

THE HEDGING POWER OF GOLD AGAINST INDIAN EQUITY SECTORS

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ABSTRACT

This study investigates gold's ability to hedge against volatility in the Indian equities market, with an emphasis on the auto and energy sectors, by employing the GARCH Model. The findings show that gold has moderate hedging potential, notably in the energy sector, where volatility persists. However, in the car sector, shocks have a short-lived impact, reducing gold's effectiveness as a long-term hedge. Despite its capacity to reduce volatility, gold's negative average returns and the model's instability emphasise its shortcomings as a reliable hedging strategy.

Keywords: Gold, Hedging Power, Indian Equity Sectors, Auto Sector, Energy Sector, GARCH.

1. INTRODUCTION

In China, there is a saying that goes, collect antiques in times of prosperity, and buy gold in times of trouble. The statement means that gold is frequently referred to as a safe haven and a store of value during times of financial crisis and societal instability. In recent decades, financial instruments have developed substantially, increasing the system's dangers. So, even in a stable age, investors require a safe haven to prevent potential threats (Dee et al., 2013). Gold, due to its unique characteristics, has traditionally been regarded as a secure asset. For thousands of years, gold has served as both a store of value and a method of exchange. It has been noted that gold represents wealth "at all times and in all places". Gold also exhibits features of a financial asset. In times of uncertainty, when investors are afraid to trade and asset values become murky, gold activity may grow due to the relative simplicity of the gold market. As a result, gold might become an appealing investment, particularly during times of financial market volatility (Baur & Mcdermott, 2010). According to (Baur & Lucey, 2010), gold is commonly referred to be a safe asset for a variety of reasons, including the fact that it was one of the original forms of money and was traditionally used to hedge against inflation. Another factor could be that gold is not connected with other sorts of investments.

Over the last few decades, India has emerged as one of the world's fastest expanding economies, attracting both domestic and international investment. However, despite its rapid expansion, the market is very volatile, driven by macroeconomic factors, geopolitical events, and sector-specific developments. Understanding the volatility and associated risks of various sectors in the Indian equity market is critical for investors, policymakers, and financial institutions that want to make educated decisions. Volatility is an important indicator of risk in financial markets, representing the degree of fluctuation in asset prices across time. In India, the equities market has been highly vulnerable to both global and domestic issues, such as crude oil price variations, monetary policy changes, trade conflicts, and political uncertainty. The NIFTY 50 Index, which represents the top 50 companies in various industries, frequently replicates the larger market's volatility. However,

different sectors within the index have varying levels of risk, making it critical to examine their particular volatility profiles. Indian stock sectors, including finance, technology, healthcare, cars, and energy, have specific issues that affect risk levels. Like, the energy sector, especially in a country like India that relies significantly on imports for fuel, is sensitive to global energy price variations and renewable energy transitions, and the auto sector, is sensitive to inflation in the country. Therefore, the primary objective of this study is to analyse the volatility patterns of the Indian equities market at the sectoral level and examine gold's usefulness as a hedging asset against sectoral risk, particularly in the face of market volatility. By doing so, it hopes to provide practical information for investors looking to balance their portfolios and protect against negative market fluctuations.

