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Hedging Stock Price Risk With Gold During the Outbreak of the Covid Pandemic

Ali baghani [1*]
Mojtaba Karimi [2]
Azin Sadat OstadRamadan [3]

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Abstract

Risk contagion refers to the transmission of information across financial markets. However, for investors, minimizing risk is crucial, and one way to achieve this is by diversifying their investment portfolio across different markets. In this research, the focus is on managing investor risk in the capital market by hedging stock price risk with gold, particularly during the COVID-19 outbreak. The DCC (Dynamic Conditional Correlation) and ADCC (Asymmetric Dynamic Conditional Correlation) models were employed for this purpose. The data used for analysis encompasses the monthly prices of Bahar Azadi gold coin and company stocks from 2017 to 2022. The research findings indicate an asymmetric correlation between the price of Bahar Azadi gold coin and the stock price of selected chemical and basic metals companies during the research period. The optimal risk hedging ratios have significantly increased in all companies during the COVID period, implying higher risk hedging costs. The research also reveals that F_khas (Khorasan steel company) exhibits the highest risk hedging efficiency, indicating its effectiveness in using gold for risk hedging. On the other hand, the symbol of Sh_iran (Iran Chemical Industries Company) demonstrates the lowest efficiency in using gold for risk coverage. These results offer an opportunity for investors to optimize their risk hedging and asset allocation strategies.

Keywords: risk hedging, stock price, gold, COVID disease

[1] *Assistant Prof., Department of Accounting and finance, Faculty of Management and Accounting, South Tehran Branch, Islamic Azad University, Tehran, Iran. Ali.baghani.58@gmail.com,* ***(Corresponding author)****
[2] *Department of Financial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran. tabakarimi622@gmail.com*
[3] *Master of Economics, Islamic Azad University, Research Expert of Kowsar Insurance Company, Tehran, Iran. A.ostadramezan@gmail.com*

Introduction

Gold is an investment asset that has gained attention for its ability to hedge inflation and generate risk-adjusted returns (Gorton and Rouwenhorst, 2006). It has been favored by portfolio managers and investors due to its weak or negative relationship with stock market indices, allowing it to offset stock market losses, particularly in turbulent periods.

Numerous studies have explored gold's role as a safe commodity and hedge for stock market indices, considering its performance during different financial crises and market conditions. These studies have utilized methods such as dynamic conditional correlations for portfolio analysis (Basher and Sadorsky, 2016).

The global economy experienced a severe contraction, a decline in employment rates, and financial market collapses with the onset of the Covid-19 pandemic in early 2020 (Yousaf and Ali 2021, Shahzad et al., 2020). The impact was initially felt in the Chinese and Asian stock markets, which then spread to the rest of the world. During the first quarter of 2020, the Chinese and Japanese stock market indices dropped by approximately 15% and 25% respectively, while international gold prices showed an opposite trend, increasing by almost 6%. Investors, fearing the virus, sought refuge in the gold market for long-term stability and value (Beckmann et al., 2015; Shahzad et al., 2020).

The decline in stock prices during times of market stress led risk-averse investors to shift from high-risk investments like stocks to low-risk investments like gold. This increased the demand for gold and subsequently its price. However, the role of gold as a safe and hedging commodity for companies listed on the Tehran Stock Exchange has not been extensively studied during the widespread outbreak of Covid-19. This lack of information leaves investors uncertain about the strength and effectiveness of gold in mitigating risk in Iran's stock markets during this unique event.

This article investigates the role of gold as a hedging, safe, or diversifying commodity for selected listed companies during extremely negative market conditions caused by the Covid-19 virus. The study calculates time-varying conditional correlations between gold and the price of each selected stock. It compares the optimal weights, hedging ratios, and effectiveness of the gold-stock portfolio before and after the Covid-19 outbreak. Additionally, the drivers of the hedged portfolio's return are determined.

2. Theoretical literature

1.2. COVID and the shock caused by it on the economy.

Globalization and international economic integration have increased the interdependence of countries' economies, leading to greater influence from external factors. It is crucial to examine the effects of foreign shocks and international impulses on individual countries' economies. Regardless of the causes of these shocks, the interconnectedness of countries through trade and international stock exchanges has facilitated the contagion of economic shocks across borders. As a result, developed countries' economic shocks have transmitted to the financial sectors of other countries worldwide, with varying impacts depending on countries' trade relationships and links to the global economy.

The outbreak of the COVID-19 virus in early 2020 rapidly plunged the world into a social and economic crisis. Studies from the International Monetary Fund highlight three channels through which the virus's spread has impacted economies:

The first channel involves pressure on national budgets and a decline in countries' gross domestic product. To curb the transmission of the virus, governments have imposed restrictions that led to business closures and reduced employment. As a consequence, tax revenues have decreased, while social payments such as unemployment insurance have surged.

The second channel pertains to international trade. Despite stimulus packages aimed at preventing economic recessions, trade has experienced a sharp decline, particularly in developing countries heavily reliant on energy and raw material exports.

The third channel relates to financial markets. The economic downturn and decreased exports have weakened national currencies and devalued countries' stock markets.

