated Moving Average (ARIMA). They found that the GMDH method provided superior results. Ghazali *et al.* (2016) conducted a comparison of agricultural products with other commodities traded on the Iran Mercantile Exchange (IME) by collecting questionnaires from 145 commodity trading experts and estimating structural equations. Their findings revealed that three major factors—governmental (weak incentive and tax policies) and structural (product standardization issues and perishability)—lead to the failure of agricultural products in the IME.

Mohammadi *et al.* (2016) compared the barley market using daily data from October 2007 to October 2011 with the Vector Autoregressive (VAR) and GARCH models. Their results showed that the price volatility of barley in the IME was higher than in the Chicago Mercantile Exchange (CME), indicating the relatively lower efficiency of the IME. Ahangari *et al.* (2017) employed numerical taxonomy and weighted taxonomy methods for 10 agricultural products in 2013 to rank the products that could be traded in the IME. Their results highlighted those factors like importance coefficient and continuity of supply are critical success factors. Based on their findings, rice, corn, wheat, and tea were identified as the most important agricultural products for trading in the IME. However, by the time of writing this article, only pistachios and saffron remained traded in the IME, with pistachio trading in decline. Pishbahar *et al.*

(2018) analyzed weekly soybean meal and corn grain prices from April 2013 to August 2016 for Asian option contracts using the Binomial Tree Method. Their results showed that increases in asset prices, price volatility, and risk-free interest rates led to higher call option prices. Conversely, a shorter time to maturity reduced the value of the option.

Amjadi *et al*. (2017) calculated hedge ratios and hedge effectiveness for corn, soybean, wheat, and cotton in the Wall Street commodity exchange using monthly data from 2014. They demonstrated that corn price risk decreased by 26%, and soybeans had 88% higher hedge efficiency compared to corn. Borzabadi Farahani *et al*. (2021) estimated the optimal static hedge ratio of the gold coin market against saffron futures contracts using daily data from June 2018 to October 2019 with copula functions and wavelet decomposition. Their results indicated the ability of saffron futures contracts to hedge gold coin spot contracts in the medium and long term. Miremadi et al. (2021) examined the efficiency of saffron futures contracts daily from December 2018 to December 2019 using the Vector Error Correction Model (VECM). Their findings showed a short- and long-term relationship between futures prices to spot prices.

Haj Seyed Javadi & Heydari (2022) forecasted daily data for saffron futures contracts from May 2019 to May 2020 in the IME using a hybrid model comprising nonlinear genetic algorithms, deep neural networks, random forests, support vector machines, and Monte Carlo simulations. Li (2012) used the Generalized Dynamic Conditional Correlation (GDCC) model, Time-Varying Transition Probabilities (TVTP), and the Markov Regime-Switching VECM (MRS-VECM) to obtain the optimal hedge ratio for natural gas futures and spot contracts from November 1994 to June 2009. Li (2012) concluded that varying the hedge ratio based on variance produced better results than a fixed ratio for strategic hedge planning. Alausa (2014), in his doctoral dissertation, used weekly data from 1977 to December 26, 2012, for wheat, corn, crude oil, heating oil, gold, silver, S&P500, and British and Canadian currencies. He employed Markov Switching VECM-MSM, Conditional and Unconditional Value-at-Risk (VaR), and ARX-MSM models to analyze extreme co-movements in commodity prices. His findings indicated that extreme price co-movements are more prevalent during volatile periods.

Moumouni (2016) estimated Monte Carlo Markov Chains and equilibrium modeling using monthly data from January 1990 to August 2015 for eight agricultural products. His results showed that static hedge strategies for rotating processes increased the risks of splitting risk between near and far futures contracts and inter-commodity hedging. He proposed that combining futures contracts with insurance would enhance hedge efficiency. Zhang & Chuan (2006) studied simultaneous price movements of oil, silver, gold, corn, and live cattle from January 2005 to December 2013 using co-integration analysis and the Granger causality test. They found that when market liquidity decreases, prices of these commodities decline collectively, leading to price shocks and increased inflation volatility. Yahya *et al*. (2019) examined temporal and frequency correlations between agricultural products and crude oil from July 1986 to June 2016 using wavelet transformation. Their method, which included the Maximum Overlap Discrete Wavelet Transform (MODWT), DCC-Student-t copula, and ARMA-EGARCH, demonstrated correlations between variables and facilitated long-term strategic planning. They also designed investment portfolios and calculated hedge ratios to minimize and manage investment risks.

Zhao *et al*. (2019) estimated the optimal hedge for daily crude oil data from December 2009 to October 2016 using the Fractionally Integrated GARCH–Extreme Value Theory–Copula–VaR (FIGARCH–EVT–Copula–VaR) approach. Their integrated method provided dynamic analysis of indicators such as mean returns, return variance, mean-to-variance ratio, and hedge efficiency. Shen (2020) studied the risk effects of COVID-19 on agricultural product prices in 2020. He analyzed weekly data from 2010 to 2020 for corn, soybean, wheat, and live cattle futures contracts using the BEKK-MGARCH model. Shen's findings showed a positive relationship between past variance and current price changes for index traders of corn and live cattle. Han *et al*. (2020) explored the variance correlation between energy (oil and gas) and agricultural products (corn, soybean, and wheat), the US Dollar Index (USDX), the Baltic Dry Index (BDI), and the Commodity Research Bureau Index (CRBI) from January 1995 to March 2017 using the VARMA-BEKK-MGARCH model. Their results indicated that the BDI, CRBI, and USDX are suitable hedge indicators under extreme conditions. Singhal & Biswal (2021) used the MRS-VAR model to estimate the optimal hedge ratio and determine the dynamic commodity portfolio for agricultural, energy, and metal commodities over the weekly period from January 2005 to December 2013. Their results showed the presence of organizational changes across all assets, indicating their behavioral dependence on economic conditions.

Rezitis *et al*. (2024) combined the Markov Switching model, four-variable VAR, DCC, and BEKK-GARCH models to estimate the impact of macroeconomic shocks (e.g., COVID-19) on energy (oil and gas) and agricultural (corn and soybean) products using daily data from July 1996 to November 2020. Their results showed that energy commodities and shock indicators could be powerful tools for hedging agricultural products. Schneider & Tavin (2024) analyzed seasonal effects on hedge strategies for agricultural products such as corn, cotton, soybean, sugar, and wheat using daily data from 2007 to 2019, gathered from USDA and FAO. Their GARCH and Stochastic Volatility (SV) models demonstrated the significant impact of price volatility on hedging strategies. They emphasized the importance of selecting an appropriate GARCH model to improve hedge ratios and stressed the influence of seasonal price fluctuations on market behavior.

