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Forecasting Performance of GARCH Family Models in the Indian Commodity Markets

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Abstract: ***The present paper examines the forecasting ability of the GARCH family models with reference to the Indian commodity markets. The study uses four futures indices of the Multi Commodity Exchange of India (MCX) which represent the commodities across sectors such as agriculture, energy and metals. MCX also maintains a composite index MCXCOMDEX that encompasses the other futures indices MCXAGRI, MCXENERGY and MCXMETAL The symmetric GARCH model and three asymmetric EGARCH, TARCH and PARCH variants have been used to test the forecasting efficiency of these models. The mixed results indicate that any single model's claim to forecasting efficiency across the four indices is not justified.***

***Index Terms*—GARCH, Commodities, Futures, Forecast**

I. INTRODUCTION

Commodities are regarded as the fourth asset class after equity, fixed income instruments and money market instruments. Constitution of the Chicago Board of Trade (CBOT) in 1848 marked the beginning of organized commodity trading on an exchange [1]. Organized commodities trading in India began in the year 1875 with the establishment of Bombay Cotton Trade Association. In 1900, futures trading in oilseeds was introduced with the setting up of the Gujarati Vyapari Mandali. Since then, India has had a rich history of trading in commodity futures till mid-1960s when it was discontinued due to war, natural calamities and ensuing shortage of commodities. Since 2003, trading in commodities has seen a phenomenal growth in India.
The Forward Contracts (Regulation) Act of 1952 laid the foundation stone for the governance of commodities futures contracts and all the commodity exchanges were regulated by the Forward Markets Commission (FMC) under the Ministry of Consumer Affairs, Food and Public Distribution, Government of India. Though the FMC was overseeing the operations in the Indian commodities markets for over 60 years, its powers were limited which is thought to be the cause for fluctuations and irregularities in the market. To streamline the regulations, curb speculations and promote growth, it was decided that the FMC would merge with SEBI (Securities and Exchange Board of India). This announcement was made by the Finance Minister in his budget speech in February 2015. This merger aims to "increase economies of scope and economies of scale for the government, exchanges, financial firms and stakeholders".

Commodity markets perform four important functions: Price Discovery, Price Risk Management, Improve competitiveness in the Imports and Exports, and provide Benefit for farmers and agriculturists[2]. To meet food and raw material requirements and manage supply-demand scenarios, forward contracting in commodities was carried out in India for a long time. But forward contracts give rise to price risk and hence, the need for this price risk management. This can be done effectively through futures contracts. A Commodity futures contract is an agreement to buy (or sell) a specified quantity of a commodity at a future date, at an agreed price when entering into the contract. While futures contracts as an investment product exists for a variety of financial instruments, its uniqueness as a commodity derivative makes it an attractive investment product

Commodity futures allow producers to insure themselves against unfavorable variations in commodity prices. The markets allow non-producer investors to receive a return for bearing a risk on commodity price fluctuations. Through organized exchanges, these risks are borne by a large number of investors/speculators for a premium. This leads to efficient price discovery since a large number of participants bring in variety of expectations and opinions on the behavior of the underlying assets.While some commodities are storable, some are not; the use of each product in production stage varies; quality differs. These features of the underlying commodities make it much more complicated for organized exchanges as it becomes difficult to handle and commands a vast amount of resources and infrastructure.

India presently has 17 commodity exchanges of which six are national level commodity exchanges. Of these, the most important ones are Multi Commodity Exchange of India Limited (MCX) National Commodity and Derivative Exchange (NCDEX) National Multi Commodity Exchange of India Ltd (NMCE). According to the Forward Markets Commission's 2013-2014 Annual Report, MCX contributed 85% of FMC's revenues and is the largest commodities exchange in India followed by NCDEX, Mumbai (11.30 %), NMCE, Ahmedabad (1.51 %), ICEX, Mumbai (0.84 %), ACE Mumbai (0.46%) and UCX, Navi Mumbai (0.72%). MCX offers trading in over 50 commodities. In addition, it maintains four Commodity Futures Indices (MCXCOMDEX, MCXMETAL, MCXAGRI and MCXENERGY), four Commodity Spot Indices (MCXSCOMDEX, MCXSMETAL, MCXSAGRI and MCXSENERGY) and three Rainfall Indices (RAINEXIDR, RAINDEXMUM and RAINDEXJAI).

