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Long Memory and Spill-over Effects of Indian Futures Markets: An Econometrics Investigation into Metal and Energy Futures

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Abstract

Futures market plays a significant in the process of price discovery and risk management. The inherent risk such as long memory and spill-over effect need to be measured for better decision making. This study examines long memory and spillover effect in metal and energy futures. Sample data consist of daily futures and spot return series from 1st September, 2005 to 30th December, 2011 for gold, silver, copper, and crude oil, and from 1st November , 2006 to 30th December, 2011 for natural gas based on availability. Using FIGARCH, it is observed that the spot and futures return of gold, silver, crude oil, copper futures and natural gas spot have shown long memory properties. Using BEKK model volatility spillover impact is observed to be statistically significant in all the commodity spot and futures returns. Bi-directional shocks transmission as can be observed across the commodities like gold, silver and crude oil which means shocks in the futures market do have impact on spot market volatility for gold, silver and crude oil.

Key Words*: Long memory, futures market, spillover effect, volatility, commodity*

JEL Classification; G13

I. Introduction

Commodity futures market is prone to risk as speculative activities and macroeconomic imbalances distort price determination process. Moreover, dynamism in futures market is a matter of concern for the investors and policy makers. The degree of risk or volatility varies over time and tends to cluster in periods of large volatility and dampen in periods of tranquillity which behaviour results in heteroskedasticity and in autocorrelation. The possible factors of high volatility may be due to supply and demand conditions, speculative trade, weather events, international price pressure, regulatory practices and the government policy changes. Higher volatility may induce investors to increase trading in futures because futures contracts constitute a convenient means to adjust their investment positions (Chen, Cuny and Haugen, 1995). It is widely acknowledged that the futures markets are more volatile than spot markets, providing additional concern to market regulators for potential transmission of volatility from the futures to spot market. The futures market volatility can be used as a leading indicator of spot market volatility. This suggests that futures market volatility can be used to forecast changes in spot market volatility based on readily available low-cost historical information (Bhattacharya, Ramjee and Balasubramani, 1986).

The persistence of price over a longer period of time is seen to have been one of the features of the commodity futures market. This feature in technical econometric jargon is termed as long memory process. In common parlance, long memory means a spell of high volatility followed by another spell of high volatility, where the price persistence can be realised over a long stretch of time. Conducting analysis on return series the study in the context of commodity futures market revealed that the return series is in possession of long memory (Helms, Kaen, and Rosenman, 1984). Understanding of the long memory process in the commodity futures market context is utmost important, since during periods of high volatility the risk of an investment increases dramatically – the investor may win or lose large amount of money if one trades commodities over that period. Ferrettti and Gilbert (2008) find that spot, three-month aluminium and copper volatilities follow long memory process.

Baillie, Bollerslev and Mikkelsen (1996) propose new class fractional integrated generalized autoregressive conditional hetroskedasticity (FIGARCH) to capture long memory process. They find the existence of long memory in financial market volatility where shocks refer to conditional variance that would die out at slow hyperbolic rate of decay determined by a fractional differencing parameter (Bollerslev and Mikkelsen, 1996). Even, agricultural commodity futures returns are prone to long memory (Tanscuhat, Chang and Mcaleer, 2009). On the contrary, Crato and Ray (2000) find that no such evidence of long memory on the returns. Ferretti and Gilbert (2008) consider the dynamic representation of spot and three month aluminum and copper volatilities. Using bi-variate FIGARCH model, they find that spot and three month aluminum and copper volatilities follow symmetric long memory processes. However, there is no evidence that the process is fractionally cointegrated. Wang, Wu and Yang (2008) use high frequency returns, realized volatility and correlation of NYMEX light, sweet crude oil, and Henery-Hub natural gas futures contracts to study long memory and asymmetry. They find long memory and asymmetric volatility for natural gas but not for crude oil futures.

It is widely accepted that volatilities move together more or less closely over time across the assets or markets. Even there has been evidence that shocks in one market affect other markets also which is called the spill-over effect. In that case, uni-variate analysis may not be useful for the investors as well as policy makers. Baillie and Mayers (1991) examine six different commodities using daily data over two futures contract and they find spill-over effect among the commodities. This study makes an attempt to examine the Indian commodity futures market dynamics in the context of metal and energy in India. Specifically, the study examines long memory in the commodity futures market and spill-over effect of these markets on their spot markets.

Tse (1999) examines volatility spillovers between the DJIA index and the index futures. Using bi-variate EGARCH model, he finds a significant bi-directional information flow i.e., innovations in one market can predict the future volatility in another market, but the futures market volatility spillovers to the spot market is more than vice versa. Both markets also exhibit asymmetric volatility effects, with bad news having a greater impact on volatility than good news of similar magnitude. Baillie and Mayers (1991) study six different commodities using daily data over two futures contract. They use Bi-variate GARCH models of spot and futures prices of commodities. The optimal hedge ratio (OHR) is then calculated as ratio of the conditional covariance between spot and futures to the conditional variance of futures. From the OHR results, they find that standard assumption of time- invariant OHR is inappropriate. For each commodity the estimated OHR path appears non-stationary, which has important implications for hedging strategies.

II. Nature and Sources of data

The study has relied upon the secondary data drawn from the Multi Commodity Exchange (MCX). The study has made use of the data for different time periods and at different frequencies for empirical investigations.