Materials and Methods

To determine an optimal dynamic portfolio strategy for hedging risk related to Round Fandoghi pistachios in the Iran Mercantile Exchange (IME) from the perspective of both suppliers and consumers, the theory of optimal portfolio selection, first introduced by Markowitz (1952), is employed. This theory illustrates portfolio selection as a trade-off between risk and return, with two primary scenarios: (1) maximizing the return or wealth of the trader at an acceptable level of risk, and (2) minimizing risk for a given level of expected return or wealth. For hedging a commodity contract, the optimal hedge ratio (b) is derived between two types of contracts: futures contracts and commodity deposit receipts. Generally, a commodity portfolio consists of multiple commodities, meaning this study seeks to determine the optimal percentage allocation to each of these contracts.

To reduce price risk, the hedger must take futures positions to maximize the reduction of price volatility in the cash market (Edwards & Ma, 1992). If the hedge ratio is not accurately estimated, the likelihood of effective hedging diminishes, as hedgers cannot determine the number of futures contracts needed (Chance, 1989). A precise estimation of the hedge ratio helps investors minimize basis risk and apply appropriate hedging strategies and techniques, such as managing trading risk from financial obligations, operational risk from currency fluctuations, and the risk of foreign currency assets. Hence, estimating the optimal hedge ratio is crucial.

The hedge ratio (h) is derived from the ratio of futures positions (Q_f) to cash positions (Q_c) as per Equation (1):

$$h = \frac{Q_f}{Q_c} \qquad (1)$$

Where Q_f is the number of futures contracts required for hedging, and Q_c represents the number of cash contracts whose risk must be hedged, assuming Q_c remains constant. By using the relationship $Q_f = hQ_c$, the number of futures contracts needed for optimal hedging can be calculated (Chen et al., 2003).

There are various methods to estimate the hedge ratio. Depending on different objective functions, optimal hedge ratios can be determined through different approaches, such as Minimum Variance (MV), Mean-Variance, Maximum Expected Utility, Generalized Gini Mean (MEG), and Generalized Semivariance (GSV). The MV method, proposed by Johnson (1960), aims to reduce portfolio risk by minimizing the variance of the hedged commodity portfolio. However, the MV method has been criticized for neglecting expected return as a factor in the portfolio. The mean-variance strategy was suggested to account for both expected return and risk (variance) in hedging a commodity portfolio. Although this strategy avoids the drawbacks of the MV method, it requires the maximization of expected utility, which in turn necessitates calculating a quadratic utility function with a jointly normal distribution, making this method computationally complex. The MEG and GSV methods are proposed to obtain hedge ratios consistent with the concept of stochastic dominance. MEG is not restricted by specific assumptions regarding probability distributions for utility functions and returns (Chen *et al.*, 2003).

Assuming that cash and futures prices do not move in perfect parallel, the simplest way to measure their relationship and construct a properly hedged commodity portfolio is to execute a "linear regression" as shown in Equation (2):

$$P_c = a + bP_f + e \quad (2)$$

Where P_c is the spot price, and P_f is the future price. To minimize the hedger's potential risk, the hedge ratio is estimated through the regression in Equation (2) and calculated using Equation (3):

$$b = \frac{\Delta P_c}{\Delta P_f} \quad (3)$$

The cash price moves in proportion to the futures price by a factor of b. When $b = 1$, the cash price and futures price move exactly in the same direction and magnitude. The net value of the futures positions perfectly offsets changes in the cash market price. This one-to-one scenario is known as "perfect hedging" or "naive hedging," though futures and cash prices may not always fluctuate proportionately. A "perfect hedge" is generally impractical, especially for cross-hedging (Chance, 1989; Siegel & Siegel, 1990).

Regression estimations on price changes $(\Delta P_c, \Delta P_f)$, percentage price changes $(\Delta P_c / P_c, \Delta P_f / P_f)$, and logarithmic differences $(\log(P_{c,t}/P_{c,t-1}), \log(P_{f,t}/P_{f,t-1}))$ have been proposed in various studies to estimate the optimal hedge ratio. The suitability of price-level regression in financial and commodity markets is a debated topic. Siegel & Siegel (1990) argued that price-level regression only captures hedging motivation and downplays speculative incentives. While statistically, price-level regression indicates a high correlation between futures and cash prices, it does not account for correlations between price changes, violating the assumptions of OLS. Additionally, time-series data often exhibit autocorrelation and heteroscedasticity in error terms, complicating price-level regression. Myers & Thompson (1989) suggested price-level regression is inappropriate, while price change regression provides better estimates for commodities like corn, soybeans, and wheat. Witt *et al.* (1987) defended the price-level model, arguing it is suitable for hedging predictions, and no clear evidence suggests that price change or percentage change regressions are superior. Ultimately, Siegel & Siegel (1990) generalized that percentage price change regression is more appropriate for financial futures contracts, while price change regression suits commodity futures contracts. Many researchers prefer logarithmic difference regression, as it better captures the non-linear relationship between futures and cash prices (Ameur *et al*., 2022; Choudhry, 2009).

This study employs the Mean-Variance (MV) method, where price risk is minimized by reducing the variance of commodity portfolio returns. The return on a hedged commodity portfolio is calculated using Equation (4):

$$r_t = r_{c,t} - \beta_{t-1} r_{f,t} \quad (4)$$

Where β_{t-1} is the hedge ratio, and $r_{c,t}$ and $r_{f,t}$ represent the log-returns of the pistachio certificate market and pistachio futures market between times t and $t-1$, calculated as $logP_{c,t} - logP_{c,t-1}$ and $logP_{f,t} - logP_{f,t-1}$, respectively.

