A Study of Volatility of Select Metals Traded in the Indian Commodity Market

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Abstract

Commodities such as gold, silver and copper have drawn considerable attention with respect to their price volatility. The spot prices of precious metals (gold and silver) not only redirects us to review the current supply and demand condition, but also reveals the predictions of future inflation and the general business and economic environment. The commodity market is where raw or primary products are exchanged or transacted. A commodity is classified as every kind of movable property; it includes only physical products such as food, electricity, metals, etc. and excludes services – government services, investments, debt, actionable claims, money, securities, etc. The present study attempts to assess the time-varying price volatility of gold, silver and copper and the nature of the volatility process. The results indicate presence of persistence in price volatility as per the estimation outputs of GARCH (1, 1) model for silver and copper metals. On the basis of the estimated results of GARCH model, it can be concluded that returns of silver and copper metals were highly volatile as compared to returns of gold during the period January 2014 to December 2016 while considering daily returns. It can also be concluded that copper is more volatile compared to gold and silver.

Key words: *ARCH, GARCH model, Volatility, Metals*

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Introduction

In recent years, academicians, investors and economists have shown a keen interest in the volatility of commodity prices. The magnitude of fluctuations in the returns of an asset is called its volatility (Dutta, 2010). Studies that focus on the volatility of commodities are gaining importance. The establishment of the fact that financial asset returns are highly predictable (Bollerslev, 1994) further sparked interest. The reason for this rising interest could be attributed to rising volatility and commodities playing a significant role in the international asset markets (e.g., Regnier, 2007; Dahl and Iglesias, 2009; Vivian and Wohar, 2012; Kang and Yoon, 2013, Creti et al., 2013; Thuraisamy et al., 2013). According to Hung et al., 2008; Cheong, 2009; Aloui and Mabrouk, 2010; Cheng and Hung, 2011, the commodity returns possess empirical formalised characteristics, namely, non-normal distribution, asymmetry, structural breaks and plump tails. Because of this, the performance of the model is affected and generates more interest in the study of volatility experimenting with different models.

Commodities such as gold, silver and copper have drawn considerable attention with respect to their price volatility. The spot prices of precious metals (gold and silver) not only redirects us to review the current supply and demand condition, but also reveals the predictions of future inflation and the general business and economic environment. These precious metals have set themselves apart from other commodities as they are used in different ways, which results in a rapid change in their demand. According to the derived demand theory, commodity prices are affected by changes in their demand based on their inputs in the final product.

The commodity market is where raw or primary products are exchanged or transacted. A commodity is classified as every kind of movable property; it includes only physical products such as food, electricity, metals, etc. and excludes services – government services, investments, debt, actionable claims, money, securities, etc. Investors, speculators and arbitrageurs use this market to deal with commodities as a separate asset class and help them assess commodity transactions in terms of demand and supply.

India has four national level commodity exchanges, namely, National Commodity & Derivatives Exchange (NCDEX), Multi Commodity Exchange of India (MCX), National Multi-Commodity Exchange of India (NCME) and the National Board of Trade (NBOT). These exchanges provide electronic trading and a settlement platform to transact spot and futures in various commodities. There is evidence of remarkable growth, both in terms of volume and value of trades, in the Indian commodity market since the operation of Commodity Futures Exchanges allows trading of futures and spot contracts on commodities. It has been noted that the volatility of pricing in commodity futures is less compared to equity and currency markets and hence, gives an opportunity to provide an efficient portfolio diversification.

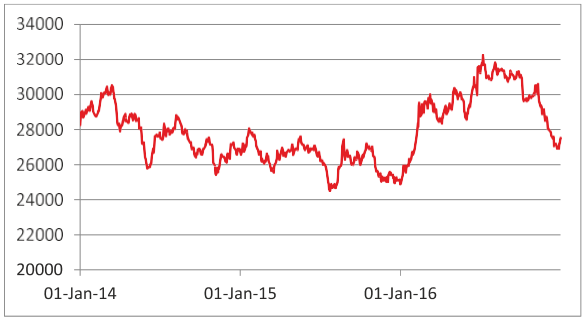
With the Indian economy gaining strength, the country' s commodity market has achieved international prominence. The large number and value of transactions from domestic and global players in the commodity market has resulted in generation of information such as demand and supply, price, climatic conditions and other market related information, which, in turn, has resulted in efficient price discovery and a large number of commodity producers and investors transacting in the futures market.

MCX, the largest national commodity exchange in the country, began operations in November 2003. The commodities offered by MCX are categorised as bullion, ferrous metals, non-ferrous metals, energy

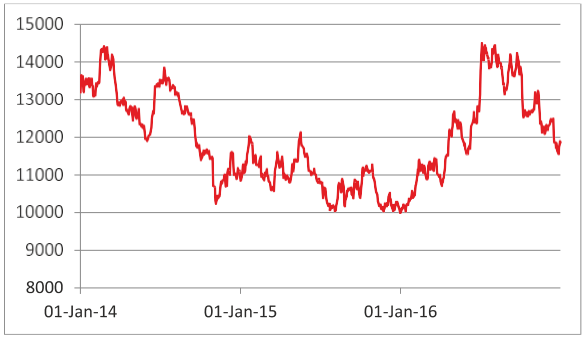
and agriculture. This paper is an attempt to examine the price volatility of three commodities, namely, gold, silver and copper. These commodities have been selected since they are highly traded on the world commodity markets and have different economic uses. These commodities are important in terms of their industrial usage with strong linkages as add-ons and substitutes across the entire economy. The price movements and volatility are considered to follow the business cycle. Gold is considered a precious metal; it is not only classified as a commodity, but also as one of the strongest monetary assets (Tulley and Lucey, 2007). Gold is a multifaceted metal which can be stored as wealth, medium of exchange and a unit of value (Goodman, 1956; Solt and Swanson, 1981). The price volatility during the period January 2014 to December 2016 of the commodities under consideration can be viewed in Figure 1.