2. LITERATURE REVIEW

There has been extensive research done on the correlation between gold and other financial assets, with regards to hedging and safe haven properties. Baur Lucey (2010) and Baur Mcdermott (n. d.) were the first to define an assets hedge or safe haven status. They did find that gold was a safe haven for stocks, but only in mature markets, and even then it was only a weak safe haven. Hood Malik, (2013) examined the hedging and safe haven attributes of gold, silver, and platinum relative to the US market volatility index (VIX). They concluded that the VIX was a better hedge against stock market risk than gold. (Dee et al., 2013) investigated the hedging ability of gold against stock and inflation risks in the Chinese stock market, determining that gold may hedge these risks for long-term investors but not for short-term investors. Furthermore, they discovered that gold did not serve as a safe haven for stock or inflation risk in China's market. (Capie et al., 2005) investigated the relationship between gold and exchange rates and discovered that gold has a negative and inelastic relationship with the US dollar, sterling-dollar, and yen-dollar exchange rates. But the strength of this relationship changed as time passed due to political reasons. Quantile regression has become a crucial instrument in financial studies, especially in contagion effect and market asymmetry researches. (Cappiello et al., 2005) used quantile regression to investigate contagion effects between foreign financial markets, discovering that contagion was more evident during bearish market conditions. (Mensi et al., 2014) applied the quantile regression technique to examine the asymmetric relationship between BRICS markets and global drivers and found that these markets have different reaction to these drivers in bearish and bullish market conditions. Also quantile regression has been applied in finance to estimate value-at-risk (Gaglianone et al., 2011), (Baur Lucey, 2010), (Baur Mcdermott, n. d. who examined gold as a safe haven asset and found that it does offer protection against stock market losses, but only during certain times, in some markets, and for some time periods. Other research, such as those by Hillier et al. (n. d. and Ziaei (2012) look at gold prices and how they affect stock and bond markets, and they find that there are different relationships in different parts of the world and at different points in time. Another thing that has been on my mind is the correlation between gold prices and inflation. Ghosh et al. (2004) found a positive long-run relationship between gold prices and inflation, suggesting that gold could serve as a hedge against inflation. Other studies though have produced conflicting results indicating that real interest rates, exchange rates, and default risk can all effect the relationship between gold and inflation. The study by Shakil et al. (2018) in this journal adds to this literature by looking at the connection between gold prices and economic variables in Saudi Arabia, one of the largest oil producers in the world. Using the ARDL (Autoregressive Distributed Lag) technique

and monthly data from 2011 to 2015, the authors provide valuable insights into the dynamics of gold prices in Saudi Arabia. Always been a huge investment, it is always a hedge or safe haven in times of financial instability. Gold's function as a safe haven from the stock market has been tested time and time again in all sorts of financial markets. (Baur Lucey, 2010) were the first to actually examine and define gold's hedge and safe haven properties, their strong and weak forms. Further research by (Baur Mcdermott, n. d. and (Ciner et al., 2013) confirmed that gold is a hedge for the US stock market especially in times of economic turmoil.

Further research based on this new perspective would be interesting in order to study gold's role in a number of the world's markets. As Gürgün Ünalmiş (2014) points out gold has served as hedge and safe haven asset in numerous international cases. Similarly, Beckmann et al. (2015) noted the dynamic relationship between gold markets and stock markets and stated that gold's hedging abilities and safe haven status could deteriorate over time. Nguyen et al. (2016) Gold is the only thing that is stable when the markets are going crazy and everything goes haywire. However, recent research contradicts this, stating that gold's ability as a hedge and safe haven is not consistent among all market sectors. According to Jain Biswal (2016) Gold is on the whole a good hedge but its efficiency varies with the industry. This research is built upon by using a quantile-GARCH model to test gold's hedge and safe haven characteristics against Dow Jones industry indices in different time periods, which shows that gold as a hedge or safe haven is not consistent across different industries (Weng et al., 2020). (Salisu et al., 2020) investigated the role of different assets in inflation risk hedging. Although past research has been somewhat ambiguous with some declaring gold a fine hedge and others siding with stocks and real estate, this paper aims to shed light on the issue by analyzing in depth the inflation-hedging properties of various assets in the United States. To accomplish this, the authors use a multivariate modeling framework to examine the link between inflation and asset returns. They include asymmetry, time dilation, structural collapses, things that many other research of the sort seemed to overlook. The article uses these factors to give a truer account of what assets are most successful in inflation hedging. The research, however, suggests that stocks and real estate are very good inflation hedges in the US and that gold has no real inflation hedging properties. This remained the case even when taking into account different frequencies of the data and additional control variables. Even worse, the study shows that the efficacy of these assets as inflation hedges shifts over time, most dramatically around the global financial crisis. In general, this paper contributes to the existing literature by providing a more refined analysis of the relationship between stocks, gold, real estate and inflation in the US. The results are very helpful to those investors who are trying to save their money from the negative effects of inflation (Salisu et al., 2020). Gold has been a stable and reliable commodity to offset financial volatility and inflation. Gold is often a "safe haven" in times of economic turmoil, maintaining its worth and even showing negative correlations with the equities markets (Baur Lucey, 2010). The same thing goes for (Ghosh et al., 2004) in that the value of gold is very stable even when the market crashes so it is a security for investors. In analyzing the Indian stock market, gold's hedging ability does not hold true across all sectors, although gold is an effective hedge against movements in broad market indices and technology sectors such as Information Technology (IT). This effectiveness is due to the global nature of the IT industry, more closely tied to international gold value movements. Although much previous research has focused on gold as a hedge and a safe haven in many financial markets, its sector-specific hedging ability in the Indian stock market has not been extensively explored. Current literature mainly concentrates on

