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Dynamic Portfolio Management including Commodities Futures in India: Evidence of DCC-GARCH Model

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Abstract:
This paper examines the performance of commodities as an alternative investment asset class in India using time varying volatility and dynamic conditional correlation measures. We have optimized weekly performance of portfolios including both financial assets and commodities. Using DCC-GARCH model, this paper estimates time varying volatility and dynamic conditional correlations for portfolio selection and optimization processes. We find that risk-adjusted returns are maximum when commodity is included in a portfolio. Our findings suggest that commodities act as an investment class in India, provide diversification benefits and enhance risk-adjusted return in a portfolio.

Keywords: *Commodity Investment, Portfolio Management, Dynamic Conditional Correlation, Diversification*
JEL Codes: G1, G10, G11, C58, C1

Introduction:

Commodities are progressively entering into the investment basket and emerging as an asset class over the last two decades (Satyanarayan and Varangis 1996; Wadhwani and Shah, 1993; Becker and Finnerty, 2000;Conover et al. 2010; Hammoudeh et al. 2014; Mensi et.al 2014). According to literature there are two important reasons behind this, first returns derived from commodity investments are comparable to financial assets (Bodie and Rosanky, 1980) and second, commodities provide hedge against the inflation (Georgiev, 2001; Dieter et al. 2008). Researchers find that factors influencing the movement of commodity prices are different than financial assets. Factors like seasonality, warehousing requirement, carrying cost, and perishability make the dynamics of commodity markets distinctly different from financial markets (Gorton and Rouwenhorst, 2006). Additionally, investment in commodities also provides inflation hedge, as inflation is nothing but the rise in the prices of commodities. Moreover, low correlation between commodity and equity markets which is supposed to be the reason for diversification is also supported by many researchers as reason for inflation hedge (Lee Luthold and Cordier, 1986; Schneeweis and Spurgin, 2000; Edwards and Caglayan, 2001, Lagesh et. al, 2014).

Further, there are two opposite schools of thoughts in literature about the performance of commodity as an investment asset class in a portfolio in addition to equity and fixed income securities. Prior to the financial crisis of 2007-08, a section of the literature reported that commodities show unique risk and return characteristics (Irwin and Landa, 1987) and provide higher returns in context of portfolio (Anson, M. P., 1998; Jensen, Johnson and Mercer, 2000). As a result there has been huge inflow of capital to the commodity markets which in literature referred as “financialisation” of commodity markets (Domanski and Heath, 2007). On the other hand a section of literature finds a contagion effect between commodity markets and financial markets in the world (Mensi et.al 2013; Tang & Xong, 2012; Chan et.al, 2011; Roy and Roy, 2017). According to them

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correlation between equity and commodity tend to rise with time and is high in recent years reducing the beneficial effect of diversification (Gilbert, 2010; Creti et al. 2013; Buyukuahin, Haigh, and Robe, 2010; Celik, 2012; Daskalaki and Skiadopoulos, 2011; Cheung & P. Miu, 2010; Silvennoinen and Susan, 2013; Paraschiv, Mudry and Andries, 2015).

Methodologically the limitation of these studies is that commodity portfolio has always been considered in static context. They have used time invariant measures like standard deviation, mean VAR and one time correlation at the portfolio selection stage. Time varying and dynamic properties of commodity futures in context of Portfolio have not been considered. Therefore, the present study empirically examines the emergence of commodities as an alternative asset class by using time varying measures of risk, return, and variance-covariance at the portfolio selection stage, followed by dynamic portfolio optimization.

The paper proceeds as follows: next section reviews the related literature. The third section presents the objectives and rationale of the study. Methodology is reported in the fourth section. The fifth section provides analysis, the sixth section discusses the results and finally the seventh section concludes and discusses managerial implications.

Literature Review:

In any organized market, an investor typically owns equity for capital appreciation and purchases bonds for fixed returns and stability. The idea of including commodities in an investment portfolio is relatively new. The pioneering study in this regard was done by Robichek, Cohn, & Pringle (1972) who computed ex-post rates of return and correlation coefficients for twelve alternative investment media and found that in order to get higher risk adjusted returns, investors should consider asset classes other than stocks and t-bill. Another important study was done by Bodie and Rosanky (1980) who compared commodity returns with the Stock returns and found that the performance of a stock-only portfolio could be increased by adding commodities during the 1950-1976 crises. The outcome of this study led to the development of a number of managed commodity funds during 1980s. Prior to February 1979, there was only one fund but by 1985, the number had grown to 94 funds, with over $600 million in assets under management (Elton & Grubber 1987). These managed commodity funds were like mutual funds which invested in forward and futures of commodity, currency & financial instruments. With this, the literature on commodity markets began to focus on evaluating the performance of these commodity funds.

Risk Return Profile of Portfolio with Commodity investment

Studies done by using varied commodity and stock indices like Goldman Sacs Commodity Index, Morgan Stanley Commodity Index, Dow Jones-AIG Index, West Texas Intermediate, London Metal Exchange, Standard & Poor 500, NASDAQ, at different time frames; (Wadhwani and Shah, 1993; Becker and Finnerty, 2000; Gorton and Rouwenhorst, 2005; Ibbotson, 2006; Conover et al.,2010; Smimou, K., 2010; and Hammoudeh et al., 2014) confirms that addition of commodity futures to portfolio enhances portfolio returns.