Figure 1: Closing price of Gold, Silver and Copper - 01 January, 2014 to 31 December, 2016

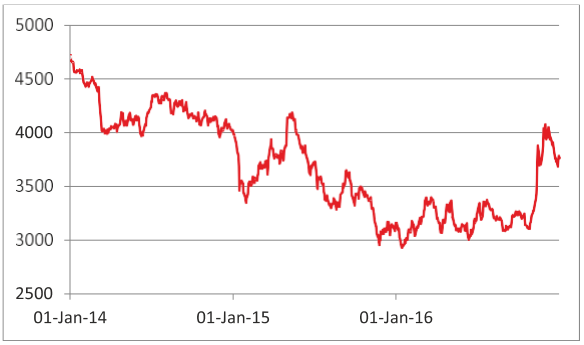
Gold



Silver



Copper



Source: Authors' computations using data from Multi Commodity Exchange (MCX) of India

To measure volatility, the generalised autoregressive conditional heteroscedasticity (GARCH) scheme was developed during the early 1980s; this became instrumental in popularising econometric modelling. Chipili (2012) studied volatility in the exchange rate and revealed that GARCH models help to estimate the path for time-varying conditional variance of the exchange rate. It also enabled the researcher to capture the appropriate conditional volatility present in the exchange rate.

Review of Literature

In the past, many researchers have shown keen interest in studying the volatility of the stock market, exchange rates and prices of commodities with reference to different regions. This section gives a brief overview of the findings and suggestions. Though there is extensive research available on this subject, the authors have considered only the latest work. The literature review on the existing topic is significant since it provides the basis to formulate the problem and offer the analysis.

Research on exchange rate volatility has been conducted in different regions and countries; some of these are briefly reviewed in the present section. One of the upcoming mediums of exchange, Bitcoin, is gaining attention across the world. The empirical work for fitting the daily Bitcoin exchange rate returns by **Liu**

***et al.* (2017)** compared the performance of a newly-developed heavy-tailed distribution, the normal reciprocal inverse Gaussian (NRIG), with the most popular heavy-tailed distribution, the Student's t distribution, under the GARCH framework. It revealed that heavy-tailed distribution performance of daily Bitcoin exchange rate returns was captured in a better way compared to the standard normal distribution. It concluded that the old fashioned Student's *t* distribution performed better than the new heavy-tailed distribution.

Omari *et al.* (2017) applied generalised autoregressive conditional heteroscedastic models in modelling USD/ KES exchange rate volatility using daily observations over the period starting 3rd January 2003 to 31st December 2015. Authors have utilised both symmetric and asymmetric models that capture most of the formalised facts about exchange rate returns such as volatility clustering and leverage effect. The volatility has been tested by applying the symmetric GARCH (1, 1) and GARCH-M models as well as the asymmetric EGARCH (1, 1), GJR-GARCH (1, 1) and APARCH (1, 1) models with different residual distributions.

Epaphra (2017) studied the modelling of exchange rate volatility for Tanzania. To detect whether there exists a symmetric effect in exchange rate data, the paper applied both the autoregressive conditional heteroscedastic (ARCH) and GARCH models. The results of the study revealed that exchange rate data exhibits the application of ARCH methodology. The application of methodology was justified by empirical regularities such as clustering volatility, non-stationarity, non-normality and serial correlation.

For financial traders, examining volatility in the commodity market is an interesting subject. One may find a large number of speculative trades in metal prices as these are generally subject to fluctuation (**Moore and Cullen, 1995**). In recent years, there has been an increasing amount of speculative activities in emerging economies, which has led to more uncertainty and greater volatility in these markets (**Gil-Alana and Tripathy, 2014**). There is much lesser research carried out to examine volatility in non-energy commodity markets, metals and agriculture as compared to stock and energy markets (**Behmiri and Manera, 2015**). In this framework, **Mackenzie *et al.* (2001)** have investigated the volatility of precious metal prices and used the univariate power ARCH model. The results reveal that there is no asymmetric effect in metal markets. To examine the volatility of gold, silver and copper prices while controlling the shocks of oil prices and the US interest rate changes, **Hammoudeh and Yuan (2008)** applied the univariate GARCH-type model. To explore the volatility of precious metal prices pre and post the global and Asian financial crises, **Morales and O'Callaghan (2011)** utilised the GARCH and the EGARCH models. The results showed a strong evidence of persistent volatility in the metal market during the global financial crisis; however, volatility was very weak during the Asian financial crisis.

One of the latest research studies by **Kruse *et al.* (2017)** utilised the GARCH model for platinum returns. The findings showed that the NRIG distribution performed better than the most widely-used heavy-tailed distribution, the Student's t distribution.

Goodwin (2012), in his research, assessed the suitability of standard GARCH (1,1) models to model (in-sample) and forecast (out-of-sample) the volatility of copper spot price returns in four equally large sub-samples during the period July 21, 1993 to March 22, 2012. The results revealed that it was highly satisfactory to utilise the GARCH models to model the conditional variance. It was also found that presence of ARCH effects was also significant. In out-of-sample forecasting, the GARCH models dominated a Random

Walk model across all four sub-samples. The study concluded that it could be interpreted that the standard GARCH (1,1) model was sufficient.

The assessment of the asymmetry and long memory effects in modelling the volatility of crude oil, natural gas, gold and silver prices was done by **Chkili *et al.* (2014)** using the GARCH models. The authors arrived at the conclusion that there was lower volatility persistence in the gold and silver markets compared to the prices of oil and natural gas**. Gil-Alana and Tripathy (2014)** applied the GARCH-type models to examine the volatility persistence and leverage effect for non-precious metal markets in India. The authors reported existence of a high degree of volatility persistence in all metals; the asymmetric effect was established for seven metals according to the TGARCH model and for ten metals according to the EGARCH model. To examine volatility spillovers between non-precious metals, **Todorova *et al.* (2014)** used the multivariate Heterogeneous Auto regressive (HAR) model. The study concluded, on one side, that volatility of other industrial metals contains useful information for future price volatility. On the other side, the own dynamics of each metal were mostly appropriate to elucidate the future daily and weekly volatility.

