A study on the volatility spillovers in Indian Commodity prices from the global commodity markets
&
calculation of time varying hedge ratios.

by

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2. ABSTRACT

There are four parts in the study. The purpose of the first part of the study is to determine volatility in prices of each base metal by ARIMA/GARCH models & study the impact of it on their consumption by regression analysis using data from 2002 to 2014.The second part is about analyzing the effects of consumption of base metals on the economy (Real GDP*) of India using annual data from 2002 to 2014. Metal price data were collected from the MCX; imports, exports & production data from the Ministry of Commerce & Industry, Govt. of India's website and British Geological Survey data base.

*Real GDP takes inflation into account, allowing for comparisons against other historical time periods.

The third part examines the volatility spillovers between spot and futures daily prices of three base metal markets viz., LME, MCX and SHFE from 10 March, 2006 to 10 March, 2015. The results confirm the long-term relationship between futures and spot prices in each market. Analyzing the futures prices, we find that LME is the most dominant futures trading platform followed by SHFE and MCX in price discovery process. Thus, MCX an emerging market platform seems to act like a satellite market. The GARCH-CCC & DCC model results confirm both cross market and with in market co-movements which become weak during the crisis period and tend to become stronger during the stable period. The study provides relevant implications for policy makers and market traders. The outcome of this study contributes to commodity market literature especially relating to information transmission between strategically linked markets.[1]

3. OBJECTIVES:

- Using univariate time series & volatility clustering models to determine volatility in prices of each base metal & study the impact of it on their consumption. Also, forecast consumption value of each metal for the next three years.
- Analyze the impact of Consumption of base metals on Indian economy (Real GDP) - by (i)constructing a consumption index using principal component analysis, (ii)linear regression analysis.
- Directional volatility spillover dynamics between different base metal prices traded across several commodity markets using VAR, GARCH-CCC, DCC models.
- Hedging strategies to mitigate risks.

4. INTRODUCTION [2]

4.1. Commodity price instability and consumption:[a]

If the price increase is significant, it will also induce some macroeconomic effects. Typically, the country which is a net importer of the commodities whose price has risen will face a drop in its national revenue and aggregate expenditure. This will eventually lead to a real exchange rate appreciation, which usually reduces taxes actually collected for any given level of the overall tax base. Indeed, price volatility leads to GDP volatility, which decreases GDP[2]. Volatility of commodity prices is thus expected to have a negative impact for both imports and exports through the macroeconomic channel.

In a general equilibrium setting, a temporary component in consumption introduces a wedge between the volatility of prices and the volatility of consumption growth. Kandel and Stambaugh[2] observed that returns can be highly volatile, even if consumption growth is not, provided that consumption growth is negatively autocorrelated.

4.2. Base Metals and the economy:

Metals as important industrial input often considered as one of the important factors that drive the Indian economy and can play a pivotal role in achieving the country's socio-economic objectives including poverty reduction goals. In a Mineral rich country like India, the minerals and metals industry can emerge as a significant vehicle to build up physical capital, create employment opportunities and develop productive capacity.

GDP is commonly used as an indicator of the economic output and growth of a country, as well as to gauge a country's standard of living. When a country exports goods, it sells them in a foreign market, i.e., to consumers, businesses, or governments in other country which bring in money to the country, increasing the exporting nation's GDP. When a country imports goods, it buys them from foreign producers. The money spent on imports leaves the economy, thus decreasing the importing nation's GDP.

Net exports can be either positive or negative. If net exports are positive, the nation has a positive balance of trade. If they are negative, the nation has a negative trade balance. Virtually every nation in the world wants its economy to be bigger rather than smaller. That means that no nation wants a negative trade balance. Because no nation wants a negative trade balance, some countries try to protect their own markets. This policy, called **protectionism**, refers to government policies designed to restrict imports from coming into the nation. A tariff, also called a duty, is a tax on imports as they come into the country.

India was little bit conservative in its development strategy which imposed higher tariff on Imports which negatively affected exports(due to lack of funds). However, the policy was shifted to the export promotion in the place of import substitution. To accelerate exports, financial incentives in the form of tax reduction on exportable commodities and import duty reduction was provided[4]. Free trade[#] is not adopted in India.

[#]Free trade means international trade that is unrestricted by tariffs or other forms of protectionism.

The formula for GDP is: GDP = C + I + G[3]

C =Total spending on Consumption.

I = Total investment (spending on goods and services) by businesses

G = Total spending by government (federal, state, and local)

Total Consumption(T)(in tonnes) =[Production+Imports-Exports-Stockpile-ReExports]

Total spending on Consumption(C)=Total Consumption(T)*Price of the commodity.

In this study, we analyze how GDP is affected by Consumption(C). Stockpile and Re-Exports are taken as zero due to the unavailability of data.

4.3. Base Metals and Volatility in Metal Prices:

Metal prices are largely controlled by consumer demand for the products that they are inputs for. Take the price of steel as an example. Hot-rolled coiled steel peaked before the financial crisis of 2008, reaching its apex in 2004 when global economies were booming. New buildings, cars and many other products were driving up the price up until 2004, and then demand leveled off or began to decline slowly. Steel fell off of a cliff in early 2009, as demand for the products and the metal itself waned. The flat-lined or declining steel prices from 2004 to 2009, when prices plummeted, can now be interpreted as an early sign of economic problems to come.

China went on a metals buying spree in 2009 and 2010, and the metals market surged once again. China stockpiled steel, iron ore and copper while prices were low because they knew that a base-metals rebound was coming. The country's government predicted the trend correctly and base metals recovered well[5]

Various time series models and factor-based models exist for forecasting volatility in metal prices. Metal prices are influenced by dynamic factors that create systematic behavior affected by various factors like Change in exchange rate, inflation/deflation, demand, supply and trade policies etc. Factor-based models are very specific to the commodities and they do not perform exceptionally better than time series models. This study demonstrates the estimation of volatility in base metal prices using ARIMA and GARCH models.

5. LITERATURE REVIEW

Among the scarce existing studies dedicated to a statistical analysis on price volatility, most of them focused on the incidence of a shock in the equity prices, foreign exchange rates, agricultural and food commodities and crude oil. Cashin P., C. McDermott, and A. Scott have worked on world commodity prices including metals but they used a different methodology and also did not correlate it to their consumption. So, in the first study, I intend to determine volatility in prices of each base metal & study the impact of it on their consumption. Also, there are large number of studies which analyze the relationship between GDP and exports, imports of consumer goods and services or minerals and metals collectively, but there is not one study which analyze the individual contribution of base metals to economy, specifically in India. In the second study, I intend to investigate short and long-run dynamic impact of exports, imports of base metals on GDP growth of India.

Cross section relationships are often implied by economic theory. Interest rate parities, for instance, provide a close relation between domestic and foreign bond rates. Assuming absence of arbitrage, the so-called triangular equation formalizes the equality of an exchange rate between two currencies on the one hand and an implied rate constructed via exchange rates measured towards a third currency. Furthermore, stock/commodity prices of firms acting on the same market often show similar patterns in the sequel of news that are important for the entire market[5]. Similarly, analyzing global volatility transmission Engle, Ito and Lin and Hamao and Masulis found evidence in favor of volatility spillovers between the world's major trading areas. From this point of view, when modeling time varying volatilities, a multivariate model appears to be a natural framework to take cross sectional information into account. Many problems in financial practice like portfolio optimization, hedging strategies, or Value-at-Risk evaluation require multivariate volatility measures.

There is however to our knowledge - a lack of analysis of the impact of base metal price instability in a market on other markets and hedging strategies to be followed. This study aims at filling this gap by testing the aforementioned impacts and by proposing the hedging strategies.

