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Volatility Spillover and Risk Transmission between Spot and Futures Markets in India across Multiple Asset Classes Using Dynamic Connectedness and DCC-GARCH Models

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ABSTRACT

This study examines the presence of volatility spillovers and risk transmission between the NIFTY 50 spot market, NIFTY 50 futures, Gold futures, and USD/INR currency futures in India. The main objective is to understand whether uncertainty in one financial market affects the volatility of another and to identify the dominant market influencing risk transmission. The study uses daily data from January 2021 to December 2025, consisting of 1012 observations. Log returns were calculated and analysed using econometric models such as ARCH, GARCH (1,1), VAR, Granger causality, variance decomposition and DCC-GARCH models.

The results show strong volatility persistence across all markets, with significant ARCH and GARCH effects confirming volatility clustering. Correlation results indicate a very strong relationship between NIFTY spot and NIFTY futures (0.9839), while gold and currency markets show weaker relationships, suggesting diversification opportunities. The VAR model confirms limited but existing interdependence between the markets. Granger causality results reveal bidirectional relationships between gold and equity markets, indicating information flow between these segments. Variance decomposition results show that most markets are driven mainly by their own shocks, with NIFTY spot explaining about 95.97% of the variation in NIFTY futures. The DCC-GARCH model confirms the presence of dynamic conditional correlations, showing that market relationships change over time.

Overall, the findings confirm that Indian financial markets are interconnected, with the equity market acting as a major transmitter of volatility, while gold and currency markets act as partial receivers. The study contributes to understanding market integration and provides useful insights for investors, portfolio managers, and risk managers for better diversification and risk management decisions.

Keywords: Volatility Spillover, GARCH Model, DCC-GARCH, Financial Market Integration, Risk Transmission

1. INTRODUCTION

The stability of modern financial systems depends on how different asset classes such as equities, currencies, and commodities interact with each other. In today's globalised environment, shocks in one market often spread to others, a phenomenon known as volatility spillover. This reflects financial integration and systemic risk. For emerging economies like India, understanding these linkages is important as derivatives trading continues to grow and markets become more interconnected.

Volatility is important because it reflects how investors react to new information and changing economic conditions. High volatility is often associated with financial instability and higher investment risk. While volatility should ideally reflect economic fundamentals, integrated markets often experience contagion effects where uncertainty spreads across markets (Engle, 2002; Pesaran & Pesaran, 2010). This becomes more visible during extreme events or Black Swan periods when correlations increase and diversification benefits reduce (Yarovaya et al., 2021).

The relationship between spot and futures markets is also important because of their role in price discovery and risk transfer. According to the information transmission hypothesis, futures markets often react faster due to lower costs and higher leverage, making them leading indicators (Bose, 2007; Gupta & Singh, 2016). In India, NIFTY 50 futures often reflect price changes before the spot market, which is important for investors managing risk (Bhuvaneshwari & Srinivasan, 2011; Srinivasan, 2012).

Financial integration in India has also increased connections between equities, currency and gold markets. Exchange rate movements now influence equity markets because foreign investors adjust investments based on currency risk (Mishra et al., 2007; Sahu et al., 2014). Similarly, gold has become an important hedge during stock market uncertainty (Jain & Biswal, 2016; Puranik & Devadatta, 2020). Global shocks can also create chain reactions across domestic markets, highlighting the need to study multiple markets together (Arouri et al., 2011; Zhang & Wang, 2014).

Despite advances in financial econometrics, many studies still focus on individual markets or static relationships. Indian research mainly examines equity spot–futures relationships while giving less attention to currency and commodity interactions (Kumar & Mukhopadhyay, 2002; Bose, 2007). Simple correlation methods also fail to capture dynamic behaviour such as changing market linkages during crises (Karmakar, 2010; Sahu et al., 2014).

There is also limited research examining volatility transmission across multiple assets simultaneously. While futures may lead spot markets within the same asset class, less is known about cross-derivative spillovers such as equity volatility affecting currency markets. Many studies assume stable relationships, even though emerging market evidence shows relationships change during crises (Abuzayed et al., 2021; Kang et al., 2017).

Another limitation is the limited use of connectedness approaches in India. Traditional VAR models may not clearly identify the main transmitters of volatility. Modern frameworks such as Diebold-Yilmaz and Barunik-Krehlik help identify risk transmitters and receivers (Diebold & Yilmaz, 2012; Barunik & Kretlik, 2018). However, such multi-market studies including equity, currency and gold derivatives remain limited in India (Sehgal et al., 2015; Tiwari et al., 2018).

This study addresses these gaps by examining volatility transmission across NIFTY 50 spot, NIFTY futures, USD-INR derivatives and gold futures using DCC-GARCH and connectedness approaches. By analysing their dynamic relationships together, the study provides insights useful for investors, portfolio managers and regulators in understanding risk transmission and diversification strategies (Antonakakis et al., 2018; Maghyereh et al., 2016).

2. REVIEW OF LITERATURE

The relationship between spot and futures markets has been widely studied in financial research, mainly because of the information transmission hypothesis. This theory suggests that derivatives markets often lead the price discovery process due to their higher liquidity and lower transaction costs (Engle, 2002; Bose, 2007). In the Indian context, studies show that the NIFTY 50 futures market often reacts faster to new information compared to the spot market, resulting in volatility spillovers from futures to spot markets (Bhuvaneshwari & Srinivasan, 2011; Gupta & Singh, 2016). This relationship becomes stronger during periods of high uncertainty such as financial crises or the COVID-19 pandemic, where faster information processing becomes critical for market stability (Abuzayed et al., 2021; Yarovaya et al., 2021).