For examining the macroeconomic dynamics, daily spot and futures closing prices of gold, silver, copper, crude oil and natural gas are collected from the MCX. Here we have considered closing prices of these commodities as it is conventionally believed that closing prices incorporate all the information during the trading day. The commodities are chosen based on the MCX's world ranking in terms of number of futures contracts traded in 2011, where silver stood 1st followed by gold, copper, natural gas and crude oil.

These futures series of the aforesaid commodities are constructed by taking into account the nearby futures contract (i.e. contract with the nearest active trading delivery month to the day of trading). The nearby futures contract is used because it is highly liquid and the most active. Also another reason emanates from the fact that the day-wise information shocks are mostly reflected in the closing prices. Daily futures and spot closing prices are taken from September 1, 2005 to December 30, 2011 for gold, silver, copper, and crude oil. Natural gas futures and spot closing prices are taken from November 1, 2006 to December 30, 2011 based on availability of data. The data period includes 38 gold futures contracts with 1872 observations, 32 silver futures contracts with 1876 observations, 31 copper futures contracts with 1893 observations, 76 crude oil futures contracts with 1894 observations and 62 natural gas futures contracts with 1554 observations.

Futures contracts and observations differ from commodity to commodity as official allocation of contracts differ commodity wise. For instance, gold has six futures contracts per year whereas crude oil has 12 contracts per year. The commodity contract over a specific time frame does not remain the same for all the commodities due to the time differential contract design of the commodity exchange. All the observations are reported excluding Sundays and holidays. Furthermore, the study has created data series in such a way that both spot and futures data are available in a given date. The data matching has been done for all the series taking into account availability of the data both for the futures and the spot for any given day. Variables has been converted to continuous log return form.

III. Graphical Analysis

The gold futures and spot return series reveal that the gold futures return is lesser volatile than gold spot return during the study period (see figure 1 and 2). The degree of volatility for the gold return series is seen to have been fluctuating over the time. The higher is the level of volatility the riskier is the investment in the market. Further, it is affirmed that volatilities remain high for a certain period of time and remain low for another stretch of time, which perhaps indicates the volatility clustering behaviour of the series. To ascertain such behaviour of the series, there is a need for robust econometric examination, which has been attempted in the subsequent section.

The volatility of commodity returns generally exhibits an asymmetric reaction to positive and negative shocks. Economic explanations for this phenomenon are leverage and a volatility feedback effect. This sub-section of the present chapter studies the volatility asymmetric

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Volume 2, Issue 1, June 2015

behaviour of the five commodities under consideration. The graphical presentations of gold and silver price series reveal that the persistent increase in gold and silver prices over the years. The sudden increase in prices of precious metal went up around the global financial crisis, due to the greater investment demand. The intensity of volatilities is found to be very high in gold spot price as compared to the futures prices during the study period (see figure 1, 2, 3 and 4). While the intensity of silver price volatility is observed to be high in the futures market as compared to the spot market. It could be attributed to the low industrial demand owing to decreasing economic activity due to the recession. Slow recovery of the US economy, Euro zones' sovereign debt crisis and sustained economic growth across the major emerging economies has kept retaining the investment demand for gold high. The study uses different econometric techniques to analyse above mentioned issues empirically.

However, the copper futures price and spot price during the study period are found to be highly instable but the degree of instability is more prominent in former series. The period of global financial crisis has pulled down both futures and spot copper price series to their lowest ebb which could be due to the lack of industrial demand owing to worldwide recession (see figure 7 and figure 8). However, the examination of log return series of copper futures and spot affirms that the intensity of volatilities is found to be very high in copper futures price as compared to the spot price during the study period. The degree of high volatility to the copper future return series could be attributable to the global financial crisis (figure 5 and Figure 6). To ascertain such behaviour of the series, there is a need for robust econometric examination, which has been attempted in the following section.

The crude oil price series both for futures and spot are found to be highly instable and it is clearly visible that the crude oil price series follows the path of business cycle. The higher is the level of economic activity the greater is the demand for crude oil, and as a result, price of crude oil triggers ahead and vice versa. The degree of economic prosperity is directly linked up with the crude oil prices in the world. The degree of volatility for the crude oil return series is seen to have been fluctuating over the time. The higher is the level of volatility riskier is the investment in the market. Further, it is affirmed that volatilities remains high for a certain period of time and remains low for another stretch of time, which perhaps indicates the volatility clustering behaviour of the series(see figure 7 and 8). The crude oil prices have attended its lowest level at the time of 2008 economic crisis. Further the Euro zone crisis has also exerted impact on crude oil futures and spot prices but the impact of global financial crisis has brought down the crude oil futures and spot series towards their respective lowest price floor. Slow global economy recovery and on set of Euro zones sovereign debt crisis and slow down of economic growth in major emerging economies like India and China have kept putting pressure on oil futures and spot prices. To ascertain such behaviour of the series, the study uses econometric techniques in the next section.

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

However, the examination of natural gas futures and spot price data are found to be highly instable and volatile in nature. During the global financial crisis the natural gas price have attended their peaks. The period other than the crises, where natural gas price series have shown their downward price spiral. The natural gas series both for future and spot show peculiar behaviour and follow a price reversal with the level of economic activities. This could be due to the fact that the availability of natural gas and the new natural gas site discoveries, better exploration methodologies and alternative sources of energies which might have put downward pressure on natural gas price over the period. However, the examination of the return series affirms high volatility and volatility clustering during the study period. But the level of volatility clustering is found to be the most prominent around the global financial crisis (see figure 9 and 10). To ascertain such behaviour of the series, there is a need for robust econometric examination, which has been dealt with in the subsequent section.