6. METHODOLOGY AND ARIMA/GARCH MODEL FOR CONDITIONAL VOLATILITY FORECASTING[6]

The data is checked for serial autocorrelations by studying the ACF and PACF plots of the data. Augmented Dickey Fuller Test (ADF) is used to identify data stationarity, the number of autoregressive parameters, p, the number or integrations, d, the number of moving average parameter, q. Conditional mean model is estimated without considering the heteroskedasticity of the residuals. The best ARIMA model for the data is selected using Akaike Information Criteria (AIC). Model checking is done, by studying the ACF and PACF plots of the residuals.

The squared residuals are then tested for conditional heteroskedasticity and conditional variance model is estimated.

6.1. Conditional Mean:

To estimate the conditional mean autoregressive integrated moving (ARIMA) model will be estimated. Autoregressive moving average process (ARMA) models are defined by the iteration between an autoregressive process (AR), and moving average process (MA). Equation below presents ARMA (p,q) model with p autoregressive terms and q moving average terms.

$$y_t = \mu + \varphi_1 y_{t-1} + \ldots\ldots + \varphi_p y_{t-p} - \theta_1\varepsilon_{t-1} - \ldots\ldots - \theta_q\varepsilon_{t-q} + \varepsilon$$

y_t is explained by its past values and errors. μ, φ_p and θ_q are the estimated parameters and $\varepsilon_{t-q} \sim N(0,1)$

If Y_t is not stationary, we transform the data using differences to make it stationary, especially in the presence of unit roots. Equation below shows the ARIMA (p,d,q) model with p autoregressive terms, d integrated orders and q moving average terms.

$$\Delta^d y_t = \mu + \varphi_1 \Delta^d y_{t-1} + \ldots\ldots + \varphi_p \Delta^d y_{t-p} - \theta_1 \varepsilon_{t-1} - \ldots\ldots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Δ^d is the difference operator, φ_p and θ_q are the estimated parameters and $\varepsilon_{t-q} \sim N(0,1)$

6.2. Conditional Variance:

Lagrange Multiplier Test is applied to test for conditional heteroskedasticity effects in the residuals from the mean model. The Equation below gives the specification of a GARCH(p,q) model

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \boldsymbol{\alpha_i \varepsilon^2_{t-i}} + \sum_{i=1}^{p} \beta_{\mathbf{i}}\, y_{t-i}^2$$

7. Results and Findings:

7.1. Aluminium:

(a) **Augmented Dickey-Fuller test**

Step 1: convert the non-stationary time series to stationary one. This is important for the fact that a lot of statistical and econometric methods are based on this assumption and can only be applied to stationary time series. Non-stationary time series are erratic and unpredictable while stationary process is mean-reverting, i.e., it fluctuates around a constant mean with constant variance. After transformation, the stationarity of the data is checked by performing Augmented Dickey-Fuller test.

Output for Aluminium:

data: log(close.data1.ts)

p-value = 0.01

alternative hypothesis: stationary

(b) Fitting ARIMA model.

Step 2: Akaike Information Criterion :

In addition to Box-Jenkins method, **corrected Akaike Information Criterion (AICc)** provides another way to check and identify the model. It can be calculated by the formula:

AICc = N*log(SS/N) + 2(p + q + 1)*N/(N – p – q – 2), if no constant term in model

AICc = N*log(SS/N) + 2(p + q + 2)*N/(N – p – q – 3), if constant term in model

Where, N : the number of items after differencing (N = n – d),

SS : sum of squares of differences, p & q : the order of autoregressive and moving average model, respectively. According to this method, the model with lowest AICc will be selected.

Based on AICc, we should select ARIMA(0,1,0).

Aluminium

Order	**AIC**
0 1 0	**-6612.4**
1 1 0	**-6611.7**
0 1 1	**-6611.7**
1 1 1	**-6609.7**
0 1 2	**-6609.7**
1 1 2	**-6607.7**
2 1 0	**-6609.7**
2 1 1	**-6607.7**
2 1 2	**-6607.8**
0 2 0	**-5762.1**

Step3: Diagnostic checking/Residual Analysis.

The procedure includes observing residual plot and its ACF & PACF diagram, and check Ljung-Box result. If ACF & PACF of the model residuals show no significant lags, the selected model is appropriate.

(c) ARCH/GARCH model:

Observe the squared residual plot. If there are clusters of volatility, ARCH/GARCH should be used to model the volatility of the series to reflect more recent changes and fluctuations in the series. Finally, ACF & PACF of squared residuals will help confirm if the residuals (noise term) are not independent and can be predicted. As mentioned earlier, a strict white noise cannot be predicted either linearly or nonlinearly. If the residuals are strict white noise, they are independent with zero mean, normally distributed, and ACF & PACF of squared residuals displays no significant lags.

The general form of ARCH(q):

$$\varepsilon_t | \psi_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \boldsymbol{\alpha_i \varepsilon^2_{t-i}}$$

where, ε_t is white noise, ψ_{t-1} is the historical data, σ_t^2 is the conditional variance, α_i are constants.

ARCH/GARCH orders and parameters are selected based on AICc as follows:

AICc = -2*Log(likelihood)+ 2(p + q + 1)*N/(N – p – q – 2), if no constant term in model

AICc = -2*Log(likelihood)+ 2(p + q + 2)*N/(N – p – q – 3), if constant term in model

Where, N : the number of items after differencing (N = n – d), p & q : the order of autoregressive and moving average

To compute AICc, we need to fit ARCH/GARCH model to the residuals and then calculate the loglikelihood using logLik() function in R and follow the formula above. Noted that we fit ARCH to the residuals from ARIMA model selected previously, not to the original series or log or differenced log series because we only want to model the noise of ARIMA model.

Aluminium

Model	N	0rder	loglik	AICc
ARCH(1)	1164	1	3325	-6645.99
ARCH(2)	1164	2	3357	-6707.97
ARCH(3)	1164	3	3365	-6721.96
ARCH(4)	1164	4	3367	-6723.94
ARCH(5)	1164	5	3367	-6721.92
ARCH(6)	1164	6	3379	-6743.89
ARCH(7)	1164	7	3388	-6759.86
ARCH(8)	1164	8	3388	-6757.83
ARCH(9)	1164	9	3389	-6757.79
GARCH(1,1)	1164	2	3403	-6799.97

The table of AICc is provided above for both constant and non-constant cases. Note the increase in AICc from ARCH(1) to ARCH(9) and GARCH(1,1). Therefore, GARCH(1,1) is the selected model.

(d) GARCH/Conditional Variance equation fit:

```
> arch01=garch(res.arima212,order=c(1,1),trace=F)
> loglik01=logLik(arch01)
> summary(loglik01)
> summary(arch01)
```

Output for Aluminium:

Call:

garch(x = res.arima212, order = c(1, 1), trace = F)

Model:

GARCH(1,1)

Coefficient(s)	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
a0	2.923e-06	1.104e-06	2.646	0.00814 **
a1	6.347e-02	1.186e-02	5.353	8.64e-08 **
b1	9.216e-01	1.548e-02	59.546	< 2e-16 **

Diagnostic Tests:

Jarque Bera Test

data: Residuals

p-value < 2.2e-16

Box-Ljung test

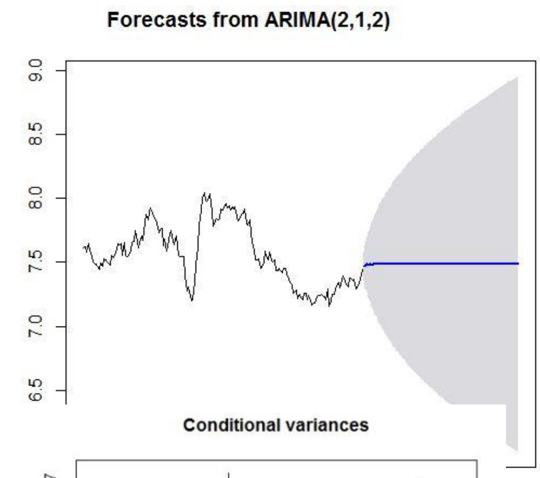
data: Squared.Residuals

p-value = 0.06752

Full GARCH(1,1) model from the results below:

$$\sigma_t^2=(2.923*10^{-6}) +(6.347*10^{-2})* \sigma_{t-1}^2+ (9.216*10^{-1})*\varepsilon^2_{t-1}$$

