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VOLATILITY SPILLOVER BETWEEN NIFTY FIFTY INDEX AND SELECTED MUTUAL FUNDS IN INDIAN STOCK MARKET: DCC GARCH TECHINQUE

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ABSTRACT

Purpose: This study aims to examine the volatility spillover effects and measure the time varying correlations between nifty fifty index and selected mutual funds in Indian mutual fund market. Methodology: The research uses Exponential GARCH proposed by Nelson (1991) to explore the direction and magnitude of spillover effects between nifty fifty index and selected mutual fund. It employs Dynamic Conditional Correlation (DCC) GARCH proposed by Engle (2002) to demonstrate the time varying conditional correlation between heteroscedastic coefficients of the share (nifty) and mutual funds market. Findings: Empirical results show that significant and asymmetric bi-directional volatility spillover effects exist in case of most of the selected mutual funds even though, the magnitude of volatility spillover is found larger in the direction from nifty to equity mutual fund. The dynamic correlation between the conditional variance of the nifty and mutual fund markets is found to be significant in case of all the selected mutual funds. It proves that significant volatility spillover effect is present between nifty fifty index and selected mutual funds. Implications: Understanding of volatility transmission and interrelationship between nifty and mutual fund market will help investors make right investment decisions, portfolio optimization and financial risk management. Policy makers and regulators can use this knowledge in planning and implementing appropriate regulatory framework. Originality/Value: Much of the past research focuses on inter market volatility spillover taking into consideration two or more different financial markets. This study focuses on intra market volatility spillover by studying the interactions of stock and mutual fund markets. Also, considering the time-varying nature of conditional correlations, this study employs EGARCH and multivariate GARCH (DCC) to capture the volatility spillover effects instead of univariate GARCH or standard linear VAR models.

Keywords: DCC-GARCH, EGARCH, Volatility Spillovers, Mutual Fund

1. INTRODUCTION

Modelling the volatility spillovers between stock market index and mutual fund returns is an important and timely topic to explore. So far, there are abundance of studies that have addressed the issue of volatility spillover across different markets. But, most of the studies have been conducted in developed countries focusing mainly on volatility spillover across two or more same or different financial markets or assets (Manera et. al. (2012); Sehgal et. al. (2014); Aftab et. al. (2015); Chen & Wu (2016) and Bala & Takimoto (2017)). There are only a handful of studies examining the volatility spillover in stock index and mutual fund market especially in India. Most of the earlier studies examining volatility spillover in stock index and mutual fund market have used the methods like GARCH, EGARCH, BEKK. There is a dearth of literature examining stock market volatility spillover in mutual fund returns using DCC-GARCH method in India. Considering the time varying and dynamic properties of volatility spillover effect in the stock index and mutual fund returns, this study examines the time-varying volatility relationship between nifty fifty and mutual funds returns by employing high dimensional dynamic conditional correlation model. Further, the study uses exponential GARCH model to quantify the magnitude and direction of volatility spillover across the underlying markets. The study is based on secondary data consisting of daily closing prices of nifty index and daily closing NAV of the selected mutual funds.

The paper is structured as follows: Section 2 contains review of literature concerning the topic of the study. Section 3 outlines the description of empirical models used in the study, section 4 explains the objectives and methodology. Section 5 describes the data analysis and major findings of the study and section 6 contains conclusions and discussions.

2. REVIEW OF LITERATURE

The need to have accurate estimation of volatility spillover and correlation in portfolio designing and optimization, pricing of derivatives, risk management and hedging strategies calls for modelling and forecasting volatility and correlations in financial econometrics (Sadorsky, 2012). Most of the research studies on volatility spillover and correlations between two or more asset classes have applied GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and its family models like BEKK (Baba, Engle, Kraft, and Kroner) and DCC (Dynamic Conditional Correlation). When there are more than two variables in a model, BEKK model can behave with poor likelihood function making optimization difficult or impossible sometimes. Dynamic Conditional Correlation (DCC) model addresses such issues and works well critically for large data sets. The bivariate DCC model is nonlinear and provides a good estimate to a range of time varying correlation processes (Engle, 2002). The seminal work of Engle (1982) and Bollerslev (1986) led to the applications of GARCH and its family of models for modelling volatility in stock market and mutual fund returns as well. Many studies have used DCC-GARCH methodology for modelling volatility spillover across different markets. Xiao & Dhesi (2010); Al-Zeaud (2014); Mohammadi & Tan (2015); Bala & Takimoto (2017); Panda & Nanda (2017) have applied DCC-GARCH for testing volatility spillover across different stock markets. Xiao & Dhesi (2010) tested the co-movements between European and US stock markets using four stock indices CAC, DAX, FTSE100 and S&P500. To examine the volatility spillover effects and to test time-varying correlations across the indices, the authors have used two multivariate GARCH models, namely BEKK (Engle and Kroner, 1995) and DCC (Engle, 2002). They found using BEKK model that there exist asymmetric volatility spillover effects widely between these markets. Within the European stock market, the UK is the main transmitter of volatility and US is the main exporter of volatility. The DCC model to test the presence of time-varying correlation in equity market showed that there is conditional as well as time-varying correlations having a mean-reverting process among them. Al-Zeaud (2014) tested the spillover between US and major European stock markets by using DCC form of EGARCH model. The author put forth that spillover effect exists from London market to New York, Paris and Frankfurt stock markets. And, unidirectional volatility spillover effects are reported from Frankfurt to Paris and from Paris to London. The impact of bad news on volatility is higher and is transmitted more robustly in comparison to volatility declines. Mohammadi & Tan (2015) studied the returns spillovers and conditional volatility in four equity markets of the U.S., Hong Kong and mainland China (two stock exchanges) by using GARCH and DCC model. The study provided the evidence of unidirectional return spillovers and ARCH and GARCH effects from US to the other countries.