Commodities' trading in India has seen phenomenal growth in the recent past as evidenced in Figure 1. It is also infamous for wild price fluctuations which is generally attributed to speculative participants[3]–[5].

Given the nature of the underlying and its relation to the Indian economy, it is of utmost importance that this market needs to be thoroughly analyzed. This paper is an attempt to capture and model the volatility in the Indian Commodity Markets using the GARCH family of models.

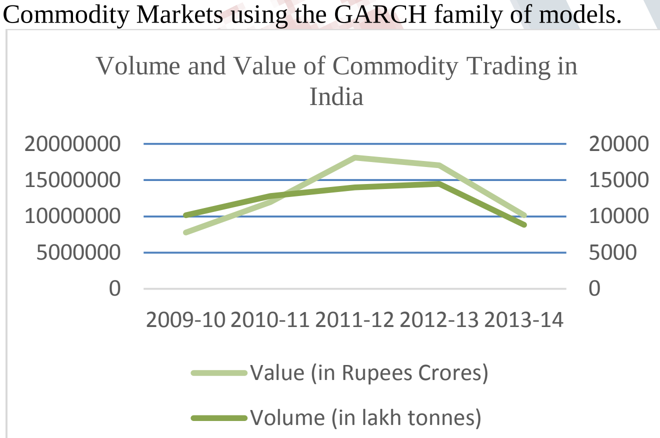

Figure 1: Growth of Indian Commodity Markets

II. LITERATURE REVIEW

Prior studies in commodities markets have focused on price discovery[2], [6], [7], lead-lag relationship between futures and spot markets[8] and efficiency of commodity markets[9]–[11]. Introduction of derivatives trading in Indian commodity markets has been a topic of much debate for producers, consumers, researchers and policy makers. While some researchers believe that commodity derivatives have increased speculative activity and volatility, some others have shown that these products have reduced volatility thereby improving stability.

Indian agricultural commodities futures markets are not yet mature and efficient [12]. But Indian Commodity markets exhibit an efficient price discovery in place [2], [6]. When Granger Causality, Co-integration and Vector Error Correction Models are applied in the process of process of price discovery on pepper prices, it was found that there is unidirectional causality from futures to spot prices in the futures market [6]. Price discovery role of futures market might be affected by liquidity and market size [13].

For agricultural commodities such as maize, chickpea, black lentil, pepper, castor seed, soybean and sugar, it has been found that the futures and spot prices are cointegrated in the long term[14]. The study also revealed a short-term relationship between the two markets and that the futures market had the ability to predict spot prices for some of the commodities and the relationship was bi-directional for a few others.

An empirical analysis of the efficiency of spot and futures markets using Johansen cointegration techniquehas found that the futures market is unable to fully incorporate information which confirmed the inefficiency of the market. The study focused on the daily futures and comparable ready prices of five commodities across six Indian commodity exchanges. Hence the Indian agricultural commodities futures markets are not yet mature and efficient [12].

An examination of the lead-lag relationship between the spot price of commodities and the associated futures contract in the Indian market scenario concluded that information first appears in futures market and then is transmitted down to the spot market. Hence, futures market enjoys greater leverage which attracts speculators. Also, speculative activity provides liquidity to the market and helps in price discovery [8]. Data for that particular study consisted of daily cash closing prices, daily futures settlement prices, total futures trading volume, and total futures open interest for the agricultural commodities barley, maize, mustard seed and pepper traded on National Commodity Exchange (NCDEX) in India.