Earlier Studies attempted to reveal the reasons for the high portfolio returns found that commodities perform better in a portfolio due to the fact that commodity returns tend to have low or zero correlations with security returns (Bodie & Rosansky, 1980; Edwards & Park, 1996; Irwin & Landa, 1987; Schneeweis and Spurgin, 2000; Jensen et al., 2002). Some other studies stated that commodity future returns shows positive correlation with unexpected inflation and exhibit upward movement under high inflation times (Greer, 1978; Bodie, 1983; Halpern and Warsager, 1998; Becker and Finnerty, 2000; Georgiev, 2001; Gorton and Rouwenhorst, 2006; Dieter et al., 2008; Jensen, Johnson & Mercer, 2010). Recently studies done by **(**Erb and Harvey, 2006; Cheung & Miu, 2010; Scott Willenbrock, 2011; Sanders and Irwin, 2012; and Diagler, 2013) found that term Structure of

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commodities and rebalancing return rather than diversification return were the reasons for favourable performance of commodities in a portfolio.

Counterviews on Portfolio Performance & Commodity Investment

There were also some studies which states that Commodity futures might not always perform better in a portfolio (Elton, Gruber and Rentzler, 1990; Schneeweis, Savanayana and McCarthy, 1991; Daskalaki and Skiadopoulos (2011); Cheung & P. Miu, 2010; Silvennoinen & Susan, 2013). Low correlation between commodity an equity markets which was supposed to be the reason for diversification return was also refuted by some studies and according to them correlation between equity and commodity tends to rise with time and is high in the recent years ,after crises (Gilbert, 2010; Creti et al., 2013; Tang & Xiong, 2013; Perry Sadorsky, 2014) .

In India, until last decade, commodities were meant to be used only for consumption and they were not considered as an investment option by the investors. In 2003, after the introduction of nationalized commodity exchanges, there was a shift in status of commodities from a consumption asset to the investment asset. Literature on Indian commodity markets has focused on the issue of market efficiency, price volatility (Maitra and Dawar, 2018), price discovery (Gupta, Choudhary and Agarwal, 2018), market integration, and a number of studies have been done in this context. But risk diversification aspect of commodity futures remains entirely unaddressed. Problems like thin volume and low market depth (Ramasundaram, 2008); no well-developed spot market (Sen & Paul, 2010); poor warehousing, absence of a well-developed grading and standardization system (Harwinder & Arjun, 2013) make the dynamics of Indian Commodity markets entirely different.

Additionally literature review suggests that the correlations and diversification benefits of commodities are time varying. But as far as portfolio selection and optimization methodology is concerned, literature extensively used the Markowitz optimal portfolio framework to examine commodity portfolio performance. Standard deviation is used as a measure of risk, and standardized covariances between various assets are used to estimate correlation for portfolio selection. Moving ahead, researchers (Giott and Lorrent, 2003; Ottenwaelter and Taramasco, 2008; Al Janabi, 2009) have used Value at Risk (VaR) as a risk input, which measures only the downside risk, in place of standard deviation. However, due to integration of financial markets and commodity markets over the years both volatility and correlation structures have become dynamic in nature (Silvennoinen and Thorp, 2013; Narayan, *et.al.*, 2014; Singhal and Biswal, 2019). Therefore, the present study is an endeavour to address the issue of time varying volatilities and correlation among asset classes, so as to obtain a more realistic picture about the performance of commodities as an investment asset

Objectives and Theoretical Framework

Major gap emerging from literature is that there is no consensus among researchers about the performance of commodities in context of portfolio. While majority of the literature confirms that commodities provides diversification benefit and inflation hedge in a portfolio, there are some recent studies which claims the contagion effect of financial and commodity markets after financial crises of 2008. According to them due to this contagion effect diversification benefits provided by commodities is reduced and they might not perform better in portfolio.

In context of portfolio management how different financial market show different conditional volatilities and time-varying correlation, between different markets remains unexplored. The multivariate GARCH model like BEKK can efficiently estimate the conditional correlation between financial markets. However the number of

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parameters to be estimated in case of multivariate GARCH is large and they rise exponentially with the rise in number of assets in the portfolio. Engle, Ito and Lin (1990) and Bollerslev (1990) introduced the Constant Conditional Correlation model, CCC-GARCH) which assumes all conditional correlations to be constant to produce a more parsimonious procedure. However, it is possible that the conditional correlations vary over time as they are updated by the conditional volatility. To solve the problem of increased dimensionality problem of the multivariate GARCH as well as the constant correlation problem of the CCC model, Engle and Sheppard (2001) introduced the Dynamic Conditional Correlation model (DCC-GARCH) which is an improvement over the CCC GARCH as it relaxes the constant correlation assumption and allow for the time-varying correlation. In DCC-GARCH model the number of parameters to be estimated increases linearly rather than exponentially (in case of multivariate GARCH), thereby solving the issue of dimensionality. Hence, methodologically, there is a gap in context of using DCC-GARCH to evaluate the performance of commodities in context of portfolio.