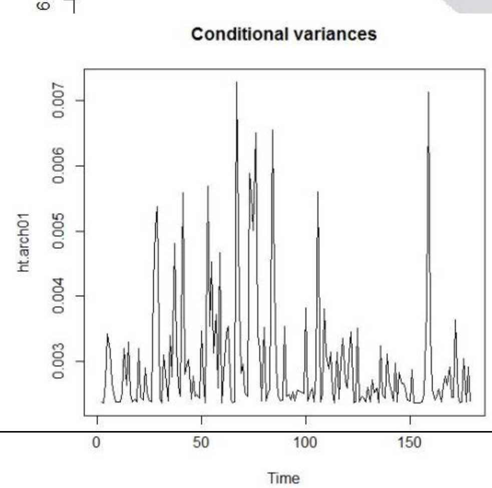
(e) <u>R code to generate :</u> (i)ARIMA Forecast:




```
forecast212=forecast(arima212,100,level=95)
#forecast for next 100 timeperiodsat 95% C.I
plot(forecast212)
```

(ii)Conditional variances(GARCH):

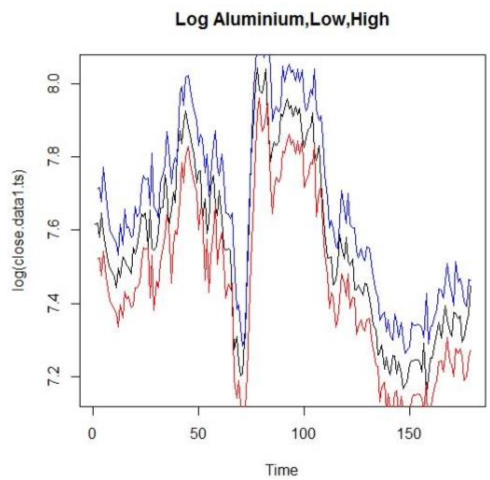
```
ht.arch01=arch01$fit[,1]^2
```



```
plot(ht.arch01,main='Conditional variances')
```

(iii)Final fit:

```
fit212=fitted.values(arima212)

low=fit212-1.96*sqrt(ht.arch01)

high=fit212+1.96*sqrt(ht.arch01)

plot(log(close.data1.ts),type='l',main='Log
Aluminium,Low,High')

lines(low,col='red')

lines(high,col='blue')
```



(f) METHODOLOGY AND ECONOMETRIC MODEL FOR REGRESSION ANALYSIS

The impact of volatility in each of the base metal prices on their consumption has been studied. For this stage, Bivariate Analysis has been carried out between conditional variance of metal price and log consumption value, considering log consumption value as the dependent and the conditional variance of metal price as the independent variable in each case.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Aluminium[b]	.	Enter

a. Dependent Variable: CAluminium

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Durbin-Watson
1	.564[a]	.318	.256	1.010

a. Predictors: (Constant), Aluminium

b. Dependent Variable: CAluminium

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.475	1	.475	5.137	.045[b]
	Residual	1.018	11	.093		
	Total	1.494	12			

a. Dependent Variable: CAluminium

b. Predictors: (Constant), Aluminium

Coefficients[a]

Model		Unstandardized Coefficients		t	Sig.
		B	Std. Error		
1	(Constant)	22.648	.670	33.808	.000
	Aluminium	-.020	.009	-2.266	.045

a. Dependent Variable: CAluminium

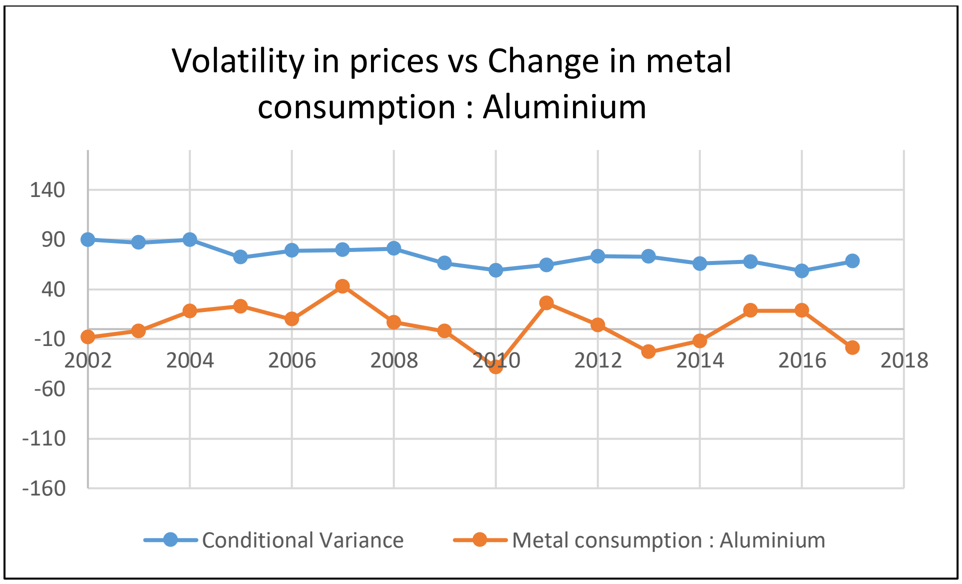
The regression fit is:

CAluminium=22.648-(0.020*Aluminium)

Then, the conditional variances are forecasted for the next three years and thus their corresponding log consumption values are found out by the relation above.

Inference

- Overall model is statistically significant(F-Test).
- All the coefficients are statistically significant
- For all cases, VIF is less than 5, so model is totally free from multicollinearity problem.



From the graph, its clear that volatility in aluminium prices are inversely proportional to its consumption, except in the financial crisis period between 2008-2011

7.2. Copper:

Augmented Dickey-Fuller Test :

> adf.test(log(close.data1.ts),alternative=("stationary"))

data: log(close.data1.ts)

p-value = 0.01

alternative hypothesis: stationary

Mean equation fit:

> arima(log(close.data1.ts),order = c(2,1,1))

Series: log(close.data1.ts)

ARIMA(2,1,1)

Coefficients:

	ar1	ar2	ma1
	-0.7283	0.0513	0.7047
s.e.	0.1313	0.0342	0.1289

log likelihood=3429.92

AIC=-6851.84   AICc=-6851.81   BIC=-6831.61

GARCH/Conditional Variance equation fit:

> arch01=garch(res.arima212,order=c(1,1),trace=F)

> loglik01=logLik(arch01)

> summary(arch01)

Call:

garch(x = res.arima212, order = c(1, 1), trace = F)

Model:

GARCH(1,1)

Coefficient(s):

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
a0	2.089e-06	1.448e-06	1.443	0.14913
a1	2.472e-02	8.934e-03	2.767	0.00565 **
b1	9.628e-01	1.576e-02	61.075	< 2e-16 ***

Diagnostic Tests:

Jarque Bera Test

data: Residuals

p-value = 2.22e-16

Box-Ljung test

data: Squared.Residuals

p-value = 0.07858

Regression 2:

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Copper[b]	.	Enter

a. Dependent Variable: CCopper

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.634[a]	.402	.347	.4521773	1.007

a. Predictors: (Constant), Copper

b. Dependent Variable: CCopper

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
	Regression	1.509	1	1.509	7.381	.020[b]
1	Residual	2.249	11	.204		
	Total	3.758	12			