the correlation between gold and the overall market indices or specific sectors like information technology and real estate. But no thought has been given to how gold affects other industries like cars and electricity. That is particularly apparent because these businesses operate in such a distinctive market place and are vulnerable to so many economic dangers.

This study will examine gold's hedging capacity, particularly in the Indian auto and energy sectors, in order to gain a more nuanced picture of gold's sectoral performance as a hedge in emerging economies.

3. RESEARCH METHODOLOGY

The study examines the Indian equities market, particularly the energy and auto industries, from year 2014 to 2024. The description and source of the variables are presented in the Table1.

Table 1: Variable Description (Source: Author Generated)

Variable Name	Source	Symbol
NIFTY Auto Index	Yahoo Finance	NIFAI
NIFTY Energy Index	Yahoo Finance	NIFEI
Gold Price	Indian Bullion and Jewellers Association	GP

The primary goal is to investigate the hedging capacity of gold in these sectors using the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) approach, which is a model designed to capture time-varying volatility in asset returns. The GARCH approach is especially valuable in this context because it takes into account time-varying risk and uncertainty, allowing for a more precise investigation of the dynamic link between gold and sector-specific stock indices. By modelling return volatility, GARCH provides a better understanding of how gold might be used as a hedge against market volatility in certain industries.

To improve the analysis's robustness, the study will first perform a pre-test utilising the ADF (Augmented Dickey Fuller) test to detect stationarity in the time series data. Stationarity is critical when working with time series data from the previous decade since it assures that the data's statistical properties do not vary over time, allowing for effective model estimation. The GARCH model will then be used to investigate volatility spillovers and the hedging efficacy of gold in India's auto and energy sectors.

Stationarity Test

The study to ensure the stationarity of the variables will conduct the Augmented Dickey Fuller (ADF) to check for the presence of a unit-root. For conducting the test for stationarity, we have used the percentage change in variables $\frac{((n-(n-1))}{n-1}$ instead of absolute values.

Augmented Dickey Fuller (ADF) Test

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^m \alpha_i \Delta Y_{t-1} + \epsilon_t \dots \dots \dots (1)$$

ϵ_t is the pure white noise error term

ΔY_t is the first difference ($Y_{t-1} - Y_{t-2}$)

In ADF Test we must prove that $\delta < 0$ i.e., reject H_0 indicating that the time-series is stationary. Therefore, the hypothesis would be:

$$H_0: \delta = 0$$

$$H_1: \delta < 0$$

GARCH Model

This GARCH model defined below allows for capturing the dynamic volatility behavior in the returns of the Auto and Energy sectors, while assessing the hedging potential of gold against these equity sectors.

Mean Equation

For the mean model, **Autoregressive Fractionally Integrated Moving Average** ARFIMA(0,0), which simplifies to a constant mean with no autoregressive or moving average components:

$$r_t = \mu + \epsilon_t \dots \dots \dots (2)$$

r_t is the return of the Indian equity sector (Auto or Energy) at time t,

μ is the constant mean return

ϵ_t is the error term or residual at time t, representing the unpredictable shocks in returns.