2.2. Risk hedging

Risk measurement is a crucial aspect of risk management. Risk hedging involves consciously accepting another risk that has a negative correlation with the initial risk, rather than avoiding risk altogether (Radpour & Abdoh Tabrizi, 2009). It aims to create a portfolio of investments in financial markets that reduces the fluctuations in investment value.

Risk hedging involves investing in two markets, G and S, with the primary objective of using investments in the G market to offset the risk associated with investments in the S market. The key challenge lies in determining the optimal rate of risk hedging for each asset unit in the S market. This rate should aim to eliminate fluctuations in the asset portfolio's base asset price by leveraging the reverse movement direction of the asset price in the G market (Eskandari et al., 2014).

One approach to determining the risk hedging ratio is through maximizing utility and minimizing risk. This involves introducing an objective function and optimizing it (either by minimizing or maximizing) to extract the optimal risk hedging ratio. The portfolio composition should be chosen in a manner that minimizes fluctuations in portfolio value. When using gold for risk hedging, the decision variable is the amount of gold required to achieve this objective, which represents the optimal risk hedging ratio (Bahrami & Mirzapour Babajan, 2011).

1.2.2. Types of risk hedging strategies

Risk hedging is one of the most important methods of risk management, which is also more general. This strategy, which is carried out by means of financial derivatives, has two methods, direct and cross.

1.1.2.2. Direct Hedging

In direct hedging, the target asset and the base asset in the futures contract are the same, resulting in an optimal hedging ratio of 100%. The purpose of engaging in futures trading to hedge immediate asset price fluctuations is to minimize risk. When the spot price of a commodity decreases, the profit from the futures selling position offsets the loss from the spot transaction. Conversely, if the spot price of the commodity increases, the loss from the futures selling position counterbalances the profit from the spot transaction (Khabiri & Abdoh Tabrizi, 2017).

2.1.2.2. Cross risk Hedging

In indirect hedging, also known as cross hedging, the target asset and the base asset in the futures contract are different. Cross hedging involves using a correlated financial instrument to cover the financial risk associated with a particular business position. The goal is to mitigate risk by purchasing another financial instrument whose price movements are linked to the original instrument. In direct hedging, the risk hedging ratio is always 100% as the hedger enters a trading position equal to the intended buy or sell amount of the underlying asset. However, if the desired asset and the base asset in the futures contract are not the same, the optimal hedging ratio may not be 100%. In such cases, hedging 100% of the risk could exceed the desired limit (Khabiri & Abdoh Tabrizi, 2017).

2.2.2. Risk hedging theories

Selecting the appropriate asset for hedging purposes is a crucial condition for implementing risk hedging strategies. Ideally, the chosen asset should have a high price and its selection can be guided by the correlation coefficient. If there is a high negative correlation between prices, hedging can be achieved by taking the same position, i.e., buying or selling both assets simultaneously.

However, if there is a positive and high correlation between the assets, risk hedging should involve taking opposite trading positions for each asset. This means covering the asset in a buying futures position with the help of another asset in a selling position, and vice versa. Initially, risk hedging strategies assumed an equal amount of price fluctuations in the assets, known as a simple or one-to-one hedging strategy. According to this strategy, taking a position equal in magnitude but opposite in sign to the current position was considered sufficient to eliminate price risk (Di-Miguel et al., 2009). However, due to the imperfect correlation between future and current situations in the real world, the simple hedging strategy cannot be considered optimal and is associated with shortcomings (Brook et al., 2002).

Incomplete hedging arises from the lack of complete correlation, leading to the emergence of non-unit hedging ratios (Banada, 2017). When the objective is risk minimization, a hedging ratio of one may not necessarily be optimal. Recent studies have focused on addressing this imperfect correlation and have developed strategies such as minimum variance hedging (Lee et al., 2016). Consequently, there are three important theories in risk hedging literature: the traditional one-to-one theory, beta theory for risk hedging, and the theory of risk hedging portfolio. Each theory aims to improve the performance of risk hedging strategies by critiquing the previous theory and addressing its limitations.

Various hedging strategies are being developed to determine how to use other markets for hedging. Optimal portfolio construction has become a crucial question for investors, and using other assets like currency, gold, or oil to cover risk has become a risk management strategy. Additionally, understanding the volatility spillover relationship between two markets is essential for determining hedging coefficients and constructing optimal portfolios (Chang et al., 2011).

Estimating the optimal risk hedging ratio and portfolio weights is highly important based on research. This information provides investors with valuable insights when implementing risk hedging strategies (Huisman et al., 2009; Yao and Wu, 2012).

Previous Studies

In addition to investigating the relationship between gold and the stock market, researchers have presented appropriate risk hedging strategies in these markets using different methods. for example:

Yousaf et al. (2021)

Research examined risk hedging in Asian stock markets using gold during the COVID outbreak. Results indicated that gold was a suitable asset for mitigating stock price risk in most Asian stock markets[1] during this period. The optimal weight of the stock-gold portfolio was lower during the COVID period compared to the pre-COVID period, suggesting that investors should increase their gold investments during this time. Hedging effectiveness was generally higher in the sub-COVID period for most Asian stock markets.

