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MODELLING VOLATILITY PERSISTENCE AND ASYMMETRY: A STUDY ON SELECTED INDIAN NON-FERROUS METALS MARKETS

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ABSTRACT

This paper deals with the analysis of the volatility persistence and the leverage effect across six non-ferrous metals spot and futures series in India. Data for aluminium, copper, lead, nickel, zinc and tin were collected from 1st January, 2009 to 30th June, 2012. Volatility persistence was determined throughout the ARCH / GARCH class of models. The leverage effect was tested using TARCH and EGARCH models. Out of the twelve non-ferrous metals series including both spot and futures, TGARCH captures asymmetric effects in seven series and EGARCH captures leverage effects in ten series. Other long memory features of the data were also examined. Testing fractional integration our results show that the series are I(1) but the squared returns display long memory features.

Keywords: Volatility persistence; price asymmetry; leverage effect; long memory

JEL Classification: G12, G13

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1. Introduction

The major non-ferrous metals such as aluminium, copper, lead, nickel, zinc and tin are important sources of raw materials for the majority of manufacturing and mining industries.[1] The growing global demand for non-ferrous metals in recent years has been mainly attributed to the imbalances in global production and consumption, rapid urbanization and industrialization. In emerging economies such as China, India, Brazil, Russia and South Africa, considerable increase in speculative activities in this market has led to elevated levels of market uncertainty and price volatility.

The literature on the volatility forecast in asset markets can be classified into two main approaches i.e. the option pricing implied volatility models, and time series based on conditional volatility models. However, it should be noted that the implied volatility approach has a number of drawbacks, such as its applicability for European options, not suitable for long term forecast and unrealistic implied volatility. Thus, in this paper we employ the second approach based on a time series framework.

Our motivation behind this work is that the volatility estimates allow us to investigate the empirical regularities, such as fat-tailedness and volatility persistence. It is well documented (Bollerslev, Engle and Nelson, 2003) that fat-tailedness in asset markets is intimately related to so-called volatility clustering, which describes the phenomena in which large changes in asset prices, of either sign, tend to be followed by large changes, and small changes are followed by small changes, reflecting market irregularities and persistence. The persistent behaviour in the returns and in the associated volatility, measured in terms of the squared returns will also be examined by means of long memory models.

[1] Some authors use the denomination “base metal” instead of “non-ferrous metal” as non-ferrous metal also comprises gold, platinum and silver. Throughout this paper we will employ “non-ferrous metal” as referring to the above-mentioned six materials.

Examining about two and half decades of data, Brunetti and Gilbert (1995, 1996) affirm that metal markets are highly volatile and time varying in nature. These authors also suggest that speculative activities are the major drivers of short term price volatility, which is very short lived. But for non-ferrous metals, the risk is influenced by the physical availability of metal, the actions of demand and supply and the influence of the financial markets. McMillan and Speight (2001) extend the study of Brunetti and Gilbert (1995) to examine non-ferrous metals price volatility through a component analysis in order to exploit the higher-frequency daily data. They analyzed daily settlement prices of six non-ferrous metals traded on the London Metals Exchange (LME), as compiled by Brunetti and Gilbert (1995), and extended to the end of 2000. By using a variant of the GARCH model which decomposed volatility into long-run and a short-run components, the study suggested that non-ferrous metals prices are not only exposed to volatility persistence but also exhibited some degree of long memory, which are ultimately stationary and mean-reverting. Long memory behaviour was also found in Panas (2001) using data from the LME market. In particular, he found some evidence of strong dependence in the aluminium and copper return series. Other articles that have also investigated long memory in metals are Panas and Ninni (2010), Arouri et al. (2012) and Cochran et al. (2012).

Watkins and McAleer (2004) apply a time varying volatility model on metals series such as aluminium and copper. Using LME daily data these authors examine the effectiveness of the AR(1)-GARCH(1,1) model. In another study, Dooley and Lenihan (2005) with data from the LME cash market and the forward market for lead and zinc evaluate the efficacy of different time series methods in forecasting. Their results show that the ARIMA model provides the best forecasting in nine out of the sixteen cases studied. Donnell and Rayner (2008) use Bayesian methods and examine the time varying volatility on the LME Index. It is found that ARCH(3) and GARCH(1,1) models are significant in estimating the volatility of the indices.

Kumar and Singh (2008) examine the time varying volatility, seasonality and risk-return relationships in a GARCH-in-mean framework for the Indian commodity market, and Mahalakshmi et al. (2012) examine the commodity derivatives behaviour in the Indian market also using ARCH/GARCH models. Using data of Composite Commodity Derivative Index of Multi Commodity Exchange (MCX) the GARCH (1,1) model was selected.

The specific aims in this paper are the following: first, to identify which time series volatility model is applicable in each of the six non-precious metals for both spot and futures prices using secondary data; second, to understand the impact of information asymmetry (leverage effect) on the volatility of each of the series; and third, to understand the inter-correlation between the various metal prices both in the spot and futures series. In addition, long memory and other features of persistence will be examined in the paper.

To achieve these objectives we use the GARCH class of models. In order to identify the best fit and its volatility persistence, we use ARCH and GARCH models. To test for the presence of asymmetric volatility TARCH and EGARCH models will be employed. Finally, long memory I(d) models will also be examined to check for the persistence in the returns, and in the volatility processes measured in terms of the squared returns.

The remainder of the paper is organized as follows: Section 2 describes the data and the methodology; Section 3 presents the empirical findings based on GARCH, TGARCH, EGARCH and I(d) models; Section 4 summarises the main findings and conclusions.

