Portfolio Risk Management in Oil, Gold, and Stock Markets Based on Dynamic Modeling and Targeted Risk Hedging

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ABSTRACT

In recent years, financial markets particularly oil, gold, and stock markets have faced significant structural shifts and regime changes, intensifying risk spillovers and creating challenges for investors and policymakers in their decision-making processes. This study aims to enhance risk management and optimize investment portfolios by exploring the dynamic nature of risk transmission and developing effective hedging strategies over the period 2016–2023. To achieve this, a comprehensive hybrid framework is employed, integrating the Markov-Switching Vector Autoregression (MS-VAR) model, the Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) model, and the Conditional Dynamic Correlation (cDCC) model. This combination allows for a more accurate examination of inter-market dependencies. The findings reveal that the degree of risk spillover varies across different regimes and intensifies notably during turbulent periods, leading to stronger correlations among markets. Moreover, the influence of oil and gold prices on the stock market index exhibits an unstable pattern, heavily shaped by political and economic conditions. Overall, the proposed hybrid model outperforms traditional approaches in detecting risk spillovers and formulating effective risk-hedging strategies, contributing to improved portfolio performance in volatile market conditions.

Keywords: Risk Spillover, Hedging Strategy, Portfolio Optimization, Oil Market, Gold Market, Stock Market

1. Introduction

Over the past decades, extensive transformations in the international financial system have led to profound changes in the structure of financial markets, significantly increasing the level of interconnection and interaction among them. These transformations driven by factors such as economic globalization, the advancement of information technology, financial liberalization, the development of derivative instruments, and the diversification of assets have made it possible for volatility in one market to easily transmit to others, thereby influencing their behavior. Under such circumstances, financial markets no longer operate in isolation but rather function as interconnected components of a complex network, wherein the transmission of risk from one market to another is not only possible but often likely and, in some cases, detrimental (Musen et al., 2020).

Within this context, one of the key concepts that has gained considerable attention in financial and macroeconomic literature is risk contagion. This phenomenon refers to a situation in which volatilities, shocks, or crises originating in one market are transmitted to others, resulting in instability across the entire financial system. The importance of understanding and analyzing risk contagion becomes even more evident when considering that many major financial crises such as the Asian Financial Crisis (1997), the Global Financial Crisis (2008), and the COVID-19 pandemic-induced crisis began with disruptions in a specific sector and subsequently spread to other sectors. Consequently, studying the transmission mechanisms of risk across various markets, particularly in developing economies, has become a critical component of contemporary financial research.

On the other hand, alongside the growing interdependence of markets, increasing emphasis has been placed on risk management concepts and strategies for mitigating price volatility. Hedging strategies comprise a set of measures designed to reduce or transfer the risks associated with fluctuations in asset prices, exchange rates, interest rates, or other macroeconomic variables. In this regard, the use of financial derivatives such as futures contracts, options, swaps, and their various combinations has expanded in both theoretical and practical frameworks of financial risk management. The necessity of designing effective hedging strategies becomes particularly evident during periods of crisis when heightened volatility and strong correlations among markets lead to increased uncertainty in financial decision-making and reduced portfolio returns (Hosseini et al., 2013). Under such volatile conditions, only through the application of accurate, data-driven analytical models can one effectively identify channels of risk transmission and develop appropriate hedging mechanisms.

Among various financial domains, the oil, gold, and stock markets hold a distinct position in the global economy and particularly in Iran’s economic structure for several critical reasons. The oil market, as one of the most important global commodity markets, plays a vital role not only in supplying global energy needs but also in ensuring fiscal stability for countries like Iran, whose foreign exchange revenues heavily depend on crude oil exports. As such, fluctuations in oil prices can quickly spill over into other economic sectors, inducing volatility in financial indicators.

The gold market, by contrast, functions as a classic safe haven asset, drawing the attention of investors during times of economic or geopolitical uncertainty. Beyond its intrinsic value, gold price fluctuations often reflect changes in inflation expectations, exchange rates, and systemic risk. Moreover, gold behaves differently compared to other markets in times of elevated risk, making it a critical component in portfolio risk management strategies (Farzanegan, Elham, 2018).

The stock market, as a fundamental platform for mobilizing and allocating financial resources within the economy, is highly sensitive to macroeconomic variables and commodity market dynamics. Frequently, changes in the oil or gold markets exert direct or indirect effects on stock indices. Given that the stock market embodies the aggregated expectations of economic agents, analyzing its dynamics can yield insights into broader economic trends and future developments.

Given the significance of these markets and the complexity of their interrelations, understanding the mechanisms of risk contagion among them and developing data-driven hedging strategies is an imperative necessity. This necessity is even more pronounced in the context of Iran’s economy, which is characterized by high dependence on oil revenues, exposure to international sanctions, pronounced exchange rate volatility, and heightened vulnerability to political and economic shocks. In such a setting, traditional models like GARCH[1] or VAR[2] fall short in capturing the nonlinear, unstable, and regime-dependent relationships across markets.

Therefore, the application of advanced and hybrid models such as the MS-VAR[3] , long-memory conditional volatility models like FIAPARCH[4], and dynamic dependency models such as cDCC-GARCH offers a more robust analytical framework (Lai, 2023). These tools provide analysts and policymakers with valuable insights into the complex dynamics governing interconnected financial markets.

A review of existing literature reveals that, while numerous studies have examined either risk contagion or hedging strategies in international financial markets, domestic studies in Iran have often focused on one or two markets in isolation. Those few studies that adopt an integrated approach typically rely on simplified methodologies with restrictive assumptions. As a result, there remains a significant gap in the simultaneous analysis of the oil, gold, and stock markets using modern, data-intensive methodologies. Addressing this gap requires the development of a comprehensive model capable of capturing market interdependencies within an interpretable structural framework, while also enabling the derivation of effective hedging strategies.

Based on the above considerations, the primary objective of this study is to develop an advanced hybrid model for analyzing risk contagion and proposing hedging strategies across Iran's oil, gold, and stock markets during the period 2016 to 2023. To this end, the study employs a combination of MS-VAR, FIAPARCH, and cDCC-GARCH models to simultaneously examine dependency patterns, volatility asymmetries, and regime shifts in market behaviors.

In the next stage, using the extracted dynamic covariance matrices, optimal hedge ratios are computed for various asset combinations and practical recommendations are presented for constructing portfolios that are resilient to risk.

Accordingly, the key objectives of this research include:

1) Analyzing the magnitude and direction of risk contagion among the oil, gold, and stock markets using the MS-VAR model;
2) Investigating long-memory conditional volatility in these markets through the FIAPARCH model;
3) Modeling the dynamic dependency structure among the markets using the cDCC approach;
4) Calculating optimal hedge ratios and offering practical hedging strategies for investors.

The structure of the article is as follows:

The first section outlines the research background and rationale. The second section reviews the theoretical foundations and related literature. The third section details the research methodology and introduces the employed models. The fourth section presents and interprets the empirical results. Finally, the fifth section provides a summary of the findings along with policy and practical recommendations.