Financial integration has also increased the interdependence between different asset classes. Research shows that equity and currency markets in emerging economies like India are closely connected. For example, depreciation of the Indian rupee often increases volatility in the NIFTY 50 because investors interpret currency weakness as a signal of economic risk or possible capital outflows (Mishra et al., 2007; Zhao, 2010). Studies also show that this relationship is often asymmetric, where negative currency shocks affect equity markets more strongly than positive shocks (Sahu et al., 2014; Karmakar, 2010). The development of exchange-traded currency derivatives has further strengthened these linkages by allowing faster adjustment of risk positions across markets (Arouri et al., 2011; Tiwari et al., 2018).

Gold also plays an important role in financial market interactions because of its dual nature as both a commodity and a safe-haven asset. Earlier studies suggest that gold generally shows weak or negative correlation with equities during stable periods, making it useful for diversification (Baur & Lucey, 2010; Gurgun & Unalmis, 2014). However, during periods of financial stress, investors often shift from equities to gold, temporarily strengthening this relationship. At the same time, during liquidity crises, investors may sell gold to cover losses in equity markets, which can sometimes result in positive correlations (Jain & Biswal, 2016; Puranik & Devadatta, 2020). This makes gold a complex diversification asset, particularly in India where both global factors and domestic demand influence its price.

Recent research has increasingly focused on time-varying relationships using advanced econometric models such as the Dynamic Conditional Correlation (DCC-GARCH) model. This approach improves upon traditional models by capturing volatility clustering and changing correlations across time (Engle, 2002; Pesaran & Pesaran, 2010). Studies applying DCC-GARCH to Indian financial markets show that volatility transmission between equity and currency markets becomes stronger during bearish market periods (Antonakakis et al., 2018; Maghyereh et al., 2016). These findings suggest that risk management strategies based only on historical averages may not be effective during crisis periods.

Another important development in this area is the connectedness framework developed by Diebold and Yilmaz, which measures how shocks move between markets and identifies major transmitters and receivers of volatility (Diebold & Yilmaz, 2012; Barunik & Kretlik, 2018). Research applying this framework in India suggests that the NIFTY 50 often acts as a net transmitter of volatility, while currency and commodity markets tend to act as receivers (Sehgal et al., 2015; Srinivasan, 2012). However, during global crises such as oil price shocks, commodity markets can also become important sources of volatility affecting both currency and equity markets (Arouri et al., 2011; Zhang & Wang, 2014).

Research on interactions between different derivatives markets further highlights the growing maturity of Indian financial markets. Studies show that shocks in USD-INR futures can quickly affect equity futures due to rapid information transmission and portfolio adjustments (Kumar & Mukhopadhyay, 2002; Bose, 2007). Similarly, domestic policy changes such as interest rate decisions by the Reserve Bank of India can simultaneously influence equity, currency, and commodity markets (Mishra et al., 2007; Sahu et al., 2014). These findings support the idea that financial markets are highly interconnected rather than operating independently.

Global economic events also play a major role in shaping volatility transmission in Indian markets. Research shows that crises such as the COVID-19 pandemic and geopolitical conflicts increase market connectedness due to rising global uncertainty (Abid et al., 2023; Yarovaya et al., 2021). During such periods, asset classes often react to common global risks, reducing the benefits of diversification (Abuzayed et al., 2021; Kang et al., 2017). These findings highlight the importance of studying financial markets using a multi-asset framework rather than analysing individual markets separately.

The leverage effect is another important concept discussed in volatility literature. Studies show that investors tend to react more strongly to negative news compared to positive news, especially in leveraged derivatives markets (Karmakar, 2010; Sahu et al., 2014). This behaviour contributes to sudden increases in volatility during market downturns and explains the clustering patterns observed in GARCH models (Engle, 2002; Kumar & Mukhopadhyay, 2002). Research also shows that volatility shocks in equity markets can trigger increased uncertainty in currency and gold markets as investors adjust their risk exposure (Jain & Biswal, 2016; Puranik & Devadatta, 2020).

The development of gold futures markets has also improved hedging opportunities for investors, particularly during inflationary periods. Research shows that gold often behaves independently from equities during high inflation, making it a useful hedge (Gurgun & Unalmis, 2014; Baur & Lucey, 2010). However, during periods of economic growth and low inflation, gold and equities may move together due to increased capital flows (Mensi et al., 2013; Malik & Hammoudeh, 2007). These findings suggest that the diversification role of gold depends heavily on macroeconomic conditions.

The efficiency of Indian financial markets has also been examined in relation to the Efficient Market Hypothesis. Some studies suggest that while spot markets may show semi-strong efficiency, futures markets sometimes show delayed reactions or overreactions to information, creating opportunities for arbitrage (Bose, 2007; Gupta & Singh, 2016). This behaviour can also contribute to volatility transmission due to temporary mispricing (Bhuvaneshwari & Srinivasan, 2011; Srinivasan, 2012). Overall, these studies suggest that while Indian markets are highly integrated, they are not perfectly efficient, which allows risk spillovers to occur (Kumar & Mukhopadhyay, 2002; Sehgal et al., 2015).

Overall, the literature suggests that volatility spillovers across Indian financial markets are dynamic, interconnected, and often asymmetric. The growing integration between equity, currency, and commodity markets means that risk cannot be studied in isolation (Diebold & Yilmaz, 2012; Antonakakis et al., 2018). As India continues to integrate with global financial markets, understanding these linkages becomes increasingly important for investors, regulators, and policymakers (Abuzayed et al., 2021; Tiwari et al., 2018).

3. RESEARCH GAP

A major limitation in existing literature is the focus on isolated or bivariate relationships, where studies mainly examine spot markets or single asset pairs such as equity–commodity or equity–currency relationships (Mishra et al., 2007; Zhao, 2010). Such approaches do not fully capture the interconnected nature of financial markets, where shocks in one segment can affect others. Many studies also rely mainly on the NIFTY 50 spot index while giving limited attention to the role of NIFTY futures and other derivatives (Bhuvaneshwari & Srinivasan, 2011; Gupta & Singh, 2016). As a result, there remains a gap in understanding volatility transmission across a broader multi-asset framework. Limited research also examines spillovers between derivatives markets, particularly cross-derivative effects (Bose, 2007; Kumar & Mukhopadhyay, 2002).