Commodity price volatility exhibits a leptokurtic behaviour [15]. It makes futures prices difficult to forecast because futures price becomes wider. Since the accuracy of forecasting is decreased, it makes it difficult for both producers and consumers to protect their welfare[16]. In addition, supply/demand, weather conditions, change in trading volumes, terms of trade shocks and exchange rates also caused an increase in price volatility [15]. These studies also establish the need for hedging commodity prices [15]. The studies on Indian commodity markets have recommended the strengthening and autonomy of the Forwards Market Commission and also the need for well-developed warehousing and market linkages to make them more efficient [2]. Literature on Indian commodity markets has mainly focused on agricultural commodities[17]–[26]or is limited to few commodities traded on national exchanges.

This study contributes to the existing literature on the Indian commodities markets by studying the Indices being maintained by Multi Commodities Exchange of India Limited (MCX) viz. MCXCOMDEX, MCXMETAL, MCXAGRI and MCXENERGY. Commodity indices capture the broad market sentiments and studying these instruments gives a macro view of the markets as compared to the micro view by studying an individual commodity. As with other markets, volatility of futures prices is a concern and there is a need to develop a model to efficiently forecast the futures prices in order to better understand the behavior of these markets. The GARCH family models have been very popular in literature for studying and modelling volatility. The usefulness of these models in studying the Indian commodity markets will provide deeper insight into the concealed behavior that these markets exhibit.

III. DATA AND METHODOLOGY

This study employs futures data of four commodity indices actively traded on the Multi Commodity Exchange (MCX) – MCXCOMDEX, MCXMETAL, MCXENERGY and MCXAGRI. The MCXCOMDEX is a composite index comprising of MCXMETAL (40%), MCXENERGY (40%) and MCXAGRI (20%). The daily closing price of the four indices has been considered for this study. MCX considers only the near month active contract price for index computation.

As with equity indices, Indian commodity market indices encompass all the commodities available for derivative trading in the market and provide a good overall sense of the commodity markets. Indices also give a macro perspective which is helpful in understanding the volatility of the market. Table I lists the four indices being maintained by the Multi Commodity Exchange of India and their components.

Table I: List of MCX indices and their components

Index	Components	Weights
MCXCOMDEX	MCXMETAL Index	40.00%
	MCXENERGY Index	40.00%
	MCXAGRI Index	20.00%
MCXMETAL Index	Gold	38.03%
	Silver	24.15%
	Copper	17.83%
	Zinc	5.00%
	Aluminium	5.00%
	Nickel	5.00%
	Lead	5.00%
MCXENERGY Index	Crude Oil	88.53%
	Natural Gas	11.48%
MCXAGRI Index	Ref. Soy Oil	19.55%
	Potato	23.80%
	Chana	20.70%
	Crude Palm Oil	15.95%
	Kapaskhalli	10.00%
	Mentha Oil	10.00%

A. *GARCH Family models*

The GARCH model is effective in capturing the time-varying nature of volatility and models it as conditional variance. It expresses the conditional variance of the error term as a linear function of the lagged squared residuals and the lagged residual conditional variance. GARCH also captures volatility clustering found to be highly evident in financial data. The GARCH approach is a common and simple way to use historical data to study volatility as it is designed to track variations in volatility through time. The GARCH model is symmetric in nature i.e., it treats both good news and bad news with equal importance. Since Leverage Effect is very common in financial data, this symmetric nature of GARCH model may prove to be a limitation. To overcome this, variants of GARCH such as TGARCH, EGARCH etc. were developed which are asymmetric in nature and capture the Leverage Effect more effectively.

B. *The GARCH (1,1) model*

In a GARCH (p,q) model given by [27], p represents the order of the moving average ARCH terms and q represents the order of autoregressive GARCH terms.