Basher et al. (2016)

Conditional correlations between emerging market stocks, oil prices, VIX, gold prices and bond prices were investigated. The results show that in most situations, oil is the best asset to hedge the risk of stock prices in the emerging market.

Mohamed El Hedi Arouri et al. (2015)

They investigated the relationship between global gold prices and stock returns in China in order to provide risk hedging strategies. They derive optimal weights and hedging ratios for stocks and gold and show how these results can be used to adopt a hedging strategy.

Yen-Hsien Lee et al. (2021)

They investigated the formation of the portfolio of Haft Group stock prices and West Texas crude oil. The results showed that the hedging effect is the highest in Canada and the lowest in Japan. In addition, Japan has the highest optimal portfolio weight and the lowest risk hedging ratio.

Bazraei et al. (2021)

They studied the risk hedging of stock prices in stock exchange industries using exchange rates. The findings revealed a symmetrical correlation between the stock prices of these industries and the exchange rate during currency crises. In both crises, the most effective risk hedging was observed in multi-disciplinary industries and investments, respectively. The highest risk hedging coefficient values were found in multi-disciplinary industries during the first crisis and in banks during the second crisis. The banking industry had the highest weighted average value of the optimal portfolio in both currency crises.

Hatami et al. (2017)

They studied the dynamics of the optimal risk hedging ratio between stock and gold markets. Results indicated an increase in the optimal hedging ratio from 2009 to 2012, followed by a regime change in the trend from 2013 to 2016. Investors are advised to utilize the gold market for covering stock market risks and to include gold as a commodity alongside stocks in their asset portfolio.

Jahangiri and Hekmati (2015)

They studied the relationship between the Tehran Stock Exchange, currency and coin market, oil, gold, the American stock market, and the European stock market index. Findings revealed no significant spillover effects between markets during periods of low returns. However, when stock markets are in a low return state, the gold market serves as an intermediary market for transmitting shocks between major global stock markets and asset markets within Iran. Conversely, during a high return state, the oil market acts as the intermediary market for transmitting shocks to asset markets within Iran.

Elmi et al. (2014)

They studied the impact of structural changes in volatility on momentum transfer and volatility spillover between the gold and stock markets in Iran. Results indicated that impulses and spillover fluctuations between these markets were

[1] Stock market of China, Indonesia, Singapore, Vietnam, Pakistan and Thailand

bilateral. However, incorrect identification of structural changes led to confusion in evaluating impulses and spillovers in the variables under study.

Nikumram et al. (2014)

They studied the contagion of currency and gold market turbulence on the capital market of listed industries, distinguishing between export-oriented and import-oriented sectors. Results confirmed the contagion effect of the parallel currency market on export-oriented stock exchange industries. However, contagion was not confirmed by the parallel gold market. Additionally, the contagion effect of import-oriented industries from the parallel currency and gold markets was not confirmed.

Falahi et al. (2014)

In their study on Iran, they found a high conditional correlation between the exchange rate and gold coin returns, and a low conditional correlation between the stock market index and the exchange rate and gold coin returns. The study suggests that the stock market is a preferable investment option compared to other assets.

The present study differs from previous research by dividing the period into two sub-samples before and after COVID to optimize and compare cross-risk hedging. The study also considers the stock price index of different companies based on stock exchange industries. Risk hedging coefficients are extracted, and companies with the highest risk hedging efficiency are identified. Additionally, the study determines optimal portfolio weights for gold and stocks before and after COVID.

Research Methodology

This applied research investigates hedging the risk of stock prices with gold during the COVID-19 outbreak in the capital market. The research uses daily data for the Bahar Azadi gold coin price and the stock price index of selected companies from December 2017 to March 2022. Capital market information by different industries is obtained from the "tse.ir" website. The price data for the Bahar Azadi coin in the free market is collected by researchers from Tehran's reputable exchanges.

To calculate price efficiency, the logarithmic difference of consecutive stock prices and Bahar Azadi coin prices is used. The natural logarithm of the net price return is defined according to Equation (16).

$$r_t = \ln(P_t) - \ln(P_{t-1}) = ln\frac{P_t}{P_{t-1}} \qquad (1)$$

To extract the optimal portfolio weight, risk hedging ratio, and hedging efficiency before and after the COVID-19 crisis, it is necessary to identify the exact start and end points of the crisis. The research employs the modified Iterated Cumulative Sum of Squares (ICSS) algorithm method to identify structural breaking points, considering the wide sequence and conditional variance h heteroscedasticity of the COVID variable. The results of this test are reported in Table 1.

Table 1- ICSS structural Breaktest results

ICSS(κ^2)	ICSS(κ^1)	ICSS (IT)
Feb/22/2020	Feb/15/2020	**Feb/22/2020**
	Feb/22/2020	**June/20/2020**
	May/2/2020	

Source: Research findings

The results indicate a breaking point during the COVID epidemic, aligned with the global crisis that emerged in late 2019. Based on the revised ICSS test, the start date of the COVID crisis is identified as March 2020.