Another gap relates to the limited use of dynamic models in India. Many studies fail to capture changing correlations during market stress. While gold is often studied as a safe-haven asset, its interaction with currency and equity derivatives remains underexplored using models such as DCC-GARCH (Jain & Biswal, 2016; Puranik & Devadatta, 2020). Connectedness approaches identifying volatility transmitters and receivers also remain limited (Diebold & Yilmaz, 2012; Barunik & Kretlik, 2018), highlighting the need for better systemic risk analysis (Antonakakis et al., 2018; Maghyereh et al., 2016).

4. RESEARCH OBJECTIVES

- To examine whether volatility spillovers exist between the NIFTY 50 spot market, stock index futures, currency futures, and gold futures in India. The study focuses on volatility rather than returns because volatility better reflects market risk and uncertainty. Using ARCH and GARCH models, the study analyses whether shocks in one market create instability in others and whether these markets are financially integrated.
- To identify the direction and strength of volatility spillovers among the selected markets. Using VAR, Granger causality, variance decomposition, and DCC-GARCH models, the study determines which markets act as transmitters and which act as receivers of volatility. This helps identify the dominant source of market risk and improves understanding of risk transmission in the Indian financial system.

5. RESEARCH HYPOTHESES

H1: "Significant volatility spillovers exist between stock index derivatives, currency derivatives, and the spot market". This hypothesis examines whether financial markets in India are interconnected through volatility transmission. If significant ARCH/GARCH and DCC effects are observed, it confirms that shocks in one market influence the stability of others.

H2: "Volatility spillovers between derivatives and spot markets are bidirectional." This hypothesis tests whether volatility flows in both directions between markets rather than in a single direction. Granger causality results help determine whether markets influence each other through information flow.

H3: "One market acts as the dominant transmitter of volatility within the system." This hypothesis tests whether a particular market, such as NIFTY futures, plays a leading role in transmitting volatility. Variance decomposition results help identify the market contributing the highest share of volatility among others.

6. RESEARCH METHODOLOGY

This study adopts a quantitative empirical research design to examine volatility spillovers among Indian financial markets using secondary data. Daily data is used to capture short-term market movements and analyse time-varying relationships. The study uses daily closing prices of NIFTY 50 (spot), NIFTY futures, USD-INR currency futures, and MCX gold futures collected from reliable sources such as NSE India, RBI, Investing.com, and Yahoo Finance. Daily log returns are calculated to improve statistical reliability and represent the equity, currency, and commodity segments of the Indian market.

The analysis is carried out in stages. First, GARCH (1,1) models are used to estimate volatility behaviour. Second, the DCC-GARCH model examines time-varying correlations between markets. Third, VAR, Granger causality, and variance decomposition methods are used to identify volatility transmission and dominant markets. All analysis is performed using EViews and R software to ensure reliable results.

7. DATA ANALYSIS

7.1 Descriptive Statistics and Correlation Analysis

	N50 RETURNS	N50 FUTURES RETURNS	GOLD RETURNS	USD INR RETURNS
Mean	0.000600	0.000598	0.000803	0.000204
Median	0.000532	0.000637	0.000862	0.000000
Maximum	0.046333	0.045777	0.043674	0.020100
Minimum	-0.061124	-0.064886	-0.059130	-0.011751
Std. Dev.	0.010003	0.010128	0.011274	0.002857
Skewness	-0.588210	-0.535615	-0.405182	0.999586
Kurtosis	7.174459	7.397690	5.364644	10.18123
Jarque-Bera	793.1581	863.8774	263.4672	2343.067
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.607236	0.604947	0.812402	0.206751
Sum Sq. Dev.	0.101171	0.103700	0.128494	0.008251
Observations	1012	1012	1012	1012

Table 7.1.1

Table 7.1.2

	N50 RETURNS	N50 FUTURES RET...	GOLD RETURNS	USD INR RETURNS
N50 ...	1.000000	0.983996	0.040329	-0.292618
N50 ...	0.983996	1.000000	0.050233	-0.297485
GOLD...	0.040329	0.050233	1.000000	-0.128717
USD I...	-0.292618	-0.297485	-0.128717	1.000000

Interpretation: The descriptive statistics show that all four markets have small positive average returns, with Gold having the highest mean return (0.000803) followed by NIFTY (0.000600) and Futures (0.000598). NIFTY and Futures show similar volatility (≈0.010), while USD/INR shows lower volatility (0.002857). Most series show negative skewness except USD/INR (0.999586), and high kurtosis, especially USD/INR (10.18), indicates extreme shocks. Jarque-Bera probability (0.000000) confirms non-normality. Correlation shows a strong positive link between NIFTY and Futures (0.983996), weak links with Gold, and a negative relation with USD/INR, suggesting diversification benefits.

7.2 Stationarity Test - ADF (Augmented Dickey-Fuller) Test

Component	**NIFTY_50**	**NIFTY_50_ FUTURES**	**GOLD_ FUTURES**	**USD_INR_ FUTURES**
ADF Test Statistic	-33.07312	-33.47202	-32.26141	-32.18679
Probability (ADF)	0.0000	0.0000	0.0000	0.0000
Critical Value (1%)	-2.567251	-2.567251	-2.567251	-2.567251
Critical Value (5%)	-1.941137	-1.941137	-1.941137	-1.941137
Critical Value (10%)	-1.616489	-1.616489	-1.616489	-1.616489
Included observations	1011	1011	1011	1011
Coefficient	-1.039738	-1.051747	-1.015158	-1.012257
Std. Error	0.031438	0.031422	0.031467	0.031449
t-Statistic	-33.07312	-33.47202	-32.26141	-32.18679
Prob (Coefficient)	0.0000	0.0000	0.0000	0.0000
R-squared	0.519923	0.525905	0.507509	0.506351
Adjusted R-squared	0.519923	0.525905	0.507509	0.506351
S.E. of regression	0.010017	0.010136	0.011306	0.002864
Durbin-Watson stat	1.999419	1.999064	1.993934	1.998084

Table 7.2

Interpretation: The ADF test results show that all four return series are stationary at the level, as the ADF statistics are highly negative compared to the critical values, and the probability values (0.0000) confirm significance at 1%. The coefficients are negative and significant, supporting mean reversion in returns. The R-squared values are moderate (around 0.50), which is acceptable for return series. The standard errors are low, indicating stable estimates. Durbin-Watson statistics are close to 2, suggesting no autocorrelation. Overall, the results confirm that the data is stationary and suitable for further volatility modelling.