Figure 1: Gold futures Return

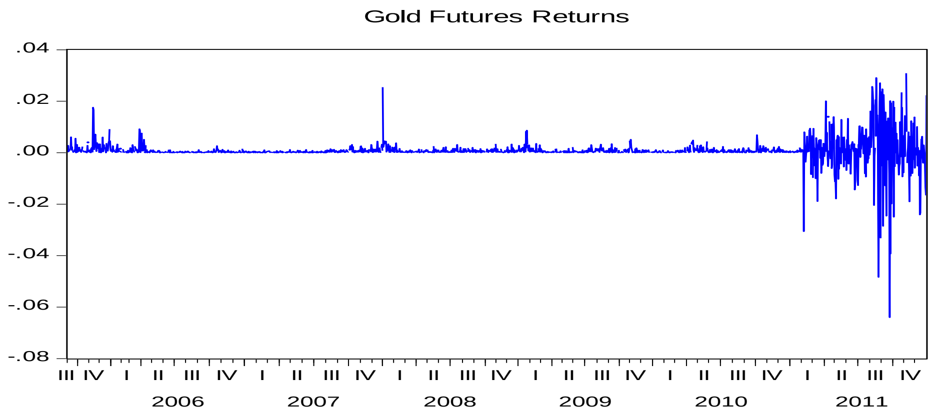
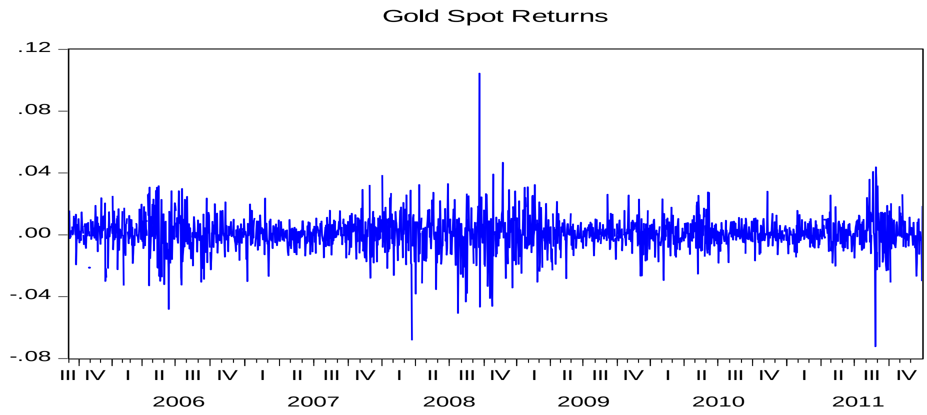


Figure 2: Gold Spot Returns



International Journal of Business Quantitative Economics and Applied Management Research
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Figure 3: Silver Futures Returns

