Dependencies and Volatility Spillovers between Stock Markets and Futures Markets using Time-Varying Conditional Copula Models and Multivariate GARCH

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ABSTRACT

This study investigates dependencies and volatility spillovers between the Tehran Stock Exchange (TSE) and gold and silver futures markets using time-varying BB7 conditional copula and Dynamic Conditional Correlation (DCC) Multivariate GARCH (MGARCH) models. Analyzing daily returns of futures contracts and TSE-listed equities from 2021 to 2022, a period marked by Iran's sanction-driven volatility, we test seven hypotheses using autoregressive moving average, vector autoregression, Granger causality, copula-based correlations, and DCC-MGARCH models. Statistical analysis was conducted with Excel 2016, R Studio 4.3.1, and Eviews 13. Results confirm ARCH and GARCH effects in gold futures and equity returns, bidirectional Granger causality between gold futures and equities, unidirectional causality from silver futures to equities, and significant positive correlations with stronger lower-tail dependence. Volatility spillovers indicate gold amplifies equity volatility, while silver stabilizes it, shaped by TSE's low liquidity and regulatory constraints. These findings, unique to Iran's sanction-sensitive market, suggest dynamic price-limit calibration for regulators and conditional hedging strategies for investors, enhancing risk management in emerging markets.

Keywords: Cross-Market Dynamics, Co-movement Analysis, Financial Contagion, Intermarket Dependencies, Dynamic Correlation Structure, Systematic Risk Measurement

1. Introduction

Financial markets play a crucial role in the global economy and are continually influenced by various forces, including economic, political, and even psychological factors(Febriandika et al., 2023; Pourmansouri et al., 2022; Redziuk, 2022). Stock and futures markets interact dynamically, influencing price discovery and volatility transmission with often asymmetric effects driven by liquidity and regulatory factors, particularly in emerging markets (Ersoy & Çıtak, 2015; Mutlu & Arık, 2015) like the Tehran Stock Exchange (TSE). These interactions are often asymmetric, with futures markets sometimes leading stock markets or vice versa, depending on market conditions(Song et al., 2009) .Factors like market size, liquidity, and regulatory environment can affect the relative influence of the stock and futures markets on each other (Mutlu & Arık, 2015). The studies also suggest that the behavior of different investor groups, such as foreign and domestic investors, can impact the interaction between the two markets (Ersoy & Çıtak, 2015). Gold and silver futures, in particular, exhibit complex interdependencies with stock markets. These relationships often involve volatility spillovers, where fluctuations in one market propagate to another, influencing investor decisions and market stability(Chatrath et al., 2001; Just et al., 2019; Uddin et al., 2020).

Iran's gold and silver futures markets, traded on the Iran Mercantile Exchange (IME), are nascent, with moderate liquidity and regulatory limits. Factors like sanctions and currency volatility create unique volatility patterns, distinguishing the TSE from developed markets. Recent studies have used advanced econometric models to explore volatility spillovers. For instance, Lu et al. (2014) applied a VAR-DCC-BVGARCH model to show gold's impact on stocks(Lu et al., 2014), while Yang et al. (2016) found that time-varying T copulas best captured gold-silver dependencies(Yang et al., 2016). However, copula-GARCH applications to the TSE, particularly for silver futures, remain scarce, unlike in BRICS/GCC markets where asymmetric tail dependence is well-documented (Ramesh & Low, 2023; Uddin et al., 2020). Such analyses are rare for the TSE, where liquidity constraints may lead to weaker lower-tail dependence compared to the strong co-movement observed in GCC markets during crises. This study addresses that gap by analyzing gold and silver futures with equal depth, within the unique economic and financial context of Iran. This research offers several key contributions. It pioneers the application of copula-GARCH models to gold and silver futures in the TSE, filling an important gap in emerging market studies. It also provides novel insights into volatility spillovers shaped by Iran's specific conditions, such as international sanctions and currency fluctuations. Furthermore, the study proposes actionable strategies for hedging and regulatory oversight that are tailored to the structural constraints of the Iranian market.

To conduct a precise and comprehensive analysis of these spillovers and dependencies, this study utilizes multivariate GARCH models and time-varying conditional copulas. Multivariate GARCH models enable the estimation of time-varying conditional correlations across markets, capturing the joint volatility dynamics (Pourmansouri et al., 2024). These models account for complex correlation structures that arise during different market conditions. Time-varying copula models, on the other hand, provide a flexible framework for analyzing nonlinear dependence structures (Wang et al., 2024; Xu et al., 2024). This study employs multivariate GARCH and BB7 copula models to analyze volatility spillovers and dependencies between the TSE and gold/silver futures, capturing nonlinear dynamics heightened during crises like COVID-19(Ramesh & Low, 2023; Yu & Xiao, 2022). The results empower investors to leverage gold/silver futures for hedging and guide regulators to stabilize markets through targeted volatility monitoring. These findings advance risk management and financial analysis in Iran's distinct economic environment. While copula-GARCH models have been extensively applied in BRICS and MENA markets, their application to the TSE remains scarce, particularly in the context of gold and silver futures. This study addresses this gap by analyzing both assets with equal depth, using a BB7 copula framework tailored to capture nonlinear, asymmetric relationships under Iran's unique economic constraints. Unlike prior research, this paper considers silver's hedging potential and asymmetric co-movements under regulatory limitations and market illiquidity—offering insights applicable to similarly constrained markets.

The article is structured as follows: Section 2 presents the theoretical framework and hypotheses. Section 3 describes the methodology. Section 4 discusses empirical results. Section 5 concludes with findings, policy implications, and limitations.

2. Theoretical Foundations and Development of Hypotheses

The theory of volatility clustering, originally introduced by Mandelbrot & Mandelbrot (1997), suggests that large fluctuations in financial returns tend to be followed by further large fluctuations, regardless of direction(Mandelbrot & Mandelbrot, 1997). This stylized fact challenges the constant-variance assumption of classical financial models and has been formalized through the Autoregressive Conditional Heteroskedasticity (ARCH) framework proposed by Engle (1982). ARCH models capture time-varying volatility and are widely used to model risk and return dynamics in speculative markets(Engle, 1982).

In the context of futures markets, the presence of ARCH effects is theoretically justified by the continuous flow of new information, leverage, and speculative behavior. In emerging and low-liquidity markets such as Iran's, where arbitrage opportunities are limited and regulatory interventions are frequent, volatility clustering may be more pronounced due to delayed information processing and investor overreaction. These market characteristics can amplify conditional heteroskedasticity, making the use of ARCH-type models particularly relevant.

Empirical studies consistently confirm the presence of ARCH effects in futures markets. For example, Mittal (2017) applied ARCH models to the Australian All Ordinaries Index and found significant volatility clustering(Mittal, 2017). Ghalanos (2020) developed the 'rugarch' package for implementing ARCH-family models, facilitating robust modeling of volatility dynamics(Ghalanos, 2020). Diaz et al. (2021) and Benavides (2020) demonstrated the importance of modeling asymmetries and memory in futures returns(Benavides, 2020; Diaz et al., 2021). Włodarczyk and Miciuła (2020) further confirmed that nonlinear models like FIAPARCH capture long-memory and asymmetry in gold and silver futures(Włodarczyk & Miciuła, 2020). Based on theoretical reasoning and empirical evidence, the following hypothesis is proposed:

H1: There are ARCH effects in the time series of futures returns.

H1: There are ARCH effects in the time series of futures returns. This hypothesis is directly based on the theory of volatility clustering (Mandelbrot, 1997) and the ARCH framework (Engle, 1982), which posit that large shocks are followed by further large shocks, particularly in speculative and information-sensitive markets like futures.