There is highest correlation between the Chinese markets under study in comparison to the other markets studied. Also, the DCC model results showed that correlation between China and other markets risen after the 2007 financial crisis. Bala & Takimoto (2017) examined volatility spillovers of stock returns in emerging and developed markets by applying variants of MGARCH models and found that in case of developed markets correlation is more implying more interaction than in case of emerging markets. Also, volatility spillovers of the stock market itself are greater in comparison to the cross-volatility spillovers especially for emerging markets. Also, the emerging markets are less efficient than the developed markets as the impact of nay shock in these markets takes longer time to dissipate. The authors suggested DCC-with-skewed-t density model for capturing the volatility dynamics if fat tails and skewness is present in the data. Panda & Nanda (2017) in their study aimed to study the short-term dynamism and long term equilibrium relationship and also the dynamic conditional correlation between South American and Central American stock markets by using VECM, variance decomposition and GARCH-DCC. The authors identified the existence of long-run equilibrium between the stock markets and strong linkages among national stock markets. The results confirm that market integration is increasing and conditional correlations in stocks are asymmetric. Also, there is more correlation towards the end of the sample period in comparison to the beginning time. Many researchers have used DCC-GARCH methodology for investigating co-movements and spillover across different financial markets such as stock market vs. commodity markets, stock market vs. currency or exchange markets. Ghorbel et. al. (2012) applied BEKK-GARCH model, the CCC-GARCH model and the DCC-GARCH model to find out the volatility spillover and the dynamic correlation between crude oil and stock index returns. They found strong evidence of spillovers of volatility from crude oil to all oil-importing and oil-exporting stock markets. Also, the estimates of DCC of the conditional correlations were reported to be significant. Demiralay & Ulusoy (2014) investigated the links between commodity markets represented by Dow Jones commodity indices and stock market represented by S&P 500 index using asymmetric dynamic conditional correlation (ADCC) model. Emphasizing on diversification benefits of commodity markets and the financialization process, the study proved the existence of highly volatile correlations which rise considerably after the 2007-2008 financial crisis. As the conditional correlations and variances are positively connected, the diversification benefits are very less. Also, external shocks impact the correlations differently. Lagesh et. al. (2014) estimated the linkages between Indian commodity futures indices and traditional asset class indices for both pre-crisis and crisis period using the DCC–GARCH model to examine the portfolio diversification possibilities. The results of the study indicated low dynamic conditional correlations between the returns of commodity indices and asset indices suggesting the potential for portfolio diversification. Commodity futures can be effectively used for strategic asset allocation. As traditional asset markets becomes more risky, there are more diversification benefits of commodity futures. Lu et. al. (2014) in their study on gold and stocks tested the dynamic volatility spillover effects between the markets by using VAR-DCC-BVGARCH model. The authors have found that there are considerable bidirectional return and spillover effects between the assets under study with stronger spillover effects from gold to stock. Time varying conditional correlations between the assets are also measured and differ considerably between positive and negative values over time. Aftab et. al. (2015) explored the linkage between currency and stock markets in China focusing on the exchange rate liberalization by applying DCC-GARCH method and suggested that there is negative relation between exchange rate and stock prices which even becomes more during the period of financial crisis. The weak relationships between both the markets point to the fact that there is gradual movements of Chinese markets towards globalization and market integration. Also, there is weak influence of market forces on the relationships between the markets. Aimer (2016) studied the volatility spillovers and conditional correlations between oil price shocks and stock indices of Middle East countries (both oil importing and oil exporting countries) using multivariate GARCH models - BEKK-GARCH and DCC-GARCH model. The results showed significant bidirectional volatility spillover impacts and interdependence between oil returns and stock markets of these countries. The dynamic conditional correlation between crude oil and index returns change considerably over time but, do not vary from oil exporter or oil importer countries. The impact of 2008 crisis on correlation coefficients is much more in comparison to the other events. Wei (2016) in his study on US dollar exchange rate and CRB commodity markets (energy and non-energy) testes the volatility surprise effects by using five MGARCH models (BEKK, CCC, DCC, VARMACCC and VARMA-DCC).

3. EMPIRICAL MODELLING

The paper follows two empirical models to analyse the volatility spillover between stock market and mutual funds returns. Firstly, it applies Exponential GARCH proposed by Nelson (1991) to explore the direction and magnitude of spillover effects between nifty fifty and mutual fund returns.

Secondly, it uses Dynamic Conditional Correlation (DCC) GARCH proposed by Engle (2002) between nifty index and mutual fund market.