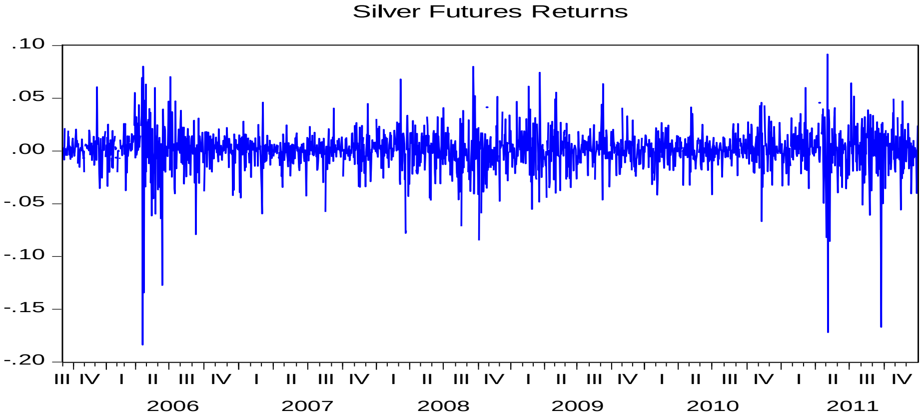


Figure 4: Silver Spot Returns

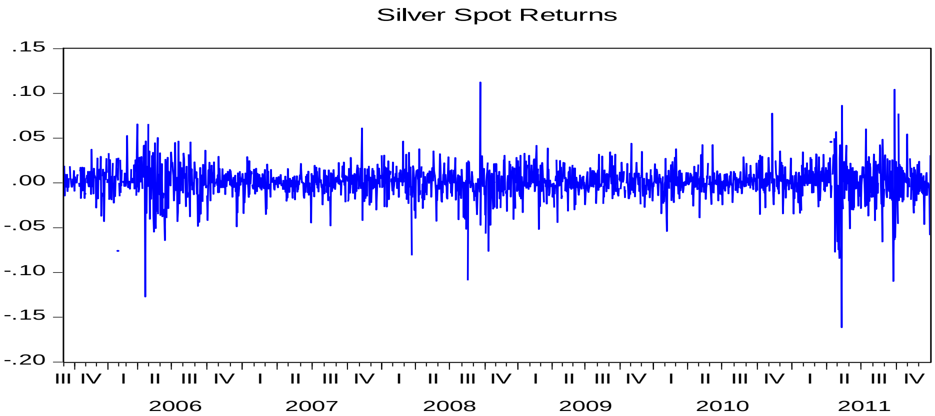
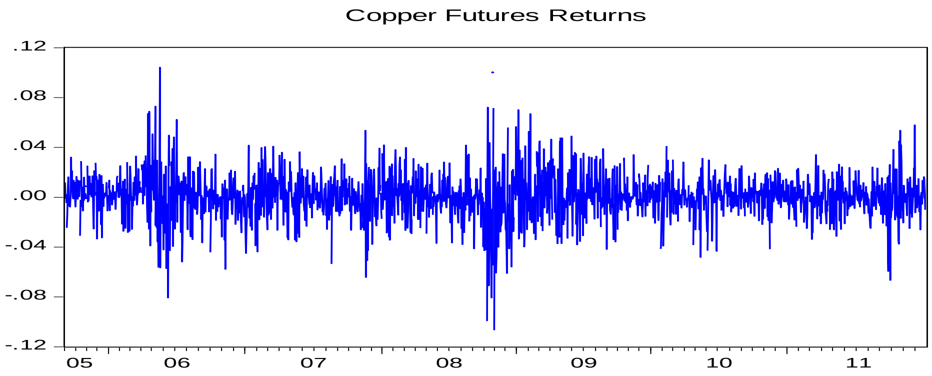


Figure 5: Copper Futures Returns



International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
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Figure 6: Copper Spot Returns