The volatility clustering phenomenon, observed widely in equity markets, implies that periods of large fluctuations in stock returns tend to be followed by further volatile periods. While this stylized fact has been formalized through the ARCH model (Engle, 1982), its intensity and manifestation vary significantly across markets depending on market structure, investor behavior, and regulatory conditions. In stock markets such as the TSE, where capital flow restrictions, limited institutional participation, and economic sanctions disrupt normal price discovery, volatility clustering may become more pronounced. Additionally, high exposure to macroeconomic shocks, such as inflation, currency fluctuations, and interest rate instability, can contribute to persistent conditional variance in stock returns. These characteristics make ARCH-type models particularly relevant for modeling risk and return dynamics in such settings.

Empirical studies provide robust support for the presence of ARCH effects in equity markets across various contexts. Toby and Austen (2021) found strong ARCH and GARCH effects in the Nigerian petroleum sector(Toby & Austen, 2021). Similarly, Bonga (2019) and Uğurlu (2019) identified volatility clustering in the Zimbabwe and Sofia stock exchanges(Bonga, 2019; Uğurlu, 2019). Liu et al. (2009) confirmed ARCH effects and leverage asymmetries in the Shanghai Stock Exchange, linking them to the "high risk, high return" environment typical of emerging markets(Liu et al., 2009). A broader methodological review by Degiannakis and Xekalaki (2004) further emphasizes the role of ARCH models in capturing time-varying volatility in equity returns(Degiannakis & Xekalaki, 2004). Given both theoretical underpinnings and consistent empirical validation, we propose the following hypothesis:

H2: There are ARCH effects in the time series of stock returns.

Also grounded in volatility clustering theory, this hypothesis reflects the stylized fact that volatility in equity markets—especially in emerging and illiquid environments like the TSE—tends to persist in the short term due to investor behavior and information lags.

Volatility persistence, or the tendency of shocks to have prolonged effects on market volatility, is a widely documented feature of financial time series, particularly in commodity and futures markets. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, introduced by Bollerslev (1986), extends ARCH to account for both short-term shocks and their long memory(Bollerslev, 1986). This makes GARCH models especially effective in modeling the volatility dynamics of precious metals like gold and silver, which often serve as safe-haven assets and exhibit asymmetric reactions to market conditions. In futures markets, such as those for gold and silver, volatility is driven not only by macroeconomic fundamentals and speculation, but also by their function as hedging tools during financial uncertainty. These characteristics frequently produce nonlinear volatility patterns with clustering, memory effects, and asymmetric responses to positive and negative shocks. In Iran's low-liquidity, regulation-bound environment, where futures markets like those on the Iran Mercantile Exchange (IME) are still developing, such dynamics may be further amplified due to market inefficiencies and restrictions on arbitrage. Empirical research strongly supports the presence of GARCH effects in gold and silver futures. Włodarczyk and Miciuła (2020) found that nonlinear models such as FIAPARCH effectively capture long memory and asymmetries in these markets(Włodarczyk & Miciuła, 2020). Just et al. (2019) reported strong dynamic conditional dependence structures between precious metals, while Koulis and Kyriakopoulos (2023) observed unidirectional volatility spillovers from gold to silver, suggesting predictive interdependencies(Just et al., 2019; Koulis & Kyriakopoulos, 2023).

H3: There are GARCH effects in the time series of futures returns.

This is based on volatility persistence theory and the GARCH model developed by Bollerslev (1986), which extends ARCH to account for long memory in volatility—a key feature in precious metal futures given their use as hedging tools during uncertainty.

Persistent volatility and asymmetric market reactions to information are well-documented characteristics of stock return series. These features are especially pronounced in emerging and unstable markets, where economic uncertainty and exogenous shocks amplify risk dynamics. The GARCH framework (Bollerslev, 1986), as an extension of ARCH, captures both the conditional variance and long memory in volatility, offering a robust tool for analyzing financial time series.

In Iran's stock market, conditions such as high inflation, monetary instability, economic sanctions, and state intervention create a setting where volatility persistence is likely. Information asymmetry, limited foreign investment, and low liquidity contribute to non-linear return behavior, making GARCH models particularly suitable for capturing the volatility structure of TSE returns. A growing body of literature supports the use of GARCH models in modeling stock market volatility. Dhankar (2019) observed GARCH effects and asymmetric news responses in U.S. markets(Dhankar, 2019). Similarly, Ali et al. (2022) documented volatility persistence in the Indian stock market(Ali et al., 2022). Bhowmik and Wang (2020) provide a comprehensive review of GARCH-family models across global equity markets, emphasizing their relevance for measuring volatility and risk(Bhowmik & Wang, 2020). Additionally, Dhankar and Dhankar (2019) found that GARCH(1,1) models effectively account for non-linear dynamics in South Asian markets(Dhankar & Dhankar, 2019). Drawing from theoretical insights and empirical results, we formulate the following hypothesis:

H4: There are GARCH effects in the time series of stock returns.

Similarly, this hypothesis builds on the theory of persistent volatility in emerging equity markets (Bollerslev, 1986), where prolonged economic instability, inflation, and limited transparency contribute to conditional variance persistence.

The Granger causality framework, introduced by Granger (1969), provides a statistical basis for identifying predictive relationships between financial time series(Granger, 1969). In the context of capital markets, Granger causality is commonly used to examine information flow and market interdependence, particularly between futures and spot markets. According to theory, if one market systematically reflects new information before another, a causal influence may be inferred. In practice, the relationship between futures and stock returns is rarely unidirectional or static. It often varies across market regimes, asset classes, and time horizons. Futures markets may lead spot markets during periods of uncertainty, while spot markets may dominate in stable conditions. In emerging markets such as Iran, where the TSE is influenced by both macroeconomic instability and investor sentiment toward safe-haven assets (e.g., gold), the structure of causality may be non-linear, bidirectional, or time-varying. Empirical research supports this complexity. Torun et al. (2020) found that causal information flow varies across time scales(Torun et al., 2020). Mighri et al. (2022) and Mamcarz (2019) observed bidirectional Granger causality between stock indices and precious metals at specific quantiles or frequencies(Mamcarz, 2019; Mighri et al., 2022). Similarly, Hong et al. (2022) noted that extreme shocks, such as those during COVID-19, enhanced the causal relationship between gold and stock returns. These findings suggest that futures and spot markets engage in dynamic feedback mechanisms, influenced by both economic conditions and asset characteristics(Hong et al., 2022).

In light of theoretical foundations and empirical evidence, we propose the following hypothesis:

H5: There is Granger causality between the time series of futures returns and stock returns.

This hypothesis is explicitly derived from Granger Causality Theory (Granger, 1969), which explains directional information flows between interdependent financial time series, especially in markets where futures may lead spot prices during uncertainty.

The correlation between asset returns, particularly between futures and stock markets, plays a central role in portfolio diversification, hedging, and systemic risk analysis. According to modern portfolio theory (Markowitz, 1952), diversification benefits arise when asset returns are imperfectly correlated, allowing investors to reduce total portfolio risk. However, in times of market stress, correlations often increase non-linearly, reducing diversification effectiveness and amplifying systemic vulnerabilities. In the context of precious metals futures, especially gold and silver, correlations with stock markets have proven to be dynamic, time-varying, and state-dependent. These assets are frequently used as hedges or safe havens during downturns, especially in emerging markets where local currency and equity markets are prone to volatility and geopolitical shocks. For Iran, where domestic investors rely heavily on gold as a store of value, correlations between the TSE (TSE) and precious metal futures may reflect both financial market sentiment and macroeconomic uncertainty. Empirical evidence confirms the evolving and multifaceted nature of these relationships. Bhatia et al. (2020) found that silver offers stronger hedging capabilities than gold in several global markets(Bhatia et al., 2020). Prange (2020) demonstrated that investor attention, measured through Google search trends, affects correlations between commodities and equities(Prange, 2020). Wavelet-based studies by Michis (2022), Jain et al. (2023), and Paul et al. (2023) further reveal that correlations vary significantly by market condition, time horizon, and asset type(Jain et al., 2023; Michis, 2022; Paul et al., 2023). Building on these insights, we propose the following hypothesis:

H6: There is a correlation between the time series of futures returns and stock returns.