In this paper, we examine the performance of portfolios consisting of both financial assets and commodities using time varying variance and dynamic conditional correlation. First, we have estimated time varying volatility and dynamic conditional correlation using DCC-GARCH model (Engle, 2009). Second, we have used both time varying volatility and DCC correlation as inputs while constructing portfolios including commodities using Markowitz's Portfolio Theory (Markowitz, 1952). Third, each portfolio performance is optimized dynamically every week based on maximum Sharpe Ratio (Sharpe, 1964).

Data Source and Preliminary Analysis

For portfolio construction, weekly closing prices of five asset classes from January 01, 2006 to February 28, 2016 have been used. Equity market is represented by Nifty 50 Index *(Nifty)* of National Stock exchange of India. The Bond market is represented by 10 year Government of India Securities Index (*GSec*) maintained by National Stock Exchange. In this paper, we have taken three sectoral indices from commodity market namely-Agriculture, Energy and Metal. Commodity futures indices constructed by Multi Commodity Exchange (MCX) have been used in this paper for commodity investments. In India MCX is the first listed commodity futures exchange which has the highest market share of nearly 85% of the total commodities traded volume. In this study MCX AGRI future index *(Agri)* for agricultural commodities; MCX ENERGY future index (*Energy*) for commodities traded in energy sector and MCX METAL future index (*Metal*) for metal sector have been used.

In our study effectiveness of commodities as an asset class is investigated by creating different portfolios. Portfolio rebalancing is done on weekly basis so as to accommodate simultaneous dynamic co-movement of different asset classes. If rebalancing is done on daily basis or on intra-day basis, in that case transaction cost would be too high and it would be quiet infeasible. If rebalancing is done on monthly basis then the idea of capturing dynamic correlation among various assets becomes irrelevant. Hence weekly data is used in the study for portfolio optimisation.

The price movements of all assets classes are plotted in Figure1 as a preliminary investigation to see the co-movements of all the assets. All the price series clearly exhibit time varying movements. During 2006 and 2007, when the prices of *Nifty* almost doubled, the prices of all other assets except *Energy* remained in the same range. In 2008, when the price of *Nifty* showed a significant decline, *Energy* reached their peak. Towards 2013, when upward rally of prices stared in *Nifty*, downward trend was found in all commodity indices.

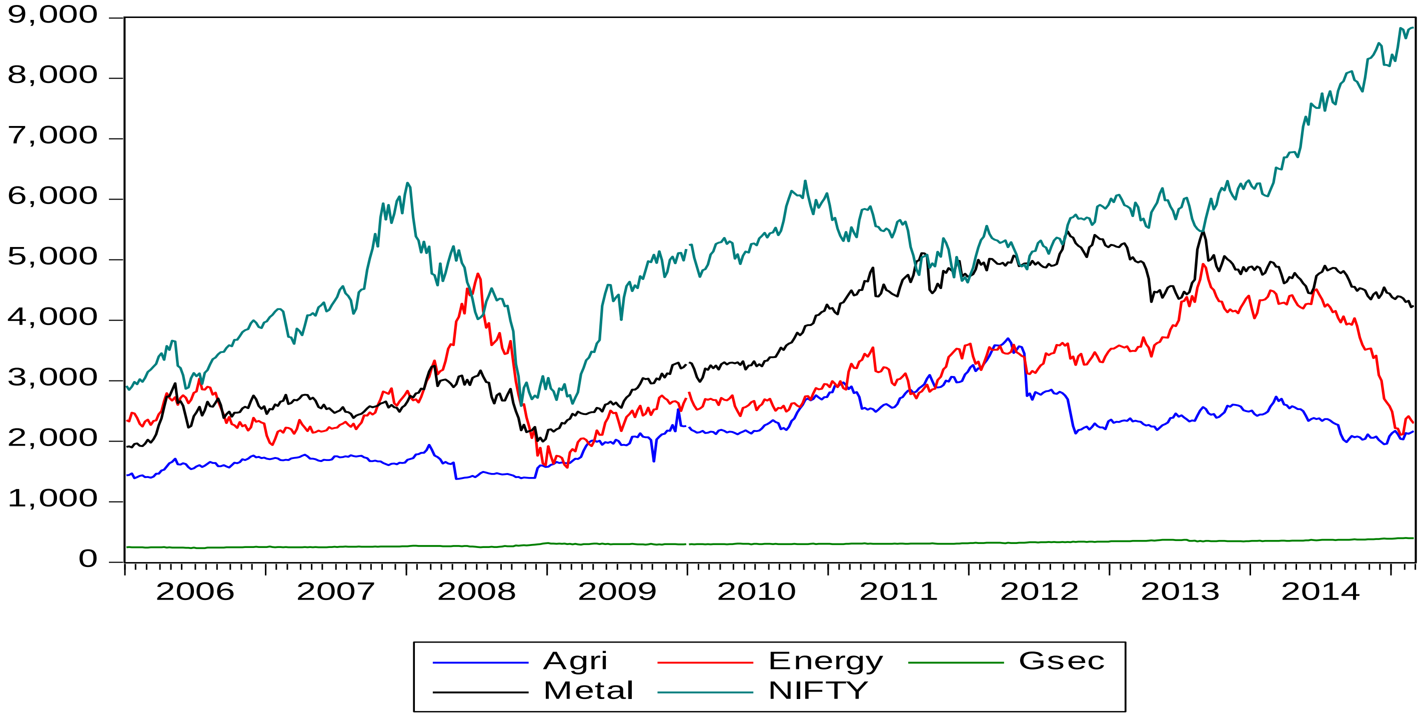

Figure 1 Weekly Price Movements of five Asset Classes (2006-16)