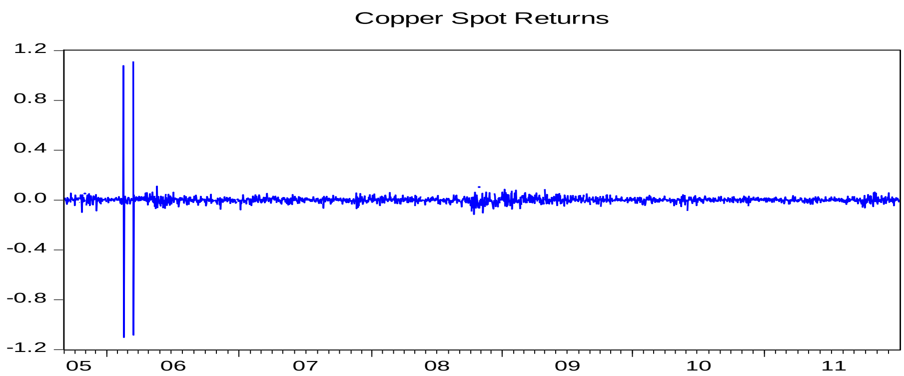


Figure 7: Crude Oil Futures Returns

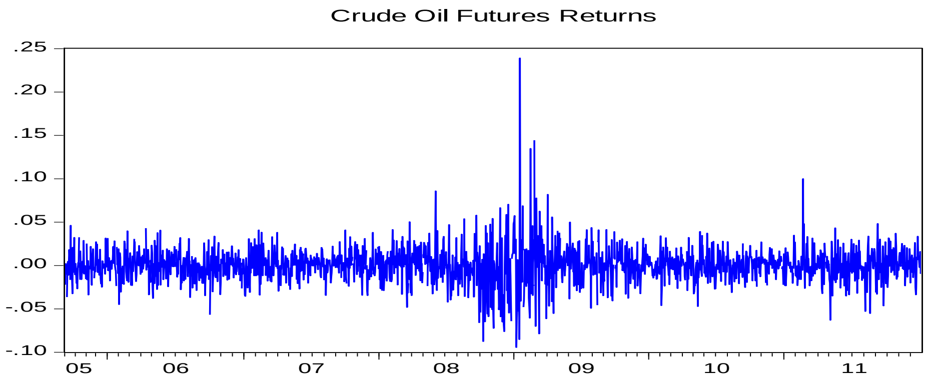


Figure 8: Crude Oil Spot Returns

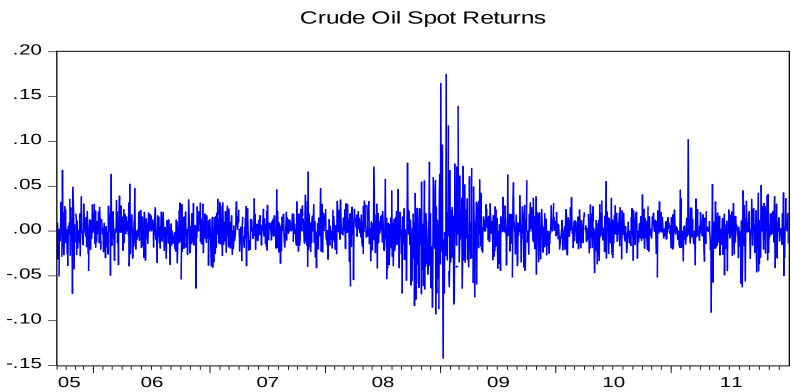


Figure 9 Natural Gas Futures Returns

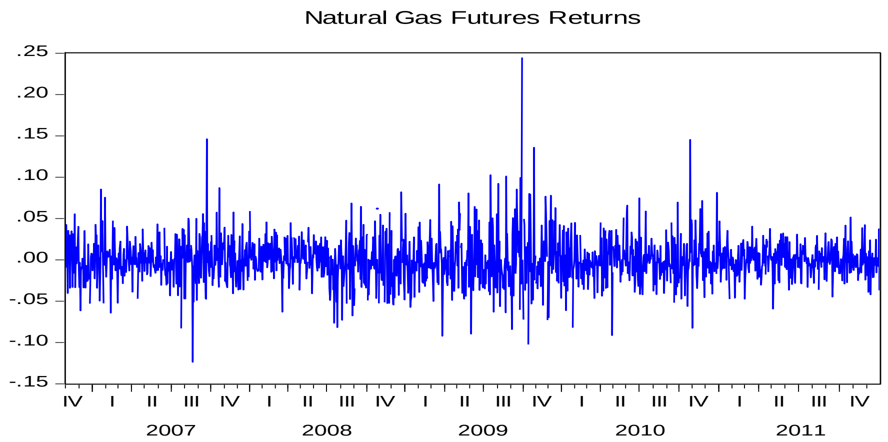
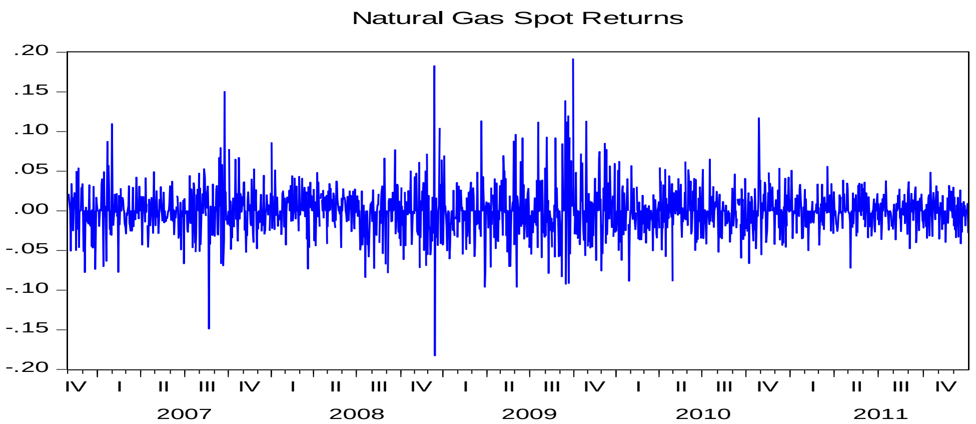


Figure 10 Natural Gas Spot Returns



International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

IV. Heteroskedasticity Effect

The study tests for the heteroskedasticity effect of the commodities futures and spots under consideration. Deploying the ARCH-LM test for the purpose, the study affirms the presence of heteroskedasticity effect in gold, silver, copper and crude oil series. However, the corresponding F-statistics and observed R-squared values for natural gas futures series under the ARCH LM test are found to be statistically not significant, which evidence, therefore, negates the presence of heteroskedasticity effect. But the ARCH LM test on natural gas spot series confirms that the series experiences the presence of heteroskedasticity effect over the time period. The absence of heteroskedasticity effect in natural gas futures could be due to the fact that the information shocks are not strong enough to destabilise the said series, which we have already noticed in the graphical analysis. As compared to the natural gas spot return and futures series found to be less volatile as suggested by the graphical analysis. Therefore, the ARCH family models are not applied to the natural gas futures as it fails to the presence of the heteroskedasticity effect.

V. Long Memory in Commodity Futures Market

Long memory can be expressed in terms of volatility persistence; a GARCH model features an exponential decay in the autocorrelation of conditional variances. However, a shock in the volatility series seems to have very "long memory" and impacts on futures volatility over a long horizon. Baillie et al. (2007) explained that the long memory refers to the presence of very slow hyperbolic decay in the autocorrelations and impulse response weights. In other words, Long memory process means a spell of high volatility is followed by another spell of high volatility. Moreover, if a period of high volatility persists over time it is said that the process governing the behaviour of the underlying variable has long-memory. On the contrary, if high volatility occurs only for a short period, the process exhibits short memory.

Long memory processes can be modelled by the IGARCH and the FIGARCH specifications but not by the simple GARCH method. This is because in the GARCH specification it is assumed that the process is stationary and thus exhibits short memory. However, this may not be the case for some volatility time series. IGARCH estimates a model where the integration coefficient is equal to 1 (this usually happens when the sum of the alpha and beta coefficients is close to one). The FIGARCH, on the other hand, assumes no previous fixed value for the integration coefficient and estimates this coefficient along with the other parameters of the model. This coefficient is usually termed as "d" where, $0 < d < 1$, the process is said to be mean reverting and possesses long memory. The implications of this are important for commodity futures markets since during periods of high volatility, the risk of an investment

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

increases dramatically – the investor can win but also can lose large amounts of money if one trades in these commodities over that period.