Variance Equation

The variance of the error term ϵ_t follows a GARCH(1,1) process, which models time-varying volatility as:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \dots \dots \dots (3)$$

σ_t^2 is the conditional variance (volatility) at time t,

ω is a constant,

α is the coefficient for the ARCH (Autoregressive Conditional Heteroskedasticity) term, capturing the impact of past squared shocks ϵ_{t-1}^2

β is the coefficient for the GARCH term, capturing the impact of past volatility σ_{t-1}^2

4. RESULTS

NIFTY Energy Index

Table 2: Weighted Ljung-Box Test (Source: Author Generated)

Weighted Ljung-Box Test on Standardized Residuals		
	statistic	p-value
Lag[1]	0.772	0.3796
Lag[2*(p+q)+(p+q)-1][2]	1.516	0.3574
Lag[4*(p+q)+(p+q)-1][5]	2.253	0.5600
d.o.f=0		
H0 : No serial correlation		
Weighted Ljung-Box Test on Standardized Squared Residuals		
	statistic	p-value
Lag[1]	0.000435	0.9834
Lag[2*(p+q)+(p+q)-1][5]	1.666561	0.6989
Lag[4*(p+q)+(p+q)-1][9]	2.952205	0.7668
d.o.f=2		

The Ljung-Box test checks for autocorrelation (serial correlation) in the standardized residuals from the GARCH model. The presence of autocorrelation in residuals would suggest that the model has not fully captured the volatility dynamics.

The null hypothesis states that there is no serial correlation in the standardised residuals (that is, the model has accounted for all autocorrelation in the data). If the p-value is more than 0.05, we cannot reject the null hypothesis. This suggests that the residuals have no substantial autocorrelation, indicating that the model has correctly captured the volatility dynamics.

Therefore, in our model the p-values for the Ljung-Box test are greater than 0.05, this indicates no significant autocorrelation in the standardized residuals. Hence, the GARCH (1,1) model fits well, and there is no missed serial correlation.

Table 3: Weighted ARCH LM Test Estimates (Source: Author Generated)

Weighted ARCH LM Tests				
	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.1185	0.500	2.000	0.7307
ARCH Lag[5]	2.4388	1.440	1.667	0.3822
ARCH Lag[7]	2.7794	2.315	1.543	0.5561

The ARCH LM test detects leftover ARCH effects (autoregressive conditional heteroskedasticity) in the squared residuals. Remaining ARCH effects suggest that the model does not fully capture volatility clustering.

The null hypothesis states that there are no leftover ARCH effects in the squared residuals (i.e., no more volatility patterns to model). If the p-value is greater than 0.05, we fail to reject the null hypothesis, indicating that there are no lingering ARCH effects and that the volatility model correctly reflects the clustering in the dataset.

We do not reject the null hypothesis because our model's p-value is less than 0.05. This shows that

there are no substantial ARCH effects in the squared residuals, showing that the GARCH (1,1) model correctly captures volatility clustering.

Table 4: Mean and Variance Return Coefficients (Source: Author Generated)

	Estimate	Std. Error	t value	Pr(> t)
mu	-0.007931	0.006784	-1.1691	0.24236
omega	0.000077	0.000160	0.4781	0.63258
alpha1	0.000000	0.014760	0.0000	1.00000
beta1	0.986613	0.026260	37.5711	0.00000

Mean Return (μ)

The μ value in our model is not statistically significant, as the p-value is more than 0.05. The average return is negative but not statistically different from zero. This implies that, while gold's returns may trend downward in the dataset, the trend is insufficient to make definite inferences regarding its solo performance in hedging the energy sector.

Variance (ω), ARCH (α_1), and GARCH (β_1) Coefficients

The ω (omega) in the variance equation, while not statistically significant, indicates that the constant volatility is modest and not statistically significant. This implies that the volatility remains stable and unchanged across time. The coefficient of lagged squared residuals (α_1) is 0, indicating that previous shocks have no lasting impact on current volatility. This suggests that gold is not very sensitive to unexpected market fluctuations. The high value of β_1 and statistical significance indicate that volatility is particularly persistent. When volatility is strong, it tends to stay that way for a longer period.

Table 5: Nyblom Stability Test (Source: Author Generated)

Nyblom stability test			

Joint Statistic: 4.5372			
Individual Statistics:			
mu	0.05985		
omega	0.08491		
alpha1	0.07038		
beta1	0.08501		
Asymptotic Critical values (10% 5% 1%)			
Joint Statistic:	1.07	1.24	1.6
Individual Statistic:	0.35	0.47	0.75

The Nyblom Stability Test evaluates the stability of parameters in a time series model, such as the GARCH model you're examining. Specifically, it determines whether the parameters remain constant throughout time or fluctuate (showing instability). This test is crucial for determining whether the model can be depended on over time or if the parameters vary dramatically, thus reducing the model's predicting reliability.