Cochran *et al.* (2015) examined the role of higher order moments in the returns of four important metals, namely, aluminium, copper, gold and silver. The analysis of the return series was conducted using the asymmetric GARCH (AGARCH) model with a conditional skewed generalised-t (SGT) distribution. The AGARCH model with the SGT distribution appeared to have the best fit for all metals examined, except gold.

Ma *et al.* (2017) investigated the widely-used GARCH model in risk management of palladium spot returns. The authors followed the work done by **Guo (2017a)** and compared two types of heavy-tailed distribution - the Student's *t* distribution and the normal reciprocal inverse Gaussian (NRIG) distribution, under the GARCH framework. The researchers were specifically interested in identifying the difference between empirical performances of quantifying palladium spot volatilities for the two distributions. The results showed that the newly-developed distribution, the NRIG, was unable to outperform the older fashioned Student's t distribution.

Saranya (2015), in his research, focused on the futures market for selected non-agricultural commodities. The study was based on data relating to futures prices and spot prices of eleven non-agricultural commodities, which included energy and precious metals. Data was collected from the website of one of the leading commodity exchanges in India for the period 2008 to 2014. The analysis of the study was based on the use of certain econometric tools such as unit root test to test the stationarity and Granger causality test to measure the lead-lag relationship between the spot and futures returns. To examine the volatility in the spot and futures returns, GARCH model was used. The study concluded that there exists a unidirectional causality in selected commodities like tin and silver while there exists a bi-directional causality in copper. In case of other commodities, namely aluminium, copper, lead, zinc, nickel, gold and silver, the coefficient of trade volume was positive and open interest was negative. The study confirmed the existence of volatility in selected non-agricultural commodities in both the spot and futures market.

Sinha and Mathur (2013) studied the volatility of five metals, namely, nickel, lead, zinc, aluminium and copper traded on the Multi Commodity Exchange (MCX). The data was collected for the period November 2007 to January 2013. The objective of the study was to assess the impact of the global financial crisis on trading of base metals. The GARCH model was applied to assess the volatility of metals. The results

revealed that there existed short term persistence in price volatility of metals and daily price volatility of base metals was influenced by the global financial crisis.

Cochran *et al.* (2012) examined the volatility of four precious metals, namely, copper, platinum, gold and silver. The returns and long-term properties of return volatility were analysed using the FIGARCH model. The results of the study revealed a significant relationship between price volatility of these metals and lagged implied volatility of the equity market in India. The results were based on modified GARCH (1, 1) model. The research concluded that there exists the impact of financial crisis on return volatility of metals. On similar lines, Morales and Callaghan (2011) examined the nature of volatility spill-overs between returns of four precious metals - gold, silver, palladium and platinum. The study considered the data during the Asian and the global financial crisis using the GARCH and EGARCH models. The results of the study revealed that the returns of precious metals were persistent during the global financial crisis while it was weak for volatility persistence during the Asian crisis in the 1990s.

Arouri et al (2012) explored the existence of long range dependence in the daily conditional return and volatility processes for precious metals, namely gold, silver, platinum and palladium. The results revealed that during the periods of crisis, platinum was not an appropriate hedging instrument while gold served as a better instrument. In terms of predictive power for volatility and returns, the FIGARCH model was the most effective.

In the Indian context, time varying volatility seasonality and risk-return relationships in a GARCH-in-mean framework for the Indian commodity market was examined by **Kumar and Singh (2008)**, while **Mahalakshmi et al. (2012)** inspected the behaviour of commodity derivatives in the Indian market from the Composite Commodity Derivative Index of Multi Commodity Exchange (MCX) using ARCH/GARCH models.

According to **Sharma and Kumar (2001),** the changes in price and instability in commodities impose a large amount of overhead on both the producers and consumers. Producers of the commodity suffer if the price contracts below the cost of production and consumers are at a disadvantage if the price surpasses a certain level. While low prices can be beneficial to consumers while encouraging them to buy more, high prices result in higher producers' gains. But a sudden fall or increase in commodity prices can be serious and may create problems for the economy. The variations in price movements have rigorous consequences such as higher speculation, formation of flawed policies on pricing and so on.

Engle (1982) and **Bollerslev (1986)** have developed the popular models of volatility clustering. To capture the volatility clusters in financial time series, the ARCH models **(Engle, 1982)** and generalised ARCH (GARCH) models **(Bollerslev, 1986)** have been comprehensively used. It has been confirmed by **Bollerslev et al., (1994)** that the GARCH-type models are superior to predict volatility in comparison to the naïve historical average, moving average and exponentially weighted moving average (EWMA) models. There are specific models to predict the variance and conditional variance. The Threshold GARCH model (TGARCH) (**Glosten et al., 1993**) and Exponential GARCH (EGARCH) model (**Nelson, 1991**) are used to predict conditional variance and are relatively steady models. This study attempts to use ARCH and GARCH models to predict conditional variance.

To estimate the volatility of fifty individual stocks**,** **Karmakar (2005)** used conditional volatility models. The study revealed that the GARCH (1,1) model

provided a reasonably good forecast. Another study by **Krishnan (2010)** was based on high frequency data for the Indian stock market. It attempted to observe the way larger and smaller errors cluster together using autoregressive conditional heteroscedasticity models. The study included stock prices of SBI and TATA to observe the volatility cluster.

The volatility in the commodity market should be studied to benefit not only those who participate in this market, but also for the economy as a whole. The commodity market in India is still at a nascent stage of development and there is huge potential to explore and study the behaviour of this market, especially since the Indian economy is an agriculture-based economy. Gold, silver and copper commodities are among the most traded on the world commodity markets and also have different economic uses. Through their important industrial uses, these commodities have strong linkages as complements and substitutes with the overall economy, and their prices and volatilities move in sync with the business cycle. This study attempts to assess the time varying price volatility of gold, silver and copper, and the nature of the volatility process.

Methodology

According to Omari *et al.* (2017), to measure volatility, traditional methods such as variance or standard deviation are lacking with respect to capturing the characteristics exhibited by financial time series data. The characteristics such as time varying volatility, volatility clustering, excess kurtosis, heavy tailed distribution and long memory properties can only be captured using the most commonly used models, namely, the Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalisation, and the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models.