2. Data and methodology

2a. Nature and sources of the data

Futures and spot series for six non-ferrous metals viz. aluminium, copper, lead, nickel, zinc and tin are examined in this study. For the futures price series, we use daily near month contract series closing prices of MCX-futures. The spot market closing prices prevailing in Mumbai are also used in this study. We have collected data from the MCX website[2], from January 1st, 2009 to June 30th, 2011. Across the series a day-wise data matching exercise has been carried out so as to bring each series into the model building framework. We use a total of 1052 observations of spot and futures prices for the six non-precious metals. These prices are converted to returns by means of first differences of the log-transformed data, i.e., $R_t = \ln(Y_t) - \ln(Y_{t-1})$, where Y_t is the corresponding price series.

2b. Methodology and models considered

Engle (1982) designed the time series volatility model, in his AutoRegressive Conditional Heteroskedasticity (ARCH), assuming that the unconditional error variance is constant, and the conditional variance is assumed to depend on past realizations of the error process. Later on, Bollerslev (1986) and Taylor (1986) generalised the ARCH model to generate the GARCH model. There are several other methods to study the volatility persistence and spillover effects across financial series, but the ARCH/GARCH models seem to be the most popular ones. Furthermore, the EGARCH model proposed by Nelson (1991) and the TARCH model of Zokian (1994) and Glosten, Jagannathan and Rankle (1993) are used to investigate the presence of leverage effects. We briefly describe these models.

ARCH model: This model proposed by Engle (1982) suggests that the variance of the residuals at time t depends on the squared error terms from past periods. The three specifications of the ARCH model, i.e., the conditional mean equation, the conditional variance equation and the conditional error distribution are presented below.

[2] www.mcxindia.com

The mean equation of the ARCH model is:

$$Y_t = \alpha + \beta' X_t + u_t, \qquad u_t / \Omega_t \sim N(0, h_t), \tag{1}$$

where X_t is a k×1 vector of explanatory variables and β is a k×1 vector of coefficients. The error term u_t is supposed to be i.i.d. with $u_t|\Omega_t \sim N(0, h_t)$, where Ω_t is the information set. The variance equation of the ARCH(P) model is:

$$h_t = \gamma_0 + \sum_{j=1}^{P} \gamma_j u_{t-j}^2 . \tag{2}$$

Thus, the squared errors follow a heteroskedastic ARMA(1,1) process. The AR root which governs the persistence of volatility shocks is the sum of the parameters of the variance equation. Generally when this root is very close to 1 the shocks die out rather slowly.

GARCH (p, q) model: The mean equation is the same as in the ARCH model, i.e., (1). The variance equation of the GARCH (p, q) is given hereunder:

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 , \tag{3}$$

where h_t is the conditional variance that depends on its own lagged values and lagged squared errors.

In the empirical application carried out in the following section the orders of the ARCH and GARCH models are selected on the basis of the AIC, the SIC and the Hannan-Quinn (HQ) criteria. After the selection of the optimal model we need to check some assumptions about the distributional pattern of the model. The diagnostics tested the following hypotheses:

i) The model should be homoscedastic i.e. it should be free from ARCH effects – LM tests;

ii) it should be free from autocorrelation – Ljung Box – Q statistics, and

iii) it should follow a Normal distribution - Jarque-Bera statistic.

GARCH models enforce the symmetric response of volatility to positive and negative shocks. This is due to the fact that the conditional variance in the GARCH equation is dependent upon the magnitude of the lagged square residuals but not on their signs. However, it has been argued that a negative shock is likely to cause a more volatile return series than when compared to an equivalent shock of good news. In the case of asset returns, such asymmetries are attributed to leverage effects. The presence of such effects is also examined in the paper. In order to study the impact of good news or bad news on the volatility of the metal series we use two asymmetric variants of the GARCH models, i.e. the TARCH and the EGARCH models.

Threshold GARCH (TGARCH) model: TGARCH coefficients evaluate the asymmetries between the effects of good and bad news. The variance equation of the T-GARCH model is specified as:

$$\text{TARCH}(p,q): \quad h_t = \alpha + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2 + \sum_{j=1}^{q} \phi_j u_{t-j}^2 D_{t-j} \quad (4)$$

In this model, we introduce a dummy variable D_{t-j}, adopting the values 0 and 1. If $u_{t-j} < 0$, D_{t-j} takes the value 1, otherwise D_{t-j} is equal to 0. So, good news and bad news have a different volatility impact on the series. The degree of good news impact is measured by γ, while the degree of bad news impact is measured by $\gamma + \phi$. If $\phi > 0$, it is concluded that there is asymmetry, while if $\phi = 0$, the impact of the news is symmetric.

Exponential GARCH (EGARCH) model: Asymmetry of different types of shocks is of no use until we are in the position to determine the dominating shocks and their impact on the series. It is therefore essential to find which one of the effects dominates in the market. The Exponential GARCH model ensures that the conditional variance is non-negative. It captures the magnitude and sign effects of shocks and thus captures the effect of asymmetric returns on the conditional volatility. The variance equation of the EGARCH model is:

$$\text{EGARCH(p,q)}: \quad \log(h_t) = \alpha + \sum_{j=1}^{q} \gamma_j \left| \left(\frac{u_{t-j}}{(h_{t-j})^{1/2}} \right) \right| + \sum_{j=1}^{w} \phi_j \left(\frac{u_{t-j}}{(h_{t-j})^{1/2}} \right) + \sum_{i=1}^{p} \delta_i h_{t-i} \quad (5)$$

In the above equation, if the signs of γ_j and ϕ_j are both positive, it means that the impact of bad and good news is the same, i.e., it is symmetric. If the sign of γ_j is positive and that of ϕ_j is negative, this means that the impact of bad news is greater in increasing the volatility as compared to the good news of the commodity series, i.e., it is asymmetric.