The expected return and the variance of the hedging effectiveness of the commodity portfolio are calculated in equations (5) and (6), respectively.

$$E(r)_t = E(r_{c,t}) - \beta_{t-1}E(r_{f,t}) \quad (5)$$

$$\text{var}(r_t) = \text{var}(r_{c,t}) + \beta_{t-1}^2 \text{var}(r_{f,t}) - 2\beta_{t-1} \text{cov}(r_{c,t}, r_{f,t}) \quad (6)$$

Where $\text{cov}(r_{c,t}, r_{f,t})$ represents the covariance between the returns of the Round Fandoghi pistachio commodity deposit certificate market and the Round Fandoghi pistachio futures market. In equation (5), assuming $\beta_{t-1} = 0$ and minimizing the variance, equation (7) yields the hedge ratio.

$$\beta_{t-1} = \frac{\text{cov}(r_{c,t}, r_{f,t})}{\text{var}(r_{f,t})} \quad (7)$$

The optimal hedge ratio is dependent on the logarithm of the futures contract return and the correlation between the futures contract and the commodity deposit. This ratio is always less than 1, as the volatility of futures contracts is generally higher than that of commodity deposit contracts (Choudhry, 2003).

The Hylleberg *et al.* (1990) method is utilized for testing seasonal unit roots. This method is one of the key approaches for assessing seasonal unit roots in time series data, particularly suitable for periodic data such as daily, weekly, seasonal, or monthly datasets. In this study, given the daily data that excludes Fridays, the Hylleberg model is defined as a 6-period equation (8):

$$\begin{cases} \Delta_6 y_t = \mu + \pi_0 L(1 + L^1 + L^2 + L^3 + L^4 + L^5)y_t + \Omega + \sum_{i=1}^{p} \phi_i \Delta_6 y_{t-i} + \epsilon_t \\ \mu = \alpha + \beta t + \sum_{j=1}^{5} \gamma_j D_j \\ \Omega = \left[\pi_{1,1}\cos\left(\frac{2\pi}{6}\right) + \pi_{1,2}\sin\left(\frac{2\pi}{6}\right)\right] y_t + \left[\pi_{2,1}\cos\left(\frac{4\pi}{6}\right) + \pi_{2,2}\sin\left(\frac{4\pi}{6}\right)\right] y_t + \left[\pi_{3,1}\cos\left(\frac{6\pi}{6}\right) + \pi_{3,2}\sin\left(\frac{6\pi}{6}\right)\right] y_t \end{cases} \quad (8)$$

Where μ is a linear combination of observable variables such as the intercept (α), trend (t), and seasonal dummy variables (D_j for all $j = 1,2,3,4,5$), and L^k is the k-th lag operator. Additionally, Ω includes variables that indicate seasonal unit root effects at frequencies 2π/6, 4π/6, and 6π/6. The term $\pi_0 L(1 + L^1 + L^2 + L^3 + L^4 + L^5)y_t$ represents the seasonal pattern determined within the data. Essentially, it filters the data by aggregating values at various seasonal lags. The term $\Delta_6 y_t$ denotes the seasonal difference of the 6-period time series, calculated as $(1 - L^6)y_t$. Furthermore, the term $\sum_{i=1}^{p} \phi_i \Delta_6 y_{t-i}$ represents lags of the dependent variable, with the number of lags (p) depending on the white noise condition of the error term (ϵ_t) (Castro *et al.*, 2012). In this study, the selection of the number of autoregressive lags is determined using a "Top-Down" approach; that is, the maximum possible lags for the testing pattern are chosen, which presumably white out the results of the error term, followed by the reduction of lags and reiteration of the test until the results deviate from white noise upon the reduction of lags. Therefore, the optimal lag is the one that exceeds the maximum lack of white noise in the error term by one unit. It is noteworthy that to prevent overfitting risks, the study also considers other criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as auxiliary metrics to balance model complexity with data fit (Enders, 2014).

Bivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are employed in econometrics for the simultaneous modeling and analysis of the volatility of two-time series. These models are derived from the generalization of univariate GARCH models, capturing the interrelationships between the volatilities of two-time series. Specifically, univariate GARCH models are designed to model the volatility of a single time series such that the volatility of a dependent variable can change over time and is contingent upon its past values. Conversely, in the bivariate GARCH model, this concept is extended to two-time series, encompassing the joint behavior of both series, including their volatilities and correlations. In essence, this model consists of three parameters: conditional variance, conditional covariance, and structural correlation. The application of bivariate GARCH models is common in financial economics for analyzing asset return co-movements, risk assessment, or modeling the joint behavior of time series (Choudhry, 2009).

Among the models mentioned in the previous section, the bivariate GARCH-VAR and BEKK-VAR models are utilized for analyzing and modeling the volatilities and dynamic relationships between multiple time series, as these models demonstrated the highest consistency and maximum likelihood with the examined data compared to other selected models. Vector Autoregressive (VAR) models are employed to capture linear dependencies among multiple time series (Sims, 1980). In the context of GARCH-VAR, VAR is used to model the relationships between the time series, while GARCH investigates the dynamic relationships of the model's volatility. Meanwhile, the BEKK-VAR model integrates the BEKK approach, which provides a systemic view of estimating GARCH models, with VAR models. This model captures the dependencies between the time series using VAR while simultaneously examining correlations and dynamic volatilities through the BEKK specifications (Asai, 2015). Furthermore, the Threshold GARCH (TARCH) model can be appended to the aforementioned model, examining the effects of negative and positive shocks on volatility. The TARCH model expands the standard GARCH framework by incorporating different effects for negative and positive shocks (Zhao *et al*., 2019).

Bivariate GARCH-VAR: This approach combines the VAR model to capture the relationships between the series with a bivariate GARCH model to consider the conditional volatilities and correlations between the series. This model is useful when there is a need to model the joint behavior of multiple time series with time-varying volatilities.

The mean and error GARCH model for the returns of the Round Fandoghi pistachio commodity deposit market ($r_{c,t}$) and the Round Fandoghi pistachio futures market ($r_{f,t}$) are calculated as equation (9).

$$\begin{cases} r_{c,t} = \mu_c + e_{c,t} \\ r_{f,t} = \mu_c + e_{f,t} \end{cases} \Rightarrow \begin{cases} e_{c,t} = \sigma_{c,t} z_{c,t} \\ e_{f,t} = \sigma_{f,t} z_{f,t} \end{cases} \Rightarrow \begin{cases} z_{c,t} \sim N_{i.i.d}(0,1) \\ z_{f,t} \sim N_{i.i.d}(0,1) \end{cases} \quad (9)$$

Where $\sigma_{i,t}$ represents the standard deviation (volatility) of contract i and $z_{i,t}$ are standard normal variables ($\forall i = c, f$).