The present work is based on empirical study and the research is explanatory in nature. The study spans the period 01 January, 2014 to 31 December, 2016 of daily data of the spot prices of gold, silver and copper collected from Multi Commodity Exchange (MCX) of India to determine the volatility of commodity returns. A total of 772 observations of spot prices for the three metals, i.e. gold, silver and copper have been used for the analysis. These prices are converted to returns by means of first differences of the log-transformed data using equation (1).

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

The data is analysed to study the extent of volatility persistence using the Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalisation, and the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models.

Non-Normality Distribution of Fat Tails

The assessment of the extent of deviation of Skewness and Kurtosis from the normality assumption of symmetry (Skewness is zero) and fixed peak value of three is done by the statistics proposed by Bera and Jarque (1982). The null hypothesis (H_0) for this test states that the distribution is normally distributed. The Jarque-Bera (JB) test statistics is calculated as--

$$JB = \frac{T}{6}\left(S^2 \frac{(K-3)^2}{4}\right) \qquad (2)$$

where, $S = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{x_t-\bar{x}}{\hat{\sigma}}\right)^3$ is the sample Skewness. Skewness or the third moment of the distribution measures the asymmetry while the fourth moment or Kurtosis measures the peakness of the distribution and is denoted by K and calculated as $= \frac{1}{T}\sum_{t=1}^{T}\left(\frac{x_t-\bar{x}}{\hat{\sigma}}\right)^4$.

the sample size, $\bar{x}$ is the sample mean and $\hat{\sigma}$ is the sample standard deviation. For large sample size, JB statistics follows chi-square (χ^2) distribution with two degrees of freedom. If the value of *p* is less than 0.01 then the null hypothesis (H_0) is rejected and it is interpreted that the distribution does not follow normal distribution.

Parametric Volatility Models

The time series volatility Auto Regressive Conditional Heteroscedasticity (ARCH) model as designed by **Engle (1982)** assumes the unconditional error variance to be constant, and the conditional variance is assumed to be dependent on past realisations of the error process. The ARCH model was further generalised by Bollerslev (1986) and Taylor (1986) to generate the GARCH model. To study volatility persistence and spill-over effects through financial series, there are a number of other methods, but the ARCH/GARCH models appear to be the most prevalent ones. The models are briefly described below.

The Autoregressive Conditional Heteroscedasticity (ARCH) Model

The ARCH model describes the return series of a financial time series as a linear function of its lag term. In an attempt to determine the ARCH effect for metal prices, the following time series least square regression equation (3) is estimated. The null hypothesis (H_0) assumes that there is no Arch effect on the return series of financial data against the alternative hypothesis (H_1) that there is an Arch effect on the return series.

$$\boldsymbol{Y_t = a + bY_{t-1} + \varepsilon_t} \qquad \text{-(3)}$$

where,

Y_t denotes returns of the commodity

a denotes constant quantity

Y_{t-1} denotes lag term of the returns of the commodity

t = 1, 2, …

After running the least square regression equation (3), the values of n and R^2 are noted and chi-square (χ^2) statistic is calculated as $\chi^2 = n \times R^2$. If the calculated value of χ^2 is less than the critical value, then we may accept the null hypothesis. The presence of ARCH effect on the return series indicates that there exists persistence volatility in the series and further, generalised autoregressive conditional heteroscedasticity (GARCH) model can be estimated.

The Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Model

The GARCH model is described by a linear function of conditional variance of its own lags. The general form of the GARCH (p, q) model is given by:

$$r_t = \mu + y_t, \qquad y_t = \sigma_t + \varepsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i y_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad \text{-(4)}$$

where, r_t is the log of returns of the time series data at time t, μ is the mean of return series, y_t is the error term from the mean equation and it can split into error term ε_t and a time dependent standard deviation σ_t, ε_t is assumed to follow (iid) with zero mean, which is assumed to have normal distribution, t distribution and skew t distribution and $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ with constraints $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$.

The basic GARCH (1, 1) model fits in most of the empirical applications of the majority of financial time series reasonably well. The GARCH (1, 1) model is given by the following equation:

Mean equation: $h_t = j_0 + j_1 h_{t-1} + \epsilon_t$ - (5)

Variance equation: $\sigma_t^2 = \omega + \alpha_1 (y_{t-1})^2 + \beta_2 (\sigma_{t-1})^2$ - (6)

Where,

j_0 denotes mean constant

ω denotes Variance Constant

α_1 denotes Coefficient of Error (ARCH effect)

β_2 denotes Coefficient of Variance (GARCH effect)

The following restrictions are imposed to guarantee a positive variance at all instances, $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$. In most of the cases, to analyse the financial time series data and to estimate the conditional volatility, the basic GARCH model provides a reasonably good model (Omari et al, 2017). However,

looking to different aspects and dynamics, there is scope for improvement in the GARCH (p, q) model introduced by Bolleslev (1986), which can better capture these characteristics of a particular financial time series.

Diagnostic Tests

Diagnostic test is performed in two parts; the first part gets fulfilled if residuals follow mean 0 and variance 1, and the second part is fulfilled if the residuals are not auto-correlated. To diagnose the first part, the condition of normality of residuals is checked; if it follows Mean 0 and Variance 1, then the condition of first diagnostic test is fulfilled. In the second, the null hypothesis of no autocorrelation using Ljung – Box (Q) Statistics is tested. If significant value (*p*) is more than 0.01, then we accept the null hypothesis that the residuals are not auto-correlated.