3.1. Dynamic correlation model

The symmetric dynamic conditional correlations (DCC) model, introduced by Engel (2002), and the asymmetric dynamic conditional correlations (ADCC) model, presented by Capillo et al. (2006), are used to examine the asymmetry of dynamic correlations between financial markets. The DCC model incorporates the Constant Conditional Correlation (CCC) model by Bollerslev (1990) and assumes that conditional correlations vary over time. This model can be estimated for multidimensional datasets using a two-step procedure. In the first step, conditional variances are obtained by estimating a series of univariate GARCH models. In the second step, coefficients for conditional correlations are estimated.

Suppose n.1 vector $\{y_t\}$ is a multivariate random process, and y_t is the logarithm of returns of stock indexes and the logarithm of returns of gold.

The innovation process has conditional mean $\varepsilon_t \equiv y_t - \mu_t$ conditional covariance matrix $\boldsymbol{H_t}$:

$$y_t = \mu_t + \varepsilon_t$$

$$\varepsilon_t = \boldsymbol{H}_{\boldsymbol{t}}^{\boldsymbol{1}/\boldsymbol{2}} z_t$$

$$z_t \sim f(z_t, o, l, v) \qquad (2)$$

$$\boldsymbol{H_t} = \boldsymbol{\sigma}(\boldsymbol{H_{t-1}}, \boldsymbol{H_{t-1}}, \dots, \boldsymbol{\varepsilon_{t-1}}, \boldsymbol{\varepsilon_{t-2}}, \dots)$$

where E_(t-1) (y_t)≡μ_t represents the average of y_t at time t-1, i.e. I(t-1). zt is a process with n.1 vector so that f(z_t;O,I,v).I.E(z_t z_t^') represents the multivariate T-Student density function:

$$f(z_t; o, l, v) = \frac{r\left(\frac{v+n}{2}\right)}{r\left(\frac{v}{2}\right)\left(\pi(v-2)\right)^{n/2}} \left(1 + \frac{z_t' z_t}{v-2}\right)^{\frac{v+2}{2}} \qquad (3)$$

where $\Gamma(.)$ is the gamma function and v is the degree of freedom for v>2. The t distribution is used because it allows modeling with thick tails. The DDC-GARCH model proposed by Engel (2002) can be successfully estimated for the large time-dependent covariance matrix. This DCC-GARCH model covariance matrix can be decomposed as follows:

$$\boldsymbol{H_t} = \Sigma_t^{1/2} \boldsymbol{C_t} \Sigma_t^{1/2}, \qquad (4)$$

where ∑_t^(1/2) is the diagonal matrix and there are conditional standard deviations along the diagonals, that is:

$$\Sigma_t^{1/2} = diag(\sigma_{1,t}, \sigma_{2,t}, \dots, \sigma_{n,t}), \qquad (5)$$

and c_t is the matrix of conditional correlations. The estimation method consists of two steps. In the first step, conditional variances σ_{it} for assets i=1,...,n are estimated using the univariate GARCH(1,1) model proposed by Bolerslov (1986):

$$\sigma_{i,t}^2 = \omega_i + a_i \varepsilon_{i,t-1}^2 + b_i \sigma_{i,t-1}^2, \qquad (6)$$

where parameters ω_i, a_i and b_i must be estimated.

In the second step, conditional correlations are estimated using the standardized residuals obtained from the first step. In particular, the time-varying correlation matrix has the following form:

$$C_t = Q_t^{*-1/2} Q_t Q_t^{*-1/2}, \qquad (7)$$

And the correlation matrix $\bar{\boldsymbol{Q}}$; $(z_{1,t}, z_{2,t}, \ldots, z_{n,t})' = (\varepsilon_1 \sigma_{1,t}^{-1}, \varepsilon_2 \sigma_{2,t}^{-1}, \ldots, \varepsilon_{n,t} \sigma_{n,t}^{-1})' Q_t = (q_{ij,t})$ is calculated as follows:

$$\boldsymbol{Q}_t = (1 - \alpha - \beta)\bar{\boldsymbol{Q}} + \beta \boldsymbol{Q}_{t-1}, \qquad (8)$$

In the above equation, z_t is the standardized residuals by the conditional standard deviation, that is, z_t is the standardized residuals of the unconditional covariance and $Q_t^{*-1/2}$ is the diagonal matrix consisting of the inverse roots of the diagonal squares of Q_t.

That is, $\boldsymbol{Q}_t^{*-1/2} = diag(q_{1,1,t}^{-1/2}, q_{2,2,t}^{-1/2}, \ldots, q_{n,n,t}^{-1/2})$. Therefore, the correlation coefficients, ρ_{ijt}, are given as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ij,t} q_{jj,t}}} \quad , i, j = 1,2, \ldots, n \text{ and } i \neq j, \qquad (9)$$

Since asymmetry is not considered in Equations 7 and 8, Capillo et al. (2006) extended the DCC model to allow for the leverage effect on the conditional correlations of asset returns and the effect curve of asset-specific news. The asymmetric generalized DCC (AG-DCC) model is expressed as follows:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) + A'^{z_{t-1}z'_{t-1}} + G'n_{t-1}n'_{t-1} + B'Q_{t-1}B, \qquad (10)$$

where the index function n.1, i.e. $n_t = I[z_t < 0] \circ z_t(I[0])$, takes the value of 1 when this argument is true and takes the value of zero otherwise.