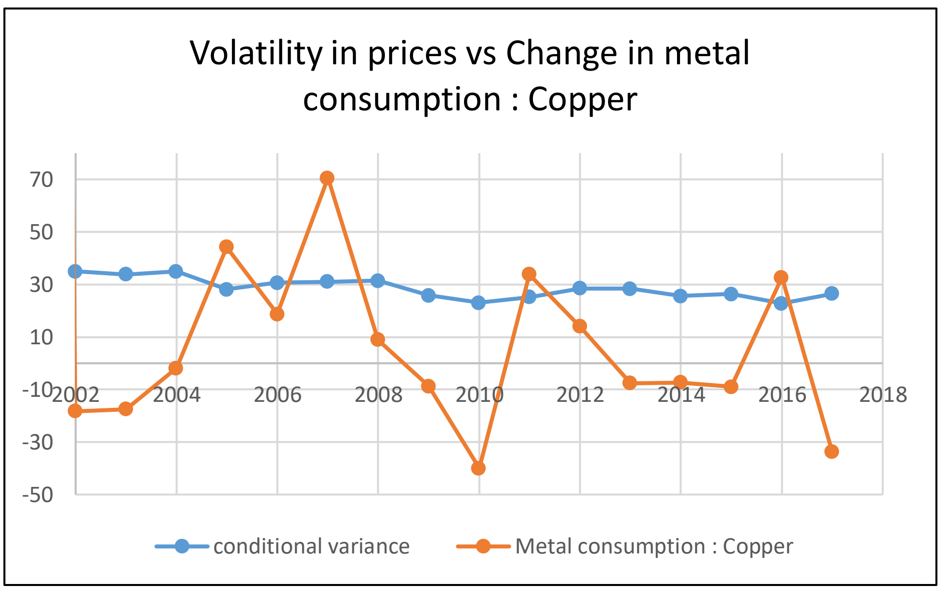
a. Dependent Variable: CCopper

b. Predictors: (Constant), Copper

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	21.292	.996		21.382	.000
	Copper	-.091	.034	-.634	-2.717	.020

a. Dependent Variable: CCopper



7.3. <u>Zinc:</u>

Augmented Dickey-Fuller Test :

> adf.test(log(close.data1.ts),alternative=("stationary"))

data: log(close.data1.ts)

p-value = 0.005

alternative hypothesis: stationary

Mean equation fit:

> arima(log(close.data1.ts),order = c(2,1,2))

Series: log(close.data1.ts)

ARIMA(2,1,2)

Coefficients:

	ar1	ar2	ma1	ma2
	-0.7039	-0.9048	0.7409	0.9427
s.e.	0.0418	0.0430	0.0347	0.0315

log likelihood=3231.95

AIC=-6453.91 AICc=-6453.85 BIC=-6428.62

GARCH/Conditional Variance equation fit:

> arch01=garch(res.arima212,order=c(1,1),trace=F)

> loglik01=logLik(arch01)

> summary(arch01)

Call:

garch(x = res.arima212, order = c(1, 1), trace = F)

Model:

GARCH(1,1)

Coefficient(s):

	Estimate	Std. Error	t value	Pr(>|t|)	
a0	1.907e-07	3.930e-07	0.485	0.627594	
a1	2.323e-02	6.570e-03	3.537	0.000405	***
b1	9.772e-01	7.295e-03	133.959	< 2e-16	***

Diagnostic Tests:

Jarque Bera Test

data: Residuals

p-value < 2.2e-16

Box-Ljung test

data: Squared.Residuals

p-value = 0.0882

Regression 3:

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Zinc[b]	.	Enter

a. Dependent Variable: CZinc

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.670[a]	.449	.399	.5232106	.720

a. Predictors: (Constant), Zinc

b. Dependent Variable: CZinc

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.454	1	2.454	8.963	.012[b]
	Residual	3.011	11	.274		
	Total	5.465	12			

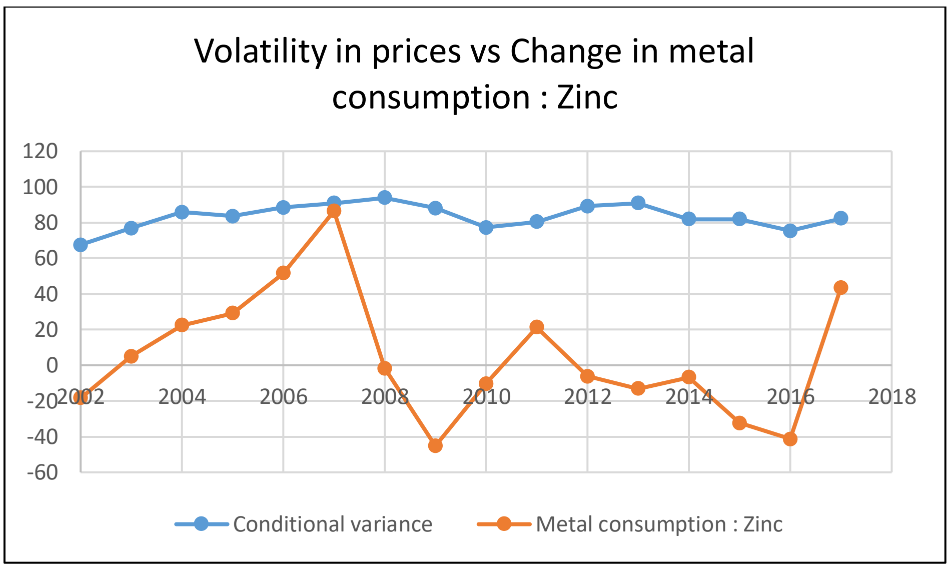
a. Dependent Variable: CZinc

b. Predictors: (Constant), Zinc

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	14.927	1.742		8.567	.000
	Zinc	.062	.021	.670	2.994	.012

a. Dependent Variable: CZinc



7.4. <u>Nickel:</u>

Augmented Dickey-Fuller Test :

```
> adf.test(log(close.data1.ts),alternative=("stationary"))
```

data: log(close.data1.ts)

p-value = 0.055

alternative hypothesis: stationary

Mean equation fit:

```
> arima(log(close.data1.ts),order = c(2,1,2))
```

Series: log(close.data1.ts)

ARIMA(2,1,2)

Coefficients:

```
        ar1      ar2      ma1     ma2
     0.4448  -0.9387  -0.4353  0.8972
s.e.  0.0373   0.0414   0.0476  0.0528
```

log likelihood=3022.05

AIC=-6034.1   AICc=-6034.05   BIC=-6008.81

GARCH/Conditional Varaince equation fit:

```
> arch01=garch(res.arima212,order=c(1,1),trace=F)
> loglik01=logLik(arch01)
> summary(arch01)
```

Call:

garch(x = res.arima212, order = c(1, 1), trace = F)

Model:

GARCH(1,1)

Coefficient(s):

```
    Estimate  Std. Error  t value Pr(>|t|)
a0 1.953e-05   6.646e-06    2.939  0.00329 **
a1 9.032e-02   1.583e-02    5.707 1.15e-08 ***
b1 8.515e-01   3.110e-02   27.374  < 2e-16 ***
```

Diagnostic Tests:

Jarque Bera Test

data: Residuals

p-value = 1.477e-14

Box-Ljung test

data: Squared.Residuals

p-value = 0.05728

Regression 4:

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Nickel[b]	.	Enter

a. Dependent Variable: CNickel

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.404[a]	.163	.087	.4937719	.890

a. Predictors: (Constant), Nickel

b. Dependent Variable: CNickel

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.524	1	.524	2.149	.171[b]
	Residual	2.682	11	.244		