Results And Analysis

Daily prices of commodities have been converted to daily returns. This study utilises the logarithmic difference of prices of two successive periods for the calculation of rate of return. As we move up and down, the converted data of return series is symmetric between the movements. If P_t denotes closing price of the commodity on date *t* and P_{t-1} be that for its previous day, then the one-day return on the commodity market portfolio is calculated as given in equation (7). Please note here that the intervening weekend or commodity exchange holidays are omitted.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) - \quad (7)$$

Where, *ln* (*w*) is the natural logarithm of '*w.*'

Initially, the statistical features are assessed and Table 1 describes the summary statistics of return series of the spot prices of metals. The results suggest that copper possesses the highest mean daily return while gold has the poorest performance in terms of mean daily return. In terms of volatility, the silver metal return is the most volatile series during the sample period. Returns are positively skewed in all metals and a fat tailed distribution has a value of kurtosis that exceeds 3. All the three metal return series have high kurtosis with the highest being 7.24 corresponding to gold returns; thus, results indicate that all metal return series are leptokurtic (fat tailed). According to Watkins and McAleer (2008), if the distribution is leptokurtic, then AR (1) - GARCH (1, 1) model is appropriate to describe the conditional variance of the data series. The authors further add that these models represent the data in terms of rolling diagnostic tests for normality, serial correlation and existence of ARCH effects. The authors commented that GARCH (1, 1) model is the most commonly used volatility model.

As the return series of these metals is leptokurtic in nature, they have higher probability of securing large positive or large negative values of returns. To test further the normality of the return series of gold, silver and copper, the Jarque-Bera test is applied. The *p*-value of Jarque-Bera test is zero for return series of the metals, thus rejecting the presence of normality. Rejection of normality of return series confirms the assumption that the model selected should account for the heavy-tail phenomenon.

Table 1: Summary Statistics of Return Series of Base Metals

	Gold	Silver	Copper
Mean	-7.83e-06	-7.15e-05	-0.000232
Median	-0.000331	-0.000256	-0.000641
Std. Deviation	0.007389	0.011485	0.0103081
Maximum	0.051452	0.0518680	0.054550
Minimum	-0.025016	-0.052026	-0.061280
Skewness	0.719386	0.312268	0.149452
Kurtosis	7.240880	5.118706	6.188898
Jarque-Bera (*JB*)	644.2708	156.7367	329.5515
J-B(P-Values)	0.00	0.00	0.00
Std dev./ mean	-943.68	-160.63	-44.43
ADF (0)	-23.589	-22.533	-22.856
ADF (*P*-value)	0.000	0.000	0.000

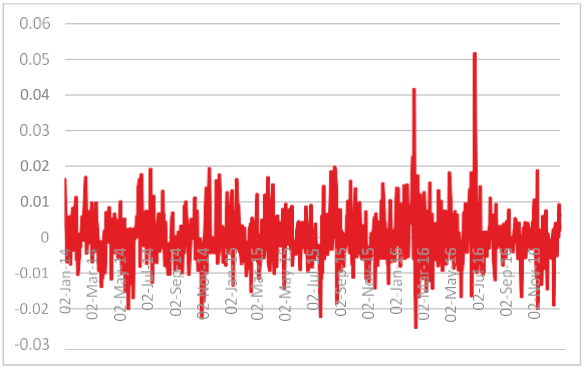
Source: Authors' calculations

Figure 2, 4 and 6 display the closing price of gold, silver and copper. All mean series move in a similar way. There are considerable ups and downs in the closing prices of gold, silver and copper over the sample period. In general, the volatility in silver and copper seems to be more evident in comparison to gold. To see it more intensely, Figure 3, 5 and 7 plot the changes in the closing prices of these metals. From these figures, it is apparent that the volatility appears in clusters and also provides evidence that time varying volatility in daily closing prices of metals is empirically shown as return clustering. This feature is referred to as the presence of ARCH / GARCH effects (Humala & Rodríguez, 2010).

Figure 2: Closing prices of Gold - 01 January, 2014 to 31 December, 2016

Source: Authors' computations using data from Multi Commodity Exchange (MCX) of India

Figure 3: Change in Closing prices of Gold - 01 January, 2014 to 31 December, 2016

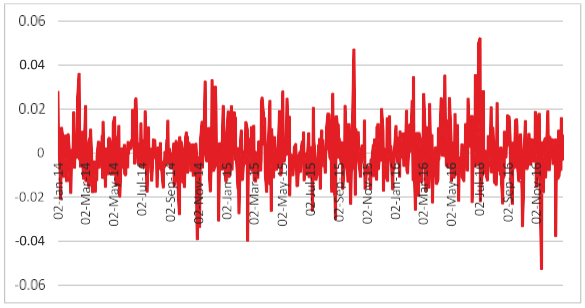


Source: Author's computations using data from Multi Commodity Exchange (MCX) of India

Figure 4: Closing prices of Silver - 01 January, 2014 to 31 December, 2016

Source: Authors' computations using data from Multi Commodity Exchange (MCX) of India

Figure 5: Change in Closing prices of Silver - Jan 2014 to Jan 2016

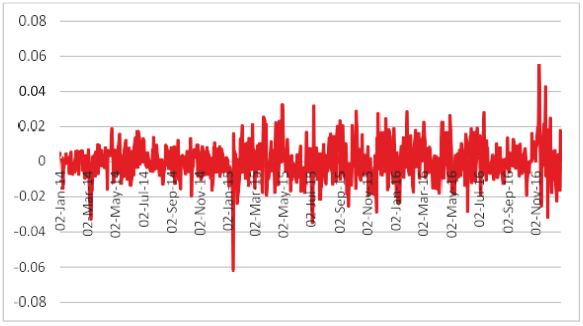


Source: Authors' computations using data from Multi Commodity Exchange (MCX) of India

Figure 6: Closing prices of Copper - 01 January, 2014 to 31 December, 2016

Source: Authors' computations using data from Multi Commodity Exchange (MCX) of India

Figure 7: Change in Closing prices of Copper - Jan 2014 to Jan 2016



Source: Authors' computations using data from Multi Commodity Exchange (MCX) of India

A prescribed statistical test is examined further to support the descriptive statistics and graphical tests of persistence. Augmented Dickey Fuller Test (ADF) (Table 2) is employed to check the stationarity of return series of gold, silver and copper.

Table 2 (a): Augmented Dickey-Fuller test of the return series of Gold

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=19)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.58909	0.0000
Test critical values:	1% level	-3.438616	
	5% level	-2.865078	
	10% level	-2.568709	

*MacKinnon (1996) one-sided p-values.