2. Literature Review

Mirzaei et al. (2023) simulated systemic risk contagion between the Iranian money and capital markets using a factor-based model. Their findings indicated that fire sales of assets and redemptions from investment funds can propagate risk throughout the entire financial system.

Mohammadi Shad et al. (2021), employing the MGARCH model, investigated risk contagion among financial, commodity, and cryptocurrency markets from 2014 to 2020. Their results emphasized the high degree of interdependence among these markets, especially in the face of major shocks.

Vahabzadeh et al. (2021), using a multivariate GARCH model and covariance dynamics, assessed the Iranian capital market's contribution to systemic risk and concluded that this market is more vulnerable than other financial sectors.

Al Ali and Abounouri (2020) calculated the optimal hedge ratios in the energy market using minimum variance and copula models. Their study showed that dynamic models such as copulas offer superior performance in risk management.

Shoja and et al (2020) examined the relationship between financial distress risk and credit risk in the banking sector. They found that financial distress directly transmits to credit risk within the banking system.

[1] Generalized Autoregressive Conditional Heteroscedasticity
[2] Value At Risk
[3] Markov Switching Vector Autoregression
[4] Fractionally Integrated Asymmetric Power ARCH

Elroy Haddad et al. (2024), utilizing the TVP-VAR dynamic model, analyzed risk contagion and optimal hedging strategies in commodity ETFs. By applying the co-skewness portfolio technique and data from March 2019 to March 2024, they demonstrated the significant impact of geopolitical shocks such as COVID-19, the Ukraine war, and maritime attacks—on ETF performance, highlighting the role of such events in increasing market correlations and risk contagion.

Argyropoulos et al. (2024) explored the relationship between downside risk and the returns of hedge funds and fund-of-funds investments. Their analysis revealed that hedge funds perform better during bullish regimes, while in bearish regimes, they exhibit lower returns relative to higher risks. In contrast, no significant relationship was found for fund-of-funds investments.

Belhosein (2019), using the VAR-BEKK-GARCH model, examined volatility spillovers between oil prices and economic indicators in the Eurozone. He found that correlation and volatility transmission vary across time periods and play a crucial role in investor decision-making.

Wang et al. (2016) investigated long-term relationships between oil prices, gold prices, exchange rates, and stock indices in industrialized countries. The findings indicated significant correlations, particularly in Germany, Japan, and Taiwan; however, no such relationship was observed for the U.S. stock market.

Chiu et al. (2015) studied tail-risk contagion across U.S. industrial and financial sectors. Their proposed CCX model effectively identified the simultaneous occurrence of shocks across industries and the financial sector. The results indicated that during financial crises, risk transmission from the financial sector to other industries intensifies.

Al-Taibi and Mishra (2015), using the GARCH-BEKK model, demonstrated the volatility spillover from the U.S. and Saudi Arabian stock markets to five GCC countries. Their findings underscored the significant transmission of turbulence from these two markets to Bahrain, Oman, Kuwait, Qatar, and the UAE.

3. Methodology

3.1. Markov Switching Model

A common approach for examining the dynamic behavior of macroeconomic variables is the use of linear time series models. While these models have often proven effective, they fall short in explaining nonlinear behaviors. One of the nonlinear models frequently employed for estimating uncertainty is the GARCH model. However, the Markov Switching model, originally introduced by Hamilton (1989) and also known as the regime-switching model, is one of the most well-known nonlinear time series models. It captures the behavior of variables across different regimes.

The Markov Switching model is a powerful tool for analyzing time series data characterized by structural breaks. It can effectively detect and analyze fluctuations and regime changes in various markets, including oil, gold, and equity markets. A review of empirical studies shows that price transmission across different market levels is often asymmetric. Therefore, models capable of capturing asymmetry are required. In this context, nonlinear models, particularly threshold models and the Markov Switching model, are widely used alternatives.

The ability of Markov Switching models to capture the behavior of economic variables undergoing regime changes has led to their widespread adoption in economic and financial research. Consequently, this study employs weekly time series data and utilizes the Markov Switching Vector Autoregressive (MS-VAR) model to assess risk transmission dynamics in Iran. This methodological approach offers a distinct advantage over previous studies.

Unlike traditional VAR, ARIMA, and linear GARCH models, which are limited by their linear nature and inability to capture the nonlinear volatility characteristics of variables, the Markov Switching model, due to its nonlinear structure, is well-suited for explaining asymmetric fluctuations. Moreover, it does not require transforming the data and directly utilizes the original time series to extract volatility patterns, making it a more suitable approach.

The general form of the Markov Switching Vector Autoregressive (MS-VAR) model is as follows:

$$\Delta r_{k,t} = \mu_{k,S(t)} + \sum_{i=1}^{I} \emptyset_{k,S(t)} r_{t-i} + \varepsilon_{k,t,S(t)}$$

The regime-switching process is defined by the transition probabilities as follows :

$$p_{ij} = Pr(S_{t+1} = j|S_t = i), \sum_{j=1}^{2} P_{ij} = 1 \forall i, j \in [1,2]$$

In the above equation, μk,S(t) denotes the vector of intercept terms. μk,S(t) also represents the vector autoregressive coefficients of the returns of oil, stocks, and gold within the Markov regime-switching process. The error term εk,t,S(t) follows a Student's t-distribution with a white noise process and exhibits regime-dependent degrees of freedom corresponding to regimes 1 and 2, which align with low and high volatility states of oil, stocks, and gold, respectively. This can be expressed as follows:

$$\varepsilon_{k,t,S(t)}|\Omega_{t-1} \sim \begin{cases} N(0, \sigma_{1t}^2) w.p. p_{1t} \\ N(0, \sigma_{2t}^2) w.p(1 - p_{1t}) \end{cases}$$

$$\varepsilon_{k,t,S(t)}|\Omega_{t-1} \sim (0, H_{k,t,S(t)})$$

Where σ2 1t and σ2 2t represent the volatilities of oil and the returns of stocks or gold in regimes 1 and 2, respectively. Ωt 1 denotes the information set at time t, and Hk,t,S(t) is the conditional covariance matrix of the time-varying market variables under the Markov regime-switching process. Following Hamilton (1989), S(t) can be defined as a first-order Markov process, with the constant transition probability matrix specified as follows:

$$Pr[S_t = 1|S_{t-1} = 1] = P$$
$$Pr[S_t = 2|S_{t-1} = 1] = (1 - P)$$
$$Pr[S_t = 2|S_{t-1} = 2] = Q$$
$$Pr[S_t = 1|S_{t-1} = 2] = (1 - Q)$$

In this matrix, 1 - P represents the probability that regime 1 is followed by regime 2. The parameters P and Q denote the probabilities that there is no change in the state of regime 1 or regime 2 in the next period, respectively. Likewise, 1 - Q is the probability that regime 2 is followed by regime 1. It is assumed that these transition probabilities remain constant between consecutive periods. The natural extension of the Markov process is to allow time-varying transition probabilities. It is assumed that $P_t = \Omega(c_1 + d_1 r_{t-1})$ and $Q_t = \Omega(c_2 + d_2 r_{t-1})$.