Total	3.206	12				

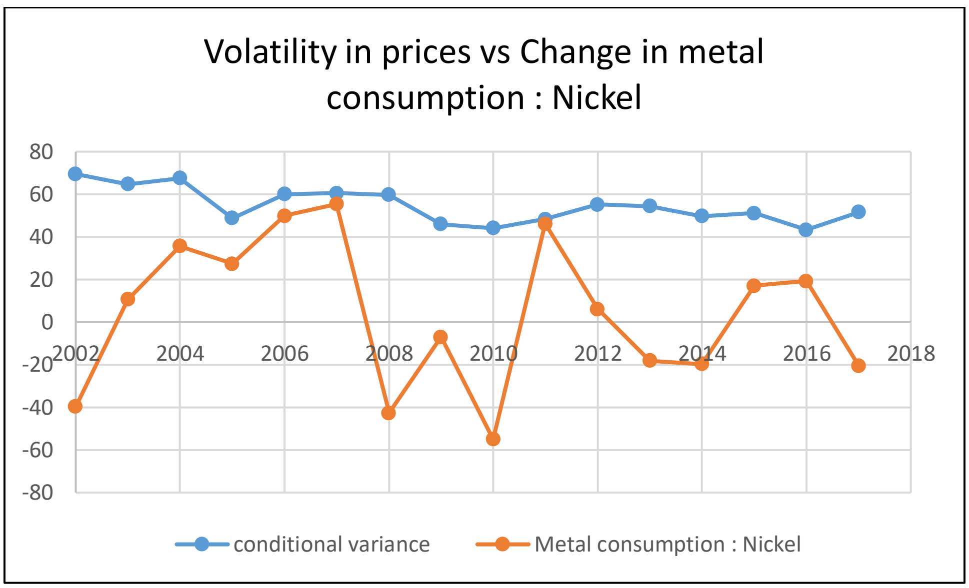
a. Dependent Variable: CNickel

b. Predictors: (Constant), Nickel

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	21.662	.966		22.429	.000
	Nickel	-.025	.017	-.404	-1.466	.171

a. Dependent Variable: CNickel



7.5. Tin:

Augmented Dickey-Fuller Test :

```
> adf.test(log(close.data1.ts),alternative=("stationary"))
```

data: log(close.data1.ts)

p-value = 0.077

alternative hypothesis: stationary

Mean equation fit:

```
> arima(log(close.data1.ts),order = c(0,1,0))
```

Series: log(close.data1.ts)

ARIMA(0,1,0)

log likelihood=3090.78

AIC=-6179.57 AICc=-6179.57 BIC=-6174.51

GARCH/Conditional Varaince equation fit:

```
> arch01=garch(res.arima212,order=c(1,1),trace=F)
> loglik01=logLik(arch01)
> summary(arch01)
```

Call:

garch(x = res.arima212, order = c(1, 1), trace = F)

Model:

GARCH(1,1)

Coefficient(s):

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
a0	3.919e-07	3.126e-07	1.254	0.21	
a1	4.424e-02	7.358e-03	6.013	1.83e-09	***
b1	9.607e-01	7.052e-03	136.226	< 2e-16	***

Diagnostic Tests:

Jarque Bera Test

data: Residuals

p-value < 2.2e-16

Box-Ljung test

data: Squared.Residuals

p-value = 0.07121

Regression 5:

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Tin[b]	.	Enter

a. Dependent Variable: CTin

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.407[a]	.166	.090	.4232575	1.211

a. Predictors: (Constant), Tin

b. Dependent Variable: CTin

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.391	1	.391	2.184	.017[b]
	Residual	1.971	11	.179		
	Total	2.362	12			

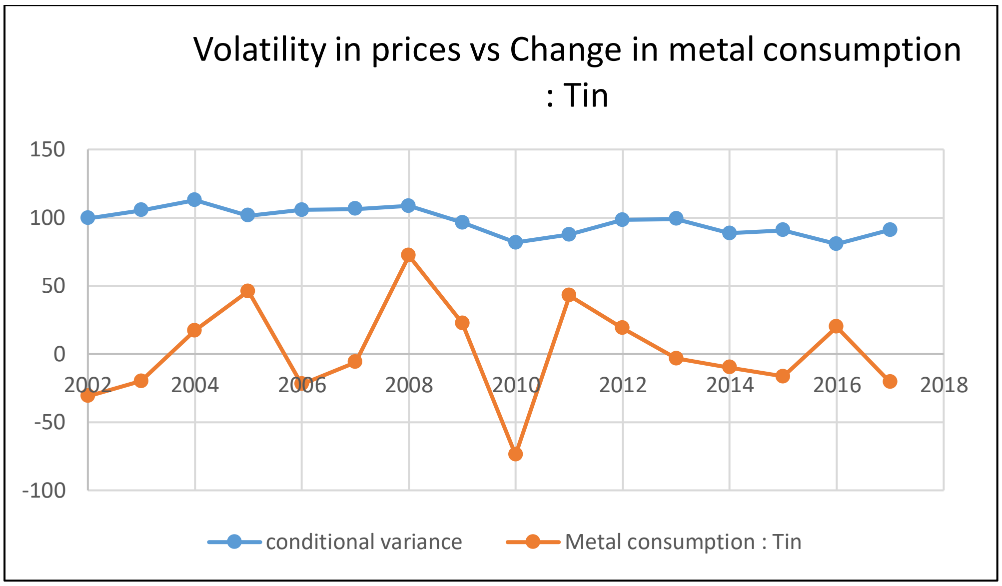
a. Dependent Variable: CTin

b. Predictors: (Constant), Tin

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	20.302	1.353		15.002	.000
	Tin	-.020	.014	-.407	-1.478	.017

a. Dependent Variable: CTin



7.6. Lead:

Augmented Dickey-Fuller Test :

```
> adf.test(log(close.data1.ts),alternative=("stationary"))
```

data: log(close.data1.ts)

p-value = 0.017

alternative hypothesis: stationary

Mean equation fit:

> arima(log(close.data1.ts),order = c(2,1,2))

Series: log(close.data1.ts)

ARIMA(2,1,2)

Coefficients:

	ar1	ar2	ma1	ma2
	-0.6472	-0.5742	0.7207	0.6402
s.e.	0.2231	0.1972	0.2094	0.1879

log likelihood=3120.37

AIC=-6230.74   AICc=-6230.69   BIC=-6205.45

GARCH/Conditional Varaince equation fit:

> arch01=garch(res.arima212,order=c(1,1),trace=F)

> loglik01=logLik(arch01)

> summary(arch01)

Call:

garch(x = res.arima212, order = c(1, 1), trace = F)

Model:

GARCH(1,1)

Coefficient(s):

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
a0	4.683e-07	4.615e-07	1.015	0.31
a1	3.157e-02	7.198e-03	4.387	1.15e-05 ***
b1	9.676e-01	7.459e-03	129.716	< 2e-16 ***

Diagnostic Tests:

Jarque Bera Test

data: Residuals

p-value = 0.0001167

Box-Ljung test

data: Squared.Residuals

p-value = 0.08628

Regression 6:

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Lead[b]	.	Enter

a. Dependent Variable: CLead

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.086[a]	.007	-.083	.8346462	.205

a. Predictors: (Constant), Lead

b. Dependent Variable: CLead

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.058	1	.058	.083	.779[b]
	Residual	7.663	11	.697		

	Total	7.721	12			

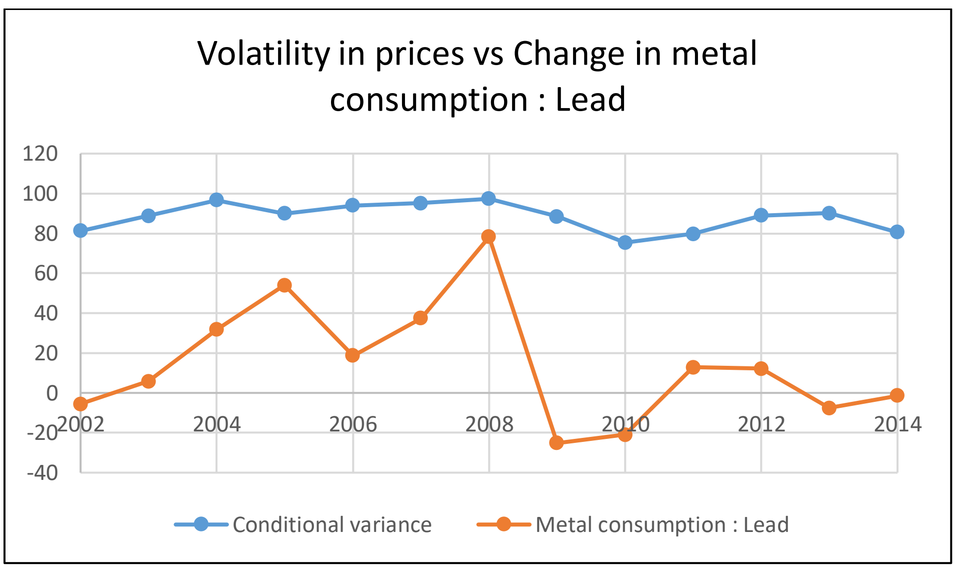
a. Dependent Variable: CLead

b. Predictors: (Constant), Lead

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	18.762	3.046		6.160	.000
	Lead	-.010	.034	-.086	-.288	.779

a. Dependent Variable: CLead



Part2 Regression:

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	log Export Value, log Production Value, log Import Value[b]	.	Enter

a. Dependent Variable: log Real GDP

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.978[a]	.957	.944	.0647053	2.267

a. Predictors: (Constant), log Export Value, log Production Value, log Import Value

b. Dependent Variable: log Real GDP

ANOVA[a]

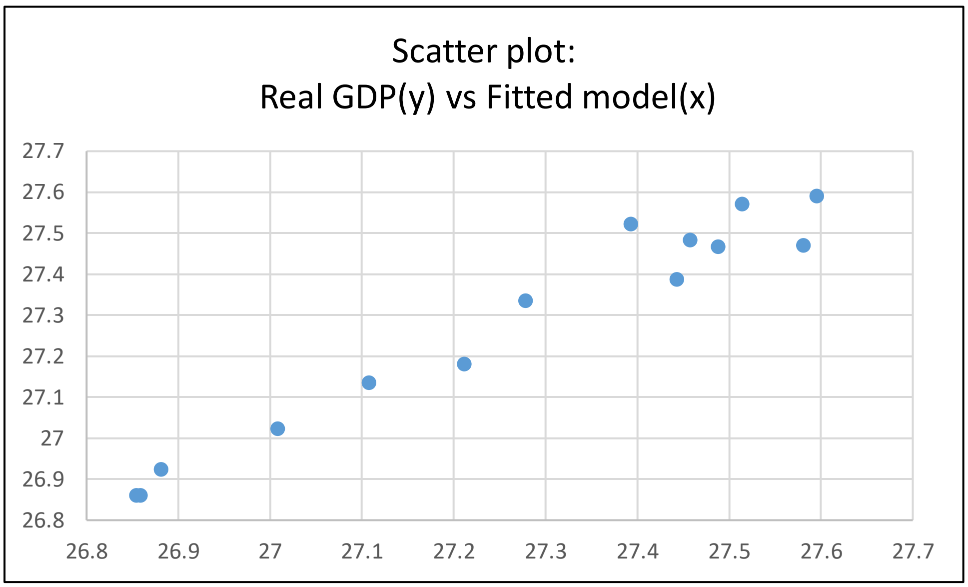
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.939	3	.313	74.743	.000[b]
	Residual	.042	10	.004		
	Total	.981	13			

a. Dependent Variable: log Real GDP

b. Predictors: (Constant), log Export Value, log Production Value, log Import Value

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19.874	2.087		9.525	.000
	log Production Value	.183	.113	.264	1.620	.013
	log Import Value	.075	.165	.338	.455	.029
	log Export Value	.090	.162	.395	.553	.003



8. Methodology: Process of Volatility Spillovers:

The GARCH-BEKK (Baba, Engle, Kraft and Kroner, 1990) model is used to model the volatility spillover dynamics between futures and spot prices and between futures prices of LME, MCX and SHFE. Apart from BEKK model, constant conditional correlation (CCC) and dynamic conditional correlation (DCC) models are employed to infer upon the constant and time-varying correlation patterns of base metal price series under consideration. A brief description of each model is mentioned below.

8.1. GARCH (BEKK) Model:

The BEKK model is the most natural way to deal with the multivariate matrix operations. In this study, the model is implemented on the residuals of the series under following specification.

Mean equation: $$\upsilon_{it} = \mu_0 + \sum_{j=1}^{2} \mu_{ij} \upsilon_{j,t-1} + \varepsilon_{it}$$

where, $\varepsilon_{it} \mid I_{it-1} \sim N(0, h_{it})$, i=1,2.

υ_{it} is the estimated residual of the sample series. ε_{it} is a random error term with conditional variance h_{it}. I_{it-1} denotes the market information at time t-1. The BEKK parameterization of multivariate GARCH model is written in the following manner:

$$H_{t+1} = CC' + A'\varepsilon_t \varepsilon_t' A + G'H_t G$$

Where the individual elements of C, A and B matrices are mentioned below:

$$\mathrm{C} = \begin{pmatrix} c11 & c12 \\ c21 & c22 \end{pmatrix}, A = \begin{pmatrix} a11 & a12 \\ a21 & a22 \end{pmatrix}, \mathrm{G} = \begin{pmatrix} g11 & g12 \\ g21 & g22 \end{pmatrix}$$

$$\begin{aligned}
\sigma_{11,t} &= c_{11} + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2 \varepsilon_{2,t-1}^2 \\
&\quad + g_{11}^2 \sigma_{11,t-1} + 2g_{11}g_{21}\sigma_{21,t-1} + g_{21}^2 \sigma_{22,t-1}, \\
\sigma_{21,t} &= c_{21} + a_{11}a_{22}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 \\
&\quad + g_{11}g_{22}\sigma_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})\sigma_{12,t-1} + g_{21}g_{22}\sigma_{22,t-1},
\end{aligned}$$

$$\sigma_{22,t} = c_{22} + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2$$
$$+ g_{12}^2\sigma_{11,t-1} + 2g_{12}g_{22}\sigma_{21,t-1} + g_{22}^2\sigma_{22,t-1}.$$

The off-diagonal elements of matrix A (a12 and a21) represent the short-term volatility spillover (ARCH effect) from market 1 to another market 2.The off-diagonal elements of matrixB (b12 and b21) represent the long-term volatility spillover (GARCH effect) in the same manner as mentioned above.

8.2. DCC GARCH model: (Conditional Variance : Dynamic Correlation Model)[10]

The GARCH-DCC involves two steps. The first step accounts for the conditional heteroskedasticity. It consists in estimating, for each one of the *n* series of returns r_{it}, its conditional volatility σ_{it} using a GARCH model. Let D_t be a diagonal matrix with these conditional volatilities, i.e. $D^{i,i}_t = \sigma_{it}$ and, if $i \neq j$, $D^{i,j}_t = 0$. Then the standardized residuals are:

$$\nu_t = D^{-1}_t(r_t - \mu)$$

Now, define the matrix:

$$R = (1/T) * \sum_{t=1}^{T} \upsilon_t \upsilon_t'$$

This is the Bollerslev's Constant Conditional Correlation (CCC) Estimator (Bollerslev, 1990).

The second step consists in generalizing Bollerslev's CCC to capture dynamics in the correlation, hence the name Dynamic Conditional Correlation (DCC). The DCC correlations are:

$$Q_t = R + \sum_{i=1}^{p} \alpha_i (\upsilon_{t-i}\upsilon'_{t-i} - R) + \sum_{j=1}^{q} \beta_j (Q_{t-j} - R)$$

So, $Q^{i,j}_t$ is the correlation between r_{it} and r_{jt} at time t.