The symbol "°" indicates the Hadamard multiplication and $\bar{Q}$ and $\bar{N}$ indicate the unconditional correlation matrices z_t and n_t. For $\bar{N} = [n_t n'_t]$, Q_t always becomes positive with probability 1 if $(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G)$ is always positive. If the matrices A, B, G are replaced by scalars α, β and γ, A-DCC(1,1) is separated from AG-DCC(1,1) model.

This study examines the asymmetric effect and does not account for asset-specific news. Using the models presented, it investigates whether the conditional correlations between gold returns and stock returns of various listed companies change over time. Additionally, it explores whether these markets experienced increases during the COVID period due to the associated shocks.

The ICSS algorithm (Inclan and Thiao, 1994) detects significant changes in variance caused by structural failures in the time series. It assumes the time series consists of normal, independent, and uniformly distributed observations. Initially, the time series has unauthorized stationary variance until a sudden, large, and unexpected event triggers a structural change in the variance. This process repeats over time, with NT representing the failure points in the non-conditional variance (Kang et al., 2011). The ICSS algorithm examines variance between failure points and the regular stretch. It is designed for conditions with conditional variance but is not suitable for processes like GARCH. Additionally, it assumes a normal distribution for the time series, which may not hold for financial data with thick-tailed distributions and skewness. Sunso et al. (2003) introduced the adjusted ICSS to address these issues for financial data with abnormal distribution and heteroscedasticity. The validity of the test results may be questioned if critical values are not properly adjusted. They did not modify Inclan and Thiao's test and called it the adjusted ICSS (Sansu et al., 2003).

3.3. Estimation of optimal hedge ratios (OHR)

The logic of the minimum strategy of variance is to invest in that amount of assets (β), which minimizes the Return variance of a portfolio consisting of stock and gold positions. If we assume R_t^H hedged portfolio return.

$$R_t^H = R_t^S - \beta R_t^G \qquad (11)$$

That R_t^S is stock return and R_t^G is gold returns and β is hedge ratios.

If the investor is in the long position in the stock, the risk hedge ratio is the amount of gold that must be sold for risk cover. he optimal hedge ratio by definition is that value of β_t that minimizes the conditional variance of the hedged portfolio (Bailey and Myers, 1991).

$$\beta_t^* | I_{t-1} = \frac{Cov(R_t^S, R_t^G)}{Var(R_t^e)} \qquad (12)$$

Volatility estimates from various types of GARCH family models can be used to construct the optimal hedging ratio (Kroner and Sultan, 1993)

After the conditional correlation matrices of the time variable $\rho_t^{DCC\ and\ ADCC}$ are estimated, the optimal risk hedging ratio corresponding to each coefficient is calculated as follows:

$$\beta_t^i = \frac{\rho_t^i \sqrt{h_t^S h_t^G}}{h_t^G}, \qquad i = ADCC\ and\ DCC \qquad (13)$$

that h_t^S and h_t^G express the conditional variance of stock and gold returns, respectively, which are extracted from the estimation of ARMA-GARCH models (Lee et al., 2014). The risk hedging coefficient means that the trading position of buying (long) one rial in the stock price index should be covered by the selling (short) position of $\beta_{SG,t}$ rials in gold. In order to compare the performance of OHR ratios obtained from the above multivariate conditional volatility models, Ku et al. (2007) defined a hedging strategy efficiency index (HE) which is obtained based on the following relationship:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \qquad (14)$$

that the variance of the hedged portfolio is obtained based on the variance of the return rate of the hedged portfolio R_t^H, and the variance of the unhedged portfolio is the same as the variance of the returns of stocks R_t^S. Larger values of HE indicate greater efficiency in hedging and greater reduction in risk. The model of optimal portfolio weights is:

$$W_{SG,t} = \frac{h_{S,t} - h_{SG,t}}{h_{G,t} - 2h_{SG,t} + h_{S,t}} \qquad (15)$$

$$W_{SG,t} = \begin{cases} 0, & if \quad W_{SG,t} < 0 \\ W_{SG,t}, & if \quad 0 \le W_{SG,t} \le 1 \\ 1, & if \quad W_{SG,t} > 1 \end{cases} \qquad (16)$$

where W_(SG,t) is the weight of the optimal holding of gold in the portfolio of one rial at time t.

h_(SG,t) is the conditional covariance between the stock price index and gold price, h_(SG,t) is the conditional variance of the stock price index and h_(G,t) is the conditional variance of the gold price at time t. Also, the weight of the stock price index in the gold-stock portfolio is equal to (1-W_(SG,t)(.

Findings

Table 2 presents the descriptive statistics of stock returns and exchange rates during the non-crisis and COVID crisis periods. The crisis period is characterized by an increase in standard deviation and changes in skewness. Most companies experienced higher standard deviations during the COVID crisis, with the highest standard deviation belonging to F_meli (National Iranian Copper Industries Company). The lowest standard deviation was observed for F_khas. Average values decreased for all companies except Sh_pdis (Pardis Petrochemical Company).