3.1. EXPONENTIAL GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY MODEL (EGARCH)

The popular non-linear model to deal with the heteroskedasticity of the data is the autoregressive conditional heteroscedastic (ARCH) model, proposed by Engle (1982). The model was generalized by Bollerslev (1986) in the form of Generalized ARCH (GARCH) model for parsimonious representation of ARCH. In the GARCH model, the conditional variance is also a linear function of its own lags. But, GARCH model is inefficient to model and forecast a series with both symmetric and asymmetric patterns and deals only with the magnitude not the positivity or negativity of the shocks. Nelson (1991) extended the GARCH model in the form of Exponential GARCH (EGARCH) model, which captures not only the asymmetric impacts of shocks or innovations on the conditional variance of future observations but also the magnitude of the shock along with its negativity and positivity. The conditional variance equation specification is (see Brooks, 2014) is:

$$In(\sigma_t^2) = \omega + \beta\, In(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (1)$$

where, σ_t^2 is the conditional variance since it is a one period ahead forecast of the variance

calculated on the basis of past information. ω, β , γ, α are the parameters to be estimated. The parameter α represents the 'GARCH' effect i.e. the symmetric effect of the model. Parameter β measures the conditional volatility persistence in the market. If β is relatively large, it means volatility takes a long time to die out following a shock in the market (see Alexander, 2009). The parameter γ measures the asymmetry or the leverage effect enabling the EGARCH model for testing of asymmetries, thus of great significance. The value of $\gamma = 0$ denotes symmetric model, $\gamma < 0$ denotes that impact of positive shocks or good news is less than the negative shocks or bad news and $\gamma > 0$ implies that positive innovations generate more volatility than negative innovations. If γ is negative and significant, it indicates the presence of leverage effect in the model. Key advantages of estimating this model are that firstly, since In(σ_t^2) is, modelled, σ_t^2 will be positive in spite of the negative parameters, thus, eliminating the requirement of imposing non-negativity constraints on the model parameters. Secondly, there are no restrictions on the parameters used in the formula (Nelson and Cao, 1992).

3.2. DYNAMIC CONDITIONAL CORRELATION GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY MODEL (DCC-GARCH)

As serial dependence is observed in spot and futures price series of the commodities, it dictates the use of some volatility associated model. So, this paper uses Engle (2002) Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCCGARCH) Model to investigate the relationship between spot and futures commodity market. This is an efficient technique in finding the linkages of two or more markets directly. Other important advantages of this approach include incorporating heteroskedasticity by standardized residual coefficient estimation (Chiang et al., 2007), correlation adjustment on the basis of time varying volatility with no volatility bias (Celik, 2012; Cho and Parhizgari, 2008; Forbes and Rigobon, 2002) and direct modelling of the variance and covariance and its flexibility. Also, in enquiring into the time-varying relationships, DCC is more useful and significant in comparison to the subjective-based structural breaks (Moore and Wang, 2014). The DCC-GARCH estimation procedure involves two steps. First of all, conditional variance is estimated with univariate GARCH for each price series, and in the second step, parameters of the dynamic time varying conditional correlation matrix is estimated using the standardized residuals resulting from the step one. This specification includes conditions allowing the covariance matrix to be always positive and the covariance to be stationary. Multivariate DCC-GARCH is modelled as: $X_t = \mu_t$ +_t+ $H_t^{1/2}\ \varepsilon_t$,, X_t is a vector of past observations H_t is a multivariate conditional variance which shows how the risk (volatility) of several assets and their relationships with each other change over time and ε_t is a vector of standardized returns. The GARCH element in DCC-GARCH model can be explained by the variance-covariance matrix as : $H_t = D_t R_t D_t$, where D_t= diag $\{\sqrt{h_{it}}\}$ is a 2 × 2 diagonal matrix of conditional time varying standard deviation from the univariate GARCH models, and

$R_t = \rho_{ijt}$ for i, j=1 and 2 is a conditional correlation matrix, which is dynamic. This model is a generalization of Constant Conditional Correlation (CCC) GARCH model of Bollerslev (1990). D_t component follows the univariate GARCH(p,q) models expressed as:

$$h_{it} = \propto_i + \sum_{q=1}^{Q_i} \gamma_{iq}\ \varepsilon_{i,t-q}^2 + \sum_{\rho=1}^{P_i} \delta_{ip}\, h_{i,t-p} \quad (2)$$

Where,

h_it=The conditional variance of the return for asset i at time t (i.e., how volatile the return is expected to be at time t, based on past data).

$\propto_i$ =The constant term (long-run average variance). It sets a baseline level of volatility.

γ_{iq}= The coefficient for past squared residuals εi,t−q2\varepsilon_{i,t-q}^2εi,t−q2 — i.e., how past shocks or surprises affect current volatility.

$\varepsilon_{i,t-q}^2$=The squared error from past q time periods.Large values mean big shocks in the past.

δ_{ip}=The coefficient for past variances hi,t−ρh_{i,t-\rho}hi,t−ρ — i.e., how past volatility influences current volatility.

P_i =order of past variances (GARCH terms)

Q_i = order of past squared residuals (ARCH terms)

The D_t matrix is always positive as its parameters are always positive. Also, R_t elements are ≤1 as these represent correlations. To ensure that R_t is positive, this matrix is decomposed into two matrices. Thus, the second step of DCC-GARCH framework comprises DCC(m,n) structure specification which is stated as:

$$R_t = Q_t^{*-1} Q_1 Q_t^{*-1} \tag{3}$$

Where,

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right) \ddot{Q} + \sum_{m=1}^{M} a_m \left(\varepsilon_{t-m} \varepsilon_{t-m}^T\right) + \sum_{n=1}^{N} b_n \, Q_{t-n}$$

$Q_1 = q_{ijt}$ is a conditional variance-covariance matrix of standardized residuals,

$\ddot{Q}$ = unconditional covariance matrix of the standardized errors ϵ_t found through estimation of equation (2).