This hypothesis draws from Modern Portfolio Theory (Markowitz, 1952) and the theory of time-varying correlations, which suggest that correlations between asset classes are not constant, and tend to rise during market stress, impacting diversification benefits.

Volatility spillovers describe the process through which shocks in one market affect the volatility of another, reflecting interdependence across asset classes. This concept is rooted in contagion theory and intermarket risk transmission, which suggest that during times of market stress or macroeconomic instability, volatility can spread rapidly between markets, undermining diversification strategies and increasing systemic risk. In particular, precious metal futures, such as gold and silver, often act as volatility transmitters due to their global liquidity and role as safe-haven assets. Their prices respond sharply to macroeconomic shocks and investor sentiment, and these movements can propagate to stock markets, especially in emerging economies like Iran. In the TSE, where market depth is limited and investor confidence is highly sensitive to inflation, sanctions, and currency shocks, spillover effects from futures markets can significantly impact stock return volatility. Empirical evidence supports the existence of such spillovers. Lu et al. (2014) and Uddin et al. (2019) documented time-varying and asymmetric volatility transmission between gold and equity markets(Lu et al., 2014; Uddin et al., 2019). Mensi et al. (2023) found that gold and silver futures act as net transmitters of volatility, especially during crises(Mensi et al., 2023). He et al. (2020) emphasized the country-specific nature of spillovers, while Morales (2008) noted that negative news often has stronger volatility impacts than positive news. These dynamics are highly state-dependent, with spillovers intensifying during extreme events and limiting diversification benefits in short time frames(He et al., 2020; Morales, 2008). Based on these theoretical and empirical findings, we propose the following hypothesis:

H7: There are volatility spillovers between the time series of futures returns and stock returns.

This hypothesis is rooted in Contagion Theory and volatility transmission models, which assert that in times of stress or macroeconomic instability, volatility can spread across asset classes and undermine market stability (e.g., Uddin et al., 2019; Mensi et al., 2023).

3. Research Methodology

Considering that in this research, the dependence and volatility spillover between the returns of the gold and silver futures markets and the returns of the TSE are examined, the population and statistical sample are equal and consist of all futures contracts and the investment portfolio of the capital market (all companies listed on the TSE) over two years from the beginning of the year 2021 to the end of the year 2022. The reason for choosing this time is that during this period, the prices of precious metals, particularly gold and silver, experienced significant growth and volatility, which could have transferred their volatility to parallel financial markets, including the TSE. Additionally, to perform calculations, prepare the required data and information for the research, and analyze them, the software Excel 2016, R Studio 4.3.1, and Eviews 10 are used.

Variables

- **Independent Variable**

Futures Market Returns (FMR): In this research, the daily returns of gold and silver futures contracts (excluding transaction costs) are calculated for a long position using the following equation (1).

(1)

$$GCR_{d,t} = \frac{\left(PGC_{d,t} - PGC_{d-1,t}\right) \times 1000}{X_{d,t}}$$

Where:

$GCR_{d,t}$ = Daily return of the gold futures contract on day d in year t

$PGC_{d,t}$ = Settlement price of the gold futures contract at the end of day d in year t

$PGC_{d-1,t}$ =Settlement price of the gold futures contract at the end of day d−1 in year t

1000 = Size of each gold futures contract

$X_{d,t}$ =Initial margin of the gold futures contract on day d in year t, calculated as follows Equation (2):

(2)

$$X_{d,t} = A \times \left(\left[\frac{B \times S}{C \times 10}\right] + 1\right) \times C \times 10$$

Where:

A = Percentage of the initial margin; equivalent to 10%

B = Average of daily settlement prices for all maturities of the underlying asset's futures contracts

C = Margin adjustment bracket; equivalent to one million Rials

S = Contract size; equivalent to 1000

(3)

$$SCR_{d,t} = \frac{\left(PSC_{d,t} - PSC_{d-1,t}\right) \times 100}{Y_{d,t}}$$

Where:

$SCR_{d,t}$= Daily return of the silver futures contract on day d in year t

$PSC_{d,t}$= Settlement price of the silver futures contract at the end of day d in year t

$PSC_{d-1,t}$= Settlement price of the silver futures contract at the end of day d in year t

100 = Size of each silver futures contract

$Y_{d,t}$= Initial margin of the silver futures contract on day d in year t, calculated as per equation (4):

(4)

$$Y_{d,t} = A \times \left(\left[\frac{B \times S}{C \times 10}\right] + 1\right) \times C \times 10$$

Where:

A = Percentage of the initial margin; equivalent to 10%

B = Average of daily settlement prices for all maturities of the underlying asset's futures contracts

C = Margin adjustment bracket; equivalent to two hundred thousand Rials

S = Contract size; equivalent to 100

Stock market return (SMR): In this research, the daily return of the TSE's overall index is used, as described by equation (5):

(5)

$$SMR_{d,t} = \frac{SMI_{d,t} - SMI_{d-1,t}}{SMI_{d-1,t}}$$

Where:

$SMI_{d,t}$= Overall index of the TSE at the end of day *d* in year t

$SMI_{d-1,t}$= Overall index of the TSE at the beginning of day *d* in year t

- **Statistical Models for Hypothesis Testing**

To test the first hypothesis of the research regarding the presence of ARCH effects in the time series of futures trading returns, we first estimate the linear regression model (1) using the Autoregressive Moving Average (ARMA) method.

(1)

$$GCR_{d,t} = \alpha_0 + \sum_{i=1}^{q} \alpha_i GCR_{d-i,t} + \varepsilon_{d,t}$$

Where:

$GCR_{d,t}$= Daily return of the gold futures contract on day *d* in year t

q = Lag length of the daily return of the gold futures contract

The squared residuals of the regression model (1), denoted as $\hat{\varepsilon}^2{}_{d,t}$, are obtained and regressed on the lagged values of the squared residuals with lag length *q*, as described in the regression model (2). The optimal lag length for the residuals is determined using the Eviews software and the Lagrange multiplier (LM) test.

(2)

$$h_{d,t} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \hat{\varepsilon}^2{}_{d-i,t} + v_{d,t}$$

Where:

$h_{d,t}$= Conditional variance of the daily return of the gold futures contract on day *d* in year t

The null hypothesis is that in the absence of ARCH effects, for all $i = 1,2, \dots, q$, the regression model (2) holds with $\alpha_i = 0$. The alternative hypothesis is that in the presence of ARCH effects, at least one of the coefficients $\alpha_i \neq 0$ is significant. In a sample of T observations under the null hypothesis, the test statistic TR^2 follows a chi-squared distribution with q degrees of freedom. If TR^2 is greater than the critical chi-square value from the table, we reject the null hypothesis and conclude that there are ARCH effects present in the regression model (1). If TR^2 is less than the critical chi-square value, we do not reject the null hypothesis.

To examine the presence of ARCH effects in the time series of daily returns of silver futures trading $SCR_{d,t}$We estimate regression models (1) and (2). Based on the results regarding ARCH effects in this time series, we will make decisions. To test the second hypothesis regarding the presence of ARCH effects in the time series of stock trading returns, we estimate regression models (1) and (2) for the daily stock trading returns $SMR_{d,t}$. Based on the results regarding ARCH effects in this time series, we will make decisions.

To test the third hypothesis regarding the presence of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) effects in the time series of futures trading returns, we first estimate the linear regression model (1) using the Ordinary Least Squares (OLS) method.