8.3. Results of DCC Garch:

#1: mcx_alum_CL #2: lme_alum_CL #3: shfe_alum_CL #4: mcx_cop_CL

#5: lme_cop_CL #6: shfe_cop_CL #7: mcx_lead_CL #8: lme_lead_CL

#9: shfe_lead_CL #10: mcx_zinc_CL #11: lme_zinc_CL #12: shfe_zinc_CL

Conditional Variance : Dynamic Correlation Model (Engle)

	Coefficient	Std.Error	t-value	t-prob
rho_21	0.837962	0.016597	50.49	0.0000
rho_31	0.151204	0.042271	3.577	0.0004
rho_41	0.166097	0.040836	4.067	0.0001
rho_51	0.071602	0.049928	1.434	0.1518
rho_61	0.127581	0.045057	2.832	0.0047
rho_71	0.596876	0.029053	20.54	0.0000
rho_81	0.525168	0.031060	16.91	0.0000
rho_91	0.178352	0.045714	3.902	0.0001
rho_101	0.007721	0.040051	0.1928	0.8472
rho_111	0.599657	0.028075	21.36	0.0000
rho_121	0.167326	0.044802	3.735	0.0002
rho_32	0.235591	0.038263	6.157	0.0000
rho_42	0.167574	0.041227	4.065	0.0001
rho_52	0.153623	0.062633	2.453	0.0143
rho_62	0.238446	0.041602	5.732	0.0000
rho_72	0.550483	0.032823	16.77	0.0000
rho_82	0.633364	0.024224	26.15	0.0000
rho_92	0.251016	0.042197	5.949	0.0000
rho_102	-0.020760	0.039270	-0.5287	0.5972

rho_112	0.696167	0.021030	33.10	0.0000
rho_122	0.276001	0.041070	6.720	0.0000
rho_43	0.283692	0.040298	7.040	0.0000
rho_53	0.151683	0.066463	2.282	0.0227
rho_63	0.598257	0.030991	19.30	0.0000
rho_73	0.147623	0.046430	3.179	0.0015
rho_83	0.240437	0.036553	6.578	0.0000
rho_93	0.510404	0.034036	15.00	0.0000
rho_103	-0.058031	0.040828	-1.421	0.1555
rho_113	0.267801	0.037183	7.202	0.0000
rho_123	0.598256	0.033800	17.70	0.0000
rho_54	0.163611	0.087794	1.864	0.0626
rho_64	0.494612	0.039663	12.47	0.0000
rho_74	0.176118	0.044913	3.921	0.0001
rho_84	0.196000	0.043252	4.532	0.0000
rho_94	0.294993	0.045792	6.442	0.0000
rho_104	0.019571	0.042930	0.4559	0.6486
rho_114	0.198413	0.044003	4.509	0.0000
rho_124	0.342772	0.043877	7.812	0.0000
rho_65	0.252850	0.10291	2.457	0.0142
rho_75	0.103688	0.058137	1.784	0.0748
rho_85	0.165139	0.071857	2.298	0.0217
rho_95	0.167480	0.070656	2.370	0.0179
rho_105	-0.024246	0.044305	-0.5473	0.5843

rho_115	0.172965	0.075686	2.285	0.0225
rho_125	0.217547	0.088388	2.461	0.0140
rho_76	0.199399	0.044991	4.432	0.0000
rho_86	0.325064	0.037861	8.586	0.0000
rho_96	0.655909	0.031341	20.93	0.0000
rho_106	-0.045005	0.041746	-1.078	0.2812
rho_116	0.352669	0.036044	9.784	0.0000
rho_126	0.746484	0.021874	34.13	0.0000
rho_87	0.827256	0.020906	39.57	0.0000
rho_97	0.262671	0.040365	6.507	0.0000
rho_107	0.009529	0.039063	0.2439	0.8073
rho_117	0.659012	0.028670	22.99	0.0000
rho_127	0.235888	0.043546	5.417	0.0000
rho_98	0.396842	0.035082	11.31	0.0000
rho_108	-0.006794	0.039531	-0.1719	0.8636
rho_118	0.780853	0.015815	49.37	0.0000
rho_128	0.374205	0.037641	9.942	0.0000
rho_109	0.021757	0.044818	0.4854	0.6275
rho_119	0.374449	0.034439	10.87	0.0000
rho_129	0.768034	0.023078	33.28	0.0000
rho_1110	-0.000072	0.042249	-0.001701	0.9986
rho_1210	-0.020467	0.042783	-0.4784	0.6325
rho_1211	0.435320	0.033890	12.85	0.0000

8.4. Results of MV-GARCH, GEKK - Estimation

Variable	Coeff	Std Error	T-Stat	Signif
1. MCX_COP_CL{1}				
2. SHFE_COP_CL{1}				
3. LME_COP_CL{1}				
13. C(1,1)	0.001734945	0.000463559	3.74266	0.00018208
14. C(2,1)	0.001158637	0.002511394	0.46135	0.64454611
15. C(2,2)	0.004018741	0.002213961	1.81518	0.06949604
16. C(3,1)	0.000784727	0.000742029	1.05754	0.29026408
17. C(3,2)	0.001500413	0.000322408	4.65377	0.00000326
18. C(3,3)	-0.000001338	0.000644013	-0.00208	0.99834177
19. A(1,1)	0.175462146	0.039196982	4.47642	0.00000759
20. A(1,2)	-1.496293418	0.458354674	-3.26449	0.00109662
21. A(1,3)	0.075788661	0.050620338	1.49720	0.13434178
22. A(2,1)	-0.013804482	0.028382947	-0.48637	0.62670816
23. A(2,2)	3.389063720	0.433939184	7.81000	0.00000000
24. A(2,3)	-0.023303394	0.025393776	-0.91768	0.35878573
25. A(3,1)	-0.124042458	0.074953509	-1.65493	0.09793965
26. A(3,2)	-1.719595884	0.399613204	-4.30315	0.00001684
27. A(3,3)	0.226933384	0.060770364	3.73428	0.00018826
28. G(1,1)	0.949712012	0.011867196	80.02834	0.00000000
29. G(1,2)	0.173753393	0.068703122	2.52905	0.01143729
30. G(1,3)	-0.024071867	0.016706394	-1.44088	0.14961930
31. G(2,1)	0.002591420	0.005069181	0.51121	0.60920342
32. G(2,2)	0.402556817	0.042552773	9.46018	0.00000000
33. G(2,3)	0.003929137	0.004230151	0.92884	0.35297151
34. G(3,1)	0.063429647	0.023717232	2.67441	0.00748605

35. G(3,2)	0.430646361	0.111701746	3.85532	0.00011558
36. G(3,3)	0.961373003	0.014787111	65.01425	0.00000000

Variable	Coeff	Std Error	T-Stat	Signif
1. MCX_LEAD_CL{1}				
2. SHFE_LEAD_CL{1}				
3. LME_LEAD_CL{1}				
13. C(1,1)	0.003805086	0.001222240	3.11321	0.00185066
14. C(2,1)	0.002104185	0.001094817	1.92195	0.05461187
15. C(2,2)	-0.000000114	0.000127082	-8.95966e-004	0.99928512
16. C(3,1)	0.001102476	0.000425358	2.59188	0.00954543
17. C(3,2)	-0.000000165	0.000138995	-0.00119	0.99905155
18. C(3,3)	0.000000030	0.000168027	1.80985e-004	0.99985559
19. A(1,1)	0.270079010	0.111414392	2.42409	0.01534661
20. A(1,2)	0.098953921	0.128523110	0.76993	0.44134085
21. A(1,3)	0.144857961	0.048014302	3.01698	0.00255311
22. A(2,1)	-0.155728451	0.093453904	-1.66637	0.09564045
23. A(2,2)	0.097874366	0.126735885	0.77227	0.43995433
24. A(2,3)	-0.013369934	0.036457671	-0.36672	0.71382426
25. A(3,1)	-0.019748366	0.084225866	-0.23447	0.81462079
26. A(3,2)	0.141147218	0.101198280	1.39476	0.16308851
27. A(3,3)	0.396528435	0.086556986	4.58113	0.00000462
28. G(1,1)	0.460832790	0.105963495	4.34898	0.00001368
29. G(1,2)	-0.424454037	0.129565012	-3.27599	0.00105291
30. G(1,3)	-0.421465795	0.029446274	-14.31304	0.00000000
31. G(2,1)	0.385757995	0.131232130	2.93951	0.00328733
32. G(2,2)	1.306327098	0.109098110	11.97387	0.00000000
33. G(2,3)	0.314170339	0.047310456	6.64061	0.00000000
34. G(3,1)	0.387597306	0.174512606	2.22103	0.02634910
35. G(3,2)	-0.164852914	0.229707414	-0.71766	0.47296402