In the final part of the manuscript we look at the persistence of the series by using a different approach based on the concept of fractional integration. The idea is that the series (either the level or the volatility, measured in terms of the squared returns) may be highly persistent, requiring a number of differences to get a I(0) stationarity process, and this number of differences may not necessarily be an integer value but a fractional one. We can consider the following model,

$$y_t = \beta^T z_t + x_t, \quad t = 1, 2, \ldots, \qquad (6)$$

where y_t is the observed series, z_t is a (kx1) vector of deterministic terms that may be an intercept (z_t = 1) or an intercept with a linear trend (i.e., $z_t = (1,t)^T$), and x_t are the regression errors, which follow an I(d) model of the form:

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots \qquad (7)$$

where L is the lag operator, d can be any real number, and u_t is supposed to be I(0), including thus potentially ARMA structures. Note that the polynomial $(1–L)^d$ in equation (7) can be expressed in terms of its binomial expansion, such that, for all real d:

$$(1 - L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d(d-1)}{2} L^2 - \ldots,$$

and thus:

$$(1 - L)^d x_t = x_t - d\,x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \ldots .$$

In this context, d plays a crucial role, since it will be an indicator of the degree of dependence of the series. Thus, the higher the value of d is, the higher the level of association will be between the observations. Processes with $d > 0$ in (7) display the property of "long memory", so-named because of the strong degree of association between observations far distant in time. These processes are related with the ARCH/GARCH models in the sense that fractional integration produces nonstationarity as long as d is equal to or higher than 0.5 and this is due to the fact that the variance of the partial sums increases in magnitude with d so as to be non-summable. Thus, both (fractional integration and ARCH) deal with the second moment properties of the series under examination. Moreover, using fractional integration in the squared (or absolute) returns appears as an alternative approach when modelling the volatility process. The methodology used in the paper to estimate the fractional differencing parameter is based on the Whittle function (an approximation to the likelihood function) in the frequency domain (Dahlhaus, 1989).

3. Empirical results

Table 1 reports summary statistics for the daily return series of both spot and futures for aluminium, copper, lead, nickel, zinc and tin. It is observed that the daily mean returns and the standard deviations for all spot series are found to be greater than their corresponding futures series. The daily spot return of lead, followed by nickel and zinc, has the highest standard deviation, while aluminium has the least deviation in the daily spot return. Aluminium has a daily mean return of 0.04% and a standard deviation of 1.46% for the spot series compared with 0.02% and 0.127% for its corresponding futures series respectively. Both tin and zinc have approximately the same mean return (0.07%), but zinc has a higher standard deviation (2.19%) than tin (1.76%). The futures return series distributions of copper, aluminium and tin are found to be positively skewed while lead, nickel and zinc futures return series distributions are negatively skewed. Kurtosis is the highest (15.420) for lead spot return and the least (4.81) for zinc futures return. On the other hand, there is strong evidence from the histograms and the Jarque-Bera statistics that the returns are not normally distributed.

<Insert Table 1 & Figures 1 and 2>

Figure 1 displays the plots of the six non-ferrous metal series. Here we see that all log price series of the non-ferrous metal move in a very similar way. Furthermore, the plot of each return series shows that heteroscedasticity is an inherent part of all the non-ferrous metal series. The daily return series (displayed in Figure 2) exhibit a great deal of volatility. Across all the sample metals, the largest shocks to the return process took place towards the end of 2011 coinciding with the turmoil in European financial markets. Also, in general, the volatility in silver and copper appear to be more pronounced than in the zinc and lead return series.

To support the descriptive statistics and graphical tests of persistence, a formal statistical test is attempted. Initially 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,

$$Y_t = C + \beta Y_{t-1} + \varepsilon_t , \qquad t = 1, 2, \ldots . \tag{8}$$

The significance of this equation was then established and the error term of each mean equation was converted into the particular residual (ε_t) metal series. Before running the ARCH models, we conducted several serial correlation and heteroscadasticity tests. To examine the presence of serial correlation, we conducted the Breusch-Godfrey Serial Correlation LM Test. Furthermore, we conducted ARCH-LM tests that examine the presence of homoscedasticity across the series. The test results confirmed that all series display heteroscedasticity in the variance distribution.

The residual generated series is used as the input to build the ARCH and GARCH models. Table 1 reveals through the Jarque-Bera statistic that the residuals do not follow a Normal distribution. The Lagrange Multiplier tests indicate that there are no ARCH effects, and the assumption of serial correlation is rejected through the Ljung Box Q –statistic. Finally, all the metal series satisfy the assumption in their respective GARCH models for the Normal distribution. Based on this, we could conclude that symmetry is a characteristic when measuring the volatility of the metal series. However, other more general GARCH(p,q) specifications should also be considered**.**

<Insert Tables 2 and 3>

Following standard approaches, it is stated that the sum of the ARCH and GARCH coefficients in the variance equation determines the degree of volatility persistence in the selected models. Table 3 reveals that for lead spot series, volatility persistence is detected under a Student-t-distribution, while for all the other series a Normal (Gaussian) one is used for the conditional distribution of the error term. Moreover, except for lead spot and zinc futures, the sum of the coefficients is smaller than 1, being especially close to 1 in the cases of aluminium, lead, tin and zinc.