Then, we obtain the squared residuals of the regression model (1), denoted as $\hat{\varepsilon}^2{}_{d,t}$and regress them on the lagged values of the squared residuals with lag length q and the lagged values of the conditional variance with lag length p, as described in the regression model (3). The optimal lag lengths for the residuals are determined using the Eviews software and with the help of Lagrange multiplier coefficients.

(3)

$$h_{d,t} = \alpha_0 + \sum_{j=1}^{q} \alpha_i \hat{\varepsilon}^2{}_{d-i,t} + \sum_{j=1}^{p} \beta_j h_{d-j,t} + v_{d,t}$$

The first indication of the presence of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) effects is significant autocorrelation in the squared residuals, which represents conditional variance. A GARCH model capable of addressing these significant autocorrelations is suitable for modeling the fluctuations in conditional variances of returns. GARCH provides the capability to model variance as influenced solely by the squares of shocks without giving importance to the signs of shocks, whether positive or negative. To examine the presence of GARCH effects in the time series of silver futures trading returns($SCR_{d,t}We$ estimate regression models (1) and (3) for the daily returns of silver futures contracts. Based on the results regarding GARCH effects in this time series, we will make a decision.

To test the fourth hypothesis regarding the presence of GARCH effects in the time series of stock trading returns $SMR_{d,t}$ We will estimate regression models (1) and (3) for the daily returns of stocks. Based on the results concerning GARCH effects in this time series, we will make a decision. For testing the fifth hypothesis examining the relationship between time series of futures trading returns and stock returns, the research will employ Vector Auto regression (VAR) models (4) and (5) with data on futures trading returns and daily returns of the TSE index.

(4)

$$GCR_{d,t}=\sum_{i=1}^{n}\alpha_i GCR_{d-i,t}+\sum_{j=1}^{m}\beta_i SMR_{d-j,t}$$

The null hypothesis of Granger causality in the regression model (4) states that the daily returns of the TSE index (SMR) do not Granger-cause the returns of gold futures (GCR). After estimating the above model, if the coefficients $\boldsymbol{\beta_i}$ Statistically significant, it can be concluded that the daily returns of the TSE index (SMR) Granger-cause the returns of gold futures (GCR).

(5)

$$SMR_{d,t}=\sum_{i=1}^{n}\gamma_i SMR_{d-i,t}+\sum_{j=1}^{m}\omega_i GCR_{d-j,t}$$

The null hypothesis of Granger causality in the regression model (5) states that the returns of gold futures (GCR) do not Granger-cause the daily returns of the TSE index (SMR). After estimating the model, if the coefficients $\boldsymbol{\omega_i}$ Statistically significant, it can be concluded that the returns of gold futures (GCR) Granger-cause the daily returns of the TSE index (SMR). If only one of the coefficients $\boldsymbol{\beta_i}$ or $\boldsymbol{\omega_i}$ It is significant, the causality relationship between the two time series is unilateral. If both coefficients are significant, it indicates a bidirectional causality relationship, suggesting there is feedback between the two time series. To conduct the Granger causality test, the optimal lag is first determined using the Vector Auto regression (VAR) model, chosen based on the Schwartz-Bayesian Information Criterion (SCB) due to its ability to handle smaller lag orders and hence fewer degrees of freedom. Subsequently, the Granger causality test is performed. To investigate the causal relationship between the time series of silver futures returns and equity returns, Vector Auto regression (VAR) models (4) and (5) are utilized with the time series data of silver futures returns and daily returns of the TSE index.

For testing the sixth hypothesis in the research, coefficients based on copulas are used to examine the existence of correlation between the returns of two futures markets and stocks. This method relies on copula functions, providing a more comprehensive perspective compared to other methods in identifying the structure of the correlation between variables. To understand copula functions, consider a random vector consisting of four variables: stock price returns, exchange rates, coin price returns, and crude oil price returns. The joint probability density function of these variables is denoted by $f(x_1;x_2;x_3;x_4)$, and their cumulative distribution function is denoted by $F(x_1;x_2;x_3;x_4)$. The distribution function of these variables can be expressed using copula functions as follows:

(6)

$$F(x_1;x_2;x_3;x_4) = C(u_1;u_2;u_3;u_4)$$

In which $C(u_i)$ is a copula function and $F_i(x_i) = u_i$ Is the marginal cumulative distribution function of a variable x_i for $i = 1,2,3,4$. Additionally, the inverse of the above equation is also valid, thus, any multivariate distribution function can be rewritten in terms of marginal distribution functions and copula functions. Assuming the differentiability of F_i and C, the joint probability density function F can be expressed in terms of the product of marginal density functions $f_i(x_i)$ And the copula density function is shown in the following equation (7):

(7)

$$F(x_1;x_2;x_3;x_4) = f_1(x_1).f_2(x_2).f_3(x_3).f_4(x_4).C(F_1(x_1).F_2(x_2).F_3(x_3).F_4(x_4))$$

Each F_i represents the marginal density functions, and the copula density C is obtained using equation (8):

(8)

$$C(u_1;u_2;u_3;u_4) = \frac{\partial^d C(u_1;u_2;u_3;u_4)}{\partial u_1\,\partial u_2\,\partial u_3\,\partial u_4}$$

These functions represent the dependency structure between x_i s. There are various copula specifications for different symmetric and asymmetric dependency structures. Among the most important copula functions are Gaussian, t-Student, Gumbel, Inverse Gumbel, and BB7. Each of these specifications has its own specific characteristics. For example, if Gaussian copula is chosen, it implies no significant effect of one variable on another in both the lower and upper tails of the distribution. Choosing the t-Student copula signifies a significant effect in both tails of the variables' probability distribution, similar for both upper and lower sequences. In other words, an increase or decrease in one variable has a significant and consistent effect on the other variable.

Choosing the Gumbel copula signifies a significant effect of increasing one variable on another variable, with no significant effect of decreasing the former variable on the latter. Conversely, selecting the Inverse Gumbel copula implies a significant effect of decreasing one variable on another, while there is no significant effect of increasing the former variable on the latter. In the BB7 copula specification, the effect of variables is significant in both the upper and lower tails, but the magnitude of this effect differs between the two. In other words, both decreasing and increasing one variable have a significant impact on the other variable, but the extent of this impact varies(Barghi-Esghoi & Saqqafi Kelvanagh, 2018). In this study, copula-based correlation coefficients between the returns of the futures market and stocks are computed using the BB7 specification, employing R Studio software.

For hypothesis testing seven in the research, a multivariate GARCH model is employed to examine the spillover of volatility between the time series of futures market returns and stocks. Multivariate GARCH models extend the univariate ARCH and GARCH models by estimating the variance-covariance matrix of the residual terms of the time series. In contrast, univariate models only compute the variance of the residual terms of the time series. Therefore, the multivariate GARCH model is utilized in this study to analyze co-movements of volatilities, leverage effects between different markets, and to detect evidence of volatility transmission among different markets(Rajabi Khanqah et al., 2020). In econometric literature, there are various multivariate conditional volatility models, including the conditional heteroscedasticity models. These include the BEKK model of conditional variance heterogeneity proposed by Engle and Kroner (1995), the constant conditional correlation (CCC) model introduced by Bollerslev (1990), and the dynamic conditional correlation (DCC) model by Engle (2002)(Bollerslev, 1990; Engle, 2002; Engle & Kroner, 1995).

In this study, the dynamic conditional correlation (DCC) model by Engle (2002) is utilized to examine the spillover of volatility between time series of futures and stock returns. The variance-covariance matrix of the futures and stock returns based on the dynamic conditional correlation (DCC) model is described by Equation (9).