The conditional variance-covariance matrix H_t is expressed in equation (10):

$$H_t = \begin{bmatrix} \sigma_{cc,t}^2 & \sigma_{cf,t} \\ \sigma_{cf,t} & \sigma_{ff,t}^2 \end{bmatrix} \quad (10)$$

The conditional variances and covariances in the bivariate GARCH model are typically modeled using a GARCH process. A Bivariate GARCH (1,1) is estimated through the following set of equations (11):

$$\begin{cases} \sigma_{cc,t}^2 = \gamma_{cc} + \alpha_{cc} e_{c,t-1}^2 + \beta_{cc} \sigma_{cc,t-1}^2 \\ \sigma_{ff,t}^2 = \gamma_{ff} + \alpha_{ff} e_{f,t-1}^2 + \beta_{ff} \sigma_{ff,t-1}^2 \\ \sigma_{cf,t} = \gamma_{cf} + \alpha_{cf} e_{c,t-1} e_{f,t-1} + \beta_{cf} \sigma_{cft-1} \end{cases} \quad (11)$$

Where γ_{ij} are the intercept values, α_{ij} are the lag coefficients of the error term from the mean model, and β_{ij} are the lag coefficients of the variance-covariance. Using the estimated values for the conditional variance of the log price difference of the futures contract $\widehat{H}_{ff}$ and the conditional covariance between the log price difference of the futures contract and the log price difference of the commodity deposit $\widehat{H}_{cf}$, the hedge ratio between the two contracts can be derived using equation (12):

$$\beta = \widehat{H}_{cf} / \widehat{H}_{ff} \quad (12)$$

Considering that the estimated conditional variance-covariance matrix is time-dependent, the computational risk hedge ratio obtained from this method is also time-dependent.

The BEKK-GARCH model is one of the variants of the bivariate GARCH models used to model conditional volatilities and covariances between two-time series. This model was developed by Baba, Engle, Kraft, & Kroner (1990), with the name BEKK derived from the initials of their last names (Engle & Kroner, 1995). The conditional mean and conditional variance-covariance equations for this model are also estimated using equations (9) and (11), and the optimal hedge ratio is obtained from equation (12). The only difference from the bivariate GARCH model lies in the computation of the variance-covariance matrix H_t, which is obtained as follows in equation (13):

$$H_t = \Gamma'\Gamma + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B \quad (13)$$

Where H_t is the 2×2 variance-covariance matrix at time t, e_{t-1} is the lag of the error components, Γ is a lower triangular matrix, A represents lagged shock effects, and B represents lagged variance and variance-covariance effects. In other words, the matrices Γ, A, and B are the parameter matrices of the variance-covariance model, estimated using equation (11).

The mean and error model of the Vector Autoregressive (VAR) model is computed as shown in equation (14):

$$\begin{pmatrix} r_{c,t} \\ r_{f,t} \end{pmatrix} = \begin{pmatrix} \alpha_c \\ \alpha_f \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} \beta_{cc,i} & \beta_{cf,i} \\ \beta_{fc,i} & \beta_{ff,i} \end{pmatrix} \begin{pmatrix} r_{c,t-1} \\ r_{f,t-1} \end{pmatrix} + \begin{pmatrix} e_{c,t} \\ e_{f,t} \end{pmatrix} \Rightarrow E_t = H_t^{\frac{1}{2}} z_t, z_t \sim N(0,1) \quad (14)$$

Where the conditional variance-covariance matrix H_t for the GARCH-VAR model is also obtained using equations (10) and (11), while for the BEKK-VAR model, this matrix is computed using equation (13).

To incorporate threshold effects (TARCH) into either of the aforementioned models, the diagonal matrix Θ can be added to equation (13). This matrix adjusts the volatility model in such a way that the impact of negative shocks (e.g., a decrease in Round Fandoghi pistachio prices) on future volatility may not be equivalent to the impact of positive shocks. This aspect is particularly relevant in financial markets, as negative returns may induce greater variations in volatility compared to positive returns of the same magnitude. Consequently, equation (15) can be used to compute the variance-covariance matrix. H_t for the bivariate model:

$$H_t = \Gamma'\Gamma + A'e_{t-1}e'_{t-1}A + \Theta(E_{t-1}E_{t-1}^{<0})(E_{t-1}E_{t-1}^{<0})'\Theta' + B'H_{t-1}B \quad (15)$$

Additionally, it is noteworthy that equation (15) can be reformulated for the bivariate model in this study as shown in equation (16):

$$\begin{cases} \sigma_{cc,t}^2 = \gamma_{cc} + \alpha_{cc}^2 e_{c,t-1}^2 + \theta_{cc}^2 e_{c,t-1}^2 e_{c,t-1}^{<0} + \beta_{cc}^2 \sigma_{cc,t-1}^2 \\ \sigma_{ff,t}^2 = \gamma_{ff} + \alpha_{ff}^2 e_{f,t-1}^2 + \theta_{ff}^2 e_{c,t-1}^2 e_{c,t-1}^{<0} + \beta_{ff}^2 \sigma_{ff,t-1}^2 \\ \sigma_{cf,t} = \gamma_{cf} + \alpha_{cf}\alpha_{fc} e_{c,t-1} e_{f,t-1} + \theta_{cc}\theta_{ff} e_{c,t-1} e_{c,t-1}^{<0} e_{f,t-1} e_{f,t-1}^{<0} + \beta_{cc}\beta_{ff}\sigma_{cft-1} \end{cases} \quad (16)$$

Kroner and Ng (1998) argued that it is possible to achieve minimal risk for a commodity portfolio using a multivariate GARCH model under the assumption that the expected return ratio for each asset is zero. Equation (17) is utilized to calculate the commodity portfolio of two contracts: the Round Fandoghi pistachio commodity deposit (c) and Round Fandoghi pistachio futures (f). Here, $w_{cf,t}$ denotes the weight of product c in the combination of products c and f, with the weight of product f equal to $1 - w_{cf,t}$. $\sigma_{cf,t}$ represents the conditional covariance of products c and f, while $\sigma_{cc,t}^2$ and $\sigma_{ff,t}^2$ are the variances of products c and f, respectively. This commodity portfolio is frequently utilized by investment managers for optimal portfolio selection, and this study employs this portfolio to analyze the selection of an appropriate product mix to mitigate trading risks and resource exposure (Zhao *et al*., 2019).

$$w_{cf,t} = \begin{cases} 0 & w_{cf,t} < 0 \\ \frac{\sigma_{ff,t}^2 - \sigma_{cf,t}}{\sigma_{cc,t}^2 - 2\sigma_{cf,t} + \sigma_{ff,t}^2} & 0 \le w_{cf,t} \le 1 \\ 1 & w_{cf,t} > 1 \end{cases} \quad (17)$$

This paper examines the price risk hedging of two contracts: Round Fandoghi pistachio futures and commodity deposit (spot) from October 19, 2018, to January 18, 2022.