Here ci and di for are unknown parameters, and Ω(0) represents the cumulative normal distribution function, which ensures that 0<Pt,Qt<1 . The terms Pt and Qt indicate the transition probabilities. The conditional probability p1t=Pr (St=1|Ωt−1) can be expressed by the following formula:

$$P_{1t} = (1 - Q)\left[\frac{g_{2t-1}(1 - P_{1t-1})}{g_{1t-1}P_{1t-1} + g_{2t-1(1-P_{1t-1})}}\right] + P_t\left[\frac{g_{1t-1}P_{1t-1}}{g_{1t} - 1P_{1t-1} + g_{2t-1}(1 - P_{1t-1})}\right]$$

The time-varying conditional variance of oil, stock index, and gold returns is modeled as an Asymmetric Fractionally Integrated ARCH (AFIARCH) process. Following Engle (2002), by specifying the variance-covariance matrix, regime-switching conditional correlations are allowed to evolve over time within the framework of a Markov-switching process.

$$H_{k,t,S(t)} = D_{k,t,S(t)}\Gamma_{k,t,S(t)}D_{k,t,S(t)}, D_{k,t,S(t)} and\ \Gamma_{k,t,S(t)}$$

In this expression, are defined respectively as the time-varying conditional variance under Markov regime switching and the correlation matrix of crude oil. In this model, the conditional correlation matrix is regime-switching and is governed by a discrete Markov regime-switching process, expressed as $\Gamma_{k,t,S(t)} = diag\{\rho_{t,S(t)}\}^{-\frac{1}{2}}$ It is defined as such. The state-dependent time-varying conditional covariance matrix and the positive definite conditional covariance matrix are expressed as follows :

$$H_{s,t,S(t)} = \begin{pmatrix} \sigma_{SI,t,S(t)}^2 & \sigma_{SI,CO,t,S(t)} \\ \sigma_{SI,CO,t,S(t)} & \sigma_{CO,t,S(t)}^2 \end{pmatrix} = \begin{pmatrix} \sigma_{SI,t,S(t)} & 0 \\ 0 & \sigma_{CO,t,S(t)} \end{pmatrix} \begin{pmatrix} 1 & \rho_{k,t,S(t)} \\ \rho_{k,t,S(t)} & 1 \end{pmatrix} \begin{pmatrix} \sigma_{SI,t,S(t)} & 0 \\ 0 & \sigma_{CO,t,S(t)} \end{pmatrix}$$

In the above equation, σ2 SI,t,S(t) and σ2 CO,t,S(t) represent the state-dependent, time-varying conditional variances for stock index returns and returns on oil and gold, respectively, in regime S(t) . The model proposed by Billio and Caporin (2005) is then employed, which introduces a Markov regime-switching dynamic conditional correlation (DCC) framework by specifying ρ t,S(t) as in the corresponding equation. Here, ρ t,S(t) denotes the Markov regime that governs the dynamic conditional correlation between the stock, oil, and gold markets at time ttt under regime S(t) . Accordingly, both the conditional variance and correlation at time ttt in regime S(t) are modeled using a combined multivariate Asymmetric Power ARCH with Fractional Integration (FIAPARCH) process. The conditional cDCC-FIAPARCH framework is expressed as follows:

$$\sigma_{k,S(t)}^{\delta_{k,S(t)}} = \omega_{k,S(t)}\left(1-\beta_{k,S(t)}L\right)^{-1} + \left[1 - \left(1-\beta_{k,S(t)}L\right)^{-1}\left(1 - \lambda_{k,S(t)}L\right)(1-L)^{d_{k,S(t)}}\right]\left(\varepsilon_{k,S(t)}\right)$$

$$\rho_{t,S(t)} = \left(1-A_{S(t)}\right) - B_{S(t)}\rho + A_{S(t)}\left\{\rho_{t-1,S(t)}^{*\frac{1}{2}} u_{t-1}u_t' \rho_{t-1,S(t)}^{*\frac{1}{2}}\right\} + B_{S(t)}\rho_{t-i,S(t)}$$

The parameter dk,S(t)} refers to the long-memory process in regime S(t). Moreover, dk,S(t) lies within the interval (0,1). The parameter γk,S(t) <1 represents the leverage effect coefficient and is commonly used to measure the degree of asymmetry in regime S(t) , where the condition γk,S(t) <1 must be satisfied. When 0<γk,S(t) <1, negative shocks exert a stronger influence on volatility than positive shocks. Conversely, when -1<γk,S(t) < 0 , positive shocks have a greater effect on volatility than negative ones. The power term δ k,S(t) takes positive and finite values and is applied in regime S(t). The term ut denotes the matrix of standardized residuals. The initial conditional correlation is denoted by ρS(t),t . Parameters AS(t) and BS(t) are estimated under the condition AS(t) + BS(t) < 1. Due to path dependence in the model, Lee and Yuede (2007) developed an equation to address this issue.

$$\sigma_{k,t}^2 = p_{1,t}\left(r_{k,S(1),t}^2 + \sigma_{k,S(1),t}^2\right) + \left(1-p_{1,t}\right)\left(r_{k,S(2),t}^2 + \sigma_{k,S(2),t}^2\right) - \left[p_{1,t}r_{k,S(1),t} + \left(1-p_{1,t}\right)r_{k,S(1),t}\right]^2$$

$$\boldsymbol{\rho_t} = \frac{\mathbf{1}}{\boldsymbol{\sigma_{SI,t}\sigma_{CO,t}}}\left\{\begin{bmatrix} \boldsymbol{p_{1,t}\left(r_{SI,S(1),t}r_{CO,S(1),t} + \rho_{S(1),t}\sigma_{SI,S(1),t}\sigma_{CO,S(1),t}\right)} + \\ \boldsymbol{(1-p_{1,t})\left(r_{SI,S(2),t}r_{CO,S(2),t} + \rho_{S(2),t}\sigma_{SI,S(2),t}\sigma_{CO,S(2),t}\right)}\end{bmatrix}\right\} - \boldsymbol{\left[p_{1,t}r_{SI,S(1),t} + (1-p_{1,t})r_{SI,S(2),t}\right]\left[p_{1,t}r_{CO,S(1),t} + (1-p_{1,t})r_{CO,S(2),t}\right]}$$

In the above equation, r2k,S(1),t and r2k,S(2),t represent the conditional time-varying and state-dependent means of stock returns, or oil and gold returns. The issue of path dependence is addressed by employing the MS-VAR-FIAPARCH-cDCC model. Accordingly, the variance–covariance matrix does not rely on the entire history of past information but instead depends on the state-dependent information at the current time. In this study, model parameters are estimated using the Maximum Likelihood Estimation (MLE) method. The probability density function of the state-dependent variables is formulated as follows:

$$f\left(r_{k,t};\theta\right) = \frac{p_{1,t}}{2\pi}\left|H_{1,t}\right|^{-\frac{1}{2}} exp\left(-\frac{1}{2}\varepsilon_{1,t}' H_{1,t}^{-1}\varepsilon_{1,t}\right) + \frac{p_{2,t}}{2\pi}\left|H_{2,t}\right|^{-\frac{1}{2}} exp\left(-\frac{1}{2}\varepsilon_{2,t}' H_{2,t}^{-1}\varepsilon_{2,t}\right)$$