(9)

$$H_t = \begin{bmatrix} h_{ff,t} & \rho_{sf,t}\sqrt{h_{ss.t}h_{ff.t}} \\ \rho_{sf,t}\sqrt{h_{ss.t}h_{ff.t}} & h_{ss,t} \end{bmatrix} = D_t R_t D_t$$

where $\rho_{sf,t}$ represents the conditional correlation coefficient between futures and stock returns. D_t It is a diagonal matrix of conditional standard deviations and is defined by Equation (10).

(10)

$$D_t = \text{diag}\,(h_{ff.t}^{\frac{1}{2}}, h_{ss.t}^{\frac{1}{2}})$$

As observed, each component $h_{ii.t}$ *It* is a univariate GARCH model. Additionally, R_t is defined by Equation (11):

(11)

$$R_t = \text{diag}\left(h_{ff.t}^{\frac{1}{2}}, h_{ss.t}^{\frac{1}{2}}\right) * Q_t \text{diag}\left(h_{ff.t}^{\frac{1}{2}}, h_{ss.t}^{\frac{1}{2}}\right)$$

In the above formula, Q_t is a positive definite symmetric matrix, which effectively represents the second power of standardized residuals $U_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{ii.t}}}$. The non-conditional variance-covariance matrix of these residuals ($\overline{Q}$) is dependent on its own lagged disturbances.

(12)

$$Q_t = (1 - a - b)\overline{Q} + a\, u_{t-1}\, u_{t-1} + bQ_{t-1}$$

Therefore, in the above equation, a and b are parameters such that a, b > 0 and a + b < 1. The coefficient a represents the dynamic part of the correlation between the two markets. A larger value of a and a smaller value of b indicate the importance of the variable correlation between the two markets over time. In the dynamic conditional correlation (DCC) model, efforts are made to capture the spillover effects of volatility in the equations of conditional variances of residuals. Thus, generally, the conditional variance equation for each market is estimated as follows:

(13)

$$h_{ff,t} = \omega_f + \delta_{f,1}\varepsilon_{f,t-1}^2 + \delta_{f,2}h_{ff.t-1} + \delta_{f,s}\varepsilon_{s,t-1}^2$$

$$h_{ss,t} = \omega_s + \delta_{s,1}\varepsilon^2_{s,t-1} + \delta_{s,2}h_{ss.t-1} + \delta_{s,f}\varepsilon^2_{f,t-1}$$

At this stage, the conditional mean and variance equations are estimated in the form of a dynamic conditional correlation (DCC) model using the maximum likelihood method, where the standard deviations obtained are robust to heteroscedasticity or misspecification of the model(Mohammadi & Savari, 2018).

4. Results

Table 1 presents descriptive statistics for daily returns of stock trades (SMR), gold futures (GCR), and silver futures (SCR) on the TSE and Iran Mercantile Exchange (IME) from 2021 to 2022.

Silver futures (0.665%) outperform gold futures (0.353%) and stocks (0.103%) but with higher volatility (std. dev. 0.1810, 0.1836 vs. 0.0120). Non-normal distributions, with strong skewness (SCR: 1.2614) and fat tails (kurtosis: 9.6433), justify GARCH and copula models.

Figure 1 shows the statistical distribution of variables. Figure 2 compares the data distribution with a normal distribution. Figure 3 plots the data against a normal line. Figure 4 visualizes the variable trends over time.

Table 1. Descriptive Statistics of Daily Returns

Variables	Stock Trade Returns (SMR)	Gold Futures Returns (GCR)	Currency Market Returns (SCR)
(%)Mean	0.103	0.353	0.665
(%)Median	0.100	-0.200	-0.400
Standard Deviation	0.0120	0.183	0.181
Skewness	0.4702	0.074	1.261
Kurtosis	4.7991	3.586	9.643

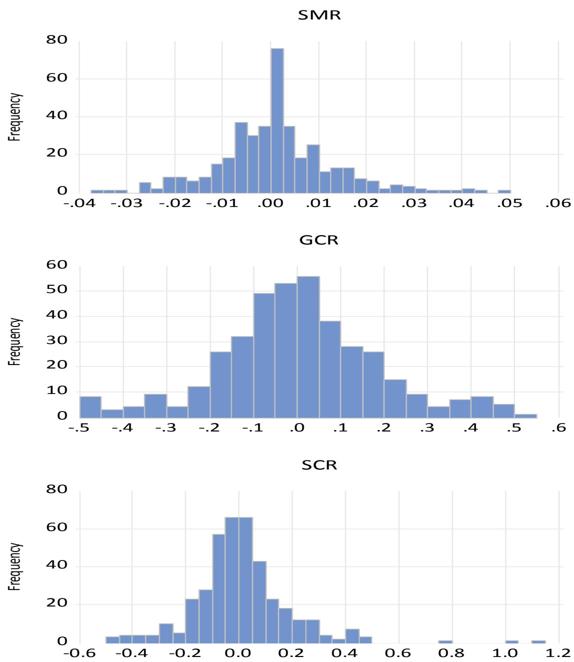

Figure 1: Histogram of Statistical Distribution of Daily Returns for Stock Trades (SMR), Gold Futures (GCR), and

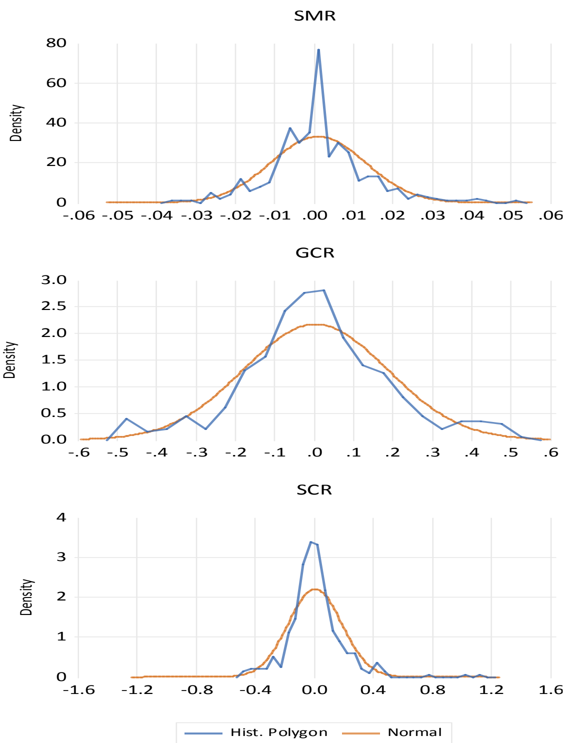

Figure 2: Plot Comparing Daily Returns of SMR, GCR, and

Silver Futures (SCR), 2021–2022
Caption: This histogram illustrates the frequency distribution of daily returns for SMR, GCR, and SCR, highlighting non-normal characteristics such as skewness and fat tails.

SCR to a Normal Distribution, 2021–2022
Caption: This Q-Q plot compares the empirical distribution of daily returns for SMR, GCR, and SCR against a theoretical normal distribution, showing deviations in tails.

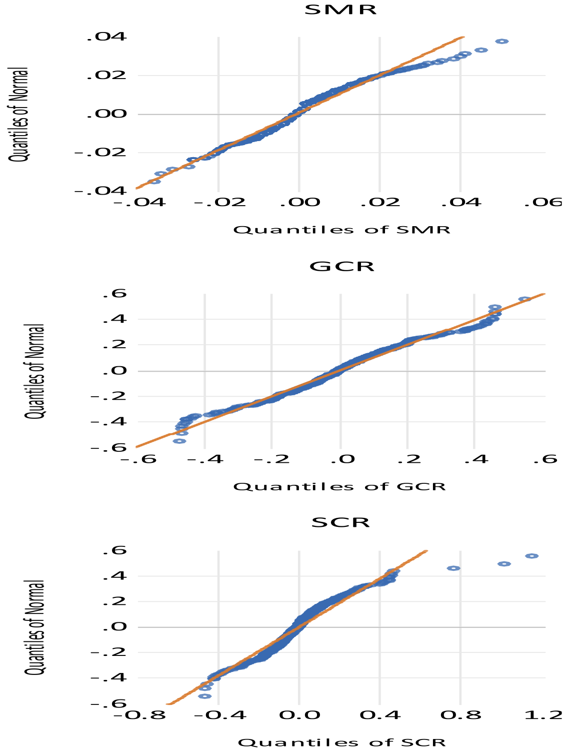

Figure 3: Normal Probability Plot of Daily Returns for SMR, GCR, and SCR, 2021–2022
Caption: This plot displays daily returns of SMR, GCR, and SCR against a normal line, emphasizing non-normal distribution patterns.