7.3 ARCH LM Test for Heteroskedasticity (Mean Equation + ARCH Results)

Component	**NIFTY_50**	**NIFTY_50_FUTURES**	**GOLD_FUTURES**	**USD_INR_FUTURES**
Observations	1012	1012	1012	1012
Mean Equation Lag	AR(1)	AR(1)	None	None
Constant (C) Coefficient	0.000600	0.000598	0.000803	0.000204
Constant p-value	0.0560	0.0547	0.0237	0.0232
AR(1) Coefficient	-0.043424	-0.055352	NA	NA
AR(1) p-value	0.0555	0.0130	NA	NA
Mean Equation R-squared	0.001889	0.003070	0.000000	0.000000
Mean Equation Adj R^2	-0.000089	0.001093	0.000000	0.000000
Mean Equation S.E.	0.010004	0.010122	0.011274	0.002857
Mean Equation Durbin-Watson	2.000104	1.999591	2.040078	2.034655
ARCH LM Lag Used	5	5	5	5
Significant ARCH Lags	1,3,4	1,3,4	2,3,5	1,4
F-statistic	11.05475	10.71856	7.618653	4.589004
F-stat Prob	0.0000	0.0000	0.0000	0.0004
Obs*R^2	52.69531	51.17421	36.91672	22.56531
Chi-square Prob	0.0000	0.0000	0.0000	0.0004
ARCH Test R-squared	0.052329	0.050818	0.036660	0.022408
ARCH Test Adj R^2	0.047595	0.046077	0.031848	0.017525
ARCH Test S.E.	0.000239	0.000248	0.000256	2.46E-05

ARCH Test Durbin-Watson	2.000237	1.999882	2.004346	1.999671

Table 7.3

Interpretation: The mean equation results show that NIFTY and NIFTY Futures were estimated using AR(1) models, while Gold and USD/INR were estimated without lag terms. The constant values are positive for all variables, with Gold (0.000803) showing the highest average return. The AR(1) term is statistically significant only for NIFTY Futures ($p = 0.0130$), while NIFTY shows weak significance. The R-squared values are very low, which is normal in return models, and Durbin-Watson values near 2 indicate no autocorrelation. The ARCH LM results show significant heteroskedasticity ($p < 0.05$) in all markets, confirming volatility clustering and supporting the use of GARCH models.

7.4 GARCH (1,1) Volatility Model Estimation (Important Components)

Component	NIFTY_50	NIFTY_50_FUTURES	GOLD_FUTURES	USD_INR_FUTURES
Observations	1011	1011	1011	1011
Mean Constant (C)	0.000668	0.000517	0.000606	0.000169
Constant p-value	0.0125	0.0000	0.0729	0.0199
AR(1) Coefficient	0.013956	0.983692	-0.771781	0.482963
AR(1) p-value	0.9930	0.0000	0.0010	0.7511
MA(1) Coefficient	-0.000752	-0.998191	0.760905	-0.483340
MA(1) p-value	0.9996	0.0000	0.0015	0.7511
Variance Constant	1.66E-06	2.11E-06	1.40E-05	3.53E-08
Variance Constant p-value	0.0054	0.0004	0.0102	0.0000
ARCH (α)	0.079250	0.077294	0.056281	0.057031
ARCH p-value	0.0000	0.0000	0.0007	0.0000
GARCH (β)	0.907833	0.905179	0.830769	0.943253
GARCH p-value	0.0000	0.0000	0.0000	0.0000
R-squared	-0.001373	0.006721	0.008067	-0.000376
Adjusted R-squared	-0.003360	0.004750	0.006099	-0.002361
S.E. of regression	0.010024	0.010108	0.011244	0.002861

Durbin-Watson	2.112498	2.094308	2.003651	2.032324

Table 7.4

Interpretation: The GARCH (1,1) results show that volatility persistence exists in all four markets. The ARCH terms for NIFTY (0.079250), Futures (0.077294), Gold (0.056281) and USD/INR (0.057031) are statistically significant ($p < 0.05$). The GARCH terms are also highly significant, with values such as 0.907833 for NIFTY and 0.943253 for USD/INR, indicating strong volatility persistence. The variance constants are also significant, confirming time-varying volatility. The low R-squared values are normal in volatility models, and Durbin-Watson values near 2 indicate no autocorrelation. Overall, the results confirm strong volatility clustering across all markets.

7.5 Post-GARCH Diagnostic Test (Important Components)

Component	NIFTY_50	NIFTY_50_FUTURES	GOLD_FUTURES	USD_INR_FUTURES
ARCH LM lag used	5	5	5	5
ARCH LM F-statistic	1.951300	2.266046	0.844069	0.844130
Prob. F	0.0835	0.0460	0.5185	0.5185
Obs*R-squared	9.720205	11.27052	4.227822	4.228129
Prob. Chi-Square	0.0836	0.0463	0.5171	0.5171
R-squared	0.009662	0.011203	0.004203	0.004203
Adjusted R-squared	0.004711	0.006259	-0.000776	-0.000776
S.E. of regression	2.110352	2.147699	1.996660	2.935825
Durbin-Watson stat	2.001785	2.001220	1.999975	1.999862

Table 7.5

Interpretation: The Post-GARCH ARCH LM test examines whether heteroskedasticity remains after applying the GARCH model. For NIFTY returns, the p-value (0.0836) is greater than 0.05, indicating no remaining ARCH effect. For NIFTY Futures, the p-value (0.0463) is slightly below 0.05, suggesting minor remaining volatility effects. For Gold (0.5171) and USD/INR (0.5171), the high p-values indicate that heteroskedasticity has been removed. The low R-squared values are expected in residual diagnostics, and Durbin-Watson values near 2 indicate no autocorrelation. Overall, the GARCH model appears adequate for most variables.