There might be some reasons to explain the differences in the volatility of the non-ferrous metal series. The speculative activities for short term gains centred on commodities such as lead spot and zinc futures have been the main source of investment in the commodity market. However, there is a need for in-depth studies to discover the reasons for the different degrees of volatility persistence observed in the data.

<Insert Table 4 here>

The results of the TGARCH model are presented in Table 4. They clearly reveal asymmetry between good news and bad news for all the futures series except lead and nickel. That means that except for the lead and nickel all other futures metal series are experiencing a far greater level of volatility due to the negative news shock when compared with a positive news shock of the same magnitude. On the contrary, all the spot price series except aluminium, nickel and zinc are asymmetric. Nevertheless, the results indicate no significant asymmetric behaviour in the nickel spot and the futures series at conventional statistical significance levels. If one chooses, for example, to express the asymmetric behaviour in the nickel spot and futures series, the result ascertains that the probability of committing Type I errors are about 95 percent and 32 percent respectively. Similarly for the aluminium spot series, lead futures and zinc spot series the probability that the series possess asymmetric behaviour is about 70 percent, 13 percent and 9 percent of Type I errors respectively. For the rest of the series the probability of Type I error is below 5 percent.

Furthermore, an attempt has been made to examine the extent of the impact of good news and bad news on the selected series. From the estimated T-GARCH model it is clear that good news has an impact of 0.0112 (the value of the coefficients of the ARCH component) and bad news has an impact of -0.0021 (the differential value of the coefficient of the ARCH component and the threshold component) on aluminium futures series but such an impact is statistically insignificant for the aluminium spot series. However, different impacts of bad news (-0.0852 and -0.0755) and good news (0.0013 and 0.0061) are observed for the copper series irrespective of the spot and futures. Finally, among all the metals, the tin spot is experiencing the greatest level of volatility asymmetry.

<Insert Table 5 about here>

The EGARCH estimates presented in Table 5 reveal that all the series except nickel and zinc futures are exposed to leverage effects. That means, negative news has a far greater impact on the volatility of most of the metal series compared to the positive news of the same magnitude. Thus, negative news has a dominating effect over positive news in the non-ferrous metal price series. However, as the EGARCH model assumes the second variance term is non-negative (absolute) this enables the sign and the magnitude to have separate effects on the volatility, thus showing the leverage effects more prominently when compared to the TGARCH model.

<Insert Table 6 about here>

Once the TARCH and EGARCH models have been run on all the non-ferrous metals series, the best model is selected on the basis of the AIC and SIC. (See Table 6). For all series, except tin spot, only one model is found to be significant at conventional statistical levels.

Across Tables 7 – 10 we employ a model of the form given by the equations (6) and (7) with $z_t = (1,t)^T$, $t \geq 1$, $(0, 0)^T$ otherwise, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (1-L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{9}$$

assuming first that the disturbance term u_t is a white noise process, and then considering the possibility of a weakly autocorrelated process. For the latter we use a non-parametric approach due to Bloomfield (1973) that approximates ARMA structures with a reduced number of parameters.

Tables 7 and 8 display the estimated values of d respectively for the two cases of white noise and autocorrelated disturbances on the log-prices series. We consider the three standard cases examined in the literature, i.e., the case of no regressors (i.e., $\beta_0 = \beta_1 = 0$ *a priori* in equation (9)), an intercept (β_0 unknown, and $\beta_1 = 0$ *a priori*), and an intercept with a linear time trend (β_0 and β_1 unknown). Together with the estimate of the fractional differencing parameter, we also present their corresponding 95% confidence bands.

<Insert Tables 7 and 8 about here>

We see in these two tables that most of the estimated values of d are within the unit root interval, suggesting that the I(1) hypothesis cannot be rejected in the spot and futures series. Evidence of mean reversion ($d < 1$) is only obtained in some cases with white noise disturbances when including deterministic terms; however, in the most realistic case of autocorrelated errors, the unit root null hypothesis cannot be rejected in any single case. This is consistent with the results obtained in many other markets across the world (Lo, 1991; Hiemstra and Jones, 1997; etc.)

<Insert Tables 9 and 10 about here>

Tables 9 and 10 are similar to Tables 7 and 8 but focused on the squared returns, which are used as proxies for the volatility. We observe that practically all the estimated values of d are above 0 implying long memory and corroborating thus the high degree of dependence in the volatility processes obtained in our previous results. Again, this is consistent with the results reported in other markets across the world (Ding, Granger and Engle, 1993; Bollerslev and Wright, 2000; etc.).

4. Conclusion

The main objective of this research was to apply several time series volatility models on various Indian non-ferrous metals. Data for six different non-ferrous metals were collected from the MCX website.

We can summarize the main results as follows:

(i) the symmetric volatility analysis using a GARCH model shows that all the non-ferrous metal series exhibit a high degree of volatility persistence. This result was also corroborated by means of long memory and fractionally integrated techniques, obtaining estimates of the differencing parameter that were significantly above 0 in all the squared return series. The GARCH (1, 1) model was selected for aluminium spot and futures, copper futures, copper spot, lead futures, nickel futures and tin spot series, while a GARCH (1, 2) was the best fitted model for nickel spot, tin futures and zinc spot.

(ii) testing the asymmetric volatility by using TARCH and EGARCH models, out of the twelve non-ferrous metals, TGARCH captures asymmetric effects in only seven series and EGARCH captures a leverage effect in ten.