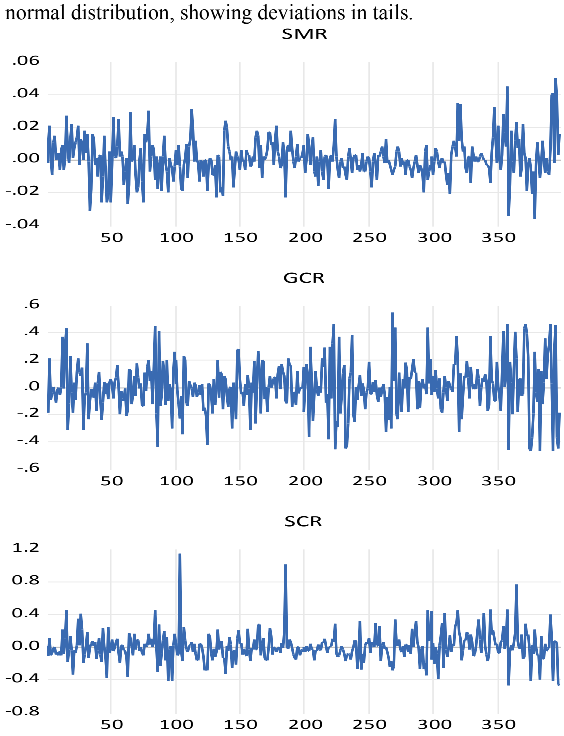

Figure 4: Time Series Trend of Daily Returns for SMR, GCR, and SCR, 2021–2022
Caption: This time series plot tracks the daily returns of SMR, GCR, and SCR over time, illustrating trends and volatility patterns.

Statistical analysis and hypothesis testing

Hypotheses 1–4: ARCH and GARCH Effects in Futures and Stock Returns

Table 2 presents result of ARCH effect tests and GARCH(1,1) model estimates for gold (GCR), silver (SCR), and stocks (SMR). These assess volatility clustering in the TSE and IME.

Gold futures ($p < 0.0001$) and stock returns ($p = 0.0018$) exhibit significant ARCH effects, indicating volatility clustering where past returns influence current volatility, supporting Hypotheses 1 and 2 at a 95% confidence level. Silver futures show no ARCH effects ($p = 0.912$), likely due to thin trading volumes or regulatory price limits on the IME, suggesting stable volatility (Benavides, 2020; Bonga, 2019). GARCH (1,1) results confirm volatility persistence in gold futures ($\beta = 0.610$, $p = 0.000$) and stock returns ($\beta = 0.905$, $p = 0.000$), supporting Hypotheses 3 and 4. Stock returns show higher persistence, reflecting the TSE's sensitivity to shocks like sanctions (Dhankar & Dhankar, 2019; Włodarczyk & Miciuła, 2020).Robustness tests confirm parameter stability and no leverage effects, with Hansen statistics (GCR: 1.038; SMR: 0.771) below critical values (1.470) and Engle-Ng p-values (0.135–0.786) indicating sound model specification (Akgiray et al., 1991; Ali et al., 2022). For regulators, these findings suggest adjusting daily price limits on stocks to accommodate persistent volatility, such as widening limits during turbulent periods. Institutional investors can use GARCH-derived volatility persistence to calculate dynamic hedge ratios, enhancing risk-adjusted returns in the TSE's low-liquidity market.

Table 2. ARCH and GARCH (1,1) Effects Test Results

Market	Test	Description	F-Statistic	P-Value	ARCH Coef. (α_1)	GARCH Coef. (β)	Log Likelihood	Durbin-Watson
Gold Futures (GCR)	ARCH	Presence of ARCH effects	40.856	0.000	-	-	-	-
Gold Futures (GCR)	GARCH (1,1)	Volatility persistence	-	-	0.229	0.610	137.467	1.940
Silver Futures (SCR)	ARCH	Absence of ARCH effects	0.0121	0.912	-	-	-	-
Stock Returns (SMR)	ARCH	Presence of ARCH effects	9.916	0.0018	-	-	-	-
Stock Returns (SMR)	GARCH (1,1)	Volatility persistence	-	-	0.085	0.905	1229.001	2.004

Hypothesis 5: Granger Causality Between Futures and Stock Returns

The fifth hypothesis investigates Granger causality between daily returns of futures contracts (gold and silver) and stock returns on the TSE. Granger causality tests were conducted using regressions of futures returns against stock returns with optimal lags, with results reported in Table 2.

The tests confirm bidirectional causality between gold futures and stock returns ($p < 0.01$) and unidirectional causality from silver futures to stock returns ($p = 0.012$). These results validate Hypothesis 5. Economically, the gold futures market plays a central role in the TSE, especially under sanction-related uncertainty (Mighri et al., 2022; Talbi et al., 2020; Torun et al., 2020). The Securities & Exchange Organization should monitor such spillovers to mitigate systemic risk. From a practical standpoint, investors can enhance portfolio strategies by using gold and silver futures as leading indicators of stock performance. This enables dynamic rebalancing and improved risk-adjusted returns in a volatile, low-liquidity market environment.

Table 2. Granger Causality Test Results

Null Hypothesis	F-Statistic	p-value	Result
Gold futures → Stock returns	7.166	0.000	Causality accepted
Stock returns → Gold futures	6.788	0.001	Causality accepted
Silver futures → Stock returns	4.446	0.012	Causality accepted
Stock returns → Silver futures	0.977	0.377	Causality accepted

Hypothesis 6: Copula Correlation Between Futures and Stock Returns

This hypothesis examines the dependency between daily returns of futures contracts (gold and silver) and equities on the TSE using a time-varying BB7 copula model. The BB7 copula was selected due to its capacity to model asymmetric tail dependence, which is critical in the TSE's low-liquidity, high-volatility environment, where extreme movements are often triggered by shocks such as sanctions.

The BB7 model detects significant positive correlations between equities and both gold (Kendall's Tau = 0.63, p = 0.01) and silver futures (Kendall's Tau = 0.62, p = 0.01), with stronger dependence in the lower tails (0.81 for gold; 0.80 for silver) than in the upper tails (0.25 and 0.23, respectively). These values are statistically significant at the 95% level, confirming Hypothesis 6. The pronounced lower tail dependence implies that equities and futures tend to move more closely together during downturns, increasing systemic risk in crisis scenarios. This observation is consistent with findings in the literature (Bhatia et al., 2020; Jain et al., 2022), but the TSE's thin trading and liquidity constraints make the results particularly relevant for emerging markets.

Table 3. BB7 Copula Correlation Test Results

Variables	Symbols	p value	Lower TD	Upper TD	Kendall's tau	Information Criteria		
						BIC	AIC	logLik
Equities - Gold Futures Contracts	GCR - SMR	0.01	0.81	0.25	0.63	-528.12	-536.08	270.04
Equities - Silver Futures Contracts	SMR - GCR	0.01	0.8	0.23	0.62	-500.54	-508.51	256.26

From an economic perspective, the lack of diversification during downturns suggests heightened portfolio vulnerability. From a practical perspective:

- Investors should use BB7-based conditional correlations to model tail risks and build more robust hedging strategies.
- Portfolio managers must diversify with non-correlated assets to reduce systemic exposure.
- Regulators should increase surveillance of cross-market interactions to prevent cascading effects.