Results and Discussion

Table 1 presents the results of the seasonal unit root test for daily data of pistachio contracts. This test examines the existence of unit roots at seasonal and non-seasonal frequencies, specifically employing the HEGY method (Hylleberg *et al*., 1990). In this table, frequency 0 represents the non-seasonal trend, indicating the presence of a unit root in the time series. The frequencies 2π/6 and 10π/6 refer to seasonal patterns with two or multiple cycles, while frequencies 4π/6 and 8π/6 correspond to specific seasonal fluctuations that may occur over shorter or longer periods. Frequency π\piπ denotes semiannual fluctuations.

For the return on the commodity deposit contract at frequency 0, the test statistic is -2.70, which is significant at the 10% level. This result suggests that the non-seasonal trend in the commodity deposit return is somewhat stable, with a possible unit root presence in this series. At frequencies 2π/6 and 10π/6, the test statistic is 2.68, which is significant at the 1% level, indicating strong and stable seasonal fluctuations at these frequencies. At frequencies 4π/6 and 8π/6, the test statistic is 3.33, also significant at the 1% level, showing strong seasonal fluctuations at these frequencies. At frequency π\piπ, the test statistic is -2.24, which is not interpretable at any significance level, indicating weak semiannual fluctuations in the commodity deposit return. Additionally, for all seasonal frequencies, the test statistic is 3.49, significant at the 1% level, indicating strong and stable seasonal fluctuations across all seasonal frequencies. Finally, for all frequencies, the test statistic is 4.24, which is significant at the 5% level, showing that when all frequencies are considered, the time series fluctuations are generally stable.

The existence of a seasonal unit root in products such as pistachios is due to their natural growth and harvest cycles. Pistachio trees flower in spring, fruit growth occurs in summer, and they are harvested in late summer to early fall. This natural cycle makes pistachio supply highly season-dependent. On the other hand, pistachio demand can also be seasonal, increasing around specific occasions, such as Nowruz and other festive seasons. Thus, both pistachio supply and demand follow seasonal patterns, impacting market prices and fluctuations (Rezaei *et al*., 2021).

For the futures contract return, the test statistic at frequency 0 is -2.96, which is significant at the 5% level, indicating a unit root in the non-seasonal trend of the futures return. At frequencies 2π/6 and 10π/6, the test statistic is 5.06, significant at the 1% level, reflecting very strong seasonal fluctuations at these frequencies. At frequencies 4π/6 and 8π/6, the test statistic is 4.14, significant at the 1% level, indicating very strong seasonal fluctuations. At frequency π, the test statistic is -2.41, which is not interpretable at any significance level, showing weak semiannual fluctuations in the future return. For all seasonal frequencies, the test statistic is 4.91, significant at the 1% level, denoting strong and stable seasonal fluctuations, and finally, for all frequencies, the test statistic is 5.56, significant at the 1% level, indicating stable fluctuations in the futures return time series.

In summary, both time series (commodity deposit contract return and futures contract return) exhibit significant seasonal and non-seasonal fluctuations, but the intensity of these fluctuations is higher in futures returns. For both series, seasonal fluctuations are much stronger than non-seasonal ones, yet semiannual fluctuations (frequency π) are weak in both series. Overall, seasonal fluctuations are a key factor in analyzing time series returns on contracts, and these fluctuations are stronger in futures contracts compared to commodity deposits.

Table 2 provides the regression coefficients and results for the returns on the commodity deposit contract ($r_{s,t}$) and the futures contract ($r_{f,t}$). The intercept in both equations is 0.01, with an insignificant standard error, indicating a lack of statistical significance. This suggests that the dependent variables, on average, do not exhibit significant changes in the absence of other effects.

Table 1- Results of the seasonal unit root test for 6 periods using the HEGY method (Hylleberg *et al*., 1990) for daily data of Round Fandoghi pistachio contracts

Seasonal and Non- Seasonal frequencies	Commodity Depositary Receipt Returns	Future Returns	Critical values in Significance Levels		
	Test Statistic	Test Statistic	1%	5%	10%
Frequency 0	-2.70*	-2.96**	-3.43	-2.85	-2.56
Frequency $2\pi/6$ and $10\pi/6$	2.68***	5.06***	2.68	1.17	0.74
Frequency $4\pi/6$ and $8\pi/6$	3.33***	4.14***	2.68	1.17	0.74
Frequency π	-2.24	-2.41	-3.43	-2.85	-2.56
All seasonal frequencies	3.49***	4.91***	3.15	2.07	1.68
All frequencies	4.24**	5.56***	4.4	3	2.44
Akaike info criterion	-4.12	-4.95			
Schwarz criterion	-2.64	-4.12			

*, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

The coefficient of the previous period's return on the commodity deposit contract ($r_{s,t-1}$) for the commodity deposit return itself is negative and significant at the 99% level (-0.10, with a standard error of 0.035). This result implies that an increase in the commodity deposit return in the prior period leads to a reduction in the current period's return. However, this coefficient is not significant for the futures contract return.

The coefficient of the previous period's futures contract return ($r_{f,t-1}$) for the commodity deposit return is positive and highly significant at the 99% level (0.19, with a standard error of 0.036), indicating a strong positive effect. This coefficient is not significant for the current period's future return. The coefficient of $r_{f,t-2}$ for the commodity deposit return is positive and significant at the 90% level (0.07, with a standard error of 0.036), indicating that the futures contract return from two periods ago has a weak positive effect on the commodity deposit return. However, this coefficient is not significant for the future return.

The coefficient of $r_{f,t-3}$ for the commodity deposit return is positive and significant at the 95% level (0.09, with a standard error of 0.034). This suggests that the futures return three periods ago had a positive impact on the commodity deposit return. For the future return, this coefficient is not significant.

The coefficients of $r_{f,t-4}$, $r_{f,t-5}$, and $r_{f,t-6}$ for both the commodity deposit and futures returns are generally not significant, indicating that returns from four, five, and six periods ago have minimal or no meaningful impact on the current returns.