$Y_t = \omega + \alpha_1 X_t + \varepsilon_t$ Where $\varepsilon_t \sim N\ (0, \sigma_t^2)$ ………………….(1)

$\sigma_t^2 = \omega + \sum_{t=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$ ………………….(2)

Where

Equation (1) represents the conditional term

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Equation (2) is the conditional variance equation
In both the above equations ω is a constant.
In Equation (2),
ε_{t-1}^2 is the ARCH term which is represents the volatility from the previous period and is measured as the lag of the squared residual form the mean equation
σ_{t-j}^2 is the GARCH term which represents the forecast variance of the previous period
The GARCH (1,1) model refers to the presence of a first order moving average ARCH term and a first order autoregressive GARCH term. The mean and the variance equations for the GARCH (1,1) model are as follows:

$$Y_t = \omega + \alpha_1 X_t + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$\sigma_t^2 = \omega + \alpha \ \varepsilon_{t-1}^2 + \beta \ \sigma_{t-j}^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

C. The Threshold GARCH (TARCH) Model

The TARCH model was introduced by both [28]and [29]independently. It is an asymmetric GARCH model factors in the 'leverage effect' and good news and bad news have differential effect on the model. An additional term ε_{t-k}^2 is added to the GARCH equation to account for possible asymmetries. As with GARCH(1,1), ε_{t-1}^2 is the ARCH term which is represents the volatility from the previous period and σ_{t-j}^2 is the GARCH term which represents the forecast variance of the previous period

$$\sigma_t^2 = \sum_{t=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

In Equation (5), $I_t = 1$ if $\epsilon_t < 0$ and 0 other wise. Good news is represented by $\epsilon_{t-1} > 0$ and has an impact of α_i while bad news is represented by $\epsilon_{t-1} < 0$ and has in impact of $\alpha_i + \gamma_i$.
$\gamma_i \neq 0$ implies that the impact of news (good or bad) is asymmetric. $\gamma_i > 0$ implies evidence of leverage effect and that bad news increases volatility.

D. The Exponential GARCH (EGARCH) Model

Nelson [30]proposed the EGARCH model which is specified by the conditional variance equation

$$\log(\sigma_t^2) = \sum_{t=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}^2}{\sigma_{t-k}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

The EGARCH model implies that the conditional variance is exponential (hence log), rather than quadratic as implied by the other GARCH variants. As with GARCH(1,1), ε_{t-1}^2 is the ARCH term which is represents the volatility from the previous period and σ_{t-j}^2 is the GARCH term which represents the forecast variance of the previous period.
While α represents the symmetric effect of the model and β represents the persistence in conditional volatility, γ in Equation (6) is a measure of the asymmetry or leverage effect.
γ =0 denotes that the model is symmetric. γ < 0 indicates that positive news generates less volatility than negative news. Conversely, γ > 0 indicates that negative shocks have a higher impact than positive news.

E. The Power GARCH (PARCH) Model

In the PARCH model proposed by Taylor[31], the standard deviation is modelled rather than the variance with the estimation of the power parameter δ. As with GARCH(1,1), ε_{t-1}^2 is the ARCH term which is represents the volatility from the previous period and σ_{t-j}^2 is the GARCH term which represents the forecast variance of the previous period. The optional γ parameter is included to capture the asymmetry. The PARCH model estimates the variance as:

$$\sigma_t^{\partial} = \omega + \sum_{t=1}^{p} \alpha_i \left(|\varepsilon_{t-1}| - \gamma_i \varepsilon_{t-i} \right)^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\partial} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Where δ > 0, $|\gamma_i| \leq 1$ for i=1, ……, r, $\gamma_i = 0$ for all$I > r$ and $r \leq p$

IV. EMPIRICAL ANALYSIS

The period of study is from May 2006 to March 2016. Daily closing data of MCXCOMDEX, MCXMETAL, MCXENERGY and MCXAGRI gives us 2921 observations. The entire sample is divided into two parts: observations for model building and hold-out-sample observations for validating the model. Data from May 2006 to December 2015, which comprises of 2858 observations is used to estimate the models. Data from January 2016 to March 2016 has been reserved as the hold-out sample for out-of-sample forecasting. Table II. displays key descriptive statistics of the four indices.