Q_t^{*-1}= diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal.

This study focuses on R_t which is $\rho_{ijt} = q_{ijt} / \sqrt{q_{ii,t}} \, q_{jj,t}$ and attempts to highlight the conditional correlation between spot and futures prices of the select commodities.

Before the EGARCH models were applied, it was necessary to test for the presence of ARCH effects. This was performed by first applying the least squares (LS) method in order to generate regression residuals. Then the ARCH LM test was applied to the residuals to see if time varying volatility clustering does indeed exist.

4. OBJECTIVES AND METHODOLOGY

The objective of this paper is to examine the volatility spillover effects and test time-varying (dynamic) correlations between nifty fifty index and selected mutual funds.

The hypothesis tested in the study is mentioned below:

Hypothesis: "There exists significant volatility spillover between nifty fifty index and selected mutual fund return in India."

Data description: The study is based on secondary data related to nifty fifty index and selected mutual funds. The data consists of daily closing nifty index and daily nav of selected mutual funds returns. The data has been collected from reliable sources such as official website Association of Mutual Fund of India (AMFI) and National Stock exchange (NSE). The data period ranges from April 2007 to April 2024 for all mutual funds and nifty index. The researchers found that use of monthly data might do aggregation and mask crucial volatility transmission channe

ls. Hence, to capture the dynamic interactions between markets daily, data are considered as appropriate (Arouri and Nguyen, 2010).

Empirical methods: The volatility spillover between the markets is examined by using

EGARCH model and DCC-GARCH model. The descriptive statistics of the nifty index and selected mutual funds is also mentioned. Since most of the asset prices in finance is found to

have the unit root, the ADF test are used on the nifty index and selected mutual funds schemes. Using intercept and trend, it is found that all price series are non-stationary at levels and are integrated to the order one i.e. I(1). The prices of nifty and mutual funds are transformed into returns as logarithmic value of the ratio of two consecutive prices using the formula:

$R_t = In\left(\frac{P_t}{P_{t-1}}\right)$.. The analysis is done using MS Excel, EViews and R software.

5. DATA ANALYSIS

This section deals with data analysis and detailed discussion of the empirical results.

5.1. DESCRIPTIVE STATISTICS

The time series analysis aims to identify and analyse the past data so that it can be used for

forecasting future values. To begin with the preliminary investigation, it is imperative to use

simple descriptive statistics. Descriptive statistics help to understand the nature and type of data collected by summarizing the large amounts of data in a sensible and understandable manner. It also helps to choose appropriate econometric model. It involves calculating measures of central tendency like mean, median and mode; measures of dispersion like standard deviation, minimum, maximum values and kurtosis and skewness characteristics of variables. The descriptive statistics in numerical form is presented in table 1:

Table 1

Table 1 Descriptive Statistics

Time series	Mean	SD	Max	Min	Skewness	Kurtosis	Jarque Bera
NIFTY-50	0.037258	1.388731	16.33432	-13.9038	-0.27916	13.97406	30144.7
Aditya Birla Sun Life Frontline Equity Fund	0.047452	1.239893	7.983136	-13.8516	-0.77109	10.37942	16970.82
SBI Blue Chip Fund	0.043528	1.241397	14.15293	-13.791	-0.47729	13.70972	29109.22
HDFC Top 100 Fund	0.047204	1.324928	14.33312	-12.8853	-0.3533	9.806067	14897.45
Nippon India Large Cap Fund	0.045912	1.332908	6.866895	-13.8798	-0.77176	8.877249	12513.1
UTI Mastershare Fund	0.042994	1.184933	7.662326	-13.0504	-0.71515	9.445766	14066.72
Franklin India Bluechip Fund	0.041608	1.228678	8.058438	-12.0791	-0.55009	8.281057	10755.81
Kotak Bluechip Fund	0.042553	1.237376	7.643999	-13.9505	-0.76548	10.26041	16586.91
DSP Top 100 Equity Fund	0.039485	1.255647	8.801947	-15.5168	-0.90545	12.38275	24137.79
Tata Large Cap Fund	0.04168	1.229893	8.128156	-14.468	-0.85295	11.77526	21818.98
Kotak Bond Fund	0.030479	0.248226	2.377625	-3.27984	-0.49431	24.08838	89581.71
SBI Magnum Income Fund	0.028113	0.211203	2.278673	-3.98493	-1.93364	55.81429	482440.7
Aditya Birla Sun Life Income Fund	0.03126	0.274095	3.158017	-4.78283	-0.93045	44.11342	300460.1
IDFC Bond Fund Income Plan	0.030477	0.256774	2.13211	-4.14271	-0.8003	32.2874	161066.5
HDFC Income Fund	0.02761	0.24234	2.249133	-3.7224	-1.41431	37.58517	218957.1
UTI Bond Fund	0.026688	0.307846	7.824935	-5.08593	1.439654	179.3789	4960528
Nippon India Income Fund	0.030148	0.248582	2.036602	-4.10244	-1.27112	35.3464	193554.9
Canara Robeco Income Fund	0.033141	0.189999	2.435004	-1.53507	0.94421	24.18537	90702.32
LIC MF Bond Fund	0.027828	0.203428	2.957398	-3.01133	-0.24789	56.5918	493643.4
Tata Income Fund	0.025864	0.197833	2.196977	-3.39792	-1.55753	44.76916	310404.9
HSBC Debt Fund	0.027268	0.225044	1.886519	-3.8481	-1.67562	41.13349	262504.9
JM Medium to Long Duration Fund	0.015032	0.245061	2.018122	-10.1295	-19.9605	804.8119	100075819.2