All the price series have been converted to returns using logarithmic return process *i.e.* log (p_t/p_{t-1}). Prior to estimating dynamic conditional correlations and variances (volatility) using DCC GARCH model for portfolio construction, we have estimated correlations among five variables to check for diversification. According to Classical Markowitz portfolio theory, an investor can maximise the returns of a portfolio by diversifying investments into asset classes having negative or very low correlation between them. Correlations among the five return series are given in table -1.

Table 1: Correlation among return series of five assets (2006-16)

Correlation	*Agri*	*GSec*	*Nifty*	*Energy*	*Metal*
Agri	1.000				
GSec	-0.049 (0.153)	1.000			
Nifty	-0.070 (0.042)*	0.045 (0.188)	1.000		
Energy	0.198 (0.00)*	-0.057 (0.098)**	-0.059 (0.087)**	1.000	
Metal	0.113 (0.001)*	-0.040 (0.252)	-0.105 (0.002)*	0.331 (0.000)*	1.000

Note: values in ( ) brackets are p-values. * denotes the level of significance at 5% and ** denotes level of significance at 10%.
Source: Author's calculations

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Returns of all the commodities indices display significant negative correlations with *Nifty* and *GSec*, which give an indication that commodities might add value in a portfolio by enhancing its risk-return profile. Correlation between *Nifty and GSec* is found to be positive in nature. However, these correlations are static and do not highlight the changes in correlation happening over the periods of time. Therefore, we have used dynamic correlation and time varying variance to examine the portfolio performance including commodities.

Table 2 presents the descriptive statistics of return series of all five indices representing three different markets in India. Returns of all the series are negatively skewed with higher kurtosis for all the return series. JB statistics are significant at the 5% level for all asset classes indicating that all the series are not normally distributed. Further, the null hypothesis of unit root is rejected for all the return series from ADF test statistics indicating they are I (0).

Table 2: Descriptive statistics of five asset classes

Parameter	*Agri*	*Energy*	*GSec*	*Metal*	*Nifty*
Mean (%)	0.086	-0.047	0.100	0.168	0.232
Median (%)	0.264	0.282	0.153	0.372	0.385
Max (%)	20.04	18.28	3.69	10.18	14.35
Min (%)	-22.84	-23.53	-4.20	-11.74	-17.37
Std. Dev. (%)	02.95	04.05	1.18	02.76	03.30
Skewness	-1.30	-0.45	-0.39	-0.87	-0.48
Kurtosis	23.10	6.59	4.70	6.17	6.26
JB P-value	0.00*	0.00*	0.00*	0.00*	0.00*
ADF Stat	-45.78	-46.68	-29.18	-50.42	-44.97
ADF P-value	0.00*	0.00*	0.00*	0.00*	0.00*

Notes: * denotes the rejection of the null hypotheses of normality and unit root at 5% significance level.
Source: Author's calculations

3. Econometric Methods

3.1 Dynamic Conditional Correlation- DCC GARCH models

In this paper DCC-GARCH model is used to extract time varying volatilities and dynamic conditional correlations for portfolio construction and optimization. Returns of all the five series are initially modelled in a Vector Auto Regression (VAR) framework and standardised residuals from VAR framework have been used for DCC GARCH modelling. Engle (2009) described this process as "De-GARCHing".

In the first step, univariate GARCH (p,q) parameters are estimated using Maximum Likelihood Estimation (MLE) method for each series. The equations are represented as:

$$y_t = \theta_0 + \epsilon_t \qquad (1)$$

$$\epsilon_t \sim N\left(0, \sigma_t^2\right) \qquad (2)$$

$$\log(\sigma_t^2) = \alpha_0 + \sum_{j=1}^{p} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \qquad (3)$$

ϵ_t is the standardised residual from removing the mean from the VAR residual series. The log of its volatility is modelled in the last equation as a function of its own lagged values and lagged standardised residuals. The β's represent the persistence of volatility and α's the GARCH effect. For the purpose of this research, the GARCH(1,1) model was found to be most appropriate.

At the second stage, time varying correlations were estimated by relying on lagged values of residuals and covariance matrices. The standardised residual from all VAR equations, $\epsilon_{i,t}$, is further standardised with respect to its standard deviation, $\sigma_{i,t}$ as follows:

$$s_{i,t} = \frac{\epsilon_t}{\sigma_t} \qquad (4)$$

The DCC process is then defined (Engle, 2009) by Q_t as:

$$Q_t = \bar{R} + \alpha(s_{t-1}s_{t-1}^{'} - \bar{R}) + \beta(Q_{t-1} - \bar{R}) \qquad (5)$$

$$\bar{R} = diag\{Q_t\}^{-\frac{1}{2}} Q_t diag\{Q_t\}^{-\frac{1}{2}} \qquad (6)$$

The model is estimated using MLE, similar to GARCH. R is the time varying correlation amongst the variables under study and can be plotted against time. The parameters α and β are restricted to be positive and to have a total less than one. Dependence on only these parameters is one of the strengths and weaknesses of this model. Irrespective of number of variables, only these two parameters need to be estimated, making it more likely to reach the optimal solution. Contrary to this, the restriction on all the variables to be following the dynamic process defined by these two common parameters is a restrictive condition.