Among these θ is the parameter that must be estimated by maximizing the log-likelihood function.

$$L(\theta) = \sum_{t=1}^{T} logf\left(r_{k,t};\theta\right)$$

3.2. Stationarity of Variables

In time series analysis, stationarity is of paramount importance and constitutes a fundamental prerequisite for the application of many statistical models. A time series process is considered stationary when characteristics such as mean, variance, and autocorrelation structure remain constant over time. In essence, stationarity reflects the stability of the statistical behavior of data across different time periods. This property enhances the reliability and accuracy of forecasts based on historical patterns. A common issue in this context is the presence of a unit root in time series, which indicates non-stationarity and instability in the statistical properties of the data. Determining whether the data are stationary or non-stationary is essential prior to model estimation, as the use of non-stationary data can lead to misleading results. Generally, the concepts of stationarity, stability, and persistence are used interchangeably in time series literature, all referring to the statistical consistency of variables over time.

3.3. Risk Hedging

One of the most effective strategies in investment risk management is the application of the minimum variance approach. The primary objective of this method is to reduce the volatility of portfolio returns by utilizing a combination of assets in such a way that the total variance of the portfolio is minimized. In this context, investors may employ instruments such as equities, gold, crude oil, or petroleum products to construct an optimal asset mix that significantly hedges against the fluctuations inherent in high-risk markets. In other words, constructing diversified portfolios comprising gold and stocks, oil and stocks, or a combination of all three markets can effectively reduce potential losses stemming from market shocks. In this study, to determine the optimal asset weights in the portfolio and the allocation ratios among different markets, the optimal hedging weight algorithm proposed by Kroner and Neg (1998) is employed. This model provides a practical tool for portfolio management under volatile market conditions, enabling investors to make more informed and optimal decisions aimed at risk mitigation.

$$w_{CO,SI,t} = \frac{\sigma_{CO,t} - \sigma_{CO,SI,t}}{\sigma_{SI,t} - 2\sigma_{CO,SI,t} + \sigma_{CO,t}}$$

$$w_{CO,SI,t} = \begin{cases} 0, & if \quad w_{CO,SI,t} < 0 \\ w_{CO,SI,t} & if \quad 0 \le w_{CO,SI,t} \le 1 \\ 1 & if \quad w_{CO,SI,t} > 1 \end{cases}$$

In the above formulas, $W_{CO,SI,t}$ represents the optimal portfolio weight and indicates that investors can hold a one-unit portfolio composed of two assets at time t. $\sigma_{SI,t}$ and $\sigma_{CO,t}$ denote the conditional variances of the stock index and crude oil or gold, respectively, at time t. $\sigma_{CO,SI,t}$ represents the conditional covariance between the returns of global crude oil or gold and the stock index at time t. Moreover, the optimal portfolio weight of the global crude oil asset is given by $W_{CO,SI,t}$ ×1.

Furthermore, the optimal hedge ratio is calculated to examine whether the inclusion of oil or gold assets in a stock portfolio can provide a hedge against investment risk in equity markets. Accordingly, the optimal hedge ratio proposed by Kroner and Sultan (1993) is utilized to minimize the conditional variance of the hedged portfolio:

$$\beta_{CO,SI,t} = \frac{\sigma_{CO,SI,t}}{\sigma_{CO,t}}$$

In addition, hedge effectiveness is evaluated to assess the robustness of the hedging strategy (HE), following the approach proposed by Ku et al. (2007).

$$HE = \left(\frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}}\right)$$

The hedged portfolio variance proposed by Bashir and Sadorsky (2016) is also formulated as follows:

$$\begin{aligned} var(R_{HE,t}I_{t-1}) = {} & var(R_{S,t}I_{t-1}) \\ & - 2\beta_{CO,SI,t}cov(R_{F,t}, R_{S,t}I_{t-1}) \\ & + \beta^2_{CO,SI,t}var(R_{F,t}I_{t-1}) \end{aligned}$$

VAR_{hedged} Refers to the variance of the hedged portfolio consisting of crude oil or gold and the stock index, whereas $VAR_{unhedged}$ denotes the variance of the unhedged portfolio, which includes only the stock index.

In this study, the Markov Regime-Switching Vector Autoregressive (MS-VAR) model is first applied to the mean process. Accordingly, a two-regime structure is represented by high and low volatility states. Subsequently, the Markov regime-switching in the mean process is integrated into the multivariate cDCC-FIAPARCH model to capture long-memory behavior and asymmetry in the variance process. Next, the risk spillover between the global oil market and the stock and gold markets will be analyzed. Finally, dynamic optimal portfolio management and hedging strategies are proposed, and the effectiveness of dynamic hedging among these markets is examined.

3.4. Data Collection Tools

To examine the risk spillover among different industries in the Iranian capital market, time series related to prices and returns will be analyzed using time series models and concepts. This approach allows for the identification of models that best describe these data, which can then be used for forecasting the required information.

Weekly and monthly return time series will be collected based on the indices of the stock market, gold, and oil industries. Subsequently, returns will be calculated using MATLAB software. To estimate and identify the appropriate models for each of these time series, ARIMA and GARCH models will be jointly examined through MATLAB coding and EViews software. The best-fitting models that accurately represent the mentioned time series will be selected based on the Okaike Information Criterion .

After determining the time series models, returns and risk will be analyzed accordingly. For data analysis, weekly prices of stock market indices, oil, and gold for the years 2016 to 2023 have been utilized.

3.5. Definition of Terms and Technical Concepts (Conceptual and Operational)

3.5.1. Spillover

Spillover of turbulence among financial markets refers to the process of information transmission between these markets. Although these markets are considered competitors, they influence the inflow and outflow of liquidity in each other's domains and consequently affect the financial and economic environment of the markets under their interdependence (Nikoomaram et al., 2014).

3.5.2. Hedging

Hedging refers to a type of investment strategy aimed at reducing the risk of gains and losses in an investment portfolio. Under normal circumstances, hedging can involve various financial instruments such as stocks, futures contracts, swaps, options, as well as different types of derivatives, over-the-counter contracts, and forward contracts (Taheri et al., 2008).

3.5.3. Financial Risk

Financial risk arises from the structure of the balance sheet, including components such as assets, asset structure, and management of assets and liabilities. This area primarily focuses on the composition of the assets within the balance sheet—whether the portfolio is skewed towards assets whose value is likely to fluctuate in the future or whether the majority of assets exhibit stability in value (Raei, 2011).

3.5.4. Investment Return

Total return, or the holding period return, is the most comparable metric for evaluating the performance of an investment regardless of the type of assets involved. Through the concept of return, one can measure returns over time or the rate of return on securities. To calculate the investment return rate, the gains obtained from the investment are divided by the initial amount invested (Abzari et al., 2007).