The t-statistic of the error term is significant at the 99% level (4.00, with a standard error of 0.528), showing the significance of the disturbance parameters and supporting the use of the Student's t-distribution for this data. The Akaike, Schwartz, and Hannan-Quinn criteria values are lower compared to competing models, indicating a good model fit. Specifically, the Akaike index is -10.54, and the Schwartz index is -10.37, highlighting that the model is relatively simple and explains the data effectively.

Table 3 continues the results from Table 2, showing significant and positive intercepts for both the commodity deposit and futures contract returns. This indicates that volatility persists in the data even in the absence of external shocks. The shock coefficients for both variables are significantly positive and high (0.28 for commodity deposit returns and 0.66 for futures returns), implying that shocks introduced into the system have a substantial impact on the volatility of both return types.

The threshold coefficient for the commodity deposit return is significant and positive (0.29 with a standard error of 0.087), suggesting that higher-than-threshold volatility has a stronger influence on future volatility. However, the threshold coefficient for the futures return is not significant, potentially indicating that volatility effects in this case are less dependent on a specific threshold.

Table 2- Results of the bivariate vector autoregressive generalized autoregressive conditional heteroskedasticity model with threshold effects (BEKK-VAR-TARCH)

Variable	Commodity Depositary Receipt Returns Coefficient (Std. Error)	Future Returns Coefficient (Std. Error)
Intercept	0.01(0)	0.01(0.001)
$r_{s,t-1}$	-0.10(0.035)***	0.02(0.016)
$r_{f,t-1}$	0.19(0.036)***	0.03(0.039)
$r_{f,t-2}$	0.07(0.036)*	0.05(0.039)
$r_{f,t-3}$	0.09(0.034)**	-0.01(0.036)
$r_{f,t-4}$	0.06(0.036)	0.01(0.034)
$r_{f,t-5}$	0.06(0.035)	0.04(0.033)
$r_{f,t-6}$	0.05(0.036)	-0.03(0.03)
t-student of error distribution	4.00(0.528)***	
Log-likelihood	3598.91	
Avg. log-likelihood	2.65	
Akaike info criterion	-10.54	
Schwarz criterion	-10.37	
Hannan-Quinn criterion.	-10.47	

The symbols *, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

The lagged variance coefficients for both the commodity deposit and futures returns are highly significant and substantial (0.96 and 0.84, respectively). These coefficients demonstrate that past volatility significantly impacts current volatility, with persistence in volatility over time through an autoregressive process.

The BEKK-VAR-TARCH model effectively captures the interplay of volatilities between the commodity deposit and futures contracts, showing that these two variables exert significant mutual influence on each other. The significant impacts of shocks and variance lag on both variables underscore the stability and transmission of volatility within these markets.

These findings emphasize the importance of closely monitoring past shocks and volatility in financial markets, as these factors notably influence future market behavior. By accounting for threshold effects, the BEKK-VAR-TARCH model provides a more precise representation of the complex market dynamics.

Table 3- Results of the variance model of the bivariate vector autoregressive generalized autoregressive conditional heteroskedasticity model with threshold effects (BEKK-VAR-TARCH)

Parameter	Commodity Depositary Receipt Returns Coefficient (Std. Error)	Future Returns Coefficient (Std. Error)	Covariance of Returns Coefficient (Std. Error)
Intercept	0.01(0.001)	0.01(0.001)***	0.01(0.001)
Shock Effect	0.28(0.047)***	0.66(0.063)***	
Threshold	0.29(0.087)***	0.17(0.185)	
Variance Lag Effect	0.96(0.011)***	0.84(0.018)***	

The symbols *, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

Table 4 summarizes the trend of the optimal ratio for integrating commodity deposit contracts of Round Fandoghi pistachios with futures contracts. This optimal ratio represents the share of commodity deposit contracts within a two-asset portfolio that includes both commodity deposit and futures contracts. The table presents the average ratio values across different days of the week and seasons, along with their standard errors.

In spring, for the month (April), the share of commodity deposit contracts at the start of the week (Saturday) is 0.55, increasing to 0.73 by midweek, and then decreasing to 0.60 by the week's end. This notable increase on Tuesdays and Wednesdays indicates a midweek preference for commodity deposit contracts. In May, the share remains consistently high, ranging from 0.78 to 0.84, reflecting a strong preference for commodity deposit contracts, with these values being statistically significant. In June, the share stabilizes between 0.64 and 0.75, indicating a consistent preference for commodity deposit contracts during this month.

In summer, (July) shares for commodity deposit contracts lower, ranging from 0.45 to 0.57, suggesting a reduced preference, with these values generally lacking statistical significance. In August, the share rises slightly to a range of 0.52 to 0.69, possibly due to market volatility or seasonal demand changes. September marks the beginning of the pistachio harvest season, with ratios higher between 0.67 and 0.76, indicating increased demand for commodity deposit contracts as summer concludes.

During autumn, (October) relatively high shares ranging from 0.66 to 0.76 develops, with most values statistically significant, which may reflect a growing preference for commodity deposit contracts. In November, the share remains elevated, ranging from 0.60 to 0.69, indicating stable demand. December records the highest values, between 0.72 and 0.77, representing peak demand for commodity deposit contracts, further supported by statistical significance.

In winter, the ratios in January, fluctuate between 0.55 and 0.68, likely due to seasonal or market fluctuations. In February, the ratios are very high, ranging from 0.79 to 0.86, with all values statistically significant, indicating this as the peak period for commodity deposit contracts. Ratios decrease in March, ranging from 0.54 to 0.67, possibly due to seasonal factors or the approaching fiscal year-end.

Overall, the results from Table 4 demonstrate that seasonal fluctuations result in a higher optimal share of commodity deposit contracts during spring and winter, while there is a noticeable decrease in summer. These seasonal changes likely stem from varying market demand across seasons. The statistically significant values observed on many days reinforce the reliability of these findings, making them crucial for optimizing investment portfolios. Additionally, the optimal ratio fluctuates across different weekdays, potentially due to daily factors such as market news or shifts in investor expectations.

This analysis empowers investors to make informed decisions regarding portfolio allocations, capitalizing on seasonal and daily market fluctuations. By leveraging insights on changes in the optimal ratios for Round Fandoghi pistachio commodity deposit contracts, investors can enhance their risk management and portfolio composition strategies. Observable shifts in these ratios, particularly the increases during spring and winter, highlight heightened demand during these periods, presenting profit opportunities. Furthermore, daily patterns, such as midweek increases, allow investors to adjust their strategies dynamically.