The results of this study can be used to predict the volatility of prices in non-ferrous metals by the Indian manufacturing sector. This research can be further extended to understand the short term volatility using high frequency data, which can be of interest to traders investing in the commodities market.

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Tables and Figures

Table 1: Descriptive statistics of daily spot and futures return series for non-ferrous metals

	Aluminium		Copper		Lead		Nickle		Tin		Zinc	
Statistic	Spot	Future	Spot	Future	Spot	Future	Spot	Future	Spot	Future	Spot	Future
Mean	0.0004	0.0002	0.0010	0.0009	0.0008	0.0006	0.0006	0.0004	0.0007	0.0006	0.0007	0.0005
Std. Dev.	0.0146	0.0127	0.0184	0.0152	0.0250	0.0195	0.0229	0.0189	0.0176	0.0169	0.0219	0.0169
Skewness	-0.106	0.0055	0.1858	0.1139	-0.6658	-0.304	-0.3533	-0.290	0.2576	0.5571	-0.7333	-0.123
Kurtosis	5.7038	5.6787	5.5392	5.0974	15.420	6.2876	9.4717	5.7390	7.3929	12.100	15.403	4.8134
Jarque-Bera	322.43 (0.000)	314.23 (0.000)	288.67 (0.000)	194.90 (0.000)	6839.3 (0.000)	489.53 (0.000)	1857.7 (0.000)	343.35 (0.000)	857.51 (0.000)	3681.3 (0.000)	6837.7 (0.000)	146.66 (0.000)
Sum Sq. Dev.	0.2243	0.1703	0.3567	0.2433	0.6566	0.4009	0.5497	0.3752	0.3253	0.3003	0.5039	0.2991

Note: Figures in parentheses indicate p-values corresponding to Jarque-Bera statistics.

Table 2: Symmetric GARCH model selection

Series	Model Name	AIC	SBC	HQIC
Aluminium Futures	GARCH 1,1*	-5.97599	-5.95276	-5.96719
Aluminium Spot	GARCH 1,1*	-5.71093	-5.68770	-5.70213
	GARCH 1,2	-5.75395	-5.72607	-5.74339
Copper Futures	GARCH 1,1*	-5.67286	-5.64963	-5.66406
Copper Spot	GARCH 1,1*	-5.31494	-5.29171	-5.30614
Lead Futures	GARCH 1,1*	-5.13692	-5.11368	-5.12812
Lead Spot	GARCH 1,1*	-5.35038	-5.52715	-5.44158
Nickel Futures	GARCH 1,1*	-5.23647	-5.21324	-5.22767
Nickel Spot	GARCH 1,1	-4.94620	-4.92296	-4.93739
	GARCH 1,2*	-4.95484	-4.92697	-4.94428
Tin Futures	GARCH 1,1	-5.45038	-5.42715	-5.44158
	GARCH 1,2*	-5.53571	-5.50783	-5.52515
Tin Spot	GARCH 1,1*	-5.35058	-5.32735	-5.34178
	GARCH 1,2	-5.35076	-5.32288	-5.34020
Zinc Futures	GARCH 1,1*	-5.42403	-5.40080	-5.41523
	GARCH 1,2	-5.44328	-5.41540	-5.43272
Zinc Spot	GARCH 1,1	-5.07315	-5.04992	-5.06435
	GARCH 1,2*	-5.08700	-5.05912	-5.07644

Note: * indicates the optimal model for the corresponding series based on selection criterion

Table 3: Optimized GARCH estimates for volatility persistence

Metal	Series	Model Name	RESID(-1)^2	RESID(-2)^2	GARCH(-1)	Volatility persistence Σ(γj+ δi)
Aluminium	Futures	GARCH 1,1	-0.008	….	1.004	0.996
	Spot	GARCH 1,1	0.097	-0.105	1.006	0.998
Copper	Futures	GARCH 1,1	0.052	….	0.925	0.977
	Spot	GARCH 1,1	0.046	…	0.934	0.980
Lead	Futures	GARCH 1,1	0.052	….	0.94	0.992
	Spot (t-Dist)	GARCH 1,1	0.718		0.384	1.027
Nickel	Futures	GARCH 1,1	0.044	…	0.933	0.977
	Spot	GARCH 1,2	0.174	-0.115	0.921	0.981
Tin	Futures	GARCH 1,2	0.278	-0.266	0.986	0.998
	Spot	GARCH 1,1	0.108	…	0.778	0.886
Zinc	Futures	GARCH 1,2	0.09	-0.092	1.003	1.001
	Spot	GARCH 1,2	0.219	-0.149	0.926	0.996

Table 4: Optimized TGARCH estimates for volatility asymmetry examination

Model Name	RESID(-1)^2*(RESID(-1)<0)	Good News	Bad News	Decision
Aluminium Futures GARCH (1,1)*	0.0133 (0.000)	0.0112	-0.0021	Asymmetry
Aluminium Spot GARCH (1,1)	0.0021 (0.6997)	0.2218	0.2198	No significant Asymmetry
Copper Futures GARCH (1,1) *	0.0865 (0.000)	0.0013	-0.0852	Asymmetry
Copper Spot GARCH (1,1) *	0.0816 (0.000)	0.0061	-0.0755	Asymmetry
Lead Futures GARCH (1,1)	0.0166 (0.1272)	0.0446	0.028	No significant Asymmetry
Lead Spot GARCH (1,1) *	0.0009 (0.0014)	0.0031	0.00214	Asymmetry
Nickel Futures GARCH (1,1)	-0.0009 (0.9531)	0.0445	0.0436	No significant Asymmetry
Nickel Spot GARCH (1,2)	-0.0171 (0.3186)	0.2902	0.2732	No significant Asymmetry
Tin Futures GARCH (1,2) *	0.0184 (0.000)	0.7577	0.7393	Asymmetry
Tin Spot GARCH (1,1) *	0.1173 (0.000)	0.0304	-0.0869	Asymmetry
Zinc Futures GARCH (1,1) *	0.0122 (0.001)	0.1147	0.1027	Asymmetry
Zinc Spot GARCH (1,2)	-0.0151 (0.089)	0.376	0.3609	No significant Asymmetry

Note: Figures in parentheses indicate p-values and * indicates significant at 5% or less probability of Type I error.