When the standardised residuals from two variables rise or fall together, then they will push the correlation up. This elevated level will gradually decrease back to the average level with the passage of time due to complete absorption of information. When the residuals move in different directions, they will pull the correlation down, which will move up with the passage of time. The speed of this process is controlled by the parameters α and β.

The DCC-GARCH model will be used to study the time varying correlations amongst the variables under study. The correlations thus obtained will shed light on the time varying contemporaneous relationships amongst the variables.

3.2 *Dynamic Portfolio Management*

In this paper we have constructed and optimized five portfolio combinations with and without commodities for comparisons. In the first portfolio, *Nifty* and *GSec* are included. The second, third and fourth sets are constructed by including only one commodity index at a time along with *Nifty* and *GSsec*. Finally, all three commodity indices such as *Agri, Metal, and Energy* are combined with *Nifty* and *GSsec*.

For portfolio construction and optimization, Markowitz portfolio theory (Markowitz, 1952) is used. In this paper time varying variance from GARCH model is used as a measure of risk in place of standard deviation. Similarly, time varying dynamic conditional correlation is used in place of simple correlation. At portfolio optimisation stage, Sharpe Ratio (Sharpe, 1964) is maximized on weekly basis so as to obtain optimal weights in each asset class. While optimising the portfolio, following constraints are considered. First, sum of the weights of all assets must be equal to one and second; value of weight in each asset must lie between 0 and 1. The same process is followed for all five set of portfolio combinations on weekly basis.

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4. Empirical Results

4.1 Time Varying Risk, Return and Correlation: DCC GARCH Results

Table 3 presents the parameter estimates of DCC GARCH model for all five asset classes. For diagnostic check, we have used the BOX Q statistic for correlation of residuals and BOX Q^2 statistic for correlation in squared residuals. The ARCH LM test is applied to examine the ARCH effect in residuals and it is found to insignificant for all five assets.

Table 3: DCC GARCH Result

Panel –A: Variance Equation Parameters					
	Agri	*Energy*	*GSec*	*Metal*	*Nifty*
ω	0.0003 (0.00)*	0.0000 (0.07)	0.0000 (0.01)*	0.0000 (0.00)*	0.0000 (0.00)*
α	0.9965 (0.00)*	0.0940 (0.00) *	0.1776 (0.00) *	0.1280 (0.00) *	0.1597 (0.00) *
β	0.0001 (0.98)	0.8741 (0.00) *	0.7688 (0.00) *	0.8275 (0.00) *	0.8089 (0.00) *
Panel- B: DCC Parameters					
θ1			0.014 (0.00) *		
θ2			0.962 (0.00) *		
Panel-C Diagnostic Test on Standardized Residuals					
Q (resid)	22.257 (0.327)	17.155 (0.07)	13.453 (0.857)	14.678 (0.795)	23.430 (0.26)
Q $(\text{resid})^2$	3.6910 (0.999)	30.708 (0.079)	12.718 (0.889)	16.837 (0.465)	17.271 (0.63)
ARCH effect	0.1021 (0.74)	2.3669 (0.12)	1.5731 (0.21)	0.8405 (0.35)	0.3670 (0.54)

Notes: p-values are reported in parenthesis. Ljung–box Q statistics correspond to a test of the null of no autocorrelation in residuals and squared residuals with lag=20. ARCH LM statistics correspond to a test of the null of no arch effect.

Source: Author's calculations

GARCH results of various asset classes indicate that the coefficient of lagged squared residual (**α**) is statistically significant for all assets. The coefficient of lagged conditional variance (**β**) is also statistically significant for all the sectors except for *Agri*. This indicates that long-run volatility persistence is not significant in *Agri*. The sum of two parameters is very close to unity and constraint of non-negativity of coefficients is also met. Panel B of Table-3 summarizes the results of DCC estimates for the combination of various asset classes. Parameters θ1 and θ2, which are associated with the short-run and long-run persistence of shocks on the dynamic conditional correlation, are statistically significant at 5% level for all asset classes. This indicates that the conditional correlations are not constant over time..

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The sum of both coefficients of DCC GARCH is less than one which ensures the stability condition of parameters.