The Joint Statistic value is significantly greater than the crucial values at 5%. As a result, the joint test demonstrates parameter instability, which means that at least one of the model's parameters varies over time. Individual stability statistics for μ , ω , α_1 , and β_1 are all lower than the critical values for individual statistics. This shows that each parameter is individually stable, despite the fact that the joint test suggests some overall instability when all parameters are evaluated together, implying that structural alterations in the model parameters may occur when considered collectively.

Table 6: Sign Bias Test (Source: Author Generated)

Sign Bias Test			
	t-value	prob	sig
Sign Bias	0.7358	0.46336	
Negative Sign Bias	0.6665	0.50641	
Positive Sign Bias	1.2186	0.22550	
Joint Effect	8.8446	0.03143	**

The Sign Bias Test helps to determine whether the model represents asymmetry in the impact of positive and negative shocks on volatility. The individual components of the Sign Bias Test indicate that there is no evident bias when examining the effects of positive or negative shocks alone, as the values are not statistically significant. This means that the model handles the shocks relatively well, without strong asymmetry between the volatility responses to positive and negative shocks. However, the joint effect is significant, which suggests that although the individual tests are not significant, when considered together, there is some level of asymmetry in the model.

Gold's volatility makes it a possible long-term hedge in the energy industry, as evidenced by the large β_1 coefficient. However, its low α_1 coefficient limits its effectiveness for predicting short-term volatility or rapid price fluctuations in energy markets. According to the Nyblom stability test, gold's hedging efficiency may change with time, providing hazards if used consistently. Furthermore, the sign bias test demonstrates that gold responds asymmetrically to market shocks, perhaps providing more protection against falls than rallies. Finally, while gold lowers volatility, its negative mean return suggests that it may not yield significant positive returns during the hedging period.

NIFTY Auto Index

Table 7: Weighted Ljung-Box Test Estimates (Source: Author Generated)

Weighted Ljung-Box Test on Standardized Residuals		
	statistic	p-value
Lag[1]	2.998	0.08335
Lag[2*(p+q)+(p+q)-1] [2]	3.450	0.10605
Lag[4*(p+q)+(p+q)-1] [5]	4.444	0.20359
d.o.f=0		
H0 : No serial correlation		
Weighted Ljung-Box Test on Standardized Squared Residuals		
	statistic	p-value
Lag[1]	0.5751	0.4482
Lag[2*(p+q)+(p+q)-1] [5]	2.5668	0.4918
Lag[4*(p+q)+(p+q)-1] [9]	5.1991	0.4008
d.o.f=2		

The Weighted Ljung-Box Test results determine if the GARCH model's standardised and squared residuals exhibit serial correlation (autocorrelation). The null hypothesis (H_0) for these tests is that there is no serial association. The p-values are higher than the conventional significance level of 5%, indicating that we cannot reject the null hypothesis of no serial connection at these lags. As a result, the standardised residuals appear to be uncorrelated, indicating that the model accurately captured the time-varying volatility.

Table 8: Weighted ARCH LM Test (Source: Author Generated)

Weighted ARCH LM Tests				
	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.2159	0.500	2.000	0.6422
ARCH Lag[5]	1.2958	1.440	1.667	0.6476
ARCH Lag[7]	1.9680	2.315	1.543	0.7241

The Weighted ARCH LM Test detects autoregressive conditional heteroscedasticity (ARCH) effects in the residuals of a time series model. The test's null hypothesis (H_0) states that there are no ARCH effects, implying that the model has not captured any additional volatility clustering. We do not reject the null hypothesis because our model's p-value is more than 0.05. This shows that there are no substantial ARCH effects in the squared residuals, showing that the GARCH (1,1) model correctly captures volatility clustering.