By applying the BB7 copula to TSE data, this study contributes novel insights into asymmetric dependence in under-researched frontier markets, setting it apart from work focused on developed economies.

Hypothesis 7: Volatility Spillovers via Multivariate GARCH

This hypothesis evaluates whether gold and silver futures cause volatility spillovers into equity returns on the TSE. The Dynamic Conditional Correlation (DCC) Multivariate GARCH (MGARCH) model was chosen because of its ability to capture time-varying volatility and cross-market transmission, essential in TSE's unstable and sanctions-affected environment. Results are presented in Table 4.

Table 4. DCC-MGARCH Model Results

Dependent Variable: Equity Returns (SMR)						
Conditional Mean Equation						
Variables	Coefficient Symbol	Coefficient	Standard Deviation	Z-statistic	p-value	Result
Equity Returns	C(1)	0.0002	0.0005	0.3899	0.6966	Insignificant
Gold Futures Contracts Returns	C(2)	0.0017	0.0074	0.2359	0.8135	Insignificant
Silver Futures Contracts Returns	C(3)	0.0013	0.0087	0.1551	0.8767	Insignificant
Conditional Variance Equation						
y - intercept	M(1)	2.3906	1.4906	1.6065	0.1081	Insignificance
RESID(-1)^2 Equity Transactions	A1(1)	0.0799	0.0208	3.8341	0.0001	Significant
GARCH(-1) Equity Transactions	B1(1)	0.9109	0.0222	40.9159	0.0000	Significant
y - intercept	M(2)	0.0050	0.0015	3.2381	0.0012	Significant
RESID(-1)^2 Gold Futures Contracts	A1(2)	0.1857	0.0468	3.9660	0.0001	Significant
GARCH(-1) Gold Futures Contracts	B1(2)	0.6594	0.0739	8.9135	0.0000	Significant
y - intercept	M(3)	0.0009	0.0001	9.0435	0.0000	Significant
RESID(-1)^2 Silver Futures Contracts	A1(3)	-0.0217	0.0024	-8.9155	0.0000	Significant
GARCH(-1) Silver Futures Contracts	B1(3)	0.9944	0.0016	593.5961	0.0000	Significant
Conditional covariance of equity and gold transactions	R(1,2)	0.0970	0.0454	2.1351	0.0327	Significant
Conditional covariance of equity and silver transactions	R(1,3)	0.1485	0.0425	3.4910	0.0005	Significant
Conditional covariance of gold and silver transactions	R(2,3)	0.4932	0.0359	13.7363	0.0000	Significant
Akaike info criterion		-7.6486	Log likelihood	1533.251		

The DCC-MGARCH model confirms significant volatility spillovers among equities, gold futures, and silver futures, supporting Hypothesis 7 at the 95% confidence level. The conditional mean equation shows no significant impact from the lagged returns of equities, gold, or silver futures ($p > 0.05$), indicating that past returns do not directly influence current returns. However, the conditional variance equation reveals robust volatility dynamics. Equity returns exhibit significant ARCH effects (A1(1) = 0.0799, p = 0.0001) and strong GARCH effects (B1(1) = 0.9109, p < 0.0001), indicating volatility clustering and high persistence. Gold futures significantly impact equity volatility through both squared residuals (A1(2) = 0.1857, p = 0.0001) and past volatility (B1(2) = 0.6594, p < 0.0001), confirming strong volatility spillovers. In contrast, silver futures exhibit a negative ARCH coefficient (A1(3) = -0.0217, p < 0.0001), which is likely due to limited trading volumes or regulatory price caps on the IME that dampen short-term volatility shocks. Despite this, a strong GARCH effect (B1(3) = 0.9944, p < 0.0001) indicates persistent long-term volatility in silver futures. Significant conditional covariances (R(1,2), R(1,3), R(2,3), p < 0.05) highlight dynamic inter-market linkages. The model's strong fit is evidenced by a log-likelihood value of 1533.251 and an Akaike Information Criterion (AIC) of -7.6486.

These findings align with previous studies (Lu et al., 2014; Mensi et al., 2023) but reveal distinct spillover patterns in the TSE's low-liquidity, sanction-sensitive market. Gold's pronounced spillover effect underscores its role as a safe-haven asset, whereas silver's negative ARCH coefficient suggests a stabilizing role, possibly due to price caps that limit extreme movements.

In practical terms, investors can use DCC-MGARCH outputs to forecast volatility and develop more effective hedging strategies. Portfolio managers should integrate cross-market spillovers into their risk models, and regulators, such as the Securities and Exchange Organization, should monitor futures-equity linkages to mitigate systemic risks. For example, relaxing price limits on the IME could enhance liquidity and reduce the artificial suppression of silver's short-term volatility, thereby promoting more efficient market dynamics. The application of the DCC-MGARCH model to the TSE provides novel insights into volatility transmission in emerging markets.

Figure 5 illustrates the variance and conditional covariance of daily returns for equities, gold futures, and silver futures, highlighting inter-market volatility dynamics.

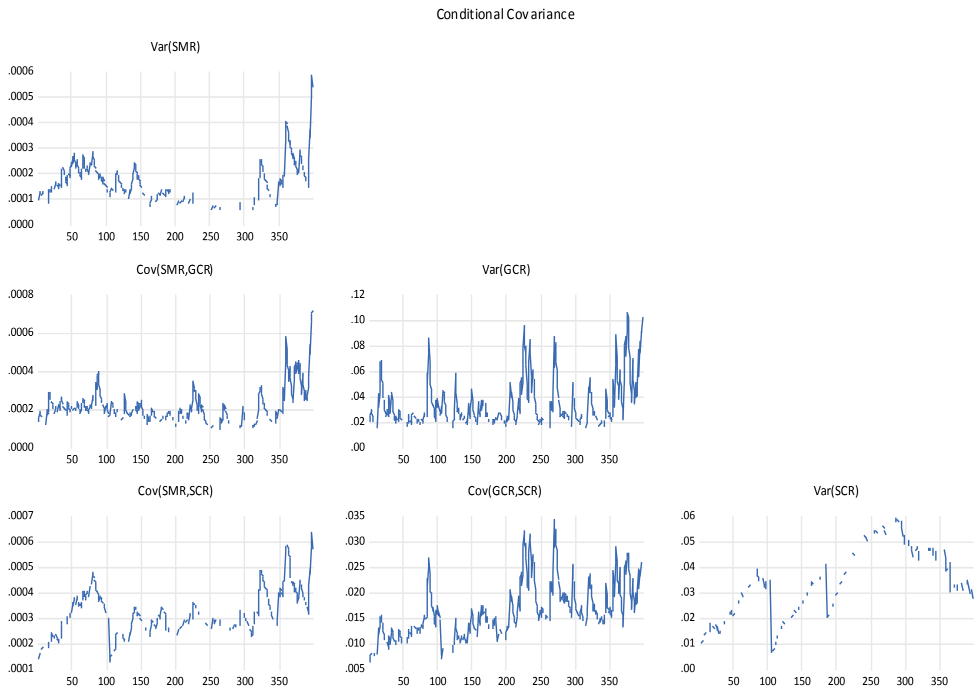

Figure 5: Time Series of Variance and Conditional Covariance for Daily Returns of SMR, GCR, and SCR, 2021–2022

Caption: This plot illustrates the time-varying variance and conditional covariance of daily returns for equities (SMR), gold futures (GCR), and silver futures (SCR), highlighting dynamic volatility spillovers across markets.