Table 5: Optimized EGARCH estimates for volatility asymmetry examination

EGARCH (1,2) $=Ln(h_t) =- \alpha_0 + \gamma_1(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + \gamma_2(\varepsilon_{t-2}/\sqrt{h_{t-1}}) + \phi_1(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + \delta \ln(h_{t-1})$				
Metal series Selected Model	decline in ε_{t-1}	increase in ε_{t-1}	Dominating	Estimates of the Optimized EGARCH model
Aluminium Futures GARCH (1,1)	-0.003	-0.025	-ve	$Ln(h_t) =- 0.018 - 0.011(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.014(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.997 \ln(h_{t-1})$ (0.000) (0.000) (0.001) (0.000)
Aluminium Spot GARCH (1,1)	-0.503	-0.003	-ve	$Ln(h_t) = 0.006 - 0.243(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.253(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 1.000 \ln(h_{t-1})$ (0.325) (0.000) (0.000) (0.000)
Copper Futures GARCH (1,1)	-0.176	0.006	-ve	$Ln(h_t) =- 0.262 + 0.091(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.085(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.978 \ln(h_{t-1})$ (0.000) (0.000) (0.000) (0.000)
Copper Spot GARCH (1,1)	-0.155	-0.031	-ve	$Ln(h_t) =- 0.216 + 0.062(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.093(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.979 \ln(h_{t-1})$ (0.000) (0.000) (0.000) (0.000)
Lead Futures GARCH (1,1)	-0.137	0.093	-ve	$Ln(h_t) =- 0.170 + 0.115(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.022(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.989 \ln(h_{t-1})$ (0.000) (0.000) (0.015) (0.000)
Lead Spot GARCH (1,1)	-0.099	-0.031	-ve	$Ln(h_t) =- 0.115 + 0.034(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.065(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.998 \ln(h_{t-1})$ (0.000) (0.000) (0.000) (0.000)
Nickel Futures GARCH (1,1)	-0.104	0.096	-ve (NS)	$Ln(h_t) =- 0.241 + 0.100(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.004(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.979 \ln(h_{t-1})$ (0.000) (0.000) (0.746) (0.000)
Nickel Spot GARCH (1,2)	-0.505	0.191	-ve	$Ln(h_t) =- 0.276 + 0.317(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.157(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.031(\varepsilon_{t-2}/\sqrt{h_{t-1}}) + 0.980 \ln(h_{t-}$ (0.000) (0.000) (0.000) (0.041) (0.000)
Tin Futures GARCH (1,2)	-0.711	-0.025	-ve	$Ln(h_t) =- 0.007 + 0.364(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.368(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.021(\varepsilon_{t-2}/\sqrt{h_{t-1}}) + 0.999 \ln(h_{t-}$ (0.000) (0.000) (0.000) (0.000) (0.000)
Tin Spot GARCH (1,1)	-0.248	0.078	-ve	$Ln(h_t) =- 1.114 + 0.163(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.085(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.879 \ln(h_{t-1})$ (0.000) (0.000) (0.000) (0.000)
Zinc Futures GARCH (1,1)	-0.189	0.103	-ve NS	$Ln(h_t) =- 0.216 + 0.177(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.031(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + 0.986 \ln(h_{t-1})$ (0.000) (0.000) (0.018) (0.000)
Zinc Spot GARCH (1,2)	-0.534	0.23	-ve	$Ln(h_t) =- 0.228 + 0.345(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.152(\varepsilon_{t-1}/\sqrt{h_{t-1}}) - 0.0037(\varepsilon_{t-2}/\sqrt{h_{t-1}}) + 0.989 \ln(h_{t-}$ (0.000) (0.000) (0.000) (0.003)

Note: Figures in parentheses indicate the level of significance for the corresponding coefficients

Table 6: Asymmetric model comparison

Series	Model Name	AIC	SIC	HQIC
Aluminium Futures	TARCH 1,1	-5.96936	-5.94148	-5.9588
Aluminium Spot	TARCH 1,2	-5.73755	-5.70502	-5.72523
Copper Futures	EGARCH 1,1	-5.69365	-5.66577	-5.68309
Copper Spot	EGARCH 1,1	-5.34177	-5.31389	-5.33121
Lead Futures	EGARCH 1,1	-5.14543	-5.11755	-5.13487
Lead spot	EGARCH 1,1	-5.35038	-5.52715	-5.44158
Nickel Futures	EGARCH 1,1	-5.23376	-5.20588	-5.2232
Nickel Spot	EGARCH 1,2	-4.94175	-4.90922	-4.92943
Tin Futures	TARCH 1,2	-5.58248	-5.54996	-5.57016
Tin Spot	TARCH 1,1	-5.3601	-5.33222	-5.34954
	EGARCH 1,1	-5.35105	-5.32317	-5.34049
Zinc Futures	TARCH 1,2	-5.43541	-5.40289	-5.42309
Zinc Spot	EGARCH 1,2	-5.06931	-5.03679	-5.05699