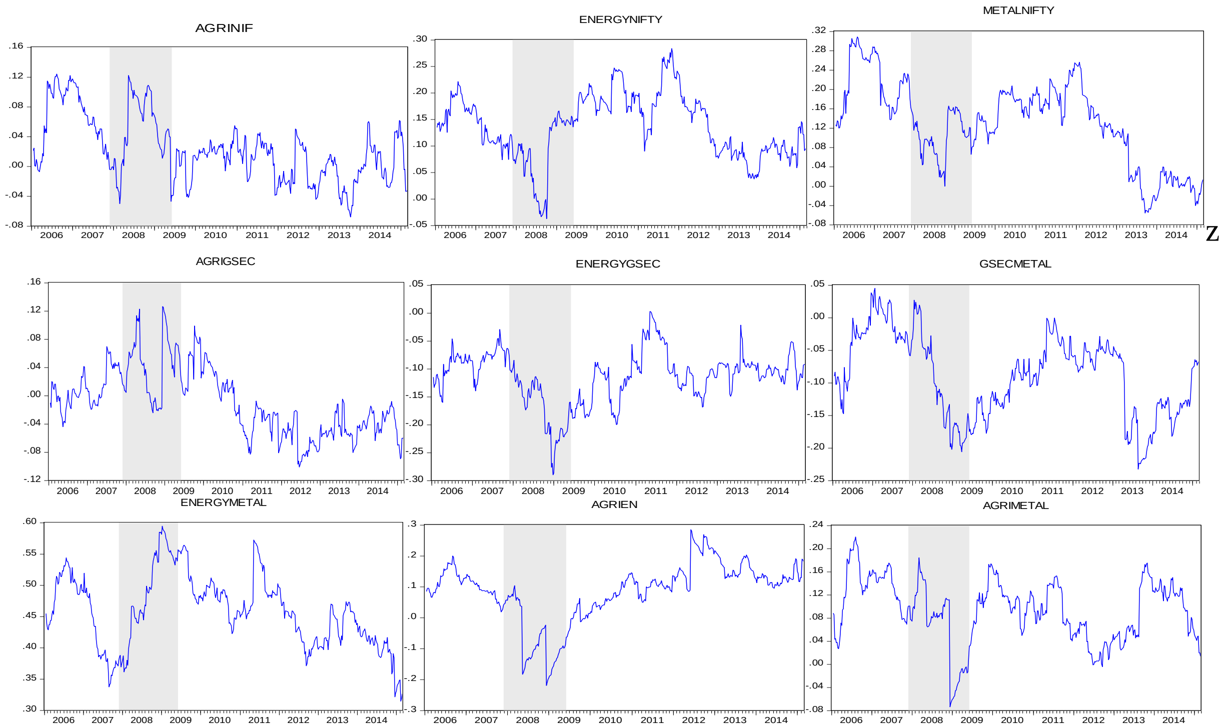

Figure 2: Plot of Time varying correlation among different assets

Figure 2 displays pair wise time varying correlation among commodities, *GSec* and *Nifty*. The shaded area in the graph corresponds to the global recession. The results reveal that *Agri* shows the highest peak of correlation with *Nifty* during crisis, *Metal* before crisis, and *Energy* after crisis. Similarly after 2010, *Agri and GSec* displays downside movement in correlation while *Energy and GSec* exhibits upward trend in correlation. This confirms that various commodity classes perform distinctively different from each other at different points of time. Correlations among commodities are also dynamic. The *Agri* and *Metal* commodities are correlated with a magnitude of around 8-15% while correlation between *Agri* and *Energy* sector is least and are around 1% -3%. Additionally, after 2013, while the correlation between *Agri and Energy* sectors increases, it decreases in case of *Agri-Metal* and *Energy-Metal* sectors. Overall, the result indicates that correlations among different commodities, *GSec* and *Nifty* are time varying. Therefore, it is not the single commodity which provides diversification over time rather different commodities provide better hedging and diversification benefits at different points of time. Thus, assuming a constant correlation between them for the entire duration of study and using the same static correlation may lead to suboptimal portfolio management.

a) *4.2 Portfolio Evaluation*

b) For a particular week, out of the five combinations, portfolio providing the highest Sharpe ratio is considered as the best portfolio combination. Figure 3 represents the weekly Sharpe ratio of five different portfolios. Figures show that the portfolios with commodities result in maximum Sharpe ratio more frequently than portfolio only with financial assets (*Nifty+ GSec*).

Weekly portfolio optimisation results are presented in Table 4 and Figure 4. The findings indicate that out of the 479 weeks, Sharpe Ratio is maximum in only 5 weeks *(i.e.* less than 1%) in portfolio without any commodities. Portfolio having combination of a single commodity along with equity and bond provides maximum Sharpe Ratio for 25-35 weeks *(i.e.* 6%-8%). This implies that adding a single

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commodity to the portfolio provides higher Sharpe Ratio than portfolio without any commodity. Moreover, when all the commodities were added to the portfolio, risk adjusted returns were enhanced for 379 weeks (*i.e.* 79%).