Table 2 (b): Augmented Dickey-Fuller test of the return series of Silver

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=19)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.53307	0.0000
Test critical values:	1% level	-3.438616	
	5% level	-2.865078	
	10% level	-2.568709	

*MacKinnon (1996) one-sided p-values.

Table 2 (c): Augmented Dickey-Fuller test of the return series of Copper

Augmented Dickey-Fuller test statistic		-22.12858	0.0000
Test critical values:	1% level	-3.438616	
	5% level	-2.865078	
	10% level	-2.568709	

*MacKinnon (1996) one-sided p-values.

The test assumes the null hypothesis that the time series has a unit root (non-stationary). The ADF test statistic -23.589, -22.533 and -22.129 (p = 0.000) respectively for gold, silver and copper return series indicates that the null hypothesis is rejected for all the considered metals i.e. return series does not have a unit root. Thus, these metal return series are stationary and hence, we can proceed further to test its volatility using ARCH and GARCH models.

The volatility has been analysed using the standard GARCH model. Before estimating the GARCH models, we must check for the presence of the ARCH effect to check the short-term volatility persistence. This check must be carried out before and after the model estimations have been performed to ascertain whether or not any ARCH effect exists or remains; if it remains, it indicates that the variance equations are still mis-specified. If the ARCH effect is present, then the data is further tested for its volatility using GARCH model to check whether there is long-term volatility persistence in the return series.

Estimation of Volatility Model

A simple AR (1) process with an intercept was estimated in order to determine the best fit linear mean function for each of the series. In an attempt to determine the ARCH effect for gold, silver and copper return series, time series least square regression equation (8) has been fitted.

$$Y_t = a + bY_{t-1} + \varepsilon_t \quad \text{-(8)}$$

The significance of this equation was then established and the error term of each mean equation was converted into the particular residual (ε_t).The estimated results are shown in the Table 3.

Table 3: Estimation of ARCH effect for Gold, Silver and Copper

Commodity	R^2	n	$\chi^2 = R^2 \times n$		Decision of ARCH effect	Result	Decision of GARCH effect
Gold return	0.00025	769	0.1576	$\chi^2_{cal} < \chi^2_{tab}$	Accept the Null Hypothesis: there does not exist ARCH effect	There is no ARCH effect in the price of Gold	GARCH effect will not be estimated for Gold prices
Silver return	0.010955	769	8.424395	$\chi^2_{cal} > \chi^2_{tab}$	Reject the Null Hypothesis: there does not exist ARCH effect	There is an ARCH effect in the price of Silver	GARCH effect will be estimated for Silver prices
Copper return	0.054235	769	41.7067	$\chi^2_{cal} > \chi^2_{tab}$	Reject the Null Hypothesis H_0	There is an ARCH effect in the price of Copper	GARCH effect will be estimated for Copper prices

As depicted from Table 3, ARCH effect does not exist for gold return series, which indicates that there is no short-term volatility persistence in the return series and hence, further GARCH model is not estimated for gold returns. On the other hand, there exists short-term volatility persistence in silver and copper return series as ARCH effect is significant in these two metal return series. Further, the GARCH model is estimated for silver and copper return series to explore long-term volatility persistence. To understand the direction of volatility of these two metal return series, a normal GARCH (1,1) is run. The equation (5 and 6) has been fitted. Table 4 reports the results of GARCH (1, 1) estimation results for silver and copper daily return series.

Table 4: GARCH (1,1) of Return on Metal Prices

Return on	Mean Equation		Variance Equation			Log Likelihood
	Mean Constant (j_0)	Coefficient of lagged return (j_1)	Variance Constant (ω)	Coefficient of Error (ARCH effect) (α_1)	Coefficient of Variance (GARCH effect) (β_2)	
Silver	-0.000214 (0.6020)	0.20956 (0.000)	2.13E-05 (0.1149)	0.047 (0.0267)	0.783 (0.000)	2373.219
Copper	-0.000373 (0.2633)	0.207985 (0.000)	5.26E-06 (0.0023)	0.129595 (0.000)	0.8262 (0.000)	2484.587

Table 4 presents the results of GARCH model which was applied on silver and copper return series. Coefficients of GARCH (β_2) in variance equation are positive and significant indicating the presence of long term persistence in volatility for both silver and copper.

Diagnostic Test for Silver Return Series

Diagnostic test is performed by checking the condition of normality of residuals. The results show that the residuals follow Mean 0 and Variance 1 (Figure 8 and 9) which fulfils the first part of the diagnostic test. In the second part, we test the null hypothesis of no autocorrelation up to order 36 using Ljung – Box (Q) Statistics. All the significant values are more than 0.05; hence, the null hypothesis is accepted i.e. there is no autocorrelation up to order 36. The results are shown in the Tables 5 and 6.

Figure 8: Diagnostic test: Normality of Residuals for Silver return series

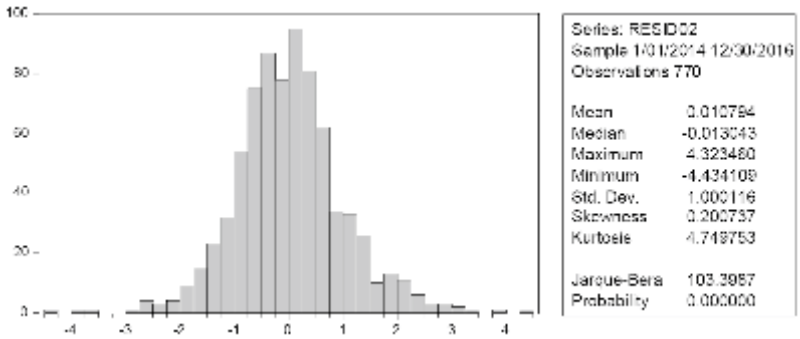


Table 5: Q STATISTIC (Correlogram of Squared residuals)

Date: 04/07/17 Time: 13:28
Sample: 1/01/2014 12/30/2016
Included observations: 770