Table 7: Estimates of d and 95% confidence intervals with white noise disturbances

	Spot series			Future series		
	No regressors	An intercept	A linear trend	No regressors	An intercept	A linear trend
Aluminium	0.99 (0.86, 1.04)	0.90 (0.87, 0.93)	0.90 (0.87, 0.93)	0.99 (0.96, 1.04)	0.99 (0.95, 1.03)	0.99 (0.95, 1.03)
Cupper	1.00 (0.96, 1.05)	0.88 (0.85, 0.93)	0.89 (0.86, 0.93)	1.00 (0.96, 1.05)	0.98 (0.94, 1.02)	0.98 (0.94, 1.02)
Lead	1.01 (0.97, 1.05)	0.90 (0.87, 0.93)	0.90 (0.87, 0.93)	1.01 (0.97, 1.05)	1.02 (0.97, 1.07)	1.02 (0.97, 1.07)
Nickle	1.01 (0.97, 1.05)	0.92 (0.88, 0.96)	0.93 (0.88, 0.96)	1.00 (0.96, 1.05)	1.01 (0.97, 1.06)	1.01 (0.97, 1.06)
Tin	1.00 (0.96, 1.06)	0.98 (0.94, 1.03)	0.98 (0.94, 1.03)	1.00 (0.96, 1.04)	0.95 (0.92, 0.99)	0.95 (0.92, 0.99)
Zinc	1.01 (0.97, 1.05)	0.87 (0.83, 0.91)	0.87 (0.84, 0.91)	1.00 (0.96, 1.05)	1.00 (0.96, 1.05)	1.00 (0.96, 1.05)

In bold the 95% confidence intervals of the estimated values of d.

Table 8: Estimates of d and 95% confidence intervals with autocorrelated disturbances

	Spot series			Future series		
	No regressors	An intercept	A linear trend	No regressors	An intercept	A linear trend
Aluminium	0.98 (1.02, 1.06)	0.99 (0.93, 1.09)	0.99 (0.93, 1.09)	0.98 (0.92, 1.07)	0.99 (0.92, 1.07)	0.99 (0.92, 1.07)
Cupper	1.01 (0.94, 1.06)	0.96 (0.88, 1.04)	0.96 (0.90, 1.04)	0.99 (0.93, 1.08)	0.99 (0.92, 1.09)	0.99 (0.93, 1.08)
Lead	1.01 (0.93, 1.06)	0.93 (0.85, 1.02)	0.93 (0.85, 1.02)	0.99 (0.93, 1.07)	0.99 (0.91, 1.07)	0.99 (0.91, 1.07)
Nickle	1.01 (0.93, 1.06)	0.93 (0.87, 1.01)	0.93 (0.87, 1.01)	0.98 (0.92, 1.06)	1.00 (0.92, 1.08)	0.99 (0.92, 1.08)
Tin	0.99 (0.94, 1.08)	0.99 (0.93, 1.07)	0.99 (0.93, 1.07)	1.00 (0.93, 1.08)	0.98 (0.92, 1.04)	0.98 (0.92, 1.04)
Zinc	1.00 (0.93, 1.07)	0.96 (0.89, 1.03)	0.96 (0.89, 1.03)	0.99 (0.93, 1.07)	0.96 (0.89, 1.04)	0.96 (0.90, 1.06)

In bold the 95% confidence intervals of the estimated values of d.

Table 9: Estimates of d and 95% confidence intervals with white noise disturbances

	Spot series (squared returns)			Futures series (squared returns)		
	No regressors	An intercept	A linear trend	No regressors	An intercept	A linear trend
Aluminium	0.19 (0.15, 0.25)	0.18 (0.13, 0.23)	0.17 (0.11, 0.21)	0.08 (0.05, 0.11)	0.06 (0.04, 0.10)	0.00 (-0.04, 0.05)
Cupper	0.16 (0.12, 0.19)	0.14 (0.11, 0.17)	0.12 (0.09, 0.15)	0.16 (0.12, 0.19)	0.14 (0.11, 0.17)	0.12 (0.09, 0.16)
Lead	0.21 (0.16, 0.19)	0.21 (0.16, 0.27)	0.21 (0.16, 0.27)	0.08 (0.05, 0.12)	0.07 (0.04, 0.11)	0.04 (-0.01, 0.08)
Nickle	0.18 (0.14, 0.21)	0.17 (0.13, 0.21)	0.17 (0.13, 0.21)	0.17 (0.14, 0.21)	0.15 (0.12, 0.19)	0.14 (0.10, 0.18)
Tin	0.10 (0.06, 0.14)	0.09 (0.06, 0.13)	0.09 (0.06, 0.13)	0.09 (0.06, 0.13)	0.08 (0.05, 0.12)	0.05 (0.00, 0.10)
Zinc	0.20 (0.15, 0.25)	0.20 (0.15, 0.25)	0.20 (0.15, 0.25)	0.10 (0.07, 0.14)	0.09 (0.06, 0.12)	0.03 (-0.02, 0.07)

In bold the 95% confidence intervals of the estimated values of d.