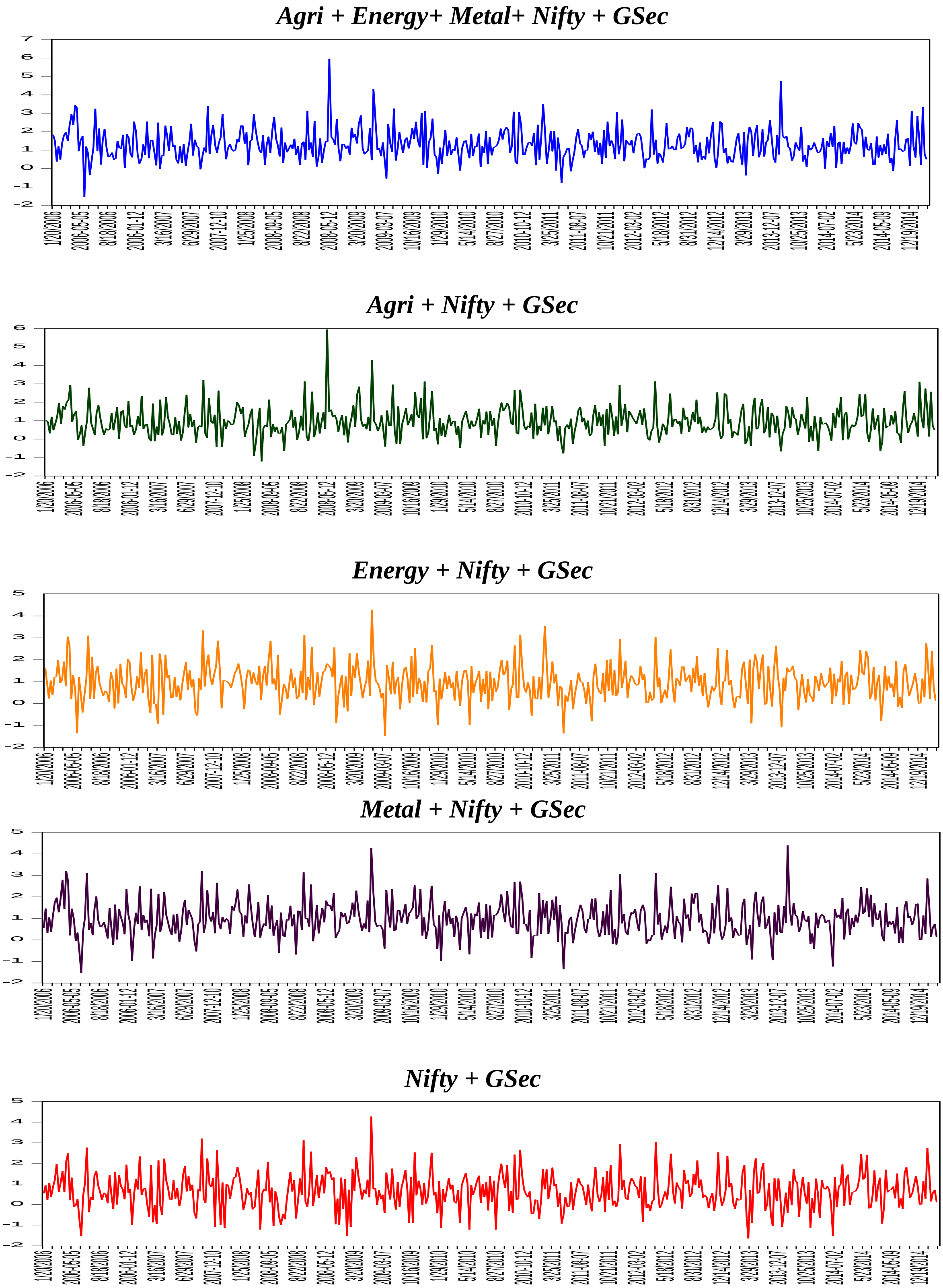

Figure 3: Weekly Plot of Sharpe ratio for five Portfolio Combinations

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Table 4: Weekly Frequency of Maximum Sharpe Ratio in different Portfolio Combinations

Portfolio Combination	No. of weeks with Maximum Sharpe Ratio
1. *Agri + Energy+ Metal+ Nifty + GSec*	379 weeks
2. *Agri + Nifty + GSec*	23 weeks
3. *Energy + Nifty + GSec*	37 weeks
4. *Metal + Nifty + GSec*	35 weeks
5. *Nifty + GSec (No commodity)*	5 weeks

Source: Author's calculations

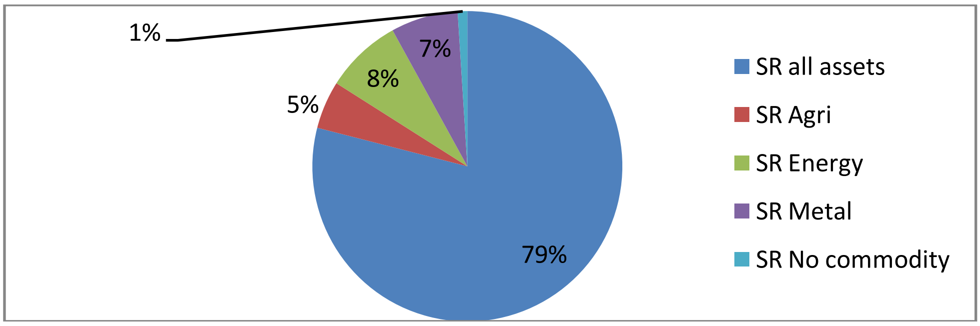

Figure 4: Percentage of Maximum Sharpe ratio for different Portfolio Combinations

We have used t-test to check whether the differences in Sharpe Ratios of commodity versus no commodity portfolios are statistically significant. The null hypothesis in each case is that mean Sharpe Ratios of both portfolio combinations with or without commodities is equal. Sharpe Ratio of all portfolio combinations and the result of t-test are presented in table 5.