a) Factional Integration GARCH Model

The FIGARCH developed by Baillie, Bollerslev and Mikkelsen (1996) can be described as follows:

$$R_t = \alpha + \delta R_{t-1} + \varepsilon_t \qquad (1)$$

$$\varepsilon_t | \varphi_{t-1} \sim N(0, h_t)$$

There are two equations for the FIGARCH model. Equation 1 is the mean equation and equation 2 is the conditional variance equation. Error term, ε_t , conditional upon information φ_{t-1} is normally distributed with zero mean and conditional variance. $\alpha,\ \delta,\ \omega,\ \beta,\ \theta$ and d are the parameters to be estimated with d being the fractional integration parameter that captures the long memory behaviour. L is the lag operator. Interestingly, the FIGARCH (1,d,1) model nests the GARCH(1,1) model (Bollerslev, 1986) for d=0 and the IGARCH (Engle and Bollerslev, 1986) for d=1. As advocated by Baillie et al. (1996), the IGARCH process may be seen as too restrictive as it implies infinite persistence of a volatility stock. Such a dynamic is contrary to the observed behaviour of agents and does not match the persistence observed after important events (Baillie et al., 1996, Bollerslev and Engle, 1993). By contrast, for 0<d<1, the FIGARCH model implies long memory behaviour and a slow decay of impact of volatility shock.

b) Empirical Analysis of FIGARCH

Long memory is one of the major features of any commodity futures market. The study uses the FIGARCH models to test for the presence of long memory in all the commodities under study. For the diagnostic checking, the study has used the Ljung-Box Q statistic at the lag (20). Ljung-Box Q (LB) test is applied with 20 lags considering it as the optimal lag length and the LBQ test results are shown in Table 4. The FIGARCH results are also reported in Table 4. The fractional coefficient values for the gold spot and futures are less than one and statistically significant which evidence suggests that both the series have shown the long memory properties. Similarly, fractional coefficient values for silver spot and futures, copper futures, crude oil spot and futures, and natural gas spot are less than one and statistically significant and hence long memory features do exist in the commodities. However, fractional

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

coefficient value of copper spot is equal to one and statistically significant. Therefore, for copper spot, IGARCH model is best fit for the long memory.

VI. Spill-over effect in Commodity Futures Market

Until now, the study has discussed the univariate models and its application for the commodities under study. However, there are evidences that spot and futures tend together over the period, and any changes in the futures market affects spot and any changes in spot market affects futures. Therefore, the study uses multi-variate GARCH (BEKK) model to check futures and spot trend as well as spill-over impact.

It is widely accepted that volatilities move together more or less closely over time across the assets or markets. To show the spill-over impact between futures and spot, multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model in vector autoregressive (VAR) framework is employed where the conditional mean and variance are estimated simultaneously. The MGARCH model is used to study the mean and volatility spill-over between futures and spot market with the BEKK parameterization of MGARCH developed by Engle and Kroner (1995). The BEKK model doesn't impose restriction of constant correlation among variables over time. Furthermore, the model incorporates quadratic forms in such a way that ensures the positive semi-definite feature of the covariance matrix. Bi-variate GARCH model is used to study the volatility transmission among two markets simultaneously.

a) Multivariate GARCH model (BEKK Model):

There are two major equations in the BEKK are mean equation and variance equation. The mean equation in the VAR-MGARCH model can be specified as;

$$R_{i,t} = \mu_i + \alpha R_{i,t-1} + \varepsilon_{it} \qquad (3)$$

and it can also be stated as:

$$\begin{bmatrix} R_{1,t} \\ R_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} R_{1,t-1} \\ R_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \; (4)$$

where $R_{i,t}$ is returns at time t; μ_i is the drift coefficient; and ε_{it} is the error term for the return of i^{th} market, Let $\varepsilon_t|\varphi_{t-1}\sim N(0,H_t)$; H_t is a 2×2 corresponding variance covariance matrix, $\varphi_{t-1}$is an information set at time t-1. The parameter a_{ij} represents the mean spill-over effect from market j to market i whereas the a_{ii} measure their own lagged response.

The BEKK parameterization for the variance equation can be written as:

$$H_t = C^{'}C + A^{'}\varepsilon_t\varepsilon_{t-1}^{'}A + B^{'}H_{t-1}B \quad (5)$$

The individual elements of A,B and C are:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

$$C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}$$

A is a 2×2 matrix of parameters and shows how conditional variances are correlated with past squared errors. The elements a_{ij} measure the effects of shocks spill-over from the market j to volatility in market i and a_{ii} measure the magnitude of impacts of shocks in market of its own volatility. B is 2×2 square matrix of parameters and show how past conditional variances affect current levels of conditional variances. Thus, b_{ij} implies the volatility spill-over from market j to market i and b_{ii} indicates persistence of volatility within the same market.

To have better understanding about the effect of shocks and volatility on the conditional variance equation, it can be expanded for the bi-variate GARCH(1,1) as :

$$h_{11} = c_{11} + a_{11}^2\varepsilon_1^2 + 2a_{11}a_{21}\varepsilon_1\varepsilon_2 + a_{21}^2\varepsilon_2^2 \quad (6)$$

$$h_{\mathbf{12}} = c_{12} + a_{11}a_{12}\varepsilon_1^2 + a_{21}a_{12}\varepsilon_1\varepsilon_2 + a_{11}a_{22}\varepsilon_1\varepsilon_2 + a_{21}a_{22}\varepsilon_2^2 \quad (7)$$

$$h_{22} = c_{13} + a_{11}^2\varepsilon_1^2 + 2a_{12}a_{22}\varepsilon_1\varepsilon_2 + a_{22}^2\varepsilon_2^2 \quad (8)$$

Equations (6), (7) and (8) show how shocks and volatility are transmitted across markets and over time. Since two futures and spot markets are used, the transmission mechanism is examined by estimating bi-variate GARCH models.