The reported results in above table evidence that all the return indexes are significantly positively skewed except negatively skewed UTI Bond Fund and JM Medium to Long Duration Fund which shows that they are asymmetrical. Kurtosis value of all skewed stock returns show that they are not normally distributed because the values of kurtosis are significantly deviated from 3. So, the descriptive statistics show that the stock returns are not normally distributed. The Jarque-Bera statistics for the above considered mutual funds time series and nifty fifty index provide further evidences regarding the departures from the normality assumption. The Jarque-Bera statistic significantly rejects the assumption of normality at 5% level for all the indexes since the P-values all the considered sector return indexes are less than 0.05.

5.2. EGARCH MODEL

The EGARCH model is used in the study in order to examine the influence of the lagged square error term of other market of the respective mutual funds. The lagged squared error term is estimated with the help of mean equation applied on the other market of the mutual fund. This squared error term is included in the EGARCH model as an exogenous regressors. The spillover effect is studied in the direction of nifty to the selected mutual funds with the help of EGARCH models as mentioned below in equation :

$$\ln(\sigma_{MFt}^2) = \omega + \beta \left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \lambda \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \ln(\sigma_{t-1}^2) + \rho\ (\varepsilon^2 * Nifty\ Garch\ Term\ (t-1)$$

where ω represents the intercept term of the EGARCH equation. It represents the long term

average volatility in the asset returns. The second coefficient of the equation β represents the

effect of the size of the previous shock which comes in the market, λ represents asymmetric

effect of volatility, α indicates the coefficient of GARCH term and coefficient of the fifth term ρ shows the significance of volatility spillover between nifty fifty index and selected mutual fund returns in the study. The results of EGARCH model in case of the selected mutual funds is shown in tables below:

Table 2

Table 2 Highly Significant Mutual Funds

EGarch Coefficients	Canara Robeco Income Fund – Growth	LIC MF Bond Fund - Growth	SBI Magnum Income Fund - Growth	Aditya Birla Sun Life Income Fund - Growth	Tata Income Fund - Growth	Kotak Bond Fund - Growth	JM Medium to Long Duration Fund - Growth	Nippon India Income Fund
ω	-0.303	-0.681	-0.403	-0.296	-0.387	-0.242	-1.064	-0.272
	(-31.863) **	(-39.440) **	(-21.177) **	(-33.292) **	(30.266) **	(-29.184) **	(-34.550) **	(-26.411) **
β	0.135	0.200	0.188	0.194	0.186	0.190	0.645	0.169
	(41.095) **	(44.964) **	(42.266) **	(44.119) **	(37.611) **	(42.592) **	(92.729) **	(39.433) **
λ	0.002	-0.023	0.010	0.008	-1.35E-05	0.036	0.309	0.017
	-0.638	(-6.263) **	(2.340) **	(0.037) **	(-0.003)	(6.655) **	(69.351) **	(3.953) **
α	0.984	0.955	0.979	0.987	0.979	0.991	0.943	0.987
	(1455.053) **	(780.927) **	(744.209) **	(1433.281) **	(1118.587) **	(1455.423) **	(447.021) **	(1231.097) **
ρ	89.913	54.927	41.224	26.818	17.953	13.35	39.955	10.895
	(47.437) **	(11.691) **	(11.477) **	(9.622) **	(4.288) **	(4.107) **	(3.760) **	(3.596) **

Table 3

Table 3 Moderately Significant Mutual Funds

EGarch Coefficients	HDFC Income Fund - Growth	HSBC Debt Fund - Growth	Nippon India Large Cap Fund- Growth	UTI Master share Fund- Growth	DSP Top 100 Equity Fund - Growth	Aditya Birla Sunlife frontline equity fund	UTI Bond Fund - Growth
ω	-0.279	-0.235	-0.505	-0.521	-0.505	-0.462 (-7.428) **	-2.2505
	(-31.002) **	(-24.645) **	(-7.650) **	(-8.010) **	(-7.690) **		(-47.128) **
β	0.165	0.188	0.169	0.175	0.177	0.177	0.816
	(47.240) **	(45.716) **	(13.554) **	(13.993) **	(15.291) **	(14.334) **	(73.693) **
λ	-0.008	-0.004	-0.105	-0.119	-0.102	-0.105	0.096
	(-2.372) **	(-1.292)	(-14.686) **	(-16.376) **	(-14.153) **	(-15.557) **	(12.374) **
α	0.986	0.991	0.959	0.959	0.96	0.965	0.849
	(1366.923) **	(1388.960) **	(143.330) **	(150.150) **	(144.938) **	(0.005) **	(2444.445) **
ρ	14.633	8.177	52.482	46.832	37.557	38.704	-42.469
	(3.385) **	(2.615) **	(2.614) **	(2.321) **	(2.090) **	(2.083) **	(-5.583) **