Table 5 Results of t-test of Commodity versus no Commodity Portfolio

Portfolio Combination	**Sharpe Ratio**	**T-TEST**
Agri + Energy+ Metal+ Nifty + GSec	1.295	11.882 (0.00)*
Agri + Nifty + GSec	0.949	5.482 (0.00)*
Energy + Nifty + GSec	0.955	-5.536 (0.00)*
Metal + Nifty + GSec	0.958	-5.618 (0.00)*
Nifty + GSec (No commodity)	0.653	

Note: Values in parenthesis are p-values. * indicates rejection of null hypothesis of no significant difference in mean returns at 5% significance level.
Source: Author's calculations

Table 5 reveals that the mean Sharpe ratio of a portfolio without commodity is least. As commodities are added to the portfolio, mean Sharpe ratio is improved and it is highest when all assets are part of the portfolio. The result of t-test indicates that null hypothesis of equality of mean Sharpe ratio is rejected in all cases and alternate hypothesis of significant difference in mean risk adjusted returns is accepted. This implies that there is a significant difference in the risk adjusted returns of portfolios with and without commodities. Therefore, it is found that returns of a portfolio can be enhanced significantly by including commodities

Results and Discussion

Empirical result indicates that the correlation and volatilities among assets is time varying and highly significant in nature. The risk adjusted returns of portfolio also enhanced significantly with the addition of commodity. Result implies that out of the total 479 weeks of the study, Sharpe ratio was highest for the portfolio having combination of all assets (commodity, equity and bond). However, the

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portfolio with a combination of only equity and bond had the highest Sharpe ratio for only five weeks validating that including commodities to the portfolio enhances risk adjusted returns of the portfolio.

Important point worth noticing is that aforementioned result is consistent for the entire duration of study (which encompasses booming, recessionary and declining phase of economy). Portfolio comprising commodities perform better in 99% of this duration which implies that commodities do act as an investment asset class and they perform better in context of portfolio in all phases of economy. However, at one point of time, one set of commodity might perform better and at another time some other commodity might perform better, therefore, best portfolio returns were obtained when all of them were added to the portfolio.

Hence, it can be concluded that commodities perform better in context of portfolio and provide significant diversification benefits at all points of time. As investors tend to diversify their investment across different asset classes, results of this study would be crucial input for investors in portfolio diversification and hedging. Additionally, using the estimates of our bivariate models, an investor can hedge his position against unfavourable effects from stock price movements by calculating the optimal holding weight of commodity in a portfolio of commodity, equity and bond in accordance to a formula given by Kroner and Ng (1998). This will help the investor to minimize risk while keeping unchanged the expected return.

CONCLUSION

This paper examined the performance of commodity as an investment asset in a portfolio using dynamic conditional correlation and time varying volatility. We have used weekly price data during January 2006 – February 2015 from three different markets such as equity, bond and commodity. First, we have estimated time varying volatility and dynamic conditional correlation using DCC-GARCH model (Engle, 2009). Second, we have used both time varying volatility and DCC correlation as inputs for asset selection while constructing portfolios including commodities using Markowitz's Portfolio Theory (Markowitz, 1952). Third, each portfolio performance is optimized dynamically every week based on maximum Sharpe Ratio (Sharpe, 1964). We find that Sharpe Ratio is maximum when commodity is part of a portfolio. Our findings suggest that commodities act as an investment class in India, provide diversification benefits and enhance risk-adjusted return in a portfolio (Bekiros et.al, 2016; Mensi et.al 2013; Mensi et.al 2017).

The empirical evidence of this paper has got important implications for fund managers while constructing and rebalancing the portfolio in two ways. First, they can look for commodity as an asset class during portfolio construction and optimization in India. Secondly, they need to rebalance the portfolio dynamically to derive optimal risk adjusted returns. This paper also creates scope for further research to examine the dynamic portfolio management across various economic regimes by including commodities in the portfolio.

Our study has got immense policy implications both for banking and mutual fund industry as an array of reforms happening in commodity derivatives and portfolio management services in India. After a recent merger of the "Forward Market Commission" (erstwhile commodity market regulator) with "Securities and Exchange Board of India, the market regulator is continuously pushing for reforms in commodity trading segment. In March 2016, the Securities and Contracts Regulations Act (SCRA) was amended by Securities and Exchange Board of India (SEBI) to include commodity derivatives as "eligible securities" which essentially meant that institutions such as banks, mutual funds and foreign portfolio investors could invest in the commodity derivatives market. In line of the above reform, Reserve Bank of India (India's central bank) in September 2017 decided to allow banks to participate in commodity derivatives (except on their own account) trading. Following this decision, banks

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in India are in discussion with officials of commodity exchanges to understand commodity trading and its implications for banks portfolio management. Almost at the same time in September 2017, SEBI allowed Foreign Portfolio Investors (FPIs) to participate in non-agricultural commodities derivatives trading in international financial services centers. Moreover, in a recent interview the market regulator said they are in advanced stages of talks on allowing mutual funds and portfolio management services to trade in commodity derivatives. In this regard, they are in discussion with the Association of Mutual Fund Industry (AMFI) which has already submitted its report to the market regulator.

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