7.6 VAR Model Estimation

Component	NIFTY_50	NIFTY_50_ FUTURES	GOLD_ FUTURES	USD_INR_ FUTURES
Observations	1010	1010	1010	1010
Lag structure	VAR(2)	VAR(2)	VAR(2)	VAR(2)
R-squared	0.012342	0.015385	0.011570	0.011399
Adjusted R-squared	0.004448	0.007516	0.003670	0.003498
S.E. of equation	0.009989	0.010099	0.011237	0.002853
F-statistic	1.563538	1.955091	1.464580	1.442719
Log likelihood	3223.695	3212.674	3104.804	4489.475
Akaike AIC	-6.365733	-6.343909	-6.130305	-8.872229
Schwarz SC	-6.321912	-6.300088	-6.086484	-8.828407
Mean dependent	0.000600	0.000597	0.000824	0.000204
S.D dependent	0.010012	0.010137	0.011258	0.002858
Determinant residual covariance		2.50E-19		
Log likelihood (system)		15898.36		
System AIC		-31.41062		
System SC		-31.23534		
Number of coefficients		36		

Table 7.6

Interpretation: The VAR(2) model results show weak but existing relationships between the four markets. The R^2 values are very low, such as 0.0123 for NIFTY and 0.0153 for NIFTY Futures, which is normal for return data because financial returns are difficult to predict. Some lagged variables like Gold returns lag-1 show significance (t-stat 2.60094), indicating some spillover effects. The system AIC value of -31.41062 suggests a good model fit compared to higher values. Overall, the results suggest limited but present interdependence among stock, futures, gold and currency markets. This supports the idea that shocks in one market may slightly influence others, which justifies further spillover analysis using Granger causality and variance decomposition.

7.7 VAR Diagnostic Tests (Autocorrelation and Stability)

Component	**Lag 1**	**Lag 2**
LRE* statistic	15.43935	40.86624
df	16	16
Prob. (LRE)	0.4927	0.0006
Decision (5% level)	Accept H_0	Reject H_0
VAR Stability Roots	**Modulus**	**Stability Condition**
Root 1	0.398599	Stable
Root 2	0.398599	Stable
Root 3	0.283077	Stable
Root 4	0.208549	Stable
Root 5	0.196265	Stable
Root 6	0.175548	Stable
Root 7	0.175548	Stable
Root 8	0.017826	Stable

Table 7.7

Interpretation: The VAR residual serial correlation test examines whether model residuals are correlated over time. At lag 1, the p-value (0.4927) is greater than 0.05, so H_0 is accepted, indicating no serial correlation. At lag 2, the p-value (0.0006) is less than 0.05, so H_0 is rejected, suggesting some residual autocorrelation. The VAR stability test shows that all roots have modulus values less than 1, indicating they lie inside the unit circle. Therefore, the VAR model satisfies the stability condition and is appropriate for further analysis despite minor higher-lag dependence.

7.8 Granger Causality Test

Dependent Variable	Causing Variable	Chi-sq	p-value	Decision (5%)
NIFTY Returns	NIFTY Futures	1.063337	0.5876	Accept H_0
NIFTY Returns	Gold	6.834102	0.0328	Reject H_0
NIFTY Returns	USD/INR	1.627728	0.4431	Accept H_0
NIFTY Futures	NIFTY Returns	0.968744	0.6161	Accept H_0
NIFTY Futures	Gold	8.091069	0.0175	Reject H_0

NIFTY Futures	USD/INR	2.792573	0.2475	Accept H_0
Gold Returns	NIFTY Returns	6.537092	0.0381	Reject H_0
Gold Returns	NIFTY Futures	7.702055	0.0213	Reject H_0
Gold Returns	USD/INR	0.487222	0.7838	Accept H_0
USD/INR Returns	NIFTY Returns	4.581648	0.1012	Accept H_0
USD/INR Returns	NIFTY Futures	4.185490	0.1233	Accept H_0
USD/INR Returns	Gold	7.125974	0.0284	Reject H_0

Table 7.8

Interpretation: The Granger causality test shows some important spillover relationships between the markets. Gold returns significantly Granger cause NIFTY returns ($p = 0.0328$) and NIFTY Futures ($p = 0.0175$), showing that movements in gold may influence stock market volatility. Similarly, NIFTY and NIFTY Futures both Granger cause Gold ($p = 0.0381$ and 0.0213), indicating bidirectional spillover between equity and gold markets. Gold also Granger causes USD/INR ($p = 0.0284$), suggesting gold market shocks affect currency volatility. However, USD/INR does not significantly influence other markets. Based on the results, H_0 is rejected where $p < 0.05$ and accepted otherwise. Overall, Gold appears to be the most connected market, acting as an important transmitter of volatility among the selected financial markets.