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

The BEKK-MGARCH model is estimated using the maximum likelihood method. The log-likehood can be written as:

$$l(\theta) = -Tln(2\pi) - \frac{1}{2}\sum \ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t$$

where T is the number of observations and θ represents the parameter vector to be estimated. To obtain the estimates of the parameters, a combination of the standard gradient-search algorithm Broyden-Fletcher-Goldfarb-Shanno (BFGS) and simplex algorithm are used.

b) Empirical analysis of Spill-over Effect

Multivariate GARCH (BEKK Model) results on commodity series are reported in Table 5. The covariance GARCH parameters a_{11} and b_{11}, which account for the conditional covariance between spot and futures returns, are all positive and statistically significant, implying strong interactions between spot and futures prices. It seems important to let the conditional covariance be time-dependent rather than restricting it to be a constant. In addition, there appears to be substantial efficiency gains in modelling the spot and futures prices jointly as opposed to a univariate analysis (Baillie, 2001). As the coefficients $\hat{\boldsymbol{a}}_{\mathbf{11}}$ and $\hat{\boldsymbol{b}}_{\mathbf{11}}$ are statistically significant indicating that future volatility in all spot and futures are influenced by the shocks and volatilities in their own market for gold, silver and copper. Bi-directional shocks transmission can be observed from significant coefficient a_{12} and a_{21} for the aforesaid series. The coefficient a_{12} is significant for the commodities of gold, silver and crude oil which mean shocks in the futures market do have impact on spot market volatility. On the other hand, coefficient a_{21} is statistically significant for gold and silver implying that shocks in the spot market do affect futures market volatility. However, coefficient a_{21} is statistically insignificant for copper, indicating that shocks in the copper spot market do not have any impact on copper futures market volatility. Coefficients b_{12} and b_{21} are statistically significant in case of gold and silver, indicating that volatility spills over from futures market to spot market and vice versa. For the diagnostic checking, the study has used Ljung-Box Q statistics at the lag (10). Ljung-Box Q (LB) test is applied with 10 lags considering it as the optimal lag length and LBQ test statistics results are reported in the table 5.

VII. Policy Suggestions

It is widely believed that higher the risk higher the return. However, higher risk does not ensure higher return always. Investor may lose huge money in one instance or may gain huge in another. The study finds long memory in all commodities under consideration. Long memory in the commodity futures market indicates a spell of high volatility is followed by another spell of high volatility. It may cause windfall gain to investors in one period and huge loss in another. The role of policy makers is inevitable to mitigate the risk of long memory by controlling shocks or extreme volatility. Moreover, the study finds that future volatility in all spot and futures are influenced by the shocks and volatilities in their own market for gold, silver and copper. Bi-directional shocks transmission are observed in commodities like gold, silver and crude oil which mean shocks in the futures market do have impact on spot market volatility. But, shocks in the spot market do affect futures market volatility only in case of gold and silver. Volatility spillover is observed from futures market to spot market and vice versa in case of gold and silver. Therefore, sophisticated policy tools and continuous surveillance on gold and silver market may reduce volatility spillover effect.

VIII. Conclusion

Examination of dynamics of commodity futures market has focused on issues around long memory and spill-over effects relating to the commodities chosen for the study. By making use of the advanced econometric techniques, it is observed that the spot and futures series of gold, silver, crude oil, copper futures and natural gas spot have shown long memory properties. Volatility spill-over impact is observed to be statistically significant in all the respective spot and futures commodities under the study. Bi-directional shocks observed across the commodities such as gold, silver and crude oil. But, shocks in the futures market have impact on spot market volatility for gold and silver. As the fractional coefficient value of copper spot is equal to one, IGARCH model, perhaps, fits the best for examining the long memory process in the series.

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

Appendix

Table 1 Descriptive Statistics Results for Gold, Silver and Copper

Statistics	Gold Futures	Gold Spot	Silver Futures	Silver Spot	Copper Futures	Copper Spot
Mean	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.000	0.000	0.000	0.00
Max. Return	0.03	0.10	0.09	0.11	0.10	1.11
Mini. Return	-0.06	-0.07	-0.18	-0.16	-0.10	-1.10
Stand. Dev.	0.004	0.01	0.01	0.01	0.01	0.05
Skewness	-2.27	-0.06	-1.56	-0.84	-0.13	0.04
Kurtosis	48.35	10.22	16.71	11.71	6.71	341.46
Jarque-Bera	162014.2	4069.53	15457.06	6149.02	1092.47	9031.27
probability	0.00	0.00	0.00	0.00	0.00	0.00
Sum	1.43	1.45	1.59	1.57	0.93	0.87
SumSq. Dev.	0.03	0.23	0.72	0.63	0.62	5.64
Observations	1871	1871	1875	1875	1892	1892

Table 2 Descriptive Statistics Results of Crude Oil and Natural Gas

Statistics	Crude Oil Futures	Crude Oil Spot	Natural Gas Futures	Natural Gas Spot
Mean	0.00	0.00	-0.00	-0.00
Median	0.00	0	-0.00	0
Max. Return	0.23	0.17	0.24	0.19
Mini. Return	-0.09	-0.14196	-0.12371	-0.18276
Stand. Dev.	0.02	0.02	0.02	0.02