In summary, the significant seasonal variations and changes in the optimal ratios equip investors to capitalize on unique seasonal opportunities and make more accurate market forecasts. This builds investor confidence and facilitates data-driven decision-making based on robust statistical results.

Conclusion

In this study, the optimal hedge ratio for Round Fandoghi pistachio commodity deposit receipts and futures contracts were examined. Results from the BEKK-VAR-TARCH model demonstrated that daily and seasonal volatilities significantly influence returns and hedge ratios. Notably, substantial fluctuations were observed on specific days and within particular periods, affecting speculative and investment decisions in the commodity exchange market. These findings underscore the importance of choosing strategies that align with market conditions and accurately timing market entry to optimize profitability.

Table 4- Summary of the trend changes in the optimal ratio of commodity deposit contracts for Round Fandoghi pistachios in the combination of commodity deposit and futures contracts

Season	Mouth	Week day	The average share of commodity deposit contracts from Portfolio (Std. Error)	Season	Mouth	The average share of commodity deposit contracts from Portfolio (Std. Error)
Spring	April	Saturday	0.55 (0.108)	Fall	October	0.73 (0.104) **
		Sunday	0.65 (0.092) *			0.76 (0.088) **
		Monday	0.71 (0.087) **			0.69 (0.122) *
		Tuesday	0.73 (0.081) **			0.67 (0.113) *
		Wednesday	0.73 (0.089) **			0.66 (0.082) **
		Thursday	0.60 (0.111) *			0.72 (0.088) **
	May	Saturday	0.83 (0.034) ***		Novemmber	0.64 (0.095) *
		Sunday	0.82 (0.047) ***			0.63 (0.095) *
		Monday	0.78 (0.062) ***			0.69 (0.105) *
		Tuesday	0.83 (0.046) ***			0.67 (0.096) *
		Wednesday	0.82 (0.046) ***			0.60 (0.088) *
		Thursday	0.84 (0.038) ***			0.64 (0.092) *
	June	Saturday	0.64 (0.104) *		December	0.72 (0.077) **
		Sunday	0.72 (0.106)*			0.73 (0.080)**
		Monday	0.75 (0.104)**			0.74 (0.073)**
		Tuesday	0.66 (0.116)*			0.72 (0.075)**
		Wednesday	0.72 (0.112)*			0.77 (0.066)***
		Thursday	0.64 (0.103)*			0.76 (0.071)**
Summer	July	Saturday	0.55 (0.151)	Winter	January	0.62 (0.103)*
		Sunday	0.48 (0.144)			0.56 (0.065)**
		Monday	0.45 (0.161)			0.62 (0.077)**
		Tuesday	0.49 (0.152)			0.66 (0.103)*
		Wednesday	0.55 (0.151)			0.68 (0.115)*
		Thursday	0.57 (0.144)			0.55 (0.124)
	August	Saturday	0.65 (0.107)*		Februray	0.79 (0.075)***
		Sunday	0.68 (0.098)*			0.79 (0.068)***
		Monday	0.69 (0.098)**			0.84 (0.054)***
		Tuesday	0.66 (0.104)*			0.86 (0.052)***
		Wednesday	0.52 (0.110)			0.79 (0.069)***
		Thursday	0.53 (0.106)			0.81 (0.066)***
	September	Saturday	0.67 (0.109)*		March	0.65 (0.129)
		Sunday	0.72 (0.095)**			0.64 (0.132)
		Monday	0.70 (0.097)**			0.67 (0.115)*
		Tuesday	0.72 (0.109)*			0.66 (0.123)*
		Wednesday	0.76 (0.110)*			0.58 (0.156)
		Thursday	0.70 (0.121)*			0.54 (0.141)

The symbols *, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

The results suggest that utilizing volatility models, especially during unstable market conditions, consistently enhances investment decision-making and mitigates potential risks. Similar findings have been reported in international financial markets regarding the impact of seasonal and daily volatilities on hedge ratios, highlighting the market volatility as a global phenomenon warranting special consideration in various countries.

Based on the present study's findings, it is recommended that investors and market participants leverage financial instruments, such as futures contracts and commodity deposit receipts, to manage existing risks and incorporate seasonal volatilities and specific weekdays into their investment strategies. Additionally, offering educational programs and creating information platforms to increase investor awareness of market behavior and volatility can improve decision-making and market efficiency. These initiatives can bolster investments and reduce risks associated with market fluctuations.

Several policy recommendations to enhance the performance of the Round Fandoghi pistachio market and improve decision-making efficiency for speculators and investors in the commodity exchange market for the Round Fandoghi pistachio are as follows:

1. Strengthening and Managing Seasonal Volatilities: Given the importance of seasonal volatilities in both time series (commodity deposit contract returns and futures contract returns), it is recommended that policymakers and market participants conduct a more detailed analysis of these volatilities and plan to address unusual seasonal fluctuations. These plans could include launching derivative financial instruments, such as options or futures contracts, that aid in managing volatility risks.
2. Supporting Hedging Tools: Considering the significant impact of shocks and past volatilities on contract returns, the development and promotion of hedging tools, like futures and other derivatives, can help investors better manage risks arising from fluctuations. This is especially crucial during periods of high market volatility.
3. Incorporating Seasonal and Daily Patterns in Portfolio Composition: The results indicate that the optimal ratio for commodity deposit contracts varies across different seasons and weekdays. Policymakers and investors should be mindful of these changes and, at appropriate times, adjust their portfolio composition based on a detailed analysis of seasonal and daily changes. This strategy aids in risk reduction and yield enhancement.