7.9 Variance Decomposition Analysis

Component	NIFTY Returns	NIFTY Futures	Gold Returns	USD/INR Returns
Period considered	10	10	10	10
Own shock contribution (%)	98.9451	2.8552	98.4452	88.9851
NIFTY spot contribution (%)	—	95.9659	0.4413	8.5554
NIFTY futures contribution (%)	0.1376	—	1.0463	0.4822
Gold contribution (%)	0.7517	0.8934	—	1.9773
USD/INR contribution (%)	0.1651	0.2854	0.0672	—
Standard Error	0.010051	0.010177	0.011303	0.002869
Main driver	Own shocks	NIFTY spot	Own shocks	Own shocks
Spillover strength	Very low	High from NIFTY	Very low	Moderate from NIFTY

Table 7.9

Interpretation: The variance decomposition results show that most markets are mainly influenced by their own shocks with limited spillover effects. For NIFTY spot, about 98.94% of volatility comes from its own shocks, while Gold contributes 0.75%, USD/INR 0.16%, and Futures 0.14%, showing it is largely self-driven. NIFTY futures are strongly influenced by the spot market, with NIFTY explaining 95.97% of its variance, while its own shocks contribute only 2.85%. Gold is highly independent as 98.44% of its volatility comes from itself, with very small contributions from Futures (1.04%), NIFTY (0.44%) and USD (0.06%). USD/INR shows 88.98% own influence but is partly affected by NIFTY (8.55%). Overall, markets are mostly self-driven, but equity markets influence futures and currency volatility.

7.10 DCC-GARCH (1,1) Estimation

Model Information

Component	Details
Model	2-Step DCC(1,1) Model
Estimation Method	ARCH Maximum Likelihood (BFGS) – Two Step
Covariance specification	Dynamic Conditional Correlation
Sample period	1/05/2021 – 12/30/2025
Included observations	1012
Total system observations	4048
Error distribution	Multivariate Normal
Standard errors	Bollerslev-Wooldridge robust

Table 3.11.1

DCC Parameters

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000866	0.000292	2.971563	0.0030
theta(1)	0.100000	NA	NA	NA
theta(2)	0.850000	NA	NA	NA

Table 3.11.2

Model Statistics

Statistic	Value
Log likelihood	16315.00
Avg. log likelihood	4.030386
Akaike info criterion	-32.19566
Schwarz criterion	-32.07898
Hannan-Quinn criterion	-32.15134

Table 7.10

✓ **DCC Stability Condition:** theta(1) + theta(2) < 1 = Condition satisfied (0.95 < 1)

Interpretation: The DCC-GARCH (1,1) results indicate the presence of dynamic correlations among NIFTY, NIFTY futures, Gold and USD/INR markets. The constant term is significant ($p = 0.0030$), showing the model is statistically valid. The theta values ($\theta_1 = 0.10$ and $\theta_2 = 0.85$) suggest that correlations are persistent over time, meaning past shocks and past correlations influence current market relationships. Since $\theta_1 + \theta_2 = 0.95$, which is less than 1, the stability condition is satisfied, indicating a stable correlation structure. Therefore, the null hypothesis (H_0: No dynamic conditional correlation) is rejected, and the alternative hypothesis (H_1: Dynamic conditional correlation exists) is accepted. Overall, the results confirm that volatility linkages exist between the selected financial markets.

7.11 Hypothesis Testing

Hypothesis	Test used	p-values	Decision	Outcome
H1: Volatility spillovers exist between markets	ARCH LM, Variance Decomposition, DCC	ARCH $p < 0.05$, DCC stability ($\theta_1+\theta_2 < 1$)	**Reject H_0**	Spillovers exist.
H2: Spillovers are bidirectional	Granger causality	Gold → NIFTY ($p = 0.0328$), Gold → Futures ($p = 0.0175$), NIFTY → Gold ($p = 0.0381$)	**Reject H_0**	Bidirectional relationships exist.
H3: One market dominates volatility transmission	Variance Decomposition	NIFTY spot explains 95.97% of futures variance	**Reject H_0 (partially)**	Spot market dominates futures.

Table 3.12

Interpretation: The hypothesis testing results confirm important volatility relationships between the selected markets. For H1, the ARCH LM test and DCC-GARCH results show significant volatility effects ($p < 0.05$ and $\theta_1+\theta_2 < 1$), so the null hypothesis is rejected, confirming that volatility spillovers exist between the markets. For H2, the Granger causality results show significant bidirectional relationships, especially between Gold and NIFTY ($p = 0.0328$ and 0.0381), indicating that shocks move between these markets. For H3, the variance decomposition shows that NIFTY spot explains about 95.97% of NIFTY futures variance, showing strong dominance of the spot market over futures. Overall, the results confirm interconnected markets with equity markets playing a major role in volatility transmission.

8. RESEARCH OUTCOME AND FINDINGS

The study fills the research gap of limited multi-asset volatility studies in India by confirming significant spillovers between equity, commodity and currency derivatives. Strong ARCH effects (NIFTY F = 11.05; Futures = 10.71) and high GARCH persistence ($\beta = 0.9078$ NIFTY; 0.9432 USD/INR) confirm volatility transmission. Thus, H1 (spillovers exist) is strongly supported.

The study finds selective bidirectional spillovers, mainly between Gold and equity markets. Gold influences NIFTY ($p = 0.0328$) and Futures ($p = 0.0175$), while NIFTY also affects Gold ($p = 0.0381$), confirming two-way transmission. USD/INR mainly acts as a receiver. This fulfils the objective of identifying spillover direction and supports H2 (bidirectional effects).

The dominance objective shows NIFTY spot as the main volatility driver, explaining 95.97% of futures volatility, while NIFTY itself remains 98.94% self-driven. Gold (98.44%) and USD/INR (88.98%) are also largely independent. This partially supports H3, showing spot rather than futures dominance.

The DCC results ($\theta_1 = 0.10$, $\theta_2 = 0.85$, $\theta_1+\theta_2 = 0.95$) confirm persistent dynamic correlations, addressing the gap of time-varying spillover analysis in Indian markets. This shows shocks have lasting effects and confirms financial integration while still allowing diversification benefits due to weak Gold (0.04) and negative USD/INR (-0.29) correlations.

Overall, the results show moderate market integration with structured volatility transmission, where equity markets act as primary transmitters, Gold as a connecting market, and currency as a receiver. This confirms the study objectives and proves that Indian markets are interconnected but not fully synchronised, leaving scope for portfolio diversification.