Skewness	0.96	0.31	0.79	0.44
Kurtosis	16.60	9.70	9.29	7.81
Jarque-Bera	15040.57	3615.37	2728.33	1551.73
probability	0.0	0.0	0.0	0.0
Sum	0.56	0.56	-0.74	-0.74
SumSq. Dev.	0.79	0.96	1.17	1.39
Observations	1913	1913	1553	1553

Table 3 Heteroskedasticity Test Results for Commodity

Variables	F-statistic	R Square	ARCH effect
Gold Futures	100.51 (0.00)	95.47 (0.00)	Yes
Gold Spot	62.25 (0.00)	60.55 (0.00)	Yes
Silver Futures	64.01 (0.00)	61.95 (0.00)	Yes
Silver Spot	71.77 (0.00)	69.19 (0.00)	Yes
Copper Futures	105.38 (0.00)	99.92 (0.00)	Yes
Copper Spot	211.89 (0.00)	190.71 (0.00)	Yes
Crude Oil Futures	29.53 (0.00)	29.11 (0.00)	Yes
Crude Oil Spot	7.2 (0.00)	7.18 (0.00)	Yes

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

Natural Gas Futures	0.00 (0.99)	0.00 (0.99)	No
Natural Gas Spot	25.11 (0.00)	24.74 (0.00)	Yes

Note: Probability values are in parenthesis

Table 4 FIGARCH Results for Commodity

Variable	**Variance Equation**				**Ljung-Box**	
	Constant	ARCH	GARCH	Fraction (d)	Q(20)	$Q^2(20)$
Gold Futures	0.00 (9.8)	0.00 (9.32)	0.82 (51.16)	0.97 (37.71)	61.5	35.12
Gold Spot	0.00 (0.36)	0.00 (0.39)	0.27 (4.28)	0.36 (7.50)	23.29	12.63
Silver Futures	0.00 (4.33)	0.00 (0.65)	-0.02 (-0.43)	0.29 (6.65)	25.99	19.95
Silver Spot	0.00 (3.12)	0.00 (0.48)	0.37 (3.37)	0.28 (6.76)	12.29	21.34
Copper Futures	0.00 (2.44)	-0.00 (-.44)	0.26 (4.56)	0.32 (6.70)	17.34	34.96
Copper Spot	0.00 (247.1)	0.00 (29.93)	0.56 (526.5)	1.00 (3330.7)	20.73	0.108
Crude Oil Futures	0.00 (2.63)	-0.00 (-1.02)	0.164 (2.65)	0.24 (5.89)	15.63	16.5

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

Crude Oil Spot	0.00 (2.23)	-0.00 (-0.64)	0.25 (5.32)	0.27 (6.27)	13.54	19.93
Natural Gas Spot	-0.00 (-0.83)	0.00 (0.032)	0.21 (4.72)	0.25 (5.98)	28.26	24.76

Note: t-statistics values are in the parenthesis

Table 5 Multivariate GARCH Results for Commodity

		Gold	Copper	Silver	Crude Oil
$VAR1$	C	0.024 (15.84)	0.23 (6.69)	0.11 (4.39)	0.094 (2.73)
	AR	-0.17 (-5.01)	-0.43 (-15.46)	-0.79 (-55.16)	-0.23 (-10.01)
$VAR2$	C	0.04 (1.90)	0.205 (6.72)	0.05 (2.24)	0.075 (2.14)
	AR	-0.035 (-1.36)	-0.16 (-9.01)	-0.84 (-8.18)	-0.11 (-5.76)
$\hat{c}_{11}$		-0.00 (-4.04)	1.19 (14.39)	0.357 (9.44)	0.108 (-2.23)
$\hat{c}_{21}$		0.03 (1.08)	0.57 (8.45)	0.353 (14.61)	-0.66 (-10.46)
$\hat{c}_{22}$		0.099 (5.19)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
$\hat{a}_{11}$		0.706 (31.05)	-6.609 (-12.87)	-0.324 (-11.54)	-0.22 (-6.18)

International Journal of Business Quantitative Economics and Applied Management Research
ISSN: 2349-5677
Volume 2, Issue 1, June 2015

$\hat{a}_{12}$	0.212 (4.45)	-0.906 (-27.11)	-2.42 (-48.92)	-0.87 (-22.16)
$\hat{a}_{21}$	0.002 (1.88)	0.22 (6.22)	0.011 (0.64)	0.13 (6.01)
$\hat{a}_{22}$	0.237 (13.36)	0.33 (10.36)	1.71 (51.05)	0.33 (8.36)
$\hat{b}_{11}$	0.907 (194.1)	0.32 (2.12)	0.44 (134.2)	1.06 (172.9)
$\hat{b}_{12}$	-0.018 (-2.19)	-0.46 (-6.95)	-0.04 (-3.5)	0.193 (10.73)
$\hat{b}_{21}$	-0.00 (-0.08)	-0.92 (-9.33)	-0.02 (-1.62)	-0.20 (-8.45)
$\hat{b}_{22}$	0.96 (216.3)	0.101 (0.74)	-0.068 (-8.39)	0.55 (15.51)
Log-Liklihood	-1849.23	-6833.66	-8088.31	-7340.63
Q(10)	62	520.27	544	481.44
Q^2(10)	15	130.07	69	67.03

Note: t –statistics values are in parentheses

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