Table 4

Table 4 Insignificant Mutual Funds

E-Garch Coefficients	Kotak Bluechip Fund - Growth	Tata Large Cap Fund - Growth	IDFC Bond Fund Income Plan - Growth	HDFC Top 100 Fund - Growth	SBI Blue Chip Fund	Franklin India Bluechip Fund - Growth
ω	-0.44	-0.454	-0.360	-0.418	-0.377	-0.270
	(-8.718) **	(-7.676) **	(-25.260) **	(-6.933) **	(-8.338) **	(-7.313) **
β	0.170	0.192	0.222	0.169	0.183	0.149
	(14.434) **	(15.879) **	(44.284) **	(14.986) **	(14.327) **	(13.741) **
λ	-0.119	-0.111	0.002	-0.083	-0.100	-0.085
	(-15.683) **	(-15.129) **	-0.655	(-13.034) **	(-16.014) **	(-14.278) **
α	0.967	0.967	0.983	0.968	0.974	0.983
	(196.453) **	(167.241) **	(914.599) **	(164.786) **	(238.924) **	(280.283) **
ρ	31.669	30.285	9.810	26.175	14.900	4.058
	-1.852	-1.647	-1.597	-1.506	-1.284	-0.338

The results indicate value of the coefficients, standard error and the probability value of all the regression coefficients in the EGARCH model for all the mutual funds selected in the study. The result indicates the there exists significant volatility spillover in the direction of nifty index to mutual fund market since the probability value of the fifth term is found to be less than five percent level of significance in case of mostly selected mutual funds. In other words, if the unexpected shock or news comes in the nifty fifty index, this will also influence the volatility in the mutual fund market on the next day. However, the volatility spillover in the direction from nifty fifty index to mutual fund market for few equity mutual funds namely SBI Blue Chip Fund, HDFC Top 100 Fund, Franklin India Blue-chip Fund, Tata Large Cap Fund and for one debt mutual fund namely IDFC Bond Fund Income Plan is not found significant. The magnitude of the spillover effect is also examined with the help of z-statistic of the fifth term included in the EGARCH equation. In the paper the EGARCH model is also applied on the variance equation of the selected mutual fund series. Here, the lagged (lag one) square of the residuals of the mean equation of the nifty are included as the exogenous regressors. The results of the volatility spillover analysis in the direction of nifty fifty index to mutual fund market is also reported in tables 2 above.

In table 2 the β (Beta) coefficient, which measures volatility persistence, is close to 1 for most funds, particularly the Kotak Bond Fund (0.991) and HDFC Income Fund (0.986). This suggests that these funds experience prolonged periods of volatility, meaning that past fluctuations continue to impact future price movements. Investors in these funds should be prepared for sustained market fluctuations, making them more suitable for those with a higher risk tolerance.

The λ (Lambda) coefficient represents the leverage effect, which indicates whether negative shocks increase volatility more than positive ones. Funds like SBI Magnum Income Fund (λ = 0.01) and Kotak Bond Fund (λ = 0.036) have positive leverage effects, meaning that downward market trends cause greater volatility than upward movements. This implies that during market downturns, these funds might experience heightened instability, making them less favorable for risk-averse investors. Conversely, funds such as LIC MF Bond Fund (-0.023) and HDFC Income Fund (-0.008) show negative leverage effects, suggesting that negative market movements do not significantly impact their volatility, making them potentially safer options in bearish conditions.

The α (Alpha) coefficient, which measures how quickly a fund reacts to new market information, is high across all funds (~0.98-0.99). This indicates that these funds rapidly adjust to new economic data, policy changes, or financial news. As a result, these funds are highly reactive to external shocks, making them more suitable for investors who actively track market trends.

The ρ (Rho) coefficient, which captures volatility clustering, is significantly high for Canara Robeco (ρ = 89.91) and LIC MF Bond Fund (ρ = 54.92). This suggests that these funds experience periods of high and low volatility in cycles rather than random fluctuations. Investors with a long-term investment horizon might find these funds attractive, as short-term volatility does not necessarily indicate long-term performance instability.

The findings **suggest that investors should select mutual funds based on their risk appetite and market conditions**. Funds with **high beta (β) and positive leverage effect (λ)** are riskier but may yield higher returns in stable market conditions. Conservative investors should focus on **funds with low beta (β), negative leverage effect (λ), and lower volatility persistence**, such as the **LIC MF Bond Fund and HDFC Income Fund**. Additionally, fund managers overseeing funds with a **strong leverage effect** should implement **risk management strategies** to hedge against market downturns, such as using **derivatives or portfolio diversification**.

Results of DCC-GARCH model

The DCC-GARCH is a multivariate GARCH model where the conditional variance of both nifty fifty index and selected mutual funds are estimated. The results of DCC-GARCH model are shown in table below where the coefficients of GARCH (1,1) are reported. The Ω indicates the intercept term of the GARCH (1,1) model, the α1 indicates the coefficient of the ARCH term in the model, β1 is the coefficient of the GARCH term of the model, the joint DCC α indicates the volatility spillover as a result of unexpected shocks as captured by errors of the mean equation whereas DCC β indicates volatility spillover between the conditional variance of the nifty fifty and selected mutual funds estimated with the help of GARCH model. The results of DCC-GARCH model in case of all the mutual funds are reported in table below:

Table 5

Table 5 Highly Significant Mutual Funds

DCC Coefficient	UTI Bond Fund – Growth	LIC MF Bond Fund - Growth	IDFC Bond Fund Income Plan - Growth	Canara Robeco Income Fund - Growth	Aditya Birla Sun Life Income Fund - Growth	HSBC Debt Fund - Growth	SBI Magnum Income Fund - Growth
Mu(μ)-Nifty	0.0007	0.0007	0.0007	0.0007	0.0007 (4.376**)	0.0007 (4.378**)	0.0007 (4.376**)
	(4.378**)	(4.373**)	(4.377**)	(4.376**)			
Omega(Ω) - Nifty	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000 (0.647)
	-0.648	-0.647	-0.649	-0.649	-0.647	-0.648	
Alpha1(α1)-Nifty	0.0956	0.0956	0.0956	0.0956	0.0956 (2.424**)	0.0956 (2.428**)	0.0956 (2.424**)
	(2.428**)	(2.426**)	(2.429**)	(2.429**)			
Beta1(β1)-Nifty	0.8979	0.8979 (23.942**)	0.8979	0.8979	0.8979 (23.923**)	0.8979 (23.968**)	0.8979 (23.923**)
	(23.962**)		(23.981**)	(23.978**)			

Mu(μ)-mutual fund	0.0003	0.0002	0.0002	0.0003	0.0002	0.0002 (12.726**)	0.0002
	(4.181**)	(3.344**)	(9.833**)	(12.301**)	(9.833**)		(11.377**)
Omega(Ω)-mutual fund	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-0.029	-0.042	-0.099	-0.073	-0.086	-0.035	-0.094
Alpha1(α1)-mutual fund	0.0714	0.0611 (11.912**)	0.0891	0.0530	0.0829	0.0694	0.0907 (3.310**)
	(769.528**)		(5.481**)	(5.141**)	(4.910**)	(4.841**)	
Beta1(β1)-mutual fund	0.9126	0.9202	0.9076	0.9425	0.9159	0.9289 (68.998**)	0.9050
	(562.543**)	(903.351**)	(59.976**)	(82.486**)	(58.733**)		(37.796**)
Joint-DCC alpha(α)	0.0060	0.0049	0.0047	0.005	0.0052 (2.858**)	0.0052	0.0065 (3.134**)
	(3.865**)	(2.910**)	(3.320**)	5(3.505**)		(2.819**)	
Joint-DCC beta(β)	0.992	0.9915	0.9923	0.9914	0.9912	0.9912	0.9896
	(516.149**)	(496.425**)	(471.505**)	(404.671**)	(355.300**)	(352.506**)	(310.511**)

Table 6

Table 6 Moderately Significant Mutual Funds

DCC Coefficient	Tata Income Fund – Growth	HDFC Income Fund - Growth	Nippon India Income Fund	Kotak Bond Fund - Growth	Aditya Birla Sunlife frontline equity fund-Growth	Tata Large Cap Fund-Growth	SBI Blue Chip Fund-Growth
Mu(μ)-Nifty	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007
	(4.373**)	(4.376**)	(4.376**)	(4.378**)	(4.366**)	(4.373**)	(4.394**)
Omega(Ω) - Nifty	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-0.648	-0.648	-0.648	-0.648	-0.641	-0.639	-0.638
Alpha1(α1)-Nifty	0.0956	0.0956	0.0956	0.0956	0.0956	0.0956	0.0956
	(2.426**)	(2.426**)	(2.429**)	(2.426**)	(2.500**)	(2.498**)	(2.389**)
Beta1(β1)-Nifty	0.8979	0.8979	0.8979	0.8979	0.8979	0.8979	0.8979 (23.572**)
	(23.943**)	(23.949**)	(23.970**)	(23.951**)	(24.330**)	(24.208**)	
Mu(μ)-mutual fund	0.0002	0.0002	0.0002	0.0002	0.0007	0.0008	0.0007
	(9.800**)	(9.603**)	(9.106**)	(10.657**)	(4.937**)	(4.855**)	(4.9413**)
Omega(Ω)-mutual fund	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.080)	(0.102)	(0.089)	(0.055)	(1.581)	(1.671)	(1.181)
Alpha1(α1)-mutual fund	0.0808	0.0849	0.0721	0.0685	0.1005	0.1098	0.1049
	(3.885**)	(3.268**)	(3.509**)	(4.446**)	(4.853**)	(5.073**)	(3.669**)
Beta1(β1)-mutual fund	0.9176	0.9128	0.9260	0.9302	0.8842	0.8739	0.8849
	(53.430**)	(43.038**)	(54.969**)	(66.039**)	(41.401**)	(38.870**)	(32.217**)
Joint-DCC alpha(α)	0.0058	0.0055	0.0054	0.0058	0.0487	0.0468	0.0446
	(2.813**)	(2.842**)	(2.791**)	(2.165**)	(4.923**)	(5.436**)	(6.047**)
Joint-DCC beta(β)	0.9910	0.9906	0.9909	0.9901	0.9277	0.9374	0.9317
	(307.936**)	(303.895**)	(282.436**)	(190.493**)	(89.149**)	(78.796**)	(72.888**)