Preliminary investigation verify the stationary of data by employing Augmented Dickey-Fuller test [32]and Philips-Perron test reveals that the raw price data is not stationary. GARCH family models assume stationary of the data series. Hence, to achieve stationarity, the returns series is used. It is calculated as

$$R_t = \left({P_t - P_{t-1}} / {P_{t-1}} \right)$$

Table II: Summary Statistics of Daily Closing Prices

	MCXCOMDEX	MCXAGRI	MCXENERGY	MCXMETAL
Mean	3319.296	2434.445	3185.105	4228.806
Median	3516.8	2343.01	3189.145	4505.98
Maximum	4689.6	3716.58	5137.1	5741.31
Minimum	1736.44	1570.77	1479.48	2096.69
Std. Dev.	625.2075	418.6217	726.3934	871.229
Skewness	-0.648681	0.748024	0.145595	-0.804573
Kurtosis	2.388679	3.525445	2.345845	2.422481
Jarque-Bera	163.8632	200.3022	40.84589	232.8559

The skewness and kurtosis statistics clearly indicate the presence of fat tails and extreme values. Kurtosis > 3 also indicates that the right tails are extreme.

To model the data for GARCH, EGARCH, PARCH and TARCH, 2855 daily observations are used. Models are estimated by the method of maximum likelihood and errors are studies for three types of conditional distributions - Gaussian, Student's t and Generalized Error Distribution(GED). Three statistics –Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Criterion (HQC) are used to rank the models. Lower the value of the statistic, better is the model. The table below displays the ranks of the models for each of the indices – MCXCOMDEX, MCXAGRI, MCXENERGY and MCXMETAL.

Individual rank of each model for the three assumptions of error distribution is indicated below the respective statistic. The last row indicates the sum of the individual ranks and the definitive rank in parenthesis.

V. RESULTS AND DISCUSSION

The results of the various tests along with test statistics have been discussed below.

Table III: Statistical verification and ranking of models for MCXAGRI

AGRI	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
AIC	-6.42899	-6.966632	-6.905238	-6.453749	-6.966632	-6.905238	-6.429641	-7.004686	-6.935546	-6.4051	-6.976142	-6.914406
	11	3	7	9	3	7	10	1	5	12	2	6
SIC	-6.416471	-6.952027	-6.890633	-6.44123	-6.952027	-6.890633	-6.415036	-6.987995	-6.918855	-6.386322	-6.955277	-6.893542
	10	3	7	9	3	7	11	1	5	12	2	6
HQC	-6.424476	-6.961366	-6.899972	-6.449235	-6.961366	-6.899972	-6.424374	-6.998667	-6.929527	-6.398328	-6.968618	-6.906883
	10	3	7	9	3	7	11	1	5	12	2	6
	31(10)	9(3)	21(7)	27(9)	9(3)	21(7)	32(11)	3(1)	15(5)	36(12)	6(2)	18(6)

The AIC, SIC and HQC for the four models across the three error distributions for MCXAGRI index have been displayed in Table (III). All three statistics strongly favour PARCH(1,1) model and Student's t distribution. The asymmetric models PARCH, TARCH are shown to be better suited for MCXAGRI than the symmetric GARCH model.

Table IV: Statistical verification and ranking of models for MCXENERGY

ENERGY	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
AIC	-5.646674	-5.69258	-5.699234	-5.645671	-5.692184	-5.698548	-5.645977	-5.691898	-5.698534	-5.646928	-5.692814	-5.699059
	10	6	1	12	7	3	11	8	4	9	5	2
SIC	-5.634155	-5.677974	-5.684629	-5.631066	-5.675492	-5.681857	-5.631372	-5.675206	-5.681842	-5.62815	-5.671949	-5.678194
	9	5	1	11	6	2	10	7	3	12	8	4
HQC	-5.64216	-5.687313	-5.693967	-5.640404	-5.686165	-5.692529	-5.64071	-5.685879	-5.692515	-5.640157	-5.68529	-5.691535
	9	5	1	11	6	2	10	7	3	12	8	4
	28(9)	16(5)	3(1)	34(12)	19(6)	7(2)	31(10)	22(8)	10(3)	33(11)	21(7)	10(3)

Table (IV) discusses the efficiency of models for MCXENERGY. The symmetric GARCH(1,1) model with GED clearly ranking above the rest. The GED distribution is better suited for this index than the other error distributions.