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.009	0.009	0.0655	0.798
		2	-0.011	-0.011	0.1541	0.926
		3	-0.013	-0.013	0.2852	0.963
		4	-0.004	-0.004	0.2983	0.990
		5	0.046	0.045	1.9129	0.861
		6	0.031	0.030	2.6785	0.848
		7	-0.016	-0.015	2.8670	0.897
		8	0.015	0.017	3.0352	0.932
		9	-0.061	-0.060	5.8978	0.750
		10	0.001	-0.000	5.8982	0.824
		11	0.060	0.056	8.6743	0.652
		12	0.030	0.028	9.3728	0.671
		13	-0.020	-0.021	9.6905	0.719
		14	-0.060	-0.054	12.499	0.566
		15	-0.051	-0.046	14.566	0.483
		16	0.007	-0.000	14.608	0.554
		17	-0.006	-0.012	14.636	0.622
		18	-0.012	-0.015	14.749	0.679
		19	-0.003	0.002	14.754	0.738
		20	-0.039	-0.028	15.988	0.717
		21	-0.019	-0.015	16.279	0.754
		22	-0.008	-0.014	16.336	0.799
		23	0.094	0.089	23.396	0.438
		24	0.007	0.002	23.434	0.494
		25	-0.022	-0.011	23.837	0.529
		26	0.019	0.032	24.129	0.569
		27	0.030	0.030	24.860	0.582
		28	0.029	0.019	25.545	0.598
		29	0.015	0.003	25.714	0.641
		30	0.042	0.046	27.139	0.616
		31	0.034	0.032	28.050	0.619
		32	-0.010	-0.003	28.133	0.663
		33	-0.022	-0.024	28.515	0.690
		34	-0.003	-0.020	28.522	0.733
		35	0.003	-0.010	28.530	0.772
		36	0.018	0.017	28.786	0.798

*Probabilities may not be valid for this equation specification.

Diagnostic Test for Copper Return Series

Figure 9: Diagnostic test: Normality of Residuals for Copper return series

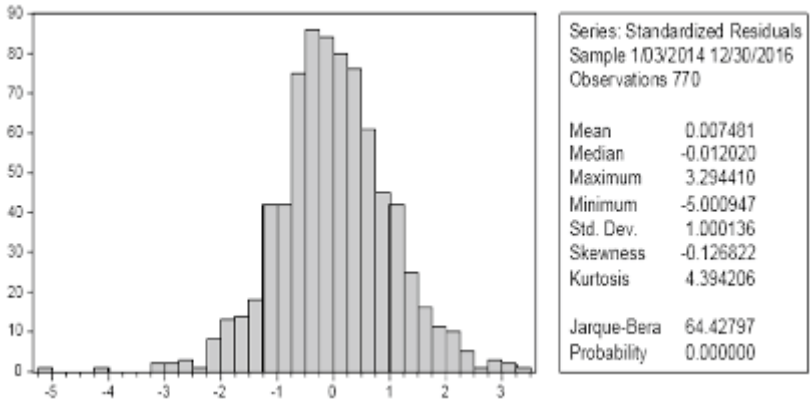


Table 6: Q STATISTIC (Correlogram of Squared residuals)

Date: 04/07/17 Time: 14:10
Sample: 1/01/2014 12/30/2016
Included observations: 770

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.071	0.071	3.8852	0.049
		2	-0.003	-0.008	3.8941	0.143
		3	-0.006	-0.005	3.9238	0.270
		4	-0.020	-0.020	4.2440	0.374
		5	-0.060	-0.058	7.0716	0.215
		6	-0.001	0.007	7.0723	0.314
		7	-0.003	-0.004	7.0794	0.421
		8	-0.026	-0.026	7.5984	0.474
		9	-0.029	-0.027	8.2425	0.510
		10	0.007	0.007	8.2773	0.602
		11	0.010	0.009	8.3581	0.681
		12	0.014	0.011	8.5044	0.745
		13	0.045	0.040	10.088	0.687
		14	-0.025	-0.034	10.592	0.718
		15	-0.034	-0.028	11.494	0.717
		16	-0.026	-0.021	12.027	0.742
		17	-0.000	0.004	12.027	0.798
		18	-0.020	-0.017	12.329	0.830
		19	-0.020	-0.022	12.640	0.856
		20	0.023	0.023	13.055	0.875
		21	0.008	0.005	13.112	0.905
		22	-0.058	-0.059	15.755	0.828
		23	0.020	0.022	16.068	0.852
		24	-0.026	-0.035	16.609	0.865
		25	0.045	0.051	18.227	0.833
		26	-0.036	-0.046	19.237	0.826
		27	-0.016	-0.015	19.442	0.853
		28	-0.005	0.001	19.462	0.883
		29	-0.008	-0.009	19.517	0.907
		30	0.025	0.027	20.011	0.916
		31	0.090	0.080	26.503	0.697
		32	0.021	0.008	26.871	0.724
		33	-0.014	-0.019	27.026	0.759
		34	0.028	0.033	27.670	0.770
		35	-0.035	-0.032	28.659	0.767
		36	-0.030	-0.020	29.372	0.775

*Probabilities may not be valid for this equation specification.

Conclusion

The key objective of this paper was to study the volatility of gold, silver and copper metals in the commodity market. After a comprehensive review of literature and studying the variations in the prices using econometric models as detailed in the previous sections of this paper, it can be concluded that there was presence of persistence in price volatility as per the estimation outputs of GARCH (1, 1) model for silver and copper metals. On the basis of the estimated results of GARCH model, it can be concluded that returns of silver and copper metal were highly volatile as compared to returns of gold during the period January 2014 to December 2016, taking daily returns. It can also be concluded that copper is more volatile in comparison to gold and silver. The results of the present study can be used to predict the volatility in prices of silver and copper metals by the Indian manufacturing sector.