Table 7

Table 7 Insignificant Mutual Funds

DCC Coefficient	UTI Master Share Fund-Growth	Kotak Bluechip Fund -Growth	Franklin India Bluechip Fund-Growth	Nippon India Large Cap Fund-Growth	HDFC Top 100 Fund-Growth	DSP Top 100 Equity Fund - Growth	JM Medium to Long Duration Fund - Growth
Mu(μ)-Nifty	0.0007	0.0007 (4.365**)	0.0007	0.0007	0.0007	0.0007	0.0007
	(4.365**)		(4.381**)	(4.368**)	(4.389**)	(4.374**)	(4.380**)
Omega(Ω) - Nifty	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-0.646	-0.637	-0.643	-0.639	-0.648	-0.648	-0.647
Alpha1(α1)-Nifty	0.0956	0.0956 (2.519**)	0.0956	0.0956	0.0956	0.0956	0.0956
	(2.5077**)		(2.447**)	(2.540**)	(2.419**)	(2.341**)	(2.425**)
Beta1(β1)-Nifty	0.8979	0.8979 (24.470**)	0.8979	0.8979	0.8979	0.8979	0.8979
	(24.444**)		(24.027**)	(24.526**)	(23.912**)	(23.583**)	(23.939**)
Mu(μ)-mutual fund	0.0007	0.0008 (5.163**)	0.0006	0.0008	0.0007	0.0006	0.0002
	(5.048**)		(4.198**)	(4.763**)	(4.025**)	(4.134**)	(11.664**)
Omega(Ω)-mutual fund	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-1.635	-1.598	-0.637	-1.453	-1.923	(1.991**)	-0.014
Alpha1(α1)-mutual fund	0.107	0.1056	0.0874	0.0921	0.0839	0.1013	0.0526
	(5.030**)	(5.075**)	(2.301**)	(4.170**)	(5.201**)	(6.981**)	(3.418**)
Beta1(β1)-mutual fund	0.8763	0.8789	0.9017	0.8934	0.8998	0.8768	0.9412
	(39.787**)	(40.939**)	(23.386**)	(38.891**)	(55.333**)	(57.528**)	(54.359**)
Joint-DCC alpha(α)	0.0482	0.0439	0.057	0.0654	0.0886	0.0552	0.0000
	(4.600**)	(4.183**)	(6.529**)	(5.2044**)	(3.770**)	(3.664**)	(0.000)
Joint-DCC beta(β)	0.928	0.9242 (56.322**)	0.9102	0.91	0.8548	0.8908	0.9126
	(64.050**)		(38.149**)	(29.543**)	(19.846**)	(17.404**)	(8.415**)

The results reported the two categories of spillovers between the nifty fifty index and selected mutual funds returns namely DCCα and DCC β. Here, DCCα shows the volatility spillover due to sudden shocks as captured by errors of the mean equation and DCC β represents the volatility spillover between the conditional variance of two markets i.e., nifty fifty index and selected mutual funds series estimated using GARCH model. Hence, the results report two aspects of dynamic correlation i.e., between the errors of the mean equation and between their conditional variance.

In case of dynamic correlation as indicated by DCCα the probability value is found to be significant in case of nifty fifty and all the selected mutual funds except one debt fund namely JM Medium to Long Duration Fund – Growth. Hence in case of almost all the selected mutual funds the significant volatility spillover as a result of unexpected shock in the market is concluded. However, in case of JM Medium to Long Duration Fund the nifty fifty and mutual fund return are not affected as a result of unexpected market news and information.

The DCC β indicates the dynamic correlation between the conditional variance of the nifty fifty index and selected mutual funds returns. The probability value is found to be significant in case of the nifty fifty index and selected mutual funds returns. This can be concluded from the results that every selected mutual fund has significant spillover effect between the nifty fifty index and mutual fund returns. The GARCH term in the univariate GARCH model indicates the presence of persistence of the volatility in the series. The sum of the coefficients of ARCH (α1) and GARCH terms (β1) is approaching to 1 indicating the presence of high persistence (decaying at a lower rate) in conditional variances. The significant dynamic correlation between the conditional variance of the nifty fifty index and selected mutual fund returns indicates that both the markets maintain the co-movement equilibrium. In other words, the volatility in one market also leads to disturbance in other markets.

6. CONCLUSIONS AND DISCUSSIONS

It is now widely accepted that volatilities have co-movements over time across nifty fifty index and mutual fund market. Understanding the temporal relations of the returns of the two markets raises the question: Is the volatility in one market leading to the volatility in the other market?

Such issue can be studied by using multivariate empirical model rather than working with separate univariate models. This study applies EGARCH and multivariate model i.e., DCC GARCH for examining the volatility spillover effects between nifty fifty index and mutual fund market in India. It is found in the study that significant and asymmetric volatility spillover effects are exhibited in case of most of the mutual funds from nifty index.

However, the magnitude of volatility spillover is concluded higher in case of equity mutual fund as compare to debt mutual funds. The higher volatility spillover from Nifty to equity mutual funds, as compared to debt mutual funds, is primarily attributed to the underlying asset composition, market dynamics, investor behaviour, and liquidity considerations specific to each asset class. Equity mutual funds are more directly influenced by the fluctuations in the equity markets, while debt mutual funds tend to exhibit more stability due to the nature of their underlying fixed-income securities. Further, DCC-GARCH model illustrates the time varying conditional correlation between heteroscedastic coefficients of the nifty index and mutual fund market. The dynamic correlation between the conditional variance of the nifty fifty and mutual fund market is found to be significant in case of all the selected mutual funds. It proves that significant volatility spillover effect is present between the markets. The study has important implications for different stakeholders connected with the mutual fund markets. Generally, also, the knowledge of volatility in any market is important for market participants. It opens doors for investors, traders and bankers in better decision making, hedging and risk management. Understanding of volatility transmission and interrelationship between nifty index and mutual fund market will help investors make right investment decisions, diversification, portfolio optimization and hence, they can lessen the financial risk involved. Financial practitioners, policy makers and regulators can use this knowledge of volatility spillover in planning and implementing appropriate regulatory framework.

CONFLICT OF INTERESTS

None.

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