Table V: Statistical verification and ranking of models for MCXMETAL

METAL	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
AIC	-6.396202	-6.492245	-6.509658	-6.391942	-6.491216	-6.508021	-6.39551	-6.491916	-6.509086	-6.409332	-6.492771	-6.51125
	10	6	2	12	8	4	11	7	3	9	5	1
SIC	-6.383684	-6.47764	-6.495053	-6.377337	-6.474525	-6.491329	-6.380905	-6.475225	-6.492394	-6.390554	-6.471906	-6.490386
	10	5	1	12	7	3	11	6	2	9	8	4
HQC	-6.391688	-6.486978	-6.504391	-6.386676	-6.485197	-6.502001	-6.390243	-6.485897	-6.503067	-6.402561	-6.485247	-6.503727
	10	5	1	12	8	4	11	6	3	9	7	2
	30(10)	16(5)	4(1)	36(12)	23(8)	11(4)	33(11)	19(6)	8(3)	27(9)	20(7)	7(2)

Table (V) discusses the statistics for MCXMETAL index. All three comparison statistics indicate that the GED is a better assumption for error distribution. It also shows the preference for GARCH(1,1) model over the rest. It should also be noted that the difference in the actual statistics for any model under the GED distribution is minimal.

Table IIII: Statistical verification and ranking of models for MCXCOMDEX

COMDEX	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
AIC	-6.614824	-6.678599	-6.683335	-6.610628	-6.677311	-6.681376	-6.614168	-6.67826	-6.68275	-6.614469	-6.675757	-6.680787
	9	5	1	12	7	3	11	6	2	10	8	4
SIC	-6.602305	-6.663994	-6.66873	-6.596022	-6.660619	-6.664685	-6.599563	-6.661569	-6.666058	-6.591518	-6.650719	-6.655749
	9	4	1	11	6	3	10	5	2	12	8	7
HQC	-6.61031	-6.673333	-6.678068	-6.605361	-6.671292	-6.675357	-6.608901	-6.672241	-6.676731	-6.606193	-6.666728	-6.671758
	9	4	1	12	7	3	10	5	2	11	8	6
	27(9)	13(4)	3(1)	35(12)	20(7)	9(3)	31(10)	16(5)	6(2)	33(11)	24(8)	17(6)

Table (VI) displays the model ranking for MCXCOMDEX index. The GED assumption is favoured along with extremely little difference in the statistics across the models. However, GARCH(1,1) is marginally better ranked than the other three.

Three (MCXENERGY, MCXMETAL and MCXCOMDEX)out of four indices show a strong affinity towards the symmetric GARCH(1,1) model. The GED error distribution assumption holds good for MCXENERGY, MCXMETAL and MCXCOMDEX. Although MCXAGRI has ranked PARCH(1,1) under the Student's t distribution as the highest, the symmetric GARCH(1,1) is also shown to be not far behind. The model specifications thus tested across AIC, SIC and HQC have not shown the effectiveness of

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asymmetric models over the symmetric models. All four indices have rejected the assumption of a normal error distribution. Hence, it can be deduced that the usual assumption of normal distribution which is frequently adopted in studying financial data is not justified.

Forecasting and performance evaluation

Forecasting performance is evaluated using the coefficients given by the forecasts output viz. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil Inequality Coefficient (Theil U). The various models and assumptions of error distributions are measured for out-of-sample dynamic forecasting performance across the four error coefficients. The forecasting ability of the four models crossed with the three error distributions is tested against the reserved test sample of 63 observations.

Individual forecasting performance rank of each model for the three assumptions of error distribution is indicated below the respective statistic. The last row indicates the sum of the individual ranks and the definitive rank in parenthesis.

A common observation across the four indices is that any single model fails to establish its predictive supremacy over the rest. There is also a disagreement regarding the error distribution assumption across the indices.