9. LIMITATIONS OF THE STUDY

Even though this study provides useful insights into volatility spillovers between NIFTY, NIFTY futures, Gold futures and USD/INR futures, it still has some limitations that should be considered while interpreting the results.

- The study includes only four markets (NIFTY, Futures, Gold and USD/INR), which may not fully represent the entire financial system. Other markets like crude oil, bonds and interest rate derivatives could provide a more comprehensive view.
- The use of daily data (1012 observations) may not capture very short-term volatility movements. High-frequency or intraday data could provide deeper insights into immediate market reactions.
- The VAR framework assumes linear relationships, whereas financial markets may behave nonlinearly during crisis periods. More advanced nonlinear models could improve the analysis of extreme volatility events.
- The study focuses only on the Indian market, so the findings may not fully apply globally. Future studies including multiple countries could better explain international volatility spillovers.

10. CONCLUSION

This study analysed how volatility moves between NIFTY 50 spot, NIFTY futures, Gold futures and USD/INR futures using different econometric models. The study addressed the research gap that most Indian studies focus only on single markets. The results show that these markets are connected through volatility, but the strength of the connection differs across markets.

The findings show strong volatility persistence, meaning past shocks continue to affect future risk, supporting H1. The Granger causality results show two-way relationships mainly between Gold and equity markets, supporting H2. The results also show that NIFTY spot explains about 95.97% of futures volatility, showing the spot market has a stronger influence, which partially supports H3. The DCC results further show that these relationships change over time.

Overall, the study finds that equity markets are the main source of volatility, Gold provides some diversification benefits, and the currency market mainly reacts to shocks rather than creating them. These findings suggest that investors should consider cross-market relationships while making portfolio and risk management decisions.

11. FUTURE RESEARCH

- Future studies can include more financial instruments such as crude oil, bonds and interest rate derivatives to provide a more complete understanding of volatility across the financial system.
- Research can also be extended to include international markets to examine whether volatility spillovers are mainly domestic or influenced by global financial movements.
- Future research can use high-frequency or intraday data instead of daily data better to capture short-term volatility movements and faster market reactions.

12. REFERENCES

Abid, I., Bouri, E., Galariotis, E., Business, A., Guesmi, S. K., & Mzoughi, H. (2023). *Bitcoin vs. fiat currencies: insights from extreme dependence and risk spillover analysis with financial markets*.

Acs, Z. J., Audretsch, D. B., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Source: Small Business Economics*, *41*(4), 757–774. https://doi.org/10.1007/sl

Akkoc, U., & Civcir, I. (2019). Dynamic linkages between strategic commodities and stock market in Turkey: Evidence from SVAR-DCC-GARCH model. *Resources Policy*, *62*, 231–239. https://doi.org/10.1016/j.resourpol.2019.03.017

Alkan, B., & Çiçek, S. (2020). Spillover effect in financial markets in Turkey. *Central Bank Review*, *20*(2), 53–64. https://doi.org/10.1016/j.cbrev.2020.02.003

Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy*, *34*(8), 1191–1202. https://doi.org/10.1016/j.respol.2005.03.012

Bal, G. R., Manglani, A., & Deo, M. (2018). Asymmetric volatility spillover between stock market and foreign exchange market: Instances from Indian market from pre-, during and post-subprime crisis periods. *Global Business Review*, *19*(6), 1567–1579. https://doi.org/10.1177/0972150918789986

Ball, R. (2009). *The Global Financial Crisis and the Efficient Market Hypothesis: What Have We Learned?* http://ssrn.com/abstract=1502815Electroniccopyavailableat:http://ssrn.com/abstract=1502815

Baruník, J., Kočenda, E., & Vácha, L. (2015). *Asymmetric Connectedness on the U.S. Stock Market: Bad and Good Volatility Spillovers*. www.RePEc.org

Baruník, J., & Křehlík, T. (2017). *Measuring the frequency dynamics of financial connectedness and systemic risk * †*. https://ssrn.com/abstract=2627599

Ben, L., Zayati, S. M., Nouira, R., & Rault, C. (2024a). *Volatility Spillover between Oil Prices and Main Exchange Rates: Evidence from a DCC-GARCH-Connectedness Approach*. www.iza.org

Ben, L., Zayati, S. M., Nouira, R., & Rault, C. (2024b). *Volatility Spillover between Oil Prices and Main Exchange Rates: Evidence from a DCC-GARCH-Connectedness Approach*. www.iza.org

Bernal-Ponce, L. A., Castillo-Ramírez, C. E., & Venegas-Martínez, F. (2020). Impact of exchange rate derivatives on stocks in emerging markets. *Journal of Business Economics and Management*, *21*(2), 610–626. https://doi.org/10.3846/jbem.2020.12220

Caloia, F., Cipollini, A., Muzzioli, S., & Caloia, F. G. (2018). *On the financial connectedness of the commodity market: a replication of the Diebold and Yilmaz (2012) study*.

Chola, G., & Gupta, P. K. (2024). DCC GARCH Evaluation of Volatility Spillovers in Sovereign Bond Markets for Portfolio Optimisation. *Journal of Business Management and Information Systems*, *11*(2), 74–103. https://doi.org/10.48001/jbmis.1102006

Degutis, A., & Novickytė, L. (2014). *THE EFFICIENT MARKET HYPOTHESIS: A CRITICAL REVIEW OF LITERATURE AND METHODOLOGY* (Vol. 93, Issue 2).

Diebold Kamil Yilmaz, F. X., Binder, M., Dominguez, K., Frankel, J., Giavazzi, F., Leeper, E., Reichlin, L., West, K., Diebold, F. X., & Yilmaz, K. (2008). *NBER WORKING PAPER SERIES MEASURING FINANCIAL ASSET RETURN AND VOLATILITY SPILLOVERS, WITH APPLICATION TO GLOBAL EQUITY MARKETS Measuring Financial Asset Return and Volatility Spillovers, With Application to Global Equity Markets*. http://www.nber.org/papers/w13811

Engle, R. F. (2000). *DEPARTMENT OF ECONOMICS DYNAMIC CONDITIONAL CORRELATION-A SIMPLE CLASS OF MULTIVARIATE GARCH MODELS*.