Skewness values increased for most companies during the COVID crisis, except for Sh_fan, F_khas, Sh_iran, Sh_pdis, F_meli, and F_oulad (Isfahan Mubarake Steel Company). The highest skewness was observed for F_khas during the COVID crisis, while the lowest and highest skewness values before the COVID crisis were associated with Shepdis. The Jarque-Bera statistic indicates a non-normal and asymmetric distribution for all companies.

Unit root tests indicate that all variables are stationary at the 99% significance level. The LM-ARCH test does not reject the presence of heteroscedasticity in the variance of the investigated variables. The return density functions of these assets have a wide sequence and a long peak, as indicated by the higher skewness coefficients compared to the normal density function.

Table 2- Descriptive statistics of the variables

Variable	symbol	Average		standard deviation		Skewness		Jarque-Bera statistics		unit root test		LM-test
		Before covid	After covid	Before covid	After covid	Before covid	After covid	Before covid	After covid	ADF	Break Point ADF	LM-ARCH
طلا	COIN	0.28	0.15	2.6	2.22	11.49	10.84	1398***	1386***	-29.53***	-30.35***	38.41***
شفن	P11	0.38	0.27	2.37	3.01	17.45	8.36	3889***	595***	-24.07***	-24.47***	2.35*** 2
فخاس	P12	0.42	0.04	2.31	2.05	23.46	21.64	8414***	7556***	-24.53***	-23.27***	5.08*
شاراك	P18	0.3	0.24	2.71	3.1	6.91	3.4	285***	5*	-22.46***	-22.61***	22.38***
تاپيكو	P24	0.25	0.2	2.41	3.17	4.83	4.49	62***	51***	-22.64***	-22.75***	8.02***
شيران	P29	0.51	0.04	3.2	3.14	6.67	5.09	267***	102***	-22.88***	-23.46***	25.35***
فخوز	P34	0.33	0.25	2.5	3.2	13.44	7.73	2077***	537***	-23.89***	-24.61***	5.09*
شپديس	P39	0.28	0.34	2.25	2.93	4.31	2.54	34***	5*	-23.43***	-23.35***	33.68***
فملي	P42	0.42	0.36	2.74	3.25	20.77	7.49	6019***	496***	-23.97***	-24.20***	14.51***
فولاد	P43	0.41	0.29	2.49	3.03	19.74	5.62	5617***	172***	-22.20***	-21.96***	15.97***

*** Significance at the probability level of .01; ** Significance at the probability level of .05; * Significance at the probability level of .10. **Source: Research findings**

4.2. Estimating the research model

The research begins by estimating the pattern of asymmetric dynamic correlation over time for companies in the chemical products and basic metals industries. If the variables do not follow this pattern, the symmetric dynamic correlation model is estimated. Due to the non-normality of returns, the DCC and ADCC models are estimated using a multivariate t distribution. Table 3 presents the estimation results of the DCC and ADCC models, showing the correlation between stock returns of companies in the chemical products and basic metals industries with gold returns.

In the table, μ represents the constant vector of the average equation and refers to a vector of coefficients for the autoregressive term (AR(1)) in the average equation. The classification of companies into different industries is done to investigate whether different groups exhibit different reactions to gold during the COVID crisis.

Table 3- Estimation of dynamic conditional correlation model parameters

correlation		ADCC			DCC		
		Coefficient	t statistic	probability	Coefficient	t statistic	probability
Chemical products industry companies	θ1	0.02	2.404	0.016	0.025	3.18	0.001
	θ2	0.878	30.27	0	0.899	26.44	0
	θ3	0.072	1.966	0.047	-	-	-
	λ	4.753	9.972	0	4.732	12.61	0
Basic metal industry companies	θ1	0.066	1.734	0.083	0.126	3.72	0
	θ2	0.494	4.803	0	0.42	4.87	0
	θ3	0.439	2.165	0.031	-	-	-
	λ	2.544	9.797	0	2.636	8.679	0

*** Significance at the probability level of .05;* *Source: Research findings*

In Table 3, the results indicate that the θ3 coefficient is significant at the 5% level for both groups of companies, indicating an asymmetric correlation between the price of Bahar Azadi coin and the stock price of chemical products and basic metals group companies. The ADCC model confirms the significance of the α and β coefficients for all variables, indicating short-term persistence (α) and long-term persistence (β). The α coefficients are lower than the β coefficients, indicating that long-term persistence is stronger. The positive and significant θ3 coefficient suggests that positive residuals have less impact on increasing conditional volatility compared to negative shocks of the same magnitude. The θ1 and θ2 coefficients for both shocks are positive and significant at the 5% level. Their sum is less than one, indicating that the asymmetric dynamic conditional correlations revert to the mean.

After estimating the DCC and ADCC models, the optimal portfolio weights for the non-crisis and crisis periods have been calculated separately for different listed companies. The change in optimal portfolio weights during the COVID crisis compared to the non-crisis period has also been examined. The optimal risk hedging ratios (OHR) between gold returns and the returns of various listed companies have been calculated. Tables 4 and 5 provide the performance of the OHR obtained from different volatility models during the crisis and non-crisis periods, evaluated based on the risk hedging efficiency (HE) index.