Table IVII: Forecast performance of models for MCXAGRI

AGRI	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
RMSE	0.005604	0.005612	0.00566	0.005642	0.005657	0.009792	0.005616	0.005619	0.005624	0.005648	0.005617	0.005631
	1	2	11	8	10	12	3	5	6	9	4	7
MAE	0.004416	0.004414	0.004421	0.004424	0.004413	0.00586	0.004417	0.004416	0.004418	0.004427	0.004416	0.00442
	3	2	9	10	1	12	6	3	7	11	3	8
MAPE	107.9694	103.643	104.9437	126.4176	108.5861	99.27312	103.6924	102.4507	101.7087	98.66175	102.888	100.5513
	10	7	9	12	11	2	8	5	4	1	6	3
TIC	0.945318	0.966736	0.977089	0.889738	0.955587	0.994665	0.966664	0.977372	0.98418	0.990323	0.973546	0.994906
	2	5	7	1	3	11	4	8	9	10	6	12
RANK	16(1)	16(1)	36(11)	31(9)	25(6)	37(12)	21(4)	21(4)	26(7)	31(9)	19(3)	30(8)

Table (VII) displays the performance of various models in forecasting the returns for the MCXAGRI index. The GARCH(1,1) model outranks the other three models in the forecasting accuracy with Student's t distribution showing better performance irrespective of the model.

Table VII: Forecast performance of models for MCXENERGY

ENERGY	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
RMSE	0.028357	0.028356	0.028355	0.028359	0.028356	0.028355	0.028357	0.023205	0.028355	0.028358	0.028356	0.028355
	9	6	2	12	6	2	9	1	2	11	6	2
MAE	0.021167	0.021176	0.021214	0.02114	0.021159	0.0212	0.021167	0.018284	0.021214	0.02115	0.021163	0.021203
	6	8	11	2	4	9	6	1	11	3	5	10
MAPE	104.3597	105.686	109.5077	101.7687	103.9931	108.0739	104.3674	99.21186	109.5027	102.8175	104.5146	108.3862
	5	8	12	2	4	9	6	1	11	3	7	10
TIC	0.990388	0.987284	0.980415	0.994233	0.990484	0.982883	0.990378	0.986886	0.980422	0.993011	0.989294	0.982244
	9	6	1	12	10	4	8	5	2	11	7	3
RANK	29(11)	28(8)	26(6)	28(8)	24(2)	24(2)	29(11)	8(1)	26(6)	28(8)	25(4)	25(4)

Table (VIII) discusses the MCXENERGY index. The assumption of Student's t distribution shows a better performance than the normal distribution for any model. PARCH(1,1) , TARCH(1,1) and EGARCH(1,1) model show better forecast performance that GARCH(1,1) indicating that asymmetric models better suited for forecasting the MCXENERGY index.

Table IX: Forecast performance of models for MCXMETAL

METAL	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
RMSE	0.0086	0.008566	0.008557	0.008598	0.008564	0.008557	0.0086	0.008565	0.008557	0.008598	0.008566	0.008557
	11	7	1	9	5	1	11	6	1	9	7	1
MAE	0.006432	0.006419	0.006419	0.006432	0.006419	0.006419	0.006432	0.006419	0.006419	0.006431	0.006419	0.006419
	10	1	1	10	1	1	10	1	1	9	1	1
MAPE	99.98338	100.7011	102.2154	100.0304	101.0738	102.2926	99.98345	100.7999	102.1764	99.97544	100.7301	102.1692
	2	5	11	4	8	12	3	7	10	1	6	9
TIC	0.978529	0.940355	0.928596	0.976744	0.937465	0.928041	0.978562	0.939563	0.928879	0.97718	0.940037	0.928885
	11	8	2	9	5	1	12	6	3	10	7	4
RANK	34(11)	21(7)	15(1)	32(10)	19(5)	15(1)	36(12)	20(6)	15(1)	29(9)	21(7)	15(1)

The forecasting performance of the four models for MCXMETAL index is discussed in Table (IX). All the four models are ranked equally here, under the assumption of the GED. The forecast ability of the various models under the normal distribution is clearly not preferred.