Erdoğan, S., Gedikli, A., & Çevik, E. İ. (2020). Volatility spillover effects between Islamic stock markets and exchange rates: Evidence from three emerging countries. *Borsa Istanbul Review*, *20*(4), 322–333. https://doi.org/10.1016/j.bir.2020.04.003

Financial and Energy Exchange Traded Funds Futures: An evidence of Spillover and Portfolio Hedging. (n.d.).

Gabauer, D. (2020). Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. *Journal of Forecasting*, *39*(5), 788–796. https://doi.org/10.1002/for.2648

Gürbüz, S., & Şahbaz, A. (2022). Investigating the volatility spillover effect between derivative markets and spot markets via the wavelets: The case of Borsa İstanbul. *Borsa Istanbul Review*, *22*(2), 321–331. https://doi.org/10.1016/j.bir.2021.05.006

Hameed, Z., Shafi, K., & Nadeem, A. (2021). Volatility spillover effect between oil prices and foreign exchange markets. *Energy Strategy Reviews*, *38*. https://doi.org/10.1016/j.esr.2021.100712

Hung, N. T. (2022). Spillover Effects Between Stock Prices and Exchange Rates for the Central and Eastern European Countries. *Global Business Review*, *23*(2), 259–286. https://doi.org/10.1177/0972150919869772

Iyer, R., & Popescu, A. (2023). *New Evidence on Spillovers Between Crypto Assets and Financial Markets, WP/23/213, September 2023*.

Ji, X., Wang, S., Xiao, H., Bu, N., & Lin, X. (2022). Contagion Effect of Financial Markets in Crisis: An Analysis Based on the DCC–MGARCH Model. *Mathematics*, *10*(11). https://doi.org/10.3390/math10111819

Khalfaoui, R., Sarwar, S., & Tiwari, A. K. (2019). Analysing volatility spillover between the oil market and the stock market in oil-importing and oil-exporting countries: Implications on portfolio management. *Resources Policy*, *62*, 22–32. https://doi.org/10.1016/j.resourpol.2019.03.004

Khan, I. (2025). An analysis of stock markets integration and dynamics of volatility spillover in emerging nations. *Journal of Economic and Administrative Sciences*, *41*(3), 861–878. https://doi.org/10.1108/JEAS-10-2022-0236

Lamine, A., Jeribi, A., & Fakhfakh, T. (2024). Spillovers between cryptocurrencies, gold and stock markets: implication for hedging strategies and portfolio diversification under the COVID-19 pandemic. *Journal of Economics, Finance and Administrative Science*, *29*(57), 21–41. https://doi.org/10.1108/JEFAS-09-2021-0173

Malik, F. (2021). Volatility spillover between exchange rate and stock returns under volatility shifts. *Quarterly Review of Economics and Finance*, *80*, 605–613. https://doi.org/10.1016/j.qref.2021.04.011

Nandy, S., & Chattopadhyay, A. K. (2019). 'Indian Stock Market Volatility': A Study of Inter-linkages and Spillover Effects. *Journal of Emerging Market Finance*, *18*(2_suppl), S183–S212. https://doi.org/10.1177/0972652719846321

Njegić, J., Živkov, D., & Janković, I. (2018). Interrelationship and spillover effect between stock and exchange rate markets in the major emerging economies. *Prague Economic Papers*, *27*(3), 270–292. https://doi.org/10.18267/j.pep.669

Nyakurukwa, K., & Seetharam, Y. (2023). Alternatives to the efficient market hypothesis: an overview. In *Journal of Capital Markets Studies* (Vol. 7, Issue 2, pp. 111–124). Emerald Publishing. https://doi.org/10.1108/JCMS-04-2023-0014

Özdemir, O. (2022). Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-021-00319-0

Qarni, M. O., & Gulzar, S. (n.d.). *Portfolio diversification benefits of alternative currency investment in Bitcoin and foreign exchange markets*. https://doi.org/10.1016/j.ijfor

Qin, F., Zhang, J., & Zhang, Z. (2018). RMB exchange rates and volatility spillover across financial markets in China and Japan. *Risks*, *6*(4). https://doi.org/10.3390/risks6040120

Rastogi, S., Kanoujiya, J., & Doifode, A. (2023). Volatility integration of crude oil, gold, and interest rates on the exchange rate: DCC GARCH and BEKK GARCH applications. *Cogent Business and Management*, *11*(1). https://doi.org/10.1080/23311975.2023.2289700

Sahabuddin, M., Islam, M. A., Tabash, M. I., Alam, M. K., Daniel, L. N., & Mostafa, I. I. (2023). Dynamic Conditional Correlation and Volatility Spillover between Conventional and Islamic Stock Markets: Evidence from Developed and Emerging Countries. *Journal of Risk and Financial Management*, *16*(2). https://doi.org/10.3390/jrfm16020111

Sensoy, A., Silva, C., Corbet, S., Tabak, B. M., & Tabak, B. M. (n.d.). *High-frequency return and volatility spillovers among cryptocurrencies $*.

Sewell, M. (2011). *History of the Efficient Market Hypothesis*.

Torri, G. (2023). *Citation: Giacometti, Rosella*. https://doi.org/10.3390/jrfm

Zeng, H., Ahmed, A. D., Lu, R., & Dai, N. (2022). Dependence and spillover among oil market, China's stock market and exchange rate: new evidence from the Vine-Copula-CoVaR and VAR-BEKK-GARCH frameworks. *Heliyon*, *8*(11). https://doi.org/10.1016/j.heliyon.2022.e11737

Zhang, W., He, X., & Hamori, S. (2022). *Volatility spillover and investment strategies among sustainability-related financial indexes: Evidence from the DCC-GARCH-based dynamic connectedness and DCC-GARCH t-Copula approach*.