Table 10: Estimates of d and 95% confidence intervals with autocorrelated disturbances

	Spot series (squared returns)			Futures series (squared returns)		
	No regressors	An intercept	A linear trend	No regressors	An intercept	A linear trend
Aluminium	0.10 (0.04, 0.15)	0.07 (0.03, 0.13)	0.02 (0.00, 0.09)	0.14 (0.10, 0.20)	0.11 (0.07, 0.16)	0.03 (-0.04, 0.10)
Cupper	0.22 (0.17, 0.27)	0.18 (0.14, 0.23)	0.17 (0.12, 0.22)	0.22 (0.18, 0.28)	0.19 (0.14, 0.24)	0.17 (0.12, 0.23)
Lead	0.04 (0.00, 0.10)	0.04 (0.00, 0.10)	0.04 (0.00, 0.10)	0.16 (0.11, 0.23)	0.14 (0.09, 0.19)	0.09 (0.04, 0.17)
Nickle	0.16 (0.10, 0.23)	0.14 (0.10, 0.19)	0.14 (0.10, 0.20)	0.21 (0.16, 0.27)	0.17 (0.11, 0.22)	0.15 (0.10, 0.22)
Tin	0.21 (0.15, 0.28)	0.19 (0.13, 0.26)	0.21 (0.13, 0.29)	0.12 (0.06, 0.17)	0.10 (0.05, 0.16)	0.02 (-0.07, 0.11)
Zinc	0.06 (0.00, 0.11)	0.06 (0.00, 0.11)	0.06 (0.00, 0.11)	0.21 (0.16, 0.28)	0.17 (0.13, 0.23)	0.08 (0.02, 0.17)

In bold the 95% confidence intervals of the estimated values of d.

Figure 1: Graph of all Metal series (Log Values) of the data used for analysis

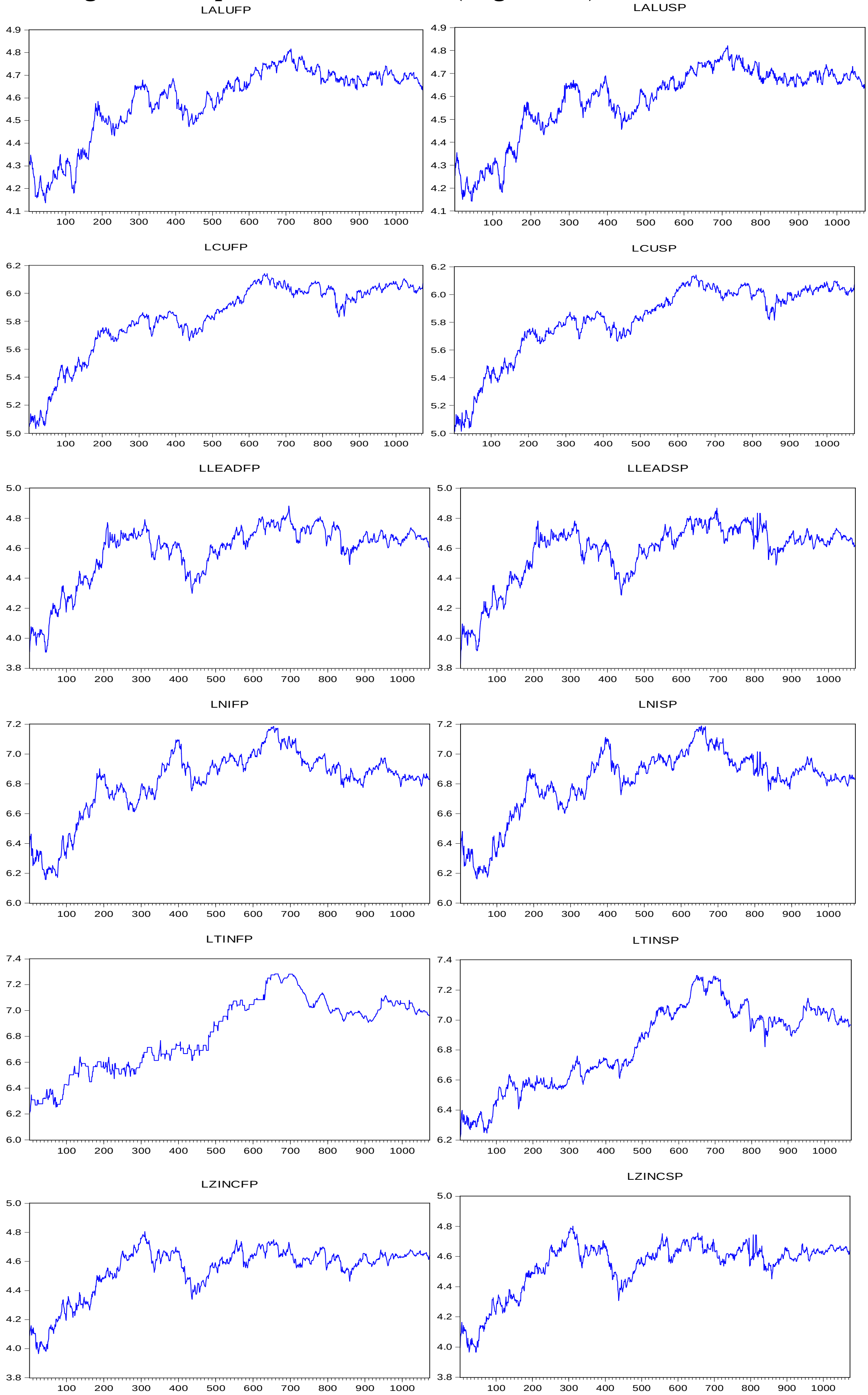

Figure 2: plot of daily spot and futures return distribution