Limitatons

The results of the study can be used taking the following limitations into consideration. The data span considers daily closing price of metals for three years only. The present empirical research focused only on the volatility of return series of three metals - gold, silver and copper, and therefore, the findings cannot be generalised to other metals. The study is based only on the multi commodity exchange (MCX) index while other indices such BSE and NSE are not used. There are other prices available under commodity derivatives like forwards, futures, options and swaps, but the focus of this research is on the spot prices only. A number of commodities traded in the category of future commodity derivatives like agro-based commodities, soft commodities, livestock, energy, precious metals, to name a few, can also be explored. Only GARCH (1, 1) model is used to study the price volatility of gold, silver and copper while the inclusion of other asymmetric GARCH-type models, testing and comparing their predictive performance can extend the current study further.

Implications

The findings of the present study indicate the presence of asymmetry and persistence in volatility, which have important implications. Precise modelling of volatility in the commodity market is a critical subject matter. It can affect the portfolio allocation decision of investors, value-at-risk management, the industrial production of manufacturers and ultimately the economic growth pattern of nations. Hence, from the point of view of policy-makers, such volatility models increase the ability to generate more accurate out-of-sample forecasting of prices and financial traders are facilitated by the value-at-risk management strategies.

This study offers adequate scope to undertake further research in related fields. Instead of considering precious metals, the study can be extended to agricultural commodities, ferrous, non-ferrous metals to name a few. This will enable a researcher to study the market efficiency and testing of inter-market co-integration. The study can further be extended by conducting a comparative analysis of domestic and international commodity markets of comparable magnitude and activity. It can also be extended to understand the short-term volatility using high frequency data, which can be a matter of concern to traders investing in the commodities market.

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APPENDICES

ARCH effect for Gold return series

Dependent Variable: RESID01
Method: Least Squares
Date: 04/06/17 Time: 13:09
Sample (adjusted): 1/06/2014 12/30/2016
Included observations: 769 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.21E-05	5.37E-06	9.697227	0.0000
RESID01(-1)	0.014328	0.036107	0.396833	0.6916

R-squared	0.000205	Mean dependent var	5.28E-05
Adjusted R-squared	-0.001098	S.D. dependent var	0.000139
S.E. of regression	0.000139	Akaike info criterion	-14.91944
Sum squared resid	1.49E-05	Schwarz criterion	-14.90736
Log likelihood	5738.527	Hannan-Quinn criter.	-14.91480
F-statistic	0.157476	Durbin-Watson stat	2.002147
Prob(F-statistic)	0.691601		

ARCH effect for Silver return series

Dependent Variable: RESID01
Method: Least Squares
Date: 04/06/17 Time: 13:18
Sample (adjusted): 1/06/2014 12/30/2016
Included observations: 769 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000112	9.98E-06	11.25267	0.0000
RESID01(-1)	0.104661	0.035908	2.914676	0.0037

R-squared	0.010955	Mean dependent var	0.000125
Adjusted R-squared	0.009665	S.D. dependent var	0.000248
S.E. of regression	0.000247	Akaike info criterion	-13.77279
Sum squared resid	4.67E-05	Schwarz criterion	-13.76071
Log likelihood	5297.637	Hannan-Quinn criter.	-13.76814
F-statistic	8.495337	Durbin-Watson stat	2.009288
Prob(F-statistic)	0.003664		

GARCH (1, 1), Model estimation for Silver

Sample (adjusted): 1/03/2014
Included observations: 770 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Date: 04/06/17 Time: 13:29 Variable Equation
Coefficient 12/30/2016

Std. Error	-0.000214	0.000411	z-Statistic	Prob.
C	-0.521555	0.6020		2.13E-05
RETURN(-1)	0.209556	0.038618	5.426394	0.0000

1.35E-05

Variance				
C	0.1149	R-squared	1.576726	0.043382
RESID(-1)^2	0.783013	Adjusted R-squared	0.021335	0.0000
GARCH(-1)	0.047022	S.E. of regression	6.416431	0.0267
		Sum squared resid		
dependent var	-0.000108	Log likelihood	Variable	
S.D. dependent var	0.011205	Mean dependent Variable:	-6.151219	
Akaike info criterion	0.096424	Method: Least Squares	Schwarz criterion	
	-6.121048	Durbin-Watson stat	Hannan-Quinn	
	-6.139608	Date: 04/07/17 Time: 14:04	(BFGS / Marquardt steps)	
	1.978040	Dependent Variable: RETURN		
		Method: ML ARCH - Normal distribution		

ARCH effect for Copper return series

Coefficient RESID01

Sample (adjusted): 1/06/2014 12/30/2016
Included observations: 769 after adjustments

Std. Error	7.85E-05	8.41E-06	t-Statistic	Prob.
C	0.000000	R-squared	9.333880	0.0000
RESID01(-1)	0.232915	0.035120	6.632005	0.0000
		Adjusted R-squared		
		S.E. of regression		
		Sum squared resid		
		Log likelihood		
dependent var	0.000102	Mean dependent var		0.000217
S.D. dependent var	0.000211	F-statistic		-14.08840
Akaike info criterion	3.41E-05			Schwarz criterion
	-14.07631	5418.988		-14.08375
Prob(F-statistic)	Durbin-Watson	Hannan-Quinn criter.		2.026638
	0.054235	0.000000	stat	0.011449
	43.98349	0.042137		

GARCH (1, 1), Model estimation for Copper

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 04/07/17 Time:14:06
Sample (adjusted): 1/03/2014 12/30/2016
Included observations: 770 after adjustments
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000373	0.000333	-1.118647	0.2633
RETURN(-1)	0.207985	0.042324	4.914158	0.0000
Variance Equation				
C	5.26E-06	1.73E-06	3.048234	0.0023
RESID(-1)^2	0.129595	0.016879	7.677824	0.0000
GARCH(-1)	0.826208	0.023868	34.61641	0.0000

R-squared	0.048543	Mean dependent var	-0.000238
Adjusted R-squared		S.D. dependent var	
S.E. of regression	0.047304	Akaike info criterion	0.010387
Sum squared resid	0.010138		-6.440487
Log likelihood	0.078935	Schwarz criterion	-6.410315
Durbin-Watson stat	2484.587	Hannan-Quinn criter.	-6.428875
	1.964606		

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