Table 4- Summary of statistics of optimal portfolio weights

	Pre-The covid_19 crisis Mean Optimal Weights	The covid_19 crisis Period Mean Optimal Weights	Difference in Optimal weights1	t–stat difference2	Prob
					t–stat
p11	0.438	0.561	0.123	-8.57	0
p12	0.368	0.371	0.002	-0.1	-0.91
p18	0.57	0.642	0.072	-5.85	0
p24	0.54	0.66	0.12	-10.28	0
p29	0.638	0.67	0.032	-2.66	0
p34	0.686	0.758	0.072	-6.91	0
p39	0.538	0.638	0.1	-8.7	0
p42	0.719	0.774	0.055	-5.12	0
p43	0.706	0.761	0.054	-5.25	0

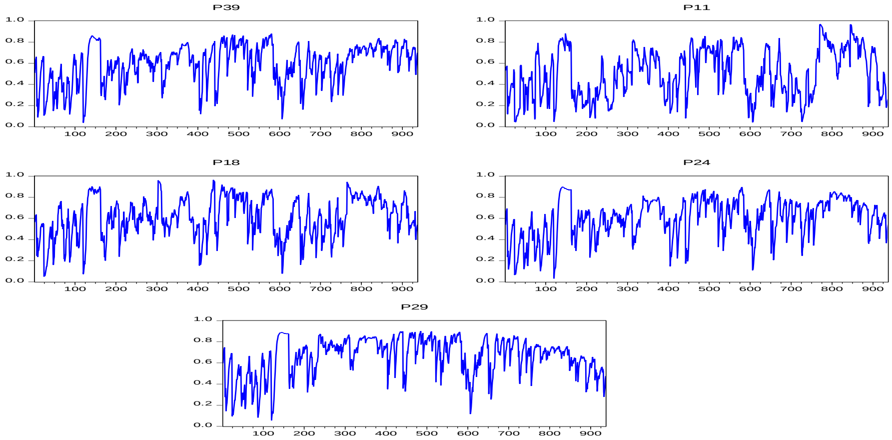
** Significance at the probability level of .05 **Source: Research findings**

1- The average optimal weight during the COVID crisis minus the average optimal weight before the COVID crisis.
2- The t-statistic is calculated for the difference of the average optimal weight.

The optimal weights were estimated using the equations provided in the third part. The findings indicate that the optimal weights for F_khas company are less than 50% in both periods. Therefore, investors should allocate less than half of their portfolio to these companies in order to reduce portfolio risk without sacrificing returns.

Interestingly, the optimal weights appear to be time-varying, as shown in Charts 1 and 2, and change during the COVID period. For example, the optimal weight of the chemical products industry in the Gold and Sh_fan portfolio increased from 0.438 in the pre-COVID period to 0.561 during the COVID period. This change may be attributed to the recovery of gold towards the end of the sample period while chemical companies continued to experience large losses.

Chart 1- The trend of the optimal weight of gold assets in the asset portfolio of the chemical group



Source: Research findings

Chart 2- The trend of the optimal weight of gold assets in the asset portfolio of the basic metals group

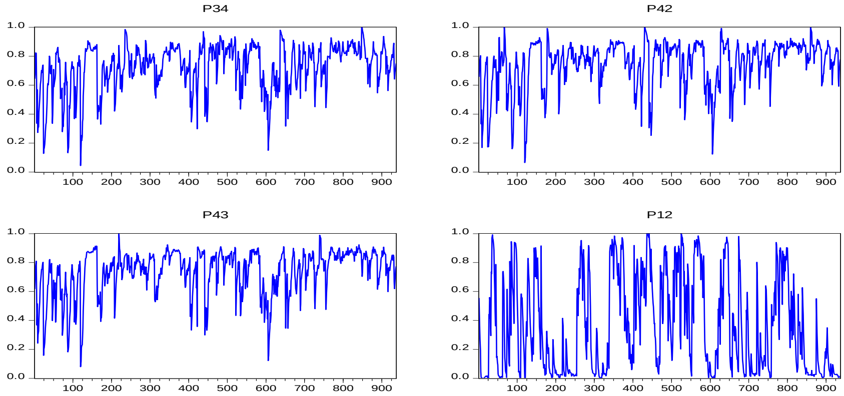


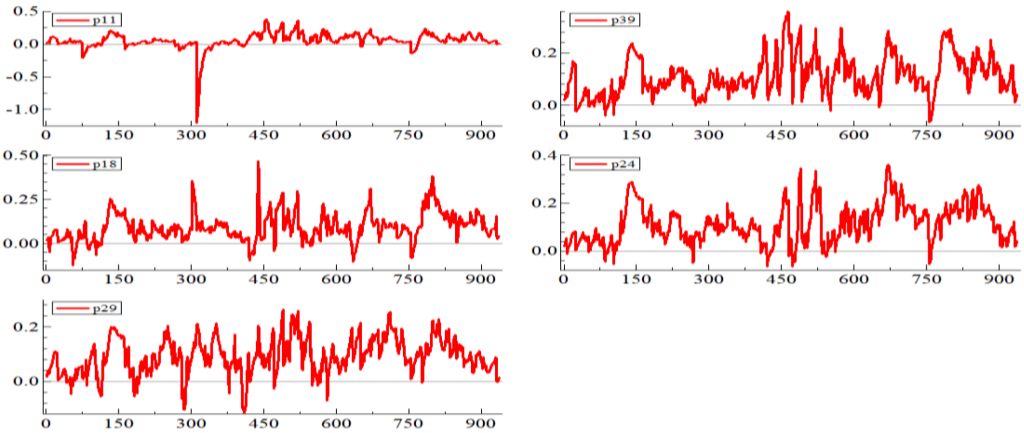
Table 5- Summary of statistics of risk hedging coefficient