3.5.5. Capital Market

The capital market, or financial market, refers to a marketplace where various financial assets are traded and exchanged. This market can encompass multiple types of markets (Raei, 2005). One of the most significant financial markets in the country is the stock exchange, where, primarily, different securities and subsequently other assets such as various commodities are traded. In this study, the term capital market refers specifically to the Tehran Stock Exchange, and all related data are extracted from this market.

3.5.6. Gold Market

The gold market includes a set of activities and trading processes where gold is treated as an asset. This market encompasses buying, selling, and investing in various forms of gold, such as gold coins, bullion, and jewelry. The gold market is divided into physical and financial segments. In this study, data are extracted from the domestic gold market, specifically from the gold investment fund indices.

3.5.7. Oil Market

One of the key markets in most oil-dependent countries is the oil exchange. Oil is considered one of the most valuable commodities globally. Approximately 161 types of crude oil exist worldwide, with Brent crude and OPEC crude being among the most prominent (Mohammadpour, 2020). Participation in the oil exchange can occur either through direct or indirect investment. Direct investment involves entry into the market via futures trading or investment funds.

4. Results

In this study, the EViews software has been employed to assess the autocorrelation of the data.

4.1. Detection of First-Order Autocorrelation

4.1.1. Durbin–Watson Test

The Durbin–Watson test is used to detect the presence of first-order autocorrelation in the residuals of a regression analysis.

$$u_t = \rho u_{t-1} + v_t \qquad v_t \sim N(0, \sigma_v^2)$$

The hypotheses in this test are formulated as follows:

$$\begin{Bmatrix} H_0\colon \rho = 0 \\ H_1\colon \rho \neq 0 \end{Bmatrix}$$

Based on the et values (estimates of ut), the DW statistic is calculated as follows:

$$d = \frac{\sum_{t=2}^{N} (e_t - e_{t-1})^2}{\sum_{t=1}^{N} e_t^2}$$

4.2. DW first-order autocorrelation formula

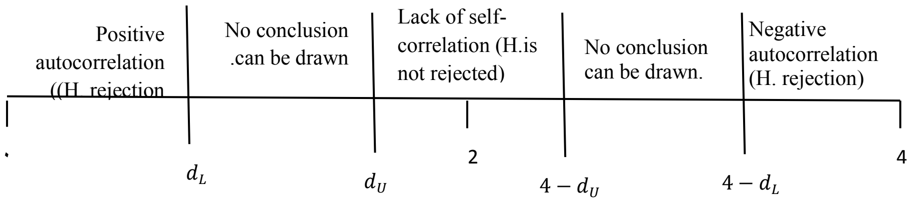
By simplifying the above equation, we obtain:

$$DW \cong 2(1 - \hat{\rho})$$

Since $\hat{\rho}$ is a correlation coefficient, it must: $0 \preccurlyeq DW \preccurlyeq 4 \ \Leftarrow -1 \preccurlyeq \hat{\rho} \preccurlyeq 1$

Therefore, three situations are possible:
The existence of positive and perfect autocorrelation between the residuals $\Leftarrow \ DW = 0 \ , \hat{\rho} = 1$ Perfect and negative autocorrelation $\Leftarrow \ DW = 4 \ , \hat{\rho} = -1$
Lack of self-reliance $\Leftarrow \ DW = 2 \, , \hat{\rho} = 0$

4.3. Reject and non-reject areas in DW



4.4. ARCH Effect Confirmation

The ARCH model is one of the earliest and simplest models developed for analyzing conditional heteroskedasticity in time series data. In this model, the variance of a time series is dependent on past error terms. It is particularly useful for data in which the variance exhibits significant fluctuations over time.
Essentially, the ARCH model describes a process in which the conditional variance at any given time is explained by the squared error terms from the previous q periods. This feature enables more effective modeling of time-varying volatility and variance dependency in time series.

A key assumption of this model is the stationarity of the data, as well as the independence between the dependent and independent variables and the error terms.

The main equation of this model, referred to as the conditional variance equation, states that the error variance at time t is derived from the sum of the squared residuals from the previous q periods.

$$\sigma_{\varepsilon t}^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \cdots + \theta_q \varepsilon_{t-q}^2 = \theta_0 + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}^2$$

Accordingly, the variance in each period depends on past error terms, which allows the model to explain the non-constant fluctuations in the data. To examine the presence of the ARCH effect in the dataset, the Lagrange Multiplier (LM) test is commonly used. The null hypothesis of this test states that no ARCH effect exists in the time series.
The LM test is based on the F-distribution, and its results determine whether the variance in the data is homoskedastic (constant) or heteroskedastic (non-constant).
In time series analysis of returns, examining the Autocorrelation Function and the Partial

Autocorrelation Function of both returns and squared returns is of great importance. Small values of ACF[5] and PACF[6] in the return series indicate a lack of significant autocorrelation, suggesting that the series is nearly uncorrelated. However, significant autocorrelation in the squared returns reveals serial dependence in volatility, which is effectively captured by ARCH and GARCH models.

Furthermore, the Engle's ARCH test provides strong evidence of conditional heteroskedasticity in the data, thereby justifying the use of GARCH family models. To assess autocorrelation, the Ljung-Box Q (LBQ) test is also employed, which evaluates the statistical significance of autocorrelations at various lags in the time series. This test helps confirm whether the selected model adequately accounts for the dependency structure of the data.

Overall, the ARCH model and its extensions, such as the GARCH model, are highly effective tools for analyzing time series with time-varying variance and high volatility, making them widely applicable in financial and economic studies.

During various time lags (from 1 to 25), the values of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) for the return series indicate the presence of serial correlation. For instance, at lag 1, the ACF value is 0.539 and the PACF value is 0.342, suggesting that returns are dependent on their own past values. As the lag increases, the ACF and PACF values generally decrease, yet in some cases (e.g., lag 15 with ACF = 0.729), a notable level of correlation remains. This implies that returns are influenced by their historical behavior and that specific patterns may exist in the data.