Table X: Forecast performance of models for MCXCOMDEX

COMDEX	GARCH(1,1)			EGARCH (1,1)			PARCH (1,1)			TARCH (1,1)		
	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED	Normal	Student's t	GED
RMSE	0.009551	0.009539	0.009533	0.009551	0.009539	0.009533	0.009552	0.009539	0.009533	0.009592	0.009596	0.009581
	7	4	1	7	4	1	9	4	1	11	12	10
MAE	0.007404	0.007397	0.00739	0.007403	0.007397	0.00739	0.007404	0.007396	0.00739	0.007452	0.007467	0.007451
	8	5	1	7	5	1	8	4	1	11	12	10
MAPE	100.4394	100.7847	100.8576	100.4442	100.8039	100.8558	100.432	100.7982	100.862	103.5438	105.6926	106.3409
	2	4	8	3	6	7	1	5	9	10	11	12
TIC	0.986043	0.966874	0.955854	0.985142	0.966265	0.955663	0.986424	0.966226	0.955644	0.949468	0.934009	0.930052
	11	9	6	10	8	5	12	7	4	3	2	1
RANK	28(8)	22(5)	16(3)	27(7)	23(6)	14(1)	30(9)	20(4)	15(2)	35(11)	37(12)	33(10)

Table (X) discusses the ranking of various models for forecasting performance for the MCXCOMDEX index. The asymmetric EGARCH(1,1) has outperformed the other models followed by PARCH(1,1) and GARCH(1,1). The results are strongly in favour of asymmetric distributions under the GED assumption for MCXCOMDEX.

Out-of-sample forecasting of the 63 samples tested against the various models under the three assumptions of conditional error distributions show that all the four indices prefer non-normal error distributions which capture the fat-tails of the data series. While MCXENERGY and MCXCOMDEX show better forecasts with asymmetric models, MCXAGRI shows a better performance under GARCH(1,1). MCXMETAL ranks all the models equally but with the assumption of non-normal error distribution.

VI. DISCUSSION

The GARCH family models are employed to capture, model and forecast volatility for the four commodity indices (MCXAGRI, MCXENERGY, MCXMETAL and MCXCOMDEX). The efficiency of the models has been tested with both in-sample forecasts and out-of-sample forecasts. Ideally, the best fit model should also be the best forecasting model. The statistics indicate that for the MCXAGRI index, while PARCH(1,1) is a better fit, GARCH(1,1) gives better forecasting performance as found in other studies also.[14], [16] and [4]

The symmetric GARCH model in its lowest order (1,1) is a better fit for MCXENERGY, MCXMETAL and MCXCOMDEX. MCXENERGY has a better forecasting performance with GARCH(1,1) for in-sample forecast and PARCH(1,1) for out-of-sample forecast. Similarly, MCXMETAL shows TARCH(1,1) as a better forecasting model for in-sample data and GARCH(1,1) for out-of-sample data. No single model establishes its superiority over the others in the sample of commodity indices used for this study, as evidenced in some other studies.[33]
It should also be noted that for every index and every model, the assumption of a non-normal conditional error distribution is evident.[33]

VII. CONCLUDING COMMENTS

This paper has attempted to examine the forecasting performance of the popular GARCH family models in the Indian Commodity Markets. It makes use of the four commodity indices maintained by Multi Commodities Exchange of India (MCX) – MCXCOMDEX, MCXAGRI, MCXENERGY and MCXMETAL.

As evident from the statistics obtained, the results are mixed regarding the best fit model and the two types of forecast for the four commodity indices. The ability of a model to cope with the asymmetry, which appears prominently in the data set, also has no bearing on the forecast performance of the model. This could also be due to the inherent parameter instability of the long data set being used for the study. In such a situation, it is difficult to arrive at a definitive conclusion regarding a single model which is ranked high for both model specification and forecasting performance. This however, does not undermine the usefulness of the GARCH models in studying time series data. Adding more specifications to the model's variance equation may better capture the essence of volatility and thereby, improve forecast ability. Also, commodities in general and agricultural commodities in particular, have been traditionally known to be influenced by exogenous variables which distort the volatility levels and make it more difficult to model than equity instruments.

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