36. G(3,3)	0.709613759	0.047931879	14.80463	0.00000000

Variable	Coeff	Std Error	T-Stat	Signif
1. MCX_ZINC_CL{1}				
2. LME_ZINC_CL{1}				
3. SHFE_ZINC_CL{1}				
13. C(1,1)	0.006661638	0.001674743	3.97771	0.00006958
14. C(2,1)	0.002075673	0.000771629	2.68999	0.00714542
15. C(2,2)	0.000000045	0.000187626	2.39354e-004	0.99980902
16. C(3,1)	-0.001070396	0.000418497	-2.55771	0.01053635
17. C(3,2)	-0.000000002	0.000124944	-1.73113e-005	0.99998619
18. C(3,3)	0.000000003	0.000049850	5.56082e-005	0.99995563
19. A(1,1)	-0.706996475	0.071496827	-9.88850	0.00000000
20. A(1,2)	0.133745725	0.058143957	2.30025	0.02143397
21. A(1,3)	0.020200490	0.065189576	0.30987	0.75665753
22. A(2,1)	-0.008612019	0.047971592	-0.17952	0.85752682
23. A(2,2)	0.073356865	0.032436712	2.26154	0.02372595
24. A(2,3)	0.084625807	0.029490023	2.86964	0.00410937
25. A(3,1)	-0.061006338	0.077242104	-0.78981	0.42964062
26. A(3,2)	-0.046716261	0.124466471	-0.37533	0.70741350
27. A(3,3)	-0.017980013	0.062736938	-0.28659	0.77442342
28. G(1,1)	0.485492835	0.075784145	6.40626	0.00000000
29. G(1,2)	-0.496568896	0.051541254	-9.63440	0.00000000
30. G(1,3)	0.122752985	0.031522650	3.89412	0.00009856
31. G(2,1)	0.309991166	0.136173900	2.27644	0.02281993
32. G(2,2)	0.858813796	0.056997137	15.06767	0.00000000
33. G(2,3)	0.420677910	0.039689039	10.59935	0.00000000
34. G(3,1)	-0.683086022	0.261353012	-2.61365	0.00895800
35. G(3,2)	-0.616834532	0.139572306	-4.41946	0.00000989

36. G(3,3)	0.408615183	0.073467172	5.56187	0.00000003

Variable	Coeff	Std Error	T-Stat	Signif
1. MCX_ALUM_CL{1}				
2. LME_ALUM_CL{1}				
3. SHFE_ALUM_CL{1}				
13. C(1,1)	0.003948294	0.000264731	14.91435	0.00000000
14. C(2,1)	-0.000372375	0.000375519	-0.99163	0.32137916
15. C(2,2)	0.001075441	0.002401308	0.44786	0.65425686
16. C(3,1)	-0.000327771	0.000657314	-0.49865	0.61802391
17. C(3,2)	-0.000261557	0.000279015	-0.93743	0.34853701
18. C(3,3)	0.000000005	0.000381669	1.26818e-005	0.99998988
19. A(1,1)	0.096814507	0.058054518	1.66765	0.09538560
20. A(1,2)	-0.096430721	0.058021424	-1.66198	0.09651583
21. A(1,3)	0.004197335	0.014546494	0.28855	0.77292868
22. A(2,1)	-0.180830301	0.063500233	-2.84771	0.00440349
23. A(2,2)	0.257435917	0.081485740	3.15928	0.00158162
24. A(2,3)	0.043847626	0.017548143	2.49870	0.01246482
25. A(3,1)	-0.069153712	0.090820863	-0.76143	0.44640039
26. A(3,2)	-0.003280727	0.059205359	-0.05541	0.95580970
27. A(3,3)	0.292702042	0.055515994	5.27239	0.00000013
28. G(1,1)	0.564558439	0.032076324	17.60047	0.00000000
29. G(1,2)	0.293408551	0.049064961	5.98000	0.00000000
30. G(1,3)	0.114358474	0.081126312	1.40963	0.15864754
31. G(2,1)	0.347043825	0.034621474	10.02395	0.00000000
32. G(2,2)	0.741993351	0.051857163	14.30841	0.00000000
33. G(2,3)	-0.097516072	0.062038570	-1.57186	0.11598255
34. G(3,1)	0.102669386	0.074470183	1.37866	0.16799827
35. G(3,2)	-0.011527152	0.023788271	-0.48457	0.62797934
36. G(3,3)	0.934387907	0.032227007	28.99394	0.00000000

9. Conclusion:

From BEKK – Garch results, it was found that, incase of copper, there is short term spillover from MCX to SHFE, LME to SHFE and long term spillover from MCX to SHFE, LME to MCX, LME to SHFE. Incase of lead, there is short term spillover from MCX to LME and long term spillover from MCX to SHFE, MCX to LME, SHFE to LME, LME to MCX. For zinc, there is short term spillover from MCX to SHFE, SHFE to LME and long term spillover from MCX to SHFE, MCX to LME, SHFE to MCX, SHFE to LME, LME to MCX, LME to SHFE. In Aluminium, there is short term spillover from SHFE to MCX, SHFE to LME and long term spillover from MCX to SHFE, SHFE to MCX.

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11. R SOFTWARE CODE FOR GARCH MODELING (VOLATILITY CLUSTERING):

```
setInternet2(TRUE)

data1<-read.csv(file.choose(),header=TRUE)

close.data1<-data1[ ,column_number]

> close.data1.ts<-ts(close.data1,frequency=1) (used tseries package)

> log.ret1<-diff(log(close.data1.ts))

> adf.test(log(close.data1.ts),alternative=("stationary"))

>acf(log(close.data1.ts),type=("correlation"),plot=TRUE)

>pacf(log(close.data1.ts),lag.max=NULL,plot=TRUE,na.action=na.omit)

>acf(log.ret1,type=("correlation"),plot=TRUE)
```

```
>pacf(log.ret1,lag.max=NULL,plot=TRUE,na.action=na.omit)
```

Arima:(used forecast package)

```
arima(log(close.data1.ts),order = c(2,1,2))
arima212=arima(log(close.data1.ts),order=c(2,1,2))
summary(arima212)
```

Residual:

```
res.arima212=arima212$res
plot(res.arima212)
acf(residuals(arima212),type=("correlation"),plot=TRUE)
pacf(residuals(arima212),lag.max=NULL,plot=TRUE,na.action=na.omit)
```

squared residuals

```
squared.res.arima212=res.arima212^2
plot(squared.res.arima212,main='Squared Residuals')
acf.squared212=acf(squared.res.arima212,main='ACF Squared
Residuals',lag.max=100,ylim=c(-0.5,1))
pacf(squared.res.arima212,main='PACF Squared Residuals',lag.max=100,ylim=c(-
0.5,1),plot=TRUE,na.action=na.omit)
```

ARCH/GARCH

```
> arch01=garch(res.arima212,order=c(1,1),trace=F)
> loglik01=logLik(arch01)
> summary(loglik01)
summary(arch01)
```

ARIMA Forecast:

```
forecast212=forecast(arima212,100,level=95) #forecast for next 100 timeperiods
```

```
plot(forecast212)
```

Conditional variances(ARCH):

```
ht.arch01=arch01$fit[,1]^2
plot(ht.arch01,main='Conditional variances')
```