The Ljung-Box Q (LQB) statistic is significantly high across all lags, with associated p-values equal to 0.000. These results lead to the rejection of the null hypothesis of no serial correlation, indicating that serial dependence in the data is statistically significant. This finding suggests that traditional linear models such as ARIMA may not be sufficient to fully capture the dynamics of the return series, and that more complex models such as GARCH or Markov-Switching may be required. Moreover, the ACF and PACF values for the squared returns (which represent volatility) are also statistically significant. For example, at lag 1, the ACF is 0.935 and the PACF is 0.506, highlighting a strong dependence of volatility on its own past values. These results confirm the presence of volatility clustering in the market periods of high and low volatility tend to occur in succession. Similar to the return series, the LQB statistics for squared returns are also very high, with p-values equal to 0.000. This further indicates that market volatility exhibits serial correlation and that models such as ARCH/GARCH are appropriate for capturing this behavior. This is typically performed using the LBQ[7] test. In this section, the Breusch-Godfrey LM test is also applied to evaluate the autocorrelation of residuals. This test follows an F-distribution, and the corresponding results are presented in the table below.
According to the table, the ARCH-LM test statistics are significantly high across all lags from 1 to 25. For instance, at lag 1, the test statistic is 292.511 with a p-value of 0.000. At lag 10, the statistic increases to 398.0532, while the p-value remains at 0.000. Even at longer lags, such as lag 20, the test statistic reaches 439.0011, again with a p-value of 0.000. The consistently low p-values across all lags (less than 0.01) lead to the rejection of the null hypothesis of no ARCH effects. Therefore, the conditional variance of the return series is significantly dependent on its past values, indicating that the variance is not constant over time. This finding confirms the presence of volatility clustering in the data, a common characteristic of financial time series. Consequently, classical models that assume constant variance, such as OLS or ARIMA, are not appropriate for analyzing these data. Instead, models like ARCH or GARCH should be employed to accurately capture the time-varying behavior of volatility. The Breusch-Godfrey test is used to detect the presence of serial correlation in the residuals of a regression model, which would violate the assumption of error independence. In this case as well, the test statistics are considerably high across all lags. At lag 1, the statistic is 305.8163 with a p-value of 0.000. At lag 10, the value increases to 449.306, with the p-value still at 0.000. Even at lag 25, the statistic remains high at 71.40069, with a p-value of 0.000. These results also lead to the rejection of the null hypothesis of no serial correlation, indicating the presence of significant autocorrelation in the residuals.

[5] Autocorrelation Function
[6] Partial Autocorrelation Function

[7] Ljung–Box Q

This implies that returns are dependent on their past values, and the assumption of independently and identically distributed (i.i.d.) observations does not hold.

Results of series correlation of returns and serial correlation

Square series of returns				series of returns				
P-value	LQB statistics	PACF	ACF	P-value	LQB statistics	PACF	ACF	break
000	39.0459	0.506	0.935	000	444.6333	0.342	0.539	1
000	445.7572	0.622	0.184	000	416.9369	0.035	0.662	5
000	279.5264	0.883	0.379	000	492.7745	0.570	0.410	10
000	279.1473	0.623	0.246	000	390.1123	0.751	0.729	15
000	39.83979	0.701	0.486	000	245.33	0.609	0.159	20
000	385.274	0.645	0.354	000	468.7581	0.383	0.647	25

Results from the variance heterogeneity test of returns

P-value	Test statistics Bruesch-Godfrey	P-value	Test statistics LM ARCH	break
000	305.8163	000	292.511	1
000	324.0592	000	336.7856	5
000	449.306	000	3980.532	10
000	449.306	000	205.5579	15
000	480.8013	000	439.0011	20
000	71.40069	000	176.6402	25

4.5. Results of the Effect Analysis Using the Markov-Switching Model

The table below presents the results of the effect analysis based on the Markov-Switching model. According to the conducted analyses and the Markov-Switching process, the values of the variables lht,ls, and lch for the dependent variables lh, ls, and lch have been calculated under two regimes, Regime 0 and Regime 1.

Based on the results presented in the above table, the following points can be concluded:

1) Regime 0 reflects more stable market conditions, where stronger autoregressive effects are observed, while Regime 1 is characterized by higher volatility and a more pronounced impact of oil prices on the stock index.
2) In Regime 0, the stock index exhibits the greatest responsiveness to both its own past values and crude oil prices.
3) When the market is in Regime 1, the influence of oil price fluctuations on the stock index intensifies, accompanied by heightened market volatility.
4) Overall, the market tends to switch between these two regimes, as the transition probabilities (P_{01} and P_{10}) are relatively high and approximately equal.
5) The coefficients related to gold prices indicate a moderate effect on the stock index, which is more significant under Regime 0 compared to Regime 1.
6) In general, the Markov-switching model reveals that the structure of inter-market relationships is dynamic, and the influence of oil, gold, and the stock index varies depending on market conditions.

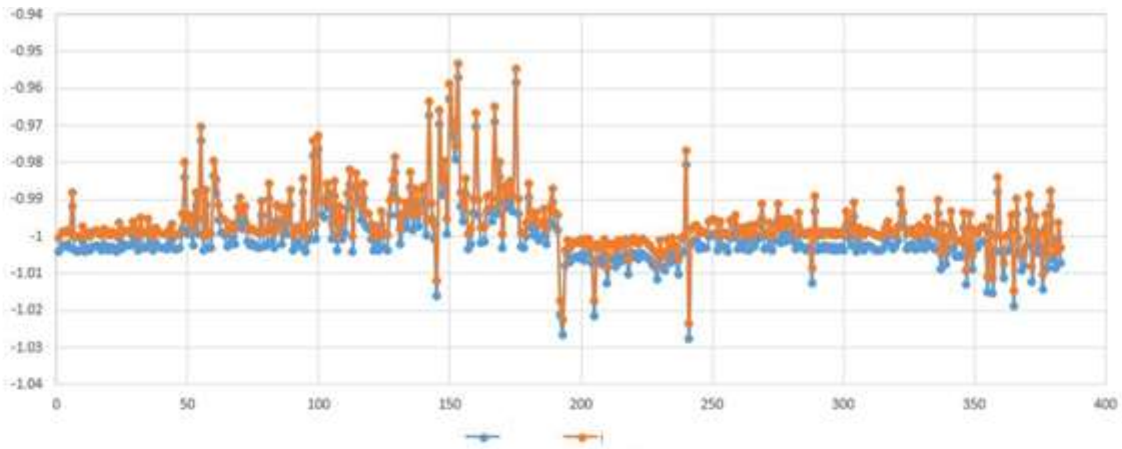
These findings suggest that shifts in market regimes significantly alter the manner in which oil and gold markets impact the stock index. The applied model has successfully captured and analyzed these dynamic interdependencies.

Dependent variable lch	Dependent variable ls	Dependent variable lh	Variables	
0.19	0.66	0.57	lh t-1	Regime 0
0.38	0.57	0.53	lh t-2	
0.15	0.08	0.83	Ls t-1	
0.67	0.58	0.11	Ls t-2	
0.45	0.22	0.97	Lch t-1	
0.57	0.95	0.43	Lch t-2	
0.80	0.08	0.33	lh t-1	Regime 1
0.30	0.77	0.30	lh t-2	
0.84	0.73	0.95	Ls t-1	
0.51	0.25	0.89	Ls t-2	
0.45	0.54	0.61	Lch t-1	
0.09	0.68	0.68	Lch t-2	
0.13				P00
0.44				P01
0.42				P10
0.35				P11
1754.6874				LNL
274.62				LR-TEST

4.6. The output charts of the MS-VAR-FIAPARCH-cDCC model

In this section, to examine the status of risk hedging, the variables of the Markov Switching model have been combined with the GARCH model. The resulting output charts are presented as follows.