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Appendix

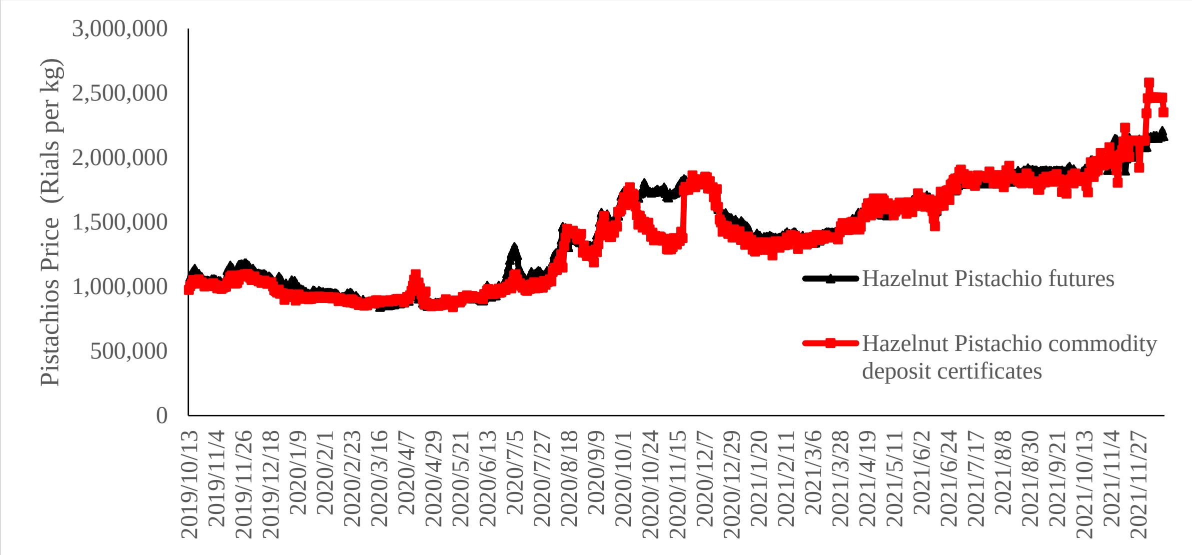

Figure A1- The Price of Future and Commodity Depositary Receipt Contracts in Iran Mercantile Exchange (Iran Mercantile Exchange, 2024)

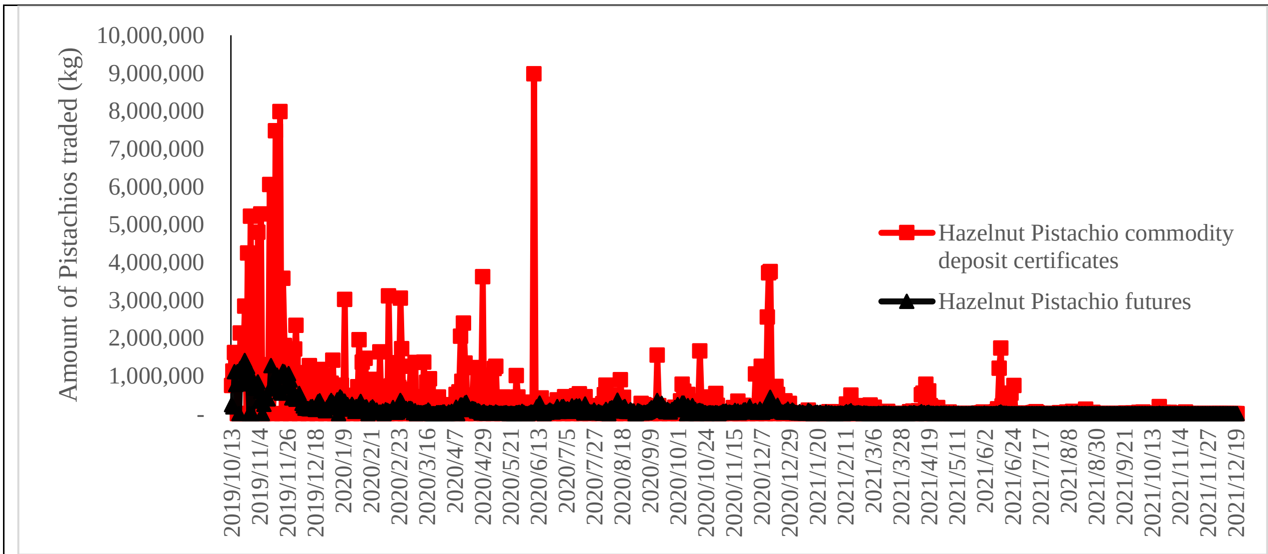

Figure A2- The Quantity of Future and Commodity Depositary Receipt Contracts in Iran Mercantile Exchange (Iran Mercantile Exchange, 2024)

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بررسی ریسک قراردادهای پسته فندقی در بازار بورس کالای ایران

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چکیده

این مطالعه بر روی پوشش ریسک پسته فندقی با استفاده از قراردادهای آتی و سپرده سرمایه¬گذاری تمرکز دارد و تغییرات ریسک و انتخاب پرتفوی بهینه را از ۲۷ مهرماه ۱۳۹۷ تا ۲۸ دی‌ماه ۱۴۰۰ بررسی می‌کند. با استفاده از نظریه سبد کالایی مارکویتز، این مطالعه از مدل‌های اقتصادسنجی مختلفی از جمله تحلیل رگرسیون، مدل‌های GARCH و آزمون ریشه واحد فصلی برای تعیین سبد کالایی بهینه جهت پوشش ریسک استفاده می‌کند. نتایج کلیدی شامل نوسانات فصلی معنادار در فرکانس‌های مختلف است که نشان‌دهنده الگوهای فصلی قوی و پایدار است. تحلیل رگرسیون روابط معناداری بین بازده‌های گذشته و کنونی را نشان می‌دهد که تأثیر بازده‌های گذشته بر عملکرد کنونی را برجسته می‌کند. مدل‌های GARCH ضرایب مثبت معناداری برای اثرات شوک و وقفه‌های واریانس نشان می‌دهند که به معنای تأثیرات قابل توجه شوک‌ها و اثرات خودرگرسیونی قوی نوسانات گذشته بر نوسانات کنونی است. نسبت بهینه قراردادهای سپرده کالایی پسته فندقی بر اساس فصل و روز متغیر است که تقاضای بازار و ترجیحات سرمایه‌گذاران را منعکس می‌کند. این مطالعه چندین پیشنهاد سیاستی ارائه می‌دهد که عبارتند از؛ تقویت و مدیریت نوسانات فصلی از طریق مشتقات مالی، حمایت از ابزارهای پوشش ریسک، توجه به الگوهای فصلی و روزانه در ترکیب سبد کالایی، پایش و کنترل نوسانات در دوره‌های حساس و توسعه سیاست‌های حمایتی در ماه‌های کم نوسان. این پیشنهادها هدف دارند عملکرد بازار پسته فندقی را بهبود بخشیده و کارایی تصمیم‌گیری‌های سرمایه‌گذاری را افزایش دهند.

واژه‌های کلیدی: رفتار فصلی داده¬ها، سبد بهینه کالایی، نسبت بهینه پوشش ریسک

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