Table 9: Mean and Variance Return Coefficients (Source: Author Generated)

Optimal Parameters				
	Estimate	Std. Error	t value	Pr(> t)
mu	-0.013590	0.005627	-2.4151	0.015732
omega	0.003659	0.000669	5.4669	0.000000
alpha1	0.345303	0.107559	3.2104	0.001326
beta1	0.000000	0.244866	0.0000	1.000000

Mean Return (μ)

The mean return (μ) is negative, showing that the asset (gold) has slightly negative returns over the examined period. This is statistically significant, showing that, while gold may reduce volatility, it may not consistently generate positive returns.

Variance (ω), ARCH (α_1), and GARCH (β_1) Coefficients

Omega (ω). Omega denotes the baseline volatility in the absence of recent shocks or volatility persistence. The number is positive and statistically significant, indicating that there is a constant level of volatility in asset returns that exists regardless of market shocks. The short-term impact of past shocks on current volatility, denoted by α_1 , is statistically significant, indicating that gold responds moderately to sudden market shocks. Recent shocks have a noticeable impact on short-term volatility. This is an important attribute for a hedging asset since it responds to market fluctuations. β_1 represents the persistence of volatility, or how much past volatility carries over into the present period. The estimate for β_1 is effectively zero and not statistically significant. This suggests that once a shock occurs, volatility does not persist in the future. As a result, while gold reacts to immediate shocks, this reaction is transient, making gold a short-term hedge but not for long-term hedge for managing volatility.

Table 10: Nyblom Stability Test (Source: Author Generated)

Nyblom Stability Test				

Joint Statistic: 2.8061				
Individual Statistics:				
mu	0.14693			
omega	0.15134			
alpha1	0.08864			
beta1	0.14161			
Asymptotic Critical Values (10% 5% 1%)				
Joint Statistic:		1.07	1.24	1.6
Individual Statistic:		0.35	0.47	0.75

The Nyblom stability test evaluates the stability of parameters in a time series model, especially in GARCH models. The null hypothesis (H_0) assumes that the parameters are constant over time. If the test statistic exceeds the critical values, it indicates instability in the model's parameters. While each individual parameter (μ , ω , α_1 , β_1) appears stable on its own, the joint test indicates that the model's parameters are unstable overall.

Table 11: Sign Bias Test Estimates (Source: Author Generated)

Sign Bias Test		
	t-value	prob sig
Sign Bias	0.2511	0.8022
Negative Sign Bias	1.3403	0.1828
Positive Sign Bias	0.2092	0.8347
Joint Effect	4.8861	0.1803

The Sign Bias Test looks for asymmetry in the response of volatility to positive and negative shocks in a GARCH model. It aids in determining if the model effectively reflects the leverage effect or if adjustments are required to account for asymmetric behaviour in the volatility process. The p-values are greater than 0.05, implying that none of the individual or joint tests show significant sign bias. The model's responsiveness to positive and negative shocks is symmetrical, meaning that it can handle both sorts of innovations satisfactorily. There is no need for additional adjustments to account for asymmetric effects such as leverage, and the GARCH model appears well-specified in terms of sign biases.

Gold has moderate hedging potential for short-term volatility in the car sector, as indicated by the significant α_1 coefficient, indicating its ability to respond to acute market shocks. The near-zero β_1 value indicates that gold's hedging ability is not sustained over time, making it less successful as a long-term hedge in the car sector. Furthermore, the instability of the model parameters and the negative mean return indicate that, while gold may reduce volatility, it may not always provide positive returns or reliable long-term protection.

5. DISCUSSION

This study investigated gold's ability to hedge against the volatility of two main sectors in the Indian equities market: autos and energy. The use of the GARCH model revealed that gold has moderate hedging potential, particularly in the short term. In the energy sector, the high GARCH coefficient indicates that gold can operate as a relatively effective hedge during periods of prolonged market volatility. However, the impact of shocks on the auto industry is more volatile, making gold a less effective long-term hedging strategy in this sector.

Despite its volatility-reducing features, gold's performance as a reliable hedging asset is hampered by negative average returns and model instability. Investors looking to hedge sector-specific risks in Indian equities should be mindful that, while gold can help to attenuate short-term swings, it may not yield large positive returns throughout the hedging period. The findings emphasise the need of sector-specific study in determining gold's function in portfolio diversification and risk management measures.

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