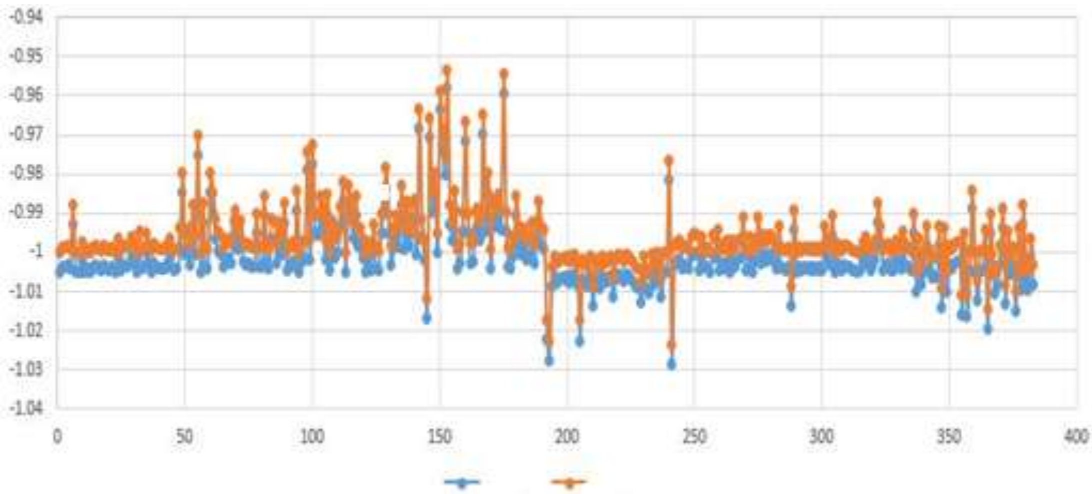
The combined MS-VAR-FIAPARCH-cDCC model reveals that the volatility of the stock and gold markets exhibits dynamic temporal characteristics, with differing behaviors across various periods. The presented chart illustrates the results of the combined MS-VAR-FIAPARCH-cDCC model employed to investigate risk hedging between the stock index market and gold returns over a sample period of approximately 400 observations. This model captures the dynamics of the conditional correlation structure between the two assets by accounting for heteroscedasticity, volatility clustering, and regime-switching behaviors within the markets.At first glance, it is evident that the values of both series predominantly lie within the range of -1.02 to -0.96.



Hedging Effectiveness Chart for Stocks and Gold ((Blue lines: Gold return – Red lines: Stock index)

These values represent the risk hedging ratios between the assets. The negative sign of the ratio is expected, as gold the second asset is typically utilized to hedge the risk of the stock index the first asset resulting in an inverse relationship manifested as a negative hedging ratio.The volatility associated with the stock index is notably higher than that of gold returns, indicating that risk hedging in the stock market exhibits more dynamic and volatile behavior compared to gold. This suggests that the stock market is more susceptible to market shocks and regime changes. In contrast, the hedging ratios related to gold demonstrate less dispersion and relatively more stable behavior, reflecting gold's role as a traditional and more stable hedging asset. Between observations 100 and 200, the hedging ratio for the stock index displays pronounced fluctuations, likely attributable to a regime shift identified by the MS-VAR model. Furthermore, since the FIAPARCH component accounts for heteroscedasticity and asymmetric volatility, some sharp fluctuations in the data may be due to the market's strong reaction to negative shocks. The cDCC model dynamically updates the conditional correlation between the two assets over time, revealing that the dependence between gold and stocks is neither stable nor constant. This time-varying correlation causes the optimal hedging ratio to fluctuate, implying that static hedging strategies may be inefficient and necessitate continuous monitoring and adjustment. Moreover, in the interval approximately between observations 250 and 350, the convergence of the lines corresponding to gold and stock returns increases, indicating a rise in correlation between these assets during this period. Under such conditions, the effectiveness of gold as a hedging instrument may diminish, as higher correlation implies greater common volatility.

The integrated MS-VAR-FIAPARCH-cDCC model demonstrates that stock and oil markets dynamically oscillate between different volatility regimes, which is crucial for identifying periods of high and low risk. The FIAPARCH analysis reveals the presence of long memory in volatility and asymmetric shock responses whereby negative news tends to generate stronger market reactions than positive news. Stock market volatility is found to be more intense and reactive, particularly influenced by macroeconomic news and monetary policy shifts, whereas oil market volatility is primarily driven by fundamental factors such as supply and demand dynamics. The cDCC component captures the evolving conditional correlations between stock and oil markets over time, highlighting the importance of dynamic correlation structures in designing effective hedging strategies. By combining these modeling approaches, the framework significantly improves the detection of volatility shocks and enhances risk management conditions, allowing investors and policymakers to better anticipate and respond to fluctuations in interconnected financial markets.



Stock and Oil Risk Hedging Chart (Blue lines: Oil prices – Red lines: Stock index)

4.7. Optimal Hedge Ratio and Hedging Strategy

Following the analysis of the risk hedging charts, the optimal portfolio weight for gold-stock combinations in export-oriented industries and the OHR[8] between gold returns and the stock index of export-oriented sectors have been calculated. Additionally, the performance of the derived optimal hedge ratios estimated using the aforementioned volatility models has been assessed. The results also include the computation and presentation of the HE[9] index, which evaluates the efficiency of the applied hedging strategies.

Metal ores	**Ceramic tiles**	**Basic metals**	**Petroleum products**	**Chemical products**	**Cement**	
0.710	0.694	0.725	0.786	0.599	0.648	Average optimal weight
19.33	16.69	25.97	25.89	19.94	20.8	t statistic
-0.52	-0.60	-0.35	0.51	0.47	0.23	HE(%)
11.10%	6.40%	10.30%	11.50%	12.50%	6.70%	Average OHR

4.8. Findings and Interpretation of Hedging Efficiency Results

The results of this study reveal important insights into the role of gold as an effective hedging instrument within various export-oriented industries. Among the sectors analyzed, the petroleum products industry stands out as the most efficient in leveraging gold to hedge against market risks. This is evident from its superior hedging effectiveness compared to other industries. On the other hand, the ceramics and tile industry exhibits the least hedging efficiency, suggesting a weaker relationship between gold prices and the risk factors affecting this sector. A critical measure examined in this study is the optimal hedge ratio, which quantifies the extent to which gold positions should be held to offset exposure in industry-specific equities. For the chemical products industry, the optimal hedge ratio is estimated at 12.5%. This implies that for every 1,000 Rials of equity exposure in this sector, investors should hold approximately 125 Rials in short gold positions to minimize risk associated with stock price fluctuations. This relatively moderate hedge ratio indicates that gold serves as a meaningful but not overwhelming hedge in this industry. In stark contrast, the ceramics and tile sector requires a considerably smaller hedge ratio of only 6.4%. This lower ratio suggests that gold provides limited risk mitigation benefits for investors in this industry. The comparatively weaker linkage may be due to unique sector-specific factors that reduce the sensitivity of ceramics and tile equities to movements in gold prices, thereby diminishing the effectiveness of gold-based hedging strategies. Beyond hedge ratios, the study also investigates the optimal asset allocation weights of gold within diversified investment portfolios across different industries. The findings demonstrate that these weights generally exceed 50%, emphasizing the crucial role gold plays in portfolio construction. Specifically, in the petroleum products sector, the average optimal portfolio weight assigned to gold reaches an impressive 78%. This means that in a portfolio valued at 1,000 Rials, about 780 Rials should be invested in gold, with the remaining 220 Rials allocated to equities of the petroleum industry itself. This substantial allocation underscores the perceived value of gold as a safe haven and a key risk management tool in this sector.