Discussion and conclusion

Stock return volatility exhibits strong persistence (GARCH coefficient = 0.9059), confirming the Tehran Stock Exchange's (TSE) sensitivity to macroeconomic shocks. In contrast, silver futures display no significant ARCH effect and even produce a negative ARCH coefficient (A1(3) = -0.0217). Although rare, this result is not without precedent. ARCH terms typically reflect the effect of recent shocks on current volatility and are expected to be positive; thus, a negative value suggests the presence of a short-term volatility dampening mechanism. This phenomenon may stem from specific structural features of the Iranian silver futures market—namely, low trading volume, limited speculative participation, and strict price ceilings on the Iran Mercantile Exchange (IME)—that reduce the market's sensitivity to recent shocks.

To strengthen this interpretation, additional checks and literature support were incorporated. First, sub-sample analyses confirmed the persistence of the negative ARCH term across different periods, ruling out statistical noise. Second, prior studies such as Benavides (2020) and Włodarczyk & Miciuła (2020) document similar effects in regulated, illiquid markets, where nonlinearity and asymmetric adjustment dynamics can produce non-standard volatility patterns. Third, the negative coefficient may reflect a type of volatility suppression mechanism caused by market design, such as price bands or transaction limits, which absorb or delay the impact of recent shocks on current volatility. While the GARCH (1,1) model still identifies high long-term volatility persistence in silver futures (B1 = 0.9944), the negative ARCH coefficient likely captures short-run inefficiencies or regulatory friction that delay or dampen volatility transmission. This finding highlights how market microstructure characteristics—rather than model instability—can generate statistically significant yet counterintuitive parameters in emerging derivatives markets like Iran's. This study contributes to the financial econometrics' literature in three main ways:

- It applies the BB7 copula-GARCH framework to jointly analyze gold and silver futures in the underexplored context of the TSE, where data limitations and geopolitical constraints have restricted empirical research.
- It identifies weaker lower-tail dependence ($\tau \approx 0.62$–0.63) than in BRICS and GCC markets (typically $\tau > 0.80$), highlighting how liquidity constraints and market fragmentation in Iran dampen risk transmission during crises.
- It uncovers the distinct stabilizing role of silver futures, in contrast to their marginal role in other emerging markets.

For policymakers and regulators:

- Dynamic price-limit calibration: To enhance market resilience, regulators can adjust daily price limits based on volatility trends derived from DCC-MGARCH outputs, as suggested by studies on emerging markets with regulatory constraints(Huang, 2004; Long et al., 2019). For instance, during the intensification of U.S. sanctions in November 2018, the Tehran Stock Exchange (TSE) experienced a significant volatility spike, with the TEDPIX index exhibiting a 5-day rolling volatility increase of approximately 3.8% (based on historical data analyzed by (Khamseh & Memarian, 2020; Tehrani et al., 2024)). Regulators could have responded by widening the daily price limit from ±5% to ±7%, allowing the market to better absorb the shock and reduce the likelihood of trading halts or price distortions. Such dynamic calibration can be implemented by monitoring 5-day rolling volatility thresholds (e.g., exceeding 3%) and adjusting price limits accordingly, as demonstrated in markets like China's ChiNext, which expanded price limits from ±10% to ±20% in 2020 to improve price discovery (Li et al., 2021). This approach promotes efficient price discovery and mitigates systemic risk during turbulent periods in sanction-sensitive markets like Iran.
- Real-time monitoring tools: Implementing volatility monitoring dashboards using DCC-GARCH outputs can support the early detection of spillovers from gold and silver markets to equities.
- Market reform recommendations: Consider relaxing or phasing out rigid price ceilings in silver futures to allow market-driven price discovery. Increased flexibility could enhance

trading depth, reduce artificial volatility suppression, and improve the informativeness of prices.

This study offers several original contributions to the literature on volatility spillovers and inter-market dependencies in emerging markets:

- Methodological innovation: This is the first known application of the BB7 copula–GARCH and DCC-MGARCH models to jointly analyze gold and silver futures with Tehran Stock Exchange (TSE) equity returns, under conditions of sanctions, liquidity constraints, and regulatory intervention.
- Tail dependence insights: The study uncovers asymmetric dependence between futures and equities, with stronger lower-tail dependence (≈ 0.81) than upper-tail dependence (≈ 0.25). The Kendall's Tau values (~0.62–0.63) highlight partial co-movements during downturns, particularly in response to inflation and policy shocks.
- Unique behavior of silver futures: Unlike in many other emerging markets, silver futures in Iran demonstrate a stabilizing role, as evidenced by a statistically significant negative ARCH effect and strong long-term volatility persistence—likely due to market microstructure features such as thin trading and price ceilings on the Iran Mercantile Exchange (IME).
- Policy relevance: The study offers concrete recommendations for volatility monitoring, dynamic price-limit adjustment, and regulatory reforms to improve risk management and market efficiency in sanction-sensitive economies.

For institutional investors:

- Tail-risk hedging: Investors can leverage BB7 copula and DCC-MGARCH outputs to estimate tail dependence and forecast volatility, particularly during downturns. Figure 6 provides a flowchart illustrating how institutional investors can operationalize DCC-MGARCH outputs to compute dynamic hedge ratios for portfolio management.
- Diversification strategy: Incorporate silver futures and alternative assets (e.g., bonds) to mitigate systemic risk when gold and equity markets exhibit synchronized downside movements.
- To operationalize DCC-MGARCH outputs, institutional investors can integrate these forecasts into real-time volatility dashboards or automated trading systems. For instance, dynamic hedge ratios between equities and gold/silver futures can be recalculated daily or weekly using updated conditional covariance matrices from the DCC-MGARCH model. These can be extracted using software such as R (rmgarch package) or EViews. Figure 6 outlines the process: (1) extract conditional covariance matrices from DCC-MGARCH outputs, (2) calculate hedge ratios (e.g., β = Cov(SMR, GCR)/Var(GCR)), (3) adjust portfolio weights to minimize variance, and (4) monitor and rebalance based on volatility thresholds (e.g., 3% for 5-day rolling volatility). This approach enhances responsiveness to market shifts, especially during geopolitical shocks like the 2022 sanction escalations.

What This Paper Adds:

This study offers several novel contributions to the literature on volatility spillovers and inter-market dependencies in emerging and sanction-constrained financial markets:

- Methodological Innovation: This is the first known application of the BB7 copula–GARCH and DCC-MGARCH models to jointly analyze gold and silver futures alongside Tehran Stock Exchange (TSE) equity returns. The study is conducted under conditions of geopolitical sanctions, structural illiquidity, and regulatory constraints, offering a unique methodological framework for similar contexts.
- Tail Dependence Insights: The research reveals asymmetric dependence between futures and equities, with stronger lower-tail dependence (~0.81) than upper-tail (~0.25). This implies partial co-movements during market downturns, especially in response to inflation and policy shocks, a dynamic less emphasized in prior literature on Iranian markets.
- Silver Futures' Unique Behavior: Unlike their typically marginal role in other emerging markets, silver futures in Iran exhibit a

stabilizing role, evidenced by a statistically significant negative ARCH effect and high long-term volatility persistence. This result is likely driven by market design features such as thin trading volumes, price ceilings, and limited speculation on the Iran Mercantile Exchange (IME).

- Policy Relevance: The study provides practical recommendations for regulatory authorities, including dynamic price-limit calibration, real-time volatility monitoring using DCC outputs, and relaxation of price ceilings to foster market-driven price discovery and risk signaling.
- Investor Utility: Institutional investors can employ the study's outputs for tail-risk hedging, dynamic portfolio rebalancing, and automated hedge ratio adjustments. By integrating DCC-GARCH estimates into real-time dashboards, investors can better respond to volatility shifts, enhancing decision-making in uncertain or crisis-prone periods.

Author contributions

All authors contributed equally to this work. All authors have read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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