	Pre-The covid_19 crisis Mean Beta	The covid_19 crisis Period Mean Beta	Difference in Beta[1]	t–stat difference[2]	Prob t–stat
p11	0.006	0.096	0.09	- 11.6	0
p12	0.074	0.083	0.009	- 0.8	- 0.41
p18	0.07	0.111	0.041	- 8.046	0
p24	0.085	0.136	0.051	- 10.24	0
p29	0.073	0.109	0.037	- 8.7	0
p34	0.091	0.138	0.047	- 5.29	0
p39	0.083	0.137	0.054	- 11.72	0
p42	0.18	0.199	0.018	- 1.89	- 0.06
p43	0.119	0.149	0.03	- 4.24	0

The findings indicate a significant increase in the optimal risk hedging ratios for all companies during the COVID period, suggesting higher risk hedging costs. Interestingly, the optimal risk hedging ratios appear to be time-varying, as shown in Charts 3 and 4, and change during the COVID period.

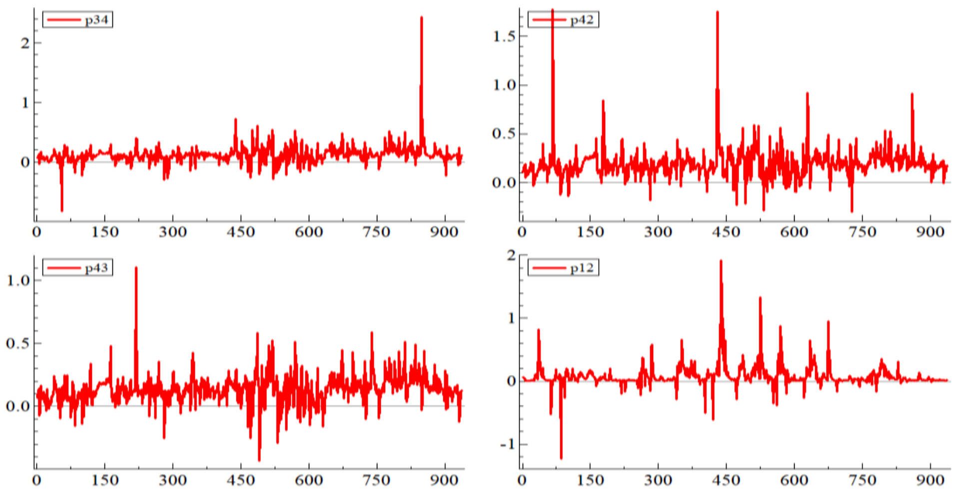
Table 6 presents the results indicating that F_khas company has the highest efficiency in risk hedging before COVID and during the COVID crisis. This suggests that F_khas is most effective in using gold to mitigate risk among the different companies. Conversely, the lowest efficiency is observed for the Sh_iran symbol, indicating that Sheeran's symbol is the least efficient in using gold for risk hedging among the different companies.

Chart 3- Trend of optimal risk hedging rate of chemical group companies



Source: Research findings

Chart 4- Trend of optimal risk hedging rate of basic metals group companies



Source: Research findings

Table 6. Summary of risk hedging efficiency statistics

	re-The covid_19 crisis HE	The covid_19 crisis HE	Difference in HE
p11	6.589	4.26	-2.329
p12	18.257	16.409	-1.848
p18	3.123	4.311	1.188
p24	2.848	5.366	2.518
p29	2.279	3.378	1.098
p34	10.746	14.812	4.065
p39	2.48	4.921	2.441
p42	14.498	12.984	-1.514
p43	9.515	13.278	3.763

Source: Research findings

Conclusion

This research aimed to investigate the possibility of hedging stock market risk by using gold during the COVID outbreak. DCC and ADCC models were employed, utilizing monthly data from 2017 to 2022 for Bahar Azadi coin prices and company stock prices. The results revealed an asymmetric correlation over time between Bahar Azadi coin prices and stock prices of the analyzed companies. The findings showed a significant increase in optimal risk hedging ratios for most companies during the COVID period, indicating higher risk hedging costs. F_khas company demonstrated the highest risk hedging efficiency before and during the COVID crisis, while V_sapa and V_omid symbols exhibited the lowest efficiency in using gold for risk hedging.

Based on these results, it is recommended that investors closely monitor the price trend of Bahar Azadi coin in their analysis. Considering the contagion and intensity of fluctuations transferred between financial markets can help preserve asset value and mitigate losses. Diversifying risk among stable financial assets can reduce potential investment losses. Additionally, investors are advised to consider the risk hedging index when assessing financial markets.

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