A particularly notable insight from the analysis is the dynamic and time-varying nature of these optimal hedge ratios and portfolio weights. The results indicate that the effectiveness of gold as a hedging instrument fluctuates over time, influenced by changing market conditions, volatility, and sector-specific risk factors. Such temporal variability implies that static hedging strategies may be insufficient or even counterproductive, potentially exposing investors to avoidable risks. Consequently, the findings advocate for the implementation of flexible and adaptive portfolio management frameworks that can continuously adjust hedge ratios and asset allocations in response to evolving market dynamics. Investors and portfolio managers should therefore monitor market signals closely and revise their hedging approaches regularly to maintain optimal risk mitigation. In addition, the significant differences observed across industries highlight the importance of tailoring hedging strategies to sector-specific characteristics. The high hedging effectiveness of gold in the petroleum products industry likely stems from the strong economic and financial interdependencies between commodity prices and gold, as both serve as

[8] Optimal Hedge Ratio
[9] Hedging Effectiveness

global indicators of inflation and geopolitical risk. Meanwhile, the ceramics and tile sector's lower hedging effectiveness may reflect its relatively isolated exposure to such macroeconomic variables. Overall, the study confirms that gold remains a vital component in risk management and portfolio diversification strategies, especially within export-oriented industries exposed to significant market uncertainties. By quantifying the optimal hedge ratios and portfolio weights, this research provides practical guidance for investors seeking to enhance portfolio resilience through gold investments. These findings carry several practical implications. First, for industries like petroleum products and chemicals, integrating gold into investment portfolios can substantially reduce exposure to adverse equity price movements. Second, for sectors such as ceramics and tile, alternative hedging instruments or strategies may need to be considered given the limited effectiveness of gold in mitigating risks. Finally, portfolio management should embrace a dynamic approach, regularly recalibrating hedging positions to align with changing risk environments.

In summary, this study sheds light on the critical and evolving role of gold as a hedging asset across diverse industrial sectors. It underscores the necessity of sector-specific and time-sensitive strategies to fully capitalize on gold's risk reduction potential. Investors who incorporate these insights into their portfolio management practices are better positioned to safeguard their investments against market volatility and uncertainty.

5. Discussion and Conclusion

This study focuses on analyzing and designing a comprehensive model to examine risk contagion and hedging strategies across the oil, gold, and stock markets. To achieve this, a hybrid modeling approach combining the Markov-Switching Vector Autoregressive model (MS-VAR) with advanced conditional volatility models such as FIAPARCH and cDCC has been employed. This integrated framework allows for a nuanced analysis of key financial variables under different market regimes and conditions. The findings reveal that risk contagion among these markets is significantly influenced by regime shifts and structural volatility changes. Each asset class exhibits distinct behavior patterns depending on prevailing market conditions. According to the results derived from the MS-VAR model, the dynamics of the stock index, oil prices, and gold prices vary notably across different regimes. In more stable regimes, the stock market index is primarily influenced by its own past values, and the impact of oil and gold fluctuations is relatively minor. However, in unstable regimes, volatility intensifies and the influence of oil and gold on the stock market becomes more pronounced. Overall, the study confirms that regime-dependent modeling provides valuable insights into the time-varying relationships between these markets. It underscores the importance of adapting risk management strategies to evolving market conditions in order to effectively mitigate risk and optimize portfolio performance. The risk contagion analysis revealed that oil, as a highly volatile asset, has a significant impact on the stock market index. However, this effect varies over time depending on economic and political conditions. In certain periods, rising oil prices lead to an increase in the stock market index, while in other periods, oil shocks result in a downturn in the capital market. On the other hand, gold acts as an effective hedge against stock market volatility, especially during crises and periods of market instability. Linear models such as GARCH and ARIMA failed to accurately capture the dynamics of risk contagion. Therefore, the Markov-switching model was employed for a more precise analysis and yielded better and more accurate results. Furthermore, the results of the cDCC model indicate that the conditional correlation between assets is dynamic and changes over time, making it impractical to use a fixed hedging strategy under all market conditions. For instance, during periods when the correlation between gold and the stock index is negative, gold can serve as an effective hedging instrument. However, when this correlation becomes positive, it is necessary to revise and adjust the hedging strategies. Additionally, oil price volatility does not have an immediate impact on the stock market in all periods, but in the long run, a balance between the two markets tends to be established.The findings of the study revealed that in the face of severe oil shocks, investors can reduce the associated risks by adjusting the composition of their asset portfolios. From a policy perspective, this research highlights the importance of recognizing market dynamics and regime shifts. It recommends that financial institutions and policymakers design their financial and economic plans in a way that mitigates the negative effects of risk contagion across markets.Overall, the study demonstrates that risk contagion among the oil, gold, and stock markets is highly dependent on changing market conditions. The stability or volatility of each of these assets varies across different time periods. Therefore, risk hedging strategies must be tailored in accordance with these market fluctuations.

Recommendations Based on Research Findings

1) Examination of Economic and Geopolitical Shocks:
   Crises, sanctions, and economic shocks can increase the correlation and risk contagion among oil, gold, and stock markets. Utilizing regime-switching models such as Markov-Switching allows simulation of these shocks' impacts under varying market conditions. These results can assist investors in better managing risks arising from crises and help policymakers formulate strategies to mitigate the negative effects of such shocks.
2) Enhancement of Risk Contagion Forecasting Models:
   Combining machine learning methods with econometric models can improve the accuracy of risk contagion forecasts. Employing algorithms like neural networks and random forests to detect complex contagion patterns between markets can support investment managers in making smarter decisions and provide a comprehensive framework for volatility prediction.
3) Analysis of Central Banks' Monetary and Fiscal Policies:
   Changes in monetary policies, such as interest rate adjustments or quantitative easing, can significantly influence the way risk contagion spreads among oil, gold, and stock markets.
4) Development of Comprehensive Models for Portfolio Risk Management:
   Applying long-memory models such as FIAPARCH can enhance the understanding of long-term volatility and nonlinear patterns in oil, gold, and stock markets, facilitating the optimization of investment portfolios and risk management processes for long-term investors.
5) Analysis of Exchange Rate Volatility and Currency Policies:
   Exchange rate fluctuations can indirectly affect oil and gold prices, and subsequently the stock market. GARCH and Markov-Switching models have been employed to study these effects. The results can be effective in designing risk management strategies for multinational corporations and global investors, as well as assisting policymakers in controlling exchange rate volatility.

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